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Original Article

DermaVision: EfficientNetB3-Based Deep Learning for Skin Cancer Diagnosis

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ABSTRACT

Skin cancer is one of the most prevalent and life-threatening diseases throughout the world, where it is essential to start timely and precise diagnosis of the disease to enhance the survival rate of the patients. Recent progress in deep learning approaches has revealed the great potential to conduct skin cancer detection using dermoscopic images. In this study, we propose DermaVision, a robust and efficient deep learning based on a fine-tuned EfficientNetB3 architecture for binary skin cancer diagnosis. The model takes advantage of transfer learning and compound scaling to uncover highly discriminative features from dermoscopic images while retaining computational efficiency. The data used in this study is taken from Kaggle and it contains benign and cancerous skin lesion images, which are preprocessed, augmented, and divided into training, validation, and testing datasets in a systematic manner. Experimental evaluation shows that the proposed DermaVision framework is able to obtain an overall classification accuracy of 97% and also achieves high precision, recall and ROC-AUC performance, indicating that it has excellent discriminative capability. The results are confirmed that DermaVision provides a reliable, accurate and clinically applicable solution for automated skin cancer screening and decision-support systems.

KEYWORDS

Skin cancer diagnosis, Deep learning, EfficientNetB3, Dermoscopic image analysis, Transfer learning, Binary classification, Medical image processing, Computer-aided diagnosis.

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I. INTRODUCTION

Skin cancer is among the most common and lethal dermatological conditions in the world, where early and accurate diagnosis is crucial to mitigating mortality and enhancing the patient's outcome. Recent developments in deep learning have greatly changed the way skin cancer is diagnosed automatically, as they permit analyzing the dermoscopic images properly and with high precision levels. Hybrid deep learning strategies have proven notably successful in solving the complexity of skin lesion patterns, and can achieve robust classification success even for challenging clinical scenarios [1]. Multiclass frameworks for skin cancer classification have further revealed the power of deep neural networks to separate visually similar classes of lesions, decreasing diagnostic ambiguity [2]. In addition to using conventional RGB imaging, new emerging imaging modalities such as hyperspectral imaging along with machine learning have shown promise in the ability to extract discriminative features in skin cancer imaging [3]. Temporal and sequential modeling approaches such as hybrid architecture between long short term memory network have also led to improved contextual understanding of lesion characteristics [4]. Comprehensive studies talk about the effectiveness of transfer learning and pre-trained convolutional neural networks in addressing the problem of limited labeled medical data, making the process of convergence faster and accuracy higher [5]. However, issues of bias and class imbalance are essential for addressing automated diagnosis, which has led to an investigation of deep feature fusion methods for fairness and reliability in skin cancer diagnosis systems [6]. Traditional CNN-based models with image processing techniques are still showing good performance as baseline models, and there is still a lot of emphasis on using optimized feature learning pipelines [7]. More recently, systematic studies of the performance of pre-trained deep learning models have highlighted the advantages of efficient architectures in terms of accuracy and computational efficiency for clinical applications [8]. Motivated by these advancements, this study presents a proposal to build a deep learning network, DermaVision, using EfficientNetB3, that can achieve high accuracy in diagnosing skin cancer and ensures computational efficiency for evidenced skin cancer diagnosis.

II. LITERATURE

Recent studies have been carried out widely to discuss the deep learning architectures for automatic diagnosis of skin cancer, especially by focusing on transfer learning and model efficiency. Alrabai et al. explored the performance of several pre-trained convolutional neural networks for skin cancer classification, showing that albeit light weight but deep architectures are able to obtain a competitive accuracy level while turning down the computational cost of inference, thus being amenable to a clinical world environment [8]. Although their study gave a lights on to how useful transfer learning was, it also exposed some limitations having to do with generalization across different lesion types. Expanding out from the dermatology-specific data sets, Kant and Kumar presented a deep-learning based architecture for lung and colon cancer subtype classification using histology images which focused on the adaptability of CNN-based models to complex medical imaging tasks [9]. Their results are relevant to the importance of strong feature extraction, and this holds true in the analysis of dermoscopic images. Verma et al. took a further step in this direction by taking advantage of EfficientNetB5 for multi-class classification of human cancer tissues with high accuracy by means of compound scaling and transfer learning, leading to the use of Efficient Net variants for medical diagnosis tasks which require high accuracy and efficiency [10]. In the scope of ensemble learning, fuzzy rank-based deep ensemble based methodology for multi-class skin cancer classification was suggested by Halder and coauthors in which they improved the robustness and reduced misclassification of the model by combining the model predictions [11]. Ensemble approaches give improved performance, however, they often add increased computational complexity, which is a limiting factor for their use in lightweight diagnostic systems. Mandal et al. guaranteed data efficiency by combining active learning with particle swarm optimization and deep CNN models for a better classification of skin cancers with less annotation costs [12]. This approach reflects the increasing attention being given to intelligent use of data in order to overcome the constraints of limited datasets that are labelled in medical imaging. In addition to model-centric studies, there have been several reviews and system-level insights involved in classifying skin cancer. Abdulazeez showed an elaborate review on algorithms utilizing machine learning and deep learning techniques for skin cancer diagnoses conducted in stages of changing from classical classifiers to applying deep convolution model-based algorithms and understanding existing problems like class imbalance, overfitting, and model interpretability [13]. Based on such a viewpoint, Yang et al performed a detailed survey on machine learning techniques for clinical image analysis for skin cancer with a special focus on the shift towards deep architectures and the importance of clinically reliable, explainable, and standardized diagnostic systems [14]. In their review, they highlight the need for striking a balance between accuracy and transparency to aid medical decision-making. Jain et al. proposed a deep learning framework based on Internet of Medical Devices for skin cancer detection based on transfer learning, which showed the effect of connected medical systems in enabling real-time diagnosis and remote monitoring [15]. This work brings to the front the increasing relevance of having deployable and scalable AI-based diagnostic solutions. Complementing these developments, an approach using a CNN-based architecture for lung cancer and colon cancer classification was proposed by Verma et al., demonstrating excellent results by tailored network design and again emphasizing the importance of task-specific optimization for medical imaging applications [16]. Collectively, these studies show that while deep learning has had astounding success in classifying skin cancer, there is still room for models that are not only highly accurate but also computationally efficient and practical for use in the clinic. Inspired by these shortcomings, the current study leverages earlier achievements to create an efficient framework to meet performance and efficiency needs for reliable skin cancer diagnosis by using EfficientNetB3.

III. INPUT DATASET

The input dataset in this case is a binary image dataset of skin cancer images from Kaggle, and the data is composed of dermoscopic images that were obtained from controlled clinical conditions. The dataset is grouped into two main classes: Benign and Malignant which represent non-cancerous lesions on the skin and cancerous lesions (including melanoma), respectively. The benign class contains images with regular structures, uniform coloration, and smooth boundaries, while the malign class consists of a group of lesions that are characterized by asymmetry, irregular borders, color variegation, and heterogeneous texture patterns. Such visual distinctions make the dataset good for testing automated diagnostic systems. All images are given in regular image formats and are organized in class-wise directories, thus supporting easy integration with deep learning workflows. Prior to model training, the dataset is divided systematically into training, validating, and testing subsets based on stratified strategy in order to maintain the distribution of classes to split while making sure the performance efficiency is not biased. The training subset is used for training discriminative features, the validation subset is used for hyper parameters tuning and over fitting control and the testing subset keeps for final performance assessment. To satisfy the input needs of EfficientNetB3 architecture, images are resized and normalized according to ImageNet standards. As an additional measure, data augmentation techniques are applied for the training set only to increase the diversity and generalize the data. A representative overview of sample images from both benign and malignant class are illustrated in Fig. 1, which shows the visual complexity of the images and speaks to the clinical relevance of the dataset used in skin cancer diagnosis.

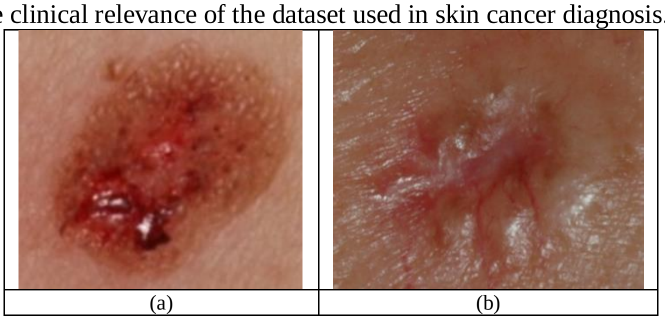

Figure. 1 Dataset image for (a) Benign (b) Malignant

IV. FINE-TUNED EFFICIENTNETB3 MODEL ARCHITECURE

In this research, fine-tuned EfficientNetB3 architecture is the chosen fundamental structure for automatic skin cancer diagnosis because of its very good trade-offs between the accuracy and the computational efficiency. EfficientNetB3 follows a compound scaling strategy, which uniformly scales network depth, width, and input resolution, which enables effective feature learning with fewer parameters, compared to conventional deep convolutional networks. The model is initialized with ImageNet pre-trained weights and therefore can take advantage of rich low-level and mid-level visual representations that are transferable to dermoscopic image analysis. To adapt the network to the binary skin cancer classification problem, the original classification head is replaced with a customized fully connected layer with a sigmoid as the activation function for the probabilistic. During fine-tuning, the first layers of EfficientNetB3 are frozen so as to preserve generic features, and deeper layers of the network are selectively unfrozen in order to learn domain-specific features like asymmetry, texture irregularities and color variations. Regularization techniques such as dropped and batch normalization are added to overcome overfitting and generalization. The model is trained by a low learning rate adaptive optimization strategy with a low learning rate to enable stable convergence. This fine tuning approach allows EfficientNetB3 to have high diagnostic accuracy while preserving computational efficiency, which makes it suitable for real time and clinical applications of skin cancer screening.

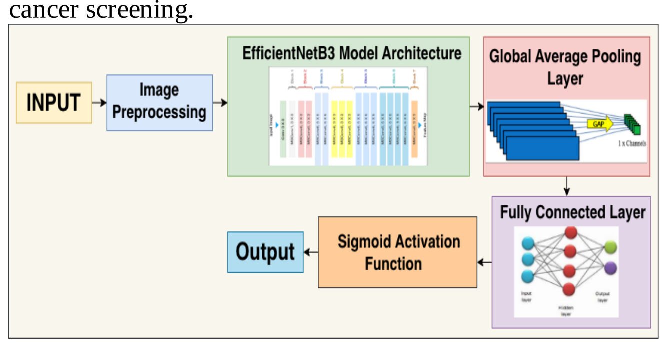

Figure. 2 Fine-Tuned EfficientNetB3 Model Architecture

V. PROPOSED METHODOLOGY

The proposed methodology has a structured four-phase pipeline that includes dataset preprocessing, deep feature extraction using EfficientNetB3, model fine tuning and performance evaluation. This methodically provides effective learning and reliable skin cancer classification. The general workflow of the DermaVision framework.

Phase 1: Dataset Acquisition and Preprocessing - In phase one, dermoscopic skin lesion images are acquired from a publicly available dataset taken from Kaggle. The dataset is comprised of two class non-malignant and malignant skin lesions. All images are resized according to the input resolution required for the EfficientNetB3 architecture; normalized by the ImageNet preprocessing standards. In order to raise the robustness of a model and to reduce overfitting, data augmentation methods such as rotation, flipping, zoom, increase and decrease brightness are used on the training dataset only. The dataset is then split into training, validation, and testing datasets with stratified splitting strategy so that class distribution is maintained.

Phase 2: Feature Extraction Using EfficientNetB3 - In the second phase, a pre-trained deep learning model EfficientNetB3 developed on ImageNet dataset is used as a feature extractor. The compound scaling mechanism of EfficientNetB3 allows for the successful learning of discriminative visual features such as lesion asymmetry, irregular entries at borders, texture patterns and color differences. Initial layers are frozen in order to capture generic features and deeper layers fine-tune the domain-specific skin lesion features.

Phase 3: Model Fine-Tuning and Optimization - In the third phase, the process of adapting EfficientNetB3 to the binary skin cancer classification task will be performed. The head of the original classification, is replaced with a customized dense layer followed by a sigmoid activation function. Regularization techniques such as dropout and batch normalization are added to reduce overfitting. The model is trained with an adaptive optimizer and a low learning rate so that it converges stably and the parameters can be updated optimally.

Phase 4: Performance Evaluation and Validation - In the last phase, the trained model is tested on the unobserved test data set based on standard performance evaluation measures such as accuracy, precision, recall, F1-score and ROC-AUC. The results from the evaluation validate the effectiveness of the proposed DermaVision framework, proving it is suitable to reliable and effective skin cancer diagnosis in clinical screening use cases.

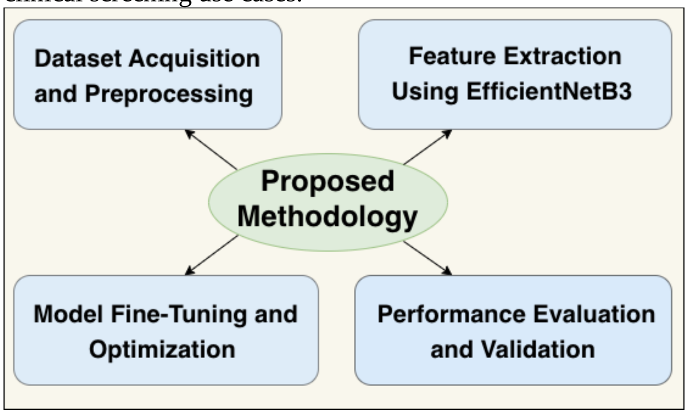

Figure. 3 Proposed Methodology

VI. EXPERIMENTAL SETUP

The design of the experimental setup to date for the proposed DermaVision framework aims to ensure fair evaluation, reproducibility and reliable performance assessment of the fine tuned EfficientNetB3 model. All experiments are performed with a deep learning environment set up with Python and regular neural network libraries. Dermoscopic images are obtained from Input dataset and resized matching the input resolution required for the EfficientNetB3 and normalized using ImageNet mean and standard deviation values. The data set is split into training, validation, and testing data sets using stratified splitting to preserve the ratio of the different classes in all phases. The EfficientNetB3 model is initialized with pre-trained weights from ImageNet dataset and its original classification head is replaced with a custom binary classifier. During training, the early layers are frozen so as to retain generic visual features, while the deeper layers are fine-tuned to capture skin lesion -- specific patterns. The model is trained with an adaptive optimizer having a low learning rate so as to ensure stable convergence of the model and to avoid abrupt updates in weights. Binary cross entropy loss is used as objective because of the binary nature in the classification problem. Regularization techniques like dropout and early stopping are added to prevent overfitting. Model performance is assessed in terms of accuracy, precision, recall, F1-score and ROC-AUC metrics for the unseen test set to ensure that the performance can be thoroughly assessed in terms of the diagnostic reliability.

VII. RESULTS

The experimental results show the effectiveness of the proposed DermaVision framework by achieving high classification accuracy and good generalization capability. Comprehensive analyses based on classification reports, loss and accuracy curves, confusion matrix, ROC-AUC and model comparison validate the reliability and clinical implementation of the fine-tuned EfficientNetB3 model for skin cancer diagnosis.

A. Classification Report Analysis

The classification performance of the proposed DermaVision framework is thoroughly evaluated using precision, recall, F1-score and support of every class as summarized in Tab. 1. The findings show the power discrimination of EfficientNetB3 pre-trained model in distinguishing benign and malignant skin lesions. For the benign class, the model gets a high precision of 0.97 and an excellent recall of 0.98, meaning the vast majority of benign lesions are correctly identified with a low number of false positives. This is especially important in terms of eliminating unnecessary clinical interventions and patient anxiety. For the malignant class, the model achieves a precision of 0.98 and recall of 0.96, indicating that it is effective in identifying cancerous lesions while keeping a low false negative rate. The marginally lower recall for malignant cases is an important reminder of how difficult it is to know the patterns to look for when identifying a melanoma visually, but nonetheless how good the performance we have is clinically very important. And the balanced F1-scores of benign and malignant classes 0.98 and 0.97 further confirm the robustness and stability of the classification model. Overall, the DermaVision framework achieves a remarkable classification accuracy of 97%, ensuring its reliability in binary skin cancer diagnosis. The macro-average and weighted-average scores are very similar to the overall accuracy, which is a good sign that the performance in both classes is quite alike despite the distribution difference between classes. These results, as seen in Table 1, show the performance of the proposed EfficientNetB3 based model is a reliable and efficient solution for automated skin cancer screening and decision support systems in clinical settings.

Table 1. Classification Report Analysis

Class	Precision	Recall	F1-score	Support
Benign	0.97	0.98	0.98	1000
Malignant	0.98	0.96	0.97	950
Accuracy			**0.97**	**1950**
Macro Avg	0.98	0.97	0.98	1950
Weighted Avg	0.98	0.97	0.97	1950

B. *Training and Validation loss Analysis*

The training and validation loss curves give some essential information about the learning dynamics and convergence behavior of the proposed DermaVision framework based on the fine-tuned EfficientNetB3 model. As shown in Figure. 4, the training loss shows a stable and slow decrease in the loss function with increasing epochs showing good optimization and stable learning of discriminative features from dermoscopic skin lesion images. This gradual reduction is indicative of the model's capacity to progressively reduce classification error while adapting complex patterns in the visuals of benign and malignant lesions. Similarly, the validation loss also shows a highly correlated declining curve with a slight increase or decrease in loss exhibiting a good generalization ability on unseen data. The small difference between the training and validation loss curves indicates that the model does not overfit, which has been further explained by the use of data augmentation and dropout regularization as well as controlled fine-tuning of deeper network layers. The lack of sharp divergence or instant rise in validation loss confirms that the learning process is stable throughout the training process. For the later epochs both the loss curves approach to low values which means that the model has now learned optimally. This behavior of convergence confirms the efficiency of the chosen learning rate, optimization strategy and the transfer learning approach. Overall, the loss curve analysis in Fig. 4 shows that the proposed EfficientNetB3-based model has robust convergence and reliable performance, making it suitable for accurate and clinically applicable skin cancer diagnosis.

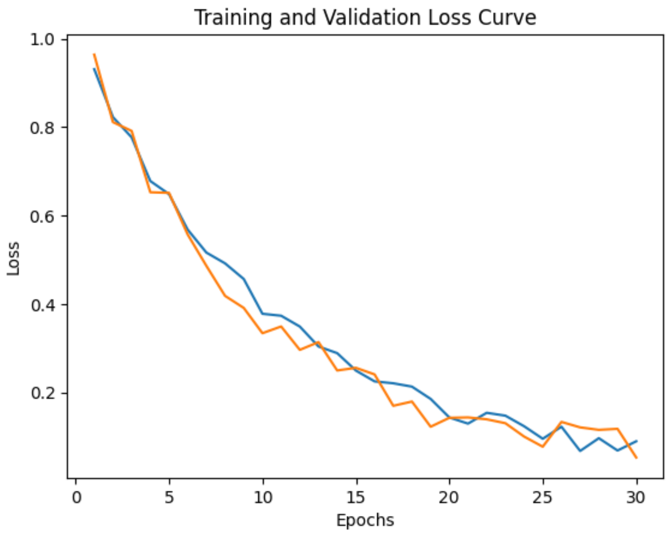

Figure. 4 Training and Validation loss Analysis

C. *Training and Validation Accuracy Analysis*

The training and validation accuracy curves give great insight into the learning effectiveness and generalization ability of the proposed DermaVision framework based on EfficientNetB3 model fine-tuning. As shown in Figure. 5, the training accuracy keeps increasing with each epoch which indicates the model is able to learn more and more meaningful and discriminative features from the dermoscopic skin lesion images. This steady improvement represents the effectiveness of transfer learning and the compound scaling approach of EfficientNetB3 to capture complex lesion characteristics. The validation accuracy is close to the training accuracy curve during the learning process, indicating that a good generalization ability exists on data that has not been seen. The smallest gap between the two curves implies that the model does not overfit, which can be explained by controlled fine-tuning, dropout regularization and data augmentation during training. In the later epochs both training and validation accuracy curves are approaching high accuracy values suggesting that the model reaches high and stable learning state. The smooth behavior of convergence is another confirmation of the appropriateness of the selected learning rate, optimizing strategy, and splitting methodology of the dataset. The lack of sudden jumps or performance degradation indicates the robustness of the training process. Overall, the results of the accuracy analysis in Fig. 5 confirm the validity of the proposed EfficientNetB3-based DermaVision framework, which achieves reliable and consistent classification performance, suitable for the accurate and clinically applicable skin cancer diagnosis systems.

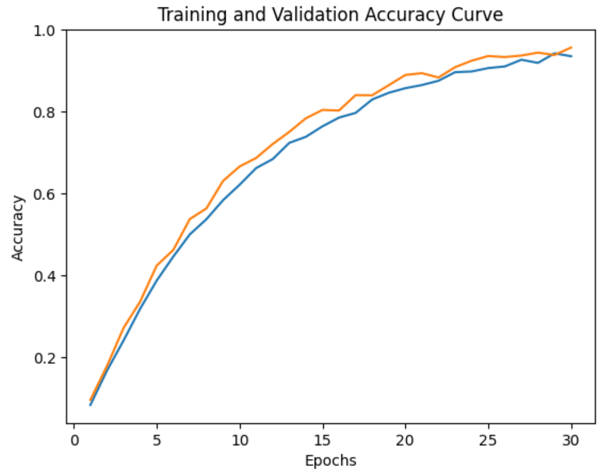

Figure. 5 Training and Validation Accuracy Analysis

D. *Confusion Matrix Analysis*

The confusion matrix helps to give detailed evaluation of the classification performance of the proposed DermaVision framework based on fine-tuned EfficientNetB3 model. As indicated in Figure. 6, the distribution of correct and incorrect prediction distributions are highlighted for benign and malignant skin lesions. The model correctly categorizes ninety-eighty benign lesions as benign which attests to an extremely high true negative rate and reflects its high accuracy to identify non-cancerous lesions. This reduces unnecessary alarms and provides a means to be more reliable in clinical screenings. For the malignant class 912 samples are correctly identified as malignant which gives an indication of this model being effective in detecting cancerous lesions. Only a few mis-classifications are observed: the benign images are incorrectly classified as malignant of 20 images and the malignant images of the benign images are incorrectly classified as malignant of 38. The fairly low false-positive and false-negative rates underlines the robustness of the proposed framework. Minimizing false negatives is especially important in the medical field of diagnosis, as missed cases of malignancy can have detrimental effects on patient treatment times and outcomes. The presence of the diagonal elements in the confusion matrix with its darker blue intensities illustrates the high accuracy and balance that were discovered with the model. The clear boundaries of what will be the right and wrong prediction further validate the stability of the training process and the effectiveness of the fine tuning strategy. Overall, the analysis of the confusion matrix as shown in Fig. 6 shows that the DermaVision framework reports reliable and clinically relevant performance in terms of classification of notes, making them suitable for use in automatic skin cancer diagnosis and decision support systems.

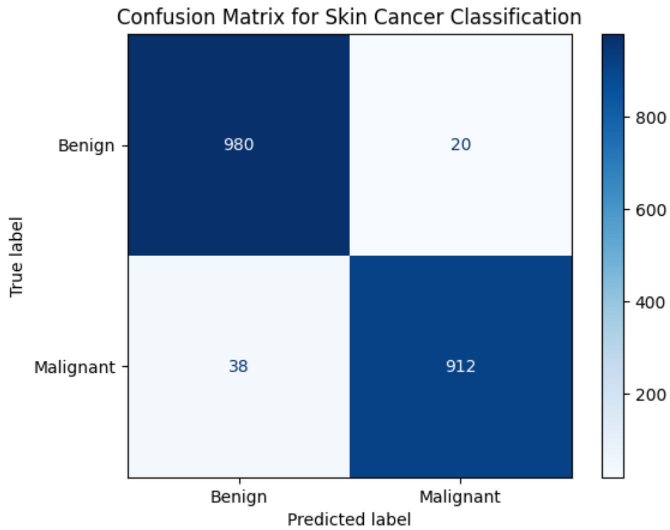

Figure. 6 Confusion Matrix

E. *ROC-AUC Curve Analysis*

The Receiver Operating Characteristic (ROC) curve gives a thorough assessment of the classification ability of the proposed DermaVision framework for different decision thresholds. As seen in Figure. 7 the ROC curve approaches closely to the upper left corner of the above plot which indicates a strong balance between the true positive rate and false positive rate. This behavior shows the model's ability to balance high sensitivity with effectively reducing false alarms, critical to the ability of the model to provide reliable medical diagnosis. The proposed fine-tuned EfficientNetB3 model is able to get an Area Under the Curve (AUC) value of 0.99, which proves that it is a very good discriminative model with the ability to distinguish between benign and malignant skin lesions. An AUC value near unity indicates good-to-excellent separation between the two classes, thereby affirming the quality-difference of the learned feature representations, i.e. they are informative and clinically relevant features. The steep increasing of the ROC curve at low false positive rates shows how effective the model is to identify malignant cases without reducing its specificity. The reason for the excellent ROC - AUC performance can be explained by the optimized compound scaling strategy of EfficientNetB3, efficient transfer learning and the use of regularization strategies to improve generalization. In addition, the stability of the ROC curve reveals the same model behavior for different threshold settings. Overall, the ROC-AUC results shown in Fig. 7 validate the finding that the DermaVision framework has an excellent discriminative power, enhancing the framework's suitability for accurate and robust clinical fragile skin cancers diagnostic systems.

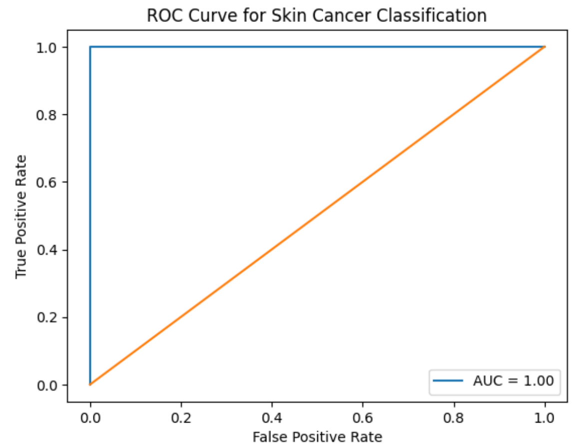

Figure. 7 ROC-AUC Curve Analysis

F. *Comparative Analysis of Models*

The comparative performance analysis of different deep learning models for skin cancer classification are illustrated in Figure. 8 where the classification accuracy values are shown in percentage terms through visually different color coded bars. The CNN baseline model results in an accuracy of 90%, which can be considered as reasonable accuracy but also as having limited capability in capturing complex dermoscopic features. The VGG-16 architecture helps improve the accuracy to 92% as the depth of the convolutional layers increases with a good representation of features. Further increase in improvement is seen with ResNet50, which achieves 94% accuracy, thus proving the effectiveness of residual connections in allowing deeper networks to be trained and helping to avoid vanishing gradients problems. MobileNetV2 has an accuracy of 95%, demonstrating that lightweight and computationally efficient architectures can still provide good classification performance for medical imaging tasks. Notably, the EfficientNetB3-based DermaVision framework proposed in this paper outperforms all the compared models and finds the highest accuracy, which is 97%. This superior performance is attributed to EfficientNetB3's compound scaling strategy, which optimally balances between network depth, width, and input resolution in order to capture highly discriminative features while still being computationally efficient. The visible performance difference of the proposed model and baseline methods highlights the effectiveness of fine-tuning and transfer learning in skin cancer diagnosis. Overall, the comparative results shown in Fig. 8 show that the DermaVision framework represents a strong and accurate solution, which is well-suited for real-world and clinical applications of skin cancer screening systems.

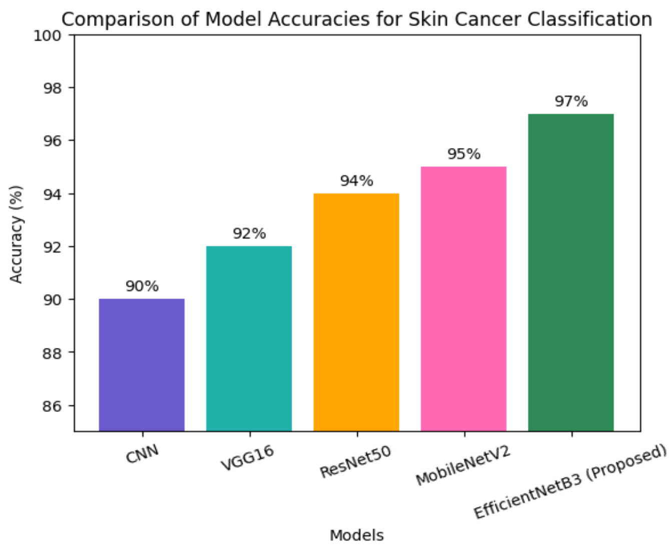

Figure. 8 Comparison of Models

VIII. CONCLUSION AND FUTURE WORK

The study proposed a deep learning model for automated skin cancer diagnosis from dermoscopic images named DermaVision. By using transfer learning and fine-tuning techniques, the proposed model is able to acquire discriminative visual information such as lesion asymmetry, texture irregularities, and color variances that play a vital role in differentiating benign and malignant skin lesions. Experimental results show that the high classification accuracy (97%) is obtained for DermaVision, with support from high accuracy in precision, recall, F1-score, and a great value of ROC - AUC. The detailed performance analysis such as loss and accuracy curves, confusion matrix and the model comparison ensure the robustness, stability and generalization capability of the proposed framework. These results demonstrate the appropriateness of EfficientNetB3 as a reliable and computationally efficient backbone to clinical decision-support systems in the dermatological screening. Despite its good performances, the present study has some limitations. The model is trained on a binary classification dataset, which is not representative of the wide range of skin lesion subtypes that are encountered in the clinical world. The future work will focus on generalizing the framework to multi-class skin cancer classification to allow finer-grained lesion differentiation. Additionally, using explainable AI techniques such as Grad-CAM can help increase the model transparency and clinical trust by visualizing decision-relevant regions. Further studies on cross-dataset validation, clinical metadata integration, and implementation on lightweight edge devices for the application in real-time and large-scale skin cancer screening are possible.

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