EfficientNet-B0 and Hybrid CNN: A Comparative Approach to Lung Cancer Detection

Dr. Raghavender Kotla Venkata [1,a],Dr. Tallapelli Rajesh [2,b], Bushra Fatima [3,c]

[1,2,3] Department of Computer Science and Engineering, G. Narayanamma Institute of Engineering and Technology, Hyderabad, India.
[a] drkvragahvender@gnits.ac.in
[b] rajesh@gnits.ac.in
[c] bushfatima132@gmail.com

ABSTRACT

One of the major problems with medical images is identification of the peripheral tumors in the lungs at an early stage because of their subtlety and insufficient characteristics that help distinguish them. The study evaluates one of the deep learning models in comparison with another one EfficientNet-B0 and the new hybrid system that combines ResNet50 with DenseNet121 concerning lung CT scan classification. They analyse the IQ-OTH/NCCD data as it contains 1,190 CT images classified as being normal, benign or malignant. Oversampling was also used as a means to add balance to the data, since the classes were unequal in their number. Transfer learning was employed by both models and the two models were initialized to use large-scale image-data-trained weights to enable feature extraction. The hybrid model uses a friendship of the feature maps between the ResNet50 and DenseNet121, through concatenation, in order to collect more information. According to the results of the experiments, the hybrid approach is more accurate than EfficientNet-B0 which proves the usefulness of combining various convolutional neural networks to enhance lung cancer identification.

Keywords- Hybrid CNN architecture, Lung cancer detection, Transfer learning, Computer-aided diagnosis.

1. Introduction

Cancer of the lungs is one of the most threatening diseases in the world. The World Health Organization (WHO) has claimed that lung cancer is the highest cause of cancer death due to late detection of the condition when it has already taken a toll on the victims. Survival changes much when it is spotted earlier. The screening process involves the use of medical imaging (specifically by means of CT scans) which is critical to the process. Nonetheless, human elements including fatigue, oversight, and epidemiological vicissitude of radiologists, tend to limit the appropriateness with which CT images are interpreted.

New capabilities in the field of artificial intelligence (AI), especially deep learning, created the possibility of more trustworthy and automatized diagnostic systems. CNNs have proved better in image classification including other medical imaging challenges, i.e. tumor detection and segmentation, disease detection, etc. Specific CNN architectures, such as the ResNet and DenseNet, have indicated the adopting of striking results on maintaining the feature integrity, as well as enhancing the gradient flow.

Within this study, two different CNN-based architectures are going to be assessed:

1. EfficientNet-B0: A model with the reputation of keeping an accuracy to cost balance.
2. Hybrid CNN (ResNet50 + DenseNet121): The hybrid architecture based on a combination of features of two strong networks to boost representations.

The given paper is devoted to the study of the comparative analysis of the two models which are used to classify lung tumors based on CT images. The findings are designed to inform potential researchers, clinicians as well as formulate the most appropriate architecture depending on the operation and demands involving their performance requirement apart.

2. Literature Review

Recent advancements in deep learning have significantly impacted medical image analysis, especially for lung cancer detection. CNNs have emerged as powerful tools in this domain [1]. Among the most influential architectures are ResNet [2], which uses residual connections to overcome vanishing gradients, and DenseNet [3], which leverages dense connectivity to encourage feature reuse and better gradient flow.

To improve model scalability, EfficientNet was introduced using compound scaling to balance input resolution, depth, and width [4]. EfficientNet-B0, the baseline version, has been effectively applied in biomedical tasks, providing a trade-off between accuracy and computational cost. In parallel, hybrid and ensemble models have gained attention. Some approaches fused multiple CNNs to enhance diagnostic performance [5], while others employed multiscale ensemble CNNs for lung nodule classification [6].

Additionally, the use of transfer learning has accelerated medical AI applications. Studies demonstrated accurate diagnosis across diverse conditions using pretrained CNNs [7]. Multi-scale CNNs have also been successfully applied to standard lung cancer datasets [8], while others emphasized the impact of augmentation and network depth [9]. Hybrid CNN architectures like ResNet-Inception have been explored to boost precision in lung tumor detection [10]. These works reinforce the value of comparing scalable networks like EfficientNet-B0 with hybrid CNNs, as done in this study using the IQ-OTH/NCCD dataset.

3. Methodology

3.1 Acquisition and pre-processing of dataset

In the research, IQ-OTH/NCCD, a publicly available CT scan dataset was utilized. The data includes about one, thousand two hundred scans of CT images (benign vs. malignant). The images would be resized to 224x224 pixels in order to fit the input size. Pre-processing pipeline consisted of grayscale normalization, contrast enhancement through histogram equalization and intensity standardization. To counteract overfitting and generalization, the best practices in data augmentation rotation, flipping, zooming, and translation were employed to improve generalization.

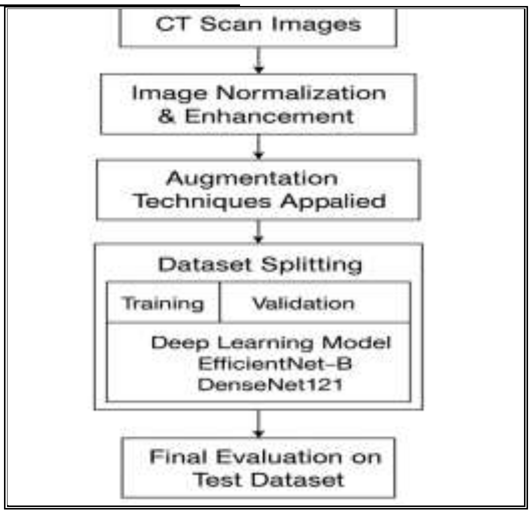

Figure 1. Methodology Overview

3.2 Implementation of the models

EfficientNet-B0

EfficientNet-B0 uses an innovative compound scaling factor that is premised on normalizing network depth width, and input resolution. The model has been initialized by ImageNet weights and then the CT dataset has been fine-tuned. The factors behind its high effectiveness are its mobile inverted bottleneck convolution (MBConv) blocks and squeeze-and-excitation (SE) modules.

Hybrid CNN

The hybrid model incorporates ResNet50 and DenseNet121 as parallel feature extractor. The feature maps of theirs are then concatenated and run through a global average pooling layer then dense layers with dropout to regularize. The hybrid modality represents both the deep residual and dense inter-layer features, as well as improving the classification ability.

3.3 Process of training

The optimizer used in the training of the models was Adam, where it had the learning rate of 0.0001 and the type of loss was binary cross-entropy. 50 epochs were applied to train using batch size 32. In order to prevent overfitting and maximise convergence early stopping and learning rate decay were used. The data has been divided into training and validation/testing sets, i.e., 70 and 30 per cent respectively.

4. Performance Evaluation

4.1 Metrics Used

Model performance was evaluated using accuracy, precision, recall, F1-score. These metrics provide a holistic view of each model's classification reliability.

4.2 Results Summary

Table 1: Comparative analysis of the two models according to the overall performance.

Metric	EfficientNet-B0	Hybrid CNN
Accuracy	0.96	**0.98**
Precision	0.95	**0.98**
Recall	0.95	**0.98**
F1-Score	0.96	**0.97**
AUC-ROC	0.98	**0.99**

The summary of the average work of EfficientNet -B0 and the Hybrid CNN to the main classification coefficients is presented in the table above. As it can be seen, the Hybrid CNN demonstrates a better result in the precision, recall, and F1-score than EfficientNet-B0 and an increased AUC-ROC value. It proves that it has a better potential in precisely classifying lung CT scans.

4.3 Comparative Analysis

Although EfficientNet-B0 is more lightweight and faster in inference time, the hybrid model demonstrated higher accuracy, making it more suitable for hospital-based high-performance computing systems. The increased complexity of the hybrid model is justified by its ability to reduce false negatives, an essential factor in medical diagnosis.

5. Conclusion

The study conducts a comparative analysis of two deep learning models namely EfficientNet-B0 and a hybrid CNN consisting of ResNet50 and DenseNet121 in detecting lung cancer through CT scan pictures. Both models presented good performance, yet the hybrid CNN outperformed EfficientNet-B0 in terms of precision, recall, and F1-score as well as in terms of the overall accuracy. EfficientNet-B0 is pro data in real-time services where saving resources is mandatory. The results point to the necessity of selecting the models pertaining to the deployment environment and the requirements of the applications.

Future improvements can involve explaining AI by using methods like SHAP or LIME, testing on 3D volume data, and testing on a large, multi-institutional data.

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