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Efficient Multi-Class Classification of NSCLC Subtypes with Transfer Learning-Enhanced CNNs on Augmented CT Data

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ABSTRACT

The second most cancer related deaths are caused by lung cancer, since this cancer type has highest mortality rate. The early diagnosis of Lung cancer is crucial as there are possibilities to increases the survival rate. Conventional diagnostic methods often rely on human interpretation of medical images which is time consuming and are prone to error. In this research we proposed a Novel hybrid model LungNetB5 for multi-class lung cancer classification and prediction. CNN and Efficient Net are integrated into single architecture which blends traditional CNN feature extraction layers with the powerful feature learning capabilities of EfficientNet. The experiments are carried on "MCLCI" dataset for NSCLC lung cancer patients. To overcome the biases, class imbalance problem was addressed using data augmentation techniques. The developed LungNetB5 model attained 92% accuracy. The predicted results show that EfficientNet class based LungNetB5 outperforms other CNN models in terms of efficiency and accuracy. In addition, it is faster and need very less parameters to train when compared to other CNN models, making it a viable experiment for extensive clinical settings and a promising tool for automated detection of lung cancer from CT images.

Keywords: *Lung cancer detection, Medical Imaging, Deep learning, Transfer learning, Data augmentation*

1. INTRODUCTION

Cancer is one of the major diseases that can start almost in any part of the body or organ and can spread rapidly to other parts affecting almost people of all the age groups. There are nearly 100 types of cancer, some of the most common types are lung, breast, cervix etc., Lung cancer has the second highest incident rate affecting the diverse population of both men and women. According to the study made on lung cancer incidence in nearly 40 countries and the report state that by 2035, there will be globally increase in lung cancer related deaths, by almost more than 3 million deaths per year due to the certain factors like environment pollution, usage of tobacco and aging population [1]. Lung cancer is divided into two types out of which 20% of cases accounts to small cell lung cancer (SCLC) and 80% cases accounts to non-small cell lung cancer (NSCLC). It is very difficult to detect the lung cancer in its initial stages because there are no prior symptoms, so to detect the presence of tumours especially in lung cancer, medical imaging procedures can be used. These imaging procedures like X-rays, CT scans, PET scans [2] are non-invasive and procedures like biopsies are invasive. Radiologists classify these medical images and determine the stage of the cancer considering the size, shape and location of the tumour. Now interpretation of these images often leads to error/inaccurate results leading to inappropriate treatment strategy. To overcome this kind of issue many researchers have developed several computational techniques to automate the medical image analysis for lung cancer classification that can result in more accurate outcomes by improving overall model's performance [3].

The shape of the lung tumour can either be of round shape or oval shape with higher diameter of 10mm are considered risk. Tumours with different size, mass and locations that can only visible in CT images and can also capture the disease advanced to the surroundings areas (malignant) as well [4]. Fig1. (a) shows a normal node and (b) shows an anomalous node that exceeds 3mm.

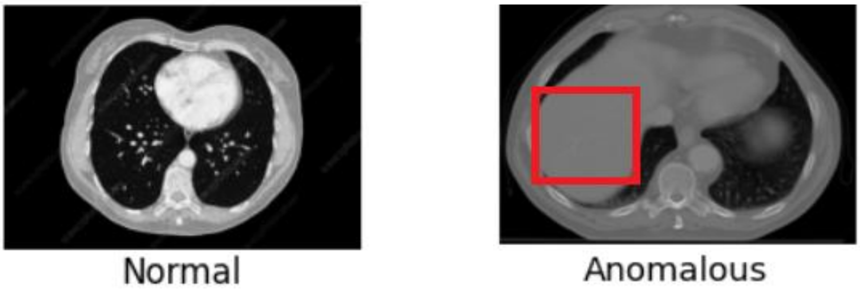

Fig 1. Lung CT images. (a) Normal, (b) Anomalous

Since 80% cases in Lung cancer are considered as NSCLC, if nodule diameter is less than 3 mm it is considered as Benign and nodule exceeding more than 3mm are considered to be malignant(anomalous) [5]. Significant changes in abnormal lung nodule in CT scan can indicate a serious health condition like cancer, considering these cases as anomalies they could be a warning signal of a major issue that needs more investigation. Compared to several other imaging modalities, CT scan images provide high resolution and are more efficient to detect malignant tumours [6]. CT scanners are used to capture lung images while rotating 360^0 regions, even the nodules attached to the bones can be discovered. Radiologists are capable of diagnosing patients accurately by finding even small anomalies. [7]

Though in the domain of medical imaging analysis there are many types of ML techniques were used to classify the lung cancer types, as these techniques are good at extracting features from images making the classification task easier. The other techniques like deep learning models gained huge recognition in medical image analysis due to its automatic feature extraction that was more efficient for tasks like classification. In addition of having DL model variants, CNN model is used widely [8], CNN is apt as data representation is learned hieratically, allowing them to extract more complex information from unprocessed data. CNN extracts important features and patterns from the images without any kind of manual feature extraction, making it more effective to classify images with similar features, it also requires huge amount of dataset to achieve good results. To avoid issues of working with multi-modal, large dataset, transfer learning is used.

Transfer learning is widely used powerful technique to handle the drawbacks of CNN model. Using TL the pre-trained CNN models will be used as baseline while the model is subsequently enhanced using a new dataset. This can be carried on by unfreezing few of the layers in the pretrained model and later summing up with some additional layers on top of pre-trained model and train the entire new model. These approaches computationally as well as automatically extract the superior features. Deep learning techniques combined with medical image analysis has a great potential to increase the efficiency, robustness and performance of lung cancer detection and classification [9]. Transfer learning is a valuable technique in medical field for detection and classification of lung cancer considering many studies carried out so far.

The main objective of this study is to determine cancer type in Lung CT images. To achieve this, our research focuses on classification of lung cancer type into four different categories namely adenocarcinoma, large cell carcinoma, normal and squamous cell carcinoma based on the thin slice CT images of lung nodules. To accomplish this lung classification task, transfer learning is applied using three pre-trained models of EfficientNet model B5 to B7. Each model is fine-tuned on slices of CT scan Lung cancer images. Fine-tuning is a method that involves adjusting these pre-trained models to specific characteristics and features of the lung cancer dataset in order to capture meaningful patterns and information. So that these models are used to perform better on a certain task by typically modifying and training only some parts of the model. It is mainly used when the dataset is limited and it is computationally expensive when developed from the scratch. These state-of-the-art CNN models are used for image classification task. By applying Transfer learning (TL), a powerful technique that allows CNN's to be applied to small datasets successfully [10].it also leverages the capabilities of CNN models to accomplish accurate classification results for lung CT images. [11]

Transfer learning with CNN model has different architectures and is an efficient and effective approach to solve image related problems ,TL+CNN along with fused data augmentation technique is used when dataset is small or there is class imbalance. By leveraging Transfer learning the CNN pretrained models can capture important features from large datasets like ImageNet and transfer this knowledge for specific task involving lung cancer segmentation. It leads to potential increase in accuracy and robustness of segmentation task [12]. EfficientNet have showed potential results related to computer vision tasks, including image recognition and segmentation. Fine-tuning these pre-trained models on medical image dataset, especially Lung cancer images, with regard to specific characteristics and certain variations found in medical images, with diversifying data using augmentation, the model will learn to generalize effectively.

This study presents an optimized approach that leverages transfer learning and data augmentation for multi-class classification of NSCLC subtypes on CT images.

Our research article primarily contributes to the following

To develop a novel hybrid CNN-Efficient Net framework LungNetB5 using EfficientNetB5 and model for multi-class lung cancer classification.

To solve the challenge posed by limited medical image data by using fused Data augmentation technique to overcome the data skewness

To evaluate the effect of data augmentation on the performance of proposed model and comprehensive experiments were carried on MCLCI dataset with applied data augmentation techniques.

To compare the novel model with other models in terms of computational capability, execution time and also to illustrate the model performance of EfficientNet model over other CNN classification models.

The sections of the paper are structured as follows: Section 2 literature review of the existing techniques for detecting lung cancer. Section 3 describes in detail the dataset used and its analysis on the proposed methodology which uses fine-tuning and transfer learning technique of the EfficientNet model. Section 4 The discussion of the experimental results conducted on MCLCI dataset and also comparison with current techniques are explained. In Section 5 the final conclusion of our investigation is presented and also it provides a feasible future direction for the research.

2. RELATED WORK

Lung cancer is a deadly disease and it is crucial for early diagnosing, so that there are chances for providing successful treatment and survival rate. This disease causes the cell to decay and multiply them uncontrollably, when these decayed cells grow rapidly affecting other parts of the body, it is necessary to detect it and treat. The process of detection, segmentation and classification of lung nodules as cancerous, most advanced medical imaging techniques are used such as X-rays [13], CT scans [14], Histopathological images [15] etc., For cancer diagnosis, CAD (Computer Aided Diagnosis) systems are considered to be performing well as they are capable of detecting earliest signs of anomalies(tumours) in lung images [16], it takes lot of time for human interpretation of these images. To automatically detect and classify the anomalies present in these images CAD based framework is needed resulting in achieving higher accuracy [17]. This section analyses ML and DL models and based on this analysis, a new framework is designed on fundamental issues such as detection, classification.

Rather than manual interpretation of the images several techniques more progressive techniques like image processing were considered to acquire, process and analyse the images. Various image processing techniques were used for manual feature extraction such as geometric was used for image transformation, for noise removal gaussian filter is used, spatial filtering and for the purpose of segmentation particle swarm optimization, fuzzy C-means clustering, watershed algorithms, morphological operations have been used. These extracted features will be transferred to the ML classifiers for segmentation and classification tasks. [18] used a classification system for multistage classification of lung cancer where threshold and watershed algorithm for segmentation, binary classifier for classification. The dataset was trained on various ML algorithms like SVM, KNN, DT, logistic regression, Naïve Bayes and RF, accuracy of 85.5% accuracy was achieved by RF. [19] proposed a classification of lung cancer as benign, malignant and non-malignant, image were processed using gaussian filter, segmented with threshold method and feature extraction is done using Gabor and GLCM filters and svm classifier achieved detection accuracy of 89.88% with polynomial kernel. Computer Aided Diagnosis (CAD) employs various Machine Learning (ML) and Deep Learning (DL) techniques, as ML works with small datasets, increase computational time and complexity due to manual feature extraction, having its own drawbacks that can be overpowered with DL models. DL model like CNN is used for image segmentation, classification and detection. [20] The authors in the paper discusses CNN and google net for automated system for detecting cancer regions and classify between normal and abnormal tumours, for this deep CNN architecture like VGG-16 was used as a base network and achieved an overall accuracy of 98%. Deep learning architectures are inherently stochastic in nature as they produce different results at every prediction which can be uncertain leading to model overfitting. To solve these issues ensemble learning is used which combines two or more models for accurate predictions on the same set. [21] uses 2D CNN ensemble learning approach to detect lung nodules, out of 2D CNN model the three CNN models are used for proposed study with this the ensemble deep learning approach provides an accuracy of 95% in lung cancer detection. when deep learning models like CNN and DCNN are powerful but they require a large amount of labelled data to train effectively leading to model overfitting. To overcome this issue transfer learning is used to train a pre-trained model on large labelled dataset and finetune it with fewer label images for solving specific medical imaging problems.TL can use pre-trained model either for layers fine-tuning or feature extraction [22] proposed a transfer learning approach for multi class lung cancer classification into three classes benign, malignant and normal using CT images, they used publicly available dataset from IQ-OTH/NCCD and used augmentation to expand the dataset samples, they used pre-trained networks like VGG-16,VGG-19 and Xception network with an accuracy of 98.83%, 98.05%, 97.4% respectively. [23] employed CNN based EfficientNetB7 model to analyse 15000 histopathological images of lung cancer to classify primary malignant categories (adenocarcinoma, squamous cell carcinoma and large cell carcinoma), the model achieved 99.7% accuracy. [24] proposed a hybrid method that uses 1503 images was used for testing, CNN with SVM automatically detect and classify multi class types of NSCLC lung cancer with 97.91% accuracy. [25] a transfer learning model was developedto classify four lung classes using lung CT images, image processing, data augmentation and hyper-parameter tuning are considered to increase the efficiency of VER-Net with 91% accuracy.

This review of literature demonstrates that leveraging the robust transfer learning-based methods are more reliable than any other machine learning techniques. When pre-trained architectures are used aids in a accurate results with increase in the depth of the architecture that leads to more complexity of parameters which reduces the model efficiency in the training and testing phase. Furthermore, while training a deep learning model like CNN, it has to deal with significant problems such a gradient vanishing problem that reduces the gradient that causes the model to overfit, these concerns has to be fixed. The weights of CNN architecture fluctuate that slows down the execution making the model complex and hard for the network to learn. There are different medical imaging modalities in which CT images provide high resolution that are used for detecting lung nodules in its earlier stages which makes the diagnostic radiologists difficult to interpret images that are prone to potential diagnostic errors that leads to treatment delay. To combat these issues of early diagnosis of disease such as lung cancer. CT images which contains a detailed information is fed to deep learning models for produce good classification accuracy. The primary objective of this study is to propose a hybrid CNN based transfer learning method for classification of lung cancer NSCLC subtypes from the CT images using Efficient Network with CNN to achieve generalization with less parameters and thus lowering the computational demands on the system.

3. MATERIALS AND METHODS

This section focuses on the dataset utilised and the methodology adopted by the proposed model for multi-class lung cancer subtype classification of non-small cell lung cancer (NSLC) based on CT images. The workflow of the suggested methodology is given in fig 2. The CT scans in the dataset are loaded then several pre-processing steps are applied for these images. Since Medical imaging is used it is difficult to annotate the data to train the model. Due to which the diversity of training dataset increases through the use of data augmentation. The proposed methodology is based upon the transfer learning approach using EfficientNet variants, that are fine tuned for the multi-class classification of lung cancer subtype into four categories namely Adenocarcinoma, Large Cell Carcinoma, Normal and Squamous-Cell Carcinoma. The pre-processing steps, data augmentation and proposed model are described detailly in the subsequent sections.

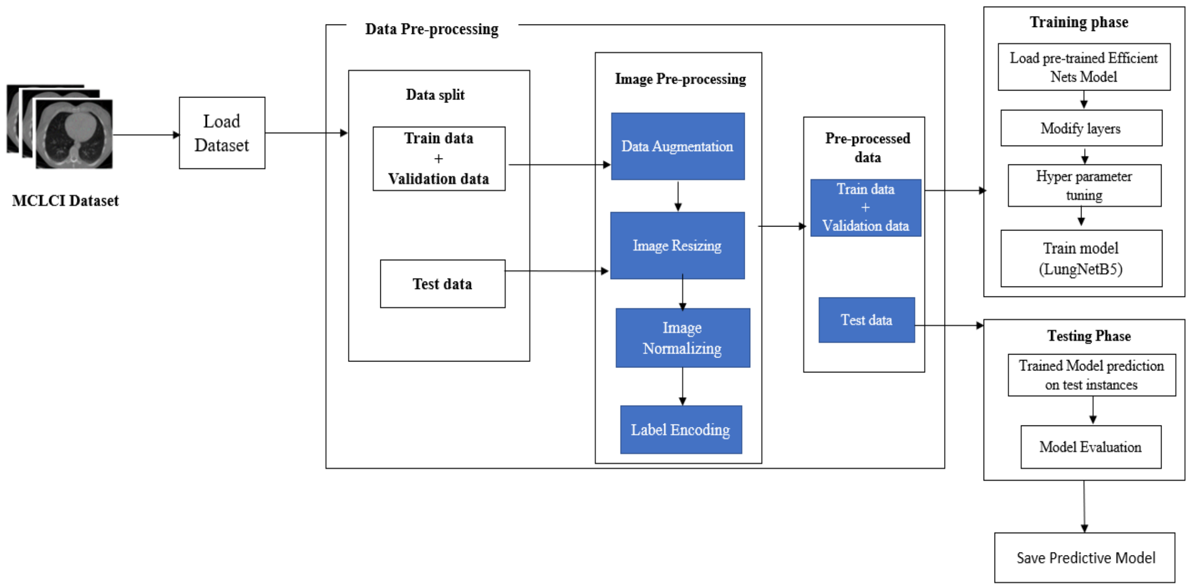

Fig 2. The workflow of our proposed approach

3.1 Dataset

The experiments were carried on Multi-class lung cancer image dataset (MCLCI) from a private clinical organization. The dataset consists of high-resolution CT scans images that are normal and are subtypes of Non-small cell lung cancer. The dataset was annotated by radiologists and oncologists. The anomalous cases are divided into four categories adenocarcinoma, large-cell carcinoma, normal and small-cell carcinoma depicted in fig 3.

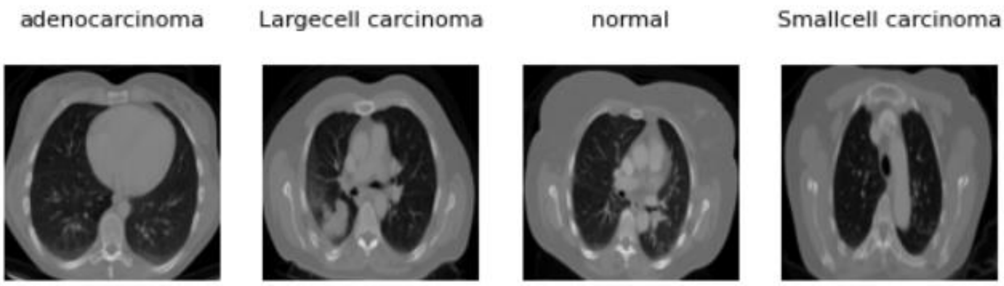

Fig 3: Subtypes of Non-small Lung cancer

Dataset of 1000 CT images were analysed with 785 being identified as malignant and 215 as normal. These CT images were originally acquired in the grayscale .PNG format having a resolution of width more than 400 and height with several values. Table 1. Represents the class-wise category of MCLCI dataset.

Table 1. Class-wise subtype distribution of the MCLCI dataset

Class	No of samples
Adenocarcinoma	338
Large-cell Carcinoma	187
Small-Cell Carcinoma	260
Normal	215
Total	**1000**

3.2. Data Pre-processing

This present section discusses the pre-processing steps applied to the dataset before training, testing and validating the model.

While processing the original CT images that consists of unwanted regions are cropped from the area of interest so to improve, image quality, reduce noise and normalize to 999+999prevent the noisy training, hence after cropping data augmentation is applied for these cropped images. Data augmentation is covered in detail in the next section. Rescaling is than applied to adjust the size of the image and pixel value to desired range of fixed resolution 240x240x3 as it can match both input shape and input tensor needed by pre-trained EfficienNet models. Image resizing is done to reduce the computational overload while model training keeping certain image features and its contextual information intact. Finally, class labels in train, test set are encoded into 0,1,2,3, for adenocarcinoma, large-cell carcinoma, normal and squamous cell carcinoma.

3.3 Data Augmentation

There are 1000 original CT image samples and data augmentation is applied for these samples to increase or diversify the dataset while generating new, modified versions of the existing dataset. This process is particularly important when dataset is imbalanced or limited. Data augmentation improves the generalization of the model and reduce overfitting. It employs various image transformations like translation, rotation, scaling, shearing, mirroring, cropping. In this study, some commonly used data augmentation techniques like rotation, height shift, width shift, horizontal flip, brightness and zooming are applied to the dataset. Here these techniques are applied only for training dataset

3.4 Overview of Proposed Architecture

In this section, the transfer learning paradigm integrated with the proposed architecture of fine-tuned EfficientNet B5 are discussed in detail.

3.4.1 Transfer Learning

CNN are often pre-trained on large image datasets that enables to automatically extract both low- and high-level features from batch normalization, pooling and convolution base layers of the model. From these features one dimensional feature vector is generated, then transmitted to one or more fully linked layers for classification. But the major drawback of CNN is that it needs a huge number of data samples to effectively train the model and avoid high bias and high variance issues. without enough data the model's performance is suboptimal. But it is very difficult to collect annotated data for purpose of research especially in the domain of medical imaging. To resolve this issue, the transfer learning technique is used. Transfer learning is a technique of ML that transfers knowledge acquired from architectures that were initially trained on benchmark dataset like ImageNet to solve the problems that are similar or different from their actual context, for example using lesser dataset to classify lung cancer. Fig 3. demonstrates the general idea of transfer learning.

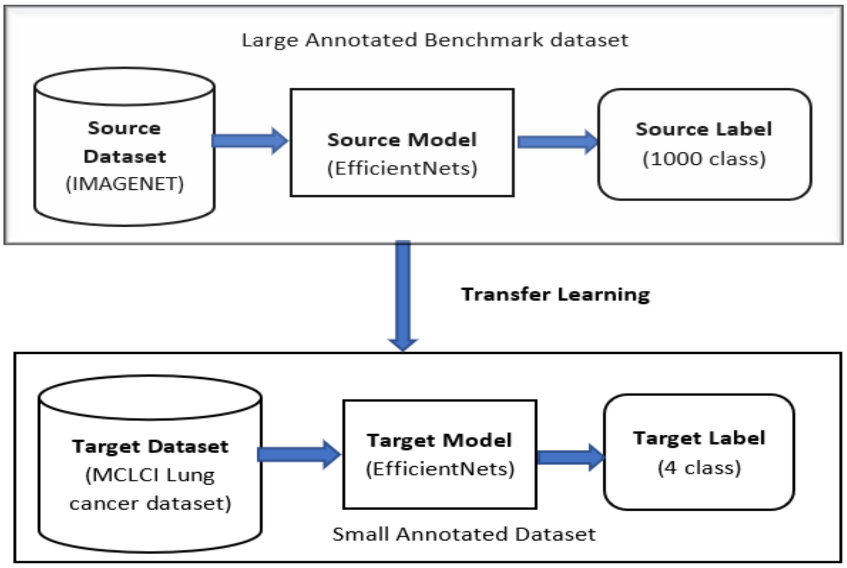

Fig 4. Transfer Learning concept

Because of the domain differences between the source and targeted dataset like CT scan, none of the CNN models can be used directly for inference and expect generalizability on hidden test instances. Rather the layers of pre-trained model are fine-tuned empirically to adjust to the images in target domain. Fine tuning is a ML technique that retrain weights received from the deep CNN architecture's top layers to solve specific problems, as these weights were primarily trained on huge dataset. By unfreezing few or some of the layers in convolution base or by using pre-trained model as a fixed feature extractor where new data is fed into classifiers for classification, later pre-trained architectures can be fine-tuned. In this study, transfer learning of three variants of the pre-trained EfficientNet model B5-B7 is performed by fine-tuning each variant explicitly on the lung cancer CT images. The feature maps are extracted from the EfficientNet and are then transferred to the fully connected layers for performing classification task. The next section explains detailly optimizing the classification layers of the fine-tuned Efficient Net architecture.

3.4.2 Classification using Fine-tuned EfficientNet model

This study involves transfer learning pre-trained EfficientNet variants, EfficientNEtB5 through EfficientNet B7, that were primarily trained on ImageNet dataset. The CT scan images of lung cancer are mainly used as to fine-tune these models. The pre-trained EfficientNet model is fine-tuned by initialising the base model considering ImageNet weights as backbone. Global Average Pooling(GAP) layer is placed on top of the backbone of Efficient Net and still keeping the weights fixed in each block of convolution base. GAP layer helps to reduce number of parameters thus simplify the network without affecting the performance of the model in terms of accuracy. A dropout layer is added with 0.5 probability to the network followed by the GAP layer. Dropout regularize helps to avoid overfitting of the model. As the dataset has 4 class labels, the output layer initially has 1000 units that are replaced by 4 units of output layer with SoftMax activation layer. Re-train the whole architecture on MCLCI Lung cancer dataset.

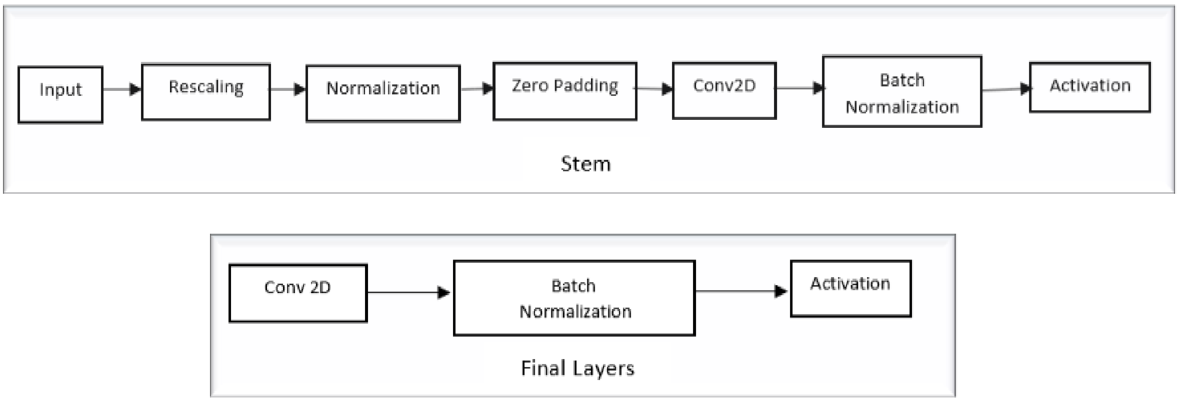

Fig 5. Stem and Final layer of EfficientNetB5

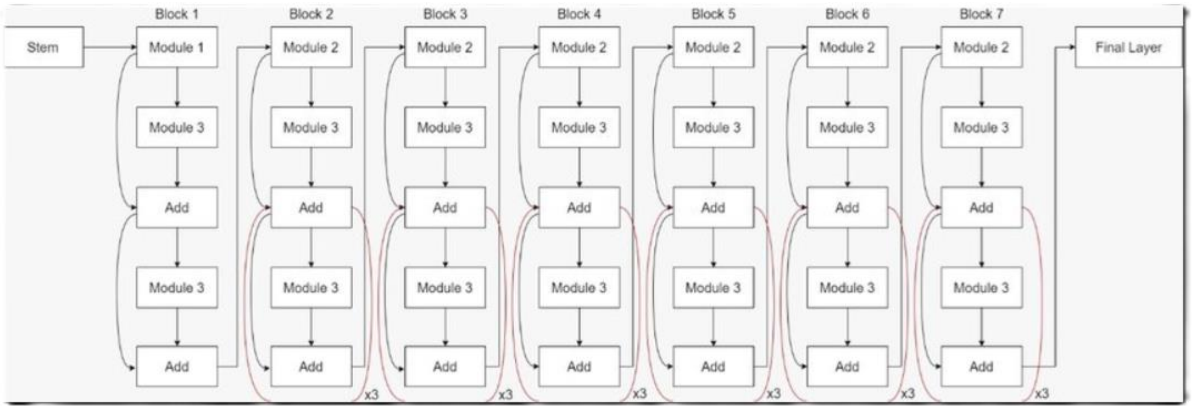

Fig 6. Building blocks of EfficientNets

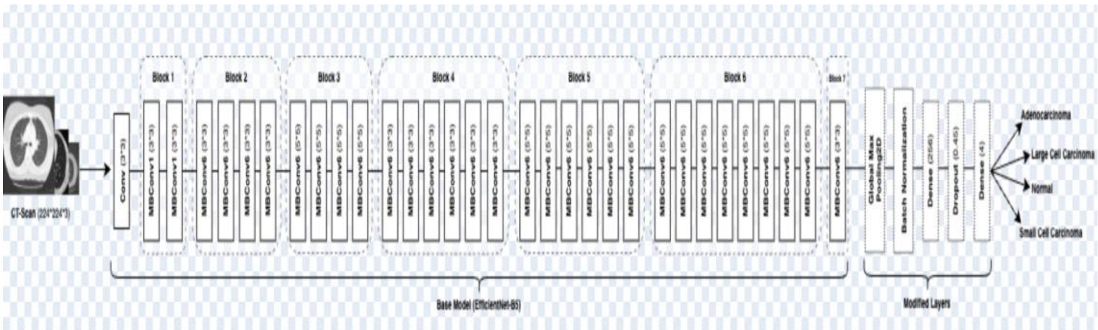

Fig 7. General architecture of LungNet B5

4. EXPERIMENTAL EVALUATION

This section discusses a comprehensive evaluation metrics used to evaluate the performance of the proposed method. It includes the system and software requirements required for the model training and evaluation. The below section provides the thorough analysis of the obtained results from the proposed method.

4.1 Evaluation metrics

It is very critical to choose the appropriate evaluation metrics that are used to evaluate the deep learning model's performance. These quantitative measures compare different algorithms and performance of different models on a specific task and assess the algorithm or model's effectiveness to solve a particular problem, to determine the areas for improvement. In this research work the evaluation metrics used are accuracy, sensitivity/recall, precision, F1 score, confusion metrics, ROC curve.

Accuracy: The accuracy of classifier is the ratio of accurately classified instances (TP+TN) to the overall number of instances (TP+TN+FP+FN).

Accuracy=$\frac{TP+TN}{TP+TN+FP+FN}$ ………………………………………. (1)

Where TP=True Positive, TN= True Negative, FP= False Positive, FN=False Negative respectively.

Precision: The ratio of true positives out of all predicted positives.

Precision = $\frac{TP}{TP+FP}$ ……………………………………… (2)

Recall (Sensitivity) : The ratio of true positives out of all actual positives

Recall = $\frac{Tp}{TP+FN}$ ……………………………………………………………… (3)

F1 score: The harmonic mean of the precision and recall

F1 score = 2. $\frac{Precision.recall}{precision+recall}$ ……………………………………... (4)

Where precision is the ratio of true positive results, recall is the ratio of true positive cases that are actual positives.

Receiver Operating Curve (ROC): A graph that assess classifier model performance at each threshold. ROC mainly represents two parameters, True Positive Rate (TPR) and False Positive Rate (FPR)

TPR= $\frac{TP}{TP+TN}$ ……………………………………………….. (5)

FPR = $\frac{FP}{FP+FN}$ ………………………………………………… (6)

Confusion matrix: A matrix used to determine the overall performance of classification model and it is a summarized form of predicted results.

4.2 Experimental setup

The Apple MacBook is used to create the proposed LungNetB5 model enabling faster training and model evaluation, that may be useful for creating and testing the suggested model. This study employs python programming, keras library and at the backend it uses TensorFlow to train the model. These experiments were conducted using apple m1 chip with 16GB unified memory. Computing power is measured in TFLOPS

4.3 Hyper-parameter settings

To attain optimal performance through model training and to obtain desired results for classification of lung cancer, many hyper parameters were fine-tuned thoroughly through empirical experimentation. Hyper-parameters like batch size, epochs, optimizers, learning rate and loss function are used.

Considering the lung cancer classification that involves distinguishing between NSCLC subtypes adenocarcinoma, squamous cell carcinoma, normal cases and large cell carcinoma, categorical cross entropy is selected as the suitable loss function. EfficientNet model B5, B6, B7 are trained by the adam optimizer with a standard initial learning rate of 0.001, additionally to optimize the learning rate, to evaluate the model's validation accuracy for every five iterations by applying a decay factor of 0.3. Further a drop connect rate of 0.2 is set to include regularization while fine tuning keeping ImageNet weights intact, meanwhile this rate initiates the regularization techniques. Training set images are divided into a batch of 32 training set images and then loaded and trained for 50 epochs, so for each epoch, approximately 10% of images were randomly separated from the training set to create a validation set. Further this validation set is used to evaluate the efficacy of the trained model and to determine if there has been an issue of overfitting. The selected variants of EfficientNet (B5-B7),ResNet152 were trained and assessed to ensure fair comparison by constant experimental and hyper parameter settings. Table 2. shows the hyper parameters optimized values used in the overall the experiment. Following fine-tuning and carrying out several experiments the hyperparameter combinations are finalized.

Table 2: Hyper-parameters list and its corresponding values

Hyper-parameters	Corresponding values
Input shape	(240,240,3)
Drop connect rate	0.2
Output activation function	SoftMax
Batch size	32
Epoch	50

Optimizer	Adam
Initial Learning rate	0.001
Decay factor	0.3
Iterations	5
Validation split	0.1
Loss function	Categorical Cross Entropy

4.4 Result analysis

In this study, DL approach is used for multi-class classification of lung cancer using CT scans and pre-trained EfficientNet. The experiments were carried on "multi-class lung cancer image dataset". The dataset consists of 1000 CT scans were collected from 125 patients out of which 338 are adenocarcinoma, 187 are large cell carcinoma, 260 squamous cell carcinoma and 215 are normal cases. Thus, collected images were in Portable Network Graphics(.png) format. Now these images were pre-processed before transferring for training purpose.

The accuracy and loss curves of the proposed model is shown in fig 8. A confusion matrix can also be used for multi-class classification and evaluate the generalization of the model on unseen dataset. The confusion matrix demonstrates the predicted label and true label respectively in X-axis and the y-axis for each class. A comparison is carried on with predicted label and true label and then summarizes the results of number of times the accurate occurrences of combined predicted and true values. Fig 9 displays the confusion matrix that helps assess classification performance of the proposed model. The fine tuning of the model over training dataset is done and are than tested separately on a test dataset. The proposed model overall accuracy is 92%, the ROC curve of 0.98 to 0.99 supports the validity of our proposed model that indicates the model can differentiate between multi-class lung cancer images. To transfer the dataset for further training, the model uses 6.5 million parameters to perform well on test dataset. Fig 10. A ROC curve is a graph used to plot the trade-off between TPR and FPR at various thresholds for classification task, allowing us to observe how the performance of classifiers fluctuates as threshold varies. A curve that appears at the top left corner represents multi-class classifier with better performance. Table 3. Shows the results of the model LungNetB5 for multi-class classification in terms of precision, recall and F1-score.

Table 3. Results of LungNetB5 model

LungNetB5	Precision	Recall	F1-Score
0-Adenocarcinoma	95%	88%	91%
1-Large cell carcinoma	74%	100%	85%
2-Normal	100%	94%	97%
3-Squamous cell carcinoma	99%	93%	96%
Accuracy			92%

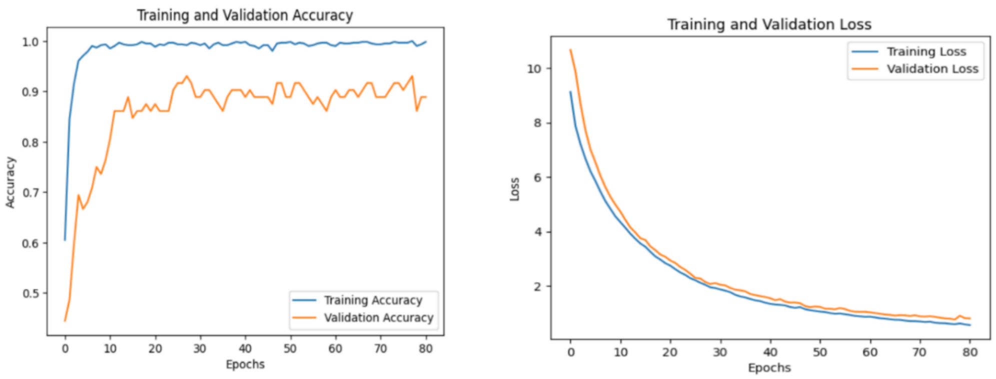

Fig 8. The proposed model Training validation accuracy-loss curve

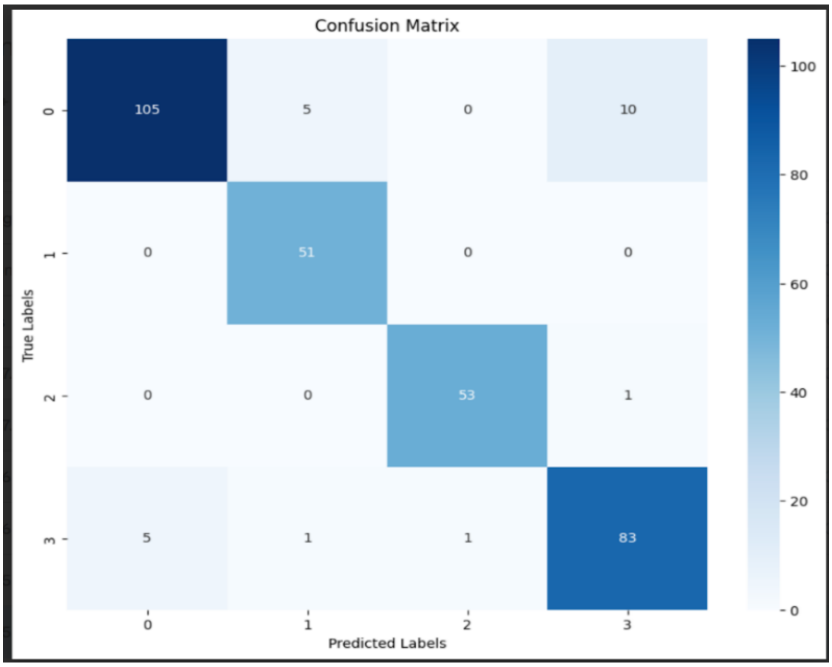

Fig 9. Confusion matrix of the proposed model

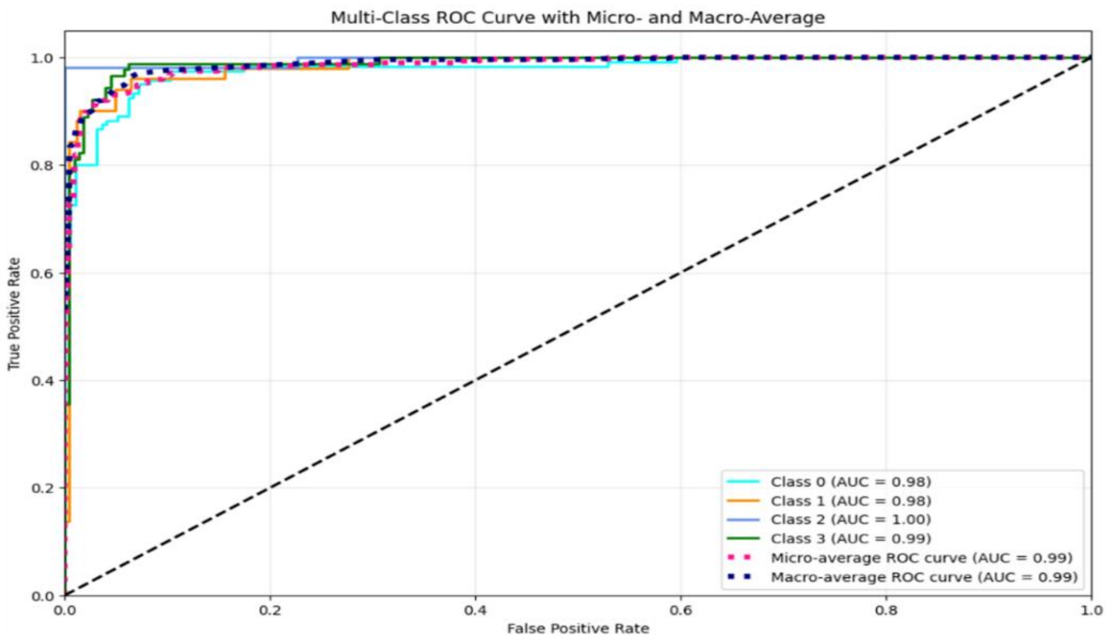

Fig 10. Roc curve on test data

4.6. Analysis of computational complexity of proposed model with other models

While comparing the complexity with the proposed LungNetB5 model that makes use of advanced architectures like. EfficientNet, CNN. The goal of this section is to analyse and compare the computational aspects of LungNetB5 with other pre-trained models like EfficienNetb6, B7, ResNet151.Our model optimizes the trade-off between model accuracy and computational cost, other models requires high number of parameters, more memory etc., This makes our model highly efficient with less training time and parameters. Table 4. Shows the comparison of computational complexity of the models

Table 4: comparison of computational complexity summary of models

Model	Train	Validation	Test	Memory usage (MB)	No of parameters
EfficientNetB6	99.82%	91%	80%	157.57	41,560,467
EfficientNetB7	99.51%	90.02%	68%	247.06	64,764,571
ResNet152	99%	91%	72%	230.4	60,192,808
LungNetB5	100%	94%	92%	110.8	28,870,452

4.7 Comparative analysis of LungNetB5 model with the Existing Studies

In recent years, there has been a significant progress in the domain of deep learning for classification of NSCLC subtypes using CT scan images. However, the majority of existing studies has primarily focused on achieving high accuracy from the online dataset which may not completely capture the complexities and variability of real-world dataset. In this study we propose a robust and efficient model for NSCLC classification, leveraging transfer learning with data augmentation techniques. To demonstrate the superiority and practical applicability of our approach, we present a comprehensive comparative analysis with state-of-the-art techniques. Our model achieves an accuracy of 92% on the real-world dataset outperforming the existing methods that reports high accuracy on the online dataset but may lack generalizability with real world scenarios. Table 3 shows the highlights the comprehensive evaluation.

Table 5: Comparative study LungNetB5 model with existing studies

Key Parameters	**Present study**	**Existing study 1 paper [26]**	**Existing study2 Paper[12]**
Methodology	Transfer Learning -Enhanced CNN	Enhanced CNN with transfer learning	EfficientNet based architecture
Source of dataset	NSCLC Augmented CT dataset	Kaggle dataset	IQ-OTH_NCCD
NSCLC subtypes	4 subtypes	4 subtypes	4 subtypes
Metrics	92% accuracy	Accuracy 96%	Accuracy 97%
Model	EfficientNetB5	EfficientNetB0	EfficientNet B1
Techniques	Random crop, flip, brightness	Rotation, Flipping, Zooming	Rotation, Flipping Scaling
Key Findings	Our model has achieved the highest accuracy and AUC, exhibiting superior performance in multi-class NSCLC classification	EfficientNetB0 outperformed traditional CNNs for NSCLC subtype classification with transfer learning	EfficientNetB5 outperformed traditional CNNs for NSCLC subtype classification

5. CONCLUSION AND FUTURE DIRECTIONS

In this current research a novel approach classification of lung cancer using a hybrid model combining CNN and EfficientNet, along with fused data augmentation that are designed to leverage the strength of both feature extraction capabilities of CNN and highly efficient architecture of efficient Net. Our model was evaluated on a real dataset of CT images and demonstrate superior performance compared to various state-of-the-art pretrained models like ResNet, EfficientNet models B4, B5, B6 models. By leveraging the acquired knowledge from large datasets, EfficientNetB5 is fine-tuned to efficiently extract the relevant features from lung cancer CT images. The experimental result shows the proposed method works efficiently by reducing the computational time and resources required for training while still maintaining higher accuracy. LungNetB5 uses EfficientNetB5 model that surpasses other CNN architectures in performance, achieving accuracy of 92%. These results emphasize the strength of LungNetB5 as an efficient method for automated lung cancer diagnosis. It has shown improved performance on small datasets and accelerate training. our hybrid model CNN-EfficientNet outperformed other traditional models both in terms of computational efficiency and accuracy proving its robustness and ability to handle complex lung cancer subtypes efficiently. Further this research can be used in other domains, optimizing model efficiency and applied in other medical domains as well like to deal with multi-modal data, improve interoperability.

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