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Research Article

Evaluating CNN variants with Transfer Learning for Multi-Class NSCLC Diagnosis

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Abstract:

Lung Cancer is the disease with serious concern, Non-small cell lung cancer (NSCLC) is a sub type of it, with most cases that has to be timely intervened for accurate diagnosis and also to improve patient outcomes. With recent developments in deep learning, particularly in convolutional neural networks, it leads to increased potential for accurate and automated medical image diagnosis. This study assesses the performance of various CNN variants with transfer learning for multi-class NSCLC subtype image classification using CT images. Results suggest that integrating CNN with transfer learning provides a robust approach for classification of NSCLC subtypes. Out of all the benchmark models LungNetB5 outperformed by 90% accuracy highlighting its potentiality in clinical decision making.

1. Introduction

Lung cancer is the second largest disease type in the world with highest mortality rate. while the disease symptoms begin to occur it often reaches the progressive state over the point of effective treatment. They raise a serious concern that need to be addressed, when compared to other cancer types. NSCLC is one of the lung cancer type with more than eighty five percent of cases with its extended subtypes that include adenocarcinoma, large-cell and squamous cell carcinoma [1]. Though there are many tests done, CT imaging is prior to be done especially for these kind of cancer for initial assessment, CT taken for a single person will be consisting of many numbers of slices, as it is taken from different angle that makes it very difficult for clinical practitioners to understand and interpret time leading to consuming long period of time, wrong results, making the delayed decisions for treatment [2].To over come this issue and to early diagnose the disease accurately, for proper treatment planning , traditional diagnosis has always attempted to find a way but by depending upon expertise from clinical background to analyse the images, that can be inaccurate at times or anomalous.

In current years, the revolution in AI, where ML and DL has gained a huge popularity with CNNs a type of neural network has risen as a favourable approach over many domains more prominently image-based diagnosis [3]. Further to train these deep neural based CNN algorithms there is a need for large data but the drawback is often the computational resources are limited. To overcome these kinds of challenges, transfer learning makes the use of pre-trained networks for certain specific tasks on a relevant domain specific data.TL has a powerful strategy of reusing of models pre-trained on large scale ImageNet to initiate training on more domain specific data. These initializations not only minimize the training time but reduces training time thus enhancing generalization especially on limited data [4].Several powerful CNN architectures were developed to address the barriers of deep learning neural networks. CNN architectures like ResNet were used to mitigate vanishing gradient issues [5], DenseNet with dense connectivity with layers reuses features and with efficient gradient flow ensuring better in achieving results with fewer parameters [6]. Efficient makes use of compound scaling to balance width, depth and resolution that is useful for imaging tasks but achieving computer accuracy and computation efficiency is difficult [7]

This research paper a light weight yet powerful CNN model named as LungNetB5 which makes use of efficientNetB5 as feature extractor through transfer learning is proposed and the model is specially designed and fine-tuned for classification of multi-class subtypes from CT images for detecting lung cancer. The proposed model performance is compared with few other CNN models like DenseNet, ResNet and VGG. The reason to chose these models was its very effective in imaging and can perform well on different architectures. Feature representation was also a main aspect, the purpose is to see how the CNN variants perform well on limited image dataset and also to understand their weakness and strength in cancer classification.

2. Related works

This study investigates various ML and DL based approaches, especially convolutional Neural Networks (CNNs) that has transformed the domain of medical image analysis. Many studies have been carried on that delves deeply to try and enhance the correct evaluation and robustness in lung cancer diagnosis that includes CT imaging. Various research works are examined so far that follows in this section with Shen proposed a CNN model, that uses multi-crop concept for classifying lung nodules in CT scans, the model outperformed traditional handcrafted features with 86.8% accuracy, demonstrating that CNNs can capture certain rich hierarchal features for volumetric data[8].Setio et al developed a multi-view CNN approach that considers different angles of nodules from CT images to improve classification accuracy, the approach enhanced sensitivity by reducing false positives[9].Antimopoulous et al developed a CNN based model for intestinal lung disease classification using high resolution CT images, that displays the applicability of deep learning in thoracic imaging[10], Rajpurkar et al, implemented CheXNet, a densenet121 trained on chest x-rays to detect pneumonia, exhibiting deeper networks outperform shallow CNNs in medical imaging[11]. Kumar et al proposed ResNet model for classifying Lung cancer, the model achieved good measure of sensitivity and specificity on a LIDC-IDRI dataset [12]. Lakhani and Sundaram adapted transfer learning with pre-trained CNNs such as GoogleNet, and also AlexNet for tuberculosis detection and stated that CNN can be effectively used for image analysis [13]. Hussein et al implemented a 3D CNN used with TL for classification benign or malignant of lung nodules obtained from CT volumetric data highlighting the importance of spatial content [14]. Zhou et al made use of attention guided work or mechanism with deep learning models to highlight these discriminative features in lung CT images, improving classification accuracy of early stage lung cancer [15]. Coudray et al developed an inception V3 model for lung cancer classification of NSCLC subtype adenocarcinoma and other subtype squamous-cell carcinoma using histopathological images with 94% accuracy showing 94% accuracy, confirming the CNN power to subtype classification [16]. Togacar et al implemented a hybrid approach combining CNN feature selection and ensemble classifiers, it showed improved performance in COVID-19 and lung cancer type detection from CT scans [17]

3. Methodology

This study utilizes a well-structured and comparative approach to examine the capability of DL models in multi-class classification of NSCLC subtypes using CT images. This methodology intends to ensure fairness across all the models with standard pre-processing, evaluation metrics. The main goal is to evaluate the adaptability and performance of CNN architectures especially lungNetB5 when applied to clinically relevant imaging data with real-world constraints.

3.1. Dataset

The dataset used in the research study consists of Lung NSCLC CT images sourced from a clinically annotated CT scan images from a healthcare. The dataset consists of four categories Adenocarcinoma, Large cell carcinoma, normal and small cell carcinoma. The original 500 CT images were in gray scale form having .png format with original resolution of 512 x 512 pixels. Table 1. Represents the class wise distribution of NSCLC dataset

3.2 Pre-processing and augmentation

This section discusses most crucial steps of this work, pre-processing and augmentation to ensure

Table1. *Represents the class wise distribution of NSCLC dataset*

Class	No of samples
Adenocarcinoma	122
Large cell carcinoma	108
Normal	122
Squamous-cell carcinoma	148
Total	**500**

the consistency and effectiveness of various DL models in classifying lung CT images into four categories - adenocarcinoma, large-cell carcinoma, normal and squamous cell carcinoma. In order to maintain consistent input dimensions, the images were adjusted or resized to a predefined resolution 224x224 pixels. Given that the scans were obtained in grayscale, the processed image should either be in a single grayscale channel or, in the case of ResNet50, DenseNet121 has to be transformed to three channel RGB format. By dividing all values by 255, the pixel intensity level is made to fall between 0 and 1 which should now be standard enhancement to help the model converge. Later a unique identified label between 0 and 3 was numerically encode the classified designations. Additionally, to strengthen model's resilience and to tackle the problem of dataset shortage. On the training dataset, many augmentation approaches were used. When applied to real-world datasets with lot of variability and noise distortions, these methods improved generalization.

The strategy includes random rotations of 15 degrees, horizontal flipping, slight zooming, less shearing and few transactions in both horizontal and vertical directions. This approach has the ability to effectively enrich the diversity of training dataset without need for increase additional samples of data. Following there was no augmentation that were applied to both test and validation dataset to ensure any kind of fair evaluation on unseen data. This procedural way for processing and augmenting was necessary for enhancing model accuracy while reducing or optimizing training on the CT image dataset.

3.3 CNN Variants

CNN have evolved significantly from the traditional form, leading several powerful variants that enhance feature extraction to improve training efficiency and boost classification accuracy. They are particularly impactful in medical imaging like lung cancer diagnosis. The widely used CNN variants are

1. DenseNet

DenseNet121 enhances gradient flow and feature reuse for introducing dense connections between layers. In this architecture, each and every layer receives the concatenated outputs of all preceding layers as input defined as $x_1=H_1([x_0, x_1, \ldots, x_{l-1}])$, where H_1 represents a composite function of batch normalization, activation and convolution. These kinds of dense connections encourage the reusable features leading to fewer parameters, improving training efficiency by reducing risk of overfitting. DenseNet121 includes four dense blocks and transition layers that down sample feature maps via 1x1 convolutions and pooling. This type of architecture is particularly effective in extracting fine-grained features which is main in distinguishing same cancer types in CT images.

2. ResNet

It is a deep learning-based CNN architecture that makes use of residual learning, which addressed issue of vanishing gradient problem that is common in very deep networks. The core idea of using ResNet, is introducing shortcuts connections that allow the input layer to be added directly to its output bypassing one or many layers. Every residual block in the ResNet learns a residual function instead of direct making represented as $y = F(x)+x$ where $F(x)$ is the output of intermediate layers. Here a much deeper configuration upto fifty layers is possible when this type of architecture is used because it can retain stable gradients and really good generalization. The reason of its wide spread trend, is its capability to learn more discriminative and unique features which are necessary for distinguishing amongst subtle patterns.

3. VGGNet

There are two variations in VGG, VGG16 and 19 which integrate with either stride1 or stride2 and have weight layers, convolution filters and max pooling. It performs better than any other kind of baseline models. Although the model is capable of capturing more complicated and hierarchal characteristics, its primary goal is to increase network depth yet maintaining a simple architecture with stacked small number of convolution filters instead of bigger ones. Due to its success in certain tasks such as image classification, it performs well especially dealing with larger datasets with millions of images. As a result, the computational cost and memory consumption are significantly higher.

4. Results analysis

This section provides the experimental results of the LungNetB5 model and also the performance of the model's performance is compared with other three established CNN architectures: ResNet50, DenseNet121 and VGG16. The work was carried on the same dataset for NSCLC subtype classification. The performance metrics were calculated and compared along with training time and parameters count used, Fig 1. depicts the breakdown of classification model performance across four classes with a confusion matrix, It also shows the true and false predictions per class determining whether the model excels or struggles. For the proposed model, it is observed that the confusion matrix displays high true positive rates along the diagonal that highlights that the classification accuracy is good and the values around the diagonal are low that is interpreted as misclassification of classes.In Fig 2. The proposed model LungnetB5, showed an increase in the training accuracy with number of epochs attaining up to 90% accuracy level by final approach. The stable growth signifies the model's ability to learn to effectively extract efficient features in the CT images. And also, the training loss decreased constantly which indicates less classification error on the dataset using for testing. Followed by this the Validation accuracy is increasing with epoch with training accuracy, that shows that the model has a good generalization of unseen data and no overfitting issues as well, pertaining to it the validation loss decreased without any notable spikes confirming the model's stability on real world dataset which is usedThe ROC curve of 0.93 to 0.94 indicates that the proposed model is capable of differentiating between multiclass NSCLC images. Fig 3. Shows the trade-offs amongst TPR and FPR of various thresholds specifically for classification tasks observing that the performance classifiers fluctuates at various threshold. The AUC for all four curves is 0.93 which implies very good separability.

4.1. Comparative Analysis of computational complexity of models

The proposed lungNetB5 model based on convolutional neural network specially tailored for lung cancer classification of NSCLC subtypes using CT images. Finding a balance between interpretability, accuracy and computational efficiency is the main goal. A comparative analysis using three well known deep learning structures – ResNet50, DenseNet121, and VGG16- was conducted to evaluate the efficacy.In contrast to other shallow models, ResNet50's fifty layers enable the model to learn more features representations. This model skip or connections help to lessen issues with vanishing gradients. Even when small datasets are used to smaller datasets with data images, its superior depth and efficiency in image classification tasks – which utilize pre-trained weights with ImageNet, a big dataset-come at the expenses of higher processing requirements and a long training period because to DenseNet121's extensive and sophisticated architecture thick connections, input from the previous layers is accepted by each layer of the network. The network requires considerable fine-tuning and has a moderate computing load. When subjected to limited data, the depth sequential design of other CNN variation, VGG16 which has more parameters causing overfitting and excessive memory usage. The proposed model performs well even with these limitations as it uses TL and CNN, the main advantage is that it has very few parameters when compared to ResNEt50, DenseNet121 and VGG16, it also consumes less training time an memory usage. With a simple design the proposed model has been competent and showed more superior performance compared with all other benchmark models. By achieving an accuracy of 90%, in classifying nearly four classes of NSCLC, LungNetB5 outperforms other CNN variants. It has been observed that has a better performance surpassing ResNet50 and DenseNet121 on training configuration. In table 2. Performance metrics of these CNN variants with proposed model is given, with the results LungNetB5 stands out offering efficient training performance for diagnosis of lung cancer that is widely used in more generic architectures. Fig 4. Illustrates the performance metrics of CNN models.

4.2 Comparative analysis of proposed model with existing model

This subsection attempts to verify the performance of the LungNetB5 model for classification of NSCLC multi-class subtype using CT images, with a comparative analysis conducted with existing research work in this field. Table 4. Presents the summary of various deep learning approaches that have been applied for NSCLC classification using CT scans. Most of the work related were carried on binary classification tasks to distinguish between benign or malignant or adenocarcinoma or squamous cell carcinoma and other studies were focused on larger dataset or hybrid feature extraction method. LungNetB5 model demonstrates strong performance for multi-class classification that covering adenocarcinoma, large cell carcinoma, normal and squamous cell carcinoma, achieving a high accuracy of 90% even with relatively small dataset containing 500 CT images. The table 3. highlights method used, subtypes and accuracy so on these studies demonstrating LungNetB5 with its competitive work. Deep learning wide studied in different fields as reported [20-35].

4. Conclusions and Future work

This study explored and evaluated various Convolutional Neural Network (CNNs) architectures for classification of different

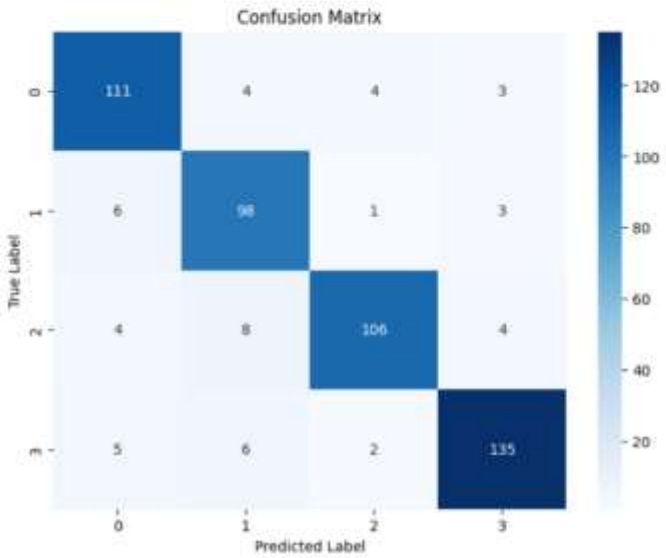

Figure 1. *Proposed model's confusion matrix*

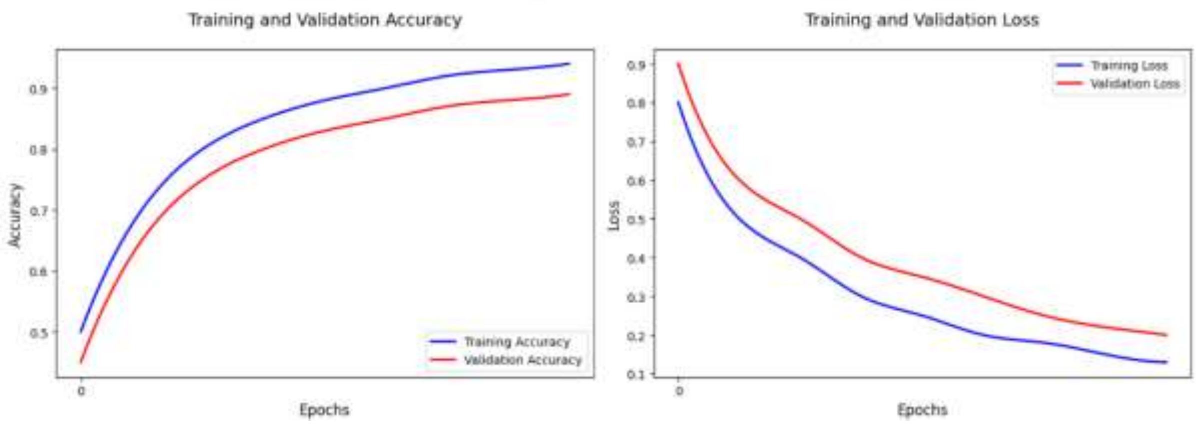

Figure 2. *Training and validation accuracy and loss*

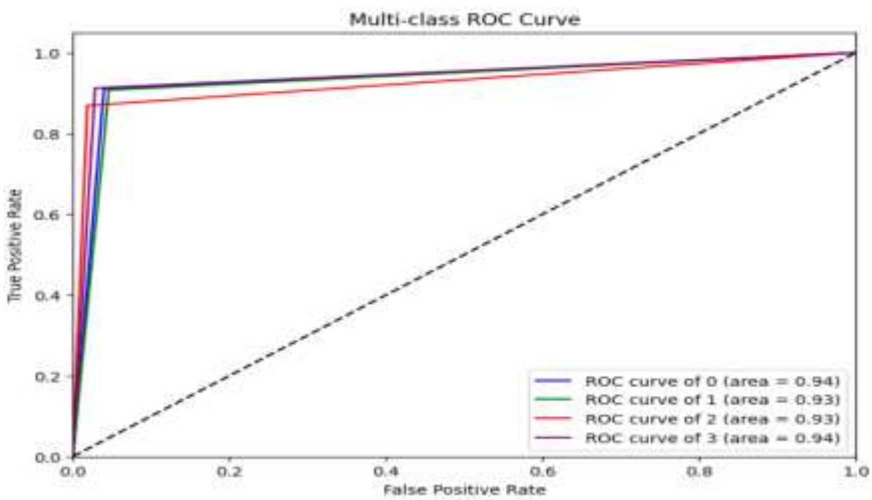

Figure 3. *Multiclass ROC curve on test data*

Table 2. *Comparative analysis with benchmark models*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1score (%)	Parameters
ResNet50	76	91.2	89.7	90.4	33,650,512
DenseNet121	78.0	88.7	86.4	87.5	80,192,361
VGG16	81.2	89.4	88.1	88.7	138.312,533
LungNetB5	90	91.2	89.7	90.4	27, 963,521

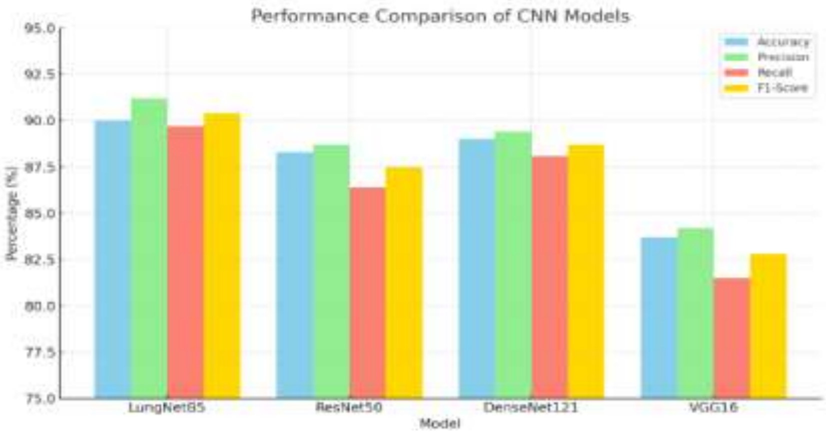

Figure 4. *Performance comparison of CNN model*

Table 3. *Comparison analysis with existing models*

Key Parameters	Proposed Model	Existing Study1[18]	Existing study 2[19]
Model	LungNetB5	EfficientNetB0	Hybrid CNN transformer
Dataset	500 CT scans	1000 CT scans	422 CT scans
Method	CNN TL	EfficientNetB0	Hybrid CNN transformer
Class	Adenocarcinoma, Large-cell carcinoma, squamous cell carcinoma, Normal	Adenocarcinoma, squamous cell carcinoma, normal	Adenocarcinoma, squamous cell carcinoma, large cell carcinoma
Accuracy	90%	88.9%	81.9%
Key Findings	proposed model uses CNN and TL for four types of NSCLC classification	Multi-class lung classification, for NSCLC subtypes	It used CNN for feature extraction and transformer for prediction

subcategories of NSCLC using CT image dataset. The LungNetB5 model is tested include LungNetB5 and two state-of-the-art pretrained architectures, ResNet50 an DenseNet151.Through comprehensive training, validating and testing on a multi-class image dataset all models achieved good accuracy. LungNetB5 model in particular proved to be a computationally efficient and accurate model making it suitable for real-world applications where data specific constraints exist. This comparative evaluation highlighted how the architectural depth, future reuse, skip connections influences diagnostic accuracy especially in distinguishing between subtle pathological differences among lung cancer subtypes. While the achieved results are promising but certain limitations remain. Though the dataset augmented was limited in size compared to large image set could affect the generalization. Future work includes expanding the dataset to include more diverse samples of high-resolution CT images. To extend word to 3D CT scan image analysis, to integrate multimodal data for prediction and also explore model's interpretability through advanced AI techniques.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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