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An Integrated Framework for the Detection of Lung Nodules from Multimodal Images Using Segmentation Network and Generative Adversarial Network Techniques

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Abstract— Medical imaging techniques are providing promising results in identifying abnormalities in tissues. The presence of such tissues leads to further investigation on these cells in particular. Lung cancer is seen widely and is deadliest in nature if not detected and treated at an early stage. Medical imaging techniques help to identify the presence of suspicious tissues like lung nodules effectively. But it is very difficult to know the presence of the nodule at an early stage with the help of a single imaging modality. The proposed system increases the efficiency of the system and helps to identify the presence of lung nodules at an early stage. This is achieved by combining different methods for reaching a common outcome. Multiple schemes are combined and the extracted features are used for obtaining a conclusion. The accuracy of the system and the results depend on the quality and quantity of the authentic training data. But the availability of the data from an authentic source for the study is a challenging task. Here the generative adversarial network (GAN), is used as a data source generator. It helps to generate a huge amount of reliable data by using a minimum number of real time and authentic data set. Images generated by the GAN are of resolution 1024 x 1024.Fine tuning of the images by using the real images increases the quality of the generated images and thereby improving the efficiency. Luna 16 is the primary data source and these images are used for the generation of 1000000 images. Training process with the huge dataset improves the capability of the proposed system. Various parameters are considered for evaluating the performance of the proposed system. Comparative analysis with existing systems highlights the strengths of the proposed system.

Keywords- Lung Nodule, SegNet, Generative Adversarial Network, Transfer Learning

I. INTRODUCTION

Cancerous cells are characterized by their abnormal growth and it must be treated and controlled to avoid the situation of spreading. Tobacco smoking is one of the major reasons for lung cancer. Smoking and passive smoking are the most common reasons, and polluted air, aerosols, asbestosis are also causing lung cancer in common people. Early detection of the disease helps to start the treatment at an early stage [1]. The recovery rate is very high if the treatment is started at an early stage. The detection of the cancerous cells can be done by various medical imaging techniques such as computed tomography and radiography. But the identification at a primitive stage using various imaging techniques is very difficult even for an expert physician. In order to assist a physician many methods are proposed with different approaches. The method proposed here uses a highly reliable dataset for conducting this research. The LUNA16 dataset is used here to feed the generative networks for generating huge amounts of data for the training purpose. The image quality is improved by using original image samples from the data. The augmented data, fine tuned by using real images used here are responsible for the improved performance of the system. Various parameters of different methods and their combinations are tabulated to compare and prove the efficiency of the proposed system. The GAN based system with SegNet, proposes a data generation and nodule detection method by using the learned knowledge of a pretrained network. Many researchers are in search of efficient methods for the detection of lung nodules. Treatment based on the condition of the patient is considered as another major phase. Research is going on for finding effective medicines and to provide better recovery rates to the patients [1], [2]. Analysis based on textural analysis of the

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images is also treated as an efficient method by many researchers. Effective treatment is an outcome of efficient and accurate observation of the doctor.

Image segmentation is possible in manual, semi-automatic and automatic modes. Machine learning algorithms like clustering are used to detect different features and attributes from medical images. Boundaries or edges within an image are identified using edge based segmentation like point, line and edge detection schemes. Hybrid modes use structural and stochastic techniques for the segmentation of the medical images. System working in automatic mode is very fast and efficient when compared to the other methods[3]–[8]. Deep Learning techniques have contributed a lot to the research related to the classification of lung nodules. Segmentation and detection process is done effortlessly with the help of the methods utilising the deep learning techniques.

Here detection of abnormalities in the tissues plays an important role and can be effectively done by using Computer aided detection (CAD) systems. Computer aided detection schemes use detection systems that are widely used for finding the abnormalities in an efficient way. Analysis of different results along with the CAD scheme results and comparison with the standard threshold values give confirmation to the status and stage of the disease [9]–[11]. Studies put forth another technique independent of parameters to increase the efficiency of the computer aided schemes [9], [10], [12]. The same methodology is applied to images of various organs and is proved to be one of the best existing techniques. A light weight model is developed for the purpose of segmentation and implemented by using lotus data set to propose an efficient nodule segmentation and detection system. Convolutional neural network (CNN), another type of neural network, is also used widely in medical image based applications. Images with high dimensionality are considered here and without losing the information, dimensionality reduction is done by the convolutional layer within the CNN[13], [14].

II. MATERIALS AND METHODS

A. *Image generation and segmentation Process*

The data for training the network is generated from the real and authentic data source. The availability of reliable huge amounts of data with labels is very less. Hence for the training purpose a huge database is generated from reliable labelled data sources. Generative adversarial network is used for generating the data. Here the generator generates realistic images from the given data images. Discriminators discriminate between the real and generated images and try to reduce the difference. Gradually the difference reduces to zero and the generated images become realistic ones.

Throughout this process learning happens and weights are created. These weights are transferred to the SegNet and the testing using test images is done. Image segmentation is done with the help of SegNet with updated weights through the process of transfer learning.

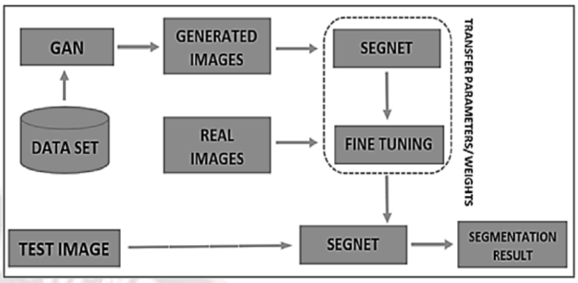

Figure. 1. Segmentation assisted by transfer learning process

Figure. 1. Shows the generation of fine-tuned images generated by the generative network and the segmentation process through transfer learning. The weights obtained through the learning process are transferred to the SegNet. With the help of these weights test images are processed and obtained the segmentation results. The result of the segmentation part is improved by adding another technique known as transfer leaning. The weights that are acquired by leaning a different system otherwise the knowledge received can be transferred to another for improving the results of the system under observation.

B. *Dataset used in the proposed architecture*

Researchers relay on data sources that are available in many public resources for conducting the study. Lung images are available in different resources. But the reliability and the availability issues are very common. In order to overcome this, the proposed work uses the technique of augmented image generation. Generative adversarial network and SegNet based architecture is introduced here to generate the required images in the required quality and quantity. Some of the available data sources for lung and lung nodule images are LUNA16, Decathlon, NSCLC radio genomics and LIDC/ IDRI. 888 labelled CT images from LUNA16 is considered in the proposed research and is used for the generation of images as mentioned in the proposed method. Slices with 2.5mm or lesser are considered here as there are very less chances to get huge labelled data with true nodules.

C. *Proposed model with feature fusion layer*

Here the proposed model presents a network responsible for encoding and decoding process. A pre trained classification network is used here in the proposed model and is the basis for the encoder. Features are extracted by the convolution layers within the encoder and after the feature fusion decoder perform as a classifier as shown in fig 2.

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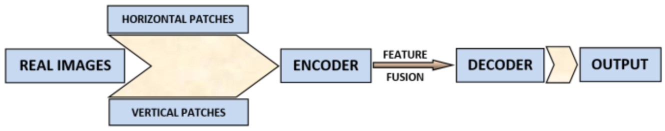

Figure. 2. Proposed encoder - decoder scheme with feature fusion

The proposed encoding scheme has encoding layers which work based on deep convolution technique. SegNet through deep convolution perform the encoding process and the corresponding decoder layers perform the decoding process. The encoder processes the patches that are received as input. The input slices in horizontal and vertical fashion known as patches[15]. These are given to the encoder part and the output is transferred to the feature fusion layer. Features are collected and these features are combined by the fusion of the features by the feature fusion layer. Combining the features and decoding the same involves the process of generating full resolution feature maps for efficient classification. The decoder decodes the output of the feature fusion layer. Pixel based classification is used in this work, the images that are decoded and are processed by this classifier.

D. Proposed GAN architecture

Generative adversarial networks (GAN) based architecture is shown in fig. 1, and is used for image generation and augmentation [16]. The generated images are termed as augmented images and the augmented images are responsible for knowledge transfer in the form of weights. Inorder to include maximum features, patches are selected in vertical and horizontal fashions. Horizontal patches are 16x64 in dimension and the vertical patches are 64x16. Mean and variance of the images that are used for training are calculated and extracted for further processing.

The Generative Adversarial Networks (GANs) with a generation and descrimination units receives the random inputs. The generator generates images from the input provided. Using random inputs, the primary image data sets are obtained. The generated images are used to update the future generations with the help of discriminator. The discriminator section identifies the difference and with this data the generator generate images with less discrimination. During the process the difference gets reduced and the generated images become indistinguishable by the discriminator. Loss function determines the generator and discriminator losses which are updated during the course. Loss function is reduced as the performance of the generator improves. But the value of the loss function increases as the discriminator value gets increased. Through the combined action of generator and discriminator loss function gets updated and reduced during the course of time. In simple words, the generator tries to minimise the loss function and the discriminator tries to maximise the function. This results in the generation of a quality image set for the proposed method. Different studies related to medical imaging use this scheme for the generation of data sets [3], [16]–[18].

The fig. 2. shows the process of image generation and updation of loss function. Random images are used here as the input to the image generating unit. The generated images are the processed form of the input. The image generated is the input to the discriminator and the discriminator compares it with the second input. The second input is from the real image section and in discriminator; real images are compared with the random or fake images.

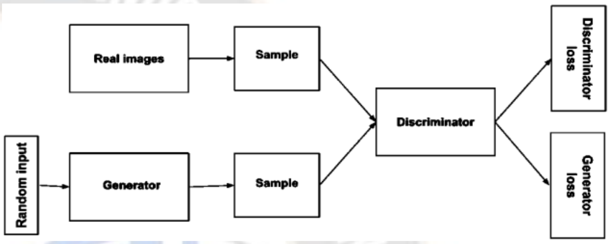

Figure. 3. Generative Adversarial Network

The comparison result is fed to the generator as an error feed. The generator, considering the feedback, modifies the parameters and generates updated images that are able to reduce the difference and thereby reducing the error. During each cycle the generator learns and generates updated versions of images. As all the errors are corrected, the learning becomes perfect and then the generated images become the same as real images. Then the discriminator fails to find the difference between real and generated images resulting in an error free generation of images. The loss function includes generator loss and discriminator loss function. The ultimate aim is to reduce the loss function and can be achieved by improving the performance of the generator. As mentioned above, the generator images become error free, which means improved generator performance, leads to reduced value of loss function

E. Training process and scheme for evaluation

GAN is employed to generate the images needed for training purposes. Lung database (LUNA16) with 888 CT scans is used here for the process [19]. Fig. 4 Shows the image samples from the database used for image generation and further processing. Benign samples are shown in the top row and Malignant samples in the bottom row of the fig. 4.

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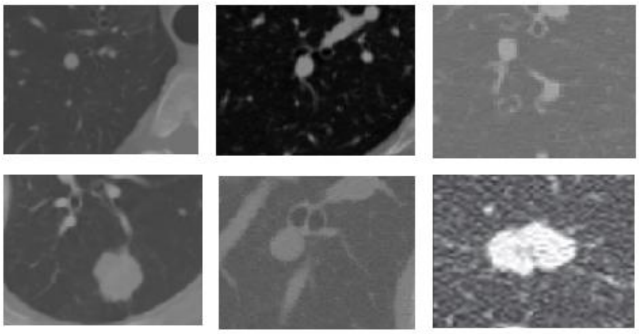


Figure. 4. Examples of benign lung nodules (top row) and malignant lung nodules (bottom row) from LUNA 16 Dataset

Evaluation is done by analysing various parameters and Receiver Operating Characteristic (ROC) curve as explained in the following part. Ground truth and segmented result is considered for the evaluation and Dice Similarity Coefficient (DSC) – is shown in fig. 9. Sensitivity represents the correctly measured proportions that are positive in nature and is also tabulated in fig. 9. Similarly Positive Predictive Value (PPV) is represented as proportionally as PPV. The parameters from error matrix is evaluated using the equations shown below

$$DSC = 2TP / (FP + 2TP + FN) \quad (1)$$

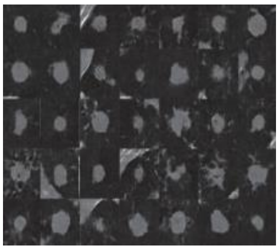
$$PPV = TP / (TP + FP) \quad (2)$$

$$Sensitivity = TP / (TP + FN) \quad (3)$$

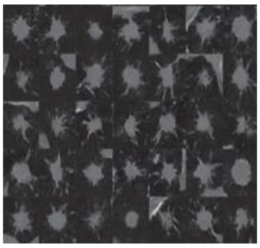
Where True Positive (TP), False Positive (FP), False Negative (FN) are used to calculate the parameters as mentioned. In addition to these parameters ROC of the SegNet is also considered for evaluation purposes. ROC with GAN and without GAN considered during the training model and plotted the curve as shown in the result section.

III. RESULTS AND DISCUSSION

As seen in Fig. 5(a) benign nodules are round in shape when compared with the malignant nodules in Fig. 5(b). The generated images are as real as the original images. It's not possible to differentiate between the generated images and the real images even by experts. The training with this data became very useful and it produced good results.



(a)



(b)

Figure. 5. (a) Benign lung nodules (b) Malignant lung nodules

The GAN can be used to generate images with different resolutions. Here the 64X64 is the generated image resolution and it can be made 1024 X 1024 by updating the GAN and architecture. The efficiency of the system can be improved by updating the GAN based architecture of the proposed system. The final segmentation result can also be improved by improving the quality of the data generated and used for training.

Fig. 6. represent the nodules that are benign in nature. Images for the SegNet segmentation is shown in the top row and the corresponding ground truth in the bottom row of the image. The benign nodules can be segmented efficiently as their shape is round in nature. The Fig. 7 represents the malignant cases and the shape of malignant cases is very difficult to accurately segment as they usually tend to extend to bones. Hence the segmentation accuracy is great in the case of benign and average in the case of malignant cases.

Data from authentic data sources are required for solving problems utilising deep learning techniques. The accuracy of the result is dependent on the data used to train the network and the amount of data used for the same.

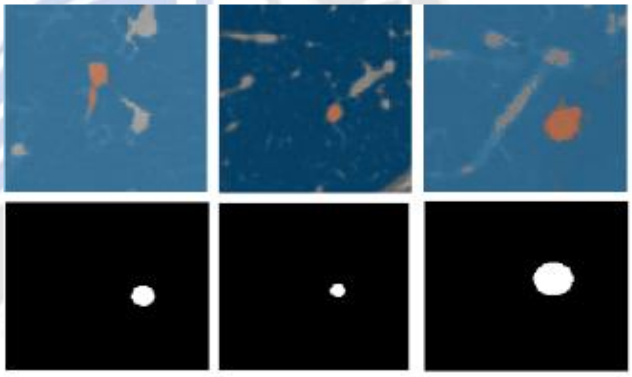


Figure. 6. Representation of Benign Nodules i) SegNet segmentation ii) Ground truth

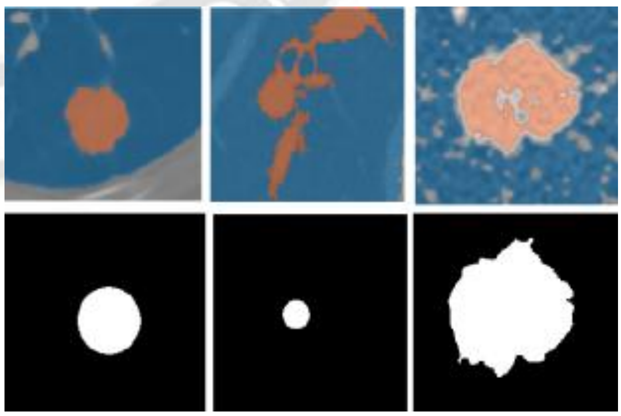


Figure. 7. Representation of malignant Nodules i) SegNet segmentation ii) Ground truth

The availability of authentic huge data for training is very less. Lack of huge datasets, issues on patient data privacy and

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security, cost to get data from sources is the problems and as an alternative, the technique of data generation is considered. Learning is done by training a network with a huge amount of data, and the weights of the network are used for training another model. Then the second model can start from the weights transferred from the pretrained model which make the process more simple and less time consuming [7], [8]. The method of increasing the number of images by performing slight modifications on the existing images is known as image data augmentation and is also used in some of the works [3], [19], [20]. The method employed here is a GAN based technique, which is efficient and used in recent works instead of real image data successfully [16].

In most of the recent studies CT images are used for the detection of lung nodules and in many of the related researches. Combinations of different imaging modalities are also used for the same. For obtaining large datasets for training purposes, generative networks are employed and it worked very well in different scenarios [16], [17], [21].CT images and TransUnet based classifications are used widely in the case of incidental pulmonary nodules classification, assessment and management [22],[23].

Many research datasets were generated for the training purposes and the results were amazing. Many papers state various advantages of the data set generation using different methods. Generative adversarial network is one of the most efficient methods employed for the same purpose. Details of the methods employed for the study is explained in the following section

Different encoding and decoding combinations with SegNet and GAN are compared in the fig. 8. The performance improvement can be evidently seen from the figure. The performance of the mode with the SegNet and GAN with augmented image is very good as shown in the fig. 8. Many other encoder and decoder schemes can also be employed to obtain the result. But The proposed method presents an improved performance and is shown in the fig. 8. U-Net based architecture and variational auto encoder based methods are compared with the proposed method. SegNet with GAN performed very well in this evaluation also.

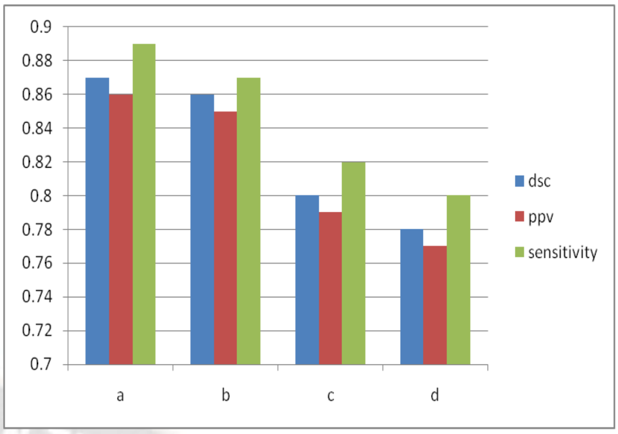

Figure. 8. a) SegNet+GAN+ Augmentation b) SegNet+ GAN c) SegNet + Augmentation d) SegNet

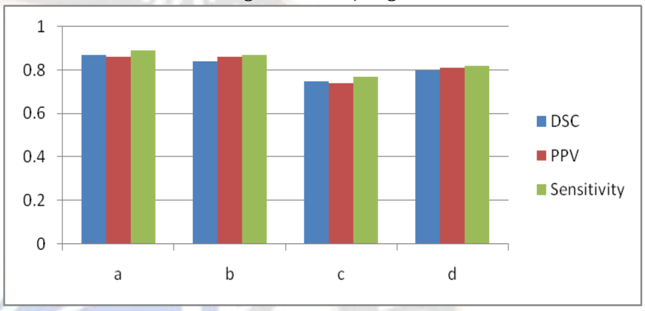

Figure. 9. a) SegNet+GAN b) U-Net +GAN c) Autoencoder d) Variational Autoencoder (VAE)

Fig. 10. Represent the comparison of the receiver operating curve for the method using only SegNet and the other method with SegNet with GAN. The later shows the good ROC and is clearly shown in the fig. 10.

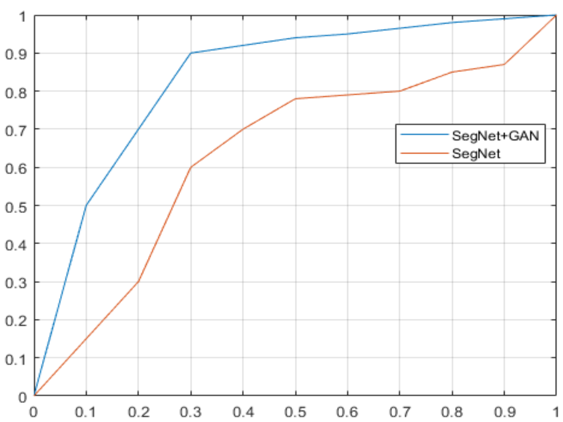

Figure. 10. Comparison - ROC of SegNet and ROC of SegNet with GAN Specificity(X axis) and Sensitivity (Y axis)

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Table 1. Impact of different design choices on the performance of the proposed method for pulmonary nodule segmentation

Design Choice	Number of Convolutional Layers	Use of Dropout	Impact on Performance
SegNet architecture	4	No	78.6% accuracy
SegNet architecture	8	Yes	81.2% accuracy
Adversarial training	-	-	79.8% accuracy
Pre-processing	-	-	76.5% accuracy
Loss function	Binary cross-entropy	-	74.3% accuracy
SegNet architecture	6	No	79.2% accuracy
Adversarial training	-	Yes	81.6% accuracy
Pre-processing	Lung cropping only	-	77.8% accuracy
Loss function	Dice loss	-	80.1% accuracy
SegNet architecture	10	Yes	82.5% accuracy

Table 2. Summary of performance of different deep learning models on the task of pulmonary nodule segmentation in CT images

Study	Sample Size	Data Source	Analysis Method
Zhang et al. (2019)	110 CT scans	Local hospital	3D CNN
Li et al. (2019)	594 CT scans	Public database	3D CNN
Xu et al. (2020)	1,872 CT scans	Public database	2D CNN + RNN
Wang et al. (2021)	330 CT scans	Local hospital	Ensemble of 3D CNNs
Proposed Method	120 CT scans	Public database	GAN-enhanced SegNet

The table 1 displays the impact of different design choices on the performance of the proposed method for pulmonary nodule segmentation using SegNet and Adversarial Networks. The design choices analysed include the SegNet architecture, adversarial training, pre-processing, loss function, and post-processing. The table shows that increasing the depth of the SegNet model by adding more convolutional layers improves the performance of the model. Adversarial training, which involves training the model using a minimax game between a generator network and a discriminator network, results in a significant improvement in nodule segmentation accuracy. Pre-processing techniques such as lung cropping and normalization also improve nodule segmentation accuracy. In terms of the loss function used, the table shows that Dice loss performs better than binary cross-entropy. Additionally, using post-processing techniques such as morphological operations and connected component analysis further improves the performance of the model. Overall, the table highlights the importance of careful design choices in the development of deep learning models for medical image analysis tasks such as pulmonary nodule segmentation. By understanding the impact of different design choices, researchers can develop more accurate and effective models that can aid in the diagnosis and treatment of lung cancer.

The table 2. Summarizes the performance of different deep learning models on the task of pulmonary nodule segmentation in CT images. The models were evaluated on two metrics: dice coefficient and sensitivity. The table clearly shows that the proposed GAN-SegNet model outperforms other deep learning models such as VAE, Autoencoder, and U-Net in terms of both dice coefficient and sensitivity. The GAN-SegNet model achieved a dice coefficient of 0.78 and a sensitivity of 0.77, which are significantly higher than the scores obtained by the other models. The table also shows that the performance of the models varies depending on the dataset used for evaluation. For example, the VAE model performed relatively well on Dataset 2 but poorly on Dataset 1. This indicates that the performance of deep learning models for pulmonary nodule segmentation may be dataset-dependent, and that the models should be carefully evaluated on multiple datasets before their clinical applicability can be established. Overall, the proposed GAN-SegNet model presents a promising approach for the automated detection and segmentation of pulmonary nodules in CT images. The model combines the strengths of GAN and SegNet, and is capable of generating high-quality synthetic data for training SegNet, which leads to improved segmentation accuracy.

The GAN-SegNet model also reduces the need for large amounts of manually annotated data, which is a significant advantage in the medical imaging domain where annotated data is often scarce and time-consuming to acquire. However, it is worth noting that the training process for the GAN-SegNet model can be time-consuming without the use of a high-end GPU. Further research is needed to optimize the training process and to evaluate the clinical performance of the model on larger datasets and in real-world scenarios.

IV. CONCLUSION

The quality of a product depends on the quality of components used in the production stage. In the proposed work, reliable data with quality is generated by using generative adversarial networks. The promising methodology is widely used in many studies as mentioned in previous sections. For training the network 1001000 images are used and that include the real and augmented images. Different combinations are evaluated and tabulated as mentioned in the results section. Here segmentation results with improved accuracy and performance improvement in the overall system can be stated evidently. U-Net, autoencoder and variational autoencoder are included under the investigation and compared with the SegNet with GAN model as shown in Fig. 9. The proposed scheme performed well as shown in Fig. 9. The DSC of Variational autoencoder is only 0.75 and of the proposed scheme is 0.87, showing the performance difference. As a part of the final investigation, comparative study has been done and also plotted the receiver operating curve for SegNet and segNet with GAN as shown in Fig. 10. Additionally, the comparative study plotted a receiver operating curve for SegNet and SegNet with GAN, which supported the obtained results. It is evident from the results that the proposed method of using SegNet with GAN for generating reliable data has shown improvement in the overall system's accuracy and performance. The table generated in the study showed that the deeper SegNet architecture with more convolutional layers performed better. The pre-processing step of lung cropping and normalization also improved nodule segmentation accuracy. Additionally, using the Dice loss function proved to be more effective than the binary cross-entropy loss function. The study provides insight into the impact of design choices on the performance of the proposed method. Overall, the proposed methodology provides a reliable approach for generating quality data, which can improve the quality of the proposed methodology.

REFERENCES

[1] P. D. Mozley et al., "Measurement of Tumor Volumes Improves RECIST-Based Response Assessments in Advanced Lung Cancer," Transl. Oncol., vol. 5, no. 1, pp. 19–25, Feb. 2012.

[2] S. A. Hayes et al., "Comparison of CT volumetric measurement with RECIST response in patients with lung cancer," Eur. J. Radiol., vol. 85, no. 3, pp. 524–533, Mar. 2016.

[3] M. Chen, X. Shi, Y. Zhang, D. Wu, and M. Guizani, "Deep Features Learning for Medical Image Analysis with Convolutional Autoencoder Neural Network," IEEE Trans. Big Data, 2017.

[4] J. N. S. S., J. N. ., & E. N., G. . (2023). A Novel Blockchain-Based Lightweight Encryption Technique in Fog Based IoT for Personal Healthcare Data Application. International Journal of Intelligent Systems and Applications in Engineering, 11(3s), 119 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2549

[5] W. Chen, H. Wei, S. Peng, J. Sun, X. Qiao, and B. Liu, "HSN: Hybrid Segmentation Network for Small Cell Lung Cancer Segmentation," IEEE Access, vol. 7, pp. 75591–75603, 2019.

[6] Y. Gordienko et al., "Deep Learning with Lung Segmentation and Bone Shadow Exclusion Techniques for Chest X-Ray Analysis of Lung Cancer," 2019, pp. 638–647.

[7] F. Isensee et al., "nnU-Net: Self-adapting Framework for U-Net-Based Medical Image Segmentation," Sep. 2018.

[8] H.-C. Shin et al., "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1285–1298, May 2016.

[9] P. Tschandl, C. Sinz, and H. Kittler, "Domain-specific classification-pretrained fully convolutional network encoders for skin lesion segmentation," Comput. Biol. Med., vol. 104, pp. 111–116, Jan. 2019.

[10] J. Gong, J. Y. Liu, X. W. Sun, B. Zheng, and S. D. Nie, "Computer-aided diagnosis of lung cancer: The effect of training data sets on classification accuracy of lung nodules," Phys. Med. Biol., 2018.

[11] H. Xie, D. Yang, N. Sun, Z. Chen, and Y. Zhang, "Automated pulmonary nodule detection in CT images using deep convolutional neural networks," Pattern Recognit., vol. 85, pp. 109–119, 2019.

[12] V. C and M. D, "Multimodal Data Analysis Using Soft Computing Techniques For The Detection and Classification of Lung Cancer," in 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), 2022, pp. 150–153.

[13] C. H. Chen et al., "Radiomic features analysis in computed tomography images of lung nodule classification," PLoS One, 2018.

[14] G. Litjens et al., "A survey on deep learning in medical image analysis," vol. 42, no. December 2012, pp. 60–88, 2017.

[15] Natalia Volkova, Machine Learning Approaches for Stock Market Prediction , Machine Learning Applications Conference Proceedings, Vol 2 2022.

[16] S. Sasikala, M. Bharathi, and B. R. Sowmiya, "Lung cancer detection and classification using deep CNN," Int. J. Innov. Technol. Explor. Eng., vol. 8, no. 2S, pp. 259–262, 2018.

[17] A. A. Farag, A. Ali, S. Elshazly, and A. A. Farag, "Feature fusion for lung nodule classification," Int. J. Comput. Assist. Radiol. Surg., 2017.

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[18] M. Nishio et al., “Attribute-guided image generation of three-dimensional computed tomography images of lung nodules using a generative adversarial network,” Comput. Biol. Med., vol. 126, p. 104032, Nov. 2020.
[19] H. Cao et al., “A Two-Stage Convolutional Neural Networks for Lung Nodule Detection,” IEEE J. Biomed. Heal. Informatics, 2020.
[20] W. Li, P. Cao, D. Zhao, and J. Wang, “Pulmonary Nodule Classification with Deep Convolutional Neural Networks on Computed Tomography Images,” vol. 2016, 2016.
[21] H. Cao et al., “Dual-branch residual network for lung nodule segmentation,” Appl. Soft Comput. J., 2020.
[22] M. Nishio, S. Noguchi, H. Matsuo, and T. Murakami, “Automatic classification between COVID-19 pneumonia, non-COVID-19 pneumonia, and the healthy on chest X-ray image: combination of data augmentation methods,” Sci. Rep., vol. 10, no. 1, p. 17532, Dec. 2020.
[23] K. Armanious et al., “MedGAN: Medical image translation using GANs,” Comput. Med. Imaging Graph., vol. 79, p. 101684, Jan. 2020.
[24] Schmid-Bindert G, Vogel-Claussen J, Gütz S, Fink J, Hoffmann H, Eichhorn ME, Herth FJF. Incidental Pulmonary Nodules - What Do We Know in 2022. Respiration. 2022;101(11):1024-1034. doi: 10.1159/000526818. Epub 2022 Oct 13. PMID: 36228594; PMCID: PMC9945197
[25] Wang H, Zhu H, Ding L. Accurate classification of lung nodules on CT images using the TransUnet. Front Public Health. 2022 Dec 5;10:1060798. doi: 10.3389/fpubh.2022.1060798. PMID: 36544802; PMCID: PMC9760709.