An In-depth Comparative Analysis of Hierarchical Deep Learning Models for Automated Skin Cancer Classification

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***Abstract*—Skin cancer is the one of the deadliest diseases among other diseases. Improving patient outcomes is largely dependent on the early and precise detection of different skin lesions. In this work, we access and compare the performance of four well-known convolutional neural network (CNN) architectures for multiclass skin tumor classification: VGG16, MobileNetV2, DenseNet201, and EfficientNetB0. We train and validate all models using the same experimental setup using the ISIC dataset, which covering 9 specific types of skin lesions. To ensure a fair comparison, a combination of quantitative and visual analysis metrics are used to evaluate model correctness. With a 91.44% classification accuracy, DenseNet201 outperformed the other models in terms of stability and performance. These findings support the use of different CNN architectures in clinical decision-making tools and offer a useful understanding of their effectiveness in dermatological image classification.**

***Index Terms*—CNN,DL**

I. Introduction

Skin tumors persist as a common and quickly spreading type of cancer in the world, representing a major public health concern. Detecting skin lesions early and accurately is essential to curb disease progression and boost patient outcomes. Conventional diagnostic approaches are highly dependent on manual dermoscopic examination, which can be time-consuming, susceptible to inter-observer variability, and reliant on the experience of the dermatologist. In actual clinical environments, the high volume of patients and the variability of cases may cap the performance of manual diagnosis. These challenges underscore the urgent requirement for automated, scalable, and reliable solutions to support clinicians in the early detection and classification of skin tumor. Here, artificial intelligence-powered automated image-based classification systems present the possibility of decreasing diagnostic mistakes, facilitating clinical processes, and enhancing access to dermatological services, especially in remote or underprivileged areas.

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Healthcare image analysis has been significantly impacted by recent advances in deep learning(DL). In particular, CNNs have demonstrated an unmatched capacity for accurately classifying images and identifying visual patterns. CNNs can automatically generate hierarchical feature representations from raw pixel data, which is different from traditional DL techniques that use hand-designed features. Because of this capabilities, CNNs are especially well-suited for applications such as skin lesion categorization, where precise diagnosis necessitates taking into account differences in shape, color, and texture. Every year, at least one new CNN architecture with variations in depth, design, computational cost, and performance behavior is released. CNNs have been shown to classify different kinds of skin lesions in dermatology with performance comparable to that of human specialists.

There is still a large gap in knowledge regarding how various CNN architectures fare under standardized conditions for complicated multiclass classification tasks. Most of the recent studies emphasize binary classification or test models across varying datasets and training procedures, rendering direct comparisons challenging. This work is inspired by the requirement of systematic comparison of various CNN models on a standardized dataset for nine-class skin cancer classification using multiclass classification. Our objective is to benchmark four of the most popular CNN architectures—VGG16, MobileNetV2, DenseNet201, and EfficientNetB0—on the ISIC dataset, under a standardized experimental framework. The goal is to examine their performance not just in terms of classification accuracy but also in computational efficiency, training behavior, and generalization ability.Our investigation into these trade-offs is designed to assist in the effective selection and integration of DL models into clinical skin tumor diagnosis workflows.

II. LITERATURE SURVEY

This research [1] introduces a CNN-based classification model for skin cancer based on 2,357 images over 9 different types of skin tumor. The model uses several convolutional and dropout layers to counteract overfitting as well as optimize performance. In testing, the model reached an overall accuracy of 77% on the test set, with additional testing indicating that this rate could increase to 85% under optimization. The performance was verified with metrics like specificity, confusion matrix, and accuracy comparison between training and validation data. The research also focused on the implementation of autotuning, data augmentation, and transfer learning techniques to reduce overfitting and enhance generalization. The relatively light architecture of the model allows for real-time deployment, which makes it viable for actual clinical application, particularly in resource-poor environments.

The research [2] offers a Machine Learning solution for skin tumor identification and classification based on a CNN trained on the HAM10000 dataset, consisting of 10,015 dermatoscopic images of different skin lesions. Preprocessing of the dataset was done by sorting images into individual class folders, resizing images to 220×220 pixels, and employing techniques for image augmentation to counter class imbalance and increase data diversity. The dataset was divided in 80:20 ratio.The model contain Convolutional, pooling, ReLU activation, flattening, and fully connected layers. These layers all aid in effective feature extraction, dimensionality reduction, and final classification.

To achieve better convergence and lower loss,it uses 12 layers, Adam as the optimizer across 50 epochs. Furthermore, a comparison analysis, which contrasts the CNN model compared to other technologies like transfer learning and Generative Adversarial Networks (GANs), demonstrates the ease of use and reliability of CNNs. Not withstanding the benefits that GANs and transfer learning offer, such as the generation of synthetic data and the use of pretrained model will show the robust results when well trained on the specific data.

This research [3] presents a DL system that is based on sequential observation of melanocytic lesions to improve early detection of melanoma, especially for high-risk patients. Unlike typical single-time-point assessments, the proposed model is trained on serial dermoscopic images with temporal evolution, enabling identification of subtle architectural changes in melanomas. While clinicians and traditional algorithms have proven to be inconsistent in diagnostic accuracy, the model developed in this study was more specific and equally sensitive but performed particularly well in distinguishing suspicious evolution in benign lesions.

The algorithm also foresaw melanoma ahead of clinicians in a high rate of cases, and therefore has potential as a prognostic aid. Despite limitations such as impaired accuracy for small or indeterminate lesions and overestimation through malignancy-skewed dataset, the study points to the model's ability to reduce unnecessary biopsies and optimize lesion surveillance. Comparison against 12 clinicians revealed that the model either matched or surpassed numerous clinicians, particularly in avoiding false positives. The approach is concerned with the manner in which dynamic lesion data can be worthwhile and suggests that such AI systems would augment clinician decision-making, especially in high-risk dermatological surveillance. Further work involves risk-based biomarker identification and testing performance in real-world clinical environments.

This work [4]suggests the utilization of a hybrid machine learning framework combining ABCD rule-based feature extraction, CNN, and K-means clustering algorithms for the improved early detection of skin tumor using an Android mobile app that is user-friendly. The system receives dermoscopic images from the ISIC archive and undergoes preprocessing processes such as digital hair removal (DHR), grayscale, and segmentation to obtain lesion regions. Important diagnostic features like asymmetry index, border irregularity, compactness, radial variance, and color features are extracted with dermatologically relevant thresholds. They are used for classification using a multilayer backpropagation model and further strengthened by convolutional layers, optimized using hyperparameter values such as Adam optimizer, cross-entropy loss, and batch size of 32 for 150 epochs.

Experimental results prove that the present model is more sensitive, specific, and classifies better than existing methods like CNNs, MLPs, and hybrid ANN-SVM systems. One of the most significant contributions of the work is integrating the model into an Android smartphone application where patients can record and analyze skin lesion images locally on the phone to obtain instantaneous predictions of potential malignancy. Although the system is found to be useful in early diagnosis, the authors point out drawbacks like risks of overfitting and computational complexity, proposing future enhancement through dataset enlargement, architecture tuning, and better privacy preservation for clinical use in real-world settings.

The research paper [5] examines the efficiency of CNN against Support Vector Machines (SVM) for classifying skin cancer. The study highlights need for early detection. Employing a database of skin tumor lesions taken from Kaggle, the authors employed image improvement methods such as CLAHE and MSRCR, feature extraction using the ABCD rule, GLCM, and shape features. CNN and SVM algorithms were trained and tested on 30 samples each. The findings indicated that CNN had a better accuracy (95.03%) and specificity (89.44%) than SVM (93.04% accuracy and 87.82% specificity). Statistical tests conducted using IBM SPSS indicated that the variation in performance was minimal, but

CNN performed better consistently numerically. CNN also performed better in classifying and segmenting melanoma and squamous cell carcinoma. The research concludes that CNNs, especially when augmented with sophisticated enhancement and optimization methods, are better suited for efficient and precise skin cancer classification than conventional machine learning techniques such as SVM.

III. Methodology

A. Overall process

This system outlines a general flow of multiclass skin cancer classification, starting from image input and preprocessing, through model training, to final classification and output.Figure1 represents the workflow of the proposed technique. The detailed explanation of each stage, including specific techniques and models used, will be provided in the upcoming sections

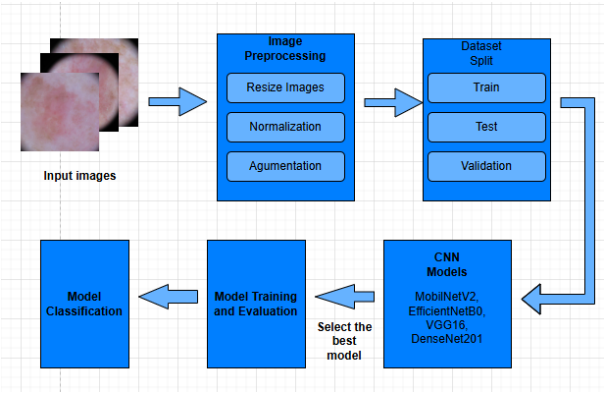

Fig. 1: Workflow of the proposed system

B. Dataset Collection and Preprocessing

The datset utilized in this study consist of 2357 images skin lesions from the ISIC dataset. Figure 2 represents the some set of sample skin lesions, [6], [7] The skin lesion images

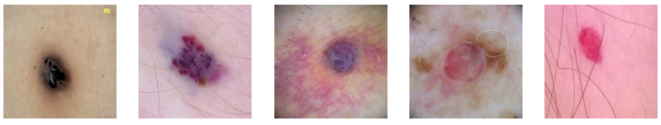

Fig. 2: skin lesion dataset sample

divided into many classes based on the type of skin tumor.The images are organized with in the single parent directory,where each sub directory represent the skin tumor class. It contain 9 classes.

C. Image Preprocessing

To ensure uniform representation across classes and alleviate potential biases introduced by class imbalance, we limited the number of images per class to a maximum threshold of 2000. Figure 3 illustrates the distribution of images across each class prior to augmentation. This preprocessing step

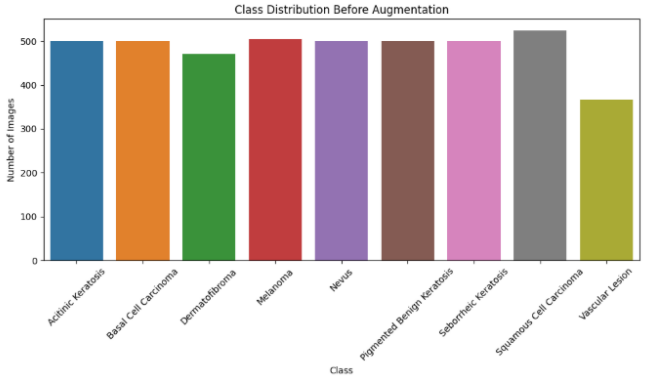

Fig. 3: Images in Each class before Agumentation

ensures that no single class dominates the training process and facilitates balanced learning across the neural network. Each image was resized to a uniform dimension of 128×128 pixels. This resizing operation ensures computational efficiency and consistency in input shape throughout the convolutional neural network. The pixel values were normalized to a range of [0,1] using min-max normalization by dividing each pixel value by 255.This transformation is mathematically expressed as:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

In our case, since pixel values are originally in the range [0,255] the formula simplifies to:

$$x' = \frac{x}{255} \tag{2}$$

from the above equation, where:

- x is the original pixel value.
- x' is the normalized pixel value.

This normalization is crucial for accelerating convergence during training and ensuring that different pixel intensities across channels do not adversely affect model performance.After this data augmentation is performed using Image data generator with some adjustments like flipping, rotation.After augmentation each class consist of 2000 images. Figure 3 illustrates the Number of images in each class before augmentation. If a class

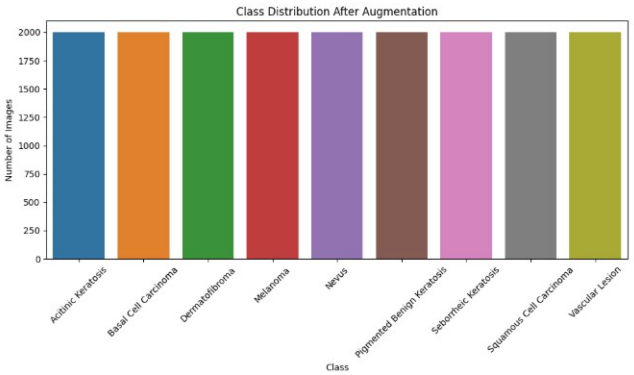

Fig. 4: Number of images in each class after augmentation.

originally had fewer samples, synthetic images were generated using augmentation to fulfill the target count.figre 4 represent the number of images in each class after the Agumentation takes place.After this, dataset is split in to training(80%) and testing(20%).from the training dataset 10% of the dataset is reserved for the validation dataset.

D. Model Architecture

Four different CNN architectures were examined in this study.They are MobileNetV2, EfficientNetB0, VGG16, and DenseNet201 models.In the upcoming section will see the detail explanation of each model.

i. MobilNetV2:

This model uses MobileNetV2 as its base, which is a lightweight and fast neural network. The default top layers are removed, so we can add our own classification layers. It uses pre-trained weights from ImageNet to help the model learn faster and better. The input image size is set to 128x128 with 3 color channels (RGB). After getting the features from MobileNetV2, we use a Global Average Pooling(2D) layer to reduce the feature maps into a single long vector by taking the average of each channel. This helps reduce the chance of overfitting. Drop out layer is add to randomly turn off some neurons, which helps the model generalize better. A Dense (fully connected) layer and ReLU activation is added to learn more complex features. Then, we apply another Dropout layer (30%) for more regularization. Figure 5 represent the architecture of the model.

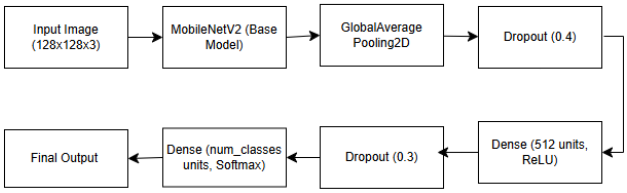

Fig. 5: MobileNetV2 Architecture

Finally, the model has an output layer with as many units as there are classes, using softmax activation to give the probabilities for each class. The model is trained using the SGD optimizer with 0.001 learning rate and momentum (0.9), which helps the model learn smoothly and steadily.

ii. EfficientNetB0:

This model is designed for classifying images into 9 categories. It starts by taking an input image of size 224×224×3 (a normal RGB image). The main part of the model is EfficientNetB0, a powerful pre-trained network, which will extract the required feature from skin lesions. This part doesn't include its original classification layers, as we replace them with our own.Figure 6 represent the architecture of the model.

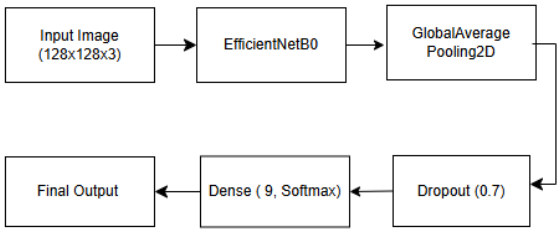

Fig. 6: EfficientNetB0 Architecture

After EfficientNetB0 processes the image, the output goes through a Global Average Pooling layer, which simplifies the data by averaging each feature map. Then, a Dropout layer is added to prevent overfitting by randomly turning off 70% of the neurons during training. And the model uses a Dense (fully connected) layer with 9 output units and softmax activation to give the probability of the lesion belonging to particular class.

iii. VGG16:

The model starts by taking an input image of size 224x224 with 3 color channels. [8] This input is fed into a VGG16 convolutional base, excluding its original fully connected layers. The weights of this base are frozen to preserve the learned features from ImageNet. The output of the convolutional base is then flattened into a one-dimensional vector, which passes through a series of fully connected layers: first a dense layer with 512 units followed by a dropout layer with a 0.2 rate for regularization.After this dense and and dropout layer was added.

Finally, the model ends with a dense output layer of 9 units using softmax activation, producing class probabilities for the nine skin disease categories. Compilation will take place by Adam optimizer, using a low learning rate, and optimized with categorical cross-entropy loss to handle the multi-class classification task effectively.Figure 7 represents the VGG16 model architecture.

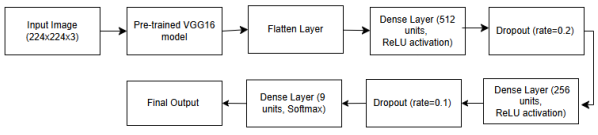

Fig. 7: VGG16 Architecture

iv. DenseNet201:

This model uses densenet201 to extract features from images and then flattens those features into a 1D vector. A dropout layer is added to reduce overfitting, also fully connected layers were added. Finally, a softmax output layer gives class probabilities for classification. This is a fairly strong model for image classification tasks using transfer learning.Figure 8 represents the DenseNet201 Architecture diagram.

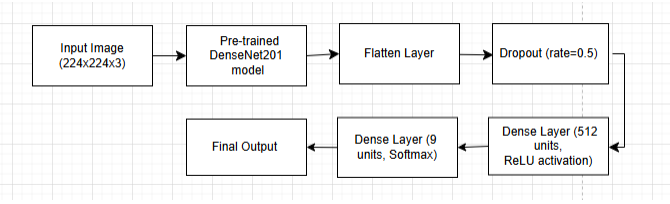

Fig. 8: DesnseNet201 Architecture

E. Model Compilation and Training:

In this stage, the model is first compiled using the Stochastic Gradient Descent (SGD) optimizer, which updates the model weights based on the gradient of the loss function. We set the learning rate to 0.001 and use a momentum of 0.9 to help accelerate convergence and reduce oscillations.Updated velocity and Gradient of the loss is calculated using below formula 3 and 4, here,

- θ = Model weights
- v = Velocity (accumulated gradient)
- η = Learning rate
- μ = Momentum
- $\nabla_\theta J(\theta)$ = Gradient of the loss with respect to the parameters

Then,

$$v_t = \mu \cdot v_{t-1} - \eta \cdot \nabla_\theta J(\theta)$$
$$\theta = \theta + v_t \tag{3}$$

This helps accelerate SGD in relevant directions and dampens oscillations. optimizer, which updates the model weights based on the gradient of the loss function. The loss function used is categorical cross-entropy, which is suitable for multi-class classification tasks. The categorical cross-entropy loss is calculated using the formula 4:

$$\text{Loss} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{4}$$

where,

- C is the number of classes.
- y_i =true label
- $\hat{y}_i$=predicted probability for class i

To improve training efficiency, we use a callback called Reduce learning rate gradually. It monitors the validation accuracy and reduces the learning rate by a factor of 0.5 if no improvement is seen for 3 consecutive epochs, down to a minimum of 0.00001. This adaptive learning helps the model learn better and avoid plateauing. Finally, the model is trained with 50 epochs and a batch size of 32.

IV. Results and Discussion

In this section will discuss the results of the experimented 4 different models.

A. MobileNetB2

The performance of the MobileNetV2 model for the classification of 9-class skin tumors was evaluated using accuracy, loss, and the confusion matrix. The model achieved a training accuracy of 88.46% with a corresponding loss of 0.3748, indicating effective learning and good generalization on the training data as shown in the figure 9 and 10. However, the validation accuracy was 66.20%. A Confusion matrix will help in identifying specific categories with higher misclassification rates. Figure 11 represents MobileNetV2 confusion matrix diagram.

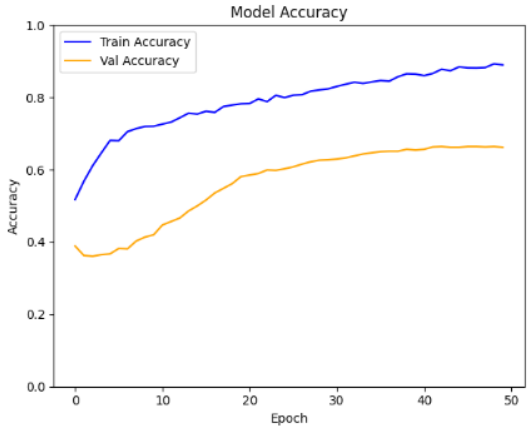

Fig. 9: Training VS Validation accuracy graph.

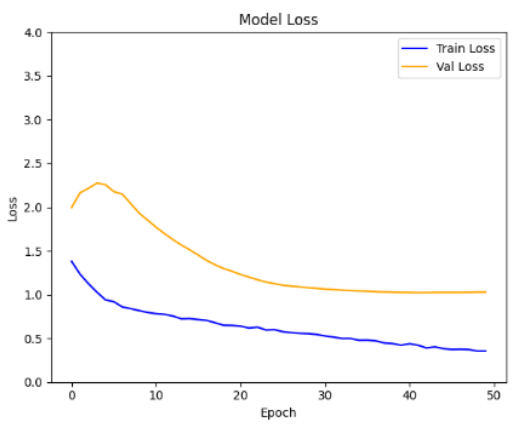

Fig. 10: Training VS Validation loss graph

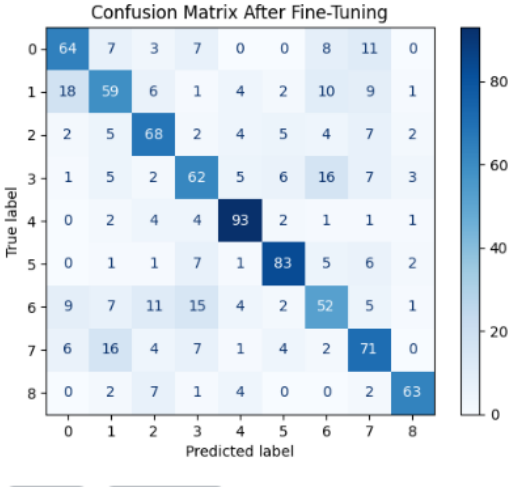

Fig. 11: Confusion Matrix for the MobileNetV2 Model

B. *EfficientB0*

This model shows the skin cancer classification across the all 9 classes. Figure 12 shows the training and validation accuracy graph curves.The validation accuracy is around 80.24%.Figure 13 shows the the training and validation loss curves,with the less training losses. Figure 14 shows the confusion matrix diagram with 9 different skin tumor classes.Most classes are well-classified, and the model has improved after the fine tuning.Higher values along the diagonal indicate better classification accuracy for each class.

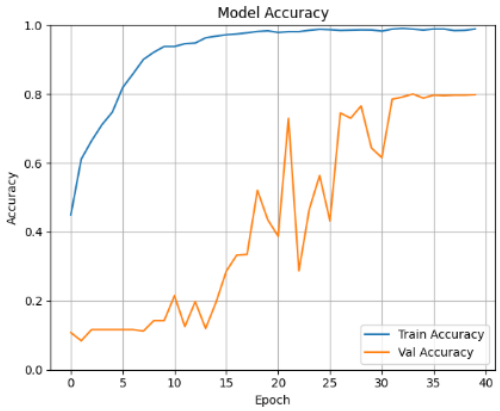

Fig. 12: Training VS Validation accuracy graph.

C. *VGG16 Model*

This model shows the skin tumor classifcation across the all 9 classes. Figure 15 shows the accuracy graph curves. The validation accuracy is around 80.32%. Figure 16 shows the training and validation loss curves, with the lowest training losses.

Figure 17 shows the confusion matrix diagram with 9 different skin tumor classes. Most classes are well-classified, and the model has improved after fine tuning. Higher values

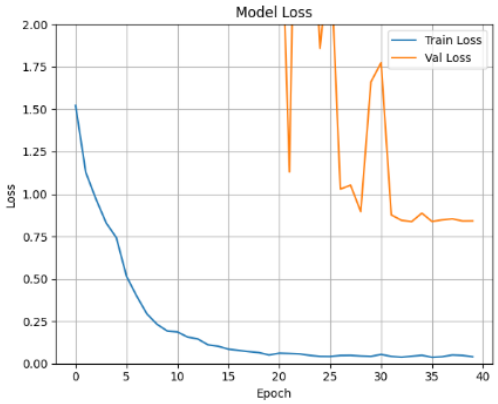

Fig. 13: Training VS Validation loss graph

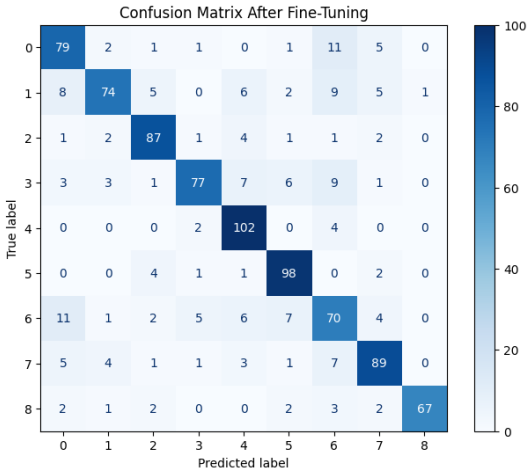

Fig. 14: Confusion Matrix for the EfficientNetB0 model

along the diagonal indicate better classification accuracy for each class.

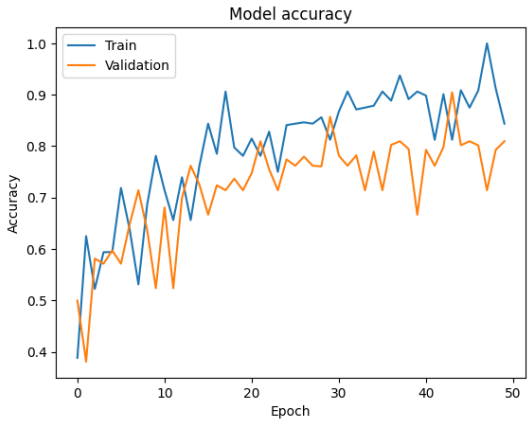

Fig. 15: Training VS Validation Accuracy graph.

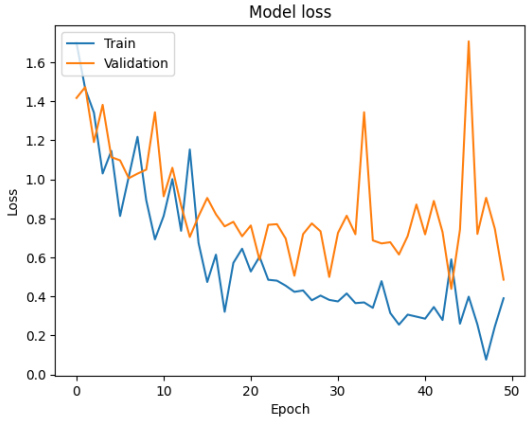

Fig. 16: Training VS Validation loss graph.

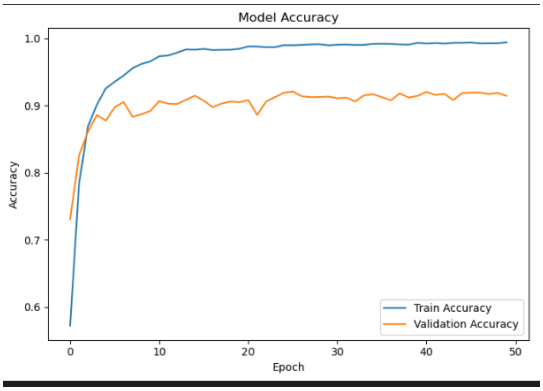

Fig. 18: Training VS Validation Accuracy graph

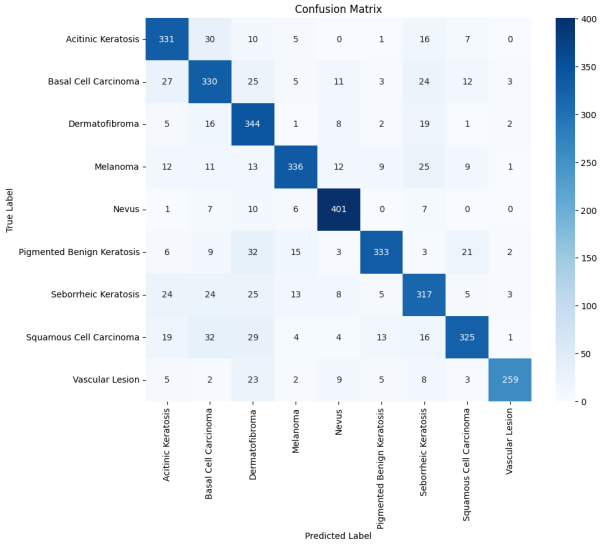

Fig. 17: Confusion Matrix for the VGG16 model.

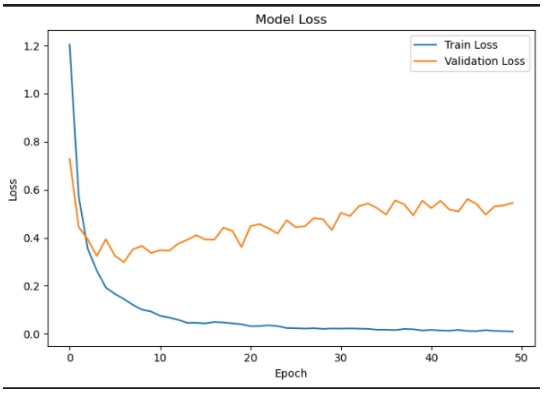

Fig. 19: Training VS Validation loss graph.

D. DenseNet201 model

The DenseNet201-based model for skin tumor classification shows solid performance across the full range of nine classes. Its deep architecture with dense connections facilitates strong feature reuse and gradient flow, improving accuracy and generalization.Figure 18 shows the Traing vs Validation accuracy graph, with Training accuracy around 99% and validation accuracy 91.44%.

The accuracy graph indicates stable learning without overfitting, while the confusion matrix in the Figure 20 shows the classification report 9 different skin tumor correct a predictions. And the figure 19 represents the training and validation loss curve with less loss around 0.1. Overall, DenseNet201 effectively handles the complexity of multiclass skin lesion classification.

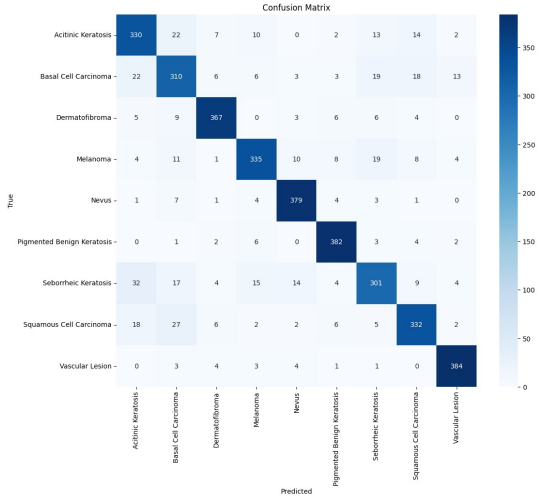

Fig. 20: Confusion Matrix for the DenseNet201 model.

V. Comparison of 4 different models

Below Table I presents a comprehensive comparison between four DL models used for skin tumor classification: VGG16, MobileNetV2, DenseNet201, and EfficientNetB0. related studies [9], [10].

Model	Accuracy (%)	Macro Avg(%)	Weighted(%)
VGG16	80.32	81	81.01
MobileNetV2	66.20	66	66.30
DenseNet201	91.44	91	91
EfficientNetB0	80.24	80.53	80.19

TABLE I: **Overall Performance Comparison of Deep Learning Models**

Among these, DenseNet201 outperforms the others by achieving the highest test accuracy of 91.44% and the lowest loss of 0.54, indicating better generalization and robustness. In contrast, MobileNetV2 achieves the lowest accuracy of 66.20%, suggesting its lighter architecture may not be sufficient for this complex classification task. VGG16 and EfficientNetB0 exhibit comparable performance, both around 80.32% accuracy. Additionally, the Macro Average and Weighted Average metrics further confirm that DenseNet201 yields superior balanced performance across all classes.

VI. Conclusion and Future work

DenseNet201 emerged as the most effective model for skin tumor multi-class classification in terms of overall accuracy and robustness, closely followed by EfficientNetB0. MobileNetV2 presents a practical alternative for resource-constrained environments, while VGG16, despite its lower performance, still provides a baseline for comparative purposes. Particularly DenseNet and EfficientNet, are better suited for complex dermatological image classification tasks, especially when multiple skin tumor types are involved.

For future work, we aim to increase the model's performance by incorporating advanced techniques such as attention mechanisms to help focus on clinically relevant regions of skin lesions. Exploring multi-modal learning by integrating patient metadata with image features could further improve diagnostic accuracy. Finally, validating these models on larger, more diverse datasets and deploying lightweight versions for real-time use on mobile or web platforms will be crucial for real-world applicability.

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