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A Lightweight-CNN Model for Efficient Lung Cancer Detection and Grad-CAM Visualization

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***Abstract*— The lungs' abnormal cell growth leads to the development of lung cancer. Early cancer identification could make treatment easier, potentially saving millions of lives annually. This study's main goal is to more rapidly and effectively classify various types of lung cancer by employing a lightweight, computationally efficient convolutional neural network (CNN) model to categorize three different types of lung cancer. With an outstanding validation accuracy of 99.48%, the suggested model surpasses the achievements of previous works. The 15,000 CT scan images in our dataset include three different forms of lung cancer. The proposed model performs exceptionally well, as evidenced by its astounding precision, recall, and F1-score, all above 99%, and by its flawless Area Under Curve (AUC) score of 100%. The proposed model has fewer parameters than the existing transfer learning models. Gradient Weighted Class Activation Mapping (Grad-CAM) was used to create class activation maps, which were then used to create a heatmap to display the classification zone.**

Keywords— Lung Cancer, lightweight CNN, computationally efficient, validation accuracy, Grad-Cam, heatmap, categorization zone.

I. INTRODUCTION

Lung cancer primarily results from mutations in lung cells, often due to inhaling toxic substances. Despite its association with exposure to harmful compounds, even non-exposed individuals can develop it [1]. Lung cancer ranks as the second-most deadly cancer globally, surpassing breast, colon, and prostate cancers combined. Early and precise identification through methods like CT scans, aided by computer-aided diagnosis (CAD), is crucial for reducing mortality rates. Among lung cancer cases, small cell lung cancer accounts for 10%–15%, while non-small cell lung cancer, including adenocarcinoma, squamous cell carcinoma, and large cell carcinoma, makes up 80%–85% of cases [2]. It has been extensively researched how transfer learning methods and convolutional neural networks can be used to diagnose lung cancer. For example, A. Sultana et al. employed a hybrid CNN-SVM model to classify three forms of lung cancer with an accuracy of 97.67% [2]. S. Makaju et al. suggested a technique to classify malignant and benign nodules using SVM and cancerous nodules were found using watershed segmentation in lung CT scan images. The suggested model correctly identified cancer 92% of the time, while the classifier correctly identified cancer 86% of the time [3]. The effectiveness of a densely connected convolutional network in distinguishing between two different forms of lung cancer through chest X-ray pictures was studied by W. Ausawalaithong et al. Before moving on to training on the dataset relevant to lung cancer, the model conducted initial training using a dataset made up of lung nodules in order to reduce the drawbacks of a confined dataset. The proposed model achieved a mean accuracy, specificity and sensitivity of 74.43±6.01%, 74.96±9.85% and 74.68±15.33% respectively. Lung nodules were located using a heatmap [4]. B. Hatuwal et al. used histological images to diagnose lung cancer. CNN was used to classify three classes of images, and the achieved validation accuracy is 97.20% [5]. N. Bhattacharyya et al. used 15,000 histopathology images to classify three forms of lung cancer. They achieved 98.24% accuracy with VGG16, 97.29% accuracy with VGG19, 98.96% accuracy with Resnet50 and 75.38% accuracy with InceptionV3 [6]. P. Malin Bruntha et al. categorized two forms of lung tumors using ResNet50 and SVM, with an 83.06% validation accuracy [7]. The accuracy attained with G. Ibrahim et al.'s proposed method of classifying lung cancer nodules as benign or malignant using CT scan images is 94.13% [8]. A. Saabia et al. used CT scans and a CNN model to classify three forms of lung cancer. The model achieved 98.40% accuracy [9]. With an accuracy of 88.5%, N. Faria et al.'s learning system (CancerDetecNN) can identify tumor tissue in pictures of the entire lung [10].

This study's inspiration came from an analysis of previous research, and the following research gaps should be highlighted:

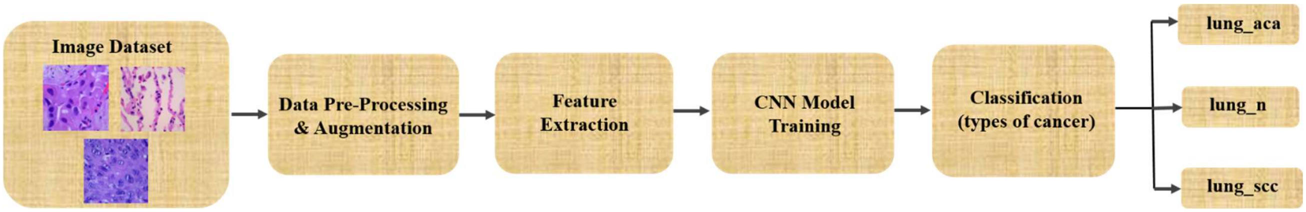


Fig. 1. A diagram showing the proposed system's flow

utilizing traditional image processing techniques, handcrafted feature extraction, and using higher parameter models. The contributions of this work are:

(1) A lightweight CNN model has been developed to categorize three different forms of lung cancer, which has provided outstanding validation accuracy and an AUC score.

(2) Computational complexity has been reduced by the model's lower time complexity.

(3) A heatmap has been implemented to locate and identify the classification zone, and the Grad-CAM approach has been used to present class activation maps that give an idea regarding the trained model's prediction principle.

These are the sections into which this study is divided: Section II discusses our methodologies, including the proposed model that we employed in our analysis and descriptions of the datasets. Section III illustrates the experimental analysis. Section IV explores the comparative analysis in depth. Section V serves as the paper's conclusion. Section VI encompasses the inclusion of references.

II. Methodologies

In this study, three different forms of lung cancer are categorized using a lightweight convolutional neural network. Fig. 1 depicts a diagram showing the proposed system's flow that was used to categorize three different forms of lung cancer.

A. Dataset Collection

For this investigation, the LC25000 Lung and colon histopathological image dataset was collected from Academic Torrents [11]. 25,000 color images total are in the collection, divided into five groups of 5,000 each. The resolution of each image is 768x768 pixels. Examples of the three classes produced from the LC25000 dataset are shown in Fig. 2.

B. Data Splitting

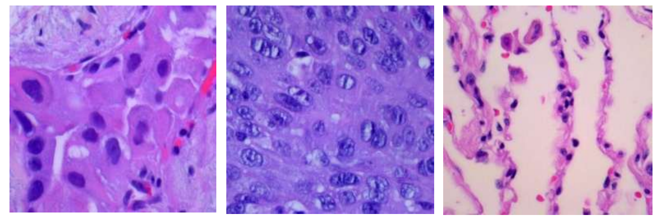
The 15000-image dataset is split into 80:20 training and validation sets. Accordingly, TABLE I shows the arrangement of the images in the dataset.

TABLE I. Splitting and Distribution of Lung Image Dataset

Classes	Training	Validation	Total
Lung adenocarcinoma	4000	1000	5000
Lung squamous cell carcinoma	4000	1000	5000
Lung benign tissue	4000	1000	5000

C. Data Pre-processing and Augmentation

To fit the developed model and use less memory during training, all of the images in the datasets were equalized and the image size was modified. The suggested approach made use of 64x64-pixel images as input. The input form is 64x64x3 because images have already been converted to RGB mode. Normalization was additionally done to improve the usability and ensure the training consistency of the model. Image augmentation is the practice of creating new, altered versions of existing photos from a particular image collection to boost its variety [12]. To enhance the diversity and richness of our dataset, we implemented three distinct image augmentation



(a) Lung adenocarcinoma (b) Lung squamous cell carcinoma (c) Lung benign tissue

Fig. 2. Lung cancer images from the dataset, showing three different classes

methods: rotation, horizontal flipping and zooming. These techniques were employed to bolster the data and introduce into our dataset.The fact that CNN's feature extraction is totally automated makes it possible to extract the best possible set of features for classification, including edge features, texture features, corner and junction features, etc.

D. Proposed CNN Model Architecture

TABLE II. Summary of Proposed Simple 2D CNN Model

Layer (Type)	Output Shape	Params
Input Layer	(64,64,3)	0
L1 (Conv2D)	(None, 64,64,32)	896
max_pooling2d (MaxPooling2D)	(None, 32,32,32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 16,16,32)	0
L2 (Conv2D)	(None,16,16, 128)	36992
max_pooling2d_2 (MaxPooling2D)	(None,8,8, 128)	0
batch_normalization (Batch)	(None,8,8, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None,4,4, 128)	0
dropout (Dropout)	(None,4,4, 128)	0
flatten (Flatten)	(None,2048)	0
dense1 (Dense)	(None,128)	262272
dense (Dense)	(None,3)	387
Total params: 301, 059 **Trainable params: 300, 803** **Non-trainable params: 256**		

The architecture of the proposed lightweight CNN model is provided in TABLE II and depicted in Fig. 3. The architecture consists of two convolutional layers, four max-pooling layers, one batch normalization, one dropout, one flatten layer, one dense layer, and one softmax layer to distinguish between three different forms of lung cancer. After various modifications in the layers, the mentioned model structure was found. The total parameter in the proposed model is very low compared to transfer learning models.

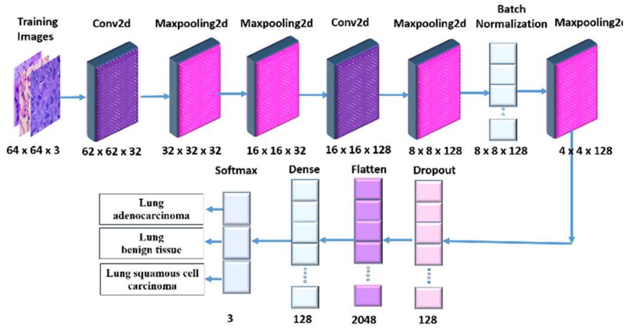


Fig. 3. Proposed Lightweight CNN Model's Architecture

III. Experimental Results

This section provides our proposed model's experimental findings and analysis.

A. Validation Accuracy

A performance statistic known as validation accuracy is used to evaluate a model's correctness on a validation dataset. The validation set performs a different function from the training set by assessing the model's performance on never-before-seen data, in contrast to the training set's primary function of parameter tweaking. Through the comparison of predicted labels in the validation set to ground truth labels and calculating the percentage of accurate predictions, the validation accuracy is determined and the suggested model has achieved a validation accuracy of 99.48%, which highlights the model's exceptional performance. Fig. 4 visually illustrates the accuracy curve of our proposed model. The model has taken only 426 seconds to train, so the time complexity of the model is very low due to having fewer parameters.

B. Classification Report

With a validation accuracy of 99.48%, our suggested CNN model has demonstrated great performance. It has attained great levels of F1 score, recall and precision of 99%. The area under the ROC curve, which is 100%, shows how well our suggested model performs. Our model possesses a total parameter count of 301,059, which is lower compared to the parameter count of transfer learning models currently in use. It takes 425.63 seconds for computation, indicating the use of lower computation resources. The report on classification is summarized in TABLE III.

C. Loss Curve

A convolutional neural network (CNN) model's loss curve typically shows how the loss function value changes over the course of training iterations or epochs. Fig. 5 visually illustrates the loss curve of our proposed model. The y-axis of the plot represents the value of the loss function, while the x-axis represents the number of iterations or epochs. The high loss values in the graph demonstrate how far the model's predictions are from the real labels. When the loss value is low, the model gets better at making predictions and learning from the training set. There are various iterations of our suggested model, some of which have a significant loss value while others have a low (near zero) loss value.

D. ROC Curve

The ROC (receiver operating characteristic) curve, a valuable tool, is utilized for evaluating criteria. It displays the classification performance at each level of a model. Fig. 6's ROC curve illustrates how well the suggested model performs.

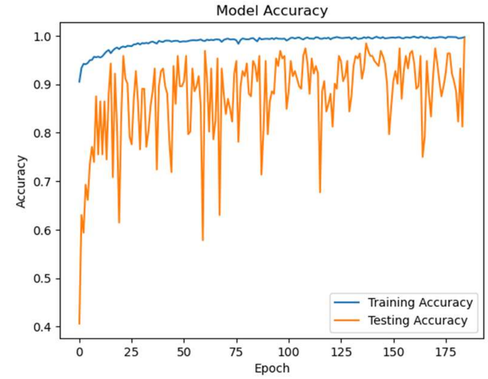


Fig. 4. Accuracy curve of the proposed lightweight CNN Model

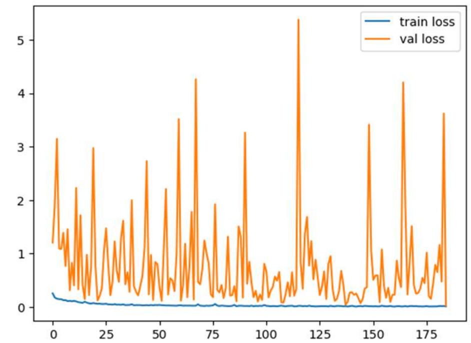


Fig. 5. Loss curve of the proposed lightweight CNN Model

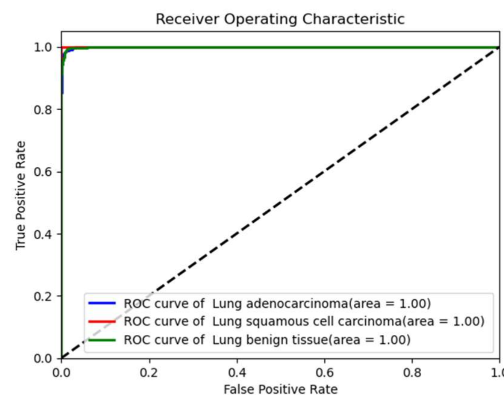


Fig. 6. ROC curve of (a) Lung adenocarcinoma (b) Lung squamous cell carcinoma and (c) Lung benign tissue

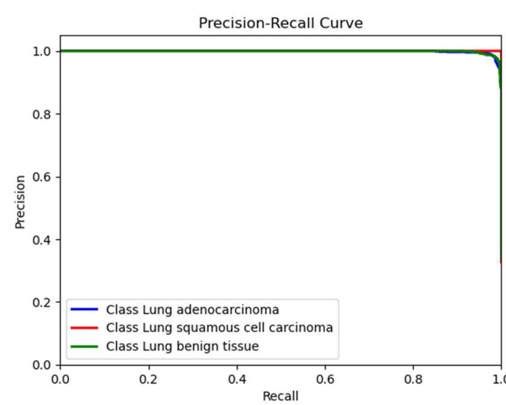


Fig. 7. Precision Vs recall curve of (a) Lung adenocarcinoma (b) Lung squamous cell carcinoma and (c) Lung benign tissue

TABLE III. THE PROPOSED MODEL'S CLASSIFICATION REPORT

Model	Accuracy	AUC (Area Under Score)	Precision	Recall	F1-Score	Total no. of parameters	Computation Time (s)
CNN	99.48%	100%	99%	99%	99%	301,059	425.63

The AUC (Area Under the Curve) of the ROC curve demonstrates the overall effectiveness of the proposed CNN model. A greater AUC (Area Under Curve) number (which ranges from 0 to 1) denotes better performance. We claim that the CNN model performs quite well because the AUC value is 1 for all classes (three classes) of our dataset.

E. Precision Vs Recall Curve

High precision (ranging from 0 to 1) and high recall (ranging from 0 to 1) are characteristics of a model that correctly predicts the majority of outcomes. The precision vs. recall curve is depicted in Fig. 7 to demonstrate how effective the suggested model is. In the classification of benign lung tissue and lung adenocarcinoma, we can see that our model produced precision and recall of 0.98, exhibiting the commendable performance of our suggested model. The excellent performance of our proposed model in the categorization of lung squamous cell carcinoma is indicated by precision and recall of 1, respectively.

F. Grad-CAM Visualization

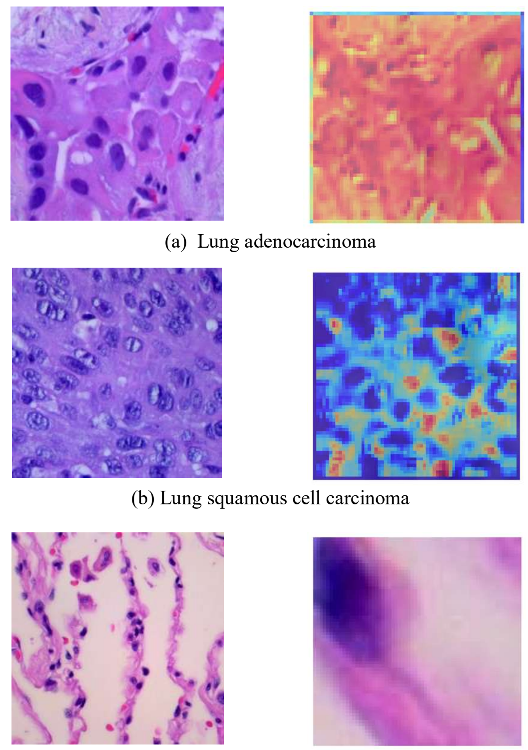
Grad-CAM is a way to make CNN-based models more transparent by showing the input regions that are essential for these models predictions. Grad-CAM, as depicted in Fig. 8, employs gradient information from the last convolutional layer of the CNN to get insights into the relevance of individual neurons relevant to a certain selection of interest [13].

G. Confusion Matrix

An error matrix, sometimes referred to as a confusion matrix, is a tabular representation that compares the predictions generated by a classification model on a given dataset with the real or actual values, trying to assess the accuracy exhibited by the model in its performance. 974 lung adenocarcinoma images were successfully identified, while 17 lung adenocarcinoma images were incorrectly identified as lung benign tissue, based on the confusion matrix in Fig. 9. It is evident that the suggested model correctly identifies lung squamous cell carcinoma. In the case of benign lung tissue, our model misclassified 17 images as lung adenocarcinomas. The confusion matrix shows that out of 3000 photos, 2966 were correctly identified, which represents the model's superb performance in previously unseen images.

IV. COMPARATIVE ANALYSIS

TABLE IV presents a comparison of the suggested model with other available research for identifying lung cancer. This comparison shows that the proposed lightweight CNN model outperforms past studies [2–10] with an accuracy of 99.48%, which is the highest among findings from the available literature. From the table it is clear that some studies [2, 5, 6, 9] have used the same LC-25000 dataset and had lower validation accuracy than the proposed model. It is notable that the experimental setup for all the works is not same. Also, the total parameter of the proposed model is very low compared to [2, 4, 6, 7, 10], which enables the model to reduce computational complexity as well as disk consumption, which is why the model can be considered lightweight.



(a) Lung adenocarcinoma

(b) Lung squamous cell carcinoma

(c) Lung benign tissue

Fig. 8. Visualization of Grad-CAM Input, Heatmap and Overlaid Images

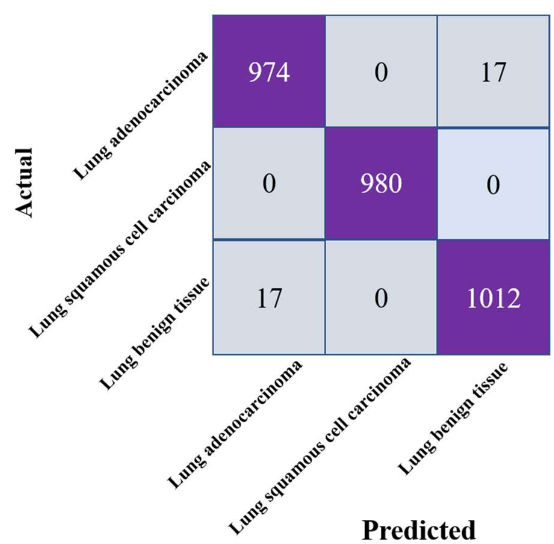


Fig. 9. Confusion matrix of the proposed model

These key differences demonstrates clearly the superiority of the proposed model over the existing models. A bar chart is shown in Fig. 10 to more clearly illustrate the similarity. The bar chart clearly shows how our work has changed how lung cancer is classified in comparison to past efforts.

TABLE IV. ACCURACY COMPARISON WITH EXISTING WORKS

Reference No.	Author	Experimental Setup	Dataset	No. of classes	Accuracy
[2]	A. Sultana et al.,2021	CNN with SVM	LC-25000	3	97.67%
[3]	S. Makaju et al., 2018	Watershed segmentation and SVM classification	LIDC	2	86.6%
[4]	W. Ausawalaithong et al., 2018	DenseNet-121	JSRT, ChestX-ray14	2	74.43%
[5]	B. K. Hatuwal et al., 2020	CNN	LC-25000	3	97.20%
[6]	N. Bhattacharyya et al., 2021	ResNet50	LC-25000	3	98.96%
[7]	P. M. Bruntha et al., 2022	ResNet50 with SVM	LIDC-IDRI	2	83.06%
[8]	Y. M. Malgwi et al., 2022	CNN	LIDC-IDRI	2	94.13%
[9]	A. A. Saabia et al., 2022	CNN	LC-25000	3	98.40%
[10]	N. Faria et al., 2023	CancerDetecNN-V5 (CNN Model)	NLST, TCGA	2	88.5%
	Proposed CNN Model	**Lightweight-CNN**	**LC-25000**	**3**	**99.48%**

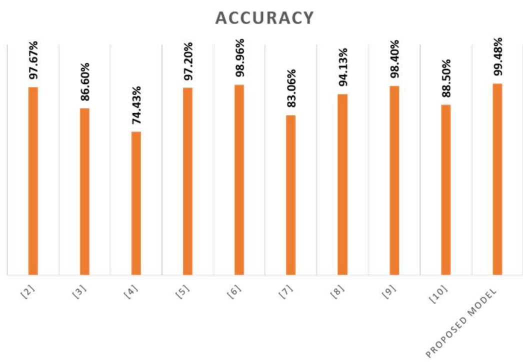


Fig. 10: Accuracy comparison of existing works with the proposed CNN model

V. CONCLUSION

This study focuses on the development of a compact convolutional neural network (CNN) model designed specifically for classifying three distinct types of lung cancer. This study's major goal was to lessen model complexity while improving model performance and accuracy. When compared to the results of the existing literature, our recommended CNN model obtains 99.48% of maximum accuracy despite having fewer parameters. The model's efficiency has been assessed using precision, recall, and F1-score as the evaluation metrics of choice. The performance of the model has been visually represented through the display of various metrics, including the accuracy curve, loss curve, ROC curve, precision-recall curve and confusion matrix. The exceptional performance of the model has been supported by an analysis of these curves. The total parameters of the suggested CNN model and computation time have been calculated to measure the model's complexity. The Grad-CAM technique was used to create class activation maps, which show the categorization the model performed. The recommended CNN model is most suited for accurately diagnosing three different types of lung cancer when all the factors are taken into account.

Our research's next step is to investigate more specialized methods for performance evaluation for various cancer types and to provide a fresh strategy in this regard. Subsequent investigations will prioritize the application of diverse deep learning methodologies for the prediction of lung cancer in future research endeavors.

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