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Critical Studies on Lesion Segmentation in Medical Images

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Abstract

In medical images, lesion segmentation is used to locate and isolate abnormal structures. It is an essential part of medical image analysis for precise diagnosis and care. However, obstacles exist in medical image lesion segmentation owing to things like image noise, shape and size fluctuation, and poor image quality. Automated lesion segmentation methods include conventional image processing techniques, deep learning (DL) models and machine learning (ML) algorithms to name a few. Thresholding, region growth, and active contour models are examples of conventional methods, while decision trees, random forests, and support vector machines are examples of ML techniques. DL models particularly convolutional neural networks (CNNs), have shown extraordinary performance in lesion segmentation because to their innate potential to autonomously collect high-level characteristics. The objective of the research is to study lesion segmentation in medical images and explore different methods for accurate and precise diagnosis and care.The research focuses on the obstacles faced in lesion segmentation in medical images, such as image noise, shape and size fluctuation, and poor image quality. The research also highlights the need for evaluation metrics, such as sensitivity, specificity, Dice coefficient, and Hausdorff distance, to assess the performance of lesion segmentation algorithms. Additionally, the research emphasizes the importance of annotated datasets for training and evaluating the performance of segmentation algorithms.

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1. Introduction

The use of imaging techniques in medicine is essential in the detection and treatment of many illnesses. For example, lesion segmentation in medical images identifies and separates abnormal structures or areas within an image, essential for accurate diagnosis and treatment planning. Lesions can appear in various forms, including tumors, cysts, and other abnormal growths, and can occur in different organs or tissues, such as the brain, lungs, liver, and bones.

Segmentation of lesions in medical images is challenging due to several factors, such as image noise, variations in size and shape, and poor image quality. Accurate and efficient lesion segmentation, on the other hand, may improve patient outcomes and quality of life by facilitating early disease identification and diagnosis. Additionally, accurate segmentation can help with therapy evaluation, disease tracking, and treatment strategy development.

For lesion segmentation, in addition to more conventional image processing methods, you can also use ML techniques or DL models. CNN, in particular, have shown excellent success in lesion segmentation because of their natural ability to autonomously acquire high-level properties.

Evaluation of lesion segmentation algorithms is crucial to assess their performance. Evaluation metrics commonly include sensitivity, specificity, Dice coefficient, and Hausdorff distance. Moreover, annotated datasets are essential to train and evaluate the segmentation algorithms performance.

1.1 Research Problem

The study addresses the challenges faced in lesion segmentation in medical images, including image noise, shape and size fluctuation, and poor image quality.

1.2 Study Objective

The study aims to delve into different methods for lesion segmentation in medical images to achieve accurate diagnosis and care. The study also investigates conventional image processing techniques, machine learning algorithms, and deep learning models, particularly convolutional neural networks (CNNs), for lesion segmentation.

The importance of evaluation metrics, such as sensitivity, specificity, Dice coefficient, and Hausdorff distance, for assessing the performance of lesion segmentation algorithms is also emphasised. Additionally, the need for annotated datasets for training and evaluating the performance of segmentation algorithms are also highlighted.

2. Critical Studies

Several studies have been conducted to create effective segmentation algorithms for lesion segmentation in medical images, suggesting that this is an active area of study. Some of the most influential works in this area are briefly summarized here.

Computed Tomography Universal Lesion Detection Using Multiple Datasets with Heterogeneous and Partial Labels, In [1], the authors presented a powerful learning strategy for lesion detection across numerous data sources. Using a “Hybrid Tri-Level Attention-Based Network, Lesion Segmentation, Diagnosis, and Severity Prediction in COVID-19 Chest CT Scans, CovTANet”, TA-SegNet was developed to segment lesions on CT slices and was first suggested in [2]. “A Multiple Layer U-Net, Un-Net, for the Liver and Liver Tumo”r is presented at "IEEE ACCESS, 2021." Un-Net (an n-fold U-Net design), which uses the output properties of the convolution units as skip links, is presented in [3] as an alternative U-Net model architecture for medical image segmentation.

CovSegNet: “A MultiEncoder-Decoder Architecture for Improved Lesion Segmentation of COVID-19 Chest CT Scans”, [4] suggests developing a region-of-interest (ROI) enhanced CT volume using a deeper 2-D network, then adding more improvement using a shallower 3-D network. The approach presented in the publication "Multi-Modal Co-Learning for Liver Lesion Segmentation on PET-CT Images," "IEEE Transaction on Medical Imaging, 2021" [5] should improve the speed with which lesions are located and diagnosed.

The connections between different multi-lesions and between various multi-lesions and vasculature were examined in "IEEE Transaction on Medical Imaging, 2022" [6] using a Relation Transformer Network for Multi-Lesion Diabetic Retinopathy Segmentation. Breast lesion segmentation using a saliency-guided, morphology-aware U-Net was suggested in "IEEE Transaction on Medical Imaging, 2022" [7]. Breast ultrasound (BUS) image lesion segmentation was proposed using a saliency-guided, morphology-aware U-Net. To Segment

Multiple Lesions in Medical Images Using a Prior Attention Network, "IEEE Transaction on Medical Imaging, 2022" The proposed network is a modification of the U-Net called the Prior Attention Network (PANet) [8]. Table 1 shows the literature survey of some of the critical studies.

2.1 Lesion Ensemble Framework (LENS)

"Universal Lesion Detection in CT: Learning from Several Datasets with Heterogeneous and Partial Labels" In [1], a new method is presented for global lesion recognition in CT scans by using various datasets with mixed and incomplete labels as training data. The authors conducted a literature survey and found that most existing methods for lesion detection are designed for a specific type of lesion and cannot be easily adapted to detect other types of lesions.

The study uses four public lesion datasets to train and evaluate the proposed approach. These datasets are Deep Lesion, LUNA, LiTS, and Kidney Tumor. When compared to previous approaches, the suggested method dramatically enhanced the accuracy of lesion identification. Four publicly available lesion datasets were used to assess the method's efficacy. When compared to the existing gold standard method, it was able to increase average sensitivity by 49%. The authors have also shared their Deep Lesion manual 3D annotations with the public.

2.2 TA-Segment Framework

"CovTANet: A hybrid tri-level attention-based net for lesion segmentation, diagnosis, and severity prediction was trained using the COVID-19 chest CT dataset. In [2] paper, the research on COVID-19 diagnosis and severity prediction based on CT images are evaluated. The authors concede that current approaches for estimating the severity of COVID-19 are inadequate, and the importance of developing new neural networks were highlighted .

"MosMedData: "Chest CT Scans with COVID-19 Related Findings" is the dataset used for this analysis. It is one of the largest openly available datasets in this field, with 1110 anonymized CT volumes with and without COVID-19-related findings that have been annotated for severity. The suggested CovTANet approach outperforms state-of-the-art techniques for COVID-19 lesion segmentation and severity grading tasks on the MosMedData dataset.

Table 1. Literature Survey of some of the Critical Studies

Research Study	Techniques used	Datasets Used	Conclusions
"IEEE Transactions, 2021" "Learning From Multiple Datasets With Heterogeneous and Partial Labels for Universal Lesion Detection in CT" [1]	Lesion ENSemble (LENS) framework: An efficient learning system for detecting lesions from a variety of different types of datasets, with a focus on simplicity. DenseNet-121 with 3D feature fusion layers a feature pyramid network (FPN)	The suggested technique is evaluated on 800 manually labeled sub-volumes in DeepLesion after being trained on four publicly accessible lesion datasets. Deep Lesion LiTS (Liver) LUNA (Lung) NIH-LN (Lymph nodes)	Recommends generating artificial lesion data to supplement training datasets using generative models. Suggests enhancing the performance of the algorithm and expanding it to handle 3D medical images.
"IEEE Transactions, 2021" describes CovTANet as a hybrid tri-level attention-based network for lesion segmentation, diagnosis, and severity prediction in COVID-19 chest CT scans. [2]	1. TA-SegNet was created with the specific goal of segmenting lesions from a CT-volume slice by slice. Fully convolutional networks (FCN) Unet networks 2. Incorporated characteristics from the lesion's location for more accurate diagnosis and prognosis of severity.	"MosMedData: Chest CT Scans with COVID-19" One of the greatest publicly accessible datasets contains 1110 anonymized CT volumes from hospitals in Moscow, Russia, annotated with severity-related COVID-19 results and without such findings.	The segmentation network (TA-SegNet) was significantly enhanced by a tri-level attention mechanism and simultaneous optimization of multiscale encoded-decoded feature maps.
A Multiple Layer U-Net, Un-Net, for Liver and Liver Tumor, "IEEE ACCESS, 2021" [3]	Un-Net, a unique model architecture for medical image segmentation that builds on the U-Net model by using the convolution units' output properties as skip connections, is known	Two datasets used in this study: There are 131 training Liver CT volumes and 70 testing volumes available in the LiTS dataset.	Successful segmentation of medical images was shown by high values of Dice's Similarity Coefficient (DSC). The article reaches the conclusion that the novel network design is adaptable, making it suitable for issues

	as an n-fold U-Net architecture.	3DIRCADb There are 20 CT scans and 15 liver tumor images in the dataset.	with varying data sample sizes.
CovSegNet: A Multi-Encoder-Decoder Architecture for Improved Lesion Segmentation of COVID-19 Chest CT Scans, "IEEE Transaction on Artificial Intelligence, 2021" [4]	"CovSegNet" A deeper 2-D network is used to construct the ROI-enhanced CT volume, which is subsequently improved using a shallower 3-D network. implemented multistage encoder-decoder modules into U-Net to enable horizontal extension (for superior performance)	1. Dataset-1: a panel of professional radiologists annotated over 1800 slices across 20 CT volumes. All of the slices have lung and infection area annotations. 2. Dataset-2: Italian Radiologist developed the "COVID-19 CT Segmentation dataset" that includes 110 axial CT images from 40 COVID patients.	Outstanding performance is provided, with a mean increase in dice score of 8.4% between the two datasets. The suggested network effectively separates COVID lesions and achieves cutting-edge outcomes on a demanding, nonclinical, multiclass semantic segmentation test, demonstrating the scheme's wide application.
Multi-Modal Co-Learning for Liver Lesion Segmentation on PET-CT Images, "IEEE Transaction on Medical Imaging, 2021" [5]	The CT and PET encoder blocks use a Shared Down-sampling Block (SDB) to eliminate false positives and enable feature interaction across various modalities. The Hierarchical Feature Co-learning Module (HFCM) used to improve feature quality.	1. The Dataset used 100 FDG PET-CT scans (fluorodeoxyglucose positron emission tomography), divided into 10 subsets for 10-fold cross-validation. 2. Shanghai BNC provides the Dataset, and experienced radiologists label the liver contour and lesion masks.	The suggested model outperforms cutting-edge multi-modal techniques in terms of accuracy. Micro-lesion detection capacity and diagnosis rate may be improved, and prompt lesion localization may be aided, by the proposed method
Relation Transformer Network (RTNet) for Multi-Lesion Diabetic Retinopathy Segmentation,	"RTNet" The Relation Transformer Block (RTB) combines a self-attention transformer and a cross-attention transformer to benefit from	1. IDRiD Dataset: available for segmenting and grading retinal image challenge 2018. 2. DDR Dataset: for the aim of lesion segmentation and lesion	The relationships between various lesions, as well as between lesions and blood vessels was investigated. Future studies should focus on improving the vascular semi-supervised learning approach

"IEEE Transaction on Medical Imaging, 2022" [6]	interactions between lesion and vascular features. Global Transformer Block (GTB) stores information persistently in a deep network, allowing it to detect the most minute lesion patterns.	identification, Ocular Disease Intelligent Recognition (ODIR-2019) has offered. There are 13,673 fundus images in this.	and fortifying the transformer structures, it has been recommended, in order to boost performance.
SMU-Net: Saliency-Guided Morphology-Aware U-Net for Breast Lesion Segmentation in Ultrasound Image, "IEEE Transaction on Medical Imaging, 2022" [7]	SMU-Net: Breast ultrasound (BUS) image lesion segmentation utilizing a saliency-guided, morphology-aware U-Net. In this instance, foreground and background saliency maps serve as guidance for the main and secondary networks.	1. Dataset 1: The UDIAT Diagnostic Center in Spain provided the 163 BUS photos demonstrated here. 2. Dataset 2: 583 BUS images derived from Egypt Hospital. 3. Dataset 3: BUS images from 1907 are available through SonoSkills and Hitachi Medical Systems Europe.	When it comes to breast lesion segmentation, the suggested method outperformed various cutting-edge deep learning algorithms and showed enhanced resilience to the size of the dataset.
Using a Prior Attention Network for Multi-Lesion Segmentation in Medical Images, "IEEE Transaction on Medical Imaging, 2022" [8]	Prior Attention Network (PANet): A unique attention-guiding decoder module is part of the proposed Prior Attention Network, and it creates ROI-related attention maps that are subsequently used to modify the feature representations, enhancing multiclass segmentation performance.	The BraTS 2020 challenge's open-source multi-modality MRI dataset is used. 369 multi-contrast MRI images make up the training set.	Superior performance in 2D and 3D segmentation tasks at lower computational cost than cascaded networks. The suggested network is applicable to 2D and 3D multi-lesion segmentation challenges, making it a universal solution.

2.3 N-Fold U-NET Architecture

The authors of the publication "A Multiple Layer U-Net, Un-Net, for Liver and Liver Tumor" [3] reviewed the literature on deep learning applications in medical image segmentation. to overcome the problems that plague more conventional approaches. This research draws on data from the LiTS dataset as well as the 3DIRCADb dataset. The LiTS dataset only contains 131 CT volumes for training and 70 CT volumes for testing, as opposed to the 3DIRCADb Dataset's 20 CT scans for liver segmentation and 15 CT scans for liver tumor segmentation. Both datasets come with their own ground truths.

The proposed Un-Net network architecture achieved better results than recent liver and tumor segmentation networks in CT scan images. The proposed models achieved a Dice's Similarity Coefficient (DSC) of 96.38% on the LiTS dataset for liver segmentation and 73.69% on the 3DIRCADb dataset for tumor segmentation.

2.4 CovSegNet Architecture

"CovSegNet: A MultiEncoder–Decoder Architecture for Improved Lesion Segmentation of COVID-19 Chest CT Scans" [4]Study provides a literature review of previous studies related to COVID-19 CT scan lesion segmentation. The authors discussed the research gaps of traditional methods and highlighted the importance of deep learning-based approaches for accurate and efficient segmentation.

Two publicly available datasets were used to verify the study's hypotheses. Twenty CT volumes totalling 1800+ slices have been evaluated by a team of radiology experts to provide the initial dataset. All of the slices include annotations indicating the location of lung tissue and infection. The second dataset, known as the "COVID-19 – dataset of CT Segmentation," was compiled by the "Italian Society of Medical and Interventional Radiology" and consists of "110 axial CT images from 40 different COVID patients". The resolution of each image is 512 pixels by 512 pixels.

2.5 Multi-Modal Architecture

The methods used in this Study [5] include:

1. To get liver outlines, a V-Net and morphological processing were used.

2. A multi-modal co-learning network is presented for segmenting liver tumors from PET-CT data.

3. An encoder branch using SDBs and two refactoring branches, one each for PET and CT modalities, make up the proposed network.

One hundred FDG PET-CT scans are used as the dataset for this study, and the data was divided into ten groups for 10-fold cross-validation. Shanghai BNC provides the dataset, and expert radiologists annotate the liver contour and lesion masks. Unfortunately, the Dataset contains a wide range of tumor volumes and variations, making automatic liver lesion segmentation challenging.

The proposed network outperformed the baseline models ($p < 0.05$) for liver tumor segmentation, with an average Dice similarity coefficient (DSC) of 0.77. Improved consistency between the two refactoring branches' predictions was another benefit of the suggested similarity loss algorithm. These findings show that the suggested network is capable of accurately segmenting liver tumors in PET-CT scans.

2.6 RTNet-Architecture

RTNet: “Relation Transformer Network for Diabetic Retinopathy Multi-Lesion Segmentation” [6] study discusses the pathological analysis of diabetic retinopathy (DR) lesions and the challenges associated with their segmentation due to sizeable intra-class variance and variations with different stages of the disease.

The suggested dual-branch relation transformer network was put to the test using cutting-edge techniques, and it was found to attain competitive performance on the IDRiD and DDR datasets. The suggested technique beat both the baseline and other cutting-edge methods on the basis of sensitivity, segmentation, accuracy, F1-score, and specificity

2.7 SMU-Net Architecture

"SMU-Net: The state-of-the-art deep learning algorithms for “breast lesion segmentation in ultrasound images” are examined in the study “Saliency-Guided Morphology-Aware U-Net for Breast Lesion Segmentation in Ultrasound Images” [7]. The authors describe the challenges of "accurate lesion segmentation in breast ultrasound images" and specifically point out the low contrast appearance, fuzzy border, and significant shape and position change of lesions.

A total of 3034 breast ultrasound (BUS) images can be found in these databases. The datasets are as follows:

1. Dataset 1: Comprises "163 BUS images acquired from the UDIAT Diagnostic Center of the Parc Taulí Corporation, Sabadell (Spain), with a Siemens ACUSON Sequoia C512 system 17L5 HD linear array transducer (8.5 MHZ)."

2. Dataset 2: Enroll "583 BUS images derived from Baheya Hospital, Cairo (Egypt) with LOGIQ E9 and LOGIQ E9 Agile systems".

3. Dataset 3: "Collects 1907 BUS images offered by SonoSkills and Hitachi Medical Systems Europe".

The "saliency-guided morphology-aware U-Net (SMU-Net)", when used to segment breast lesions in ultrasound images, outperforms a number of other cutting-edge deep-learning algorithms, according to this research.

2.8 PANet-Architecture

"Prior Attention Network for Multi-Lesion Segmentation in Medical Images" [8] study discusses using cascaded networks in medical segmentation. Many various kinds of lesions, such as those seen in the liver, brain, multiple sclerosis, and the prostate, have been segmented using a cascaded network. The multi-modality MRI dataset that is publicly available and was utilized in this study was gathered as part of the BraTS 2020 challenge.

The results of this study show that the suggested Prior Attention Network (PANet) performs better in 2D and 3D segmentation tasks than cascaded networks while using fewer computational resources. Experimental findings exhibit the superior performance of the proposed PANet over the state-of-the-art techniques on the BraTS 2020 dataset in terms of the Dice similarity coefficient (DSC) and the Hausdorff distance (HD).

3. Discussion on Existing Methods

3.1 Strengths of Existing Methods

- Conventional methods, such as thresholding, region growth, and active contour models, have been extensively utilized for lesion segmentation in medical images.
- ML techniques, including, random forests, support vector machines, and the decision trees resulted in promising lesion segmentation outcomes.

• Convolutional neural networks (CNNs) the deep learning model, in particular, have shown outstanding performance in lesion segmentation due to their capacity to extract high-level features on their own.

3.2 Weaknesses of Existing Methods

- Conventional methods may struggle with image noise, shape and size fluctuation, and poor image quality, leading to suboptimal segmentation results.
- Machine learning techniques heavily rely on feature engineering, which can be time-consuming and may not capture all relevant information.

Table 2. Details of used Backbone Network and Evaluation Metrics in the Critical Studies

Architecture Used	Algorithms Used	Evaluation Metrics Used
Lesion ENSemble (LENS) [1]	Algorithm used in LENS is a 2.5D truncated DenseNet-121 Feature pyramid network (FPN) and 3D feature fusion layers	Average Sensitivity at 1/8, 1/4, 1/2, 1, 2, 4, and 8 FPs per sub-volume
TA-SegNet [2]	Fully convolutional networks (FCN) Unet networks	Accuracy Precision Dice Score

		Intersection-over-union (IoU) score
N-Fold U-NET [3]	Dilated convolution (DC) Dense structure	Dice's Similarity Coefficient (DSC) Volumetric Overlap Error (VOE) Relative Volume Difference (RVD)
CovSegNet [4]	“2-D network for generating region-of-interest (ROI)-enhanced CT volume” “shallower 3-D network for further enhancement with more contextual information”	Sensitivity Specificity Dice Score Intersection-over-union (IoU) score
Multi-Modal [5]	Shared Down-sampling Block (SDB) Hierarchical Feature Co-learning Module (HFCM)	Dice Score
RTNet [6]	“Relation Transformer Block”(RTB) “Global Transformer Block” (GTB)	Area-under-the-curve of precision and recall (AUC_PR) curve Area-under-the-curve of receiving operating characteristic (AUC_ROC) curve
SMU-Net [7]	U-Net with an additional middle stream and an auxiliary network	M-IoU Sensitivity F1-score Precision
PANet [8]	coarse-to-fine strategy lesion-related spatial attention mechanism	Precision Dice Recall

3.3 Challenges Identified in Existing Methods

- Conventional methods face challenges in handling image noise, shape and size variation, and poor image quality.
- Machine learning techniques may struggle with feature selection and may not capture complex relationships in the data.
- Deep learning models require extensive computational resources and large annotated datasets for training, which may not always be available.

Overall, while existing methods have shown strengths in lesion segmentation, they also have weaknesses and face specific challenges that need to be addressed for more accurate and efficient segmentation results. Table 2 shows the details of used algorithm and Evaluation Metrics in the critical studies.

4. Pre-processing Steps, Feature extraction and popularly used Tools, in Lesion Segmentation

4.1 Pre-processing Steps

Pre-processing is an important step in lesion segmentation [9], [10], as it helps to improve the quality of the images and make them more suitable for feature extraction and segmentation. Some common pre-processing steps include:

Intensity normalization: This involves normalizing the intensity of the images to a common range, such as 0 to 255. This helps to improve the contrast of the images and make the lesions more visible.

Noise reduction: This involves removing noise from the images, which can be caused by factors such as electronic noise and sensor noise. Noise can interfere with lesion segmentation, so it is important to remove it before proceeding.

Image segmentation: This involves segmenting the image into different regions, such as the lesion, the background, and other anatomical structures. This can help to improve the accuracy of lesion segmentation, as it allows the algorithm to focus on the relevant region of the image.

4.2 Feature Extraction

Feature extraction [11] is the process of extracting relevant information from the pre-processed images. This information can then be used to train a lesion segmentation model. Some common features used for lesion segmentation include:

Intensity features: These features are based on the intensity of the pixels in the image. Some common intensity features include the mean, median, and standard deviation.

Texture features: These features are based on the texture of the pixels in the image. Some common texture features include the Haralick texture features and the Gabor texture features.

Shape features: These features are based on the shape of the lesion in the image. Some common shape features include the area, perimeter, and eccentricity of the lesion.

4.3 Popular Used Tools in Lesion Segmentation

There are a number of popular tools [12], [13] that can be used for lesion segmentation. Some of these tools include:

Deep learning frameworks: Deep learning frameworks such as TensorFlow and Pytorch can be used to train and deploy lesion segmentation models. These frameworks provide a variety of tools and resources that make it easy to develop and deploy lesion segmentation models.

Lesion segmentation software: There are a number of lesion segmentation software packages available, such as 3D Slicer and ITK-SNAP. These packages provide a variety of tools and features that make it easy to segment lesions from medical images.

Cloud-based lesion segmentation services: There are a number of cloud-based lesion segmentation services available, such as Amazon Web Services (AWS) Recognition and Google Cloud Vision AI. These services [14], [15] provide a convenient and easy way to segment lesions from medical images.

5. Solutions to Enhance the Lesion Segmentation

Generative models can be used to enhance lesion segmentation in a number of ways. One way is to use a generative model to generate synthetic lesion images that can be used to train or augment existing lesion segmentation models. This can be particularly useful in cases where there is limited labelled data available. Another way to use generative models for lesion segmentation is to develop a generative model that can directly segment lesions from medical images. This type of model is typically trained on a dataset of labelled medical images, and it learns to generate segmentation masks for new images that are similar to the images in the training dataset.

Here are some specific examples of how generative models have been used to enhance lesion segmentation:

- Generative adversarial networks (GANs) have been used to generate synthetic lesion images that can be used to train or augment existing lesion segmentation models.

- Variational autoencoders (VAEs) have been used to develop generative models that can directly segment lesions from medical images.

Generative models have the potential to significantly improve the performance of lesion segmentation models. However, there are still some challenges that need to be addressed before generative models can be widely used in clinical practice. One challenge is that generative models can be difficult to train, and it could be sensitive to the hyperparameters used during training.

6. Conclusion

The research focuses on the obstacles faced in lesion segmentation in medical images, such as image noise, shape and size fluctuation, and poor image quality. The research also highlights the need for evaluation metrics, such as sensitivity, specificity, Dice coefficient, and Hausdorff distance, to assess the performance of lesion segmentation algorithms. The study explores various methods for lesion segmentation in medical images, including conventional image processing techniques, machine learning algorithms, and deep learning models, particularly convolutional neural networks (CNNs). The study highlights the exceptional performance of deep learning models, specifically CNNs, in lesion segmentation due to their ability to autonomously extract high-level characteristics.

The study contributes by providing insights into the strengths and weaknesses of existing methods, highlighting the potential of deep learning models, and emphasizing the importance of evaluation metrics and annotated datasets for training and evaluating segmentation algorithms. In this study pre-processing steps, feature extraction and popularly used tools in lesion segmentation arediscussed. At last, this study provides the solutions for enhancing the lesion segmentation inr future researches.

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