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Deep Learning based Semantic Segmentation on LowDose CT Scan Towards lung Nodule Cancer Prediction: A Comparative Analysis

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Abstract—Image segmentation plays a crucial role in computer vision and image processing with important applications such as scene understanding, medical image analysis etc, a field with a rich history of exploration. In this context, the prevalent success of deep learning model has driven the creation of innovative image segmentation techniques. It conducts a comparative analysis of various architectural paradigms, including U-Net, DenseNet, AlexNet, CoatNet, and VGG19.

Through meticulous experimentation conducted in Python, the study aims to ascertain the efficacy of these architectures, striving to identify the most promising approach. The outcomes and implications drawn from the results pave the way for future avenues of research and development.

IndexTerms—medicalimage segmentation,

deeplearning, semantic segmentation, u-net, alexnet, vgg19, Coatnet, densenet

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I. INTRODUCTION

Lung cancer ranks among the leading causes of cancer-related mortality worldwide. and causes the largest number of cancer associated fatalities. There are estimated to be 20 million cases and 9.7 million fatalities. The estimated figure for individuals who were alive in the 5-year period after receiving a diagnosis for cancer was 53.5 million.Between the two sexes, 1 in 9 men and 1 in 12 women lose their lives due to the disease. This research examines the use of DL models which is also critical in identifying lung cancer was aimed to improve diagnostic precision and efficiency. Deep learning models have been an incredible aid to doctors for yielding precise image segmentation which streamlines in the early and accurate identification of sickness. This research makes use of LIDC-IDRI dataset with different models which leverages Region Of Interest (ROI) for bettering lung nodule detection. These models delve into providing reliable detection of the affected regions via precisely segmenting images , hence fostering the decision making ability of the professionals Im-age segmentation has been fundamentally vital and inevitable as it yields reliable and dependable results.The intrinsic goal is to transform an image into a more comprehensible and meaningful representation by leveraging ROI. Irrespective of the methods, results vary.This project monumentally delves into comparing the performance of different deep learning models, specifically Convolutional Neural Networks utilized on dedicated GPUs to mitigate latency and enrich efficient computations. Patient's images have been thoroughly evaluated to minimize image artifacts and to provide resourceful insights. Moreover the ultimate motive in and of itself is the comparison of DeepLearning models and bettering patient outcomes

II. LITERATURE REVIEW

The application of deep learning methods in lung cancer detection has shown significant promise in enhancing the accuracy and efficiency of diagnosis. Various studies have employed datasets such as LIDC-IDRI to develop and test deep learning segmentation models, focusing particularly on Region of Interest (ROI) prioritization to improve lung nodule detection Tekade suggested a U-Net segmentation-based hy-brid model with a 3D multipath VGG network incorporated in a computer-aided detection system. This synergy improved nodule detection accuracy and malignancy classification [1] .Mazzone and Midthun tested the efficacy of low-dose com-puted tomography and asserted that it enhances the detection of early stages and decreases lung cancer death rates [2], [3]. Bonney, on the other hand, reported minimal success with earlier screening methods such as chest X-rays and sputum cytology [4]. A number of studies utilized machine learning classifiers in diagnosis. Asuntha used k-NN, Naive Bayes, and AdaBoost classifiers, supplemented with a Fuzzy Particle Swarm Optimization (FPSO) algorithm for the selection of optimal features [5]. Begum compared various ensemble clas-sifiers and determined that performance was greatly affected by hand-crafted feature tuning,impacting reproducibility [6]. Singh used a convolutional neural network (CNN)-based CAD model for the classification of CT images [7].Elnakib et al. applied improved deep learning algorithms like AlexNet, VGG16, and VGG19 coupled with a genetic algorithm (GA) with a 96.25 accuracy and a sensitivity of 97.5 [8]. Teles et al. evaluated LDCT screening in risk populations and detected a reduced rate of detection in lowrisk groups [9]. Jadoon highlighted multiview image fusion through Multiresolution Rigid Registration (MRR) with ResNet-18 to improve lung nodule segmentation [10]. Arunkumar et al. compared the performance of artificial neural networks (ANN), k-nearest neighbors (KNN), and random forests (RF) and concluded that ANN performed better than other models when followed by proper image preprocessing and segmentation methods [11]. Nasser established that ANN-based systems could be made to attain superior diagnostic accuracy (96.67) when accompanied by appropriate feature selection strategies [12]. Al-Tarawneh constructed a multi-stage image processing pipeline based on Gabor filters and watershed segmentation in order to extract the features from enhanced CT images [13]. Montez et al. integrated spiral CT and PET imaging, presenting a follow-up protocol with decreased false positives and increased diagnostic confidence [14].Deep learning remains a prevalent method. Sang et al. proposed a hybrid model that incorporated R-CNN, U-Net, and Gradient Boosting Machines (GBM), with an AUC of 0.99 Nasrullah et al. [15]. Shafi and Mahima both confirmed CNNbased approaches and SVMs for classifying malignant nodules accurately Devarapalli et al. [16], Shafi et al. [17]. Alakwaa created a multi-phase architecture based on thresholding, transformed U-Net, and 3D-CNN to enhance segmentation and ultimate classification Alakwaa et al. [18]. Makajua investigated the effectiveness of traditional classifiers like LDA and CDA, supporting multi-stage classification models Makaju et al. [19]. Zhang et al. created a DenseNet-based CNN architecture that is able to reach expert-level performance, making it clinically applicable Zhang et al. [20]. Tulasiramu designed EFFI-CNN, which utilized effective convolutional layers and gained competitive performance with public datasets Ponnada and Srinivasu [21]. They proposed combining CNN with data augmentation using GAN, with

93.9 classification accuracy and fewer false positives Suresh and Mohan [22]. Sreekumar utilized the C3D network to detect malign nodules and predict malignancy scores with a sensitivity of 86 Sreekumar et al. [23]. Zhang et al. put forward a better 3D Dense U-Net architecture for efficient tumor segmentation based on thin-plate spline transformation Zhang et al. [24]. Rajaguru employed a probabilistic neural network (PNN) coupled with an altered crow search algorithm, thus resulting in better classification accuracy Chakravarthy and Rajaguru [25].Wang et al. compared LDCT to other screening methods and established its diagnostic superiority, albeit without any noticeable difference in mortality

Wang et al. [26]. Wu used U-Net and VGG16 for the detection of small-cell lung cancer, highlighting the worldwide effect of early diagnosis Wu and Zhao [27]. Sharif integrated TransSegNet and CNN with preprocessing methods such as stain normalization and attained 99.62 accuracy in histopatho-logical image analysis Talib et al. [28].Kavya applied Res-U-Net and Gaussian smoothing for segmentation and clas-sification with 96.45 accuracy, with noted constraints on dataset diversity Malligeswari and Kavya [29]. Wani examined explainable AI with ConvXGB and DeepXplainer to interpret deep learning models to clinicians Wani et al. [30]. Pasupathy incorporated an optimized SVM and beetle swarm optimiza-tion, reaching 99.35 accuracy and filling ensemble learning gaps Venkatesan et al. [31]. Rana used dual attention modules and deep transfer learning with VGG backbones and reached

88.41 accuracy but reported generalization problems based on limited datasets Kumar et al. [32].Kumar created an enhanced U-Net with metaheuristics and supervised training for the purpose of automatic nodule detection with 95.5 accuracy Said et al. [33]. Advanced pixel and patch enhancement techniques were proposed by Said, enhancing segmentation accuracy to

97.83 Riaz et al. [34]. Riaz employed MobileNetV2 and transfer learning, obtaining 93.22 while cautioning against the risk of overfitting Naseer et al. [35]. Akram utilized a variant of U-Net for lobe

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segmentation and combined it with ResNet and SVM to obtain 92.13 accuracy Damayanti et al. [36]. These works show that AI-based models—particularly those with the integration of CNNs with sophisticated segmentation techniques—can greatly improve the detection of lung cancer. Yet, a number of challenges still remain, such as overfit-ting, dataset diversity constraints, model uninterpretability, and clinician-incorporation hurdles. Future work must place more emphasis on explainable AI, cross-domain dataset validation, and real-time clinical implementation to make the disparity between practice and research meet

III.METHODOLOGY

A.U-net

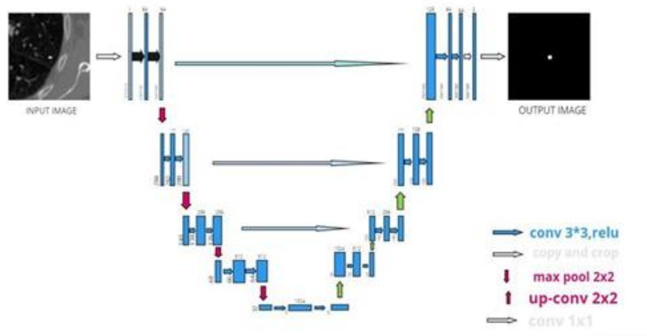

Figure 1. Architecture of the U-Net model illustrating the encoder-decoder layers used for lung nodule segmentation.

U-net is a convolutional neural network initially tailored for biomedical image segmentation, has been designed to work effectively with less dataset while fostering enhanced segmentation accuracy. Its encoder and decoder architecture is optimized for efficient execution on contemporary graphics processing units (Gpus). The fundamental purpose of U-Net architecture is to augment a conventional contracting network through a series of successive layers. These layers uplift the output resolution by employing upsampling operations.

B. Densenet

Dense Net is a convolutional deep learning model renowned for its compactness and superior performance. DenseNet fos- ters dense connectivity between layers, enabling each layer to directly access gradients from all preceding layers. This intricate interconnection scheme enhances feature propagation and facilitates deeper networks without the vanishing gradient problem. This results in unparalleled parameter efficiency, improved gradient flow, and heightened feature reuse, leading to state-of-the-art results across various tasks while requiring fewer parameters. In essence, DenseNet embodies a paradigm shift in deep learning, offering remarkable efficiency and efficacy in model training and inference.

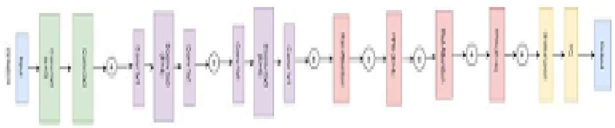

Figure 2. Block diagram representation of the DenseNet architecture used for feature extraction and classification.

C.Coatnet

CoAtNet is a groundbreaking deep learning model designed to excel in handling both spatial and temporal information with remarkable efficiency. Unlike conventional architectures, CoAtNet integrates cross-attention mechanisms to dynamically focus on relevant spatial and temporal features, optimizing per- formance across diverse tasks such as action recognition and video understanding. This innovative approach enhances fea- ture interaction and adaptability, enabling CoAtNet to achieve state-of-the-art results while maintaining computational effi- ciency. With its unique blend of spatial and temporal attention mechanisms, CoAtNet represents a significant advancement in deep learning, empowering models to effectively process complex spatiotemporal data with unprecedented accuracy and speed

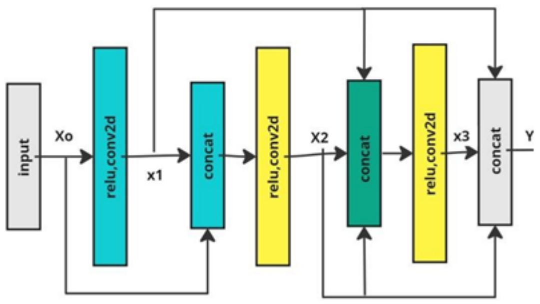

Figure 3.CoAtNet architecture block illustrating convolutional layers integrated with attention for hierarchical feature learning.

D. Alexnet Alex
Net is a deep learning model that revolutionized the field of computer vision. Its groundbreaking architecture fea- tured several key innovations, including the use of convo- lutional layers, ReLU activation functions, and overlapping pooling layers. These elements collectively enabled AlexNet to extract intricate features from images with unprecedented accuracy and efficiency. Moreover, its utilization of GPU acceleration paved the way for accelerated training times, setting a new standard for deep learning scalability. AlexNet's success not only solidified the prominence of convolutional neural networks in computer vision but also sparked a new era of innovation in deep learning research and application

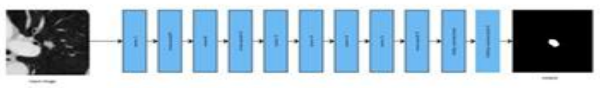

Figure 4. AlexNet deep learning framework highlighting convolution, maxpool- ing, and fully connected layers.

E.Vgg19
Deep learning model comprising 19 layers, including 16 convolutional layers and 3 fully connected layers. VGG-19 achieves exceptional accuracy by systematically extra features through stacked convolutional operations. Despi straightforward design and simplistic layout this project set a gold standard in the field, serving as a benchmark subsequent models and inspiring countless innovations in d learning research and excels in its ability to systemati extract intricate features from images, contributing to unparalleled accuracy and reliability

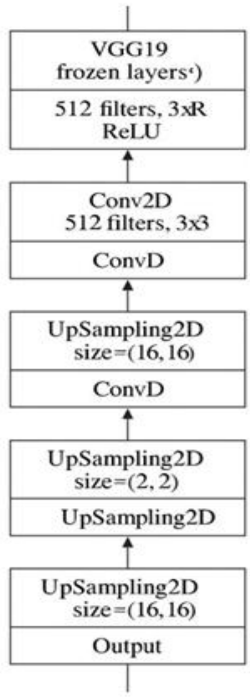

Figure 5.VGG19 deep learning model adapted with Conv2D and UpSam- pling2D layers for feature extraction and image output generation.

IV. RESULT AND DISCUSSION

A. Dataset description
The LIDC-IDRI database contains four veteran thoracic ra- diologists lesion annotations. LIDC-IDRI contains 1,018 low- dose lung CT's of 1010 lung patients. The given image below is raw mode of patient's lung before segmentation. The data collectively comprise of 2,44,547.Each case contains images from a clinical thoracic CT scan and an XML file related to it that records the result of a two-stage image annotation task performed by four experienced thoracic radiologists Seven academic centers and eight medical imaging companies joined to build this

dataset containing 1018 cases. Each of the cases contains images from a clinical thoracic CT scan and a single XML file containing the result of a two-phase annotation process performed by four experienced thoracic radiologists. In the first blinded-read phase, radiologists assessed the Ct scan and identified the presence of lesions

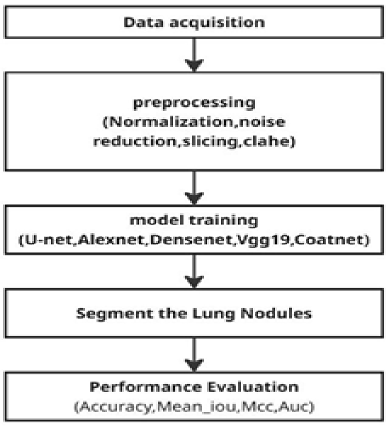

Figure 6. Workflow of proposed study showing the data acquisition,pre-processing,modeltraining, segmentation,comparitive analysis .

B. Sample images

The figures given are the depiction of sample images of the patient's lung / lung nodule regardless of the malignancies.

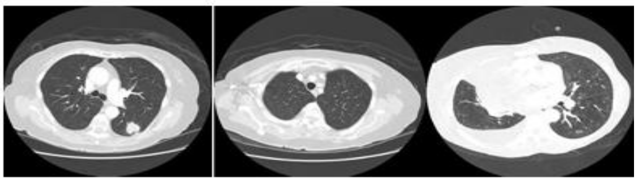

Figure 7. Example CT scan slices from the LIDC-IDRI dataset before segmentation.

C. Pre-processing

In this paper, Raw CT scan images are often noisy and con- tain irrelevant regions that can hamper accurate segmentation. Image quality is improved using preprocessing step first. Slices from Region of Interest (ROI) are extracted to focus only on the lung parts. The Gaussian filtering and median smoothing is then used to mitigate the CT scanning artifacts. At the same time, the process preserves the structural details of the nodules. In order to make the model robust and to avoid overfitting, various data augmentations such as random rotation, random horizontal and vertical flip, scaling, and contrast enhancement are applied. Increasing the variety in a dataset helps models to better generalize while training.

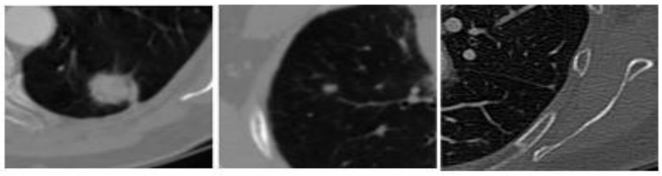

Figure 8. Preprocessed CT images from the LIDC-IDRI dataset after slicing and ROI (Region of Interest) extraction.

D.U-net

Following 150 epochs of training, the model achieved a notable 92.17 accuracy rate and demonstrated an impressive Intersection over Union (IoU) score of 40.17 affirming its ro-bustness in accurate data classification and object delineation

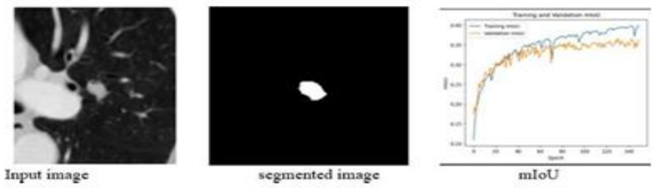

Figure 9.segmented lung nodules using U-Net, along with the corresponding mean Intersection-over-Union (IoU) score visualization.

E.Alexnet

Following 150 epochs of training, AlexNet exhibited non- convergence, evidenced by sustained loss stagnation. Despite optimization efforts, the mean Intersection over Union (mIoU) remained below 70.26, indicating suboptimal performance.

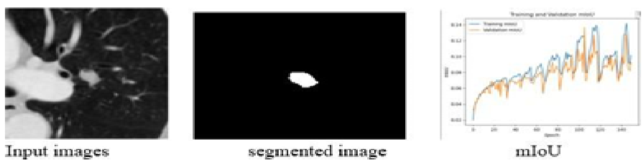

Figure 10.segmented lung nodules using AlexNet, with mean IoU values indicating non-convergence in training.

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F.Densenet

Following 150 epochs, DenseNet achieved 67.56Because of how its highly-connected structure let features be reused across layers, it is especially good at detecting small nodules with subtle intensity changes. DenseNet improves the segmentation of small and hard-to-detect nodules over other architectures by allowing later layers to directly access fine-grained features from earlier layers, thus preserving important spatial information.

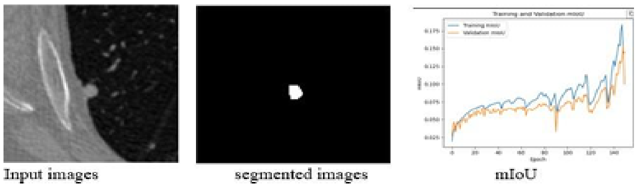

Figure 11.segmented lung nodules using DenseNet, with improved delineation of small nodules compared to other models.

G.Coatnet

Following 150 epochs of training, the optimization process failed to converge, leading to stagnation in the loss function. Despite iterative refinement, the Intersection over Union (IoU) metric, coupled with accuracy 40.67, exhibited negligible improvement, with IoU 15.35.

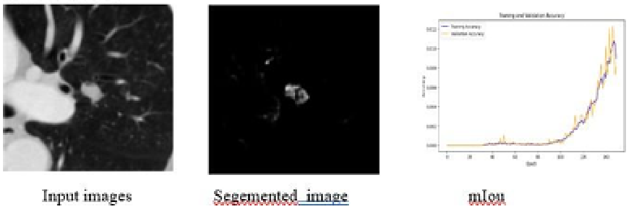

Figure 12.segmented lung nodules using CoAtNet, showing poor convergence and lower IoU performance.

H.Vgg19

Following 150 epochs of rigorous training, VGG-19 show- cased notable convergence, with loss consistently decreasing. Encouragingly, both the Intersection over Union (IoU) 30.17 and accuracy surpassed 62.52, highlighting significant progress in model performance.

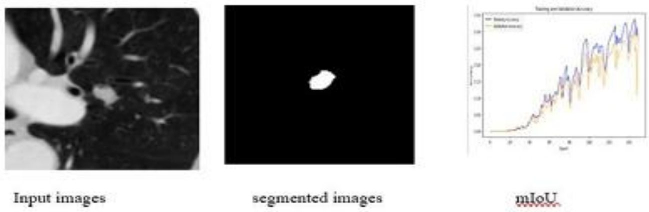

Figure 13.segmented lung nodules using VGG19, with moderate accuracy and IoU performance.

I. Comparative analysis The experimental results showcase a clear sacrifice between segmentation accuracy and computational workload among the tested models. U-net seems to be the ideal model with the highest accuracy 92.17 with a relatively moderate computa- tional cost, making it an ideal choice for real time clinical

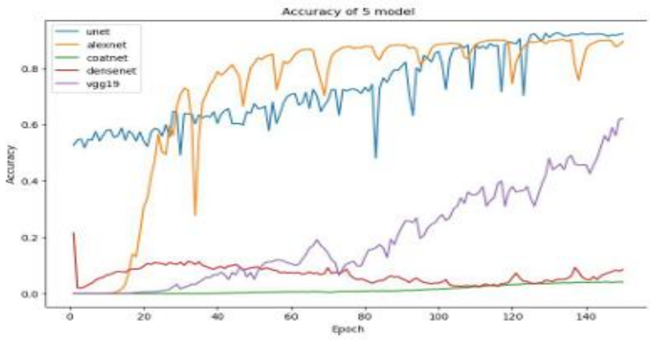

Figure 14. The provided graph depicts the accuracy of five different mod- els—UNet, AlexNet, CoatNet, DenseNet, and VGG19—over 150 epochs

analysis. Densenet despite being effective in detecting smaller nodules due to its feature reuse, demand higher gpu memory and delayed time because of its dense connectivity. VGG 19 test model meets the accuracy standard but demands large overhead consumption due to its 19 layer architecture. In contrast, alexnet trains in limited time with less overhead con- sumption but lacks to produce reliable output, while Coatnet regardless of its attention mechanism, it struggled on both ends even with limited dataset. This conclusion conveys that advanced models might offer brand new architectures whereas simple model like U-net satisfies the healthy standards be- tween segmentation and computational efficiency The results of the experiment for U-Net, Alexnet, Densenet, CoatNet and VGG19 after training for 150 epochs are listed in TABLE 1. The performance of U-net outperforms AlexNet, VGG19, CoatNet and Densenet in metrics of TABLE 1.

METRICS	U-NET	ALEXNET	COATNET	VGG19	DENSENET
ACCURACY	92.17	89.83	40.67	62.52	67.56
MCC	92.36	49.87	58.42	36.32	89.02[11
AUC	98.81	98.85	94.46	97.31	98.83
MEAN_IOU	40.17	70.26	15.35	30.17	40.52

TABLE I
PERFORMANCE COMPARISON OF U-NET, ALEXNET, COATNET, VGG19, AND DENSENET ACROSS DIFFERENT EVALUATION METRICS.

CONCLUSION

The investigation revealed U-Net's superior performance when applied to the LIDC-IDRI dataset, surpassing CoatNet which struggled to converge effectively. Challenges arose from the dataset's size, leading to interpretability issues and data constraints. Consequently, the study endeavors to mitigate these challenges by leveraging region of interest (ROI) consid- erations within the models. While significant progress has been made, further research is warranted to enhance CoatNet's effi- cacy for segmentation tasks, thereby advancing the field's ca- pabilities.Future research will focus on leveraging transformer- based models to address the limitations encountered with CoatNet and further enhance segmentation performance on the LIDC-IDRI dataset. Transformer architectures, such as Vision Transformers (ViTs) and Swin Transformers, will be explored for their advanced attention mechanisms and ability to handle complex medical imaging tasks. This approach aims to improve accuracy, interpretability, and scalability in medical image segmentation, paving the way for more effective and reliable diagnostic tools.

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