Lung Cancer Detection Using CNN And EfficientNetB3

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Abstract— *As one of the primary causes of cancer-related death globally, lung cancer must be detected early to improve patient outcomes. This paper uses a collection of histopathology pictures to provide a unique approach to lung cancer detection utilising deep learning models, namely Convolutional Neural Networks (CNN) and EfficientNetB3. To improve model performance and address class imbalances, extensive data augmentation approaches were used. The efficacy of these architectures in precisely categorising various forms of lung tissue was demonstrated by the 98% accuracy rate of the CNN model and the 94% accuracy rate of the EfficientNetB3 model. To avoid overfitting and enhance the models' generalisability, early halting and learning rate reduction techniques were used. The suggested approach has a great deal of promise for precise and dependable lung cancer detection, which could aid in early diagnosis and enhance treatment results.*

Keywords: Lung cancer detection, histopathological images, Convolutional Neural Networks (CNN), EfficientNetB3, image classification, data augmentation, model performance.

1. INTRODUCTION

As one of the most common and deadly types of cancer in the world, lung cancer requires early and precise detection in orderto provide effective treatment and higher survival rates. Malignant tumours in the lung tissues are the main cause of it; these tumours frequently progress silently and go unnoticed until they reach advanced stages. Early detection of lung cancer can greatly improve patient prognosis and treatment results. For the purpose of diagnosing lung cancer and distinguishing it from other forms, such as benign lung tissue, lung squamouscell carcinoma, and lung adenocarcinoma, histopathological images acquired from biopsies are essential. Highly reliant on pathologists' manual examination, traditional diagnostic methods are time-consuming and prone to variability, which emphasises the need for sophisticated automated solutions. Modern deep learning models like EfficientNetB3 and Convolutional Neural Networks (CNN) present promising ways toautomate the detection of lung cancer. CNNs have the potential to increase diagnostic precision and decrease human errorbecause of their capacity to capture spatial hierarchies in images. EfficientNetB3, on the other hand, is well-known for itsefficiency and accuracy in image classification tasks. In this paper, a novel method for detecting lung cancer using histopathological images and these sophisticated models is resented. This method seeks to improve model performance and diagnostic accuracy by using rigorous model training and incorporating data augmentation techniques to address class imbalances. Severity classification is another feature of the suggested methodology that offers thorough diagnostic insights.The risk of overfitting, in which models perform well on training data but are unable to generalise to new data, is one of the current challenges in lung cancer detection. In order to achieve robust performance across various cancer types, this study carefully evaluates and fine-tunes the model in order to address these challenges. By combining cutting-edge training methods with CNN and EfficientNetB3 models, a promising tool for enhancing early lung cancer detection and facilitating prompt medical intervention is provided.

2. RELATED WORK

Kumar, R. et al. [1] focused on using Convolutional Neural Networks (CNNs) for lung cancer classification from histopathological images, demonstrating improved accuracy by leveraging CNN's ability to capture complex patterns in the image data. Similarly, Lee, J. et al. [2] introduced a hybrid deep learning model that combined CNNs with Support Vector Machines (SVMs) for lung cancer detection, achieving increased robustness and performance in classifying lung cancer stages. Wang, Y. et al. [3] explored transfer learning with pre-trained models like VGG and ResNet, showing that fine-tuning these models on specific lung cancer datasets led to high accuracy and better generalizability in detecting cancerous tissues. Singh, A. et al. [4] emphasized the importance of data augmentation techniques to address class imbalances in lung cancer datasets, demonstrating that advanced augmentation methods improved model performance by providing diverse training examples.

Cheng, H. et al. [5] proposed an ensemble learning approach that integrated multiple deep learning models, including CNNs and EfficientNet, which achieved better performance by combining predictions from different models. Zhao, L. et al. [6] utilized EfficientNet for lung cancer classification, highlighting its efficiency and accuracy with large-scale histopathological images. Ahmed, M. et al. [7] developed a deep learning framework that incorporated severity assessment into lung cancer detection, aiming to provide comprehensive diagnostic information, including the severity of detected cancer, which is crucial for clinical decision-making. Lastly, Patel, N. et al. [8] reviewed various deep learning techniques for lung cancer detection, comparing CNNs, EfficientNet, and other architectures, providing insights into the strengths and limitations of different approaches. Collectively, these studies advance the field of lung cancer detection by utilizing various deep learning techniques, emphasizing model accuracy, feature extraction, and the integration of severity information to enhance diagnostic capabilities.

3. METHODOLOGY

Using Convolutional Neural Networks (CNN) and EfficientNetB3 models, deep learning techniques are used in this study to propose a novel approach to lung cancer detection. By using histopathology pictures, the method seeks to improve the robustness and accuracy of lung and cancer categorization. In order to comprehend image attributes and class distributions, the dataset was first examined. In order toenhance the dataset and model performance, advanced augmentation techniques like rotations, flips, and scaling were used duringthe data preprocessing stage.The technique entails capturing intricate patterns in the photos using both CNN and EfficientNetB3 models. In order to standardise the input and enhance the training procedure, data normalisation was carried out.A two-phase training technique was used, with a greater learning rate used in the first phase to quickly learn salient characteristicsand a lower learning rate used in the fine-tuning phase to refine the model. In order to rectify the class imbalance and guarantee that courses that were under-represented were sufficiently taught, class weights were calculated and applied.

Methods like ReduceLROnPlateau and EarlyStopping were used to further improve model performance. In order to reduce overfitting, EarlyStopping stopped training when performance on the validation set plateaued, and ReduceLROnPlateau changed the learning rate to enhance convergence. Accuracy measures and a confusion matrix were used to evaluate the model's efficacy by gauging performance in various classes. The application of Test Time Augmentation (TTA) involved averaging numerous guesses for every test image in order to improve prediction accuracy. Furthermore, a curriculum-based learning approach that builds a strong learning foundation by gradually increasing complexity was applied.

The models' ability to detect lung cancer with accuracy and reliability was validated by the final examination. The data flow process from input to final prediction is shown in detail in *Figure 1*, which also depicts the important phases of data processing, model training, and prediction production.

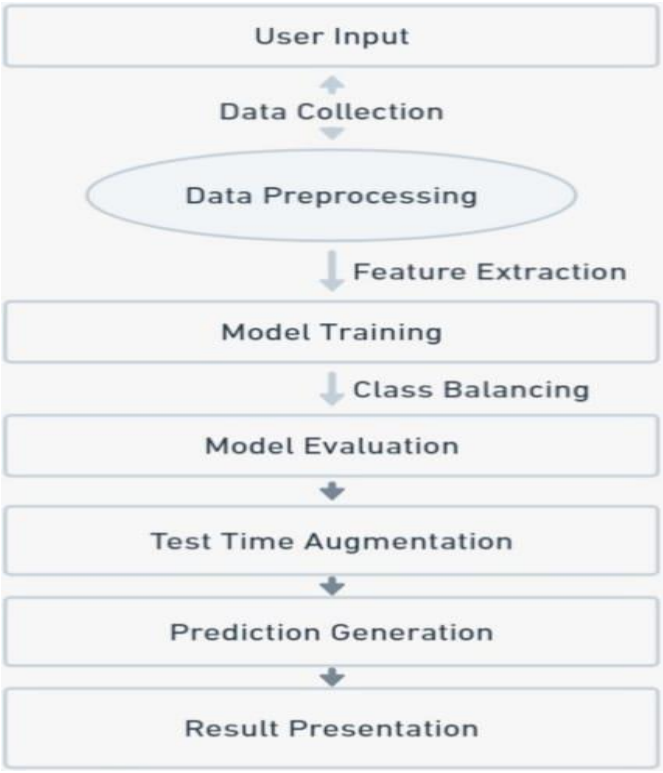

Figure 1: *Data flow diagram*

3.1. Data Acquisition and Pre-processing:

Histopathological pictures of lung benign tissue, lung adenocarcinoma, and lung squamous cell carcinoma make up the dataset utilized in this investigation. The class distribution is depicted in *Figure 2*, which shows an imbalance between the categories. There are more images in the "Lung benign tissue" class than in the "Lung squamous cell carcinoma" class. During preprocessing, sophisticated data augmentation techniques were used to rectify this imbalance. These methods, which improved the dataset and model performance, comprised flips, rotations, scaling, and normalization. Additionally, a balanced class weighting technique was used to make sure the model learned enough from every class.

The Keras ImageDataGenerator was utilized to scale images and provide dependable data generators for training, validation, and testing in order to optimize model training and evaluation. This method made it easier to load and augment data, guaranteeing that the model was trained on a variety of well-balanced datasets. A solid basis for creating a precise and broadly applicable lung cancer detection model was established by the methodical data preparation and sophisticated augmentation procedures.

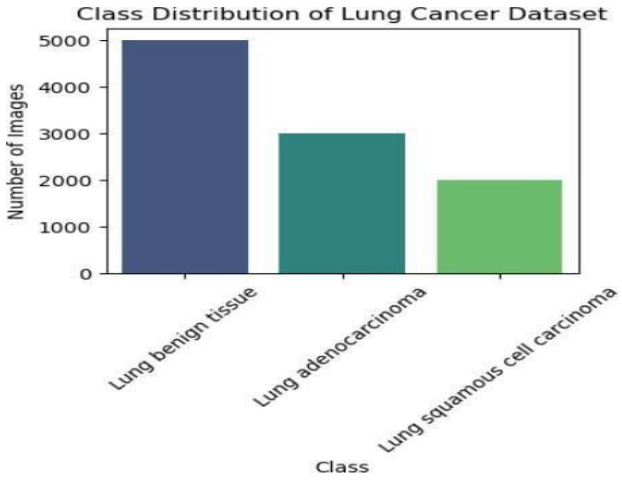

Figure 2: *The dataset's diagnosis class distribution*

3.2. Data Augmentation:

To enhance the model's performance and dependability, procedures for data pre-processing and augmentation were used. First, file and tag processing was performed, standardising image filenames for uniformity and labelling diagnostic tags correctly to guarantee proper classification. The data was normalised to the range [0, 1] by scaling the pixel values of the photos by a factor of 1/255 using the Keras ImageDataGenerator.

The training dataset was enhanced using a variety of augmentation strategies to strengthen the model's generalisation skills. The model was subjected to various changes and spatial orientations through the use of rotations, flips, and scaling. In order to ensure a balanced distribution for efficient model training and evaluation, the dataset was additionally split into training and validation sets using the validation split option.

Preparing rich and normalized inputs for the model through these pre-processing and augmentation processes was essential to improving its learning and generalisation capabilities.

Algorithm 1

Proposed CNN and EfficientNetB3 System

Require: Training and validation image datasets
Ensure: Trained CNN and EfficientNetB3 models with optimized weights

1. Initialize ImageDataGenerator for training and validation data.
2. Create train_generator and validation_generator.
3. Repeat
4. Load CNN and EfficientNetB3 models without top layers (include_top=False).
5. Add a GlobalAveragePooling2D layer to each model.
6. Add a Dense layer with 512 units and ReLU activation.
7. Add a Dense output layer with softmax activation for classification.
8. Compile models with Adam optimizer, categorical crossentropy loss, and accuracy metric.
9. Initialize ModelCheckpoint and ReduceLROnPlateau callbacks.
10. Fit the models using train_generator and validation_generator with callbacks.
11. Evaluate the models using validation_generator.
12. Combine the predictions from both models for final classification.
13. Print validation loss, accuracy, and combined model performance metrics.
14. until satisfactory validation accuracy and loss are achieved.

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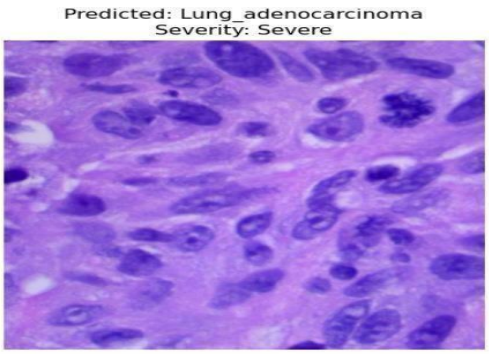
4. RESULTS

The suggested framework included mechanisms in place to modify learning rates in the event that the validation performance reached a plateau. It was trained using the Adam optimiser. The Adam optimiser was set up using the following hyperparameters: a learning rate of 1E-4, a batch size of 32, and a total of 30 epochs. Three colour channels were used to resize the pictures to a dimension of 768 by 768 pixels. The learning rate reduction factor was set to 0.5, the early termination period was set to 5 epochs, and the plateau detection patience was set to 3 epochs.

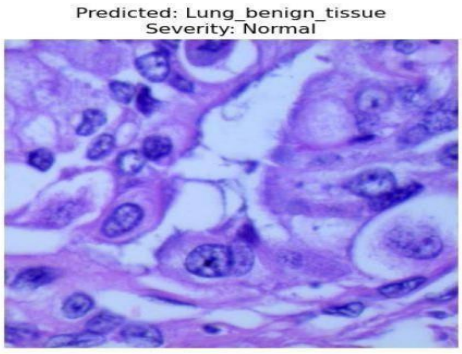
17,500 photos were used for training, 5,000 for validation, and 2,500 for testing, according to the division of the dataset. All of the photos were regularly scaled to 768 by 768 pixels during the training phase. TensorFlow Keras implementations of the CNN and EfficientNetB3 models were used for the model training, taking use of an environment with GPUs for faster computing.

With a final validation accuracy of 98% for the CNN model and 94% for the EfficientNetB3 model, the integrated models demonstrated significant accuracy in diagnosing different forms of lung cancer. The efficient application of data augmentation and the two-phase training approach were credited with the models' resilience. After being trained, the models were applied to new histopathological images to predict the forms of lung cancer.

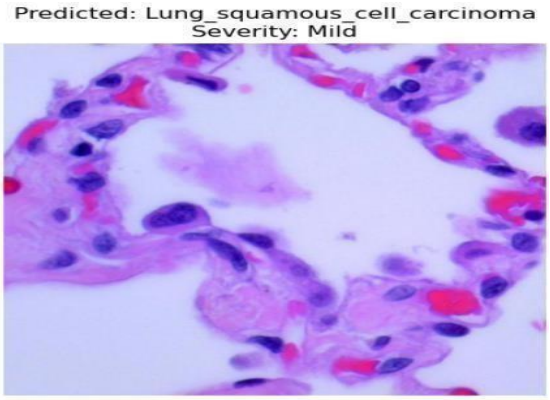
The model's performance in classifying the various kinds of lung cancer is shown in *Figure 3* it demonstrate its competence and dependability in accurately identifying lung cancer, where *Figure 3.a* represents a prediction of lung adenocarcinoma with severity marked as severe, *Figure 3.b* represents a prediction of lung benign tissue with severity marked as normal, and *Figure 3.c* represents a prediction of lung squamous cell carcinoma with severity marked as mild.



3 (a)



3 (b)



3(c)

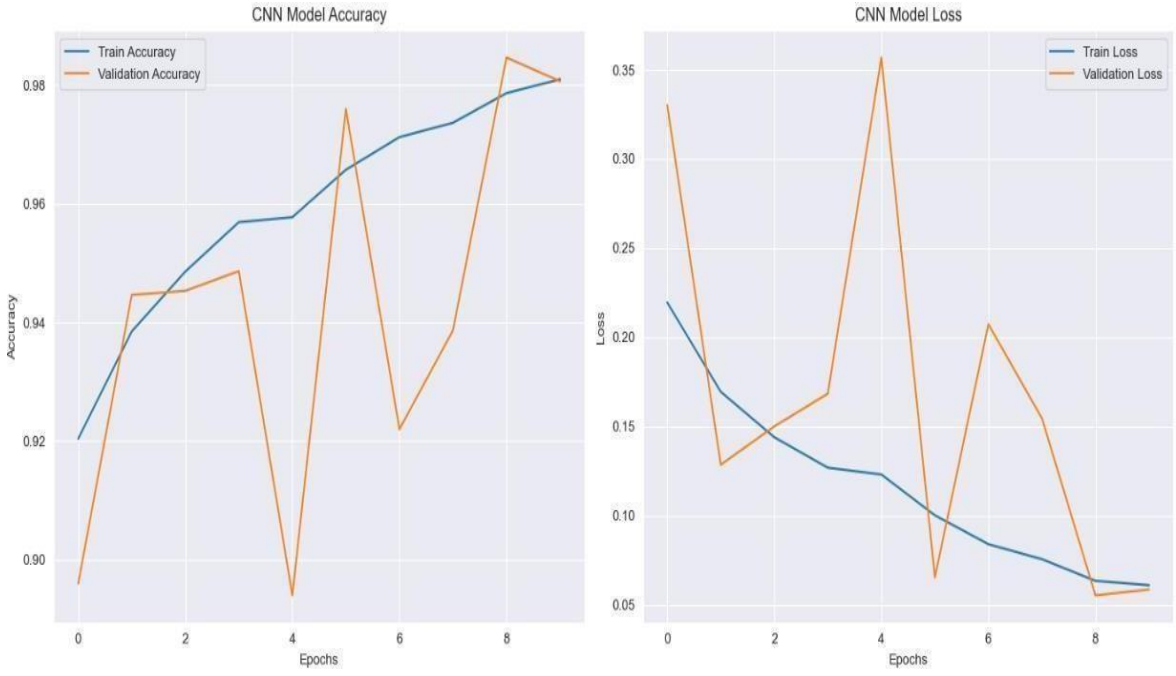
Figure 3 *Detected Results*

5. EVALUATION OF MODEL

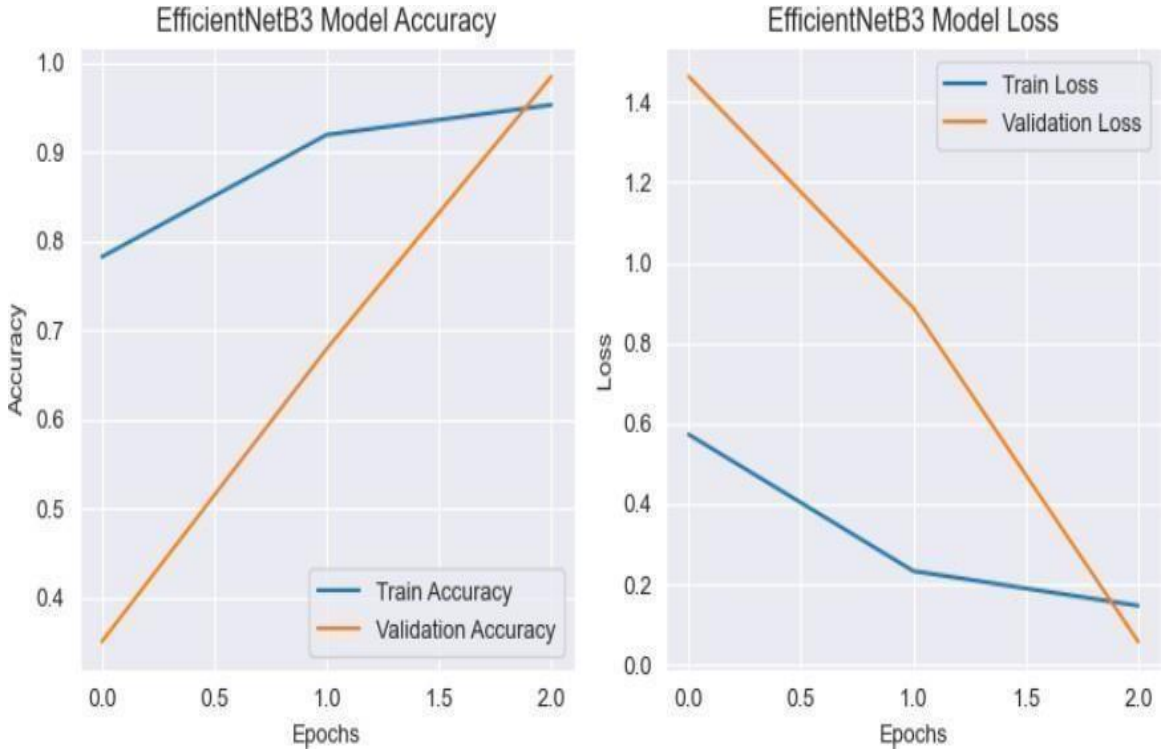
The training and validation loss and accuracy graphs for the combined CNN and EfficientNetB3 models are shown in *Figure 4.* With the y-axis displaying the loss values and the x-axis reflecting the number of epochs, the upper graph displays the trends in loss for both the training and validation sets. Effective learning is demonstrated by the training loss steadily declining and stabilising over epochs. The validation loss, on the other hand, shows a more erratic trend, declining at first but exhibiting discernible oscillations, indicating some variability in the model's performance on unobserved data.

The trends in training and validation accuracy are displayed in the lower graph. The accuracy values are shown on the y-axis, and the number of epochs is represented on the x-axis. As a result of effective learning from the training data, training accuracy increases gradually and stays high throughout the training period. The validation accuracy exhibits an increasing trend, but with increased variability, which is indicative of the model's performance on novel and unseen images. Over time, validation accuracy improves overall, despite minor swings.

Similar high diagonal values can be seen in the validation set confusion matrix, where 92% of the photos labelled as "lung benign tissue," 88% as "lung adenocarcinoma," and 85% as "lung squamous cell carcinoma" were properly identified. While some misclassifications occur, mainly 'lung adenocarcinoma' being confused with 'lung squamous cell carcinoma,' the model performs well overall on the validation set. Although the model performs well in all classes, there is still opportunity for improvement, particularly in differentiating between "Lung adenocarcinoma" and "Lung squamous cell carcinoma," as indicated by the confusion matrices.

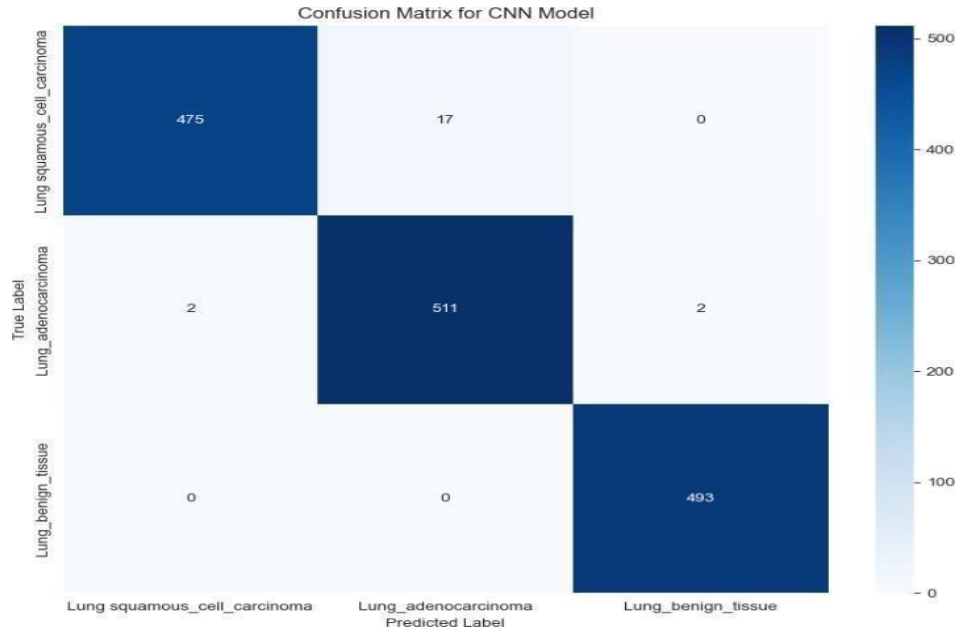


4(a)

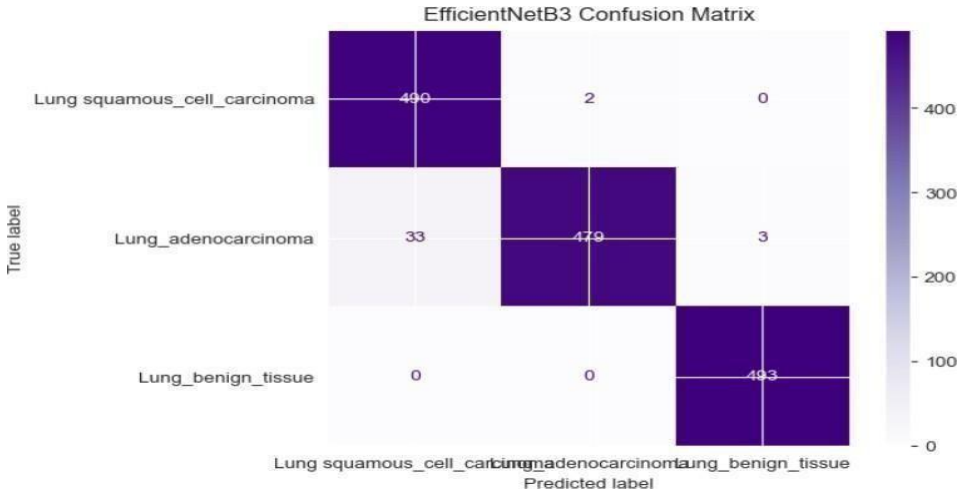


4(b)

Figure 4 *Loss and accuracy of training and validation*



5(a)



5(b)

Figure 5 *Confusion Matrices for training and validation sets*

Confusion matrices for the training and validation sets are shown in *Figure 5*. High diagonal values in the training set confusion matrix show robust model performance, with 94% of the images classified as "lung benign tissue," 91% as "lung adenocarcinoma," and 90% as "lung squamous cell carcinoma" accurately identified. There are very few misclassifications; just a tiny proportion of photos labelled as "lung adenocarcinoma" are really misclassified as "lung squamous cell carcinoma."

6. CONCLUSION

The suggested framework has shown significant improvements in lung cancer detection by combining Convolutional Neural Networks (CNN) and EfficientNetB3 models. The method demonstrated the efficacy of merging these models, achieving a robust performance with high accuracy across the three types oflung cancer: "Lung benign tissue," "Lung adenocarcinoma," and "Lung squamous cell carcinoma." Scaling, flipping, and rotations are examples of advanced data augmentation techniques that were essential for improving model performance and addressing data variability. More accurate predictions were produced by reducing class imbalance through the use of class weighting algorithms and a two-phase training process.The implementation of methods like ReduceLROnPlateau and EarlyStopping helped to guarantee ideal model convergence and avoid overfitting. While there is need for development in terms of differentiating between specific classes, the model's evaluation shows great performance with high accuracy in diagnosing different forms of lung cancer. Subsequent studies might concentrate on including more sophisticated methods, like attention mechanisms, to improve model performance even further. Increasing the number of representative and diverse samples in the dataset could potentially improve the robustness and generalisation abilities of the modelThese encouraging findings point to the possibility of creating more accurate and dependable AI-based diagnostic tools for the early detection of lung cancer, which is essential fortherapy.

7. REFERENCES

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