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ADVANCED BIOMEDICAL IMAGE ANALYSIS FOR EARLY LUNG CANCER DETECTION USING VISION TRANSFORMERS AND GANS

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Abstract

Diagnosis of lung cancer in advanced stages is critical issues, that substantially impacts survival rate and existing methods often lacks precise and timely detection of disease causes raise in mortality rate. To address this issue, this study presents an advanced technique such as Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) for lung cancer detection. This study process begins with the lung image data acquisition, followed by data preprocessing step to remove the noise. The ViTs methods employed for capturing complex spatial relationships feature in the images, while GANs create artificial training data to enhance the robustness of the model. The wild horse optimization employed for fine tuning the models parameters for optimal results in classifying lung cancer images as benign or malignant. The system's performance evaluated using accuracy, precision, recall, and F1 score metrics and the proposed system has significant improvements in lung cancer diagnosis accuracy and speed than the existing methods. Overall, this advancement ultimately contributing an enhanced patient outcome and reduced costs for healthcare and it fight against the lung cancer.

Keywords: Vision Transformers (ViTs), Generative Adversarial Networks, lung cancer, early detection, biomedical image.

1. Introduction

Lung cancer is a disease caused by the involuntary increase of cells in the lung tissue. Early detection of cancerous cells is of vital importance in the lungs providing oxygen to the human body and excretion of carbon dioxide in the body as a result of vital activities [1]. A key component of clinical analysis for the diagnosis of human disease is the development of computer-aided detection (CAD) systems. Lung cancer requires more attention among the various disease examination processes due to its higher mortality rate [2]. Diagnostics for lung cancer in its early stages and treatment monitoring for lung cancer depend heavily on medical imaging technologies. For the purpose of detecting lung cancer, a number of medical imaging modalities, including computed tomography, magnetic resonance imaging, positron emission tomography, chest X-ray, and molecular imaging techniques, have been thoroughly studied [3, 4]. Every suspected nodule should be subject to a thorough analysis, and each nodule's information should be combined [5]. The identification of lung nodules is crucial for cancer detection, as variations in their morphology are linked to increased cancer risk [6]. Because lung cancer is still a major threat to people all over the world, better early diagnosis techniques are desperately needed. Even though lung cancer diagnosis is made possible by valuable technology, there are still certain limitations that prevent timely and accurate diagnosis, which can lead to unfavorable outcomes and delayed treatment [7]. Early detection of lung cancer is associated with a better prognosis. The potential for a liquid biopsy to identify and extract tumor-related biomarkers from bodily fluids is enormous [8].

This study innovatively integrates the deep learning models for lung cancer detection for improving robust classification on medical imaging. This study objective is to clearly addressing the advanced disease detection that reduces the dependency on labelled clinical data. This main contribution of this study introduces the novel ViT-GAN framework for lung cancer detection improves the classification performance. The Vision Transformers for advanced feature extraction and Generative Adversarial Networks for data augmentation, the proposed method achieves higher performance metrics. This method improves robustness and significant in disease classification in more efficient for improving diagnostic outcomes in medical imaging.

2. Related works

In this study [9] suggests a radiomics in early lung cancer diagnosis for classifying the lung nodules, to measure the histopathology, adenocarcinoma characteristics and prognostic model. This study significantly enhances the precise disease diagnosis and improve the risk stratification can improve the patient-doctor collaboration and make necessary decisions in lung cancer screening and management.

This paper [10] employs transfer learning model as, Convolutional Neural Network (CNN) with the AlexNet model for classifying lung tumors as malignant or benign efficiently. This study improves the early lung cancer detection accuracy while tackling the issue faced by the traditional methods for diagnostic methods. The study has improved accuracy values shows an efficient and timely intervention for saving lives.

This study [11] employs a novel machine learning (ML) model ensuring advanced diagnostic efficiency and accuracy of lung cancer stage classification. The limitation of traditional diagnostic methods tackled by this study and remains a substantial result of faster, non-invasive, and reliable tool. The preprocessing methods and class imbalance correction method used for enabling the customized treatment plans and eventually improves the patient outcomes in lung cancer care.

In this study [12] the Kaggle IQ-OTH dataset's 1,190 CT scan images were analyzed using deep learning (DL) techniques for early lung cancer detection. By applying stringent image preprocessing techniques, such as affine transformations and Gaussian noise addition, the study seeks to improve diagnostic accuracy and predict malignancy. A validation accuracy of 98% and an F1 score of 97% are shown in a performance comparison of classifiers, which includes traditional CNN, ResNet50, and InceptionV3. The goal is to successfully identify high-risk individuals in order to enable early intervention and prevent lung cancer's long-term health effects.

This study [13] suggests a ML for classifying lung cancer subtypes using medical images for precise and timely diagnoses. The Principal component analysis (PCA) employed for reducing the dimensionality, and performing the region of interest (ROI) recognition and radiomic feature extraction are used in conjunction with a deductive approach and secondary datasets. The model, which combines CNNs and support vector machines (SVMs), performs better than the existing methodologies. The goal is to lay the groundwork for cutting-edge lung cancer diagnostics that will enable individualized treatment regimens and better patient outcomes.

This paper [14] proposes a multi-classification approach for lung nodule detection and classification using artificial intelligence on computed tomography (CT) scan images to enhance early detection and improve survival rates. The study employs various preprocessing steps for image enhancement, followed by feature extraction using VGG16 transfer learning and morphological segmentation. A deep learning architecture, combined with seven different machine learning algorithms, classifies lung nodules into malignant, benign, and normal categories, achieving high accuracy. The purpose is to develop a computationally effective model that reliably identifies lung nodules, facilitating timely interventions for better patient outcomes.

This research [15] proposes a comprehensive analysis of lung cancer prediction methodologies using various ML and DL techniques, models. The purpose is to enhance the accuracy and efficiency of lung cancer diagnosis through CAD by automating the analysis of CT scan images, thereby reducing human error and facilitating early detection. By integrating these advanced techniques, the study aims to improve patient outcomes through timely interventions and better prognostic capabilities.

3. Proposed Methodology

3.1.Data Acquisition

In this step, the data is collected for performing the improved lung cancer diagnostic system. This process focus on the computed tomography (CT) scans imaging modalities collection due to their high-resolution images and cross-sectional views of the lungs allows more significant identification of abnormalities in the lung and pulmonary nodules. Initially, this process started with the LIDC/IDRI existing database collaborations for identifying the annotated lung CT images. To security and data privacy regulations of patient details must be taken into the account for further processing the patient data.

After establishing data source, the imaging data is collected that includes various stages of lung cancer as well as healthy data. This dataset can improves the models diversity by training it and frequently checks the quality of data to ensure the all images are correctly annotated. To offer a basis of studies, further preprocessing and analysis steps are employed on the gathered dataset to cover variations in patient demographics, disease types, and imaging techniques [16-18].

3.2.Data Pre-processing

To reduce the noise in the input images, an anisotropic diffusion method is employed by maintaining the structural features of images as edge. This system allows basic idea of smoothening towards long edges instead of across them. The formulation is can be as below,

$$\frac{\partial I}{\partial \mathrm{t}} = \nabla.(c(a, b, t)\nabla I) \tag{1}$$

Where, I denotes image intensity over t time, and $c(x, y, t)$ denotes the diffusion coefficient and it is defines as follows,

$$c(x, y, t) = e^{-\left(\frac{|\nabla I|}{K}\right)^2} \tag{2}$$

Here, K refers the threshold parameter have ability to control the sensitivity of the diffusion to edges. By continuously performing this method, the detailed information about edges is produced [19].

3.2.1. Wavelet Transform

To improve the feature and noise, the wavelet transform is employed for an image that can convert into frequency components, which is known as more powerful tool.

The continuous wavelet transform $W_f(x, y)$ is represented in mathematically as,

$$W_f(x, y) = \int_{-\infty}^{\infty} F(t)\psi_{x,y}(t)dt \tag{3}$$

Where,$F(t)$refers original image and $\psi_{x,y}(t)$ refers the wavelet function scaled by x and translated position by y. After transformation, noise reduction is attained by applying a threshold to the coefficients:

$$\widehat{W}_f(x, y) = \begin{cases} W_f(x, y), & if\left|W_f(x, y)\right| > T \\ 0, & otherwise \end{cases} \tag{4}$$

Where, T denotes threshold.

3.2.2. Adaptive Histogram Equalization (CLAHE)

To improve image contrast, CLAHE reorganizes the intensity levels with the help of local histogram distributions. Using this technique improves the structures in lung CT scans in more clearly visible. The process is expressed as follows,

$$S_i = Clip(h_i.PDF(I)) \tag{5}$$

Where $S_i$denotes histogram value of j-th region, h_i denotes local histogram, and PDF represents the probability density function. The resulting intensity I′ is computed as,

$$I' = CDF(I).\max(I) \tag{6}$$

The cumulative distribution function (CDF) is calculated over local regions. The interpretability of Lung CT is greatly enhanced by CLAHE that prevents over-amplification of noise and increases local contrast. When combined, these preprocessing methods can enhance the lung CT image quality, improving the precise analyses and diagnostics for the early detection of lung cancer [20].

3.3.Feature Extraction

In the CT lung images feature extraction process, the Vision Transformers (ViTs) remains substantial powerful tool for extracting the important feature with the integration of self-attention mechanism to efficiently extracting the complex spatial relationships in images [21]. Consider I as input image is split into fixed-size non-overlapping patches. When the image with size of $H \times W$ and is divided into P×P size of N number of patches can be calculated as:

$$N = \frac{H \times W}{P^2} \tag{7}$$

While generating the series of patch embeddings, the patches flattened into $P^2 \times C$ vector size with C channels. The each patch I_i is mathematically presented as,

$$a_k = Flatten\ (I_i). W_p \tag{8}$$

Where, W_p denotes learnable projection matrix. Patch embeddings are enhanced with positional encodings PE to preserve the spatial relationships between patches. It shows as,

$$a_k^{input} = a_k + PE_k \tag{9}$$

Typically, sine and cosine functions are used to derive positional encodings, which enable the model to discern the location of each patch within the overall image. To weigh the importance of various patches in the images, the self-attention mechanism is employed. The input embeddings A as,

$$Q = AW_Q; K = AW_K; V = aW_V \tag{10}$$

Where, W_Q, W_K, W_V denotes the learnable weight matrices for queries, keys, and values, respectively. The attention scores A calculated as follows,

$$A = Softmax\left(\frac{QK^T}{\sqrt{d_i}}\right) \tag{11}$$

Here, d_i refers the key vectors dimension, and it division d_i serves to stabilize gradients during training. The multi-head attention mechanism employed for capturing several aspects of the data. By carrying out several attention operations concurrently, this enables the model to focus on various areas of the image at once. The multi-head attention output is calculated as,

$$MultiHead(Q, K, V) = Concat(H_1 \dots, H_h)W_o \tag{12}$$

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Where, each head H_k computes attention independently, and W_o refers output projection matrix. After that, output of the multi-head attention fed into the feed forward neural network (FFN) for further processes. Here applying two linear transformations with ReLU activation in between,

$$FFN(a) = ReLU(aW_1 + y_1)W_2 + y_2 \tag{13}$$

Where, W_1, W_2 denotes the weight and y_1, y_{22} refers the bias terms.

The feedforward networks model can generates a feature representation suitable for a range of downstream tasks. A novel classification token aggregates data from all patches for each classification task that is frequently added to the input sequence. While using the Vision Transformers in the feature extraction process, this method efficiently extracts complex spatial relationships and features from lung CT images, enhancing the model's capacity to recognize important indicators of lung cancer. The self-attention mechanism enhances the focus on relevant patches that improves the diagnostic performance and accuracy [22].

3.4.Data Augmentation

In ML, the data augmentation remains crucial in medical imaging field where the annotated datasets are limited. The Generative Adversarial Networks (GANs) technique is employed for augmenting the input data. The GANs can able to produce high-quality synthetic data with more attention while strengthening the previous datasets that increase model robustness, and reduce problems like overfitting [23].

The GAN neural networks consist of Generator (G) and Discriminator (D) network, which can trained simultaneously in a competitive framework, often referred to as a min-max game. The Generator's aims to develop an synthetic data which is identical from the real input data, while the Discriminator's can accurately classify input data as real (from the actual dataset) or fake (generated by G) [24]. The process can be expressed as following equations,

$$\min_G \max_D \mathbb{E}_{a\sim p_{data}}[\log D(a)] + \mathbb{E}_{a\sim p_z}[\log(1 - D(G(a)))] \tag{14}$$

Whre, $D(a)$ denotes probability of input x real sample from the training dataset, whereas $G(a)$is the synthetic sample generated by the G from a noise vector z sampled from a predefined distribution p_z. The GAN can minimize G's loss while rising the loss of the D. The G optimizes its objective function to fool the D by minimizing,

$$L_G = -\mathbb{E}_{a\sim p_z}[\log D(G(z))] \tag{15}$$

This G can produce samples that D classifies as real. In contrast, the Discriminator aims to maximize the classification process effectively by minimizing:

$$L_D = \mathbb{E}_{a\sim p_{data}}[\log D(a)] - \mathbb{E}_{a\sim p_z}[\log(1 - D(G(a)))] \tag{16}$$

Updating D and G once in a while dual training process. To optimize L_D, D is first trained on both synthetic and real samples. After that, G is trained to minimize L_G in order to generate better synthetic samples. The Generator generates samples that are more realistic over time, making it more difficult for the Discriminator to discern between real and fake. This back-and-forth training process is continued [25]. Once the Generator has received enough training, it can generate high-quality synthetic samples from random noise inputs, which can be expressed mathematically as:

$$Synthetic\ Data = G(z) \tag{17}$$

In the context of lung cancer detection, augmenting the dataset with synthetic CT scan images generated by GANs can address classes as malignant or benign ones. This proposed augmentation is crucial because ML and DL models rottenly perform the poorly when trained on imbalanced datasets. By generating additional synthetic data for underrepresented classes, GANs can ensures that the model learns to recognize features from both malignant and benign nodules effectively. Overall, in medical imaging the variability in imaging conditions, patient demographics, and disease presentations can significantly impacts the performance of the model and also improves better patient management and care.

3.5.Wild Horse Optimization

To fine tune the model parameters the Wild Horse optimization algorithm employed for strike the balance between the exploration and exploitation strategies that precisely improves the classification accuracy. The Wild Horse metaheuristic optimization methods inspires by the natural habitat of wild horses. The exploration and exploitation conditions are utilised for discovering the new regions of solution space and refined solutions over the promising areas.

1. **Initialization**: An initial population of wild horses, each representing a potential solution in the form of a vector of model parameters, is created at the start of the algorithm. The parameters of the neural network are weights and bias, learning rates and so on. The initialization considered as follows,

$$A_k = [a_1^k, a_2^k, \dots, a_1^d] \text{ for i=1,2,…,n} \tag{18}$$

Where N denotes number of horses, and d refers parameter space dimensionality.

2. **Fitness Evaluation**: Based on the predefined objective function, the fitness function of each horse is assessed using the loss function related to the classification task. It can be shown as follows,

$$L(\theta) = -\frac{1}{n}\sum_{k=1}^{n}\left[b_k \log(\hat{b}_k) + (1-b_k)\log(1-\hat{b}_k)\right] \tag{19}$$

Where b_k and $\hat{b}_k$ refers true label and predicted probability respectively.

3. **Exploration and Exploitation**: Based on own and known positions, the horses can adjust their positions. The position update rule is represented as below equations,

$$A_k^{t+1} = A_k^t + \propto . (A_{best} - A_k^t) + \beta . R_v \tag{21}$$

Here, t denotes current iteration, α can controls the step size to best-known solution, and β introduces randomness to encourage exploration.

The algorithm processes until reaches the stopping criterion as a maximum number of iterations or a convergence threshold on the loss function. The model ideal parameter derived from the horse with the highest fitness score. This can be represented as:

$$\theta_{final} = A_{best} \tag{22}$$

The wild horse optimization algorithm is beneficial for training models because it can effectively explore the parameter space and free from local optima. For DL models, it is crucial due to the loss function's landscape might contains large number of local minima. A robust model with better generalization of unknown data is significant in the medical field, by striking a balance between exploration and exploitation. Overall, the wild horse optimization algorithm significantly enhances the lung cancer images classification accuracy by fine-tuning model parameters.

4. Results and Discussion

Dataset

The Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI) dataset is used in the study, that consists of 1,018 clinical CT scans. Here, the 400 scans are unlabeled dataset. The remaining 488 scans were then allocated for final evaluation (400 scans) and fine-tuning (88 scans) after the dataset was split into training, tuning, and testing sets.

Simulation setup

The proposed ViT-GAN method simulation process for lung cancer detection is conducted in MATLAB, with its capabilities for image processing and DL tasks. This system setup utilized a NVIDIA GTX 1080 or higher GPU, with 16 GB of RAM to handle the large datasets and complex model training efficiently. The experimental training conducted for learning rates of 0.001 for four different values of epochs 5, 10, 20, and 50.

Performance metrics

The proposed system for lung cancer detection is assessed using the following metrics,

Accuracy (ACC): This metric assess the overall system correctness in lung disease classification.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{23}$$

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Where, TP = True Positives, TN = True Negatives, FP= False Positives, and FN = False Negatives. Precision (P): It reflects the proportion of lung disease accurately classification over all the instances,

$$P = \frac{TP}{TP+FP} \tag{24}$$

Recall (R): This metrics emphasizing the proposed model ability to find all lung disease instances.

$$R = \frac{TP}{TP+FN} \tag{25}$$

F1 Score: It is mean of precision and recall and expressed as follows,

$$F1\ Score = \frac{2 \times P.R}{P+R} \tag{26}$$

Comparative Analysis

The performance of this study compared with the existing methods VGG16, Xception, and VGG19 based on various metrics.

Table 1. Performance Evaluation of Different Techniques for Lung Cancer Detection: Accuracy Metrics Over Epochs.

Epoch	Accuracy			
	VGG16	Xception	VGG19	Proposed Method
5	0.83	0.80	0.86	0.93
10	0.89	0.88	0.90	0.94
20	0.91	0.90	0.92	0.95
50	0.94	0.93	0.95	0.97

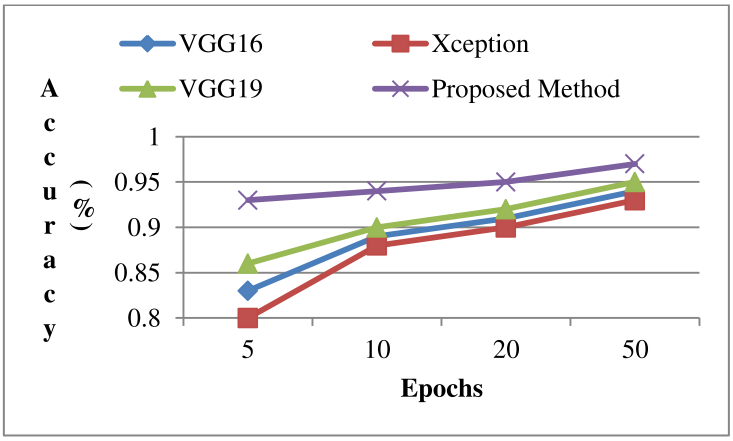

Figure 1. Accuracy Performance of existing and proposed Models

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Figure 1 and table 1 show the accuracy of various methods used for detecting lung cancer across varying epochs. For instance, at 5 epochs, the existing VGG16, Xception, VGG19 has accuracy of (83%), (80%), and (86%) which is lower than the Proposed Method with 93%. This trend is followed over 10 epochs; the proposed method has 94% accuracy while VGG16, Xception, and VGG19 have an accuracy of 89%, 88%, and 90% respectively. At last for 20 epochs, the proposed method has better accuracy of 97% outperforms other existing models, that showcases the proposed method's robustness in the lung cancer classification.

Table 2: Comparative Analysis of Precision Scores

Epoch	Precision			
	VGG16	Xception	VGG19	Proposed Method
5	0.82	0.79	0.85	0.90
10	0.85	0.84	0.87	0.92
20	0.88	0.86	0.89	0.94
50	0.91	0.90	0.94	0.96

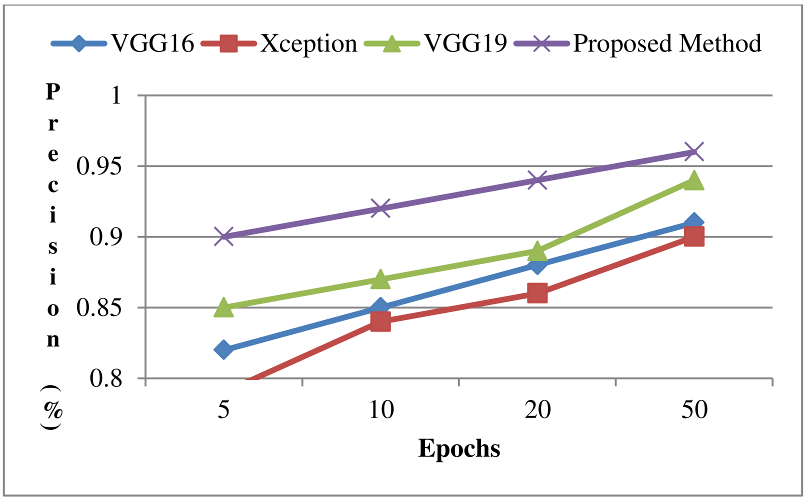

Figure 2. Precision Performance Analysis

Figure 2 and table 2 shows the proposed method improved results across all epochs than the existing methods. At 5 epochs, the proposed system has precision of 90%, compared to VGG16 of 82%, Xception of 79%, and VGG19 of 85%. As training increased to 20 epochs, the proposed method achieved a precision of 96% compared to VGG16 of 91%, Xception of 90%, and VGG19 of 94% shows the proposed method ability to correctly classify the lung cancer effectively.

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Table 3: Recall Rate Assessment of Various methods

Epoch	Recall			
	VGG16	Xception	VGG19	Proposed Method
5	0.79	0.76	0.82	0.92
10	0.84	0.80	0.86	0.93
20	0.87	0.85	0.89	0.95
50	0.91	0.89	0.93	0.96

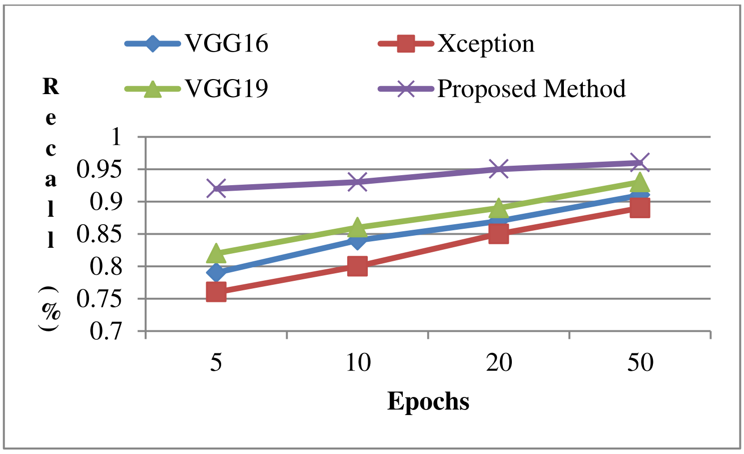

Figure 3. Recall Performance analysis of various methods

Figure 3 and Table 3 emphasized the proposed method and existing method. For instance, at 5 epochs, the proposed method has recall 92%, higher than VGG16 of 79%, Xception of 76%, and VGG19 of 82%. At 10 epochs, proposed method recall is improved to 93%, then showing slower progress. At 20 epochs, the proposed method has recall of 95%, compared to the VGG16, Xception, and VGG19 reached 87%, 85%, and 89%, respectively. At 50 epochs, proposed method has recall of 96%, showing effectiveness in minimizing false negatives compared to existing methods.

Table 4: F1 Score analysis

Epoch	F1 Score			
	VGG16	Xception	VGG19	Proposed Method
5	0.80	0.77	0.83	0.91
10	0.84	0.81	0.86	0.92
20	0.87	0.85	0.89	0.94
50	0.91	0.89	0.93	0.96

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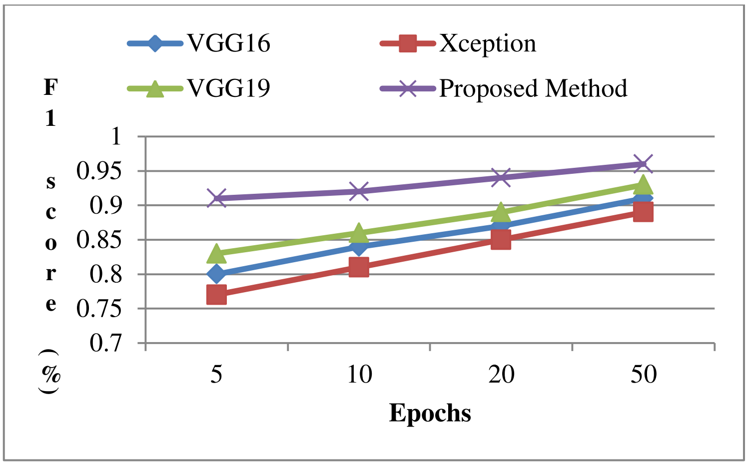

Figure 4: F1 Score Performance of Different Models

Figure 4 and table 4 shows the F1 score proposed method's overall performance. At 5 epochs, the proposed method has F1 score of 91%, significantly higher than VGG16 (80%), Xception (77%), and VGG19 (83%). At 10 epochs, the proposed method has F1 score to 92%, while the others reached 84%, 81%, and 86%, respectively. At 20 epochs, the proposed method has F1 score of 94%, with significant results than other methods. Finally, at 50 epochs, the proposed method achieved an F1 score of 96%, significantly classifying lung cancer images compared to existing methods that has advantages of the proposed method across all evaluated metrics.

5. Conclusion

In this study, a novel ViT-GAN-based approach was proposed for lung cancer detection, demonstrating superior performance compared to traditional models. The results of this study have 97% accuracy, 96% precision, 96% recall, and 96% F1 score, highlights the proposed method's efficacy in significantly classifying the lung cancer images as malignant or benign nodules. Despite its limitations, the suggested system requires strong hardware, such as GPUs, because training ViTs and GANs involves computational costs, particularly when using high-resolution medical images. Furthermore, as the GAN-generated data might not accurately capture all the subtleties seen in clinical data, the system's reliance on synthetic data augmentation could introduce some biases. In subsequent research, methods such as model compression and deployment hardware optimization could be investigated to further improve the computing efficiency of the model. Additionally, adding more diverse and annotated clinical data to the dataset will enhance the model's ability to generalize to actual clinical circumstances. Incorporating explainable AI techniques would yield valuable insights into the model's decision-making process, hence enhancing its interpretability and reliability for clinical application.

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