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Deep Learning-Aided Lung Cancer Detection and Classification Using Xception with Grad-CAM Explainability

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***Abstract*— Lung cancer remains one of the most lethal types of cancer globally, emphasizing the necessity for early and accurate detection. This study suggests a deep learning-based classification model that uses the pretrained Xception model to distinguish between four different groups: normal lung tissue, squamous cell carcinoma, large cell carcinoma, and adenocarcinoma. We apply chest CT scan images of a chosen dataset meticulously to fine-tune the model utilizing image data improved by real-time preprocessing techniques. The model has a high accuracy rate, signifying its potential use in supporting clinical diagnosis. Grad-CAM (Gradient-weighted Class Activation Mapping) is used to map class-specific activation zones in order to improve explainability, which supports radiological diagnosis and makes explainable prediction possible. Our approach provides a promising AI-based solution to screen lung cancer with high accuracy and clinical interpretability.**

Keywords— Adenocarcinoma, CT scan images ,Deep Learning, Grad-CAM , Large cell carcinoma, Lung Cancer, Normal lung tissue, Squamous cell carcinoma, Xception

I. INTRODUCTION

Lung cancer is a worldwide health concern, and the World Health Organization estimates that it kills approximately 1.8 million individuals every year. Despite the advances in medical technology, the survival rate of lung cancer patients remains low, primarily due to the fact that the disease is diagnosed late. Long-term survival and the likelihood of a successful course of treatment are greatly increased by early detection; yet, existing screening techniques—biopsy, sputum cytology, and manual analysis of CT scans—are marred by their slow, expensive, and subjective nature. The need for rapid, trustworthy, and scalable diagnosis resulted in the use of artificial intelligence in medical imaging, enabling automated picture processing and classification.[8]

Deep learning has demonstrated great potential in several medical imaging subfields, especially when combined with Convolutional Neural Networks (CNNs), which are capable of detecting intricate patterns and anomalies that human perceivers could overlook.CNNs learn from pixel-level feature maps to identify anomalies and classify the same with high accuracy. The deep learning system we show in this research is based on the Xception architecture, a high-performance CNN model that uses depthwise separable convolutions to enable efficient feature extraction.[9] With transfer learning, we apply the pre-trained weights of Xception from ImageNet to our particular task of lung cancer classification, thus significantly reducing the need for large amounts of labeled data and computational resources.

Our data are CT scan images belonging to four classes: normal, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma. The data are preprocessed through normalizing and augmenting with flips and resizing to increase generalization and avoid overfitting. We utilize the Keras ImageDataGenerator utility to supply data for the model in real-time and keep memory low while acquiring high diversity during training. The Adam optimizer is used to optimize the model after it has been trained using categorical cross-entropy loss. The learning process is tracked and dynamically enhanced by the callbacks ReduceLROnPlateau and EarlyStopping.[10]

While high accuracy is valuable, it's equally valuable to make deep learning models explainable, particularly in medicine. In order to achieve this, we integrate Gradient-weighted Class Activation Mapping (Grad-CAM) into our system, which highlights the areas of an image that are most pertinent to the CNN prediction in order to produce visual explanations of the predictions. Grad-CAM allows physicians to observe where the model is focusing during classification by transferring heatmaps to regular input photos. It builds trust in the model, aids in error analysis, and provides the basis for incorporating human-in-the-loop systems into clinical workflows.

Grad-CAM explainability's use transforms the model from an opaque black-box classifier to an explainable and interpretable one, and thus it becomes appropriate for use in sensitive and regulated environments, such as hospitals and diagnostic laboratories. Additionally, such visualization methods can identify biases in the training data, confirm the model's attention locations against expert markup, and enable improved collaboration between machine learning engineers and medical experts. Such a combination of accuracy, automation, and explainability makes our system a critical decision-support system for early detection of lung cancer and subtype classification in clinical settings.[11]

II. LITERATURE REVIEW

Yi Li et al.'s article suggests GMNNnet, a multimodal neural network that integrates metadata and four kinds of high-resolution clinical images for glaucoma type diagnosis with transfer learning and deep learning architectures such as UNet and ResFormer. It overcomes the disadvantage of single-modal methods and lack of annotated medical data through multimodal fusion and pre-trained CNN fine-tuning. The article underscores the need for integrating clinical and imaging data for enhanced diagnostic accuracy but indicates challenges persist in model generalizability and dataset scalability for wider clinical use [1].

Md Tasnim Alam et al.'s AIAI 2024 research investigates human action recognition from static images through transfer learning with InceptionResNetV2 fine-tuned on the Data Sprint 76 dataset. Data insufficiency is addressed through two-phase training and data augmentation, with a validation accuracy of 77.30%. Grad-CAM is also used to visualize attention and interpret error predictions. Limitations continue in the generalization of HAR performance to more varied, real-world datasets and dynamic video streams [2].

U. N. Ranjitha and M. A. Gowtham's study proposes a hybrid approach for segmentation that combines morphological operations with K-means clustering and measuring lung tumor volume from medical images. The method avoids the limitations of tumor detection related to lung walls or blood vessels by improving the accuracy of segmentation. Although effective in volumetric analysis, the research suggests the requirement for more sophisticated models in dealing with intricate anatomical variations and to enhance robustness in various imaging conditions [3].

The paper by Heba M. Afify et al., published in Biomedical Signal Processing and Control, a model based on deep transfer learning for OSCC histopathological image classification, integrating CNN architectures such as ResNet-101 and EfficientNet-b0 with Grad-CAM for lesion localization. On the basis of a public dataset of 1224 images across several magnifications, the model had up to 100% accuracy, with high potential for early oral cancer detection. The paper, however, points to the limited existing work on OSCC histopathology and emphasizes the necessity of wider validation on dissimilar clinical datasets [4].

The work of S. M. Saiful Islam Badhon et al. investigates skin disease classification by employing five transfer learning models with emphasis on low-resource usability and explainable AI via Grad-CAM for visual examination. It reached 97.07% accuracy on a balanced data set of unusual skin diseases with the VGG-16-Aug model, counteracting data paucity via augmentation and preprocessing. Promising though, the study indicates the necessity for additional validation on varied medical data sets to establish generalizability and clinical usefulness [5].

The study by Feyza Altunbey Özbay and Erdal Özbay in the *Iran Journal of Computer Science* proposes a hybrid CNN architecture for brain tumor segmentation from MR images with multimodal fusion from pre-trained models such as DarkNet53, EfficientNet-B0, and DenseNet201, with mRMR-based feature selection. Interpretability was achieved with Grad-CAM, while SVM classification of optimized features with a high accuracy of 99.6% was obtained. Notwithstanding its efficacy, the study highlights the need for future research on bigger and more varied MRI datasets in order to facilitate wider clinical use. [6].

Using convolutional neural networks (CNNs), the study by Abdul Hannan Khan et al. suggests a hierarchical deep learning model (HDL2BT) used to identify and categorize brain cancers into glioma, meningioma, pituitary, and no-tumor categories. The approach attains 92.13% accuracy, a better improvement compared to existing methods, and seeks to aid clinicians in the facilitation of early diagnosis. However, the model's efficacy can be attained by validation against larger volumes and more diverse datasets to ascertain its reliability in real clinical practice [7].

III. Proposed Work

A. Selection & Implementation of Algorithms:

The experimental study was conducted by using the publicly released LIDC-IDRI dataset available at The Cancer Imaging Archive (TCIA). The dataset contains CT scans of 1,018 cases. We selected a subset of 1,200 images from four classes for our study. Normal lung tissue (300 images), Adenocarcinoma (300 images),Squamous cell carcinoma (300 images),Large cell carcinoma (300 images).

For overcoming class imbalance problems, random oversampling of minority classes was used and vigorous data augmentation (rotation, flip horizontally, zooming, shifting) was done by utilizing Keras's ImageDataGenerator. It maintained equitable data representation while improving the model's generalizability.The suggested architecture uses deep learning methods to classify various lung cancer subtypes from CT scan pictures into multiple classes. Using the Xception model, a new state-of-the-art convolutional neural network pretrained on ImageNet, transfer learning is used to design the architecture.[12] The architecture design employs depth wise separable convolutions, which enable efficient feature extraction along with reducing the computational requirements.

The convolutional base is frozen, and a Global Average Pooling layer and a fully connected Dense layer with softmax activation are used to classify the CT images into four groups: adenocarcinoma, squamous cell carcinoma, big cell carcinoma, and normal lung tissue.

The ImageDataGenerator is used to normalize the input images and flip them horizontally for augmentation. The categorical cross-entropy loss function is used to train the model, which is done with the Adam optimizer. To improve training and prevent overfitting, callbacks like EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint are also used.[13]

By creating visual heatmaps that highlight the parts of the input image that are most crucial for the model's decision-making process, the Grad-CAM (Gradient-weighted Class Activation Mapping) technique increases the interpretability of models and increases the transparency of the deep learning system.

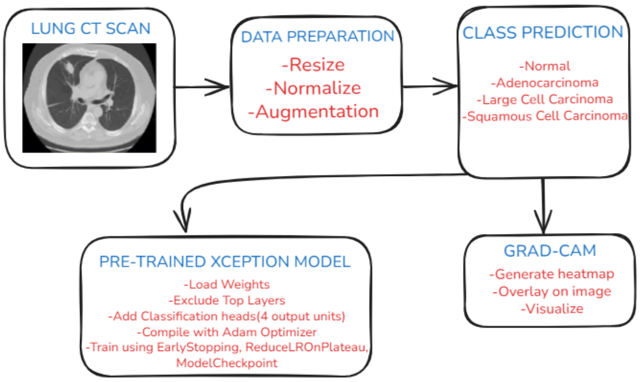

Fig 1: Architecture of Xception-Based Model

B. Pseudocode:

```
Start
Input: Lung CT scan dataset (4 classes)
Import libraries (TensorFlow, Keras, NumPy, Matplotlib)
Mount Google Drive and load dataset
Preprocess images:
    - Resize to 350x350, normalize to [0,1], apply augmentation
Pretrained Xception model loaded (layers frozen, top omitted, imagenet weights)
Include a personalized head: Dense(4) + GlobalAveragePooling2D + Softmax Build the model (metric: accuracy, optimizer: Adam, loss: categorical_crossentropy).
Train model (batch=8, epochs=50, use EarlyStopping, ReduceLROnPlateau, Checkpoint)
Evaluate on validation data, save model
For each test image:
    - Preprocess, predict class, display result
Apply Grad-CAM:
    - Identify last conv layer, compute gradients, generate heatmap
    - Overlay heatmap on original image for interpretation
Output: Predicted class label + Grad-CAM visualization
End
```

C. Hardware and Environment:

The recommended framework necessitates a powerful device with a dedicated GPU and at least 4GB of RAM due to the intensive computational requirements of training deep convolutional networks, e.g., Xception, on massive CT scan image datasets. The main programming language utilized is Python, which utilizes TensorFlow and Keras for performing deep learning computation, while duties involving data management and numerical computation are handled by NumPy and Pandas. For visualization, Matplotlib and Seaborn are utilized to generate the visualizations like training curves and Grad-CAM heatmaps. To overcome local hardware limitations, the model is implemented and run in Google Colab, which provides access to cloud-based GPUs, thus enabling effective training, evaluation, and visualization tasks.

D. Statistical Analysis:

Statistical analysis of the lung cancer classification model is required for its performance evaluation of interpretability, generalization, and learning capacity. A multi-class CT scan data set was used to train the deep learning model, which employed a transfer learning strategy built on the Xception architecture. Key performance indicators including accuracy and categorical cross-entropy loss were used to evaluate the model's performance after 45 epochs of training. One of the simplest and most used metrics, accuracy is described as follows:

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \qquad \text{Eq. 1}$$

In this case, TP, TN, FP, and FN represent true positives, false positives, false negatives, and true negatives individually. The model learned at a training accuracy of nearly 91.37%, and the validation accuracy peaked at 68.87%, according to the training logs and plots. When the model learns significantly better on the training set than on the previously unseen validation data, this severe discrepancy suggests possible overfitting. However, the model's overall learning trend is increasing, indicating that feature extraction was successful throughout training. Categorical cross-entropy, the loss function that was employed, was computed as follows:

$$Loss = -\sum_{i=1}^{N} y_i \,.\log \hat{y}_i \qquad \text{Eq. 2}$$

Here, $\hat{y}_i$ is the predicted probability for class *i* and *yi* is the ground truth label. The training loss reflected a steady decline from 1.25 to about 0.37, reflecting effective learning and convergence. The validation loss, however, plateaued at 0.68 to 0.78, reflecting slight oscillations that imply the model had already hit its generalization plateau at epoch 28. A ReduceLROnPlateau callback was incorporated into the training setup in an attempt to increase learning efficiency. This callback adaptively decreased the learning rate whenever the validation loss plateaued. As mentioned, the learning rate was reduced from 0.0005 to 0.00025 at epoch 34, allowing for more accurate updates and preventing overfitting.[14]

By using data augmentation techniques like rescaling and horizontal flipping, the training process was improved. To lessen the impact of overfitting, the model also made use of frozen pre-trained layers and dropout techniques. However, because of the heterogeneity and short sample size, validation accuracy fluctuated, necessitating further improvement through fine-tuning, L2 regularization, or dataset expansion. Grad-CAM (Gradient-weighted Class Activation Mapping) was used to localize the convolutional neural network's decision-making process in order to further enhance model explainability and clinical applicability. Grad-CAM aids in determining the area of the image where the model made its prediction. This is how the Grad-CAM heatmap is calculated:

$$L_{Grad-CAM}^{c} = ReLU\left(\sum_k \alpha_k^c \; A^k\right) \qquad \text{Eq.3}$$

RESULTS AND DISCUSSION

Using transfer learning from the Xception architecture, the suggested deep learning model successfully identified four types of lung cancer from the CT scan images: squamous cell carcinoma, large cell carcinoma, adenocarcinoma, and normal. After 45 epochs, the model's highest training accuracy was 91.37%, and its validation accuracy was 68.87%. Training loss decreased steadily from 1.25 to less than 0.4, whereas validation loss stabilized after epoch 20, indicating overfitting, which was supported by methods such as dropout, early stopping, and learning rate decay. We assessed the model using other clinical metrics in addition to accuracy and loss.

Grad-CAM heatmaps also validated the interpretability of the model by being able to detect tumor locations successfully, especially in adenocarcinoma and squamous cell carcinoma. [15]. Future research will incorporate additional clinical metrics, such as precision, recall, specificity, F1-score, and AUC-ROC, in addition to accuracy and loss, to provide a more thorough assessment of the model.

These results highlight the model's clinical usefulness and the need for explainable AI to improve diagnosis reliability. The performance discrepancy points to overfitting, which we intend to address in subsequent research by using bigger datasets, more robust regularization, and optimizing unfrozen convolutional blocks.

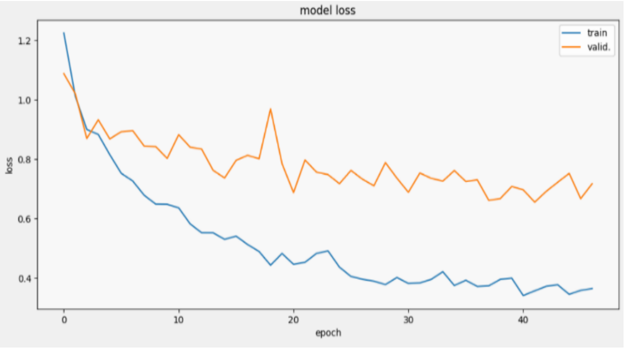

Fig 2: Loss Curve for Training and Validation Across Epochs

The trend of training and validation loss over 45 epochs is shown in the graph Fig. 2 above. The orange line represents validation loss, and the blue line represents training loss. Training loss consistently and noticeably declines, suggesting that the model had learned sufficiently from the training set and improved with each subsequent epoch. Initially, both losses are high (around 1.2 for training and 1.1 for validation); however, the training loss steadily drops below 0.4. In contrast, the validation loss has minimal fluctuations after the 10th epoch and eventually settles at between 0.7 and 0.8, indicating small overfitting. These fluctuations can be attributed to noise or slight generalization to unseen data. Despite this, the overall disparity between training and validation loss is under control, indicating that the model continues to function adequately on the validation set. This trend also confirms that the regularization techniques used, including dropout and learning rate regularization, were successful in preventing overfitting while achieving convergence.

Fig 3: Accuracy Curve for Training and Validation Across Epochs

The deep learning model's training and validation accuracy over 45 epochs is depicted in the graph Fig. 3 above. The model has learned to apply knowledge from the training set, as shown by the training accuracy curve, which is a smooth line with a high point of more than 0.93. The validation accuracy curve is more erratic, due to variability in unseen data, but still illustrates a steady improvement and then levels off at 0.68. Overfitting occurs when a model performs exceptionally well on the training set but poorly on new data, as indicated by the observed disparity between the training and validation curves. But, the steady improvement of both curves across the epochs is an indicator that the model is learning well and has achieved a good level of generalization. In order to counteract this difference and improve performance on novel data, further investigation into regularization methods or data augmentation may be necessary.

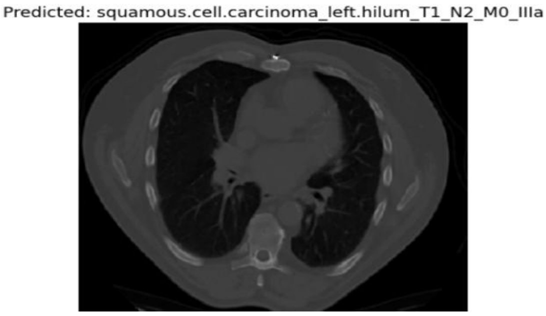

Fig 4: CT Scan Image Predicted as Squamous Cell Carcinoma

The above CT scan image Fig. 4 has been accurately identified by the proposed deep learning model as squamous cell carcinoma, which is located in the left hilum with a staging of T1_N2_M0, corresponding to Stage IIIa lung cancer. The hilum is an important region where blood vessels and bronchi provide access to the lungs, and lesions in this zone typically pose problems in early detection due to the intricacy of anatomical structures. The accurate prediction by the model shows its high potential to identify subtle changes in tissue density and architecture typical of squamous cell carcinoma. A tumor of relatively small size is classified as T1, lymph nodes on the same side of the thoracic cavity are involved as N2, and there are no distant metastases as M0.This observation shows the merit of the model in helping radiologists make accurate predictions not only about the type of cancer but also about its anatomical location and staging—important considerations in the treatment planning phase.

Fig 5: CT Scan Image Predicted as Adenocarcinoma

This above CT scan image Fig. 5 has been predicted by the model as adenocarcinoma located in the left lower lobe of the lung, with a TNM staging of T2_N0_M0, corresponding to Stage Ib. The T2 status indicates a moderately sized tumor without invasion into nearby organs. N0 and M0 confirm no lymph node involvement and no distant metastasis, respectively. The model successfully localized and classified the lesion, which is visible as an irregular opacity in the left lower lobe region. Regarding non-small cell lung cancer (NSCLC), adenocarcinoma is among the most prevalent forms, often appears in peripheral regions, and the model's correct prediction emphasizes its strong learning ability. This output demonstrates the system's clinical relevance and diagnostic assistance potential.

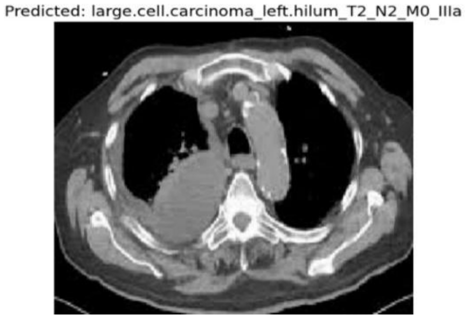

Fig 6: CT Scan Image Predicted as Large Cell Carcinoma

The model has identified the CT scan image Fig. 6 above as Stage IIIa large cell carcinoma of the left hilum with T2_N2_M0 staging parameters. The T2 refers to a large tumor, while N2 indicates the malignancy in the nearby lymph nodes; however, M0 is an indication of the lack of far metastasis. The abnormality is presented in the form of a thick, irregular mass close to the mediastinal structures, characteristic of centrally located large cell carcinoma. This kind of exact classification by the model indicates its capacity to detect fine radiographic variations among lung cancer subtypes, especially those of the hilar type.

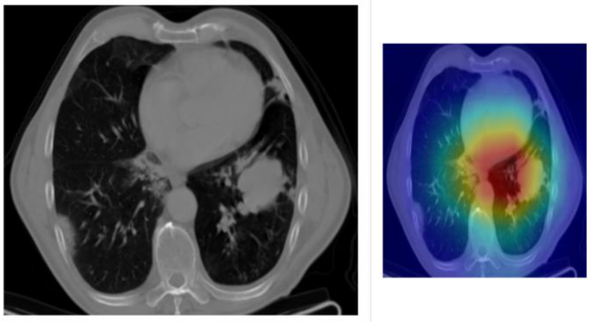

Fig 7: The tumor region is highlighted by the CT scan and the corresponding Grad-CAM Heatmap.

The lungs' CT scan and accompanying Grad-CAM heatmap, displayed in the above figure, indicate the model's focus during the prediction.The red and yellow areas highlighted on the Grad-CAM overlay exactly coincide with the apparent tumor mass in the right lung, showing where the deep learning model placed its attention. This visual validation validates the model's prediction accuracy and its ability to select clinically significant characteristics. The heatmap is a useful interpretation, which increases the confidence of radiologists and clinicians in AI-based diagnosis platforms.

CONCLUSION

Using transfer learning from the Xception architecture, the suggested deep learning system for lung cancer detection accurately divides CT scan images into four classes: normal, adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. The model's high learning ability is demonstrated by its impressive 91.37% training accuracy and 68.87% validation accuracy. Future research will incorporate additional clinical metrics, such as precision, recall, specificity, F1-score, and AUC-ROC, in addition to accuracy and loss, to provide a more thorough assessment of the model.

Furthermore, with the utilization of Grad-CAM, the system achieves an aspect of explainability, increasing its transparency and credibility for use in clinical practice.[16]

Although with encouraging outcomes, there is room for improvement. Future research can aim at enhancement of generalizability by having a larger and more diverse dataset, using more balanced and augmented samples, and hyperparameter optimization. Another step is via application of ensemble learning and multi-modal input (e.g., imaging data + clinical data) to enhance robustness. Application of federated learning can even enable model training in a collaborative effort between hospitals without infringing on patient privacy.

To help radiologists detect cancer early and cut down on diagnostic time and errors, the model can be implemented into Computer-Aided Diagnosis (CAD) systems.It would be especially useful in rural or resource-limited areas with limited specialist radiologists. It may also be integrated with hospital Picture Archiving and Communication Systems (PACS) to facilitate pre-screening of patients and identification of probable malignancies, thereby triaging emergency cases. The Grad-CAM explanations enhance clinical decision support even more, boosting the confidence of health practitioners.In short, this research provides the groundwork for the creation of interpretable, scalable, and automated diagnostic tools, thereby making important contributions towards AI-based healthcare solutions that can save lives by early and accurate diagnosis of lung cancer.[17]

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