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A Review on Automated Segmentation of Lung Lesions in Chest CT Scans Using Hybrid Approaches

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Abstract

One of the most common causes of mortality worldwide is Lung cancer, an early diagnosis crucial for a patient's survival and recovery. Automated segmentation of lung lesions in chest CT has become a pre-eminent focal point for research, particularly with the development of hybrid methods combining traditional image processing with advanced deep learning methods such as CNN. These hybrid approaches aim to minimize individual methods limitations by controlling their merge strengths to enhance segmentation efficiency, precision, and clinical utility. This review comprehensively analyzes different hybrid techniques, such as deep learning improved by rule-based systems, multi-scale feature extraction, and ensemble learning. As well as inspect their clinical effect, particularly in improving diagnostic accuracy and optimizing treatment procedures. Despite their possibility, these approaches still face significant challenges, such as computational complexity, data requirements, and the requirement for explainable AI (XAI). Upcoming advancements in lung lesion segmentation will focus on refining these models to achieve faster processing, improved accuracy, and integration with diagnostic tools to protect transparency and ethical considerations.

Keywords: Medical Image Segmentation, Deep Learning, CNN, Machine Learning, CT Lung Image.

التقسيم الآلي للآفات الرئوية في فحوصات الأشعة المقطعية للصدر باستخدام نهج هجينة

رائد حامد لطيف ، أ.م.د. أحمد فائق حسين

الخلاصة:

يُعد سرطان الرئة أحد أكثر أسباب الوفيات شيوعًا على مستوى العالم، مما يجعل التشخيص المبكر أمرًا بالغ الأهمية لبقاء المرضى وتحسين فرص تعافيهم. وقد أصبح التقسيم الآلي للآفات الرئوية في صور الأشعة المقطعية للصدر محورًا رئيسيًا للبحث، خاصة مع تطور الأساليب الهجينة التي تجمع بين تقنيات معالجة الصور التقليدية وأساليب التعلم العميق المتقدمة، مثل الشبكات العصبية الالتفافية (CNN). تهدف هذه الأساليب الهجينة إلى تقليل قيود كل منهج فردي من خلال الاستفادة من نقاط القوة المشتركة، مما يعزز كفاءة ودقة التقسيم ويزيد من فائدته السريرية.يستعرض هذا البحث بشكل شامل مختلف التقنيات الهجينة، بما في ذلك التعلم العميق المدعوم بالأنظمة القائمة على القواعد، واستخراج الميزات متعددة المقاييس، والتعلم التجميعي(Ensemble Learning) ، مع التركيز على تأثيرها السريري، لا سيما في تحسين دقة التشخيص وتحسين إجراءات العلاج. وعلى الرغم من إمكاناتها الواعدة، لا تزال هذه الأساليب تواجه تحديات كبيرة، مثل التعقيد الحسابي، ومتطلبات البيانات الضخمة، والحاجة إلى الذكاء الاصطناعي القابل للتفسير (XAI) لضمان الشفافية والفهم السريري.تركز التطورات المستقبلية في مجال تقسيم آفات الرئة على تحسين هذه النماذج لتحقيق سرعة معالجة أكبر، ودقة محسنة، واندماج سلس مع الأدوات التشخيصية، مع الالتزام بمعايير الشفافية والاعتبارات الأخلاقية.

1 Introduction

Carcinoma is the vast, mutual reason for human death. [1]. In developing countries, billions of people lack and depend on polluting energy. (WHO) estimates that more than 4 million early deaths happen yearly from household air pollution-related diseases [2]. The existing data proposes that both biological (sex) and social (gender) effects can influence the lung cancer ratio. Fig.1 illustrates the estimated lung cancer statistics in the United States for the year 2021 [3].

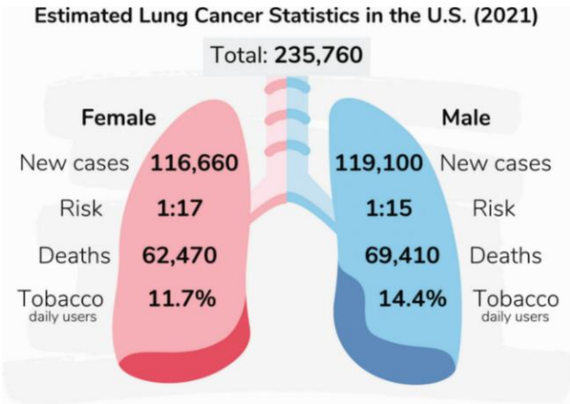

Figure (1): Estimated lung cancer statistics in the U.S. (2021).

In recent years, as studies have shown, new patients with 36 cancers and whole cancers have united in 2020. number of all new cases in each of the lung cancer sites is 11.4%, and many new deaths are, and many new deaths are 18% for whole sites [4]. Lung cancer is the formulation of malignant lung tumors because of the uncontrolled growth of lung tissue cells. The survival rate of lung cancer patients in all stages is so less than about 14% with a time, an extent of about 5-6 years. Thither are two main kinds of lung carcinoma classified depending on cell characteristics: the first one is big cell lung carcinoma, which makes up about 80-85% of total patients, and the second is small cell lung cancer, which makes up about 15-20 % of total cases [5]. The major trouble with lung cancer is that most of these cases are discovered in the later stages of cancer, making treatments harder and notably reducing the survival chances. So, diagnosis of lung cancer in its earlier stages can raise the survival chances to 60-70% by giving the patients essential treatment [6]. Lung cancer growth depends on the diffusion of cancer in the lungs and tumor size. Lung cancer is classified into four stages in order of riskiness: First-stage Cancer is close to the lung, second and third stage Cancer is close to the chest, and fourth stage Lung cancer has expanded from the thorax to other parts of the body. Lung cancer detection can be done using several imaging instruments like Computed Tomography, Magnetic Resonance Imaging (MRI), (PET scan), Computed and Chest X-rays. Tomography images are mostly chosen over other modalities because they are more reliable. This shows a high chance of individual errors and can lead to the classification of cancer. So, an automated system is of ultimate prominence in leading the radiologist in the appropriate diagnosis of lung cancer[7].

Reports show that early diagnosis increases the possibility of effective treatment and survival. But, the accuracy of traditional technologies faces big challenges, requiring new approaches that can improve the quality of diagnosis. The main challenges of traditional methods are differences in lesion sizes, low contrast, and the effects of external factors like the machines used and imaging conditions. In spite of the dependence on traditional computer vision techniques like threshold and edge-based segmentation, these approaches often suffer from inconsistent performance, essentially in complicated cases or poor-quality images. Studies show that the segmentation precision using these methods can be wrong, especially in cases where there is a high propinquity between healthy and infected tissues.

Hybrid approaches combine artificial intelligence (AI) with traditional techniques to achieve the best performance on tasks like medical image segmentation. These approaches influence the durability of both approaches, where AI is used to scan large amounts of complex data and extract deep types using convolutional neural networks. CNNs are used to get characteristics from medical images, while particular rules are applied to address cases where high propinquity between healthy and infected tissues can lead to misdiagnosis. Hybrid approaches can also let the system use deep learning to recognize patterns and generate good impersonation of the data while increasing the accuracy and control of traditional techniques[8], [9].

In a recent study, researchers improved model accuracy by combining deep learning techniques with rule-based systems.[10]. This shows the importance and efficiency of hybrid approaches in enhancing the medical segmentation process and giving more accurate and reliable results.

This research aims to comprehensively review hybrid approaches combining different segmentation methods to increase lung lesion segmentation's precision, robustness, and clinical applicability. This study aims to analyze the advantages of hybrid analyses in lung lesion segmentation by comparing the results of hybrid techniques.

2 Fundamentals of Lung Lesion Segmentation

Medical image segmentation is a very important and difficult mission in medical image inspection. The changeable size, form, and position of objects is a paramount stage in image processing implementation. It distinguishes pixels of the image into multiple classes that allow the analysis of the objects included in the area.

2.1 Traditional Segmentation Techniques

Include several approaches such as thresholding, edge detection, region growing, clustering, and edge detection. These methods depended on pixel intensity and spatial relations. Still, they often require accurate parameter tuning and less generalization, making them foundational but limited compared to new deep-learning approaches[11]. Multilevel thresholding is a method that does this job, but the trouble is discovering the better group of thresholds that completely segment each image.[12]. Supervised Segmentation is classified into a discontinuity-based technique (Edge-based) or a Similarity-based technique [13], [14]. That is divided into two techniques, classic region-based and thresholding techniques, which are simple to execute and produce active segmentation results. It hangs on the relevance between the Hounsfield unit (HU) rate in CT images and body parts. This technique is classified into 2-level and multi-level thresholding. In the previous class, a threshold amount is utilized to divide the image into two similar front and background areas. At the same time, the later technique is used to segment an image into three or extra areas based on pixel density, known as a histogram. After segmenting an image, the chosen thresholding values are significant due to large image thresholds[15] [16].

2.2 Machine Learning and Deep Learning Techniques

The appearance of machine learning, especially deep learning, has transformed medical image segmentation. Algorithms like CNNs and U-Nets have successfully detected complex patterns in lung lesions. These methods outperform traditional techniques, processing complex patterns and big datasets while showing improved generalization, making them the best technique in medical image analysis[17]. **Semantic segmentation** is a technique that associates each digital image pixel with a class label area within an image, allowing accurate recognition of anatomical structures and pathological areas. This technique is good for tumour disclosure, organ description, and disease localization. Deep learning, mostly convolutional neural networks (CNNs) and models like U-Net, have improved in precision and effectiveness, even with complicated and high-resolution medical images such as MRI, CT, and US [18] [19]. **Instance Segmentation** is a form of image segmentation that transacts by detecting and delineating every discrete instance of an object shown in an image. Instance segmentation detects all instances of a class with more functionality of demarcating dismissed instances of any segment class. It is also called a combination of object detection and semantic segmentation functionality. Instance segmentation has a good output format as it generates a segment map for each category and instance of that class. This technique is gradually applied in pathology, radiology, and surgical planning, allowing accurate tumor edge delineation, segmentation of combination anatomical structures, and detection of multiple lesions in the same area [20] [21]. **Panoptic segmentation** provides a universal approach to image segmentation. It stands out by segmenting objects and classifying them together. So, panoptic segmentation can be interpreted as viewing everything within a given visual field. This technique is a hybrid, combining semantic and instance segmentation strengths. Improve deep learning, mainly hybrid models merging convolutional neural networks (CNNs) with attention mechanisms, have improved panoptic segmentation precision in the medical field [22], [23]. Segmentation of Medical images commonly deals with either direct use of 3D images to train models[24], [25], but several approaches to the 3D image slice-by-slice[26]. The main drawback is its expensive computational cost. Deep learning Segmentation [27]. Techniques vary notably from the conventional by using pre-known architectures (CNN) that have a numeral of parameters in which the values of demand are to be specified by training [28][29]. Deep learning is a main development in the computer field and has presented wonderful perfection higher than the hand-designed procedures. The overall process, like network designing, training, and valuation, is the combined base of all those works. At the same time, the major variations are the data and network architecture used for training and evaluation. CNN for image segmentation usually depended on an encoder-decoder architecture. The encoder job is down-sampling or shrink path to progressively decrease the volume of the impersonation while capturing semantic contextual details, and the decoder mission is up-sampling or extending the track planner back the exemplification to its premiere size, which will make pixel-wise foretelling. The fundamental structure blocks of CNN for image segmentation are convolutional, pooling, and transposed convolutional layers. Other components, such as overstep connections, allow straight links between the down-sampling and up-sampling paths [30]. Fig.2.

Limitations scan protocols. Small lesion size and limited annotated datasets [31]. Control these problems in the Lungs.

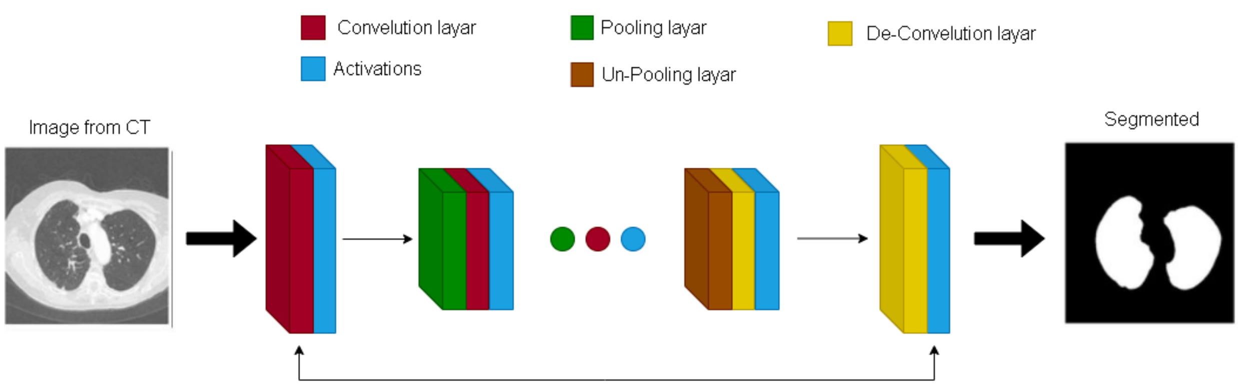

Figure (1): Typical process of segmentation with deep learning: A convolutional neural network (CNN)

Lesion Segmentation, like lesion heterogeneity, low contrast, the presence of artefacts, and variability, needs advanced machine learning techniques and the development of more advanced approaches, such as hybrid models [32].

3 Hybrid Approaches in Lung Lesion Segmentation

Merge traditional image processing techniques with a new machine learning approach to get better accuracy and efficiency in recognizing and outlining lung lesions in CT scans[33]. These approaches target the restriction of each separate method and influence their combined strengths[34]. Several hybrid strategies have been explored:

Deep Learning Enhanced by Rule-Based Systems

Integrate the interpretability and domain-specific cognizance of rule-based systems with the feature extraction ability of Convolutional Neural Networks (CNNs)[35]. This combination makes segmentation precision treat problems better and enhances outcomes in medical image segmentation.

Ensemble Learning

Is a technique that uses multiple machine learning models (e.g., CNNs, random forests, SVMs) to produce better results. Based on the training, models are called homogeneous or heterogeneous. Used to improve generalization and reduce overfitting, making it a strong approach in different machine-learning tasks[36], [37].

Multi-Scale Feature Extraction

One of the types of hybrid approaches that combine various scales of image data to catch global context and small details[38]. Integrating classical image processing with deep learning increases model precision, especially in complex tasks like medical image analysis, where different feature scales are important for accurate segmentation.

Integrative Shape and Texture Analysis

This method integrates geometrical form descriptors with texture analysis to better distinguish between lung lesions. Shape analysis seizes the structural properties of lesions, while texture analysis discovers fine intensity differences that lead to additional accurate and overall segmentation[39].

4 Challenges and Future Directions:

Hybrid methods for lung lesion segmentation face many challenges that need to be improved in terms of efficiency, accuracy and applicability. The most important of these challenges are:

Computational Complexity and Efficiency Hybrid approaches can optimize these models for faster processing times without compromising accuracy by Pruning, including removing unnecessary or minimal paramount parameters from the model to minimize its size and computational requirement. Techniques like structured pruning (removing entire neurons or channels) have thus gained interest since they effectively lower storage and computational costs [40]. Unstructured pruning (removing individual weights) is tested. By comprehensive experiments conducted on common models like ResNet-18, findings show that EGP [41] effectively compresses deep neural networks whilst keeping a competitive performance grade. **Model pruning** When pruning non-essential nodes in deep networks, the model size was reduced while retaining the segmentation accuracy. This approach allows the model to be used on less powerful hardware without sacrificing accuracy, which improves efficiency [40]. **Quantization** is the process of approximating uninterrupted signals by a set of separated symbols or integer values. Quantization decreases the accuracy of the numbers used in computations [42], seriously decreasing memory usage and speeding up conclusion times. Quantization is an effective solution to reduce the computational requirements of models, especially in medical applications. **Integration with Artificial Intelligence (AI)** The future of lung lesion segmentation is growing by combining hybrid approaches and AI-driven diagnostics. These hybrid models usually integrate machine learning and deep learning to increase medical image examination and analysis accuracy and robustness. One of the most emerging trends in AI integration for lung lesion segmentation is Explainable AI (XAI): Explainable AI is earning importance as a key to the "black-box" complexity ingrained in many deep learning models[41], [42]. In lung lesion segmentation, where precise and interpretable results are required, XAI enhances trust by providing clinicians with insights into how and why a model makes a specific decision. This is critical in clinical applications, where comprehension of the decision-making procedure is key to consenting and acting on AI-generated results. The XAI provides useful prudence in the model's decision-action process, assists doctors in conception, and supports the prediction [43]. This is especially important in distinguishing possible biases or errors in the model.

To minimize these limitations, we propose an improved framework that combines traditional segmentation techniques with deep learning segmentation techniques, uses advanced hybrid architectures such as (CNN-RNN) model to improve feature extraction, reduces model complexity to reduce the real-time computational complexity of applications, uses interpretable AI techniques to provide clinicians with visual and textual explanations of segmentation results, and improves clinical confidence and usability.

5 Data Challenges and Solutions in Medical Image Annotation

Acquiring Large and Annotated Datasets may require High Costs and Time, and annotating huge datasets, particularly in the medical imaging field, demands skilled knowledge, which is time-consuming and costly. The requirement for a large size of a labelled datum can be a serious impasse in training high-performing hybrid models. Several solutions used partially deal with the problem such as using **transfer learning** on pre-trained models like ResNet-50 has decreased the need for big explain datasets by evident rate, enabling models to be trained on fewer images. This technique is particularly useful in medical applications where explained data is limited or rare [44], **Data Augmentation** such as rotation and scaling, increase the size of data and improve the robustness of models to deal with the high variability in medical images. Data augmentation permits models to learn from more possible cases, enhancing their capability to generalize to new data[45], and **Semi-Supervised Learning** provides another in cases of shortage of labelled data, where a small part of labelled data is used to prove the model, while unlabeled data is used to complete the learning process. This approach minimizes the need for comprehensive coding and improves the activity of the model [46].

6 Comparative Analysis of Hybrid Approaches:

To execute a comparative analysis of hybrid approaches in the case of medical image analysis, starting with Performance Metrics and then pros and cons, after that limitation and their performance across different tasks.

6.1 Performance Metrics

To evaluate the efficacy of hybrid approaches, common metrics such as the Dice coefficient, which is a very utilized metrical in medical image analysis and computer vision, are applied to quantify the likeness between groups of data, like binary masks or segmentations of an image [47], [48], Jaccard index or Jaccard Similarity Index is also known as Intersection-Over-Union. It is known as the ratio of the space of the interference between the predicted segmentation and the basis truth segmentation to the space of union between the predicted segmentation and the basis truth segmentation[49] [48], sensitivity, specificity, and Harsdorf space (HD) between two borders is a measurement of the longest distance that one has to transportation if moving from a given point on a border and going to the other border [50]. Those metrics give insights into the accuracy and reliability of segmentation algorithms.

6.2 Review of Key Studies

The paper [51] progresses a two-stage hybrid method of deep learning networks. (c-GAN) A provisory obstetric adversarial network has segmented the lung section at the first stage. The c-GAN is used for precise lung segmentation with lung anomaly. In the second stage, a ResNet50 was utilized to obtain the characteristics of the segmented lung image. The execution of the suggested two-stage deep learning network has improved seriously due to the stage-good refinement of deep learning algorithm execution. This study [52] proposes using a hybrid DL model Deep Learning technique formed by integrating a pulsation-coupled Neural Network (PCNN) and a Convolutional Neural Network (CNN). For automating cancer classification and detection in lung examination. The paper's main aim is a hybrid DL model built on PCCN&CCN. This, at the latest, increases the goodness of the model medical images. This research [53] suggests a lung computer help diagnosis system depends on a deep hybrid learning model. The central points of this model are segmentation, feature extraction, and optimal feature selection. The model was built using VGG-16 and resnet50. By PCA dimensionality decrease and features combination technique, big feature expression potentiality and low-side attributes are getting. The hybrid approach of the suggested model is very accurate. It can successfully stop fake detection. This paper [54] proposed an automatic algorithm for precisely segmenting lungs from chest CT images. Firstly, an input image is divided into a combination of non-overlapping fixed-sized images. Then, a deep convolutional neural network model is built to remove the first lung areas. segmentation is after that complete, on the preprocessed chest CT image, and finally locally purified lung contours according to corresponding super pixel contour with their neighboring dot statics procedure. This paper [55] presents a hybrid approach integrating Convolutional Neural Networks (CNNs) with decision trees to detect lung cancer. By using CNNs for feature extraction and decision trees for classification, the method increases accuracy and interpretability in analyzing CT scans and X-rays, which are considered promising improvements for early diagnosis and patient results. This paper [56] presents a hybrid deep learning method of lung carcinoma stage estimation employing particle group optimizer for improvement portion and convolutional neural network for classification objective. The suggested hybrid method had shown 95.8% precision. The existing results are matched with many states of algorithms with consideration to improvement and classification. This paper [35] proposed a novel approach named hybrid intelligence that combines basic rule-based control and deep learning approach with gated recurrent units (GRUs), basic recurrent neural networks (RNNs), and long short-term memory (LSTM). Deep learning approaches easily increase and adjust control conclusions depending on the historic datum and domain-specified rules, which lead to rising method efficacy, stabilization, and flexibility in adaptive microgrids. The results offer the big implement models indicating high precision and efficiency in power prediction. This paper [37] proposed a deep multi-level semantic incorporation network called DMF-Net to extract noise from thoracic CT images. A mixed dataset, including high-resolution CT images with specified and blind noise, is applied to validate the suggested de-noising approach. experiential results show the efficacy of the DMF-Net compared to other techniques in the case of peak signal-to-noise ratio and structural likeness measure with a drastic decrease in the processing power needed. This paper [38] proposed a local multi-scale context. they also adopted an advantage pyramid network (FPN) to join SCMs to extract universal multi-scale features. The multi-level, multi-scale feature was extracted, and precise spatial information was also held. overall experiments and general datasets demonstrate that the suggested MMS-Net attained accurate segmentation and outperformed. This paper [57] offered a novel segmentation algorithm based on random forestry, deep convolutional networks, and multi-scale super pixels for precisely segmenting lungs from thoracic CT images. The algorithm is examined using CT images influenced by interstitial lung infections. The algorithm can be dependable for lung domain segmentation of pathologic CT images with very good precision, and it is useful to help radiologists discover the existence of pulmonary diseases and quantify their form and size in clinical investigation. This paper [58] proposed Hybrid-DDM, which combines two deep learning models with a machine learning model. To generate and validate a sharpness estimate model for infectious respiratory diseases (IRDs). using CT images from a multi-center dataset. The Hybrid model demonstrates improved execution and efficiently estimates acuteness in COVID-19 and other viral pneumonia cases. This study [59] presents a tumor diagnostic model built on a deep learning-enabled support vector machine (SVM). The suggested computer-aided design (CAD) model distinguishes the pathological alteration in the soft tissues in lung carcinoma lesions. It's preferable to other approaches, including complex deep learning and hybrid approaches. Experimental results show that the present method can seriously help radiologists detect lung tumors without delay and assist in the appropriate treatment of patients. This [60] study presents a hybrid approach integrating machine learning, neural networks, and probabilistic models to improve automated cancer diagnosis using low-dose CT scans. main innovations contain a split method for reducing split errors. Many experiments and results have shown that the activity of these experimental approaches enhances the effectiveness of low-dose CT scans. This paper [61] proposes splitting lung tumors from Magnetic Resonance Imaging (MRI) images with threshold segmentation. Integrating the duo methods decreases the comprehensive size of the feature group needed for any futurity classification procedure executed using DNN. The suggested DWAE-DNN image classifier is used for a lung imaging dataset with a Radial Basis Function (RBF) classifier. An investigation found that the DT classifier allows the greatest execution in the DWAE-DNN, relying on the network's execution of image testing. This paper [62] presents a new approach called double tasking Wasserstein obstetric adversarial network U-shape network (MWG-UNet) as a segmentation model of a lung domain and heart disease merits of the observation mechanism to increase the segmentation precision of the generator to enhance the efficiency. The results demonstrate that the suggested approach has a large ability in lung domain segmentation. The segmentation outcome on lung fields is obtained with very good accuracy. The paper [63] proposes a hybrid deep-learning network model. The lung parts of the HRCT images were segmented using a modified U-Net++ model. The multi-scale modified U-Net++ module has been used for efficient lung segmentation with lung anomaly. They extracted the image's features from a segmented lung and then categorized it in the second step using a (RAPNet) Refined Attention Pyramid Network. The suggested hybrid deep learning network model's double tasking Wasserstein obstetric adversarial network U-shape network (MWG-UNet) as segmentation model a lung domain and heart. The observation mechanism has merits in increasing the segmentation precision of the generator and enhancing efficiency due to the gradual improvement in the DL method performance. The research [64] presents a fully automated framework that depends on Capsule Networks to identify COVID-19 infection from normal and (CAP) Community-Acquired Pneumonia cases by applying thoracic Computed Tomography scans. They suggest a hybrid deep learning model that combines clinical and demographic data, as well as CT scans, to classify COVID-19 and non-COVID cases using a Random Forest Classifier. The suggested hybrid model identifies the extremely paramount predictive factors that raise the Explainability of the model. This paper [65] proposed a novel hybrid approach by combining multiple techniques, consisting of both traditional image processing methods (random forest) and machine learning (specifically, a random forest classifier), to segment lungs from CT images accurately. method targets removing the effects of the factors and leading to accurate segmentation of the lungs from CT images. approach can segment lungs from chest CT images with perfect efficiency in a fully automatic mode, and it is of large help for lung lesion diagnosis in the (CAD) computer-aided detection system. The[66] paper suggested a novel segmentation model to distinguish lung illness from chest CT scans to acquire this. present a learning architecture integrating U-Net with a two-parameter logistic division for precise image segmentation. The hybrid model is called U-Net++, and detection utilizes computed tomography (CT). executing focuses on determining the particle composition of lung nodules, a significant part of diagnosis and therapy planning. The valuation shows a good precision for the hybrid approach. The study [67] suggested applied Two hybrid AI models from the COVLIAS system, VGG-SegNet (HDL 1) and ResNet-SegNet (HDL 2), were applied to segment the thoracic CT lungs. An already trained COVLIAS model was used in the validation datum to segment the CT lungs and compare them to MedSeg. The execution of COVLIAS and MedSeg were comparable. but COVLIAS appeared to improve computing time more than MedSeg. The paper [68] suggests an enhancement of U-Net with residual links, appending a plug-and-play, movable channel attention block and a hybrid expanded attention convolutional (HDAC) layer to implement medical images. segmentation for various missions perfectly and successfully, which is called HDA-ResUNet, which completely uses the feature of U-Net. The segmentation results are all increased precise than U-Net with fewer parameters, and the trouble of slow convergence velocity of U-Net is fixed. This paper [69] presents a search optimization approach to optimize the initial segmentation of the lung parts. Then the Active Contour method is used to segment the nodules for the segmented lung image. So, to carefully turn the post-processing next to the nodule segmentation process, the Markov Random Field technique has been utilized. The suggested lung and nodule segmentation technique experiment results have been presented. This research [70] targets to find a novel 2D–3D hybrid convolutional neural network to supply dependable lung segmentation results in the clinical setting. Contouring quality was evaluated, and the visual assessment was perfect for evaluating clinical acceptability. The hybrid CNN model reached precise lung segmentation on traditional slice-thickness CT of progressing lung cancer patients and has perfect clinical utility. This study [71] suggests a method for diagnosing COVID-19 from thoracic CT images by a double multiscale dilated fusion network for segmenting tiny lesions in CT images. The model generally used the power of multiscale deep characteristic fusion inside the encoder and decoder modules. post-region of interest (ROI) fusion is introduced in the post-processing step, which accurately quantifies the infected area of the lung. The paper [72] suggests a technique for creating a 3D model of lung tumors from CT scans using an integration of GAN and LSTM models with help from ResNet. This model is the primary one that used a GAN model to reconstruct 3D lung tumors. The experimental feedback shows that the suggested approach demonstrates an adequate performance level compared to other methods run for the same objective.

Fig. 3 illustrates the segmentation performance of different hybrid approaches, demonstrating the variations in accuracy and efficiency.

Table (1): Comparative Analysis of Hybrid Approaches

No.	Ref.	Hybrid approach	Dataset	Pros	Cons	Accuracy %
1	[51]	(c-GAN), ResNet50	ILD Database	No need for manual ROI, full image covering, more accuracy, and less time.	Cannot mark the specific region infected by interstitial lung disease, and limited disease is covered.	Accuracy: 89.39 Sensitivity: 89.39%
2	[52]	Pulse Coupled Neural Network (PCNN) and a Convolutional Neural Network (CNN)	NSCLC-Radiomics database	Enhances early tumor detection, suggesting a promising approach for real-time clinical diagnostics.	High computational requirements and interpretability and interpretability concerns represent unresolved issues that warrant additional investigation.	97.43%
3	[53]	VGG-16, resnet50, and grey Wolf optimizer	Kaggle Data Science Bowl (DSB) 2017	A high accuracy denotes its effectiveness in lung cancer classification. The Grey Wolf Optimizer is applied for feature selection, which makes it not difficult to execute.	The hybrid approach is complicated and needs skill and computational resources. The system's scalability to greater datasets or more complex medical images is also not experimented with.	96.56%
4	[54]	DCNN model and a two-pass contour refinement of local and global.	interstitial lung diseases (ILDs)	high accuracy in the segmentation of lung area from CT images, especially in challenging regions such as juxta-pleural lesions. DCNN reduces computational time, which makes the algorithm more efficient	The quality of CT images can influence the performance of the approach. Limited to the types of lung conditions means Limited Generalization. complex implementation due to the two-pass contour improvement	Accuracy: 99.24% DSC: 97.95% Sensitivity: 96.74%
5	[55]	Convolutional Neural Networks, Decision Trees	The dataset includes X-rays, positron emission tomography (PET) scans, and computed tomography (CT) scans obtained from various sources, including publicly available repositories and clinical archives.	Improved lung cancer detection progress using hybrid models improved accuracy and early diagnosis. confirm the equilibrium between accuracy and interpretability	doesn't provide specific details or quantitative results from studies or experiments. Integrate CNNs with decision trees may present complexity in model implementation and integration.	Accuracy: 97.43% Sensitivity: 96.25% Specificity: 96.89%
6	[56]	particle swarm optimizer for	LIDC-IDRI	The proposed approach presents high accuracy	A limited number of images from a dataset means that mean	Accuracy: 98.12%

		improvement part and convolutional neural network for classification aim		for tumor detection compared to other CNN algorithms	cannot Generalization result for several types of lung diseases	DSC: 96.90% Sensitivity: 96.85%
7	[35]	basic rule-based control and deep learning approach, comprehensive gated recurrent units (GRUs), basic recurrent neural networks (RNNs), and long short-term memory (LSTM)	LIDC-IDRI, Kaggle	The hybrid approach can improve the adaptability and efficiency of microgrid (MG) operations. The methodology is flexible for different datasets and modelling tasks.	Hybrid approaches complicate the system, making it further challenging to execute and maintain. does not discuss how well the proposed approach generalizes	Accuracy: 99.24% DSC: 97.95% Sensitivity: 96.74%
8	[37]	architecture DMF-Net includes 3 parts: DFEB, CFB, and PFRB.	Kaggle	The DMF-Net shows big improvements in noise removal from CT images. The model shows powerful generalization ability with several types of noise.	The architecture is very complex, which increases the difficulty of application, correction, and optimization. Training Time may be longer, especially with large datasets. The model's efficiency using just high-resolution CT and X-ray images	-
9	[38]	multi-level and multi-scale feature extraction network (MMS-Net)	ISIC 2017 dataset	MMS-Net Multi-Level and Multi-Scale methods enhance the accuracy of medical image segmentation. Reduced training datasets (50% and 20% of the data), appearance robustness, and efficacy in several scenarios.	Complicated architecture may require more time for training on large datasets. The need for accurate tuning of parameters and careful design of model layers may present challenges in the application.	Accuracy: 95.40% DSC: 87.60% Sensitivity: 87.50%
10	[57]	random forest (RF), deep convolutional network, and multi-scale super pixels	Interstitial lung disease (ILD)	high segmentation accuracy segmenting lungs from CT images. Combining (CNN) with (RF) improves comprehensive performance. helpful for assisting radiologists in detecting pulmonary diseases	The algorithm may suffer from over-segmentation in areas with unclear boundaries, leading to imprecision in the segmentation. The algorithm applies to a few lung disease, potentially limiting its generalizability.	Accuracy: 99.38% DSC: 96.45% Specificity: 97.89%
11	[58]	Hybrid-DDM	805 COVID-19 patients collected from a single center	The Hybrid-DDM model shows improved power to estimate disease severity. It provides useful insights into disease acuteness depending on lesion types.	The study used data mostly from South Korea. The effectiveness of datasets from other countries is required to ensure generalizability. Lesion Information Features give beneficial information, but depending on these features, they may miss other relevant radiological features in CT images.	AUC: 0.830 Sensitivity: 73.9%
12	[59]	hybrid model (CNN + SVM)	LUNA16	The approach is additionally precise and fast compared to other methods, allowing for flexibility in model	The approach requires high computational power and a high chance of overfitting. The hybrid model	Accuracy: 94%

				design. It can be especially useful when data is limited	relies on the quality and size of the input images.	
13	[60]	CNN, HSCNN mode	LIDC-IDRI	This method helps reduce unnecessary radiation exposure in patients and improves diagnostic precision. Give a more reliable and precise assessment of the disease cases.	Due to the system's complications, multiple components in a single model may lead to application challenges. Noisy or incomplete data may affect model performance.	91.4%
14	[61]	Deep Wave Auto-Encoder (DWAE)-Deep Neural Networks (DNN)	MRI scans of 153 individuals	DWAE used for feature extraction decreased the feature combination size, enhancing the performance of the DNN. Besides clustering techniques, the combination improves network performance, and the approach shows strong results based on metrics.	Overfitting may be a concern due to high accuracy, insufficient dataset size, and incorrect threshold selection, which can lead to incorrect area segmentation and affect the model's performance.	98.67%
15	[62]	MWG-UNet (multiple tasking Wasserstein generative adversarial network U-shape network)	Japanese Society of Radiological Technology (JSRT)	Enhancement Segmentation Accuracy: The hybrid approach raises the model's power to generalize various types of medical images	A combination of WGAN and U-Net, along with extra SE blocks, raises the complexity of the model, which may lead to extended training times. The bounded dataset used may have affected the model's ability to generalize.	Accuracy: 94.24% DSC: 85.18% Sensitivity: 97.40%
16	[63]	improved U-Net++	HRCT chest (protocol)	The method shows accurate detection and classification of lung anomalies with high accuracy and reliability. A short processing time of about 10 seconds, making it useful for real-time applications.	The hybrid approach involves multiple stages leading to complicated implementation, high computational costs and complication, and the precision of the model based on the quality and variety of the training datum.	Accuracy: 99.10% Sensitivity: 98.05%
17	[64]	CT-CAPS	CT scans data for 176 COVID-19 cases, 76 normal cases, and 60 CAP (community-acquired pneumonia) cases.	Integration permits for a better overview of the patient's condition, leading to more accurate predictions. The model, which minimizes computational cost and training time	limit the generalizability due to the model being trained and validated on an in-house dataset (limited Dataset Size). The complexity of the Model may make it harder to publish and maintain in a clinical setting	Accuracy: 90.8% Sensitivity: 94.5% Specificity: 86.0%
18	[65]	traditional and machine-learning methods	LIDC-IDRI	The approach shows high accuracy in the segmentation of lungs from CT images. The approach performs well with different types of lung images, including those that have different diseases	more complexity, computational cost, and parameter tuning must be accurate, which may limit its generalizability and real-time application.	DSC: 0.9867
19	[66]	U-Net++	LUNA-16	High Accuracy segmentation of complex medical images like CT scans.	A large number of layers and parameters are computationally more intensive than simpler models. This can lead to longer training times. The dataset size	Accuracy: 90% Sensitivity: 89%

					and the quality of labels may limit the model's execution.	Specificity: 90% DSC: 91.76%
20	[67]	COVLIAS system: VGG-SegNet and ResNet-SegNet	dataset contains 72 adult Italian patients (empirical database)	improves the accuracy of segmentation, detects small portions of the lungs, and is capable of treating differences in image formats, including PNG, JPEG, DICOM, and NIfTI.	This model is extra complex, so there is a possibility of overfitting, particularly if the training data is not sufficiently varied or comprehensive. This may limit the generalization.	AUC: 0.95%
21	[68]	HDA-ResUNet mode	Kaggle, LiTS 2017, DSB 2018, ISBI 2012	The HDA-ResUNet model presented the best segmentation results compared to the traditional U-Net, with good computational resources and training time.	It utilizes a 2D network, but it missing some inter-slice information, which can be influential for tasks requesting 3D spatial context. wherever the lack of inter-slice information may affect segmentation goodness.	Accuracy: 99.34% DSC: 79.9%
22	[69]	Cuckoo Search Optimization, Active Contour, and Markov Random Field	LIDC-IDRI	Optimization of initial segmentation, good performance metrics in the experimental results, and improved overall segmentation performance compared to a single technique.	time-consuming and might not generalize well across different datasets. The accuracy of the final segmentation depends on the success of the initial lung segmentation	DSC: 78.9%
23	[70]	2D–3D hybrid convolutional neural network (CNN)	105 locally advanced non-small cell lung carcinoma patients	The hybrid CNN model shows a strong possibility for clinical application and presentation of accurate segmentation that can decrease the burden on clinicians.	The segmentation errors are more pronounced at the starting slices where the RML shows, particularly conventional CT images with 5 mm slice thickness. The studies were first completed on CT images of patients with locally advanced, which may limit its generalizability.	Accuracy: 99.62% DSC: 0.94
24	[71]	Dual multiscale dilated fusion network (DMDF-Net)	50 chest CT scans from various patients with COVID-19 infection.	efficient Segmentation of Lung and Infection areas, more computationally effective, needs low-cost hardware resources	The model's execution with different datasets is limited, specialized for COVID-19 infection segmentation, and does not expand to another kind of lung diseases or infections, which limit Generalization	Accuracy: 96.56% DSC: 91.76% Sensitivity: 95.28%
25	[72]	(ResNet, LSTM, and GAN) and segmentation techniques (Snake Optimization and GK method)	LIDA-IDRI	provides a highly detailed and accurate 3D reconstruction of lung tumors; the approach leverages the strengths of each model, potentially outperforming traditional methods in accuracy.	The generalizability of the model to larger datasets is limited due to the evaluation of the relatively small LUNA dataset. Complexity leads to high computational cost and time. difficulty in detecting Small Tumors.	Hausdorff Distance: 2.99 Euclidean Distance: 1.06

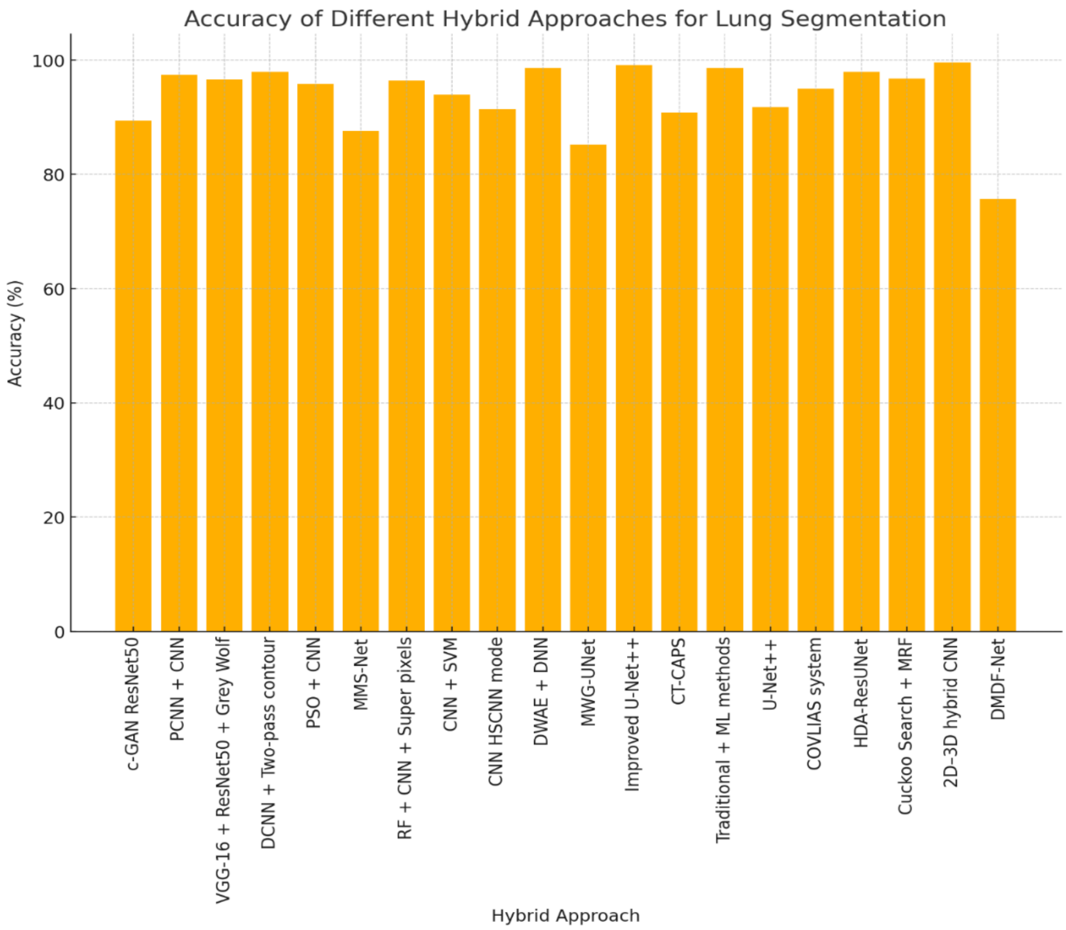

Figure (2): Accuracy of Different Hybrid Approaches for Lung Segmentation

7 Strengths and Limitations

Several advantages are evident when using the hybrid approach in medical imaging, especially for lung cancer detection and segmentation. This approach eliminated the manual selection of the Region of Interest (ROI), which allowed the use of the whole image and reduced the time for processing with the same extent of accuracy. In mixed approaches, efficiency and accuracy are combined, as well as the possibility of interpretation of results. Hybrid approaches have the potential to reduce unnecessary radiation doses, improve the segmentation process, and produce detailed 3D representations of lung tumors, making them more valuable in clinical practice. reducing the task burden of clinicians and, at the same time, increasing internal practice accessibility and systematic diagnostic efficiency and treatment. Providing significant enhancement in noise cancellation within any data and noise. achieving high reliability with as little training data as possible and with the lowest possible demand on computational resources.

There are several issues with the given hybrid approaches in medical imaging, specifically the detection and segmentation of lung diseases. These models are cumbersome due to the heavy computations involved, the complex set of parameters that need to be tuned, and the need for technical personnel to handle them. The basic issue is that they require large amounts of computation time, often involve extending training duration, and demand great data input accuracy, which creates problems when used with large or diverse data. Reliance on high-quality CT images and the focus the model has on particular lung diseases make the model generally less useful in a medical case or with other modalities. also, the projection of such an architecture complicates the task of segmentation as it is prone to errors in an area that is not well-defined or where the data from the adjacent slices is crucial but unavailable.

8 Applications in Clinical Practice

8.1 Current Implementations

Some of these hybrid approaches and strategies for segmenting the clinical images involve using deep learning integrated with traditional strategies that have been tested practically in the scientific field. One such example is the hybrid models in radiology operating for most lung cancer diagnoses. These models can be primarily based on CNNs combined with other conventional approaches, image processing, or feature extraction enhancing the segmentation operations and overall performance.

For instance, the case is the Diagnostic accuracy of the pulmonary embolism. A hybrid method detected pulmonary embolisms from CT pulmonary angiograms (CTPA) [73]. In these cases, there's usually used of hybrid approaches to regions of interest, at the same time a convolutional neural network (CNN) is implemented for a unique segmentation of the embolism. This integration has greatly helped radiologists to adopt image evaluation in a shorter time as the concept facilitates the location of regions of interest. Increased timing and accuracy of detecting the supply of embolisms permits the short handling of the trouble and the corresponding decrease of the dying toll from the not-on-time treatment. And also, the case of lung nodule detection in low-dose CT scans. The proposed 3D hybrid model incorporated with traditional functions has been applied to several radiology departments for pulmonary nodule segmentations in low-dose CT scans [74]. Integrating deep learning with conventional detection approaches to more accurate delineation of nodule boundaries. Their impact has additionally desired the detection charge of early small nodules, which the standard CNN models fail to discover due to their small size. Incorporation of this model into sufferer's care processes has been discovered to enhance diagnostic precision, consequently facilitating early action.

8.2 Clinical Impact

Integrating hybrid segmentation models in clinical practice has improved patients' diagnoses [75], especially in lung cancer and other pulmonary diseases. These models have enhanced the detection accuracy of lesions, thus enabling early diagnosis and accurate treatment planning. The hybrid models' effectiveness in diagnosing Lung cancer and early detection is better in the localization of lung lesions, particularly when a scan contains small or low-contrast nodules. The use of deep learning in combination with conventional image processing means the algorithm does not miss certain fine details, improving the detection rate. Therefore, Lung cancer could be detected at an earlier stage through such models, leading to more patients undergoing surgery or medical examination to increase the survival rate[76]. Another benefit from more precise segmentation and classification of the lesions is the potential for increased sophistication of the treatment plan, as motivated by the knowledge of tumor characteristics and responsiveness to the therapy.

Hybrid segmentation techniques are also being used to observe the progress of chronic pulmonary conditions like COPD (Chronic Obstructive Pulmonary Disease) [77], [78] and interstitial lung disease [79]. These techniques can accurately segment affected lung regions, presenting clinicians with detailed premeditation into disease progression.

9 Ethical Considerations in Automated Segmentation

Implementing automated segmentation algorithms in medical imaging raises several ethical concerns. Ensuring fairness, transparency, and trust in these technologies is essential for their integration into clinical practice. The most critical ethical concerns are:

Patient Privacy and Data Security

With the development of automated segmentation algorithms, patient privacy and data protection are very important. Considerable ethical concerns increase, especially when using huge datasets often containing sensitive personal health information. Secure patient privacy is paramount to ensure trust and compliance with legal regulations. One of the main considerations is data anonymization, which means that before data can be utilized for developing segmentation algorithms, it should be anonymized by eliminating any identifiable data. This operation includes identifying outright identifiers like names, addresses, and social security numbers. There are many techniques to safeguard the privacy of such healthcare data, such as a distributed deep learning method called (SplitNN)[80], which does not share raw data or model specifics with (hospitals). Safe data Storage is also important. If data is stored locally or in the cloud, it must be secured using a sophisticated encryption approach. When sharing datasets for collaborative research or with another team, there must be accurate agreements on data use[81].

Bias and Fairness

Automated segmentation systems can be reflected in the training data. This is concerning in healthcare, where biased models can lead to different treatment results for various demographic sets, like race, sex, or age [82]. For instance, a segmentation model trained fundamentally on data from a single ethnic group might execute badly on images from patients of other ethnicities. It's essential to train models on various datasets representing different population sets to minimize bias. This assists in ensuring model generalization over several demographics and anatomical differences [83].

Transparency and Explainability

Automated segmentation models, predominantly those that include hybrid or deep learning approaches, demand a high level of translucency. Clinicians need to trust these techniques and comprehend how they make decisions, particularly when the results impact crucial medical decisions[84]

Explainability

Artificial Intelligence plays a main role in enhancing the reliance and transparency of AI-based diagnostic systems, particularly in medical imaging. This information gives medical physicians better insights into how the system reached its conclusions, raising trust in its use in clinical settings, where making an accurate decision may be crucial for patients. So the use of explainable AI can help improve quality and prove the reliability of models in different scenarios, helping to avoid the hazard of blind dependence on algorithms[85].

Bias and Fairness

Confirming various and representative training data is critical to prevent biased models that may execute badly. Research refers to the fact that models exclusively trained on data from one ethnical group commonly test a notable drop in performance when tested on various groups. Neglecting variety in training data can lead to unbalanced models, resulting in biased conclusions in healthcare, where some groups may receive minus precise diagnoses or curing. To cancel this, strategies should be used to ensure inclusivity in data, like collecting various training samples and selecting a balanced demographic exemplification[86].

Clinical Acceptance

Clinicians have accepted explainable models more because they can better understand and trust the technology. This is important in hybrid models where AI and human experience are combined in decision-making. Transparency assists minimize the space between AI recommendations and clinical rulings, leading to more influential and secure patient care.

10 Conclusion

In summary, the discovery and segmentation of lung lesions is a sensitive challenge in medical imaging because of the inequality in lesion shape, size, and contrast. Traditional segmentation techniques like thresholding and edge detection have presented basic visions, but they generally fall short in treating complicacy and small differences ingrained in medical images. The coming of deep learning, particularly convolutional neural networks (CNNs), has crucially advanced the scope, permitting more accurate and durable segmentation results.

Hybrid methods, which merge traditional image processing methods with machine learning techniques, enhance comprehensive diagnostic solutions using the strengths of intelligent technology and human experience. These approaches increase lung lesion segmentation's accuracy, robustness, and qualification. Deep learning developed by rule-based systems, ensemble learning, and multi-scale feature extraction are examples of how hybrid methods enhance segmentation precision and clinical utility.

Although wide trends for hybrid models merge traditional machine learning and deep learning, they have great accuracy and feature extraction advantages. but the rise in complexity, possibility for overfitting, and challenges in general applicability to different clinical datasets remain serious obstacles.

Future research should concentrate on extensibility, computational ability, and larger generalization to ensure that these models can be used in various, real-world clinical settings.

Future researchers should focus on models developed for medical designers suitable for use in scientific environments with limited computing resources. Hybrid models represent an influential stage in medical image segmentation, bridging the gap between traditional techniques and modern machine learning and giving more accurate, less time-consuming, and clinically important diagnostic results.

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