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EFFICIENT U-NET FOR INSIGHTFUL LUNG CANCER DIAGNOSIS

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Abstract—Lung cancer detection often relies on interpreting subtle nodules in CT scans, a task demanding precise segmentation tools beyond simple image classification models. While existing methods utilizing other architectures might achieve decent accuracy, they often struggle with limited CT scan datasets and scalability, hindering their real-world impact. Our paper addresses the imperative need for enhanced lung cancer detection by integrating the Efficient U-Net architecture, which is implemented to achieve better results on image classification tasks while using low computational resources, it means achieve high accuracy can be achieved with few parameters and makes computation less expensive compared to other models, with the Luna16 dataset. Our proposed model excels in feature extraction and overcoming vanishing gradients, ensuring sharper and more accurate nodule segmentation in CT scans. The Luna16 dataset, a diverse and annotated benchmark, facilitates comprehensive learning and adaptability to various nodule types and imaging conditions**.**

Keywords— *Efficient U-Net, Visual Explainability Techniques, Localization, Gradient images.*

I. INTRODUCTION

Early and precise diagnosis of lung cancer is essential to improve person under care's report. However, existing methods heavily rely on radiologists' interpretations of subtle nodules in CT scans, a process prone to human error. To address this challenge, researchers have explored deep learning models for automated lung nodule segmentation. While existing methods using architectures like transformers or U-Nets achieve promising accuracy, limitations remain. These limitations include difficulties in handling limited CT scan datasets and a lack of interpretability, hindering their real-world application.

This approach in the paper addresses this critical need by introducing a novel approach for lung cancer detection that leverages the power of Efficient U-Net architecture. We integrate this innovative architecture with the Luna16 dataset, a comprehensive and well-annotated benchmark for lung nodule segmentation. We compared the Residual U-Net model's execution and Efficient U-Net model's efficacy. EfficientNets are more computationally efficient compared to ResNets, by leveraging depth-wise separable convolutions and efficient building blocks, efficientNets reduce the computational cost of model inference and training.

EfficientNets have achieved better results in performance on image classification benchmarks on ImageNet. This translates to achieving high accuracy with a smaller number of parameters and few computational resources compared to traditional methods. They consistently outperform ResNets in terms of accuracy while maintaining efficiency. This combination empowers our model to excel in feature extraction and mitigate vanishing gradients, ultimately leading to sharper and more accurate nodule segmentation in CT scans. By achieving superior segmentation performance, our work has the ability to improve lung cancer nodules segmentation efficiently.

INTRODUCTION TO DEEP LEARNING

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Deep learning division of Artificial Intelligence inspired by the human brain. Imagine your brain is made up of billions of interconnected neurons that learn by processing information. Deep learning mimics this structure using artificial neural networks. These networks have multiple layers, and information gets passed between them, like signals traveling between neurons, as the network processes more data, it gets better at identifying patterns and making decisions. It's like your brain learning from experience. This allows deep learning to excel in tasks that were once difficult for computers, like image recognition and speech understanding.

In the medical field, deep learning is making waves. One exciting application is in medical imaging, like CT scans and X-rays. Deep learning models can be trained to analyse these images with incredible accuracy, helping doctors detect abnormalities like tumours or fractures. This can lead to earlier diagnoses.

For example, researchers are developing deep learning models that can identify lung cancer nodules in CT scans. These nodules can be very small and difficult for even trained radiologists to spot. However, training prototypes of deep learning on massive datasets of labelled scans, allowing them to train the subtle patterns that differentiate cancerous nodules from healthy tissue.

Deep learning also holds promise in drug discovery and personalized medicine. By analysing vast amounts of medical data, these models can help researchers identify potential new drug targets and predict how a patient might respond to different treatments. This can lead to the development of more effective and personalized therapies.

II. LITERATURE

Iftikhar Nazeer introduced classification method for lung cancer that is built with rectified U-Net based nodule detection and lobe segmentation model that comprises of three parts of execution. In the first step lobe are segmented involving slices of CT scans and the mask is predicted with rectified U-Net architecture, the next step nodule is extracted by mask utilization that is predicted and rectified architecture of U-Net employs labelling and the last step is using a altered AlexNet, along with a SVM is considered to categorise nodules in two ways cancerous and non-cancerous. The results of segmentation, extraction of nodule, and categorisation of nodules of lung from the experiment of the proposed methodology have displayed significant outcomes on the dataset of LUAN16 that is publicly available [5]. Xiangson proposed the DMC-U-Net network which is a combination of an insubstantial residual framework, feature up sampling fusion in multiscale level and Module of X/Y Channel Attention and includes mechanism of Coordinate Attention. The arrangement of the proposed network initially residual units substitutes the convolution components of U-Net, and the residual components's convolution are replaced with Depth wise Separable Convolution with fewer factors and low processing of the design and make the better executable prediction prototype and training model, next the parallel direction diffusion in the upsampling technique of u-net substitutes the processes of transposed convolution and PixelShuffle, the convolution that is transposed replaced and utilized in the first U-Net, which provides the ability to the model to record information in a better manner at different scales, combining feature fusion of multiscale level module previous to PixelShuffle makes the conventional Efficient Sub-Pixel Convolutional Neural model to improve, that focuses to the expansion of constant field, and lastly, the attention mechanism of CCA addition next to the fusion of up sampling can perform a improved spatial information recovery [6]. Jiangdian Song 's model is an architecture based on end to end that is used to execute complete segmentation automation based on various categories of nodules of lungs and heterogeneity images within the nodule's generation for the medical use. A Fusion loss is taken into account in model of Faster R-CNN that is founded on crossroads between generative adversarial network union loss. When the nnU-net and four other models are compared with the suggested model, this procedure performed better than the others [7]. Barath had build a prototype that is based on the U shaped network architecture, the prototype is built to analyze the chest radiographs that are publicly available throughout the internet. They used the classification that is based on pixels, there is no data augmentation present in this work. The model gives the output of segmented masks of lungs within in short span of time proving its capability [1]. Kapoor's work introduced the models that smartly detects the cancer present in Colon and Lungs with the help of

Histopathological images, based on the various features the different kinds of image analytical methods are differentiated. This prototype also focuses on providing the medical facilities to the nations that are not equipped with high-end medical equipment. As the lung and colon cancers are most occurring cancer kinds around the world this model provides the capability to have a diagnosis for the cancer in the initial phases. [2] Chen's analysis work on CT scans gives a less efficient result and its dependency on the experience level of the medical examiners. Segmentation process that uses CAD system increases preciseness along with the efficiency in the process of diagnosis. In this work, several deep learning segmentation models are evaluated and tested the impacts of various other methods used for preprocessing in order to find the finest strategies for initial processing and training to perform segmentation of lung nodules [8].

Vibhav introduced This advanced model is tailored for precise detec-
tion and segmentation of lung regions, a critical task in lo-
cating lung tumors accurately for treating life-threatening
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III. METHODOLOGY

This section will outline the specific steps taken to develop and evaluate our lung cancer detection approach using Efficient U-Net.

1. Data Acquisition and Preprocessing

- Data Source: We will utilize the Luna16 dataset, a publicly available and well-annotated benchmark for lung nodule segmentation in chest CT scans.
- Preprocessing: The CT scans will undergo preprocessing steps to ensure consistency and improve model performance. This includes:
  - Converting the train data images into numpy arrays.
  - Converting the images from single channel to 3 channels.
  - Loading the masks in binary encoded image.
  - Converting both train and test data's datatype from int to float 32.
  - Normalization of pixel intensities.

2. Efficient U-Net Model's Architecture

- Encoder: Describe the use of pre-trained EfficientNetB2 backbone for feature extraction.
- Decoder: The up sampling of the extracted features that are combined with corresponding features from the encoder path for accurate localization.
- Final Layer: The final layer which id convolutional layer using a sigmoid activation function for segmentation mask generation.

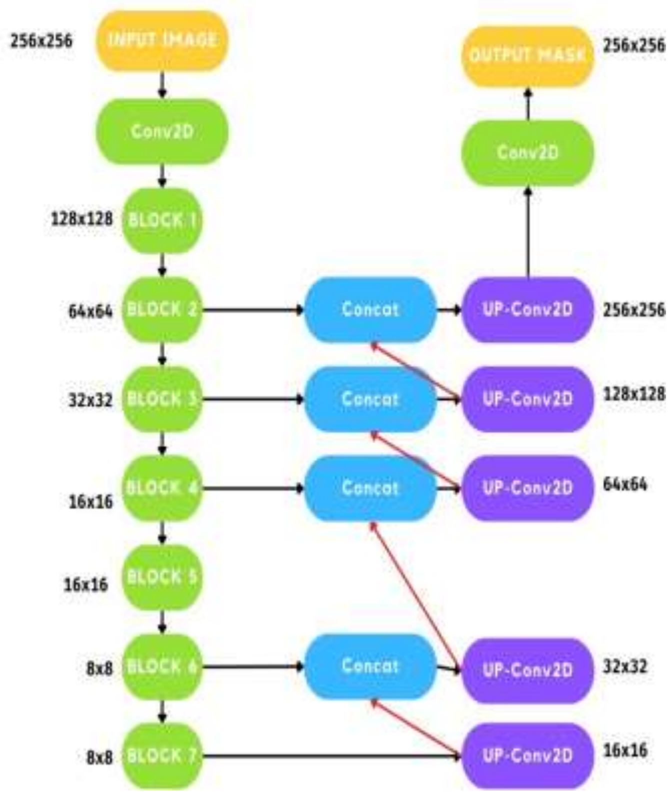

Fig. 1. Efficient U-Net

3. Model Training

- Training Loss Function: We define the Dice loss function that calculates the discrepancy of the segmentation mask that is predicted and the target truth labels (nodule annotations) in the Luna16 dataset.
- Optimizer: Adam optimizer that modifies the model weights by updating them during training based on the calculated loss.
- Training Parameters: Training the model with a validation split of 10% of training data
keeping the batch size of 2, keeping the number of epochs to be 40 and with a verbosity to be true.

4. Assessment criteria

- We score the trained model of Efficient U-Net on a held-out test set from the Luna16 dataset. Common metrics used for segmentation tasks include:
  - Precision: Focuses on the proportion of predicted positive pixels that are actually true positives
  - Sensitivity (Recall): Calculates the total of true positive nodule pixels estimated by the model.
  - Epsilon Score (Escore): Escore is another metric for imbalanced classification tasks. It considers both precision and recall but focuses more on penalizing the model for missing positive class instances. Similar to precision, for lung nodule segmentation, a high recall is more crucial, making Escore less suitable than recall (sensitivity) itself.
  - AUC: AUC is a good metric for imbalanced datasets, where positive class instance (nodules) is much fewer than negative class instances (background pixels) in a CT scan image.
  - IOU Score: The Intersection over Union (IoU) score measures how well your segmentation model overlaps with the actual object in an image.

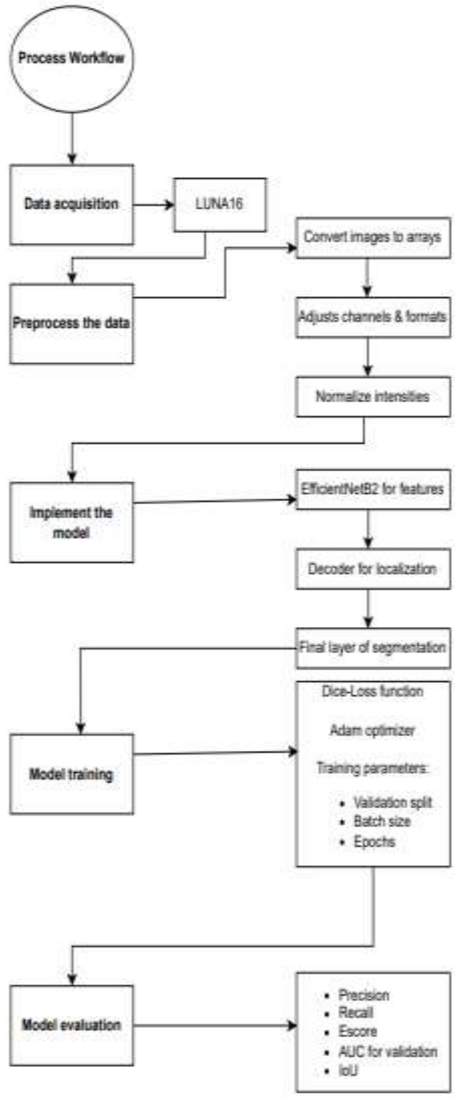

Fig. 2. Approach Flowchart

Mathematical equation used for evaluation

The mostly used evaluation metrics for models in the category of image segmentation are used to analyse the capability of our efficient network, Sensitivity (Recall), Dice loss, Precision, Accuracy and F1-Score. We first calculated true positive (TP), false positive (FP), true negative (TN), and false negative (FN). These performance measures are mathematically expressed as follows:

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$

Precision= $\frac{TP}{TP+FP}$

Recall = $\frac{TP}{TP+FN}$

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F1 - Score = 2 x $\frac{Precision * Recall}{Precision+Recall}$

Dice Loss = $\frac{2*\sum p_{true}* p_{pred}}{\sum p_{true}^2 + \sum p_{pred}^2 + \epsilon}$

STEPS IN LUNG NODULE SEGMENTATION

Step 1: Data Preprocessing

1. Importing training and test datasets.
2. Converting the train data images into numpy arrays.
3. Converting the images from single channel to 3 channels.
4. Loading the masks in binary encoded image
5. Converting both train and test data's datatype from int to float 32.

Step 2: Model Preparation

1. Using segmentation_models library to load the unet architecture.
2. Using the efficientnet architecture as the backbone.
3. Loading the pretraining encoder weights from imagenet architecture.

Step 3: Model compiling

1. Using the training metrics recall, precision, Aut, jou score, Escore.
2. Using the loss function to be DiceLoss, which is best suited for segmentation models.
3. Using the optimizer function to be adam optimizer.

Step 4: Using the optimizer function to be adam optimizer

1. Training the model with a validation split of 10% of training data.
2. Keeping the batch size of 2.
3. Keeping the number of epochs to be 40 and with a verbosity to be true.

Step 5: Model Evaluation

1. Evaluating the model using training data.
2. Using the test dataset to use the prototype on fresh available information.

Results: The lung nodule segmentation model gets trained for 96.25% of AUC, 0.7145 of f1-score, 0.6605 of IOU_Score, 28.59% of Loss, 79.02% of precision, 99.95% of sensitivity. The outcomes for the Efficient U-Net model segments the lung nodules are 97.69% of AUC, 0.8267 of f1-score, 0.6366 of IOU_Score, 28.28% of Loss, 78.10% of precision, 94.95% of sensitivity.

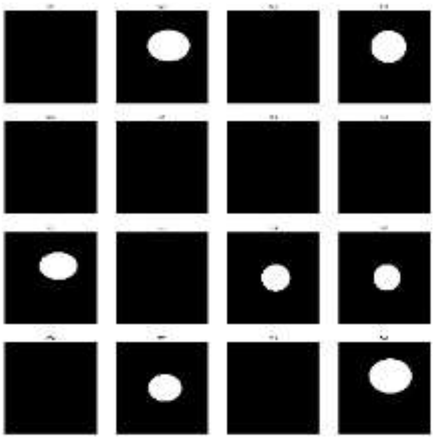

Fig. 3. Target masks

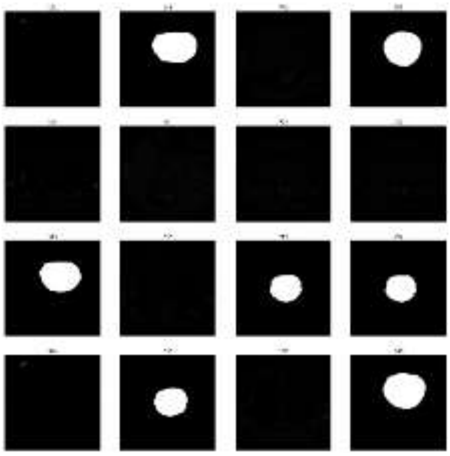

Fig. 4. Predicted masks

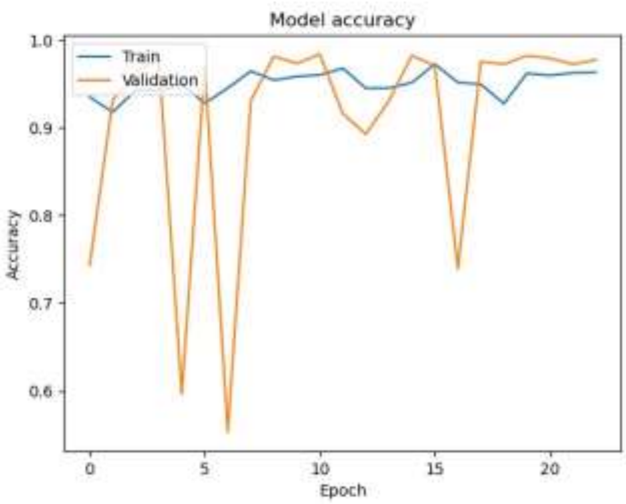

Fig. 5. Analysis in terms of accuracy

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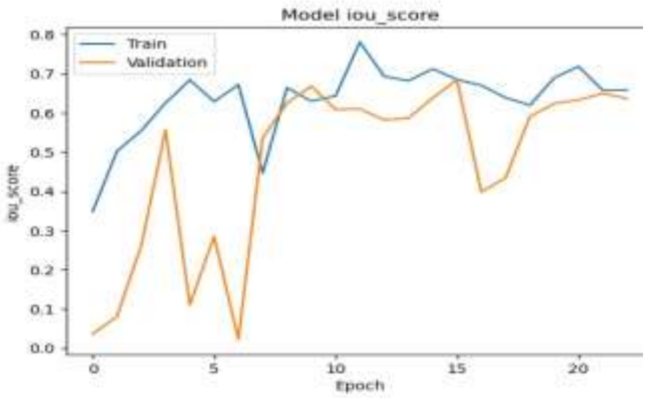

Fig. 7 Analysis in terms of IoU score

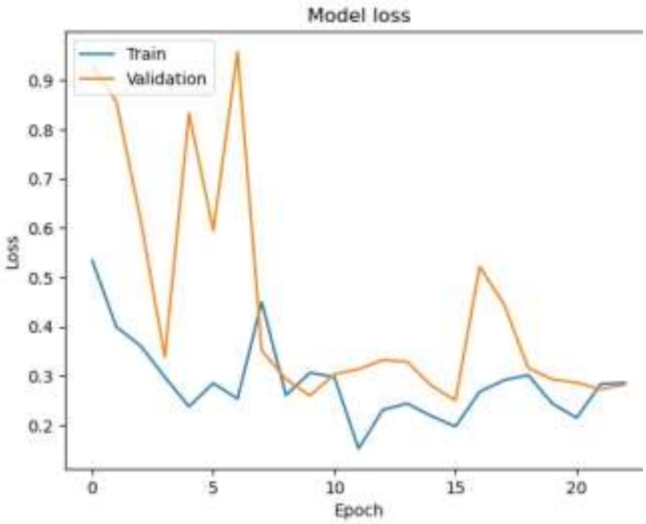

Fig. 8 Loss analysis of mode

IV. CONCLUSIONS

Finally, the paper presents a great perspective for lung cancer nodules segmentation using deep learning. Our model leverages the power of the Efficient U-Net's architecture, renowned for computational efficiency, and trains on the comprehensive Luna16 dataset. By comparing its performance with the traditional Residual U-Net model, we demonstrated the advantages of Efficient U-Net in lung nodule segmentation tasks.

Our findings highlight the potential of Efficient U-Net to attain high accuracy in nodule segmentation with less number of parameters and lower computational cost. This creates outcome for fast and more rapid analysis of CT scans, potentially leading to elevated diagnosis of lung cancer.

Future research directions include achieving high accuracy, future work could explore methods towards the improvement in the interpretability of the Efficient U-Net's model in the theme of lung nodule segmentation. This would provide better improvement in model transparency to understand its reasoning and build trust. in its clinical application. Further validation on widely diversified datasets from clinical settings is crucial to ensure the generalizability and robustness of our model for real-world lung cancer detection. Developing perfect integration of the model into existing medical examination workflows would pave the way for its practical implementation in lung nodule cancer diagnosis and planning its cure. By addressing these aspects, we can further refine our model and contribute significantly to the fight in opposition to lung cancer.

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