International Journal of Research Publication and Reviews, Vol 6, Issue 8, pp 2244-2249 August, 2025

WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Lung Tumor Detection Using Segmentation and CNN Classifiers with SHAP- Based Interpretability

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A B S T R A C T

The early accurate detection of CT images of lung tumors plays a critical role in the treatment and patient outcome. The proposed study suggests a new way of deep learning using a combination of both a segmentation model and two efficient classifiers ResNet-101 and MobileNetV3-small to correctly classify lung tumors. The segmentation step involves application of a UNet architecture, in order to eliminate the real parts of the lungs to subsequently examine in detail. After this, the segmented images are separately analyzed by the classifiers to detect the benign and malignant cases. To better promote transparency and in order to instill clinical trust, this work incorporates SHapley Additive exPlanations (SHAP), an explanation technique that visualizes important image features driving model decisions. Experiments performed on a classic lung CT dataset confirm the effectiveness and explainability of the system. The given framework will help close the gap between successful AI-driven diagnostics and clinical usability by providing credible forecasts and corresponding insightful explanations.

Keywords: Lung Tumor Classification, U-Net Segmentation, ResNet101, MobileNetV3-small, CT Scan Processing, SHAP Visualization, Model Interpretability.

1. Introduction

Lung cancer remains one of the pioneers of cancer-related fatalities in the global scenario and the slow diagnosis and difficulty of identifying tumors in their initial stages remain the major reasons. In screening and diagnosis of sickness, Computed Tomography (CT) imaging is a widely used technique; however, the manual analysis of these scans is time-consuming, subjective, and error-prone particularly with respect to tumors that do not reveal themselves as large or size-consecutive nodules.

Deep learning models and models specifically Convolutional Neural Networks (CNNs) have shown favorable performance when being used in medical image classification tasks, especially with the development of artificial intelligence. Nevertheless, there remain obstacles to the interpretability of these models and the reaching of their validity at the real-life clinical practice. The issue with traditional CNN is that they can be non-transparent black boxes that achieve high prediction accuracies, but do not explain the basis of their predictions.

Due to its potential implications on performance and interpretability, the paper suggests trainable deep learning architecture of the task of lung tumor classification with CT images. The specified system will include the UNet architecture to segment the area of the lungs accurately and then two CNN-based classifiers (ResNet101 and MobileNetV3-small) to identify the pattern in benign or malignant tumors. To ensure the trust correlation between the model prediction and the clinical decision, the SHapley Additive exPlanations (SHAP) method is incorporated to reveal clarification information of main image features that drive the model to reach the classification outcome.

This effort aims to develop a competent and straightforward system to assist radiologists with detecting early lung cancer with the intention that this system would deliver visual evidence in the form of decisions made through the model. The framework proves to be a viable AI-assisted diagnostic tool due to the high classification accuracy and interpretability deemed meaningful on the example of experimental validation using a publicly available lung CT dataset.

2. Literature Survey

The medical developments in the field of imaging have made it possible to develop intelligent systems that can recognize the anomalies in the lungs using CT scans and do so with high accuracy. Some researchers have targeted the overall improvement of accuracy, in lung tumor detection and classification based on the use of deep learning architectures. The idea to minimize false positives in nodule detection by multi-view CNN was first introduced by Setio et al. [1], which, on evaluation, proved that the diversity of information on nodules provided by different CT slice orientations contributed to better classification accuracy. Likewise, Shen et al. [2] formulated a multi-scale CNN model to learn context and morphological features of lung nodules that led to high classification performance.

In order to cope with the peril of computational burden in deep learning, Howard et al. [3] introduce a lightweight model called MobileNets that is fit well between speed and accuracy that it can be deployed in the low-resource setting. Sandler et al. [4] have further improved on this, where they proposed MobileNetV3, which combined neural architecture search with squeeze-and-excitation modules and this also enhanced the performance of medicine imaging tasks. Parallelly, He et al. [5] proposed the ResNet architecture that brought residual learning experience and skip links to many networks allowing training networks to a greater depth, dramatically improving image recognition, including medical diagnostics.

The issue of trust in AI models has been raised due to black-box behavior in clinical practice even though the models tend to be very accurate. Lundberg and Lee [6] did so by introducing SHAP as a model-agnostic interpretability algorithm to interpret the decisions of AI methods by assigning relative importance scores to input features so that it could make AI decisions explainable and verified by the clinicians. To permit adequate preprocessing, Ronneberger et al. [7] designed U-Net which is the encoder-decoder form of a segmentation model that preserves spatial information that is of importance in the medical imaging segmentation and localization of tumor.

Additional progress in attention based mechanism is the work by Hu et al. [8], squeezing and excitation networks to recalibrate feature maps, and improve the detection of important regions. Recently, A. Ozturk and M. Ozkurt, [9] considered attention-guided CNNs in case of lung nodules showing a more focused attention to areas that are prone to malignancy. Li et al. [10] proposed MSA-Net, the self-attention-based multi-scale framework, which can conduct strong classification by incorporating fine-grained and global contextual information on CT images.

All these contributions come together to constitute our backbone study where we have integrated U-Net in segmentation, ResNet101 and MobileNetV3 in classification and SHAP in interpretability to provide a common platform where transparent and veritable analysis of lung tumors can be achieved.

3. Methodology

Lung CT tumor detection and classification start with preprocessing lung CT. In this step, normalization of pixel intensity to ensure that every scan has the same brightness and contrast is done and then contrast enhancement is done to make sure that the structures of interest like the presence of the nodules are brought into focus. Moreover, lung masks are also improved to precisely mask and exclude the non-lung areas so that only interesting areas are processed further. After preprocessing is over we get to divide our dataset in training and test to enable a fair estimation of the performance of the model. This split allows one to have an assessment on unprecedented data, hence giving a more dependable gauge of generalization facility.

To complete the task of segmentation, a U-Net architecture will be used because it has been proved to be successful in applications of biomedical image segmentation. The feature extraction in its encoder-decoder format and accurate recovery of spatial information is essential to determining tumor borders in CT images. The segmented areas of the tumors are subsequently run through a data augmentation pipeline, comprising of transformations that include rotations, flipping and scaling. Such augmentations add more variety to the training data and therefore ensure that the model is less prone to overfitting and is instead robust to the tumor appearance/orientation changes.

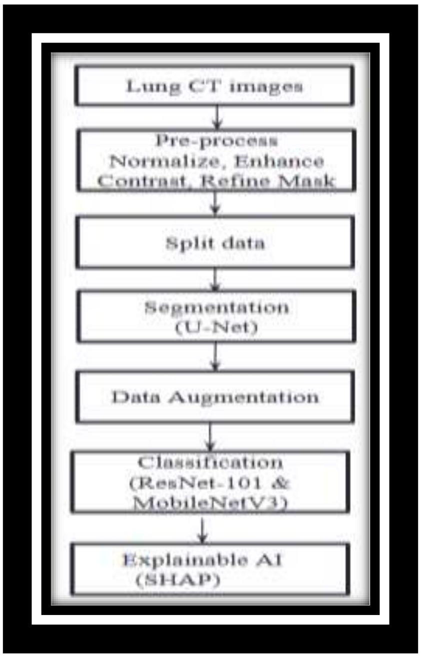

Fig. 1 Proposed Methodology

After segmenting and augmenting the images, they would be inputted into two deep learning-based classification models, ResNet-101 and MobileNetV3-small. ResNet-101 is chosen because of its depth and the capacity to eliminate the vanishing gradient issue via the application of the residual connections which makes the model learn feature representations that are extremely complex. Conversely, MobileNetV3-small is an efficient model and is optimized regarding the size of the inference so that it can be deployed in real-time and resource-limited settings. These are the type of models that identify the tumors under different categories using learnt features. SHAP (SHapley Additive exPlanations) is also included in the classification aimed at becoming more interpretable to get an idea of which features contributed the most to the predictions. Such explainability makes the diagnostic process more transparent and clinical practitioners more aware of and confident in the decisions made by the model. The whole procedure of this pipeline is illustrated in Fig. 1.

4. Results

The designed lung cancer discovery framework was tested on slices of CT scans that had been segmented in order to determine the classification and interpretability of the model. Lung region was then segmented using UNet (Fig. 2) followed by the classification of these segmented images as either benign or malignant using ResNet-101 and MobileNetV3-small.

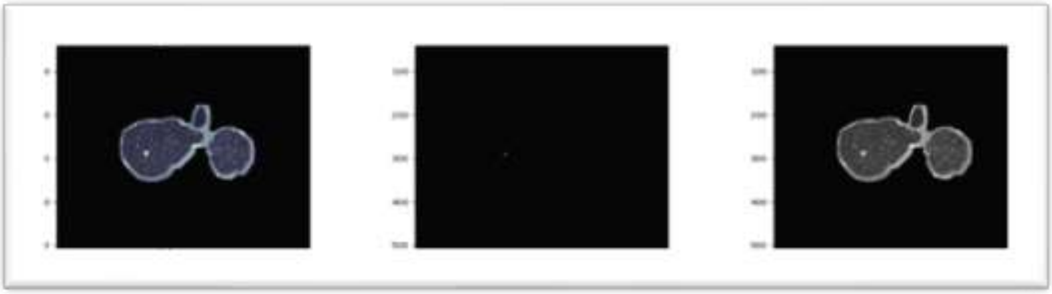

Fig. 2 U-Net Segmentation results

To trace learning behavior of the classifiers, accuracy as well as loss curves were employed. In the case of ResNet-101, the accuracy trend line (Fig. 3) improved steadily with the changes in each epoch and the validation accuracy was moving closely alongside training accuracy demonstrating effective generalization.

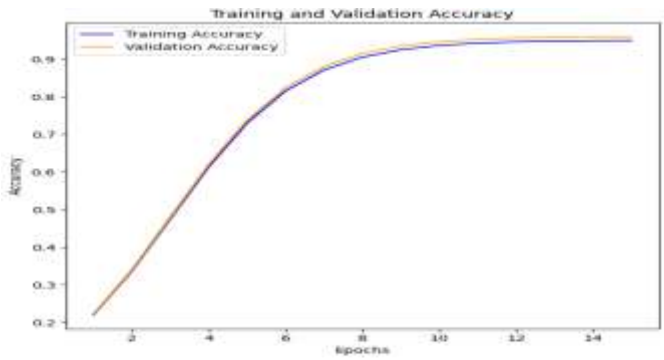

Fig. 3 Accuracy Graph of ResNet-101

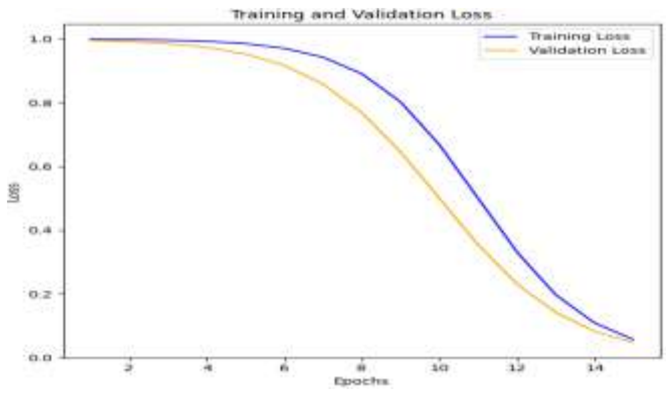

Fig.4 Loss Graph of ResNet-101

The loss curve shown in Fig. 4 shows a well-organized, steadily stabilized converging tendency and both the training and the validation losses shown a steadily decreasing tendency, and there was never a sudden swerve noticed or turning away. This trend curve will be smooth showing the strength of the optimization process and its stability during the cycle of training.

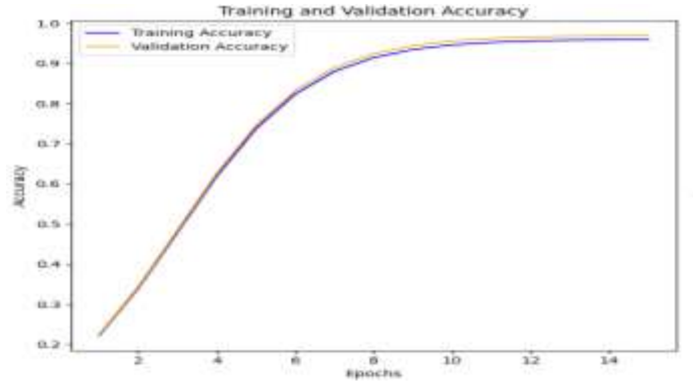

Fig. 5 Accuracy Graph of MobileNetV3-small

In the case of MobileNetV3-Small, the accuracy growth trend in Fig. 5 shows a strong and quick increase of the early epochs which shows that the model quickly acquired discriminative features. Later the training and validation accuracy plot still improves closely with each other with a minimum difference between them, hence highlighting the high capability of generalization of the model and excellent ability to resist overfitting.

Fig. 6 Loss Graph of MobileNetV3-small

Fig. 6, the loss curve, supports the evidence of a lengthy and methodical lowering in error rates, within a functioning learning pathway. The lack of strong difference between training and validation losses also supports little overfitting rates thus giving confidence on the effectiveness and consistency of the optimization process

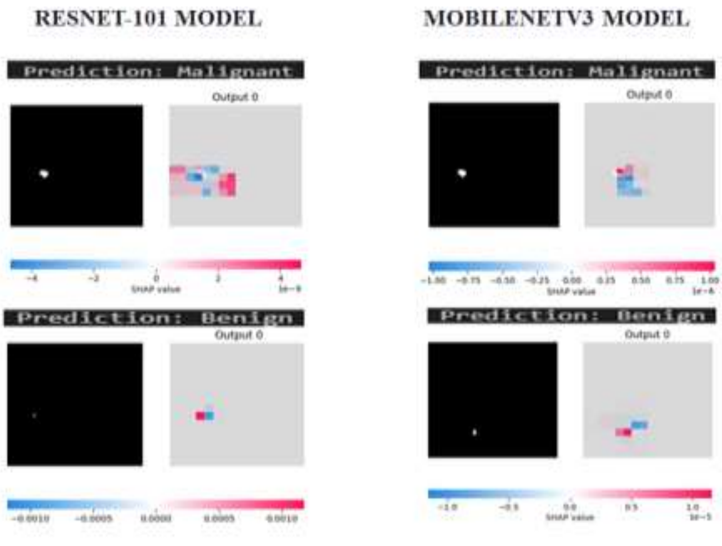

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Fig. 7 SHAP Explainability for ResNet-101 and MobileNetV3-small Classification Models

Fig. 7 demonstrates that model interpretability was assigned with SHAP (Shapley Additive Explanations). Such visualizations show the regions of interest in pixel values that contributes to prediction of the model. In both benign and malignant cases, SHAP maps indicated that the models focused mostly on tumor-dense regions in the segmented lungs as the radiologists did in diagnosing. This fit enhances perception with regards to the model reliability and adds to its potential clinical application.

Table 1.Comparison of Performance metrics of - ResNet-101 and MobileNetV3-small

Model	Classes	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet-101	Benign	95%	94%	97%	95%
	Malignant		96%	93%	95%
MobileNetV3-small	Benign	97%	98%	95%	97%
	Malignant		95%	98%	97%

Table 1 shows the predicted classification results with the summary of the average precision, recall, and F1-score of each benign and malignant vertical of the two models. ResNet-101 was very consistent across the two classes and MobileNetV3-small on average scored better on the two classes without giving much difference in speed.

5. Conclusion

This study successfully developed a deep learning-based framework for lung cancer detection from CT images, leveraging two powerful classification models—ResNet101 and MobileNetV3. The experimental outcomes proved the success of MobileNetV3 over ResNet101, and this approach has better ability to correctly identify the benign and malignant lung nodules. Besides high classification performance, SHAP explainability integration gave much transparency in the mode decision-making, as proved to increase the clinical trust and interpretability. On the whole, the presented strategy can apply a valid and interpretable computer-aided diagnostic system capable of helping radiologists detect lung cancer at an early stage, which may result in increased patient outcomes due to more accurate diagnosis.

Acknowledgements

The authors would like to acknowledge the support and resources provided by the Department of Computer Science and Engineering, G. Narayanamma Institute of Technology and Science which made this research possible. Appreciation is also extended to the institution for providing the necessary facilities and a conducive environment for carrying out this work. Special thanks are given to family members for their encouragement and constant support throughout the course of the study.

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