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A Survey on Optimized CT Scan Analysis for Lung Cancer Detection Using Convolutional Neural Networks

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Abstract: Lung cancer is a major cause of death around the world, so finding it early can help people get better treatment and have a better chance of surviving. Computer-Aided Diagnosis (CAD) systems have emerged as valuable tools in medical imaging, assisting in the early identification of lung tumors using Computed Tomography (CT) scans. However, accurate detection remains a challenge due to the irregular shape, varying location, and low contrast of tumors in CT images. To know these challenges the study presents a novel tumor and nodule segmentation model based on a Convolutional Neural Network (CNN). The model integrates preprocessing techniques such as image filtering for enhancement and postprocessing methods utilizing morphological operations for precise segmentation. Additionally, an active contour algorithm is employed to refine tumor boundary detection. We tested the model with sensitivity analysis on a benchmark dataset.
Keyword: Lung Cancer Detection, Computer-Aided Diagnosis (CAD), CT Scan Analysis, CNN, Tumor Segmentation, Nodule Detection

I. INTRODUCTION

Cancer is a major health problem around the world concern, among lung cancer is among the most prevalent and deadliest types. In the U.S., it accounts for over 27% of all cancer-related deaths, with around 350 daily fatalities. Early detection dramatically improves survival rates, with up to 87% survival for early-stage diagnoses compared to just 19% in later stages. Doctors commonly use CT scans to look for diseases or injuries and lung cancer detection due to its high accuracy, but challenges like low contrast, complex lung anatomy, and irregular tumor shapes hinder precise diagnosis. Computer-Aided Diagnosis (CAD) systems, especially those powered by machine learning and image processing is helpful in enhancing detection speed and accuracy. These systems helps to reduce the human error and medical costs, yet manual analysis remains slow and error-prone. Detecting small nodules, an early indicator of lung cancer, is particularly difficult due to their similarity to other lung structures like blood vessels. Therefore, advanced imaging and segmentation algorithms are essential for reliable early diagnosis. Nodules, which can indicate early-stage lung cancer, are tiny and hard to detect. Identifying them requires high-quality imaging and advanced image processing algorithms. Differentiating nodules from similar structures like blood vessels is often difficult, necessitating enhanced detection.

II. LITERATURE SURVEY

1) Lung Cancer Detecting Conditions Through Deep Learning

A study published in 2024 proposed the ML pipeline for identifying lung cancer through CT images, combining classical method in digital image analysis techniques with classical machine learning algorithms. We collected data from the Lung Image Database Consortium (LIDC) for this study. Preprocessing the techniques like image resizing, normalization, and noise filtering were applied to enhance the quality of the CT scans. Following this, To separate lung nodules, we used well-known image processing techniques like thresholding, region growing, and morphological operations.

However, the study is not without its limitations. One significant drawback is its reliance using only one dataset can affect the generalizability of the results across diverse populations and imaging protocols. Additionally, despite its title suggesting a deep learning approach, this study does not make use of any end-to-end including models like CNNs, which are currently considered state-of-the-art for image-based medical diagnostics. Furthermore, the use of manually engineered features rather than learned representations limits the scalability and adaptability of the system. The absence of cross-validation techniques or evaluation on external datasets also poses a risk of overfitting, suggesting that the reported performance metrics might not hold when deployed in real-world clinical environments.

2) Multi-Task Deep Using Margin Ranking Loss in a Model for Lung Nodule Detection

In a 2019 study, researchers introduced MTMR-Net, a joint learning deep network aimed at enhancing lung nodule analysis from CT images. The architecture is designed to perform two tasks simultaneously: classification of nodules as cancerous or non-cancerous, and regression of multiple attribute scores such as margin, lobulation, and texture. One of the key innovations of the model lies in its use of a Siamese network architecture combined with margin ranking loss, which is particularly effective in improving discrimination in borderline or ambiguous cases. The backbone of the system is based on a ResNet architecture, where the attribute scores are incorporated into the classification task through feature concatenation. This design fosters a cause-and-effect learning structure in which the semantic attributes directly inform the final diagnosis, thereby improving both performance and clinical relevance.

Despite its strengths, the study acknowledges several limitations. Although the integration of attribute information enhances interpretability to some extent, the model still functions as a deep neural network, and its decision-making process remains largely opaque to clinicians. Another limitation is the use of 2D CT image slices rather than full 3D volumetric data, which may restrict the model's ability to fully capture spatial context—an important factor in nodule assessment. Additionally, the reliance on a fixed set of eight predefined attributes could constrain the model’s flexibility and focus, particularly if some attributes contribute less significantly than others. Finally, while the inclusion of margin ranking loss improves performance on marginal cases, the model still struggles with highly ambiguous nodules, which continue to challenge automated classification systems.

3) A 3D Probabilistic Deep Learning System for Detection and Diagnosis of Lung Cancer Using Low-Dose CT Scans

The 2020 study presents a fully integrated, end-to-end diagnostic system that leverages 3D CNNs to perform both nodule detection (Computer-Aided Detection, or CADe) and malignancy diagnosis (Computer-Aided Diagnosis, or CADx) using chest CT scans. The workflow begins with preprocessing of 3D CT data, which is then passed through a V-Net–based segmentation network to identify potential lung nodule candidates. These candidates are subsequently processed through two cascaded CNN models: the first performs risk ranking based on the likelihood of malignancy, while the second employs an attention-based multiple instance learning (MIL) framework to generate a patient-level cancer classification. A notable feature of the system is its incorporation of Bayesian model using MC dropout and vast ensembles, which allows the model to produce well-calibrated probabilistic outputs — an essential factor for increasing clinical trust in AI-based diagnostic tools. Despite its advanced architecture, the system has several important limitations. One major concern is the LUNA16 dataset's lack of annotations for large nodules, which are often indicative of malignancy; this deficiency could result in false negatives during the detection phase. Furthermore, the result of overall system is heavily dependent on its correctness of the CAD e component—if a malignant lesion is missed at this stage, the downstream CADx component has no fallback mechanism to recover, representing a significant vulnerability in the pipeline. While the model does incorporate uncertainty estimation techniques, omitting these components could lead to overconfident predictions, undermining reliability in clinical applications. Lastly, the system’s performance has only been validated on controlled public datasets, and its generalizability to real-world, heterogeneous clinical environments remains largely untested.

4) Multi-task Deep Learning with Margin Ranking Loss for Lung Nodules Analysis

In 2019, MTMR-Net was introduced as a joint learning deep network that jointly performs malignancy classification and semantic attribute regression for lung segments in thorax region’s CT scans. The model architecture is depend on a 50-layer Res Net and includes two parallel branches—one for binary classification (benign vs. malignant) and another for predicting eight clinically relevant attributes, such as texture, spiculation, and margin. To improve performance in ambiguous cases, the model integrates a Siamese network with a margin ranking loss, enabling comparative learning between nodules. These tasks are trained simultaneously using a combined loss function incorporates cross-entropy, mean squared error, and margin ranking loss. This multi-task learning approach not only boosts predictive accuracy but also contributes to interpretability by linking diagnostic decisions to specific semantic attributes. The system was trained and evaluated using 2D slices from the LIDC-IDRI dataset, with final predictions averaged across slices. Despite its strengths, MTMR-Net has several limitations. Processing CT scans as 2D slices risks losing important 3D spatial context, which could impact diagnostic precision. The exclusion of nodules with a malignancy score of 3—a category representing diagnostic uncertainty—limits the model’s robustness in real clinical environments where ambiguous findings are common. Furthermore, relying solely on the LIDC-IDRI dataset raises concerns about generalizability to other populations and imaging conditions. Lastly, the architecture's complexity, particularly the addition of Siamese and multi-branch components, increases computational demands, which can create difficulties in real-time or resource-constrained clinical deployment.

5) Lung cancer Detection using Deep Learning Techniques.

The 2024 study investigates the use of deep learning steps for lung cancer findings of low-dose computed tomography (LDCT) scans, which demonstrates strong capability in early cancer detection. Despite LDCT's clinical benefits, it comes with challenges such as overuse, cost concern ,and radiation exposure. To address these, the authors introduce a novel "split-method" combines deep learning, customary ML algorithms, and in-depth case inspection. This method uses standardizing LDCT images to reduce variability, followed by deep learning-based feature extraction. These features are later input into machine learning classifiers to separate between cancerous and non-cancerous lung segments. This system is evaluated using performance metrics such as accuracy, sensitivity, and specificity, highlighting the potential of the approach to improve diagnostic efficiency and reliability. However, several limitations affect the robustness and scalability of the proposed system. One major concern is data heterogeneity—differences in imaging techniques and equipment across hospitals can introduce inconsistencies in CT scans, impacting model performance. Additionally, the presence of artifacts such as motion blur or image noise may interfere with the model's ability to extract accurate features. The generalizability of the system is also limited, as its performance made grade when applied to populations or imaging protocols not well represented at the time of training data. Lastly, the computational demands of DL architectures remain a barrier to real-time clinical deployment, especially in resource-limited healthcare settings.

6) Segmentation and Classification of Lung Cancer Using Deep Learning Technique

In 2024, a study was investigated on feature separation and classification of lung cancer using histopathology images, applying deep learning models to analyse microscopic cellular patterns. The authors employed a U-Net architecture for precise segment of tumor regions within histological slides, followed by the application of three powerful convolutional neural network ResNe t-50, VGG 16, and EfficientNet-B5—for classifying the segmented regions. To enhance regions. To enhance overall accuracy and robustness, an ensemble model combining the outputs of these three classifiers was constructed. This approach allowed the model to better capture subtle morphological variations present in tissues samples, significantly improving prediction performance. Despite its strengths, this study is limited in a few key areas. The methodology is specifically tailored for the histopathological data and does not extend to radiological modalities like CT scans, limiting its applied to broader applicability to broader clinical workflows involving imaging diagnostics. Additionally, while ensemble methods often lead to higher accuracy, they also increase both training and inference times, making real-time deployment more challenging. The paper also lacks discussion on clinical validation or practical implementation in healthcare settings, leaving questions about its real-world utility and scalability unanswered.

7) Detection and Classification of Lung Cancer Using CNN and Google Net

The 2022 study explored the application of convolutional neural network (CNN), including GoogleNet—an advanced deep CNN architecture developed by Google—for finding and grouping of lung cancer using Computerised Tomography scan images. The designed model is used to classify between non-cancerous and cancerous lung tissues, achieving an impressive precision rate of 98%. The use of GoogleNet allowed for efficient feature extraction and deep hierarchical learning, which contributed to the model's high classification performance. This approach highlights the strength of modern CNN architectures in clinical image analysis is identified for early detection tasks where subtle visual distinctions are critical. However, the study leaves several important aspects unaddressed. While the reported precision is high, it remains unclear whether this system was examined based on a binary classification task or tested for more difficult tasks involving multiclass categorization (e.g., benign vs. malignant vs. non-cancerous). Additionally, the paper provides limited knowledge of its dataset used, including key factors like image numbers, class balance, or patient demographics. Furthermore, essential details on preprocessing techniques or data augmentation strategies are missing, which affects the reproducibility and scalability of the results. These omissions limit the transparency and practical applicability in real-world clinical environments.

8) Automatic Detection and Classification of Lung Cancer CT Scans Based on Deep Learning and Ebola Optimization Search Algorithm

The 2023 study introduced a mixed DL approaches that combines a CNN for trait removal with the Ebola Optimization Search Algorithm (EOSA) to enhance classification performance. This system was implemented to a lung CT scan dataset and designed to classify images into three categories: normal, benign, and malignant. By leveraging EOSA—a bio-inspired optimization technique—the framework aimed to fine-tune classification decisions based on extracted features, ultimately fulfilling an accuracy of 93.21%. The integration of integration of algorithms with lifelong learning represents an innovative direction, particularly in addressing complex classification problems involving subtle visual differences in medical images.

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Despite its novelty, the approach has several limitations. The EOSA algorithm, although promising, is relatively untested in the medical imaging domain, and its performance may be highly sensitive to hyperparameter settings, potentially affecting model stability. Furthermore, while the reported accuracy is respectable, it falls short of results achieved by other, less complex CNN-based models in the literature. The study also lacks external verification on independent datasets, raising concerns about the model's generalizability. Additionally, the increased complexity of the hybrid design could pose challenges for real-world clinical implementation, particularly in settings with limited computational resources or where interpretability is essential.

9) Deep Lung : 3D Deep Convolutional Nets for Automated Pulmonary Nodule Detection and Classification

Published in 2017, this foundational study introduced Deep Lung, among the earliest fully automated architecture for lung cancer findings and grouping using 3D CNNs. The architecture was designed to process full 3D CT volumes, permitting it to preserve spatial context—an essential factor in exactly identifying pulmonary nodules and assessing malignancy. The system operated in an end-to-end manner, performing both nodule detection and cancerous cells grouping within a unified pipeline. Classified on the LIDC-IDRI dataset, Deep Lung demonstrated diagnostic performance as good as experienced radiologists, marking a significant step forward in the utilize of Artificial Intelligence for clinical image review at the time.

Despite its pioneering contributions, the study had several drawbacks when viewed in the context of more recent advancements. As an early deep learning model, Deep Lung lacks many of the architectural optimizations and training strategies found in later systems, which could impact efficiency and scalability. Additionally, the use of 3D CNNs significantly increases computational demand, making real-time or resource-constrained deployment more challenging. The findings did not explore integration into actual clinical workflows, leaving questions about its readiness for practical application in healthcare settings. Nevertheless, Deep Lung remains a critical reference point in the evolution in cancer diagnosis.

10) Deep Learning Algorithm for Diagnosis of Lung Cancer

This study conducted a detailed review and combined study to measure usefulness of deep learning models in the detection are effective in lung cancer. Major scientific databases including PubMed, Scopus, Web of Science, and IEEE Xplore were searched using relevant keywords such as "deep learning," "lung cancer," "diagnosis," "CNN," and "neural networks." Inclusion criteria targeted peer-reviewed studies that utilized deep learning algorithms on clinical or imaging data (such as CT, PET, or X-rays) and reported diagnostic performance metrics like accuracy, sensitivity, specificity, or AUC. Studies not written in English, lacking performance evaluation, or not employing deep learning were excluded. Key data extracted from the selected studies included publication year, sample size, dataset used, deep learning model type (e.g., CNN, RNN), and relevant performance outcomes. Quality and risk of bias were assessed using the QUADAS-2 tool, while pooled diagnostic metrics were computed. In cases of significant statistical heterogeneity—determined using the I^2 statistic—a random-effects model was applied.

Despite its methodological rigor, the meta-analysis faces several notable limitations. The included studies exhibited high variability in datasets, model architectures, and evaluation metrics, making direct comparisons challenging. Furthermore, publication bias is a concern, as studies with positive or favourable outcomes are often to be published, potentially inflating pooled metrics. Many of the reviewed models lacked external validation, relying instead on internal datasets for both training and testing, which raises questions about their generalizability to broader populations. Lastly, interpretability remains a common concern, as many deep learning models function as black boxes, limiting their transparency and reducing clinical trust—a critical factor for adoption in healthcare settings.

III. METHODOLOGY

In this method, we are proposing, we detect cancerous nodules supported by Chest tomography pictures of the lungs by the utilize of CNN. Firstly, we extract chest regions from Chest tomography image, and at that part, each of the slices is segmented to urge tumors CNN architecture is trained by inputting the segment in the previous step. After which, CNN is employed to check the patient scans then the soft max layer determines the ultimate outcome. The ultimate goal is to find malignancy or benignity of the patient's lung nodule.

To begin with, these scanned images are subjected to preprocessing techniques to improve its level and suppress noise. Reduced dose CT scans often suffer from poor contrast and artifacts that can obscure small nodules. To mitigate this, a Gaussian filter is applied to smoothen the images by attenuating high-frequency components, while preserving key structural features. Additionally, a Sobel filter is used to highlight important edge information, which aids in defining potential tumour boundaries. These preprocessing steps signifies that whether the DL model is consistent, clean, and optimized for accurate analysis.

Following preprocessing, a specialized CNN model is employed for tumour segmentation. This system have many convolutional and activation layers, trained to detect specific patterns associated with lung segments. CNN is developed to operate on small image patches and incorporates learning rate adjustments and regularization techniques to prevent overfitting and optimize convergence.

A. Flow Diagram

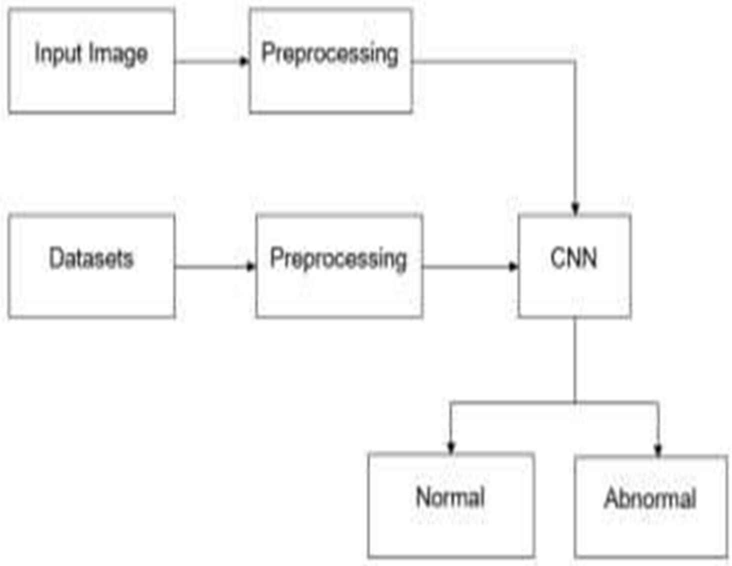

Fig -2: Flow diagram for the CNN architecture

B. Pre Processing

Current CT images have low quality due to low contrast and CT devices. So, it is difficult to differ in lung , kidney, heart, and liver textures. Hence, improved image is essential. In this study, Gaussian filter utilized to increase image structure. Gaussian filter is used as low-pass filters that change high-frequency pixels passing through low-frequency pixels. A low-frequency pixel is a pixel that has a small difference in brightness between its pixel and its neighboring pixel. A Sobel filter is used for the picture to give the clarity of the picture at it's initial edges.

C. Segmentation

The convolutional neural network (CNN) with multiple layers and activation functions processes the enhanced CT images. The CNN identifies specific regions of interest, such as potential tumors .To detect the tumor in lungs CT scan images, a convolutional neural network with 14 convolution stages and 7 activation functions, rule integration stage is used. First, the pre-processed selected with the initial value of 0.0001. To avoid overtraining, this description has been increased to 0.3. The maximum number of courses is 1000. The rule with the least error is considered the source model. This network is designed with a patch model. Also, the density layers are changed to their convolution equivalent for the final segmentation. The loss function and regularization method are used to update the rules and weights, as exhibited .

D. Tumor Identification

Abrasion and expansion operators are the most basic operators among the morphological operators, and the desired goals could be achieved by combining them. In addition , opening and closing operators and image complement could be useful. Because of the variation in tumor size and their random location, it seems very difficult to give a practical relationship. Using the morphological operators is done in a similar way that the final image is as same as one that contains the tumor At first ,an image opening step is perform done the output image of the CNN.

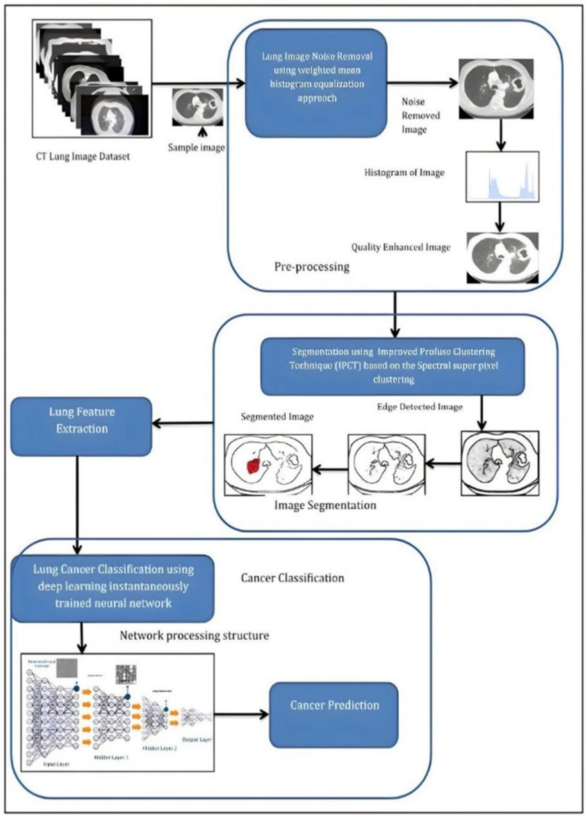

Fig.-3.-Overview of the proposed CNN-based lung cancer detection system from CT scan images.

E. Convolution Neural Networks (CNN)

CNN is a kind of a Deep-NN that consists of many concealed layers such as the convolutional layer, rectified linear unit layer, pooling layer and a completely connected normalized layer. To reduce the memory CNN largely shares its weights in the convolutional layer and thereby improving the performance. we use a deep learning methodology to detect candidate nodules present in Chest tomography scans. The ultimate aim is to train DCNN to detect lung protuberance in sub-quantity of Chest tomography images. This can be used to identify the boundary and location of candidate nodules in unprocessed Chest tomography images. The CNN is formed a group of twenty layers, these twenty layers are partitioned into 2 parts. In the first part valuable volumetric information of the input data is extracted using Convolutional Neural Network. The network further consists of numerous convolution layers, Rectified linear unit, & max pooling layers. Classifier is the next part of the Convolutional Neural Network. A Deep CNN consists of many hidden layers such as fully-connected layer, thresholding layer. Finally, softmax layer is used to identify the result.

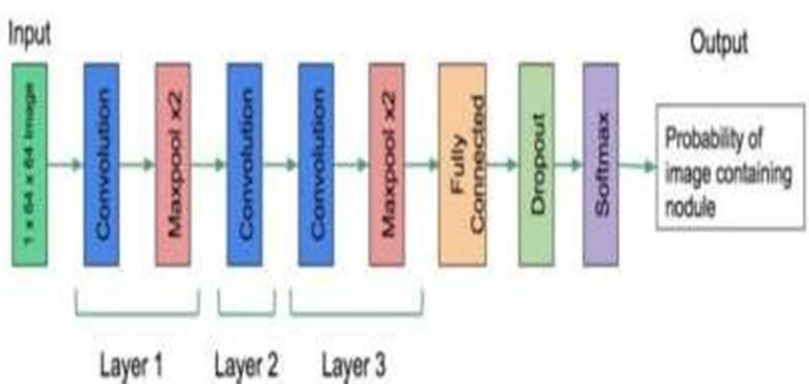

Fig -3: Flow of CNN model.

F. Technology Description

Lung cancer diagnosis in recent stage is a challenging yet critical challenge in the field of healthcare imaging. CT scans provide detailed cross-sectional views of the thorax region and are commonly used to detect abnormalities in lung tissues. However, accurate identification of lung tumors in these scans is difficult due to several factors. The low contrast between healthy tissue and tumors. Variations in tumor size, shape, and location.. Noise and Artifacts in CT images; The requirement for expert interpretation

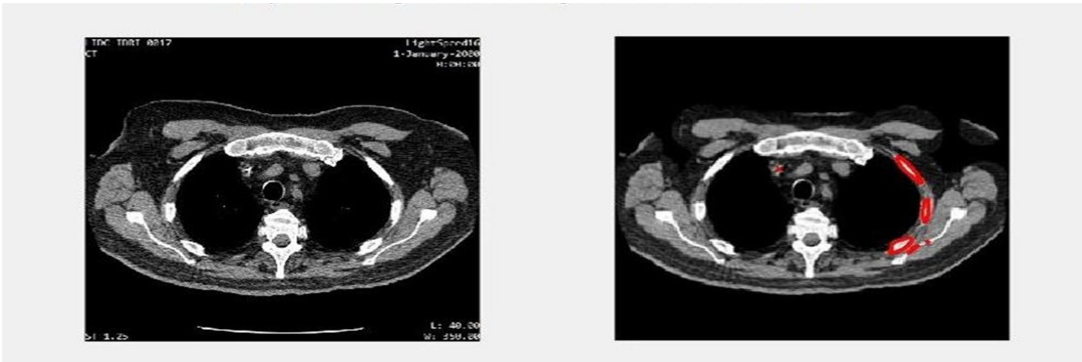

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Fig-1: Lung Cancer Detection Using CNN.

Traditional manual examination by radiologists is time-consuming and subject to human error. Hence, there is a strong need for automated systems that can assist in tumor detection. CNNs a class of deep learning algorithms, are well-suited for image analysis and have experimented fabulous result in identifying and classifying medical abnormalities.

G. Advisory Model

For detecting lung cancer using Computed Tomography scan images and CNNs the adversary model represents that potential conditions under which the system may fail or be misled. One primary adversarial challenge arises from the presence of noise and image artifacts introduced during CT scan acquisition or post-processing. These perturbations can degrade image quality and cause the CNN to misinterpret normal tissue as abnormal, or vice versa. Another major challenge is the structural similarity between cancerous and non-cancerous in the lung regions. Non-cancerous formations such as blood vessels, scarring, infections, or pulmonary edema may mimic the appearance of malignant nodules, confusing the segmentation algorithm and leading to false positives or negatives. This is further complicated by tumors that are small in size, located along the lung boundaries or overlapping with anatomical features, making accurate detection even more difficult. Additionally, the data bank utilized to examine the CNN may itself introduce adversarial conditions if it is imbalanced or lacks sufficient diversity. A model trained on data that underrepresents certain tumor types, sizes, or demographic groups may perform poorly in present health-care settings. Such data-driven biases reduce the transferability and fairness within the prototype.

Another adversarial concern is linked to the black-box nature of DL models. While CNNs are effective at attribute selection and classification, they often lack transparency. This causes to trust issues among clinicians who require interpretable and verifiable outputs, especially when patient's detection and cure decisions are involved. To mitigate these adversarial conditions, Our approach incorporates robust preprocessing to filter noise and enhance contrast, similar operations to refine segmentation masks, and the Active Contour Algorithm to improve boundary detection. These components work together to reduce false detections, improve model resilience to noisy inputs.

IV. DISCUSSION

The multi-stage methodology employed this research demonstrates a thought integration of classical image processing techniques with modern deep learning strategies for lung segments analysis in Tomography images. The integration of Gaussian and Sobel filters in the preprocessing stage enhances picture quality and emphasizes key structural features, laying a strong foundation for downstream analysis. By ensuring that noise and contrast issues are addressed early in the pipeline, its prediction of segmentation and classification stages is greatly enhanced. A choice of a CNN for both segmentation and classification tasks proves to be effective. The customized CNN, with 14 convolution layers and 7 activation layers, is tailored to identify complex patterns associated with lung nodules, while morphological operations and the Active Contour Algorithm (ACA) contribute to more precise boundary delineation. This combination allows for accurate tumour localization even in challenging cases involving small or irregular nodules.

The patch-based training strategy and regularization methods employed ensure model robustness and help avoid overfitting. Furthermore, the layered structure of the CNN—input, convolution, ReLU, pooling, flattening, and fully connected layers—provides a streamlined path from raw image to final prediction. Evaluating the model using accuracy, sensitivity, and the Dice Similarity Coefficient allows for a reliable comprehension of system's performance.

V. CONCLUSION

This approach effectively addresses key challenges in automated lung tumor sensing, like low image contrast, irregular tumor shapes, and noise among the scan data. Through the integration of image enhancement, CNN-based segmentation, morphological postprocessing, and final classification, the system achieves high levels of accuracy and sensitivity. The inclusion of performance evaluation metrics and optimization strategies makes the model not only technically sound but also clinically relevant.

However, despite its strengths, the methodology could benefit from future enhancements such as incorporating 3D volumetric data instead of 2D slices, performing cross-dataset validation to improve generalizability, and reducing computational complexity for real-time deployment. Overall, this pipeline presents a robust and scalable approach for supporting radiologists in early and accurate lung cancer diagnosis.

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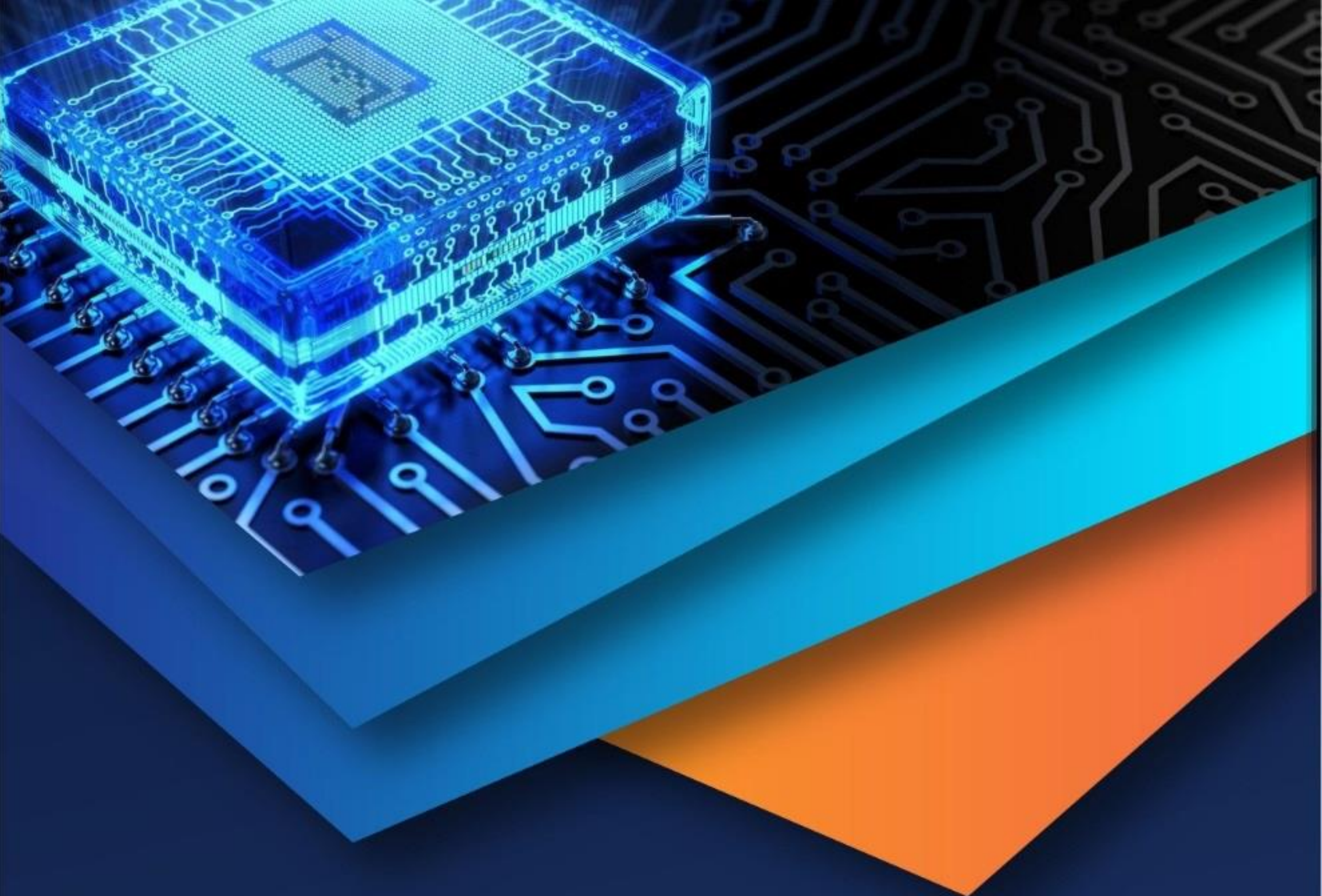

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