EfficientNetB1 Model for Lung Cancer Detection using Biopsy Images

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***Abstract*—Lung cancer, a pervasive and life-threatening ailment, necessitates early and precise diagnosis. This research endeavors to employ Convolutional Neural Networks (CNNs) to automate the detection of lung cancer in histopathological biopsy images, addressing challenges associated with timely and accurate diagnosis. Given the error-prone and time-consuming nature of manual assessment by pathologists, an automated approach becomes imperative. The study encompasses a comprehensive scope, including enhancing interpretability, classifying specific lung cancer subtypes, real-time intraoperative analysis, and extending the application to other cancer types. The methodology involves the utilization of a pre-trained Efficient Net-based model for image classification, showcasing its efficacy in discerning between benign and malignant lung cancer cells, as evidenced by robust training results. Moreover, the model exhibits potential for personalization in lung cancer diagnosis and treatment. Research findings affirm that machine learning models, specifically the EfficientNet-based architecture, markedly improve lung cancer detection accuracy. The model's proficiency in subtype differentiation and its capacity for real-time surgical analysis represent significant strides in lung cancer diagnostics and treatment. In conclusion, this project addresses the critical imperative for accurate and timely lung cancer diagnosis, providing a promising advancement in combatting this devastating disease. The developed model holds transformative potential in radiology and oncology, serving as a valuable tool for medical professionals and contributing to enhanced patient outcomes.**

Keywords—EfficientNet-based model, Convolutional Neural Networks (CNNs), Cancer detection.

I. INTRODUCTION

The most recent IARC research estimates that there will be over 19.29 million new instances of cancer worldwide in 2021, with the United States accounting for roughly 11.8% of these cases, making it the country with the second-highest percentage of new cases worldwide [9]. At 11.4 percent of all cancer cases, lung cancer is still significantly more common than other cancer forms. [10]

There are numerous phases involved in diagnosing an illness, from gathering samples to educating specialists to make decisions based on the findings. Grouping and forecasting of many biological data types have been carried out with AI techniques. By utilizing deep learning (DL) techniques, computers can already interpret and handle high-dimensional information, such as images, 3D body scans, and motion pictures. Machine learning methods comprise a number of procedures for managing digital data. Initially, pre-processing is employed to eliminate any potentially affecting noise from the raw photos, ensuring their precision. Every unique feature of the picture that was saved throughout the preparatory stage is obtained during the feature extraction step. After that, in the feature selection process, the most important traits are identified from the extracted data [11].

The code represents a comprehensive deep learning approach to lung cancer classification using a pre-trained EfficientNetB1 model. It begins by setting up the necessary environment, including configuring random seeds and defining constants. The dataset, consisting of lung images categorized into three classes (No Cancer, Adenocarcinoma, Squamous Cell Carcinoma), is then prepared for training and validation. A Convolutional Neural Network (CNN) model is constructed, incorporating a pre-trained EfficientNetB1 base with frozen weights, followed by additional dense layers for feature extraction and classification. The training process involves compiling the model with the Adam optimizer and sparse categorical cross entropy loss, and training is monitored using callbacks, including learning rate reduction on plateau. The model's performance is visualized through accuracy and loss plots.

The code also includes data visualization elements, such as a bar plot illustrating the distribution of classes in the dataset. A confusion matrix and a classification report are generated to evaluate the model's performance on a validation subset. Furthermore, the script demonstrates how to save and load model weights for future use. Finally, sample predictions on the validation dataset are visualized to assess the model's ability to correctly classify lung images. Overall, the code provides a holistic framework for building, training, evaluating, and visualizing a deep learning model for lung cancer classification.

II. REVIEW OF THE LITERATURE

In [1], the paper introduces a hybrid deep learning model designed for the classification of lung tissue images from the Lung and Colon Cancer Histopathological Image dataset. This model incorporates three sub-extractors: the

inception_v3 network, HOG, and Daisy, which extract image features from various perspectives. The extracted features are subsequently input into a 3-layer Fully Connected Network for classification. Notably, the model achieves an impressive accuracy of 99.97% on the validation set, demonstrating high accuracy across different cancer types. In summary, the proposed model effectively classifies lung tissue images with precision.

In [2], the paper explores lung carcinoma detection through deep learning methods, specifically employing Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNNs). These methods exhibit potential in precisely identifying and classifying nodules in chest radiographs or CT scans. To enhance detection results and computational efficiency, the study incorporates Particle Swarm Optimization (PSO). The PSO-RNN method for lung cancer diagnosis is developed using training and testing data from CT scans of 19 patients, with the goal of reducing training time and improving detection accuracy.

In [3], lung cancer is acknowledged as a lethal disease, prompting the utilization of deep learning to identify small cells in histopathological images. The significance of data preprocessing in categorizing pathological images is emphasized, and data visualization is employed to enhance the comprehension of large datasets. Artificial neural networks are utilized for categorizing medical images, and the paper underscores the importance of early detection of lung cancer for improved treatment options.

In [4], the research centers on employing Deep Learning (DL) and Digital Image Processing (DIP) to automate the identification of cancer cells, specifically targeting colon and lung cancer. The study illustrates the efficacy of AI-guided diagnosis in precisely classifying cancer cells and expediting the diagnostic process. Furthermore, the utilization of Convolutional Neural Networks (CNN) has yielded promising results, achieving a notable 96% accuracy in identifying polyps in colonoscopy images.

In [5], a hybrid lung cancer classification model is introduced, attaining an impressive accuracy of 99.96% through the application of deep learning. The model incorporates Inception_v3, HOG, and DAISY feature extraction methods. Implemented in Python 3.7.9 with PyTorch 1.7.1 and Torchvision 0.8.2, the study utilizes the Lung and Colon Cancer Histopathological Image dataset. Evaluation metrics encompass accuracy, weighted average precision, recall, and F1-Score. The visualization of confusion matrix results for models employing different feature extractors is also presented.

In [6], the document outlines a study focused on classifying lung cancer images through the application of various machine learning algorithms. It provides in-depth details on the catBoost algorithm, as well as linear discriminant analysis (LDA), linear regression (LR), and classification and regression trees (CART). The research employs a dataset comprising 15,000 lung cancer histopathological images and attains a substantial prediction accuracy of 99.80% with the CatBoost algorithm. Additionally, the document delineates the methodology, encompassing data analysis, image processing, and classification, with the objective of improving early detection and prediction of lung cancer through deep learning-based models.

In [7] Lung cancer is a major concern, with AI models being used to assist in classifying cancer cells. EfficientNetB2 showed superior accuracy, and clustering techniques were used for grading. The study aims to alleviate the burden on pathologists, especially in regions with limited access to pathological centers. Histopathological images provide detailed insights into cancer grade, enabling the development of accurate AI models. Various datasets and models have achieved accuracies ranging from 86% to 99%.

In [8], The research presents a deep-learning approach for lung cancer detection using histopathological images. The proposed CNN model outperforms previous methods, achieving over 99.5% accuracy. The study validates the model's effectiveness using a dataset of lung histopathology images. The research contributes a lightweight deep-learning strategy for accurate lung cancer diagnosis, integrating feature extraction and classification. The findings demonstrate the potential of end-to-end CNN-based systems for automated computer-aided lung cancer detection.

With such small data sets, earlier research produced somewhat meager outcomes. In addition, a number of prior procedures are intricate and suffer from overfitting and imbalance issues. In this study, we present a novel approach that can accurately overcome the aforementioned shortcomings of previous work in this field on both small and large data sets. Furthermore, the proposed model is an end-to-end lightweight model that lowers computing complexity.

III. Approach

This section provides an overview of the dataset used in this study. An overview of the recommended lung cancer detection technique is then given.

A. Description of the Histopathological image dataset used

We used the LC25000 dataset [22] to provide a score to our study. This dataset's 25,000 images were divided into 5 groups, each containing 5,000 pictures. Every JPEG image is 768 pixels by 768 pixels in resolution. The lung squamous cell carcinomas, lung adenocarcinomas, benign lung tissues, and colon adenocarcinomas are the five categories. We decided on the class associated with lung cancer. All the data in this study have been standardized to have dimensions of (32, 180, 180, 3). Twelve thousand images, or 0.8 percent of the total, were set aside for training, and three thousand images, or 0.2 percent, were set aside for testing. Figure 1 displays pictures from the LC2500 lung histopathology sample. The first set of images is labeled for adenocarcinoma, the second for benign tissue, and the third for squamous cell carcinoma.

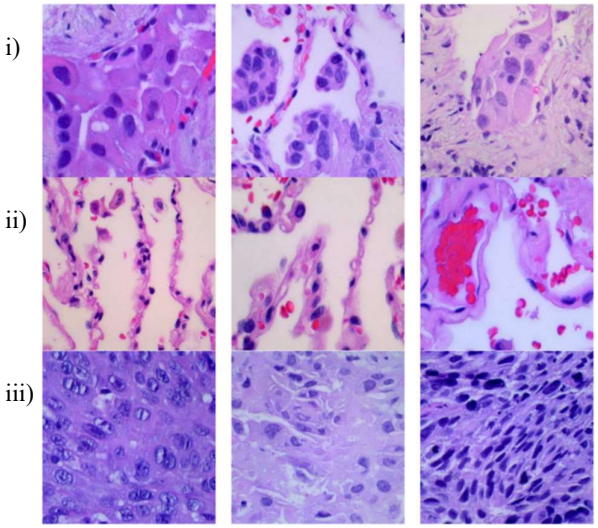

Fig. 1. Images of lung histopathological samples: (i) adenocarcinoma, (ii) benign tissue, (iii) squamous cell carcinoma.

B. *The Proposed Approach*

Our findings present a comprehensive approach to developing and evaluating a deep learning model for the classification of lung images into three distinct categories: "No Cancer," "Adenocarcinoma," and "Squamous Cell Carcinoma." The methodology encompasses several key stages, each aimed at ensuring robust model performance and providing insights into the classification process. Initially, the paper details the data preprocessing and exploration phase, wherein the lung image datasets are loaded and processed using TensorFlow's image dataset utilities.

The datasets are split into training and validation sets, and an analysis of class distribution is conducted to identify potential data imbalances. Visualizations, including bar plots, are employed to illustrate the distribution of images across different classes, facilitating a deeper understanding of the dataset's characteristics. Subsequently, the model construction and training strategy are described, focusing on the utilization of transfer learning with the EfficientNetB1 architecture as the base model. Additional dense layers are appended to the base model to facilitate classification. The training process is managed through the implementation of appropriate callbacks, including early stopping and learning rate reduction, to prevent overfitting and optimize model performance. Performance metrics such as accuracy and loss are monitored and visualized over 25 epochs to track the model's learning progress. Figure 2 illustrates the suggested model's architecture. Following model training, the paper discusses the evaluation phase, wherein the trained model is assessed using the validation dataset. Sample predictions are generated and visualized to provide qualitative insights into the model's performance. Additionally, quantitative analyses, including the generation of a confusion matrix and a classification report, offer a more in-depth understanding of the model's classification accuracy and potential areas for improvement. Moving on, we further explore avenues for further analysis and visualization, including the visualization of learning rate schedules and the generation of sample predictions on the validation dataset. These analyses contribute to a comprehensive understanding of the model's learning process and predictive capabilities, enhancing the interpretability and reliability of the classification results.

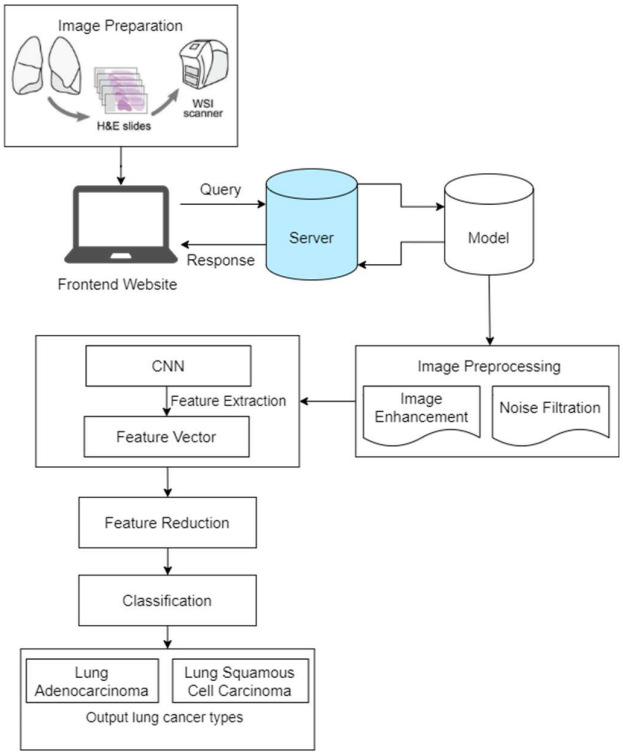

Fig. 2. System Architecture of the CNN model.

IV. RESULTS

In this study, histopathology images were utilized to construct a deep learning framework aimed at classifying lung cancer. The proposed convolutional neural network (CNN) model was assessed using histological images of lung cancer employing the EfficientNetB1 architecture, and the outcomes were subjected to thorough analysis.

The data were partitioned using an 80-20 split for training and testing, respectively, employing Python 3.7. Key performance metrics, including accuracy, precision, recall, and F1-score, were prioritized for evaluating the system's generalization and classification capabilities. The dataset consisted of a total of 5000 images across three classes: No Cancer, Adenocarcinoma Class, and Squamous Cell Carcinoma Class.

The specific definitions of these metrics are elaborated below:

- Precision = $\frac{Tp}{Tp+FP}$
- Recall = $\frac{Tp}{Tp+Fn}$
- Accuracy = $\frac{Tp+Fn}{Tp+Tn+Fp+Fn}$
- F1-Score = $\frac{Tp}{Tp+FTp+0.5*(Fp+Fn)n}$

Where Tp = True Positive, Fp = False Positive, Tn = True Negative and Fn = False Negative

A.GUI Results and Analysis

In this section we present the results that we have acquired from the processing of the lung cancer detection models on our graphical user interface .The GUI that we have incorporated for this project is the Gradio library for seamless and efficient creation of web apps for visualization of machine learning models.

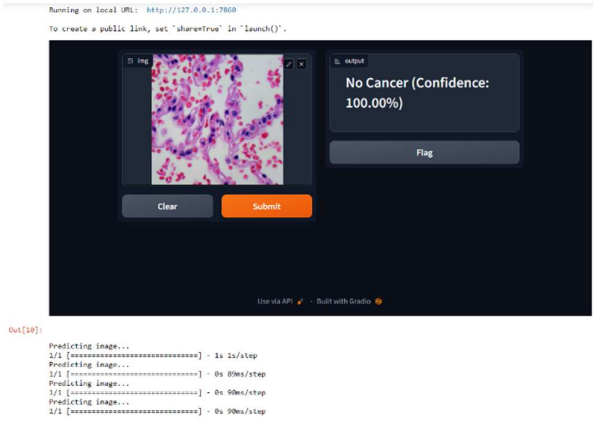

Fig. 3. GUI representation for EffecientNetB1 model for no-cancer biopsy image

Figure 3 offers a comprehensive depiction of the integration between biopsy image input and the graphical user interface (GUI) for data visualization .The user is given an input field to insert the biopsy images which can further on be submitted or cleared off to feed a new image to the model , once the image has been processed the results show up adjacent to the image with the class of the lung cancer corresponding to the image there also a flag option to flag or mark certain predictions for ambiguous prediction or prediction which need more scrutiny.

For example the above biopsy image fed to the model was one of no cancer and the model has accurately determined the cancer class and conveyed this information alongside the confidence level of its prediction.

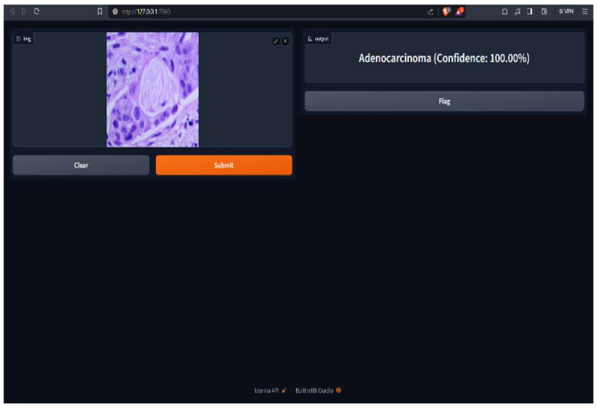

Fig. 4. GUI representation for EfficientNetB1 model for adenocarcinoma

Figure 4 displays a biopsy image of adenocarcinoma was inserted which has been identified correctly by the model subsequently showing 100 percent confidence in its prediction.

V. Discussion

A. EfficientNetB1 CNN Model Performance

In this section, we delve into the assessment of the EfficientNetB1 CNN Model's performance across 25 epochs of training.

A notable trend observed was the consistent improvement in both Accuracy and Loss of the CNN Model with each epoch, with occasional exceptions, as depicted in Figure 4.

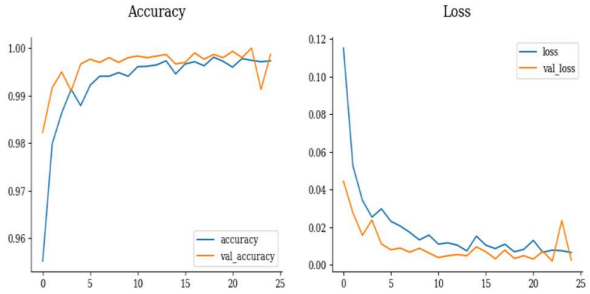

Fig. 5. Accuracy and loss of the EfficientNetB1 model.

Likewise, the Confusion Matrix, which delineates the predicted and actual outcomes of the model for each of the three classes, provided the subsequent classification results: -

Table. 1. Output of the model

Class	Precision	Recall	F1-Score	Support
No Cancer	0.33	0.33	0.33	981
Adenocarcinoma	0.33	0.33	0.33	977
Squamous Cell Carcinoma	0.36	0.36	0.36	1042
Accuracy			0.34	3000
Macro Average	0.34	0.34	0.34	3000
Weighted Average	0.34	0.34	0.34	3000

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb1 (Functional)  (None, 1280)             6575239

 dense (Dense)               (None, 128)               163968

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 6,739,594
Trainable params: 164,355
Non-trainable params: 6,575,239
_________________________________________________________________
```

Fig. 6. Summary of the EfficientNetB1 CNN architecture.

B. VGG16 CNN MODEL PERFORMANCE

In this section, we delve into the assessment of the VGG16 CNN Model's performance across 25 epochs of training. Unlike the EfficientNetB1 Model, the VGG16 Model exhibited significant fluctuations in both Accuracy and Loss with each epoch; especially in the val_accuracy and val_loss functions. While these fluctuations could suggest a general trend of improvement or decline, it cannot be conclusively said so, as depicted in Figure 7.

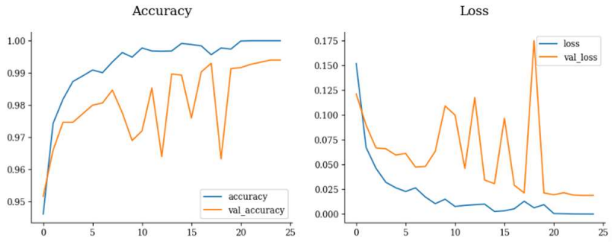

Fig. 7. Accuracy and loss of the VGG16 model.

The VGG16 CNN architecture is summarized in Figure 8, which displays four layers: Lambda, Functional, Dense, and Dense 1: -

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lambda (Lambda)             (None, 256, 256, 3)       0

 vgg16 (Functional)          (None, 512)               14714688

 dense (Dense)               (None, 128)               65664

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 14780739 (56.38 MB)
Trainable params: 66051 (258.01 KB)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

Fig. 8. Summary of the VGG16 CNN architecture.

C. RESNET50 CNN MODEL PERFORMANCE

In this section, we delve into the assessment of the ResNet50 CNN Model's performance across 13 epochs of training.

The results of the ResNet50 CNN model were inconclusive, with no clear trend observed in both Accuracy and Loss. Although accuracy increased with each epoch, the val_accuracy function displayed an opposite behavior. The same inconsistency was observed in the Loss function as well, as illustrated in Figure 9.

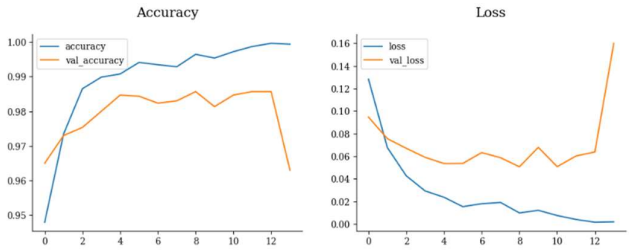

Fig. 9. Accuracy and loss of the ResNet50 model.

The ResNet50 CNN architecture is summarized in Figure 10, which displays four layers: Lambda, Functional, Dense 2, and Dense 3: -

```
Layer (type)                 Output Shape              Param #
=================================================================
 lambda_1 (Lambda)           (None, 256, 256, 3)       0

 resnet50v2 (Functional)     (None, 2048)              23564800

 dense_2 (Dense)             (None, 128)               262272

 dense_3 (Dense)             (None, 3)                 387

=================================================================
Total params: 23827459 (90.89 MB)
Trainable params: 262659 (1.00 MB)
Non-trainable params: 23564800 (89.89 MB)
```

Fig. 10. Summary of the ResNet50 CNN architecture.

D. COMPARISION BETWEEN THE THREE MODELS

In this section, we will do an in-depth comparison of the EfficientNetB1, ResNet50 and VGG16 models. We explore the accuracy and loss metrics of these models and present our findings in Figure 11. Our analysis reveals a distinct contrast in both accuracy and loss among the three models. The EfficientNetB1 model consistently demonstrates higher accuracy than the other two models, with ResNet50 closely following, although it experiences notable fluctuations in accuracy at the beginning and end of the training. Conversely, the VGG16 model exhibits an oscillating trend in accuracy, with an overall inconclusive pattern that gradually stabilizes towards the end of the training period.

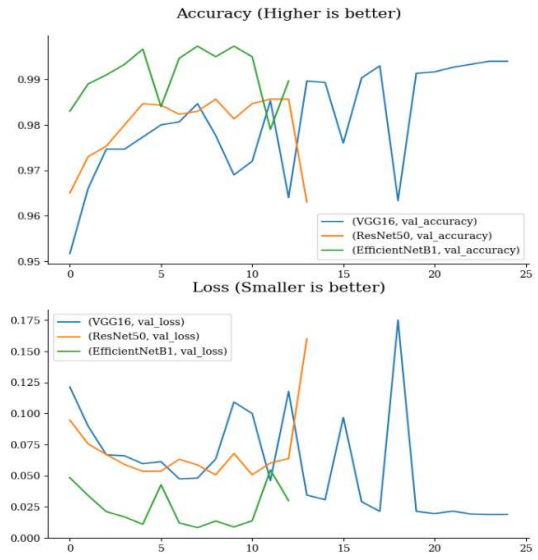

Fig. 11. Comparison of Accuracy and Loss for all three models

Now, as for the comparison of the Confusion Matrices of all the three models, we see that barring some insignificant differences, all three models successfully align with the predicted and the true labels; indicating that they were largely successful in classifying the lung cancer biopsy images into the Adenocarcinoma, Squamous Cell Carcinoma and Benign Tissue labels; as depicted in Figures 12,13 and 14.

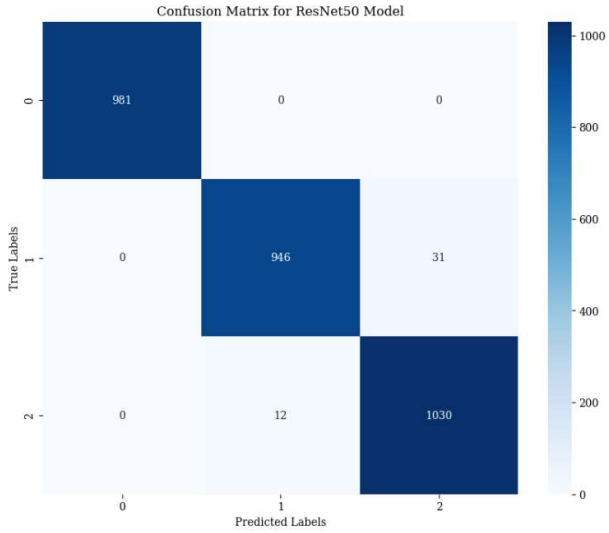

Fig. 12. Confusion Matrix of ResNet50 Model

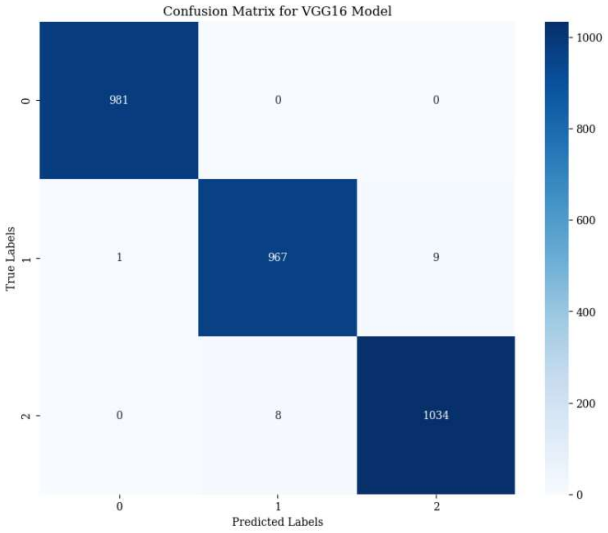

Fig. 13. Confusion Matrix of VGG16 Model

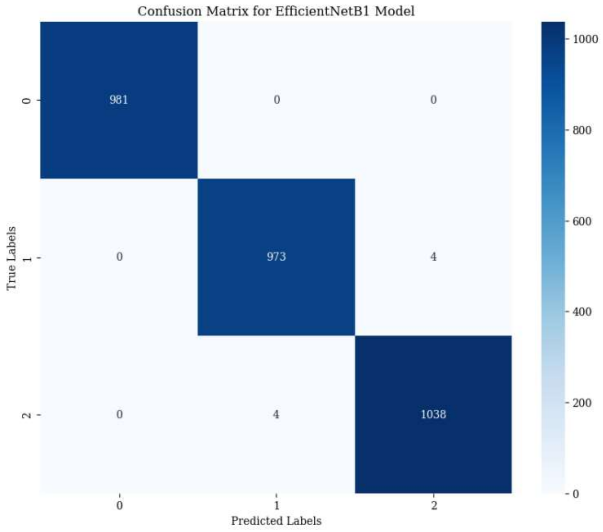

Fig. 14. Confusion Matrix of EfficientNetB1 Model

VI. Conclusion

To categorize lung tissue images from the Lung and Colon Cancer Histopathological Image dataset (LC25000) [12], a hybrid deep learning model is proposed in this study. The 768 x 768 photos that were obtained from LC25000 were subsequently scaled to 224 x 224 so that they could be used as model input. A feature extractor and a classifier make up the model.

The main contribution of this work is the suggestion of a lightweight deep-learning approach for end-to-end CNN-based lung cancer diagnosis using EfficientNetB1 model. After comparison with other models such as ResNet50 and VGG16, EfficientNetB1 was deemed to be more effective in all parameters viz. Accuracy, Loss, Precision, Recall, etc. The efficacy of the suggested system is evaluated and contrasted with other methods in this field using a database

of histopathology images. According to the results, our method outperformed most previous deep-learning lung cancer diagnosis methods. Our model's highest accuracy is 0.995 percent. Compared to earlier deep models, the proposed method for diagnosing lung cancer is more robust and efficient. In the future, we plan to investigate our deep model's performance on more datasets. In addition, we may apply optimization strategies in conjunction with our deep model to identify the most optimally recovered deep features.

Looking forward for future applications, the methodology could be extended to include other cancer types as well, along with integrating multi-modal data for more comprehensive analysis, exploring personalized medicine approaches, enabling real-time intraoperative analysis, validating the model on diverse datasets, and investigating optimization strategies for further performance enhancement. The potential of deep learning models for detection of cancer is revolutionary and will enhance patient outcomes, and contribute to the advancement of science in the future.

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