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Lung Cancer Classification Using Combination Of Efficientnet And Visual Geometry Group Algorithm

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Abstract: Lung cancer is one of the leading causes of mortality All around the world. It is classified into three main types: Adenocarcinoma of the lung (ACA), Non-small cell lung cancer (N), and Squamous Cell Carcinoma of the lung (SCC). Lung Cancer Classification is crucial on development of effective treatments. This study aims to improve the accuracy of lung cancer classification through the integration of a hybrid model, which combines two Convolutional Neural Networks architectures, namely EfficientNet-B7 and VGG-16. A set of histopathology images was subjected to testing, with the data split into three categories: 60% for training, 30% for validation, and 10% for testing. Prior to use, each image underwent a preprocessing process, wherein it was resized to 256x256 pixels. The model test results achieved an accuracy, precision, recall, and F1-score of 98.73%, which is superior to the EfficientNet-B7 base model. The findings of this study demonstrate the potential of hybrid models to improve accuracy in lung cancer classification. The utilization of hybrid models has the potential to contribute significantly to the beginning diagnosis and appropriate Lung Cancer Therapies. Future research will focus on improving the model through the application of image segmentation techniques and expanding the scope of classification to other types of lung cancer. Optimization of the hybrid model architecture using novel techniques such as the attention mechanism or transfer learning will be conducted to improve the efficiency and accuracy of the model. Additionally, a system that can be integrated into clinical practice will be developed.

Keywords: Convolutional Neural Network, Classification, EfficientNet-B7, Histopathology, Lung Cancer, VGG-16

INTRODUCTION

Lung cancer is one of the leading causes of mortality worldwide, affecting both men and women (Hatuwal & Thapa, 2020)By 2022, cancer is projected to be the top cause of mortality, with 20 million new cases and about 9 million deaths. 7 million deaths (UICC, 2024). are linked to major risk factors, particularly smoking and exposure to cigarette smoke. Exposure to harmful chemicals, radon gas, environmental air pollution, and family history are significant risk factors for developing lung cancer (Buana & Agustian Harahap, 2022). Early diagnosis and accurate classification of lung cancer are crucial for effective treatment and better patient outcomes. The diagnostic process usually involves a physical exam, imaging tests CT scans, X-ray, or MRI, and a tissue biopsy (Faria, Campelos, & Carvalho, 2023). Lung cancer is classified by the type of cells involved. This study focuses on three

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common types: adenocarcinoma (ACA), non-small cell lung cancer (N), and squamous cell carcinoma (SCC) (Larxel, n.d.). These three types were chosen for their high prevalence in most lung cancer cases. Although other types exist, such as small cell and large cell carcinoma, focusing on ACA, N, and SCC is crucial for accurate classification.

Over the last decade, Convolutional Neural Networks (CNNs) have become a mainstream method for diagnosis and classification in the healthcare field (Yunius, n.d.). CNN is used to diagnose various diseases such as pneumonia, brain tumors, Covid-19, heart disease and lung cancer (Candra, Wibisono, Ayu, & Afrad, 2024; Elektronik & Komputer Udayana, n.d.; Irsyad, Jati Setyadi, & Amal, 2023; Nugroho & Yulia, 2021; Umri & Delica, n.d.). The main advantage of CNN is its ability to extract relevant features with high accuracy, thereby increasing the reliability of diagnosis compared to conventional methods (Alzubaidi et al., 2021) Although many models show promising results, each has limitations. For example, EfficientNet variants from B0 to B7 efficiently classify lung cancer considering depth, width, and resolution, but require extensive training and long computing time (Anjum et al., 2023). DenseNet is used for lung cancer classification via CT scans and histopathology images, but is computationally demanding (Uddin, 2024). The MobileNet model is very efficient for devices with limited computing resources, but its accuracy is lower than more complex models (Khultsum, Sarasati, & Taufik, 2022). The U-Net model for three-dimensional segmentation of lung cancer nodules provides accurate results, but is susceptible to overfitting with limited data (Pribadi, n.d.). VGGNet is able to predict lung cancer with high precision, but requires large computing power (Ozaydin, Student, & Ahmad, n.d.). Additionally, combining CNNs with manual feature fusion improves model accuracy, but requires domain expertise and is prone to overfitting (Iqbal, Qureshi, Alhussein, Aurangzeb, & Kadry, 2023).

EfficientNet is an efficient CNN model for medical image classification (Gunawan & Setiawan, 2022). featuring B0 to B7 and utilizing joint scaling to balance depth, width, and resolution (Tan & Le, 2019). VGGNet is a CNN model that uses 3x3 convolutional layers for image feature extraction (Pang et al., 2020). VGG-16 and VGG-19 are commonly used in medical diagnosis and image processing due to their high accuracy (Matlani & Shrivastava, 2019). EfficientNet has also proven effective for classifying lung cancer images (Agustiani et al., 2023). This model often overfits on small or unrepresentative datasets (Shinde, Ailani, Bulbule, Dangi, & Bagga, 2021). To overcome this limitation, a combination of VGG-16 was used to improve accuracy and reduce overfitting on the backbone (Matlani & Shrivastava, 2019).

The primary objective of this study is to develop a hybrid model that integrates the capabilities of EfficientNet-B7 and VGG-16 for the classification of three distinct types of lung cancer: adenocarcinoma (ACA), squamous cell carcinoma (SCC), and non-small cell lung cancer (N). The combination of EfficientNet-B7 and the feature extraction capabilities of VGG-16 resulted in enhanced accuracy, reduced overfitting, and decreased computational requirements. This model employs histopathology images derived from biopsy or surgical specimens for the analysis of lung cancer (Larxel, n.d.; Nisa', Suciati, & Yuniarti, 2024). The evaluation was conducted using performance metrics that facilitate comparison with the EfficientNet-B7 base model, with the objective of enhancing accuracy and efficiency in the medical field.

LITERATURE REVIEW

Lung cancer is a lethal disease that affects individuals worldwide, is the leading cause of death, and continues to grow at an alarming rate. Therefore, that is imperative for developing an accurate system to assist medical personnel in their efforts to diagnose and treat this disease. Several research studies have developed various models in the field of lung cancer that are implemented on the LC2500 dataset.

Chehade, development of a computerized diagnostic system with which use from the XGBoost model as feature engineering for the classification of adenocarcinoma (ACA), squamous cell carcinoma (SCC), and non-small cell lung cancer (N) tissues. This model provides superior interpretation compared to deep learning models. Furthermore, the SHAP (SHapley Additive exPlanations) method was employed to elucidate the model output, thereby identifying the image features that exert the most influence on lung cancer classification. This approach yielded highly accurate results, with an accuracy of 99.53% and an F score of 99.33%. The model achieved a score of 99.33%, and provided a

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comprehensible explanation of the contribution of each feature to the model's decision. This research not only demonstrated high classification performance but also offered transparency in the decision-making process, which is a crucial aspect in the medical field (Chehade, Abdallah, Marion, Oueidat, & Chauvet, n.d.). In a study published by Agustiani, a lung cancer classification model was developed using digital pathology images, comprising 15,000 images. The study employed a shallow convolutional neural network (CNN) architecture comprising five layers, including three convolutional layers and two fully connected layers. The model achieved an accuracy of 98.53%. Its design facilitates rapid diagnosis by doctors, while not replacing the role of experts entirely (Agustiani et al., 2023). Pradhan, developed a novel model for the automatic classification of lung histopathology images. This model employs color normalization techniques to enhance image contrast, cancer segmentation with the saliency-driven region edge-based top-down level set (SDREL) method, and feature extraction using AlexNet and the gray-level co-occurrence matrix (GLCM). Furthermore, the model utilizes the enhanced locust optimization algorithm (EGOA) and random forest classifier for feature selection and network classification. The results demonstrate that the model achieves a Classify with 98.50% accuracy, that is higher than existing methods. That model comprises three main phases: feature extraction, selection, and network classification. The linear computational complexity of the model is a result of the EGOA (Pradhan, Bhuiyan, Mishra, Thieu, & Coman, 2022). Raju, proposed the MobileNetV2 and InceptionResnetV2 models for the early detection of lung and colon cancer using GradCam and SmoothGard visualization techniques. The experimental results demonstrated an accuracy of 99.86% for lung cancer, indicating that this model is effective in automating cancer detection and improving performance compared to existing approaches (Raju & Rao, 2022). Hamed, developed an innovative method for automatic classification of lung tissue histopathology images using Convolutional Neural Networks (CNN) combined with Light Gradient Boosting Model (LightGBM) models. This model achieved 99.6% accuracy with a very fast processing time. This technique demonstrates that the use of CNN for feature extraction and LightGBM for lung tissue classification can significantly reduce computation time and improve the accuracy of lung cancer diagnosis (Hamed, Salem, Badr, & Tolba, 2023). In their study, Wadekar, modified a pre-trained Convolutional Neural Network (CNN) model, Visual Geometry Group19 (VGG19), to classify lung cancer biopsy images with improved augmentation techniques. This enhanced model achieved up to 97.73% accuracy in detecting lung cancer. This research demonstrates that a fine-tuned VGG19 model can achieve superior performance compared to existing methods, with the objective of detecting cancer in real-time and in a more efficient manner (Wadekar & Singh, 2023).

In another study, Rajasekar, evaluated six distinct deep learning models for the objective of lung cancer diagnosis, including convolutional neural network (CNN), gradient-descendent convolutional neural network (CNN Gradient Descent), VGG-16 and VGG-19, Inception V3, and Resnet-50. The CNN GD model exhibited the most optimal performance, with a detection accuracy of 97.86%, a precision of 96.39%, a sensitivity of 96.79%, and an F-score of 97.96%. This research underscores the advantages of CNN GD in more accurately and efficiently classifying lung cancer (Rajasekar, Vaishnnave, Premkumar, Sarveshwaran, & Rangaraaj, 2023). Ananthakrisnan, developed a convolutional neural network (CNN) architecture with a novel model approach, AdenoCanNet Softmax classifier and AdenoCanSVM SVM classifier, for the purpose of detecting and classifying adenocarcinoma using histopathology images from the lungs. The results demonstrated that AdenoCanNet achieved a testing accuracy of 98.77% for the lung dataset, outperforming existing architectures such as VGG16, VGG19, LeNet-5, and ResNet50. This study concluded that for larger datasets, the proposed model exhibited superior performance compared to existing deep learning architectures (Ananthakrishnan et al., 2023). Shanmugam, proposed a machine learning technique for the early detection of lung cancer using histopathology images. Their approach involves image preprocessing, segmentation using a modified kernel-based Fuzzy C-Means (KFCM) algorithm, and dimension reduction using Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO). The classification results achieved an accuracy of 85.01% using the Decision Tree with GWO feature extraction. This increased to 91.57% with the combination of Grey Wolf Optimization-Invasive Weed Optimization (GWO-IWO) and RAdam algorithm, demonstrating a significant improvement in lung cancer classification accuracy compared to previous methods (Shanmugam & Rajaguru, 2023). Ren,

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developed the LCGANT framework to overcome overfitting in lung cancer classification. The framework comprises LCGAN, which generates synthetic Images and transfer model for lung cancer with VGG-DF regularization. The VGG-DF dataset contains both Real and synthetic images generated by LCGAN. Experiments show that LCGANT achieves accuracy, precision, sensitivity, and F1 score of 99.84%. These results show that the framework is effective in overcoming overfitting and improving performance compared to other methods (Ren, Zhang, & Wang, 2022).

METHOD

In this section, we will describe the methods applied in carrying out this research. Fig. 1. Will explain the steps implemented in this research.

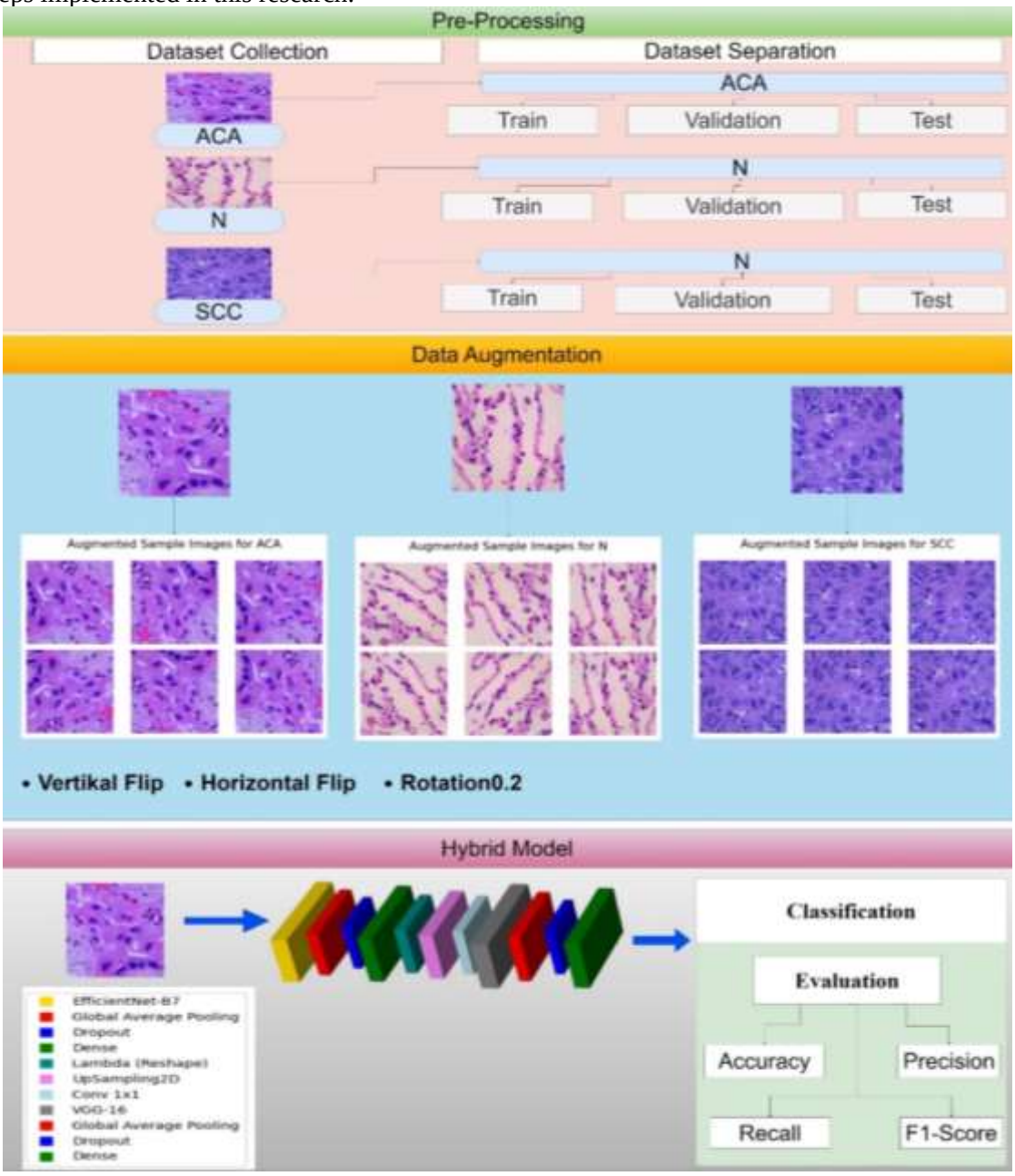

Fig. 1. Research methodology

Pre-Processing

In this study, the dataset is derived from histopathological biopsy images of surgical examination results of patients suspected of having lung cancer. The initial dataset, designated LC25000, is transformed by Larxel in the Kaggle platform (Larxel, n.d.). The resulting dataset consists of 25,000

*corresponding author

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768 x 768 pixel images in JPEG format, consisting of biopsy images of colorectal cancer and lung cancer. This study exclusively considers lung cancer images. Subsequently, the 15,000 images from three types of lung cancer biopsies were labelled as either adenocarcinoma (ACA), squamous cell carcinoma (SCC), or non-specific (N). Fig. 2 illustrates the distribution of images across the three classes.

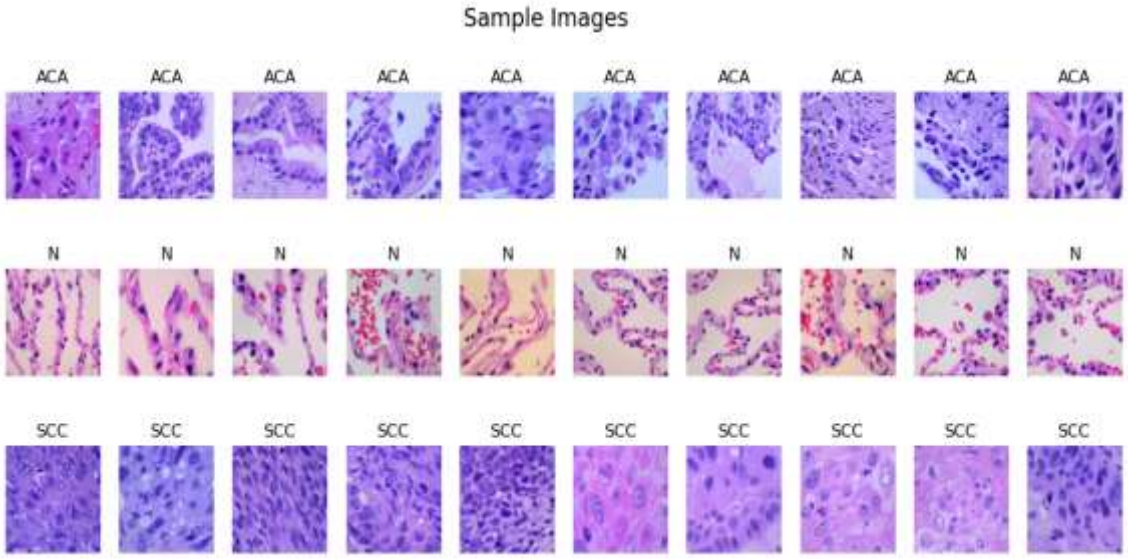

Fig. 2. Each lung cancer image class sample

In Fig. 2, ACA is represented by glandular cells with large nuclei and basophilic cytoplasm (dark blue or purple on H&E staining), which exhibit irregular growth patterns and frequently penetrate the surrounding tissue. N represents normal tissue, characterized by small nuclei and lighter, uniform cytoplasm. SCC is represented by squamous cells with large nuclei and eosinophilic cytoplasm (pink or red on H&E staining), often accompanied by keratinization. These three types exhibit distinctive histologic characteristics and are crucial for the identification of lung cancer.

To ensure comprehensive representation of each lung cancer class, consideration was given to the appropriate proportions. Upon completion of the data collection process, the data was divided into three separate sets: training (60%), validation (30%), and testing (10%), as illustrated in Table 1. This division was implemented to guarantee that each lung cancer class is adequately represented in each set.

Table 1. Data sharing ratios across the three lung cancer classes

Label / Data	ACA	N	SCC	Total
Training	3000	3000	3000	9000
Validation	1500	1500	1500	4500
Testing	500	500	500	1500
Total	5000	5000	5000	15000

Prior to the commencement of the training process, all images are resized from 768x768 pixels to 256x256 pixels. This particular size was selected on the grounds of both computational efficiency and the need to preserve image clarity and important features without compromising the authenticity of the images in question (Yarats, Kostrikov, & Fergus, n.d.). Subsequently, the images are subjected to data augmentation techniques, including vertical and horizontal random flipping, as well as random rotation up to 20% of 360 degrees, as illustrated in Figure 3. This is done to enhance the diversity and robustness of variations in the dataset (Putri & Dkk, n.d.).

*corresponding author

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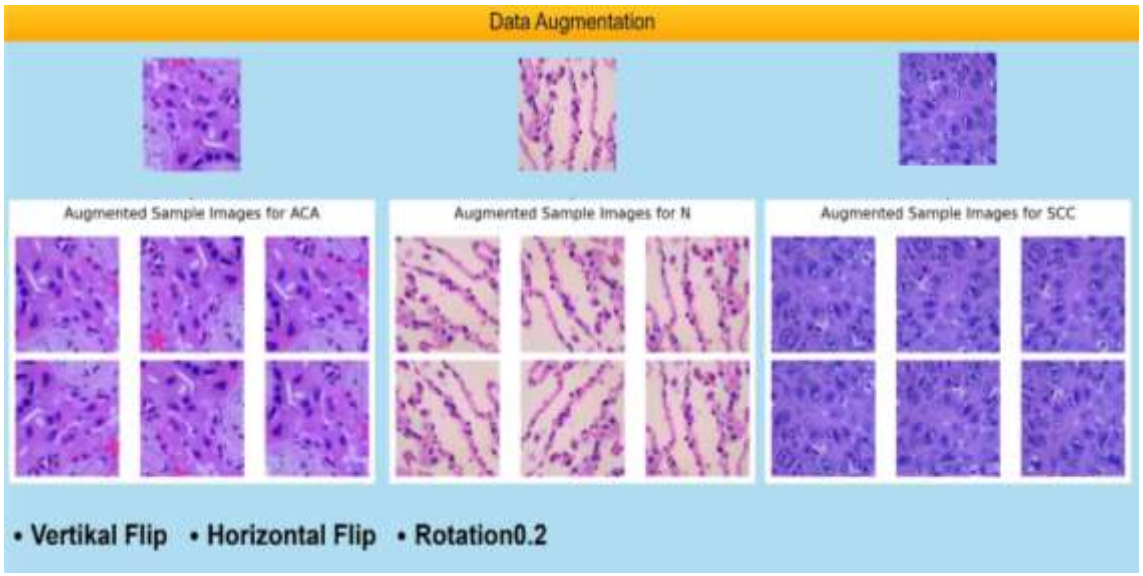

Fig. 3. Data augmentation of ACA, N, SCC

Proposed Model

In this study, we designed and proposed a hybrid model combining EfficientNet-B7 and VGG-16 to improve accuracy in lung cancer classification, as illustrated in Fig. 4. This model will be compared with the EfficientNet-B7 base model. This process illustrates how the integration of disparate CNN architectures can enhance accuracy and efficiency from image classification, as evidenced by prior studies on the incorporation of CNN architectures for classification systems (Canayaz, 2021). And hybrid deep learning models (Wu, Li, Liu, Jiang, & Shi, 2022).

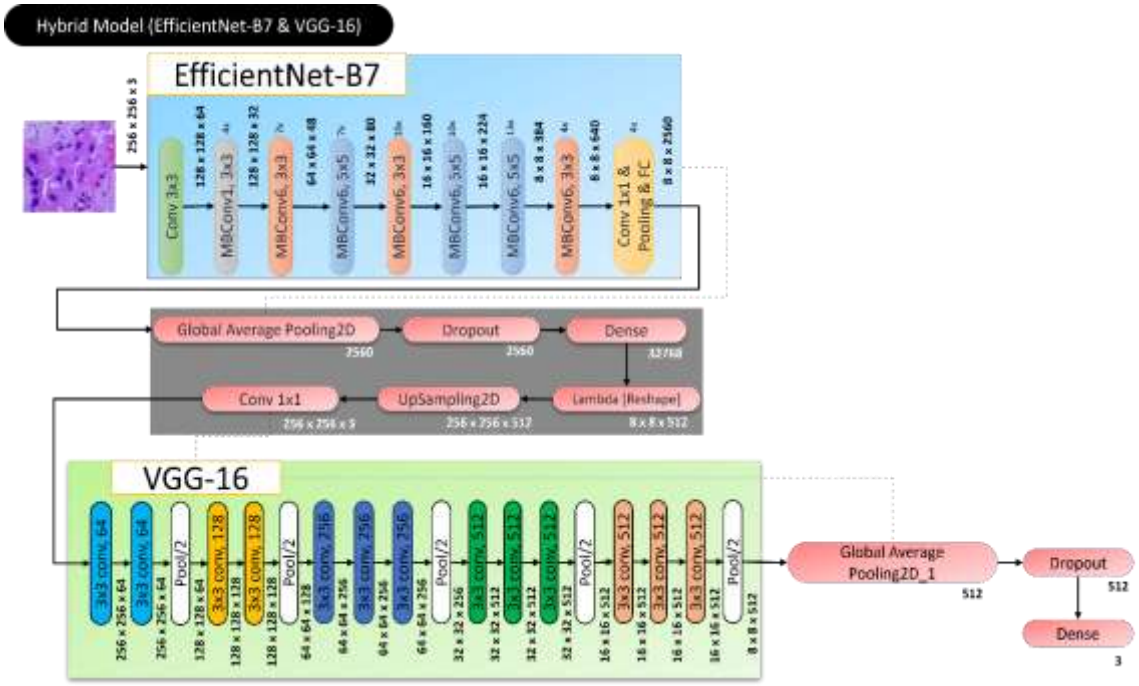

Fig. 4. Hybrid model architecture

In Fig. 4 the model receives an augmented 256×256×3 image that is processed with a 3×3 convolution layer comprising 64 filters. It then passes through a series of mobile inverted bottleneck convolution (MBConv) layers with varying kernel sizes and a gradually increasing number of filters until it reaches the final 8×8×2560 layer. The objective of this process is to extract important features

*corresponding author

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through various levels of convolution depth and complexity, which is optimized by the use of MBConv for computational efficiency (Tan & Le, 2019). After processing, the resulting features undergo global average pooling to reduce the dimension to 2560. A dropout layer is then applied to prevent overfitting, followed by a dense layer with an output of 32768. The feature is then reshaped to 8×8×512, ensuring that the extracted features can be processed without losing important information. The reshaped features pass through an upsampling layer to obtain a size of 256×256×512, which is compatible with the required input, before being processed through a 1×1 convolution layer that maintains the spatial resolution while adjusting the number of channels for compatibility (Matlani & Shrivastava, 2019). Subsequently, the features undergo processing by the entire convolution and pooling layer, which comprises convolution blocks with a 3×3 kernel and an increasing number of filters (64, 128, 256, 512). Following this, global average pooling is performed once more to reduce the dimension to 512. Subsequently, a dropout layer is employed to prevent overfitting, followed by a dense softmax output layer comprising three layers, representing the final classification. In the designed architecture, the use of categorical cross-entropy as the loss function is also applied. Furthermore, Adam is utilized as the optimizer, with a learning rate setting of 0.001 (Yu & Zhu, 2020).

Evaluation

Following the completion of a series of tests on the proposed model, the subsequent stage is the evaluation stage. In this stage, the performance of the generated model is evaluated using a testing dataset comprising 1,500 images. The performance measurement is conducted using a classification matrix, commonly referred to as a confusion matrix. This matrix is a widely utilized performance measurement tool in classification problems, particularly when the results are two or more classes. The following formulas are employed to calculate several classification performance evaluation metrics based on the confusion matrix:

$$accuracy = \frac{number\ of\ correctly\ classified\ images}{total\ number\ of\ images} \quad (1)$$

$$precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

$$recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$

The confusion matrix is comprised of four main cells, which represent the four potential prediction outcomes in a classification problem:

True Positive (TP): Correctly predicted positive class
False Positive (FP): Incorrectly predicted positive class
True Negative (TN): Correctly predicted negative class
False Negative (FN): Incorrectly predicted negative class

The term "accuracy" quantifies the proportion of correctly classified images relative to the total number of images. Precision is defined as the proportion of positive predictions that are, in fact, positive. Recall is defined as the proportion of actual positives that are correctly detected. The F1-score is defined as the harmonic mean of precision and recall, which provides a measure of the balance between the two.

Based on the calculated values of accuracy, precision, recall, and F1-score, the performance of the model is evaluated and compared with the EfficientNet-B7 baseline model to measure the improvement gained from using the hybrid model. The evaluation process ensures a comprehensive assessment of the model's performance across multiple metrics, providing a robust analysis of its classification capabilities.

*corresponding author

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RESULT

In the training process, 150 epochs are utilized. Training and validation will be terminated if there is no improvement in the validation loss value after a number of epochs, due to the application of early stopping with a patience setting of 10. The optimal value of the model will be employed for performance evaluation in lung cancer classification. A series of tests were conducted using both the hybrid model and the EfficientNet-B7 base model as a means of comparing their respective performance in the classification of lung cancer, with a batch size of 32.

Training and Validation Results

Based on test results with the base model EfficientNet-B7, the model successfully traversed 46 epochs throughout training and validation. The model achieved the best validation loss value on the 36th epoch at that point. the resulting training accuracy reached 95.40%, while the validation accuracy reached 97.93%. the resulting training loss value was recorded at 0.1138, while the validation loss was 0.0568. A graph displaying the comparison of training accuracy vs validation accuracy, as well as training loss vs validation loss, is shown in Fig. 5.

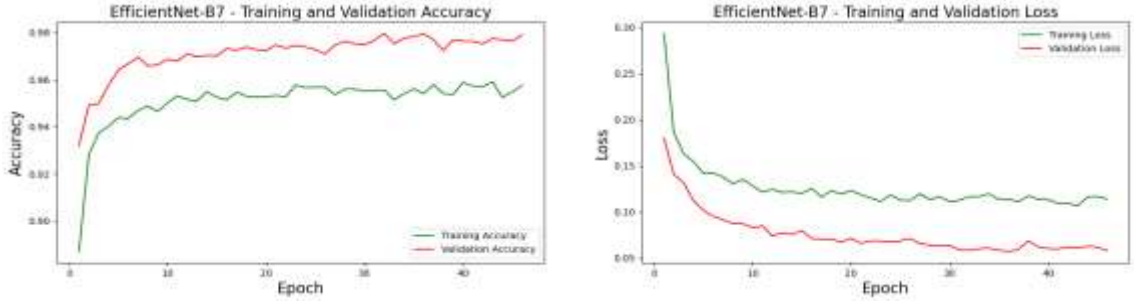

Fig. 5. Training and validation accuracy vs training and validation loss of EfficientNet-B7 base model

The designed hybrid model successfully traversed 30 epochs throughout training and validation. The model achieved the best validation loss value on the 20th epoch at that point. the resulting training accuracy reached 96.61%, while the validation accuracy reached 98.51%. the resulting training loss value was recorded at 0.0893, while the validation loss was 0.0396. A graph displaying the comparison of training accuracy vs validation accuracy, as well as training loss vs validation loss, is shown in Fig. 6.

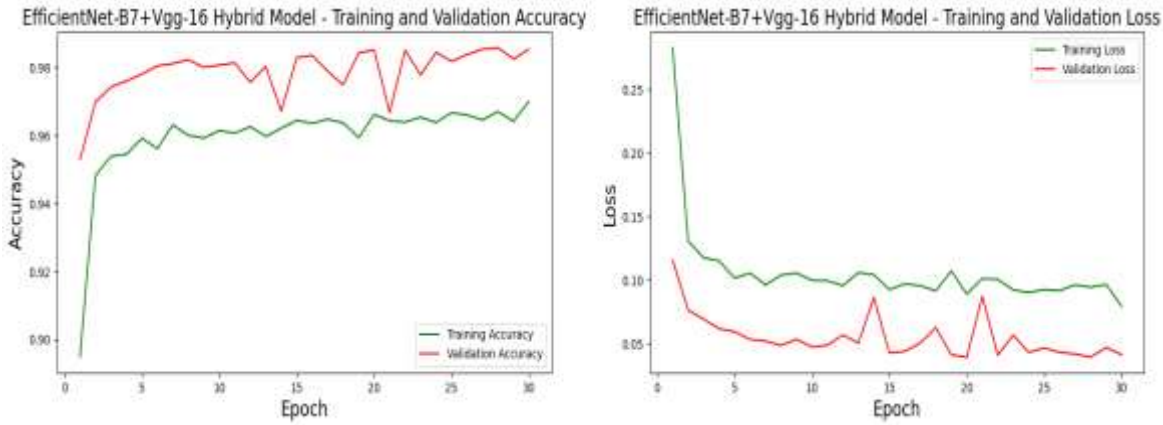

Fig. 6. Training and validation accuracy vs training and validation loss Hybrid model

The results of the model performance evaluation can be summarized and compared in Table 2. Overall, the performance evaluation demonstrates that the tested model is capable of effectively classifying lung cancer in both the training and validation stages.

*corresponding author

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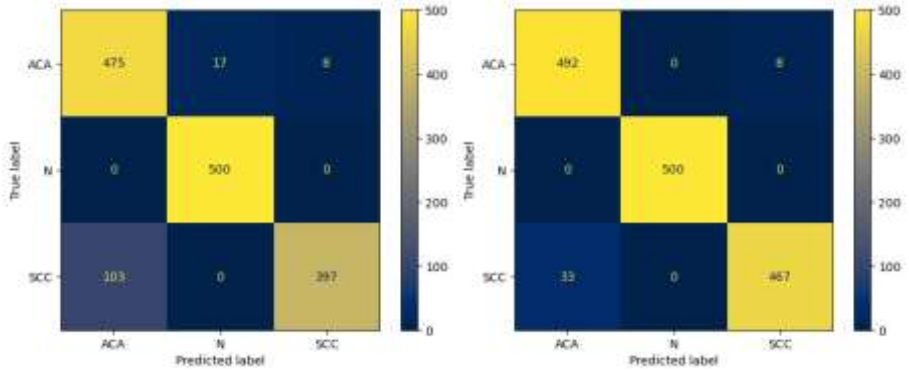
Table 2. Model evaluation on training set and validation set

Model	Training Set		Validation Set	
	Accuracy (%)	Loss	Accuracy (%)	Loss
EfficientNet-B7 model	95.40	0.1138	97.93	0.0568
Hybrid model	96.61	0.0893	98.51	0.0396

Testing Results

Following the completion of the model training and validation process, the subsequent stage is the testing of the model. This testing process involves the use of 1,500 lung cancer biopsy images, which have been resized to 256x256 pixels. The results of this testing will be evaluated in order to analyzing the types of classification errors that occur, with the use of a confusion matrix. The test results of our EfficientNet-B7 model are presented in Fig. 7(a), while the test results of the hybrid model are presented in Fig. 7(b).



(a) (b)

Fig. 7. Confusion matrix model EfficientNet-B7 (a), Confusion matrix Hybrid model (b)

The confusion matrix analysis of Figs. 7(a) and 7(b) indicates that the majority of images in the testing phase were classified accurately by all models. However, misclassification did occur in certain instances, particularly in the ACA and SCC classes. A number of metrics including accuracy, precision, recall and F1 score are used to evaluate the performance of the model. This metric provides the ability of the model to accurately identify and differentiate between different types of lung cancer. They are invaluable for a comprehensive assessment of model performance, particularly in cases where there is an imbalance between the number of classes in the dataset. This allows us to gain insight into the reasons behind the model's tendency to ignore certain classes. Accuracy, Precision, Recall, and F1 Score values on the test set for all designed models are available at Table 3.

Table 3. Test Set Accuracy, Precision, Recall, and F1 Score Values

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNet-B7 model	97.67	97.67	97.67	97.67
Hybrid model	98.73	98.73	98.73	98.73

As demonstrated in Table 3, the EfficientNet-B7 basic model exhibited an accuracy value of 97.67%, precision of 97.67%, recall of 97.67%, and F1 score of 97.67%. The hybrid model shows the highest accuracy value of 98.73%, precision of 98.73%, recall of 98.73% and F1 score of 98.73%. The results of the performance evaluation indicate that the entire developed model has achieved excellent accuracy, precision, recall, and F1 score in lung cancer classification. Nevertheless, the hybrid model

*corresponding author

demonstrated superior accuracy in classifying three types of lung cancer, namely, adenocarcinoma (ACA), squamous cell carcinoma (SCC), and non-small cell lung cancer (N). Evaluation of the accuracy, precision, recall, and F1-score values revealed that the hybrid model consistently achieved the highest results across all metrics. This study corroborates the significance of integrating the EfficientNet-B7 and VGG-16 architectures in hybrid models to enhance the precision of lung cancer classification. The combined architecture has been demonstrated to yield superior outcomes compared to the base model, exemplifying the efficacy and efficacy in processing histopathology images.

DISCUSSIONS

In this study, we developed and proposed a hybrid model of which combines the EfficientNet-B7 architecture with the VGG-16. The designed model demonstrated high levels of accuracy, precision, recall, and F1 score, particularly when tested and compared with the EfficientNet-B7 base model. This indicates that the hybrid model has good performance and quality in classifying ACA, SCC and N. Comparisons will be made between the hybrid model and other models that have been proposed in previous research on lung cancer classification. Table 4 presents the results of a comparison. Please be aware that the table only includes the best results for comparison from each study. A review of the results presented in Table 4 reveals that there is considerable variation in the classification categories and models employed in these studies, despite their shared focus on the task of lung cancer classification. It should be noted, however, that there is no model that is inherently superior to any other model. Accordingly, performance metrics such as accuracy, precision, recall, and F1 score remain useful indicators for evaluating studies on the classification of lung cancer in its entirety.

Table 4. Comparing earlier studies on the categorization of lung cancer

Study	Class	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ours	ACA, N, SCC	Hybrid (EfficientNet-B7+VGG-16)	98,73	98,73	98,73	98,73
Raju et al (Raju & Rao, 2022).	ACA, N, SCC	MobileNetV2 & InceptionResnetV2	99,95	99,95	99,80	99,90
Hamed et al (Hamed et al., 2023).	Benign tissue, SCC	CNN-LightGBM	99,60	-	-	99,60
Chehade et al (Chehade et al., n.d.).	Benign tissue, ACA, SCC	XGBoost	99,53	99.33	99.33	99.33
Wahid et al (Wahid, Nisa, Amaliyah, & Puspaningrum, 2023).	ACA, N, SCC	ResNet-18	98.82	-	-	-
Agustiani et al (Agustiani et al., 2023).	ACA, N, SCC	CNN	98.53	-	-	-
Pradhan et al (Pradhan et al., 2022).	Benign tissue, ACA, SCC	EGOA-Random Forest	98,50	98,92	97,98	99.08
Rajasekar et al (Rajasekar et al., 2023).	ACA, N, SCC, LCC	CNN GD	97,86	96.39	-	97,96

*corresponding author

Wadekar et al (Wadekar & Singh, 2023).	ACA, N, SCC	Modified VGG-19	97,73	-	-	-
Setiawan et al (Setiawan, Suhadi, Husni, & Pramudita, 2022).	ACA, N, SCC	CNN-Gamma Correction	87.16	86.67	87.00	87.00

Table 4 presents the findings of Raju, who achieved 99.95% accuracy by combining MobileNetV2 and InceptionResnetV2 with GradCam and SmoothGrad (Raju & Rao, 2022). Hamed, demonstrated that a CNN combined with LightGBM can achieve 99.60% accuracy and a F1-score (Hamed et al., 2023). Chehade, achieved 99.53% accuracy by using XGBoost (Chehade et al., n.d.). Wahid, found that ResNet18 exhibited the greatest degree of superiority, achieving 98.82% accuracy, in comparison to other models within the test, including ShuffleNet V2, GoogLeNet, and a simple CNN (Wahid et al., 2023). Agustiani, developed a specialized CNN with an accuracy of 98.53% (Agustiani et al., 2023). Pradhan, EGOA-Random Forest was used with an accuracy of 98.50% (Pradhan et al., 2022). Rajasekar, tested six different algorithms, including Convolution Neural Network (CNN), CNN Gradient Descent (CNN GD), VGG-16, VGG-19, Inception V3, and Resnet-50. CNN GD achieved the highest accuracy of 97.86% (Rajasekar et al., 2023). Wadekar, achieved 97.73% accuracy using a modified VGG-19 (Wadekar & Singh, 2023). Setiawan, achieved an accuracy of 87.16% using a CNN with gamma correction (Setiawan et al., 2022).

In addition, our hybrid model showed satisfactory accuracy, precision, recall, and F1 score of 98.73%. Although this model performed well, there is a significant difference between the current results and previous studies in terms of accuracy. For example, Raju showed the effectiveness of the combination of MobileNetV2 and InceptionResnetV2 which achieved an accuracy of 99.95%. This combination offers several advantages. First, the computational efficiency of MobileNetV2 is an important factor. Second, the ability of InceptionResnetV2 to handle variations in image scale and resolution is an important advantage in this context. Furthermore, the integration of GradCam and SmoothGrad techniques improves the interpretability of the resulting model (Raju & Rao, 2022). Hamed et al., the combined approach of CNN and LightGBM achieved an accuracy and F1-score of 99.60%. This approach offers two advantages: first, the ability of LightGBM to process data very quickly and efficiently; second, the ability of LightGBM to handle imbalanced data, a common challenge in medical image classification (Hamed et al., 2023). Chehade achieved 99.53% accuracy using XGBoost, demonstrating the superiority of this approach in terms of regularization. This feature prevents overfitting, improves model generalization on different datasets, and increases the speed and efficiency of data delivery in large datasets (Chehade et al., n.d.). This comparison revealed that these models achieved higher accuracy than our hybrid model.

In our study, the hybrid model showed satisfactory performance. However, there are some limitations that need to be considered. One is the higher complexity of the architecture due to the combination of EfficientNet-B7 and VGG-16, which requires more computational resources and slows down the inference process. In addition, our model showed suboptimal efficiency in handling high-resolution images and had difficulty in distinguishing between ACA and SCC lung cancer subtypes, both of which have similar histopathological characteristics. To overcome these limitations, future research will focus on optimizing the hybrid architecture model through the integration of novel techniques, such as attention mechanisms or transfer learning, to improve model efficiency. In addition, the dataset coverage will be expanded to include rarer lung cancer types, with the aim of improving the model's classification capability and accuracy. Despite the results observed in our initial study, future research will prioritize developing more efficient models that are able to handle complex transformations in lung cancer histopathology data.

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CONCLUSION

This study uses a hybrid model and compares it with the baseline model developed by EfficientNet-B7. Before use, the dataset undergoes a balancing process to ensure an even distribution. An early stopping technique is applied to stop training when there is no further improvement, while an image augmentation technique ensures generalization, with a batch size of 32. The experimental results show that the hybrid model, which combines the EfficientNet-B7 and VGG-16 architectures, has the best performance with an accuracy, precision, recall, and F1-score of 98.73%. The use of this hybrid model provides significant improvements compared to the baseline model. The hybrid model shows satisfactory performance in classifying three types of lung cancer (adenocarcinoma, squamous cell carcinoma, and small cell carcinoma) through histopathology biopsy images. These findings demonstrate the potential of the combination of hybrid models in improving the performance of deep learning models for other medical classification tasks. The success of this hybrid model shows its novelty in several important aspects. First, the combination of EfficientNet-B7 and VGG-16 not only improves the accuracy but also the stability and consistency of the classification results, as evidenced by the equally high values of precision, recall, and F1-score. Second, this study uses innovative dataset balancing and image augmentation techniques, which help in improving the generalization of the model. Third, this approach demonstrates the ability to overcome the challenges in histopathology image classification, which often have significant visual variations and high levels of complexity.

Future research should focus on further developing the existing model by considering additional factors that may affect the classification performance. This may involve the application of novel techniques, such as attention mechanisms or transfer learning, as well as optimizing the classification ability to enable the detection and classification of a wider range of cancer types. In addition, it is important to develop a system that can integrate the classification results into clinical practice, thereby helping healthcare professionals to detect and classify lung cancer types more accurately. Model testing can also be improved by combining other algorithms. Expanding the scope of the study by considering other types of lung cancer classification and comparing the model performance with other classification methods will provide a more comprehensive understanding of the developed model. The main novelty of this study lies in the innovative hybrid approach, the use of advanced data augmentation and balancing techniques, and the potential for application in broader clinical practice, indicating that this model is not only effective in current classification but also has prospects for further development. in adaptation in various other medical fields.

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