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LUNG CANCER CLASSIFICATION FROM CT-SCAN IMAGES USING AN EFFICIENT CNN WITH TRANSFER LEARNING

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Abstract
Lung cancer remains one of the leading causes of mortality globally, and early diagnosis plays a critical role in improving patient treatment and reducing mortality rates. However, the interpretation of medical images, such as Computed Tomography (CT) scans, is highly complex and demands significant clinical expertise. This research focuses on the fine-tuning an efficient Convolutional Neural Network (CNN) based approach, with particular emphasis on the EfficientNet-B0, for detecting lung cancer from CT scans into three classes: Normal, Malignant and Benign. The training data contains 1,097 CT scan slices obtained from 110 individuals. The proposed framework involved data acquisition, image preprocessing, offline data augmentation and data balancing, followed by fine-tuning and training the pre-trained EfficientNet-B0 model with a new set of dense layers and a softmax activation as an output layer and Comparative analysis against other CNN architectures, including ResNet-50, Xception, InceptionV3, VGG-16, and MobileNetV2. Experimental findings show that the proposed fine-tuned EfficientNet-B0 achieved a comparatively higher accuracy of 97.67%, outperforming the comparative studies. These results demonstrate the strong potential of the proposed network as an automated diagnostic tool in medical imaging. However, the limited dataset size represents a constraint, which may affect generalization to unseen data. Future work should focus on enlarging the training data via instances from real fields, applying more advanced image augmentation strategies, adjusting hyper parameters, and exploring novel architectures including U-Nets and Vision Transformers. Overall, this study validates the role of CNN-based approaches, particularly EfficientNet-B0, for lung cancer identification and establishes a basis for future research in the area of medical imaging.

INTRODUCTION

Globally, cancer is still a leading factor of death, being the cause for nearly 10 million deaths in 2020 [1]. Among all cancer types, lung cancer exhibits an exceptionally high mortality rate and continues to pose a critical global health challenge that demands accurate and prompt diagnosis. It causes more mortality cases than breast, prostate, and colorectal cancers together, ranking it as the leading cancer worldwide [2]. Almost 25% of all cancer-related mortality cases are linked to lung cancer. In 2020, research reported around 2.21 million newly diagnosed cases and nearly 1.8 million mortalities resulting from lung tumors [3]. The increasing incidence of lung cancer is subjective to multiple factors, such as tobacco smoke, environmental pollutants, occupational exposures, viral infections, ionizing radiation, and unhealthy lifestyle habits. Genetic susceptibility further increases individual risk. Moreover, socioeconomic inequalities, limited accessibility to the health system, and insufficient early identification strategies complicate the situation, leading to a large number of patients being observed at final stages, where therapies can be more constrained and less reliable [4–6]. Its symptoms commonly include fatigue, shortness of breath, and a persistent cough. However, beyond these typical signs, the symptoms can vary significantly among individuals, which make diagnosis particularly challenging. In some cases, lung cancer may remain symptomless, allowing the disease to progress without any noticeable signs [7].

The main obstacle in the control of lung cancer is its early diagnosis, because the condition mostly presents non-specific symptoms; thus, it is hard to diagnose it in time and it silently gets to advanced stages. The traditional methods of diagnosis, such as the manual assessment of computed tomography (CT) scan images and biopsy-based identification, need more processing time, can suffer from subjectivity issues, and require vast clinical skills [8]. Due to such challenges, more advanced and reliable diagnostic methods are necessary that can effectively detect lung cancer at initial stages and thus enable timely intervention and increase the chances of survival of the patients. The latest research in artificial intelligence (AI) and machine learning (ML) has shown substantial potential in the solution of these problems. Deep learning (DL) models, including the CNNs, have key benefits in healthcare visual data evaluation. CNN based models can automatically extract key patterns from input images, providing a basis for improved accuracy and generalization of lung cancer detection [9]. Radiologists can efficiently use AI models to automatically identify lung nodules on CT scans of the chest, which presents a key challenge in the naked-eye approach because lung cancer nodules are difficult to detect due to their small size and subtle and complex nature. Such systems play a key role in the early identification of lung cancer, eliminating the workload of radiologists, and improving diagnostic accuracy. According to recent literature, AI-based CT diagnostic tools have the potential to be successfully used to detect lung cancer, which confirms their possible wide clinical applicability. Deep learning models are used as an alternative to conventional diagnosis techniques, as they are considered accurate as well as fast, allowing for the assessment of more patients within much shorter periods [1].

Although the techniques of deep learning-based image processing have achieved impressive results, there are several challenges associated with them, such as the absence of large and high-quality training data with proper annotations. In medical images, the complex patterns in images are difficult for humans to label correctly as per concerned categories. Such issues make neural networks weaken in effectively extracting useful patterns in images and differentiating them in the target classes. Thus, to overcome these limitations, it is necessary to introduce new methods to develop an efficient DL model. In order to address the issues mentioned above, this study applied multiple preprocessing techniques with image augmentation to improve the performance of the suggested approach used to predict lung cancer from CT scan images. EfficientNet-B0 is one of the CNN architectures that are known for their high performance as well as computational efficiency.

It is highly appropriate in the identification of lung cancer utilizing medical photos, including CT scans, due to its high sensitivity in extracting features of the input image. EfficientNet-B0 follows a compound scaling strategies and allows balancing network depth, width and input resolution, allowing the learning of complex and discriminative lung tissue features. This study provides an automatic and accurate classification of normal, benign, and malignant lesions in the lung area. The suggested framework is based on an already trained EfficientNet-B0 as a backbone of the model used for lung cancer identification through CT scans which are publicly accessible. The pre-trained model was fine-tuned with two dense layers, each followed by dropout and an output layer based on the softmax activation function. To train the model efficiently, image processing and augmentation strategies with class balancing were utilized. Incorporating the fine-tuned EfficientNet-B0 in the diagnosis procedure, this framework aims to build an automatic system that enhances the accuracy of the diagnosis and minimizes the time and workload of the clinical process.

RELATED WORK

Lung cancer can be diagnosed efficiently using DL architectures that have the capacity to automatically identify important characteristics in input data. The section is an overview of current developments in AI-based detection and specifically the CNNs that can improve diagnostic accuracy, efficiency, and early diagnosis. One of the significant technological improvements in the area of medical photo evaluation is the utilization of deep learning-related computer-aided diagnosis (CAD) systems. The systems overcome the weakness of the traditional CAD methods by using deep learning techniques; especially CNNs. DL models have gained popularity in the area of medical imaging because they can automatically extract significant patterns from visual data. Thus, the practice of DL has become the trend in the diagnostics of lung diseases prediction as well [1].

Kapoor et al. [4] examined the performance of a pre-trained network called VGGNet to identify lung tumor from histopathological images. The training images were taken from an openly accessible dataset to fine-tune and examine the model. The obtained outcomes indicated that the VGG16 was an effective tool to identify lung tissue into normal, malignant and benign. The experiment established the sensitivity of the approach in the diagnostics of lung cancer, noting the ability of the network to deal with complicated histopathological processes and enhance the accuracy of diagnosis. Gautam et al. [10] suggested a new ensemble deep learning (DL) network that could effectively detect early lung cancer and is able to correctly identify the degree of lung cancerous nodules based on the images of CT scans. It combined three CNN networks, ResNet-152, EfficientNet-B7 and DenseNet-169, and used a weight optimization technique, which combines ROC-AUC with F1-scores to optimize the accuracy. This method, in comparison to other techniques, obtained better results, had low false negativity, and demonstrated great prospects of better lung tumor identification and patient outcome.

Dritsas and Trigka [11] used machine learning to build a novel model for early prediction of lung tumor and enable timely intervention to help minimize complications related to this severe disease. The research has highlighted the strength of the Rotation Forest algorithm, in which its performance has been rigorously assessed based on standard measures, including precision, recall (sensitivity), accuracy and F-measure, and claimed that it is an accurate and generalized algorithm in risk level prediction. In [12], the researchers have used a three-dimensional convolutional neural network (3D-CNN) to identify the nodules in the lungs and determine their malignancy. The LUNA16 dataset was used for network training and assessed on both the LUNA16 dataset and the one collected locally, which had a Dice Similarity Coefficient (DSC) of 80.74%. This is the measure of segmentation performance that was frequently utilized in the analysis of the model performance, and it showed that the network is effective at differentiating the malignant areas and the healthy lung tissue.

Bherje et al. [13] proposed a DL-based model to identify lung tumor based on the CT scan photos. Their CNN-based method achieved a mean classification of 72.41%. The study focused on the relevance of deep learning approaches in practical clinical settings in order to identify the presence of lung cancer at its early stages. A methodology of lung cancer detection using deep residual learning was suggested by Bhatia et al. [14]. It applied the UNet architectures and ResNet to extract features in a CT scan and then used the Random Forest and the XGBoost classifier to detect malignancy in the images. Despite the potential of the framework to find cancer-related features, its general performance was constrained by decreased prediction accuracy. Ali et al. [15] developed a deep learning algorithm that takes CT scan photos to predict the existence of malignant lung symptoms. The reinforcement learning strategy was used in the study, and it showed improved results on using more training data. Still, the authors noted that they had over fitting problems and recommended that this limitation can be overcome by using larger and more diverse datasets. Al-Shouka and Alheeti [16] used the already trained VGG-16 network model based on fine-tuning to identify malignant lung tissues from lung CT scans. This method greatly reduced the computational cost as well as improved the diagnostic accuracy. The research has emphasized the usefulness of transfer learning to enhance model reliability and efficiency to detect lung cancer.

Huang et al. [17] utilized the pre-trained VGG16 architecture to categorize CT scans of lungs into normal, malignant and benign. The results proved the fine-tuned VGGNet to be applicable to clinical practice with high accuracy in the differentiation of various lung conditions. Heidari et al. [18] suggested a deep model for localization of malignant lung tumors through the combination of DL training with federated learning and block chain. Their FBCLC-Rad had guaranteed privacy-preserving and secure data sharing and data integrity. The method had a remarkable level of accuracy of 99.69 on CIA and the local dataset using multiple datasets, such as the CIA, LUNA16, KDSB, and a local dataset. To examine the power of Capsule Neural Networks (CapsNet) to substitute non-capsule CNNs to improve the recognition of spatial hierarchies in lung CT scans, Bushara et al. [19] used a hybrid approach. They presented the VGG-CapsNet network, a mixture of VGG feature extraction and capsule networks. The model did better than traditional CapNet and CNN-based ensembles with 98.61% accuracy and an AUC of 98% on the LIDC-IDRI data. In another research work, Bushara et al. [20] came up with LCD-CapsNet, a hybrid deep learning model that integrates CNNs with CapsNet to classify lung cancer using CT scan images. The model was effective in working with large-scale data and maintaining spatial relationships. The experimental performances on the LIDC-IDRI dataset showed high performance with 94% accuracy, 95% precision, 94.5% recall, an AUC of 0.989 and high specificity.

The reviewed literature demonstrates the efficiency of the deep learning techniques in the lung cancer localization, further identifying the limitations connected with data asymmetry, generalization, and model efficiency. In order to mitigate the effect of these issues, this study used the fine-tuned EfficientNetB0 because it has a balanced trade-off between the accuracy and computation cost. Besides, image augmentation and class balancing strategies were utilized to increase the resilience of the model and ensure class balancing. The following section elaborates on the details of the proposed methodology.

PROPOSED METHOD

The proposed approach focused on building an efficient and lightweight CNN model based on transfer learning for the prediction of lung cancer in CT scan images. A pre-trained network, EfficientNet-B0, was fine-tuned using two dense layers and an output layer. The CT scan slices used for model training were preprocessed before loading for model training. It is a challenging task in medical imaging to gather large sets of labeled images. Consequently, the size of the training dataset was artificially increased by using data augmentation techniques. The proposed model was fine-tuned and optimized for the identification of three categories of lung CT scans, such as benign, malignant, and normal. *Figure 1* depicts the general flow of the study, and all the steps are explained in depth in the following section.

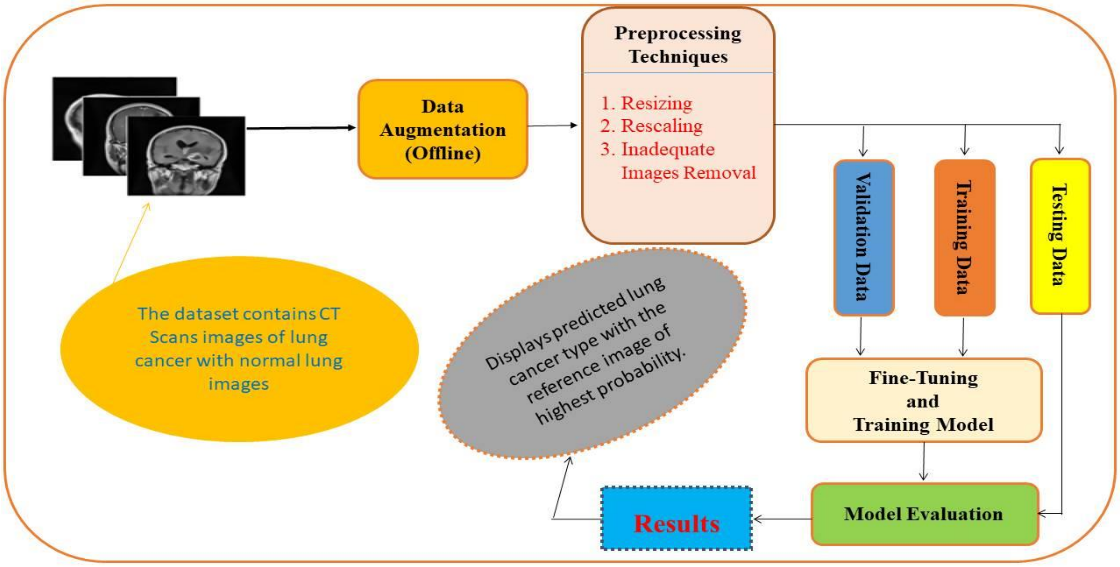

Figure 1: General Flow of the Study

Training Dataset

A large and high-quality dataset is necessary for training a deep learning algorithm based on supervised learning because the nature of the dataset has a direct impact on both the accuracy and the generalization of a model. The well-known lung cancer dataset available publicly on Kaggle, known as IQ-OTH/NCCD, was used in this study [21]. A total of 1,097 chest images, comprising CT scan slices from 110 cases, constitute the dataset. The cases include individuals of both genders across diverse age groups, educational backgrounds, places of residence, and living conditions. As shown in *Figure 2*, the cases in this study were labeled as benign, malignant, or normal. Out of the 110 instances that were examined, 40 were found to be malignant, 55 were healthy and 15 were benign. Initially acquired in DICOM format with a resolution of 512 by 512, the CT scan slices utilized in the work were subsequently converted to JPEG for accessibility. The Kaggle repository makes the IQ-OTH/NCCD dataset accessible to the general audience [22]. *Table 1* shows the detailed information of the proposed training dataset.

(a) Benign (b) Malignant (c) Normal

Figure 2: Show Training Samples

Table 1: Shows the Origional Dataset with Distribution across Training, Validation and Testing

Class	Patients	Images	Training (70%)	Validation (20%)	Testing (10%)
Normal	55	416	291	83	42
Benign	15	120	84	24	12
Malignant	40	561	393	112	56
Total	110	1097	768	219	110

Image Preprocessing

Image preprocessing is a significant step in enhancing the generalization and accuracy of deep learning models. It is regarded as one of the basic steps of CNN model training because the effect of preprocessing methods directly influences the performance of the model. This study resized all the images to equal size to fit the fixed input size specifications of CNN architectures. To balance the model performance and cost of computation, all images were resized to 256 x 256 pixels. Moreover, image normalization (rescaling) was also done by setting the pixel intensity data of the image to the range [0, 1]. This step guarantees an accelerated convergence time, stabilizes the optimization process, and promotes an efficient learning process based on gradient, and it leads to an improved model performance and reliability.

Image Augmentation

The concept of data augmentation is an established method in both machine learning- and deep learning-based training models. It is applied to artificially expand the quantity and variety of a training dataset through generating new samples of the available data. This method is successful in reducing over fitting, improving generalization of the model and assessing resistance to real-world fluctuations. Commonly used augmentation techniques are rotation, scaling, flipping, shearing, cropping, and color-related manipulations like variations in brightness and contrast and adding noise. These changes bring significant variation and maintain the content of the images. Care must be taken to ensure that the augmented samples remain representative of the original training data. *Figure 2* shows augmentation techniques utilized in this study.

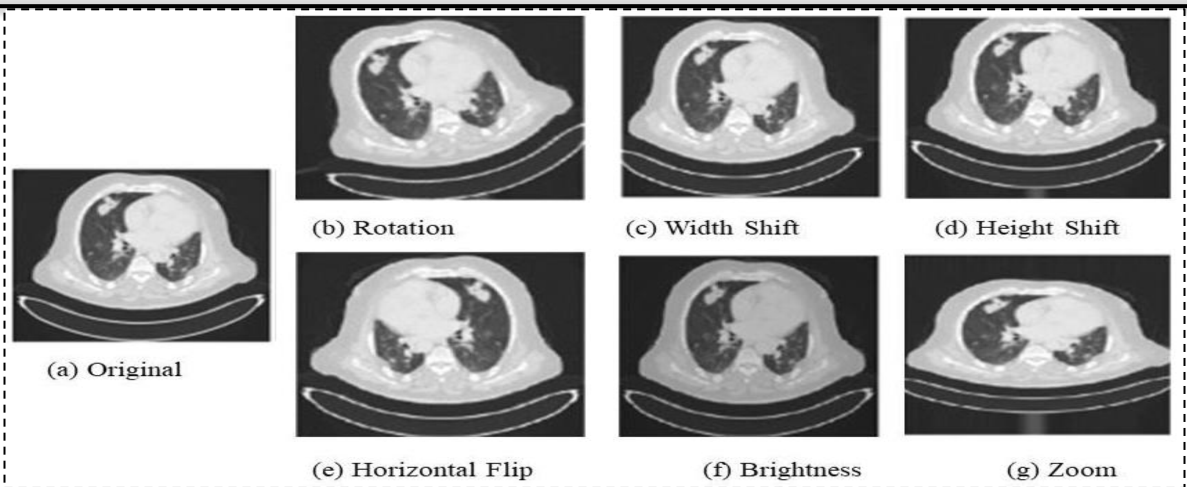

Figure 3: Image Augmentation Techniques Used in this Study

There are two ways to perform data augmentation, such as offline and online augmentation. Offline augmentation is performed before model training, and all the augmented images are saved to the disc. Online augmentation is applied during model training, and the images are not physically saved to any storage device; this is also called 'on-the-fly augmentation'. Both techniques have their pros and cons depending on the nature of the dataset and task at hand. Offline augmentation is considered more reliable as the augmentation techniques are in control of the developers. It also speeds up training but increases storage usage and also needs more labor as compared to online augmentation. On the other hand, online augmentation saves storage as well as labor but slightly slows training. In the proposed study, offline augmentation was used to enlarge the training images and also ensure class balancing. Care must be taken to ensure that the augmented samples remain representative of the original training data [23]. Figure 2 shows augmentation techniques utilized in this study. After using offline augmentation, the entire training dataset was carefully examined to eliminate low-quality or irrelevant images, thereby ensuring that the model is trained on clean and reliable data. Table x shows the strength of the dataset after data augmentation.

Table 2: Shows the Offline Augmented Dataset with Distribution across Training, Validation and Testing

Class	Original Images	Augmented Images	Training (70%)	Validation (20%)	Testing (10%)
Normal	416	1000	700	200	100
Benign	120	1000	700	200	100
Malignant	561	1000	700	200	100
Total	1097	3000	2100	600	300

Proposed Model

The proposed study used an efficient CNN model automatically detect lung cancer in CT scan images with the use of fine-tuning a pre-trained network. To construct the proposed architecture, an already trained EfficientNet-B0 model was modified by adding a new group of fully connected layers. Given three classes of lung images, two disease classes and one normal class, the algorithm was refined with two dense layers with containing neurons of 256 and 128, respectively, and with softmax activation as the final layer. In order to mitigate the chance of over fitting, a dropout rate of 30% was added after every dense layer.

EfficientNet-B0: The base model of EfficientNet is EfficientNet-B0, released by Tan et al. [24], which is the first in a sequence of seven versions (EfficientNet-B0-B7). It was developed to maximize

recognition score as well as computational efficiency using a compound scaling strategy. The use of this strategy ensured that there was an effective balance between model depth (number of layers), width (neurons per layer) and input picture resolution. In comparison with traditional architectures that scale these dimensions separately, EfficientNet implemented a coherent scaling methodology, resulting in high performance at reduced computational cost.
The important properties of EfficientNet-B0 are compound scaling which simultaneously scales depth, width and resolution to optimize accuracy at the same time maintaining computational efficiency.

The architecture has Mobile Inverted Bottleneck Convolution (MBConv) blocks which greatly lowered the complexity of the computation without compromising the identification score. It is also based on the Swish activation mechanism, which improves non-linearity and the propagation of gradients. Squeeze-and-Excitation (SE) technique used for attention mechanism was implemented in the model and recalibrates channel-wise representations of features dynamically, and an optimized network topology was obtained using Efficient Neural Architecture Search (NAS) allowing the automatic search to identify highly effective model configurations.
Unlike other architectures of the past that scaled network depth (number of layers), width (neurons per layer), or input resolution independently, EfficientNet used a compound scaling approach which scaled all the three aspects in a balanced way. The combination of this approach results in a better trade-off between the model accuracy and the computational complexity. The equations that characterize the scaling process are the following:

$$d = \alpha^{\emptyset}, w = \beta^{\emptyset}, r = \gamma^{\emptyset} \tag{1}$$

Where:
d denotes the model's depth,
w represents the network's width,
r represents the input image dimensions,
α, β, γ represent the coefficients of the scaling, and
ϕ is a user-defined parameter for adjusting that regulates the whole size of the network.
Instead of standard convolutional layers, MBConv building blocks that were initially utilized in the models of the MobileNet family were used to reduce the computation cost but preserve the accuracy of the classification. These blocks had depth wise separable convolutions and built in expansion phase to augment the extraction of features of the input data. Also, EfficientNet family has replaced the conventional ReLU activation by Swish activation function, which is defined as:

$$f(x) = x.\alpha(x) = x.\frac{1}{1+e^{-x}} \tag{2}$$

Where $\boldsymbol{\alpha}$(x) represents the sigmoid activation function used in the above equation. In contrast to ReLU, which doesn't allow values less than zero, the Swish activation criterion permits the small negative numbers, which are beneficial to propagate the gradient and improve the performance of the model. Squeeze-and-excitation (SE) blocks were also used in EfficientNet-B0. Their purpose is to dynamically adjust the channel-wise feature responses, obtained by generating global attention weights, improving the learning capabilities of the network. Moreover, in contrast to using manual design of the network, EfficientNet-B0 was created with the help of neural architecture search (NAS) to find the optimal architecture, including width, depth and input size that will be most effective for both accuracy and computational resources. All these new strategies allowed EfficientNet-B0 to be more accurate in detection using fewer parameters, resulting in a very efficient and powerful visual data interpretation solution.
To accurately identify lung cancer, the already trained model called EfficientNet-B0 was fine-tuned with a new custom set of dense layers and a softmax activation function. In this study, two FC layers with neurons containing 256 and 128 were used, respectively. A dropout layer was used after each layer with a 30% dropout ratio to reduce the rate of over fitting. Figure 4 shows the detailed structure of EfficientNet-B0, sourced from [25] with the new fine-tuned classification head.

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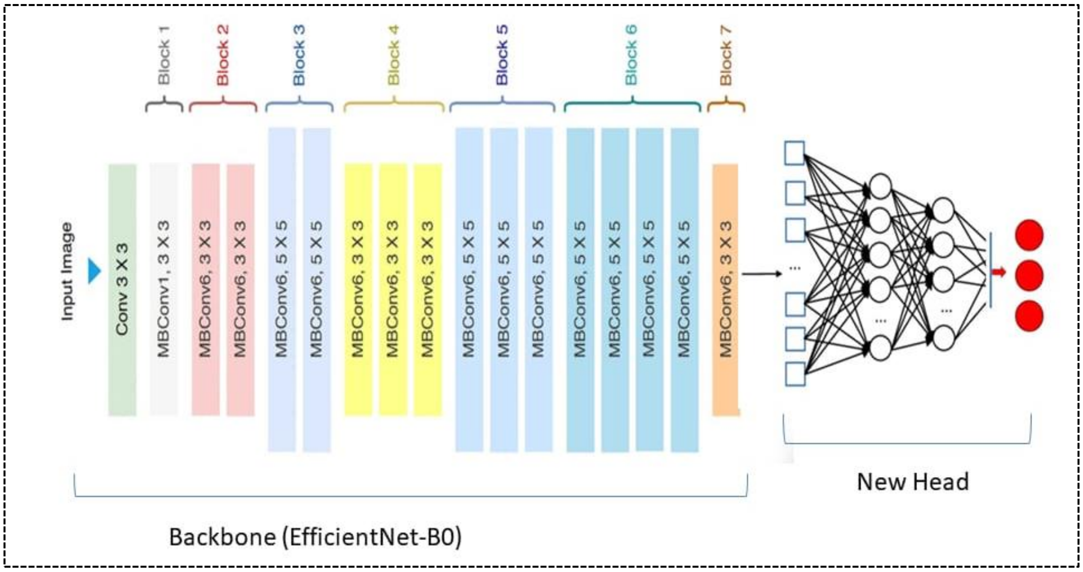

Figure 4: Architecture of the Proposed Fine-tuned EfficientNet

EXPERIMENTS AND RESULTS

This section contains a thorough description of the evaluation metrics, model training scenario, and model evaluation results on test data. It also contains the ablation study as well as a comparison with previous studies.

Training Environment

Deep learning-based models need powerful hardware compared to the environment of convolutional techniques like machine learning. CNNs are mostly used for visual data such as images and videos. Visual data needs more computations compared to textual data. Therefore, in this study, Google Colab was used, which provides GPUs, necessary for visual data interpretation. *Table 3* contains the details of hardware and software used in this study.

Table 3: Experimental Setup (Training Environment)

Component	Details
Deep Learning Framework	TensorFlow 2.19.0
Programming Language	Python 3.12
Numerical Computing	NumPy 2.0.2
API	Keras 3.10.0
Visualization	Matplotlib 3.10
Memory (RAM)	12 GB
Compute	NVIDIA GPU
Platform	Google Colab

Performance Evaluation

To examine the performance of the proposed approach, various mathematical methods are used. The most common and comprehensive methods are accuracy, recall, F1 score and precision, used for model evaluation. The proposed study also used these four methods to evaluate the model.

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ Predictions} \tag{3}$$

$$Precision_{(class_i)} = \frac{TP_i}{TP_i + FP_i} \tag{4}$$

$$Recall_{(class_i)} = \frac{TP_i}{TP_i + FN_i} \tag{5}$$

$$F1\_score_{(class_i)} = 2 \cdot \frac{Precision_{(class_i)} \times Recall_{(class_i)}}{Precision_{(class_i)} + Recall_{(class_i)}} \tag{6}$$

Here true positives (TPs) represents the correct identification of the target category. False positives (FPs) exhibits the prediction of other classes as the target category. False negatives (FNs) represent the prediction of the actual class as other classes.

Experiments and Results

The aim of the proposed approach was to build an efficient DL model to successfully identify lung malignant nodules from CT scans. Building such models for quick and accurate diagnosis of human diseases using AI techniques needs deep knowledge of model architecture and preprocessing techniques. In this study, because of the small and imbalanced image data, transfer learning was employed. EfficientNet-Bo was used as a backbone of the network and was fine-tuned and trained with a new set of dense layers and the softmax activation function (used for multi-category identification) as the output layer. The model was trained with multiple strategies, including training on plain data as well as on augmented datasets. Both the online and offline data augmentation techniques were applied on training data for bringing enlargement and variations in the training dataset. *Table 4* presents the evaluation outcomes of the suggested network on plain data. As compared to training the model on plain data and training with online augmentation, the model produced a comparatively higher detection score after training with offline data augmentation. *Table 5* contains the detailed outcomes of the model on both online and offline augmentation.

Table 4: Performance Evaluation of the Proposed Approach on Test Data (Plain)

Category	Precision	Recall	F1-Score
Benign	66.67	83.33	74.07
Malignant	98.11	92.86	95.41
Normal	95.24	95.24	95.24
Average	86.67	90.48	88.24

Table 5: Performance Evaluation of the Proposed Approach on Test Data (Augmented)

Augmentation	Online			Offline		
Class	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Benign	78.57	91.67	84.50	96.97	96.00	96.47
Malignant	1.00	96.43	98.18	98.99	98.00	98.50
Normal	97.62	97.62	97.62	97.06	99.00	98.12
Average	**92.06**	**95.24**	**93.43**	**97.67**	**97.67**	**97.70**

The model was trained up to 102 epochs using an early stopping mechanism. *Figure 5* presents the training/validation accuracy and loss graphs of the fine-tuned network. To show the actual predictions of the network, *Figure 6* contains the confusion matrix with actual and predicted results.

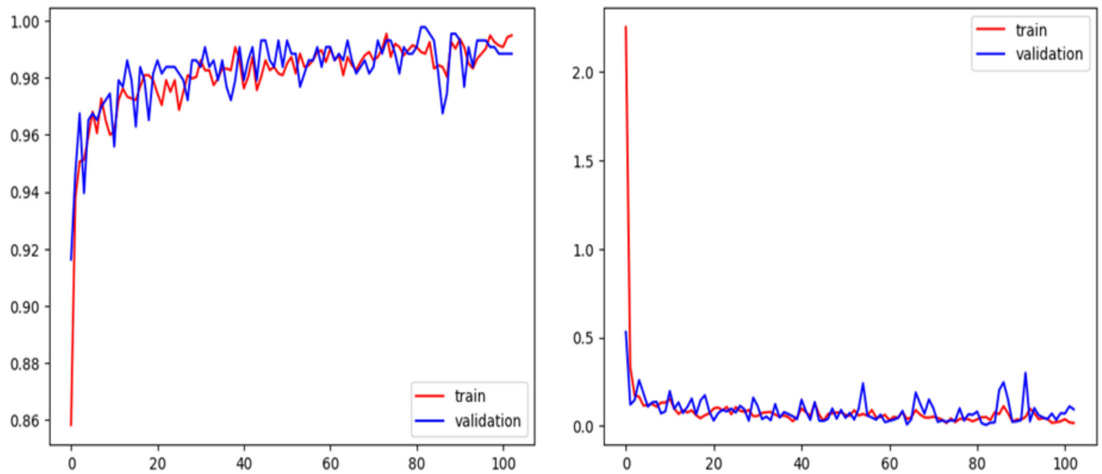

Figure 5: Shows Accuracy and Loss Progress

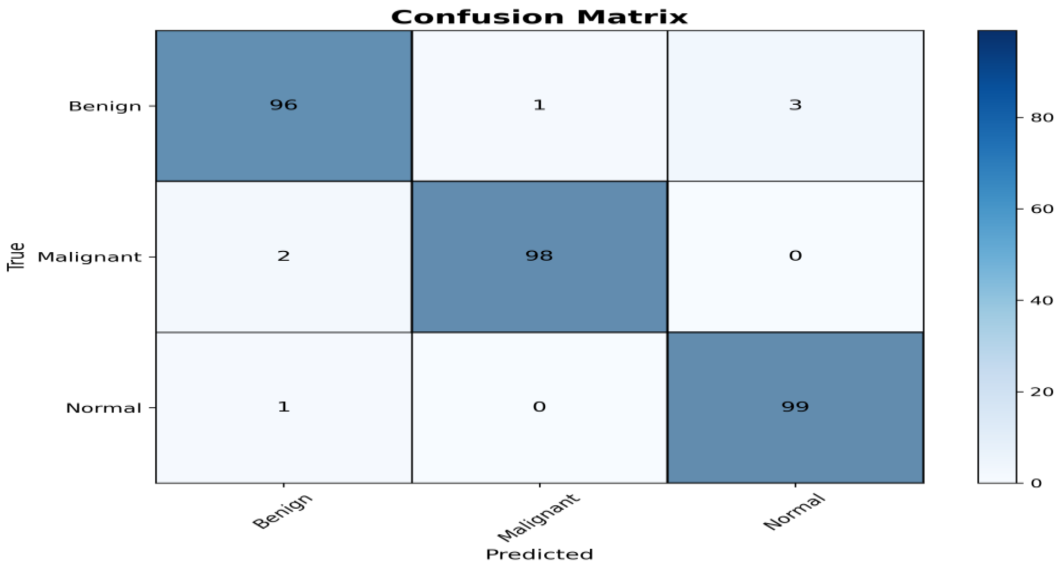

Figure 6: Shows the Overall Correct Predictions of the Model

Before finalizing the EfficientNet-B0 as the proposed pre-trained backbone, various well-known pre-trained networks were fine-tuned and trained. Some models with good results are depicted in *Table 6* in contrast to EfficientNet-B0.

Table 6: Shows Results Comparsion of Various Pre-trained Models

Backbone	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
MobileNet-V2	95.02	96.22	95.60	96.25
Inception-V3	95.02	94.22	94.60	95.36
VGG-16	94.01	93.16	93.48	93.85
Xception	93.20	92.70	92.92	93.05
ResNet-50	93.69	92.26	92.90	92.87
Proposed	**97.67**	**97.67**	**97.70**	**97.67**

Performance Comparison with Existing Methods

A comparative analysis was made with previous studies to support the relevance of the proposed framework to the identification of lung cancer. The comparative process contained previously conducted methods that used the same classes of lung cancer, as summarized in *Table 7*. This comparison highlights the methodological advancements and shows a higher performance of the suggested approach in the field of lung disease identification.

Table 7: Performance Comparison of Existing Deep Learning Methods with the Suggested Model

Ref#	Author	Year	Method	Images	Accuracy
[26]	Shah *et al.*	2023	Ensemble 2D CNN	CT Scans	95.00%
[27]	Jena *et al.*	2021	DGMM-RBCNN	CT Scans	87.79%
[28]	Sori *et al.*	2020	DFD-Net	CT Scans	89.10%
[29]	Chai *et al.*	2024	VGG-16	CT Scans	86.71%
[30]	Lanjewar *et al.*	2023	Dense-Net	CT Scans	95.00%
Proposed			Fine-tuned EfficientNet-B0	CT Scans	97.68%

Ablation Study

The aim of this research was to build an AI approach to efficiently detect lung cancer from CT scan images. CNNs are well-known algorithms used for image and video data processing. Because of the small size of the images used for training, transfer learning was preferred compared to training from scratch. To finalize a pre-trained network, various pre-trained networks, including VGG16, DenseNet121, ResNet50, InceptionV3 etc., were used, but EfficientNet-B0 performed well. Efficient Nets are considered accurate as well as resource efficient due to their well-managed structure, ensuring balance among input size and layered structure, including both depth and width of the model.

After finalizing the backbone, the next step was to fine-tune the backbone for the new task of lung cancer identification. Multiple input sizes, including 224 x 224, 256 x 256 and 300 x 300, were used, but the model training with an image size of 256 x 256 performed well in both accuracy and computational efficacy. The network was trained utilizing multiple training sessions, such as using plain data, online data augmentation and offline data augmentation. The model performed well on offline data augmentation. Both the well-known optimizers Adam and SGD were used, but Adam obtained the same accuracy as SGD but took fewer training epochs. The number of dense layers was changed continuously and multiple ratios of dropout were used, but two dense layers followed by 30% dropout each achieved high results.

In conclusion, the final fine-tuned approach is based on a pre-trained model, EfficientNet-BO. The model was trained with two fully connected (FC) layers containing 256 and 128 neurons, respectively, each followed by 30% dropout. SoftMax activation was used as a final layer. The Adam optimization technique with a learning rate of 0.0001 was utilized, and the model was trained using offline data augmentation, obtaining 97.67% accuracy.

CONCLUSION

This study exhibits the training and assessment of a fine-tuned EfficientNet-B0 model for detecting lung cancer from CT scans into normal, malignant and benign categories. The proposed model with data preprocessing, class balancing, and a new head of dense layers followed by a softmax activation function demonstrated a high classification accuracy of 97.67%, surpassing other CNN architectures, including ResNet-50, Xception, InceptionV3, VGG16, and MobileNetV2. These findings show the power of the proposed framework as a valid and effective diagnosis tool, which can be utilized to assist in the early identification of lung tumor in clinical practice. Although the results of the deep neural network are promising, the small size of the dataset is one of the challenges in generalizing to real field data, which necessitates additional improvements in the future.

In future studies, we aim to increase the training data by adding more CT scan images to improve the accurateness and generalization of the algorithm. More advanced image processing and data augmentation strategies can be utilized to enhance the model fine-tuning process and reduce over fitting. More complicated architectures such as Vision Transformers or 3D CNNs can be tested, and the results can be compared with the proposed model. Moreover, integrating interpretability methods like Grad-CAM can enhance model transparency and clinical trustworthiness, supporting broader adoption in diagnostic workflows.

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