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Lung Tumor Classification Optimizer with Augment Input Images

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Abstract

This work focuses on the accurate classification of lung tumors in Computed Tomography (CT) images to determine tumor type and stage, essential for guiding treatment decisions. In this research, pretrained model VGG19 and Generative Adversarial Networks (GANs) models are used to classify the lung tumor in order to enhance the classification accuracy by increasing the diversity of the training dataset. The dataset comprises 1097 CT image samples, with 120 classified as benign, 561 as malignant, and 416 as normal cases. The coding for this work was developed using Python, with TensorFlow as the deep learning platform, and simulations were conducted on Google Colab. Performance metrics such as accuracy, sensitivity, specificity, and F1 score are evaluated to assess the effectiveness of the classification model. The datasets were obtained from the Iraq-Oncology Teaching Hospital.

Keywords: GAN, Lungs Tumor, Augmentation, Benign, Malignant

1. Introduction

Lung cancer (LC) remains a major cause of death worldwide. Timely detection is paramount in saving lives. CT is a key tool in diagnosing lung cancer. Yet, manual analysis of these scans is slow, prone to inaccuracies. Given these limitations, computational technique like AI algorithms were utilized to speed up and improve the accuracy of detecting lung cancer

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in CT images. The experiments were achieved on the IQ-OTH/NCCD benchmark dataset, which categorizes lung cancer patients into benign, malignant, or normal groups.

GAN are a type of AI algorithm used for unsupervised learning. This technique can make new type of sources that resemble your training data. In image processing, GANs are particularly powerful. One network, the generator, creates new images, and the other network, the discriminator, evaluates them for authenticity. Through this method, the generator learns to create images that look so realistic that they can't be distinguished from actual images, the discriminator becomes adept at telling real images from generated ones. This adversarial process leads to the generator creating high-quality images that can be remarkably realistic.

2. Literature Survey

Lung cancer, the most prevalent cancer among human beings, represents a significant global health burden. According to the reports, there were approximately 1051,30500 new cases of cancer in 2021, making up about 13% of all cancer diagnoses for that year [1-2]. This work [3] can be directly utilized to simplify the complex process of data reconstruction in extraction and classification by employing Deep Neural Networks (DNN). This study compares CNN and GAN-CNN, particularly cGAN, classification of CT scans of lung nodes into two categories [4]. This research [5] introduces a data augmentation technique named Forward and Backward GAN (F&BGAN), based on GANs. F&BGAN is planned to produce good synthetic medical images.

In this study [6], the authors have proposed a new model that combines a MDGAN network with an encoder for the classification of two nodes. In this work [7-8], the authors propose a technique to classify the two nodes called Fuse-TSD. This algorithm combines texture, shape, and information learned by deep models at the decision level to improve classification accuracy. This study [9-10] introduces a solution for a challenging problem using a MBEL architecture depends on 3D-CNN, referred to as MBEL-3D-CNN. In this study [11-12], the authors utilize features extracted from the Over Feat network in natural images, for the purpose of detect the nodes in CT image. The architecture proposed a 2-D CNN to detect the nodes in lungs. Additionally, data augmentation and dropout techniques are used to prevent overfitting [13-14].

3. Methodology

Figure 1 illustrates the semi-supervised GAN architecture used in this research, where lung CT images serve as the input to the model.

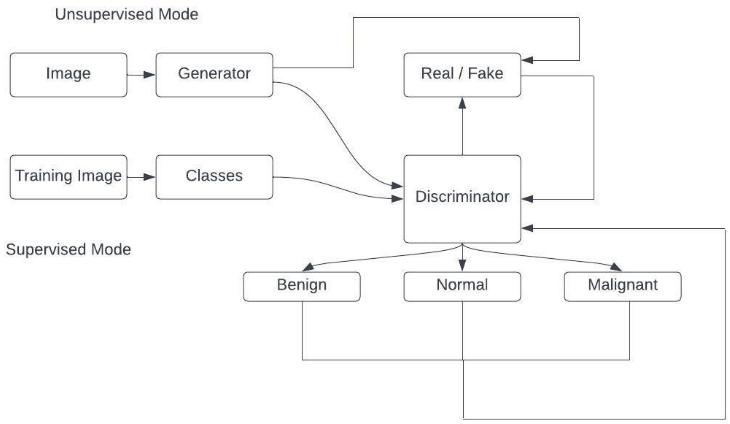

Figure 1. Block Diagram of Proposed Work

In this work, to generate the semi supervised GAN model by using three approaches. The first approach involves sharing the feature extraction weights of a standard GAN discriminator model to create two models, one for supervised mode and one for unsupervised mode. The second approach designs a single discriminator model for both modes by modifying the standard GAN discriminator model to have multiple outputs. In third approach, where the output layers of the supervised model are given as inputs to the unsupervised model. Initially, a supervised model with k classes is designed. Subsequently, the unsupervised model is created by using the output prior to the activation function of the supervised model. For GAN development, architecture is illustrated in Figure 2.

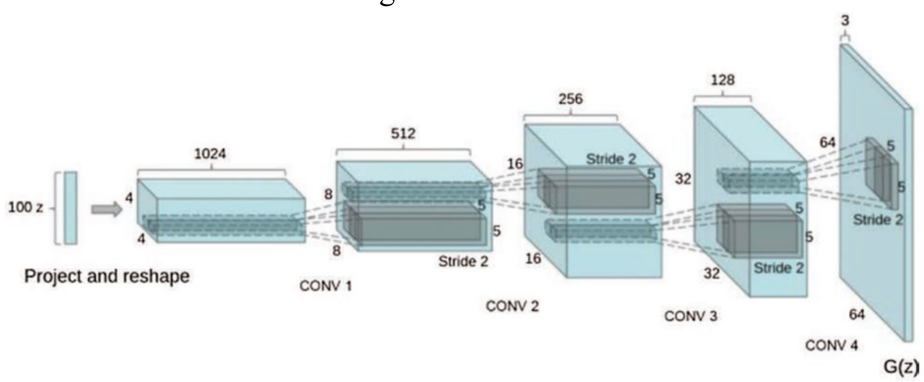

Figure 2. GAN Architecture

In the GAN architecture used in this research, downsampling is achieved through the use of strided convolutions. After each convolution operation, batch normalization is applied to stabilize the training process. The tanh activation function is used to introduce non-linearity into the network. To optimize the weights of the model, the Adam optimizer is employed with a learning rate set to 0.0002. The hyper tuning parameters of generator and discriminator are listed in Table 1 and 2.

Table 1. Model Parameters of Generator

Model Parameters	**Values**
Input	Random Points(128)
Output	Images(300*32*32)
Loss Function	Binary Cross Entropy
Optimizer	Adam
Activation Function	tanh Function

The Table 1 represents a basic configuration for training a GAN to generate images. The GAN consists of a generator network that takes 128 random points as input and produces images with dimensions of 300 by 32 by 32 pixels. The generator uses the tanh activation function in its output layer to confirm the generated images have pixel values in the range [-1, 1].

The discriminator network is trained to tell the difference between real and fake images using a binary classification method. To improve the performance of both the generator and discriminator networks, the Adam optimizer adjusts their weights based on how well they performed in distinguishing the image.

The Table 2 represents a discriminator in a GAN used for image generation tasks. The discriminator takes generated images, each represented as a 32 by 32 matrix with 128 channels, as input. It then classifies these images as real or fake, outputting a binary value for each image.

Table 2. Model Parameters of Discriminator

Model Parameters	**Values**
Input	Generated Images(32*32*128)
Output	Real or Fake (Binary Value)
Loss Function	Binary Cross Entropy
Optimizer	Adam
Activation Function	tanh Function

The discriminator is trained using a method that measures how well it can tell the difference between real images and fake ones by comparing its guesses to the actual labels of the images. The Adam optimizer is used to update the discriminator's weights based on the gradient of the loss function, making it more accurate in distinguishing between real and generated images. Finally, the tanh activation function is used in the output layer to ensure the discriminator's output is in the range [-1, 1], aiding in the binary classification task.

4. Result and Discussion

The proposed model is compared with the pretrained VGG 19 network (Table 3) as referenced in [15]. Unlike the pretrained model, the proposed model incorporates an augmentation process, which is not performed in the VGG 19 network.

Table 3. Performance Metrics

S.No.	**Metrics**	**VGG19**	**Proposed GAN**
1	Accuracy	95%	97.5%
2	Sensitivity	88.79%	92%
3	Specificity	98.25%	98.50%
4	F1 Score	93.28%	96.11%

The proposed GAN model demonstrates superior performance compared to the pretrained VGG19 network across several key metrics. The GAN model achieves higher accuracy (97.5% vs. 95%), indicating a greater overall correctness in predictions. It also exhibits improved sensitivity (92% vs. 88.79%), showing a better ability to identify positive cases. Additionally, the GAN model has a slightly higher specificity (98.50% vs. 98.25%), which means it is more effective at identifying negative cases. Furthermore, the GAN model's higher F1 score (96.11% vs. 93.28%) highlights a better balance between precision and recall, leading to an enhanced overall performance.

The limitations of the proposed method with GAN are complex training process and longer training times. The model was trained for 3000 epochs. The average loss of the model was found to be 0.29. Figure 3 shows generated image samples by using GAN.

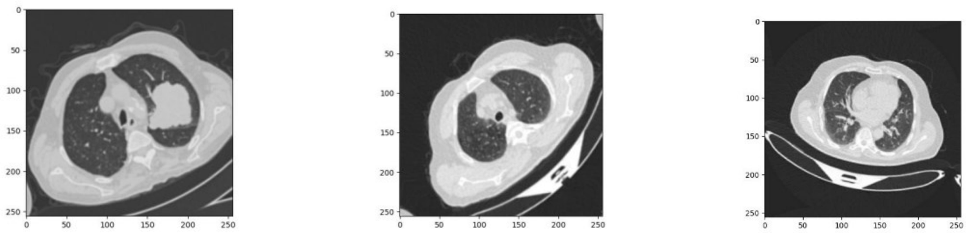

Figure 3. Generated Image Samples

Figure 4 represents the training loss is 31.8%, indicating the average error throughout the training process. This loss metric is essential for assessing the model's capability to distinguish between tumor and non-tumor classes. Figure 5 shows an accuracy of 97.2%, providing a clearer insight into the model's overall performance.

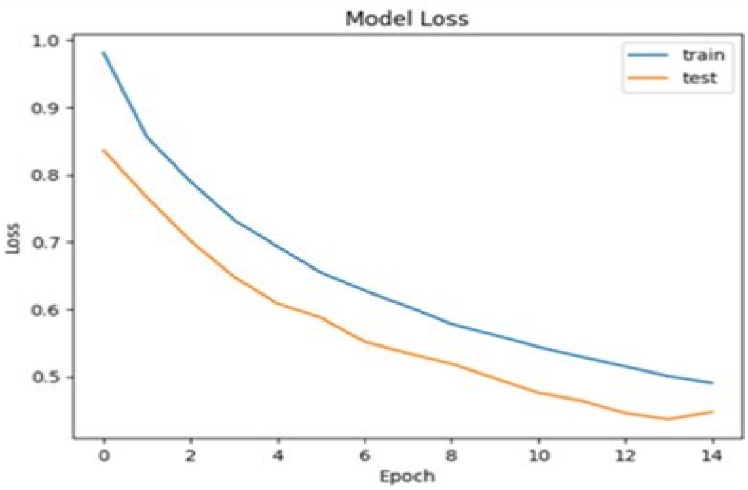

Figure 4. Training and Testing Loss

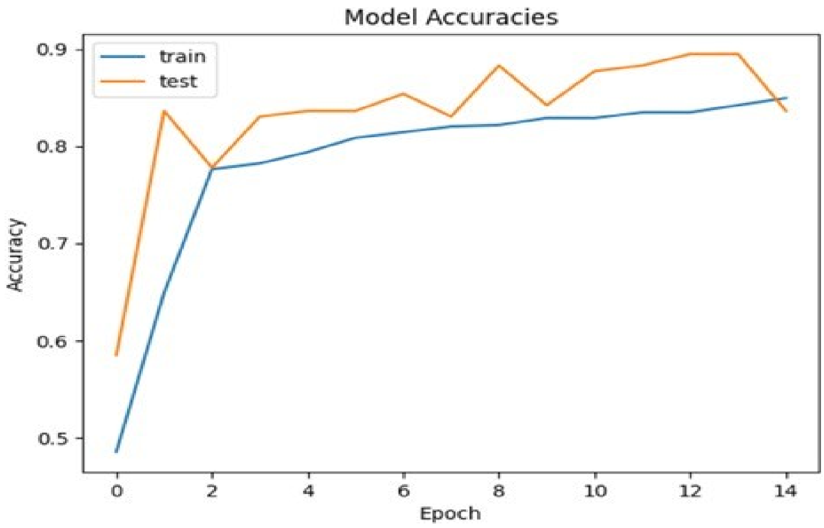

Figure 5. Training and Testing Accuracy

5. Conclusion

In this research, the proposed method utilizing a GAN (Generative Adversarial Network) for medical image classification offers substantial improvements over the traditional approach using VGG19, a pretrained convolutional neural network. The GAN-enhanced model achieves higher accuracy, sensitivity, specificity, and F1 score, indicating its superior performance in detecting and classifying medical conditions from images. In future work, explore hyperparameter tuning and optimization techniques to improve the performance and stability of the GAN model.

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