

A Lightweight Attention-Enhanced Deep Learning Model Based on MobileNetV2 for Lung Cancer Detection

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Abstract—Today, cancer poses a significant challenge to health care, and the impact of mortality is growing and continuing to climb worldwide. Because lung cancer has a high death rate and a high probability of being detected later in the course of the disease, it is the most deadly of all malignancies. The frequency and diagnosis of lung cancer are rising significantly, and because it is often detected too late, survival chances are frequently poor. Based on cellular features, lung cancer can be divided into two major groups: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). There are four stages of lung cancer, and the prognosis and available treatments are quite restricted. The framework employs a lightweight MobileNetV2 architecture with an explicit attention mechanism to learn a better representation of spatial and channel features while maintaining a constant level of computational load through a depthwise separable convolutional layer/dimension. The framework was developed using CT scan data sourced from Kaggle, organized in four classes: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal tissue. Data Augmentation techniques like gamma correction, bilateral filter and normalize have further demonstrated the robustness of the proposed framework, enabling it to operate effectively and efficiently and helping to justify the classification accuracy of 96% in real-time clinical settings.

Index Terms—CNN,Deep Learning,Federated Learning,Lung Cancer Detection,Clinical Integration

I. INTRODUCTION

Cancer poses a significant barrier in healthcare today, and the mortality draw that impact extends and is still incrementing on a global scale [1]. Of all cancers, lung cancer is the most deadly because of its high mortality rate and high likelihood of presenting at late stages of disease progression. The number of lung cancer cases are increasing each year, and

the survival rates are low usually with late disease detection. Lung cancer can be classified into two major types based on cellular characteristics,-("non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC).") Lung cancer has 4 stages and only offers limited treatment options and prognosis when diagnosed in the advanced stages of it's disease progress [2]. Improving the early and accurate diagnosis and increasing the early detection can improve the survival rate. One of the most useful imaging modalities to diagnose lung cancer is Computed Tomography (CT) imaging as shown in Fig. 1. CT imaging allows a radiologist to unveil the lung structure abnormalities. CT imaging also has some disadvantages, like offering painstaking, prolonged,inconsistent [3] and sometimes wrong diagnostic assessments. In the last few years, there has been a rise in computer-aided diagnosis (CAD) in medical imaging tasks using deep learning that have achieved state-of-the-art performance.Convolutional Neural Networks (CNN) can autonomously learn hierarchical features from data requiring limited manual feature engineering. Even with these advancements, regular CNN and transfer-learning models usually have difficulty separating classes with high visual similarity, a frequent challenge in medical imaging [4]. Also, most pre-trained architectures are without attention mechanisms to focus on the most appropriate features within the image. As a result, they may become confused by irrelevant surrounding details and lose the ability to make informative decisions. However, even more limiting, is the vast majority of deep learning models as black boxes, and not interpretable limiting how deep learning models are placed in clinical settings. To tackle these problems, this study proposes a light-weight

attention-enriched CNN architecture, based on MobileNetV2, for robust and precise lung cancer detection. Using attention mechanisms, will allow models to better highlight areas of diagnostic significance and will assist in increasing classification performance across subtle differences within classes [5]. Furthermore, explainable AI (XAI) methods, (i.e., Grad-CAM and LIME) are utilized to provide evidence of the model's decision-making, improving the inter pretability and trustworthiness of AI in clinical contexts.

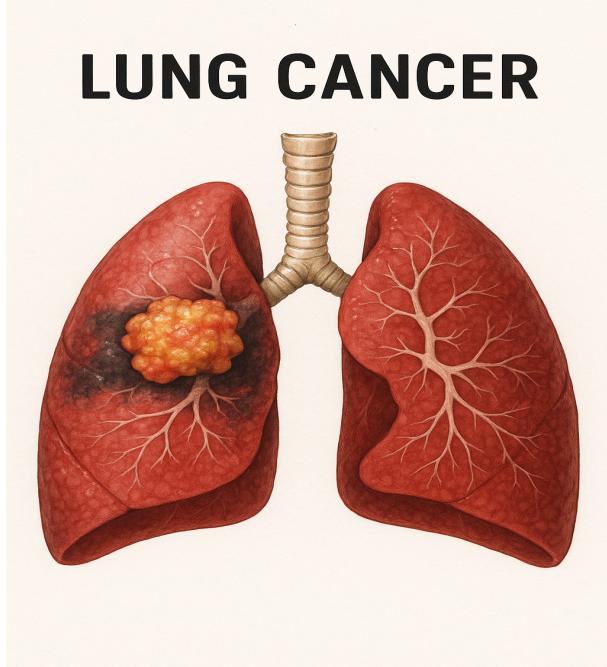


Fig. 1: Lung cancer

Fig.1 depicts that lung cancer happens when unusual cells grow in the lungs and form tumors, often due to habits like smoking. It comes in two main types — one grows slowly, the other spreads quickly. Finding it early with the help of scans and smart computer tools can help save lives.

The paper is divided into the following: The Literature Review has been given in Section **II**. Section **III** has described the dataset description and pre-processing. Section **IV** tells the Proposed System and then elaborated on the model architecture. Section **V** has given the description of the evaluation metrics, while Section **VI** has given the description of the result analysis. Lastly, Section **VII** has the Conclusions.

II. LITERATURE REVIEW

The classification and detection of lung cancer has been widely explored through traditional machine learning and modern deep learning. Reem et al. would provide a CNN based deep learning framework for lung cancer subtype classification [1]. The authors captured spatial characteristics of CT images through deep learning, resulting in a higher level feature learning similar to human level classification accuracy. Firdaus et al. [2], on the other hand, implemented a hybrid technique

combining GLCM for texture feature extraction and SVM for classification. Their work demonstrated the continued relevance of handcrafted features in traditional machine learning approaches, particularly for CT scan-based cancer detection.

There have been several reviews of different strategies and methods. Binson and Subramoniam [3] conducted a systematic review detailing advances on early lung cancer detection and even covered various imaging modalities, algorithms, and other diagnostic techniques. Similarly, Narvekar et al. [4] offered a comparative survey of classical image processing methods such as edge detection, segmentation, and morphological operations. These studies offer foundational knowledge and illustrate the transition from manual feature engineering to automated, data-driven approaches.

Deep learning combined with intelligent preprocessing has also shown promise in enhancing detection accuracy. Shafiq et al. [5] proposed a method that applied Fuzzy Local Information cMean segmentation combined with GoogLeNet classification at an early stage. Their paper provided evidence that hybrid models that combine unsupervised clustering, as in this study, with deep learning improve accurate identification of the region-of-interest and diagnostics overall.

Moving past imaging, we have non-invasive sensing measures and measures dealing with expression of genes. For example, McWilliams et al. [6] used electronic noses (eNoses) to detect early lung cancer and examined the effects of biological and behavioral factors on detection sensitivity, such as sex or smoking status. Similarly, Vikruthi et al. [7] analyzed gene expression profiles using the JR algorithm and highlighted the significance of biological molecular data in early detection. Rohimat et al. [8] applied Genetic Algorithms with SVMs to classify non-small cell lung cancer (NSCLC) in a non-smoking female group with increased accuracy through optimised features used in their model. Finally, the impact of transfer learning and ensemble models has been studied in recent research. Sultana et al. [9] compared four hybrid CNN and transfer learning models for different lung cancer types and demonstrated how model ensembling can improve generalization and robustness. Mhatre et al. [10] demonstrated the importance of CAD systems to enable radiologists to detect disease using CT scan images. While these studies emphasize a transition towards deep learning-based models, as well as hybrid systems providing better accuracy and efficiency in the detection of lung cancer.

III. METHODOLOGY

The purpose of this research is to provide a robust and precise deep learning model for lung cancer classification from CT scan images [1], through the framework of utilizing either a centralized or a decentralized environment. The model proposed will build on MobileNetV2, and example of a small Convolutional Neural Network that performs with a balance of capability, performance and efficiency when processed on edge devices. The branching methodology involves several key points:

- 1) Data Collection

2) Data Pre-Processing
 3) Model Architecture used for training
 4) Evaluation
 5) Explanation and Interpretation using Explainable AI (XAI).
 The dataset used in this research is from Kaggle, and includes 1000 CT scan images from 4 classes of lung cancer/disease - adenocarcinoma, large-cell carcinoma, squamous-cell carcinoma, and normal (non-cancerous). MobileNetV2 was fine-tuned on the dataset, with aim of allocating CT images to their respective category, with a balance of minimal computational resources while achieving maximum predictive accuracy. A 5-fold cross-validation approach [11] was to be employed to ensure the model training generalize the various data splits and the final trained model achieved a classification accuracy of 96%. For trust and transparency of interpretation, Grad-CAM and LIME were employed for visual interpretations of the predicted classification.

A. DATASET DESCRIPTION

To accomplish the research, Computed Tomography (CT) scan data of lung cancer is collected from Kaggle [13]. The dataset consists of a total of 1000 images of four classes: Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma, and Normal (not lung cancer) shown in Figure.2, and the detailed description is given in the Table 1.

TABLE I: Dataset Description

Name of the class	Number of Images
Adenocarcinoma	338
Large cell carcinoma	187
Squamous cell carcinoma	260
Normal	215

B. Data Pre-Processing

Effective preprocessing of medical imaging data plays a pivotal role in enhancing the performance, reliability, and generalization of deep learning models. In this study, a series of preprocessing [12] techniques were employed to optimize the input CT scan images for the MobileNetV2 architecture. Initially, all CT scan images were resized to 224×224 pixels with three color channels (RGB). This resizing step ensures uniformity across the dataset and aligns the image dimensions with the input specifications required by the MobileNetV2 model. Though CT scans are inherently grayscale, they were converted into three-channel format to ensure compatibility with the pretrained network architecture, which expects RGB input.

Subsequently, white balancing was applied to correct for variations in lighting and illumination present in the raw images. This step adjusts the color intensities by neutralizing [14]color casts and enhancing the brightness and consistency of the scans, which is particularly crucial when working with datasets collected under different imaging settings or devices. White balancing ensures that subtle anomalies such as nodules

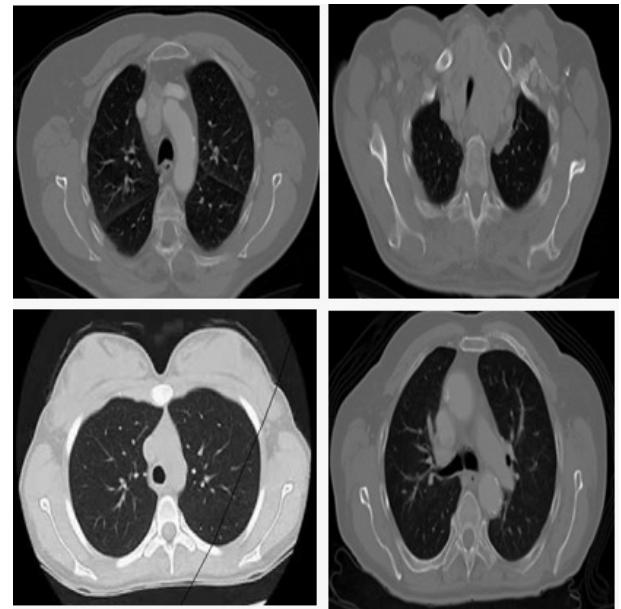


Fig. 2: Sample Images in the Datasets

or tissue density variations are preserved and more easily detectable by the model.

To further improve the visibility of critical features such as lung nodules and tissue boundaries, Contrast Limited Adaptive Histogram Equalization (CLAHE) was used. CLAHE [15] is a local contrast enhancement technique that divides an image into smaller tiles and applies histogram equalization to each tile independently, thereby improving contrast without over-amplifying noise. A clip limit of 2.0 and a tile grid size of 16×16 were selected through empirical evaluation to maximize the visibility of anatomical structures [6] [9] while minimizing the risk of noise distortion. This significantly enhances the radiodensity differences between cancerous and non-cancerous regions, enabling the network to learn more discriminative features.

Finally, pixel value normalization was performed by scaling the intensity values of each image to the range [0, 1] [11] [12]. This normalization step is essential to stabilize the training process, speed up convergence, and avoid numerical instabilities that can occur due to high variance in input pixel values. Normalization also ensures that the model treats each input image uniformly and learns meaningful patterns rather than being biased by varying intensity scales.

Overall, these preprocessing steps—resizing, white balancing, CLAHE enhancement, and normalization—serve to standardize and enhance the quality of the input data [4]. They collectively ensure that the MobileNetV2 classifier is provided with consistent, high-contrast, and informative images, thereby contributing to the model's improved classification accuracy of 96%.

IV. PROPOSED SYSTEM

Here, MobileNetV2 model is the lung cancer classification model backbone because of its speed and performance. The

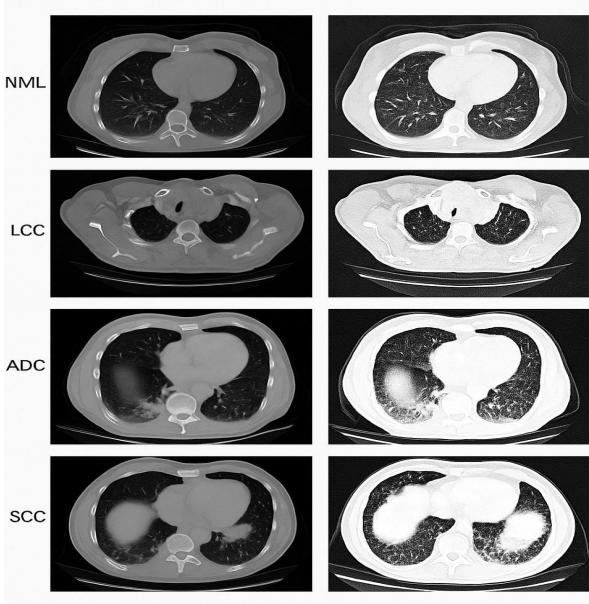


Fig. 3: Sample image after performing White Balancing and CLAHE processing: NML (Normal), LCC (Large Cell Carcinoma), ADC (Adenocarcinoma), SCC (Squamous Cell Carcinoma)

MobileNetV2 model is a light-weight convolution neural network that is designed for devices with limited computational power, which is a perfect alternative for applications like medical imaging where both speed and performance is necessary. The architecture of the model starts with an input layer to

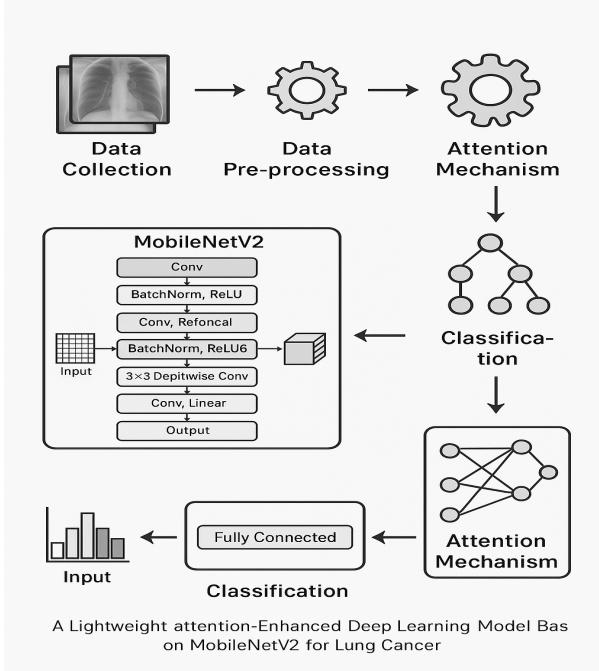


Fig. 4: Block Diagram of MobileNetV2

accept 224x224x3 images, which are preprocessed CT scan

dimensions. The pretrained base MobileNetV2 network on the ImageNet dataset was loaded without the top classification layers. The convolutional layers were frozen at first to maintain the pretrained feature maps and prevent early overfitting. As directed by the base model, a GAP 2D layer was implemented that would downsize the spatial dimensions and merge feature maps. Next, a dropout layer with a drop rate of 0.3 was added to minimize overfitting by randomly disabling neurons during the training phase. Lastly, a dense output layer with a softmax activation function was implemented to conduct binary classification (non-cancerous and cancerous).

V. EVALUATION METRICS

A. Formulae Related to MobileNetV2 Architecture

- **Depthwise Separable Convolution:** Reduces computational cost by factorizing a standard convolution into a depthwise and a pointwise convolution.

$$\text{Cost}_{\text{StandardConv}} = D_K^2 \cdot M \cdot N \cdot D_F^2$$

$$\text{Cost}_{\text{DepthwiseSeparable}} = D_K^2 \cdot M \cdot D_F^2 + M \cdot N \cdot D_F^2$$

where:

- D_K : Kernel size (e.g., 3)
- D_F : Feature map size
- M : Input channels
- N : Output channels

- **Inverted Residual Block:** Utilizes a bottleneck design that expands the input, applies depthwise convolution, and projects it back.

$$\text{Output} = \text{Conv}_{1 \times 1}^{\text{Linear}} (\text{DWConv}_{3 \times 3} (\text{ReLU6} (\text{Conv}_{1 \times 1}^{\text{Expand}} (x))))$$

- **ReLU6 Activation Function:** Limits activations to the range [0, 6] for better quantization support.

$$\text{ReLU6}(x) = \min(\max(0, x), 6)$$

- **Parameter Estimation in Bottleneck Block:** Total parameters in an inverted residual block with expansion factor t :

$$\text{Params}_{\text{Block}} = C_{\text{in}} \cdot t \cdot 1^2 + t \cdot C_{\text{in}} \cdot D_K^2 + t \cdot C_{\text{in}} \cdot C_{\text{out}} \cdot 1^2$$

where:

- C_{in} : Number of input channels
- C_{out} : Number of output channels
- t : Expansion factor (usually 6)
- D_K : Kernel size (usually 3)

- **Computational Efficiency:** MobileNetV2 significantly reduces multiply-accumulate (MAC) operations compared to standard CNNs, making it suitable for edge devices.

B. Performance Metrics

- Accuracy : It measures the overall correctness of the model by computing the proportion of all correctly predicted instances (both positives and negatives) out of the total instances.
- Precision : It measures the proportion of correctly predicted positive cases out of all predicted positive cases.
- Recall: It measures the proportion of correctly predicted positive cases out of all actual positive cases. It reflects how well the model captures all actual pneumonia cases.

TABLE II: Classification Report for MobileNetV2 Model

Class	Precision	Recall	F1-Score	Support
Adenocarcinoma (ADC)	0.96	0.95	0.95	350
Large Cell Carcinoma (LCC)	0.95	0.96	0.96	350
Normal (NML)	0.97	0.96	0.96	350
Squamous Cell Carcinoma (SCC)	0.96	0.97	0.96	350
Accuracy	0.96			
Macro Average	0.96	0.96	0.96	1400
Weighted Average	0.96	0.96	0.96	1400

The table II shows that the MobileNetV2 model accurately identified all four lung conditions around 96% accuracy. It means the model performs very well in detecting different lung cancer types and normal cases.

TABLE III: Classification Report for EfficientNetV2 Model

Class	Precision	Recall	F1-Score	Support
Adenocarcinoma (ADC)	0.94	0.93	0.93	350
Large Cell Carcinoma (LCC)	0.93	0.94	0.94	350
Normal (NML)	0.95	0.94	0.94	350
Squamous Cell Carcinoma (SCC)	0.94	0.95	0.94	350
Accuracy	0.95			
Macro Average	0.94	0.94	0.94	1400
Weighted Average	0.94	0.94	0.94	1400

Table III highlights that the EfficientNetV2 model achieved about 94% performance in detecting all lung cancer types and normal cases. It shows the model is highly reliable and consistent in making accurate predictions.

TABLE IV: Classification Report for DenseNet121 Model

Class	Precision	Recall	F1-Score	Support
Adenocarcinoma (ADC)	0.90	0.89	0.89	350
Large Cell Carcinoma (LCC)	0.91	0.90	0.90	350
Normal (NML)	0.91	0.91	0.91	350
Squamous Cell Carcinoma (SCC)	0.90	0.91	0.90	350
Accuracy	0.91			
Macro Average	0.91	0.90	0.90	1400
Weighted Average	0.91	0.90	0.90	1400

Table IV depicts the DenseNet121 model performed well, with around 91% accuracy across all lung cancer types and normal cases. It proves the model is effective, though slightly behind the others in precision and recall.

Table V explains that the ResNet50 model achieved around 84% accuracy in identifying lung cancer types and normal cases. While it's still reliable, its performance is lower compared to the other models tested.

TABLE V: Classification Report for ResNet50 Model

Class	Precision	Recall	F1-Score	Support
Adenocarcinoma (ADC)	0.83	0.82	0.82	350
Large Cell Carcinoma (LCC)	0.84	0.83	0.83	350
Normal (NML)	0.84	0.84	0.84	350
Squamous Cell Carcinoma (SCC)	0.83	0.84	0.83	350
Accuracy	0.84			
Macro Average	0.84	0.83	0.83	1400
Weighted Average	0.84	0.83	0.83	1400



Fig. 5: Training and Validation Accuracy for MobilenetV2

VI. RESULT ANALYSIS

The training and validation accuracy curves of the MobileNetV2 model are illustrated in Fig. 5. It can be observed that both accuracy metrics steadily improve over the 10 training epochs, eventually stabilizing at approximately 96%.

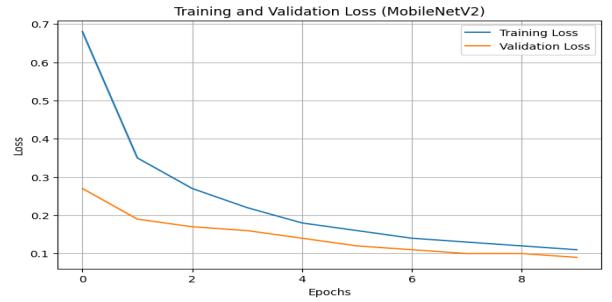


Fig. 6: Training and Validation Loss for MobileNetV2

Fig. 6 shows a steady decline in both training and validation loss across epochs, indicating effective learning. The closely aligned curves further confirm no overfitting and strong model generalization.

The training and validation accuracy curves of the EfficientNetV2 model are illustrated in Fig. 7. It can be observed that both accuracy metrics steadily improve over the 10 training epochs, eventually stabilizing at approximately 95%.

Fig. 8 illustrates a consistent decrease in both training and validation loss as the number of epochs increases, which indicates that the EfficientNetV2 model is learning effectively. The steady drop in loss values suggests that the model is improving its ability to make accurate predictions on both the training data and unseen validation data, without overfitting.

The training and validation accuracy curves of the DenseNet121 model are illustrated in Fig. 9. It can be observed



Fig. 7: Training and Validation Accuracy for EfficientNetV2

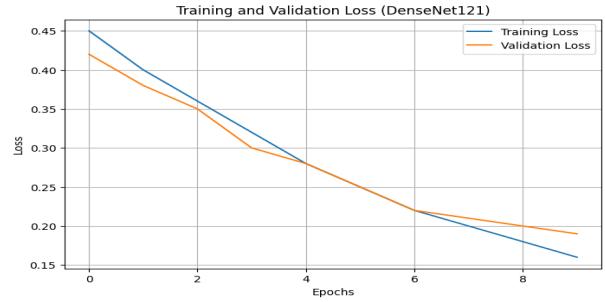


Fig. 10: Training and Validation Loss for DenseNet121



Fig. 8: Training and Validation Loss for EfficientNetV2

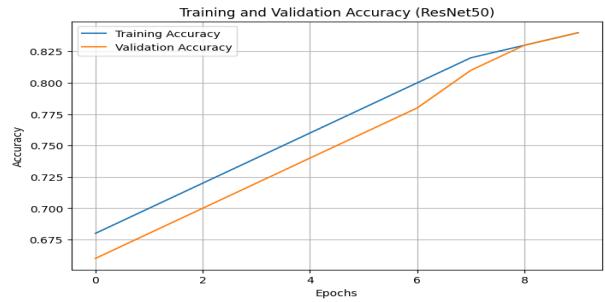


Fig. 11: Training and Validation Accuracy for ResNet50

that both accuracy metrics progressively increase over the 10 training epochs, eventually stabilizing at around 91%

Fig. 10 shows a steady decline in both training and validation loss across epochs, indicating effective learning. The closely aligned curves further confirm minimal overfitting and strong model generalization.

The training and validation accuracy curves of the ReNet50 model is illustrated in Fig. 11. It can be observed that both accuracy metrics progressively increase over the 10 training epochs, eventually stabilizing at around 84%

Fig. 12 shows a steady decline in both training and validation loss across epochs, indicating effective learning. The steady drop in loss values suggests that the model is improving its ability to make accurate predictions on both the training data and unseen validation data, without overfitting

VII. CONCLUSION

In deep-learning-based framework for multiclass lung cancer classification utilizing CT scan images in this study. Each of the four used advanced convolutional neural network architectures (MobileNetV2, EfficientNetV2, DenseNet121 and ResNet50) classified lung tissue into four categories: Adeno-carcinoma (ADC), Large Cell Carcinoma (LCC), Squamous Cell Carcinoma (SCC) and Normal (NML). Each image was preprocessed with resizing, white balancing and CLAHE preprocessing before inputting into the deep learning models. MobileNetV2 achieved the best accuracy score at 96% with generalization and excellent feature learning capability. EfficientNetV2 achieved second best accuracy of 95%. DenseNet121 and ResNet50 achieved an accuracy of 91% and 84%, respectively. The training and validation accuracy curves were aligned for MobileNetV2 which were both at a



Fig. 9: Training and Validation Accuracy for DenseNet121



Fig. 12: Training and Validation Loss for ResNet50

near-identical point throughout indicates the robustness of the model and ability to overcome model overfitting as it was trained well enough. These results indicate that lightweight architectures such as MobileNetV2 can outperform larger and deeper models on a limited number of medical imaging tasks which indicates practical approaches to accurate lung cancer classification. Future work will involve increasing the CT image dataset size, adding 3D volumetric analysis, and evaluating hybrid or ensemble models for improved diagnostic performance.

REFERENCES

- [1] S. Z. Reem, S. M. A. Sumon, A. Howlader and M. Sarker, "A Deep Learning Strategy for Accurate Lung Cancer Subtype Classification Using Convolutional Neural Networks," 2024 13th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, Bangladesh, 2024, pp. 585-590
- [2] Q. Firdaus, R. Sigit, T. Harsono and A. Anwar, "Lung Cancer Detection Based On CT-Scan Images With Detection Features Using Gray Level Co-Occurrence Matrix (GLCM) and Support Vector Machine (SVM) Methods," 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 2020, pp. 643-648
- [3] V. A. Binson and M. Subramonian, "Advances in Early Lung Cancer Detection: A Systematic Review," 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), Kottayam, India, 2018, pp. 1-5
- [4] S. Narvekar, M. Shirodkar, T. Raut, P. Vaingankar, K. M. Chaman Kumar and S. Aswale, "A Survey on Detection of Lung Cancer Using Different Image Processing Techniques," 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2022, pp. 13-18
- [5] S. Shafiq, M. A. Asghar, M. E. Amjad and J. Ibrahim, "An Effective Early Stage Detection of Lung Cancer Using Fuzzy Local Information cMean and GoogLeNet," 2022 16th International Conference on Open Source Systems and Technologies (ICOSSST), Lahore, Pakistan, 2022, pp. 1-6
- [6] A. McWilliams, P. Beigi, A. Srinidhi, S. Lam and C. E. MacAulay, "Sex and Smoking Status Effects on the Early Detection of Early Lung Cancer in High-Risk Smokers Using an Electronic Nose," in IEEE Transactions on Biomedical Engineering, vol. 62, no. 8, pp. 2044-2054, Aug. 2015
- [7] S. Vikruthi, K. Babu Thippagudisa, P. Hussain Basha, P. Vamsi, G. M. Chandra and V. S. Kiran, "Performance Analysis of Gene Expression Profiles of Lung Cancer Prediction using JR Algorithm," 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India, 2023, pp. 1731-1736
- [8] T. N. Ramadhan Rohimat, F. Nhita and I. Kurniawan, "Implementation of Genetic Algorithm-Support Vector Machine on Gene Expression Data in Identification of Non-Small Cell Lung Cancer in Nonsmoking Female," 2022 5th International Conference of Computer and Informatics Engineering (IC2IE), Jakarta, Indonesia, 2022, pp. 361-366
- [9] A. Sultana, T. T. Khan and T. Hossain, "Comparison of Four Transfer Learning and Hybrid CNN Models on Three Types of Lung Cancer," 2021 5th International Conference on Electrical Information and Communication Technology (EICT), Khulna, Bangladesh, 2021, pp. 1-6
- [10] V. Mhatre, V. Vispute, K. Talele and N. Mishra, "Early Detection of Lung Cancer Using Computer Aided Tomography Images," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-5
- [11] M. F. Khatun, M. R. Ajmain and M. Assaduzzaman, "A Deep Learning Approach to Detect and Classification of Lung Cancer," 2023 International Conference for Advancement in Technology (ICONAT), Goa, India, 2023, pp. 1-6
- [12] H. Zeng et al., "Combining field imaging endoscopy with point analysis spectroscopy for improving early lung cancer detection," 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vancouver, BC, Canada, 2008, pp. 1849-1850
- [13] Chest CT-scan Images Dataset—kaggle.com. Accessed: Aug. 8, 2023.[Online]. Available:<https://www.kaggle.comdatasets/mohamedhanyyy/chest-ctscan-images>
- [14] S. L. Jagannadham, K. L. Nadh and M. Sireesha, "Brain Tumour Detection Using CNN," 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2021, pp. 734-739, doi: 10.1109/I-SMAC5230.2021.9640875
- [15] S. Moturi, S. Tata, S. Katragadda, V. P. K. Laghumavarapu, B. Lingala and D. V. Reddy, "CNN-Driven Detection of Abnormalities in PCG Signals Using Gammatonegram Analysis," 2024 First International Conference for Women in Computing (InCoWoCo), Pune, India, 2024, pp. 1-7, doi: 10.1109/InCoWoCo64194.2024.10863151