

GAN-Based Lung Tumor Image Segmentation Framework Using UNet and TransUNet

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ABSTRACT

Deep learning-based methods have advanced medical image segmentation performance in recent years. However, these methods require further improvement and large amounts of annotated images to train. Image segmentation is mainly based on pixel-wise annotations, but obtaining annotated data is costly and stressful. Generative Adversarial Networks (GANs) are used to generate additional training data synthetically to avoid these costs and benefit from small datasets. Current mainstream GAN networks achieve high accuracy when trained on large, annotated datasets. Still, the potential annotated small datasets in medical image analysis have not been addressed much. This paper presents a novel approach to image segmentation that leverages GANs' powerful generative capabilities to address inherent challenges in segmentation tasks. Our method integrates a GAN framework in which the generator produces synthetic images, while CNN methods segment lung tumour images from both real and synthetic datasets. Afterwards, the results are compared to demonstrate the effect of data augmentation on lung tumour image segmentation. The experimental results show that our GAN-based Trans-UNet segmentation approach outperforms the UNet segmentation method, with the Trans-UNet on the synthetic data achieving increases of 0.6%, 0.7%, and 0.4% in Dice, PPV, ACC, and Sens, respectively, providing significant validation of the effectiveness of our approach. These results demonstrate the potential of GANs for addressing challenges in medical image segmentation and highlight the proposed method's improved accuracy and robustness.

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1. Introduction

In the last few years, the use of artificial intelligence (AI) to analyse medical multimedia, such as images, to facilitate accurate disease detection has attracted increasing attention from researchers. The development of medical AI-based models requires considerable media-based data, such as computed tomography (CT), Magnetic resonance imaging (MRI), and X-rays. (Nasimova et al., 2021). Currently, limited medical image databases are publicly available, usually small or consumed, or large but unlabelled. Therefore, He et al. (2020) have resorted to creating synthetic images due to high demand for medical datasets. Accordingly, generating synthetic tumor image datasets has received considerable attention. Generative adversarial networks (GAN) have become the most efficient methods for creating synthetic images, and researchers have proposed hundreds of hybrid algorithms based on them (Singh & Raza, 2021; Suganthi, 2021). However, traditional methods for assessing image quality, such as pixel intensity and noise, may not be sufficient to capture the complexity of synthetic medical images. It's important to note that natural images, such as those of people and animals, are distinct from medical images (Fabiani et al., 2016). Natural images are typically 2D with 3 channels and can be found in various formats, such as 2D Grayscale, 3D, and 4D. The relative pixel intensity determines their ability to detect edges and gradients. In contrast, medical images are often 3D or 4D, focusing on the intensity of each pixel and even the noise that can convey information about diseases in tissues or organs (Fabiani et al., 2016). Understanding these differences is not just important but crucial in developing AI models for medical imaging (Medeiros da Nobrega & Rodrigues, 2017).

Moreover, the location plays a crucial role in medical images but is unimportant in standard images. This underscores the urgency of developing methods specifically tailored for evaluating medical images, which cannot be used to assess natural images (Ma et al., 2024). The need for improved methods in medical image evaluation is pressing, given the widespread use of medical images, especially for detecting tumors and representing information about human diseases.

Diagnosis from lung tumour CT scans can be improved using image segmentation techniques, which identify lung features and lung nodules (Sarkar et al., 2024). The main contributions of this research are:

- This work focuses on data augmentation using images synthesized from a generative model GAN that can improve the training of deep learning methods in the context of image segmentation tasks. The image segmentation is divided into two methods: UNet, which works with fewer training images and achieves more accurate segmentation, and Trans-UNet, which combines both Transformers and UNet as a robust method for tumor image segmentation.
- This study aims to assess the segmentation performance of the real-based method and then compare it to the GAN-based method, especially when dealing with small datasets. The experiments have been performed on the lung tumor dataset collected from the King Abdulaziz Specialist Hospital in Al-Jouf, Saudi Arabia.
- This research illustrates the feasibility of using deep generative models for earlier lung tumor diagnosis. It enlightens the audience about the practical implications of such advancements in medical imaging and deep learning.

The remainder of the paper is organized in section 2. All related work and background knowledge for this research are provided. Section 3 presents the proposed framework; section 4 presents Training and measurement metrics; section 5 Presents the Analysis of experimental results; section 6 discusses the system pragmatically; and section 7 concludes the work.

2. Related Work

Most previous studies have focused on automatic tumor image segmentation depending on computed tomography (CT) images. CT image data are abundant because CT is low-cost and time-saving, making it commonly used in operative planning. In 2005, Liu and others developed a semi-automatic method for liver contour delineation on improved CT images. The study used a gradient vector flow (GVF) followed by a snake algorithm; it was applied to 551 CT liver images. A preliminary liver contour was obtained by computing the GVF field, and unwanted edges were eliminated, spreading throughout the liver. The evaluation relied on error ratios between the radiologist's manual results and computer results at different widths. The liver segmentation results showed that the average difference ratio was 5.3% (Liu et al., 2005). In continuation of the previous study in 2007, Gui and others presented a hybrid semi-automatic technique for delineation liver contours by CT scans. The study used a generalized gradient vector (GGVF) followed by a snake algorithm. The results showed that the liver could be correctly extracted, and that the model could be used for other organ segmentation, since the proposed approach did not use specific liver information (Gui et al., 2007). Furthermore, based on liver regions, Lim and others presented a new method for automatic segmentation on CT scans to measure the volume. The study used a morphological filter to generate the initial liver contour via region labelling and clustering. After that, the model was compared with the experimental volume measurement obtained using the radiological manual tracing method. The research proved that the algorithm used is an effective automatic segmentation method for CT liver images, particularly for the first diagnosis step of computer-aided surgery (CAS) systems (Lim et al., 2006). Looking at CT images of lung cavities can be used to improve surgical planning for treating lung cancer. The main challenge in surgical planning is automatically segmenting lung lobes. Wei and others used a lobe segmentation algorithm with a two-stage approach: find fissure regions using fissure sweeping and identify fissure locations using a wavelet transform. The result showed that the algorithm's segmentation and visualization require about 5 minutes for both lungs (Wei et al., 2009). In an extension of lung segmentation, Mesanovic et al. proposed a technique to accurately segment the lung CT images. The segmentation technique starts by choosing the initial pixel from the image's dark side. To ensure the segmentation process finishes exactly, one pixel is added when touching the edges of the image as the border. This technique has had a computational time per segmentation ranging from 5 to 20 seconds per slice (Mesanovic et al., 2011). Segmented CT of multiple organs from the abdomen by DenseVNet deep-learning algorithm into four organs for an endoscope to navigate, and another four organs for navigational landmarks (Gibson et al., 2018). The proposed technique was compared with two existing deep learning methods to assess improvements in segmentation accuracy and to illustrate the architectural factors driving these improvements. The study found enhanced overlap across all abdominal organs, with small organs like the gallbladder showing the greatest improvements, while the segmentation accuracy of the duodenum has been less well studied (Gibson et al., 2018). Moreover, described how to produce automatic semantic segmentation by using a 3D fully convolutional network that was trained and evaluated on an abdominal CT scans dataset. This study aimed to train models that used pixel-wise segmentation and efficient implementations of the fully convolutional network FCN. The results demonstrated cutting-edge multi-organ segmentation performance (Roth et al., 2018). Compared to the traditional image classification approach and the deep learning approach using white blood cells WBCs based on some attributes such as size, color, and texture. Deep learning approaches require more computational resources than standard approaches, which are used for

training increases (Akkus et al., 2017). Considerably, deep learning methods are suitable for small-sized images, which are proper for cell images. Also, in a traditional image processing strategy, the classification outcomes are significantly impacted by the segmentation and feature outputs. Nonetheless, depending on the resources, any approach may be considered for classifying WBCs (Hegde et al., 2019). Kim and Ye (2019) Created an innovative loss function depending on the Mumford-Shah function for image segmentation using deep learning. The proposed method supports semi-supervised and unsupervised segmentation, and on top of that, it can be enhanced with a supervised semantic segmentation, Table 1 presents a survey of various techniques for tumor image segmentation based on CT images.

The success of generative models in medical imaging, such as image migration and image processing, has led to the development of deep generative models that rely on multiple hidden layers. The development of deep generative models has attracted attention; there are common as Restricted Boltzmann Machines (RBM) (Smolensky, 1986), Variational Auto-Encoders (VAE) (Kingma & Welling, 2013), and Generative Adversarial Networks (GAN). Goodfellow et al. (2020) proposed the GAN as a deep generative model. GAN is a training of a generative model to generate a sample set that closely resembles the actual sample set. Given that recently published scientific papers concern GANs used for generating synthetic medical images, Mendes et al. (2023) presented a novel GAN application for medical images that used two generative adversarial networks with CT scans to generate artificial lung images from semantic masks and labels. Researchers implemented efficient approaches to show the high quality of generated images. Tiwari et al. (2023) proposed a novel method that combined a hybrid Recurrent Neural Network- Generative Adversarial Network (RNN-GAN) with a Gaussian filter. The study used lung tumour images to accurately classify affected lung nodules and those unaffected. Swaminathan et al. (2024) constructed a prediction model to diagnose lung tumors in a patient early, depending on the optimization method by salp-shuffled shepherd and using the CNN model VGG16 to classify the segmented output images. Y. Wang et al. (2024) developed the GP-WGAN, a deep predictive model to predict nodule growth patterns using generative AI methods in follow-up LDCT (low-dose computed tomography) scans. The results illustrated that the predictive model improved diagnostic accuracy and accelerated clinical management. In this way, E. WANG et al. (2024) developed a GAN-based model for predicting real-time dosimetry. The dosimetry prediction model is essential for expediting radiation planning and assisting with clinical decision-making.

Table 1: Survey of Various Tumors and Segmentation-based CT Images

Reference	Year	Description	Advantages	Limitations
Medeiros et al. (2019)	2019	The approach used a new Fuzzy Border Detector for lung segmentation.	High accuracy and optimal time	With a smaller coverage area, the result may be affected by small variations.
Liu and Pang (2020)	2020	A novel algorithm for lung segmentation from CT scans through wavelet transformation combined with a set of morphological processes.	Automatic and easily implemented.	over-segmentation of non-lung tissues.
Chen et al. (2021)	2021	U-Net network (DC-U-Net) has been merged with dilated convolution.	The model can expand without an increase in parameters.	High number of data sets. In individual cases, the segmentation process was discontinued.
Lian et al. (2022)	2022	Segmentation-based model for COVID-19 diagnostics by using the DRD U-Net model and classification by combining WGAN and DNN classifiers.	COVID-19 image recognition is more efficient, and the model separates COVID-19 patients from other pneumonia patients.	Small sample size for the diagnosis of COVID-19 images.
Liu et al. (2019)	2019	Super-pixel generation method for automatic lung segmentation. Random forest algorithm to extract the Lung region, and multi-scale edge to detect suspicious nodules.	The generated super-pixels can preserve the continuity of image details.	The segmentation of suspicious nodules stuck together.
Shen and Xu (2023)	2023	The dual-module architecture of HarDNet68 and Transformer for extracting local and global image features.	HarDNet68 (decoding), Transformer (encoding), and feature adaptation fusion module.	Lack of verification of the connection mode and on the 3D medical image.
Benedetti et al. (2022)	2022	The study proposed a novel approach using the U-Net architecture, resulting in a notable improvement in the DSC metric in the most critical situations.	Does not require the usage of extra data samples or add to the workload in terms of time and computation.	The approach consumed additional storage space and processing power due to the zoom levels used in U-Net training.

3. Proposed Framework

In this paper, the proposed tumor image segmentation consists of four parts: data collection, preprocessing, a

generator using GAN, and segmentation using CNN architectures, Figure 1.

3.1 Step 1: Data Collection

The Lung tumor dataset was collected for this study from the King Abdulaziz Specialist Hospital in Al-Jouf, Saudi Arabia, started July 4, 2024, to Aug 15, 2024. It consists of 75 images extracted from CT scans (67% for men, 33% for women) between 2019 and 2023 (Figure 2). Radiologists specialising in tumour image processing have carefully annotated the Ground Truth for every lung image in the dataset. As required, the original 512×512 image is resized to 256×256 (see Annex 1 and Annex 2).

3.2 Step 2: Preprocessing

The preprocessing is responsible for resizing images and labels to a uniform size, applying Gaussian and Median Blur to reduce image noise, normalising image and label pixel values to the range $[0, 1]$, and converting segmented labels to binary masks.

3.3 Step 3: Using GAN

Random images are fed into the generator as input, producing a synthetic dataset that resembles real data. The GAN is only used to generate images to make the generated data usable; it must be associated with its respective labels by making a simple modification to the conventional GAN architecture, which jointly generates images and their corresponding labels.

3.4 Step 4: CNN Architectures

The CNN architecture segments the input image using optimisers and then extracts features from the lung tumour image. The input images from the original and synthetic datasets are directly fused by the training model, which runs the UNet and Trans-UNet four times, enabling the effective measurement of the proposed model and improving the segmentation network's accuracy, thus producing the final lung tumour image segmentation.

4. Training and Measurement Metrics

The proposed method was trained and tested using Google Colab. The model used 74 images of real data and 200 images of synthetic data, with an ADAM optimizer and Gaussian Blur and median Blur as filtering to reduce and smooth image noise throughout the network training process. The data was divided into 60% for training, 20% for validation, and 20% for testing. This paper uses popular performance indicators for tumour image segmentation to quantitatively evaluate the results.

The Dice coefficient metric is widely used to measure the similarity between two sets; it can also measure the similarity between the real segmentation and the predicted segmentation. The coefficient ranges from 0 to 1, where 0 indicates no overlap and 1 indicates two datasets are identical.

$$\text{Dice coefficient} = \frac{2TP}{2TP+FP+FN} \quad (1)$$

Accuracy is a measure of consistency or similarity between the predicted segmentation output and the real segmentation values.

$$\text{ACC} = \frac{TP+TN}{(TP+FN)+(FP+TN)} \quad (2)$$

Positive predictive value (PPV) is the probability that the percentage of predicted positives is positive. A high PPV indicates that a positive image segmentation result is likely correct.

$$\text{PPV} = \frac{TP}{TP+FP} \quad (3)$$

Sensitivity is a key metric in image segmentation; it measures the model's ability to correctly identify positive instances among all actual positives. A high Sensitivity score indicates that the model is effective at identifying positive cases.

$$\text{SENS} = \frac{TP}{TP+FN} \quad (4)$$

Where TP represents True Positive from the number of pixels that are classified as (Functional Tissue Units) FTUs, FP represents False Positive from the number of pixels that are misclassified as FTUs, FN represents False Negative which is the number of misclassified pixels from FTU as background, and TN represents True Negative which is the number of

classified pixels from FTU as background.

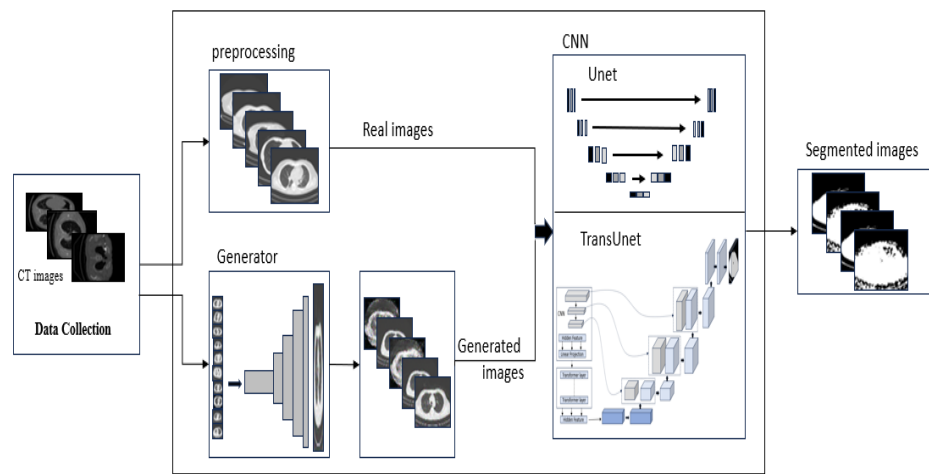


Figure 1: Proposed Framework

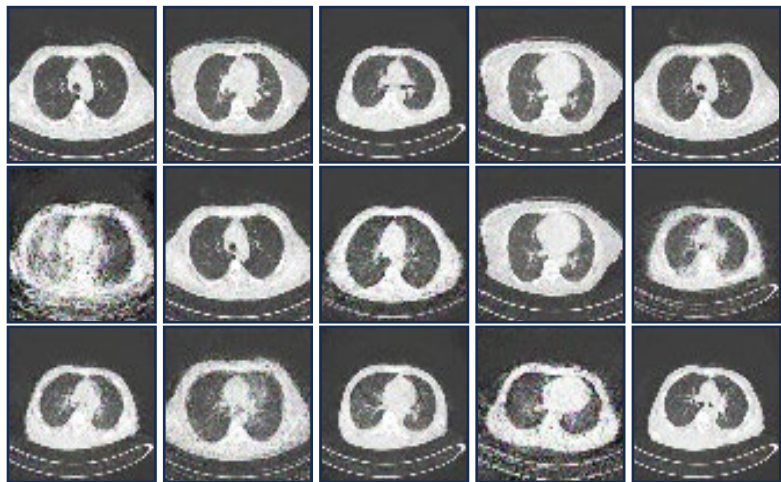


Figure 2: Sample of Lung Tumor Dataset

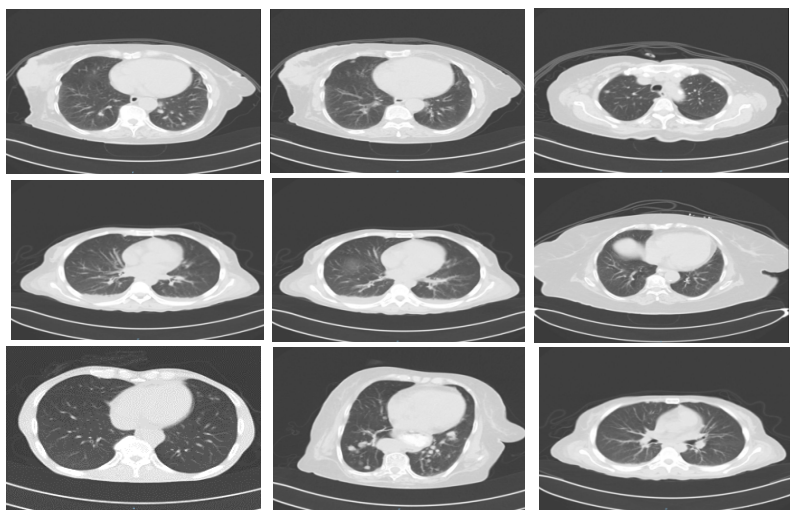


Figure 3: Sample of Synthetic Images

5. Analysis of Experimental Results

In the context of lung tumor segmentation in medical imaging, GANs can support the dataset to detect and delineate

the precise locations of lung tumors. The GAN is responsible for generating realistic lung tumor segmentation images from random noise. Random images were inserted from the original dataset and generated an output that should resemble lung tumor segmentation images. In this study, the Auxiliary Classifier GAN (AC-GAN) was employed to generate large, high-quality images and to achieve excellent results with a stable effect on the training process. As a result, 200 synthetic images of lung tumours were produced as a GAN-based dataset. Figure 3 is a sample of synthetic images.

The experiments of tumor image segmentation are implemented on real and synthetic image datasets in four network models, and the outcomes are compared. The segmentation results for all different evaluation setups of the lung tumor CT images are shown in Table 2. Table 2 shows the results of different segmentation methods on both real and synthetic datasets. For the real dataset, the Dice, PPV, ACC, and Sens results of the U-Net network are 0.981, 0.976, 0.981, and 0.985, respectively. On the other hand, the U-Net of the synthetic data increased by 0.4%, 1.2%, 0.4%, and -0.1% on Dice, PPV, ACC, and Sens, respectively. Also, for the real dataset, the Dice, PPV, ACC, and Sens of the Trans-UNet network results are 0.985, 0.987, 0.985, and 0.983, respectively. Otherwise, the Trans-UNet results of the synthetic data increased by 0.7%, 0.8%, 0.6%, and 0.5% on Dice, PPV, ACC, and Sens, respectively. The models achieved relatively good segmentation performance across different evaluation metrics on the two datasets. The four comparison networks are operated in the same experimental setting in this research; Figure 4 and Figure 5 show their visual effects.

Table 2: Segmentation Performance Comparison between Training on Real Data and Synthetic Data

Datasets	Method	DICE	PPV	ACCURACY	SENS
Real Dataset	U-Net	0.9809	0.9765	0.9811	0.9856
	TransUnet	0.9850	0.9871	0.9853	0.9830
Synthetic Dataset	U-Net	0.9858	0.9871	0.9851	0.9840
	TransUet	0.9916	0.9951	0.9913	0.9882

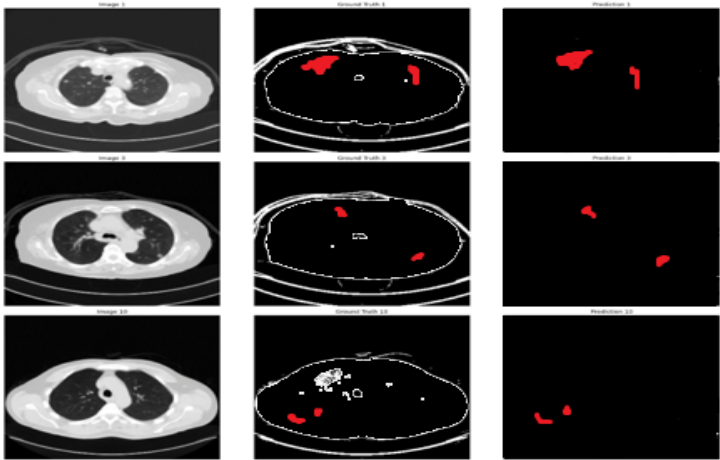


Figure 4: The Result of Lung Tumor Image Segmentation in Real Images Dataset

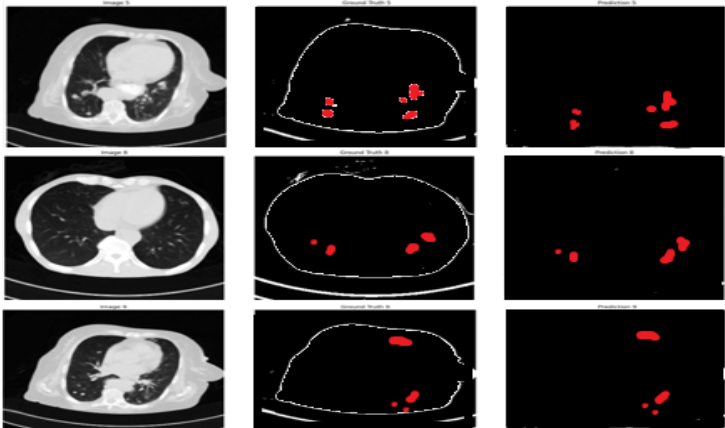


Figure 5: The Result of Lung Tumor Image Segmentation in Synthetic Images Dataset

Figure 4 shows the segmentation effect of several networks on the dataset of real images. The algorithms can

completely distinguish tumour regions but may produce simple omissions in segmentation of targets with blurred edges. Figure 5 shows the segmentation effect of several networks on the dataset of synthetic images, where the models can obtain the best segmentation performance and segment the edge information of tumor regions. In Figures 4 and 5, all neural network models segment lung tumours well, yielding relatively clear results. However, the segmentation results on synthetic images with similar backgrounds are better than those of the models in this paper. The visualization results of synthetic images have solved the issue of similar backgrounds, detected lung tumors with varying shapes and sizes, and segmented the image more clearly and accurately. Comparisons of the other models' accuracy across all datasets are shown in Figures 6 and 7. The comparative analysis of the figures demonstrates that all models converge quickly across all datasets. Finally, the Trans-Unet model in the synthetic dataset almost achieved a high accuracy rate.

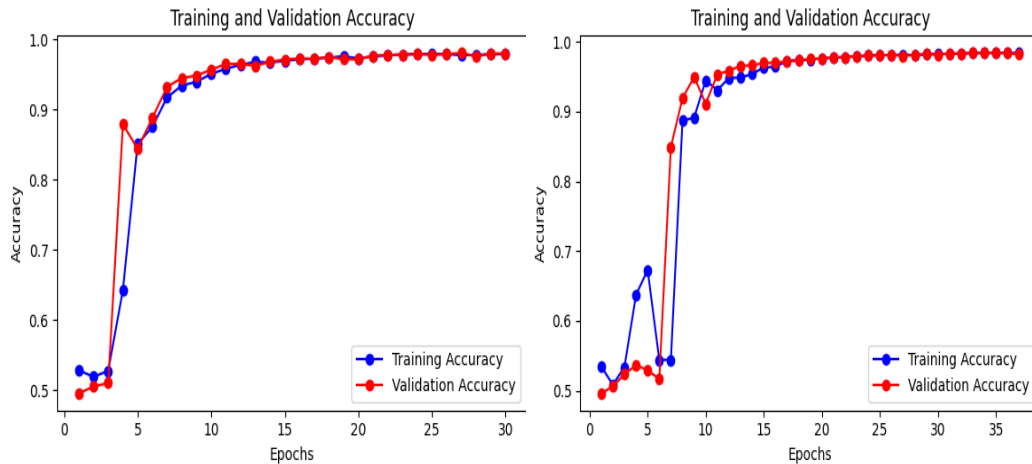


Figure 6: The Accuracy of Unet and Trans-Unet with the Original Dataset

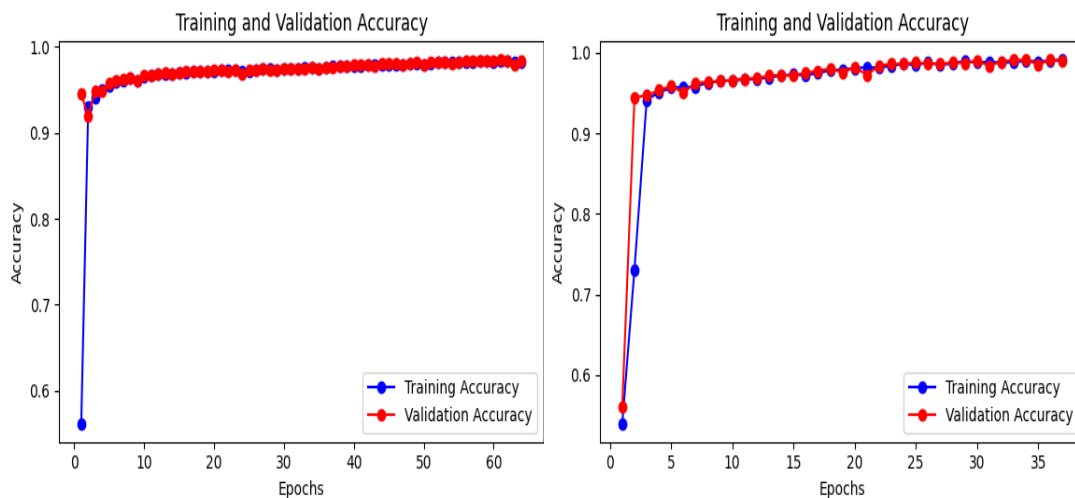


Figure 7: The Accuracy of Unet and Trans-Unet with the Synthetic Dataset

6. Discussion

The quality of medical images can have an impact on people's lives and health because they are essential for detecting illnesses. The accurate evaluation of the tumor image quality is more crucial than the evaluation of regular images. Due to the scarcity of datasets that support advances in tumor detection, GAN algorithms that simulate authentic images have been developed. Many models and metrics have been proposed to evaluate the synthetic medical images quality that generated by GAN. Also, many experts, such as the Unet network, have applied CNN modules to improve the effectiveness of tumor image segmentation. However, most network models based on the UNet structure have inaccurately extracted geometric features, such as the image's lines, edges, and shapes, during the analyzing stages. Therefore, this paper proposes a dual module of ACGAN and CNN for Intensive training and image feature information extraction. This study compared the use of real images with the Unet and TransUnet networks and the effect of introducing synthetic images to

the same networks. The ACGAN module improves the Transnet network structure, which runs faster and is directly used for tumour site extraction of lung tumour images. The TransUnet module used the synthetic dataset, which increased the network segmentation performance and improved the quality of lung tumor image segmentation. The results from the objective evaluation index and the segmentation diagrams have achieved the best performance in Dice, PPV, ACC, and Sens evaluation metrics. Although the model has extensively evaluated the network's performance on four methods and two datasets, Unet with real and synthetic lung tumor datasets and TransUnet with real and synthetic lung tumor datasets, the networks still need to improve because the model used a 2D medical image segmentation dataset in the experiment. It didn't try to verify the 3D images.

7. Conclusion

This study formulated a specific lung tumor metric and CNN techniques to evaluate real and synthetic images. Synthetic images were generated using the ACGAN algorithm, and the results from the different CNN methods were compared. The Trans-Unet method makes it easier to locate lung tumors than the Unet method, especially when using a synthetic dataset as input. The evaluation by using the Unet and Trans-Unet networks of real and synthetic images has advantages, as it can evaluate the diversity and quality of synthetic images and measure the distribution distance of synthetic images from real images. On real and synthetic datasets, the Dice of the Trans-Unet method in this paper reached 0.985 and 0.992, respectively, and the PPV reached 0.987 and 0.995, respectively. This demonstrates that the segmentation effect of the Trans-Unet algorithm, utilizing generated images from the GAN network, is superior to that achieved with real photos, with an accuracy of 0.99. In future work, the study will focus on further optimizing the model structure, applying it to additional tumor datasets, and enhancing the GAN performance of the network model, offering a promising outlook for the field.

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