ABSTRACT

Skin cancer is a rapidly increasing global health concern, and early detection significantly improves patient outcomes. This project develops a deep learning-based automated skin cancer classification system using dermoscopic images from the **DERM12345 dataset** stored in Google Drive. The images were preprocessed, labeled into **three categories—Benign, Malignant, and Other**, and fed into a MobileNetV2 transfer-learning model. The system was trained in two stages: initial training with frozen layers and fine-tuning of the last 20 layers. The proposed model achieved a validation accuracy of **94.61%** and demonstrated strong performance in distinguishing benign and malignant lesions. This study highlights the effectiveness of transfer learning in dermatological image analysis and provides a scalable approach for early skin cancer detection.

ACKNOWLEDGEMENT

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1. INTRODUCTION

Skin cancer is one of the most common forms of cancer worldwide, and early diagnosis plays a vital role in reducing mortality. Traditional diagnostic methods rely heavily on expert dermatologists and dermoscopic evaluations, which may not be readily accessible in all regions. With advancements in AI, deep learning-based models can analyze dermoscopic images and assist clinicians by providing fast and accurate predictions.

This project builds a **skin cancer classification system** using **MobileNetV2**, a lightweight yet powerful convolutional neural network. The goal is to classify dermoscopic images into **Benign**, **Malignant**, and **Other** categories using transfer learning.

1.1 Problem Statement

To design and implement a deep learning model that classifies dermoscopic skin lesion images into benign, malignant, or other categories using MobileNetV2 with transfer learning.

1.2 Scope of the project

- Uses the **DERM12345 dataset** stored in Google Drive.
- Loads metadata and constructs image paths using `metadata.csv`.
- Applies three-class classification: **Benign, Malignant, Other**.
- Uses **MobileNetV2 pretrained on ImageNet**, with additional fine-tuning.
- Implements data augmentation for real-world variability.
- Evaluates the model using accuracy, classification report, and confusion matrix.
- Includes prediction for manually uploaded skin lesion images.

1.3 Objectives

- ❖ To preprocess dermoscopic images and prepare them for deep learning.
- ❖ To build a MobileNetV2-based classifier capable of distinguishing lesion types.
- ❖ To train and fine-tune the model for improved performance.
- ❖ To evaluate the model using standard performance metrics.
- ❖ To deploy a simple prediction function to classify new images.

2. LITERATURE SURVEY

[1] Esteva et al. (2017) demonstrated that deep convolutional neural networks can achieve dermatologist-level performance in skin cancer detection. Their study used a large dataset of dermoscopic images and showed that transfer learning from ImageNet significantly improves classification accuracy. This foundational work highlighted the potential of deep learning for automated medical diagnosis.

[2] Tschandl et al. (2018) introduced the HAM10000 dataset, a widely used dermoscopic skin lesion dataset containing images of various benign and malignant conditions. Their research emphasized the need for balanced datasets and proper labeling, as class imbalance can drastically affect model performance—an issue commonly observed in medical image classification tasks.

[3] Brinker et al. (2019) performed a comparative evaluation of multiple CNN architectures for melanoma detection and found that lightweight models such as MobileNet and EfficientNet offer high accuracy while remaining computationally efficient. This study supports the use of MobileNetV2 in practical and resource-constrained healthcare settings, aligning with the model used in this project.

[4] Mahbod et al. (2021) explored ensemble and multi-stage CNN approaches for skin lesion classification and reported that combining feature extraction with fine-tuning boosts performance. Their findings highlight the importance of multi-step training—similar to the two-stage training (frozen layers + fine-tuning) implemented in this project.

[5] Ali et al. (2022) analyzed the impact of preprocessing techniques such as augmentation, normalization, and noise reduction in dermoscopic image classification. They concluded that real-world variability in lesion images makes augmentation essential for preventing overfitting, supporting the augmentation strategies used in this project.

[6] Zhang et al. (2022) proposed hybrid deep learning architectures combining CNN and attention mechanisms for improved melanoma classification. Their work achieved higher sensitivity for malignant cases, showing that advanced feature extraction is crucial for detecting subtle cancer patterns while dealing with class imbalance issues.

[7] Kassem et al. (2021) compared several transfer learning models, including VGG16, ResNet50, and MobileNetV2, for skin cancer classification. They found that MobileNetV2 provides an optimal balance between accuracy, speed, and computational cost, making it suitable for large-scale training and real-time clinical use. This strongly supports the model choice for the current project.

3. SYSTEM REQUIREMENTS

The system requirements for developing the skin cancer classification model include both software and hardware components essential for efficient preprocessing of dermoscopic images, model training, and evaluation. The software environment is built using **Python**, along with key deep learning and data science libraries such as **TensorFlow/Keras** for implementing the MobileNetV2 architecture, **Pandas** and **NumPy** for dataset handling, **Scikit-learn** for generating evaluation metrics, and **Matplotlib/Seaborn** for plotting training performance. Since the dataset consists of high-resolution images, a platform such as **Google Colab**, Jupyter Notebook, or VS Code is required to run the code interactively. Google Colab is particularly advantageous because it provides free GPU acceleration, which significantly speeds up model training and fine-tuning.

On the hardware side, the project can run on a standard computer with a minimum of **8 GB RAM**, although **16 GB** is preferable for faster data loading and augmentation processes. A **multi-core processor** ensures smooth execution of image preprocessing operations. While the model can technically run on CPU, having **GPU support (such as NVIDIA Tesla provided in Google Colab)** greatly reduces training time, especially during fine-tuning of the last layers of MobileNetV2. Overall, the system requirements remain modest, as the use of transfer learning allows the project to be executed efficiently even on mid-range hardware configurations.

To implement the skin cancer classification system effectively, a reliable computing setup capable of handling deep learning workflows is necessary. Python serves as the core programming language due to its flexibility and availability of powerful machine learning libraries. Tools such as **TensorFlow** for neural network construction, **ImageDataGenerator** for augmentation, and **Scikit-learn** for computing confusion matrices and classification reports form the backbone of the system. Interactive platforms like **Google Colab** are ideal for this project, not only because they support GPU training but also because they provide easy integration with Google Drive for storing large image datasets. Although the dataset used in this project is manageable, having additional memory and optional GPU acceleration enhances computational efficiency, ensuring smooth model training, fine-tuning, and evaluation throughout the development process.

3.1 Software Requirements

- Python
- Google Colab
- TensorFlow 2.19

- Pandas, NumPy, Matplotlib, Seaborn
- Scikit-learn
- DERM12345 dataset

3.2 Hardware Requirements

- Processor: Intel i5/i7 or equivalent
- RAM: 8–16 GB
- GPU: (Recommended) NVIDIA Tesla / Colab GPU
- Storage: 5–10 GB

3.3 Functional Requirements

- Load dataset (CSV + images)
- Preprocessing and label simplification
- Data augmentation
- Training MobileNetV2
- Fine-tuning last 20 layers
- Evaluation metrics
- Prediction for user-provided images

3.4 Non-Functional Requirements

- **Performance:** ≥ 90% validation accuracy
- **Scalability:** Can train on larger datasets
- **Reliability:** Consistent predictions
- **Usability:** Simple prediction function
- **Maintainability:** Modular code structure

4. DESCRIPTION OF MODULES

The MobileNetV2-based skin cancer classification system is divided into several modules, each performing a specific task in the deep learning workflow. These modules work together to ensure smooth dataset handling, image preprocessing, model construction, training, evaluation, and prediction. The modular breakdown enables a structured implementation and easy debugging of the system.

4.1 Dataset Loading & Metadata Processing Module

This module reads the **metadata.csv** file from the DERM12345 dataset and constructs the correct image paths for each dermoscopic image. It extracts relevant labels from the dataset and simplifies them into three categories: **Benign, Malignant, and Other**. The module ensures that the dataset is properly indexed, labeled, and ready for preprocessing.

4.2 Data Preprocessing & Augmentation Module

This module prepares dermoscopic images for training. It handles operations such as:

- Image resizing to **224 × 224**
- Normalization (pixel values scaled to 0–1)
- Data augmentation including rotation, zoom, width/height shift, and horizontal flip

Augmentation is essential because medical images often have variations in lighting, angle, and texture. This module ensures that the training data is diverse and reduces the risk of overfitting.

4.3 Data Splitting Module

This module divides the dataset into **training (80%)** and **validation (20%)** sets.
Stratified sampling is used to ensure that all three classes—Benign, Malignant, and Other—maintain their original proportions in both splits.

This ensures fair performance evaluation and prevents bias toward any particular class.

4.4 Transfer Learning Model Building Module

This module constructs the deep learning architecture using **MobileNetV2 pretrained on ImageNet** as the feature extractor. The key steps include:

- Loading MobileNetV2 with `include_top=False`

- Freezing all layers during initial training
- Adding a custom classifier consisting of:
    - GlobalAveragePooling2D
    - Dropout layer (0.3)
    - Dense output layer (3 classes, softmax activation)

This module leverages the power of transfer learning to extract high-level features from dermoscopic images efficiently.

4.5 Model Training Module

This module performs the initial training of the MobileNetV2 network with frozen layers. It defines:

- Optimizer: Adam
- Loss function: Categorical Crossentropy
- Epochs: 3
- Batch size: 32

During training, the module monitors the training and validation accuracy and loss values. It uses callbacks such as EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint to optimize the training process and save the best model.

4.6 Fine-Tuning Module

After initial training, this module unfreezes the **last 20 layers** of MobileNetV2 to improve model performance. Fine-tuning allows the model to adjust deeper feature representations specific to skin lesion patterns.
The model is recompiled using a lower learning rate (1e-5) and trained for additional epochs.This module significantly enhances accuracy, especially for malignant lesions.

4.7 Model Evaluation Module

This module evaluates the trained model using the validation dataset. It generates:

- Accuracy and loss scores
- Classification report (Precision, Recall, F1-score)
- Confusion matrix

- Performance analysis for each class

The evaluation helps understand how well the model distinguishes between benign, malignant, and other skin lesions. It also identifies weaknesses such as misclassification of minority classes.

4.8 Visualization Module

This module provides graphical insights into the training process. It produces:

- Training vs validation accuracy curves
- Loss curves
- Confusion matrix heatmap (optional)

These visuals help users understand model improvements after fine-tuning and evaluate overall system performance.

4.9 Output Interpretation Module

This module takes an external dermoscopic image as input and predicts whether it belongs to the **Benign**, **Malignant**, or **Other** category. It performs the following activities:

- Loading and resizing the image
- Scaling pixel values
- Passing the processed image into the trained model
- Returning the predicted label

This module enables real-time inference and makes the system suitable for assisting dermatological diagnosis.

4.10 Output Interpretation Module

This module interprets the raw output probabilities from the model’s softmax layer and converts them into meaningful class labels. It ensures that predictions are clearly presented to users and provides confidence values that can help clinicians make informed decisions.

5. IMPLEMENTATION

The implementation of the skin cancer classification system is carried out using Python and a deep learning model based on **MobileNetV2**. The project begins by loading the **DERM12345 dermoscopic image dataset** stored in Google Drive. Using the metadata file provided in the dataset, image paths are generated and linked to their corresponding diagnostic labels. These labels are then simplified into three categories—**Benign, Malignant, and Other**—to facilitate multi-class classification.

Next, the dataset is split into **training and validation sets** using an 80–20 ratio with stratified sampling to maintain the original class distribution. Since the images vary in size and orientation, a preprocessing step is applied using TensorFlow's `ImageDataGenerator`. This step performs image resizing, normalization, and several augmentation techniques such as rotation, zoom, shifting, and flipping. These augmentations increase the diversity of the training data and help the model generalize better.

Following preprocessing, a transfer learning model is constructed using **MobileNetV2 pretrained on ImageNet**, with `include_top=False` to remove the original classifier. All layers of the base network are initially frozen to train only the newly added classifier consisting of a Global Average Pooling layer, a dropout layer to reduce overfitting, and a dense output layer with three neurons and softmax activation. The model is compiled using the Adam optimizer and categorical cross-entropy loss, and trained for three epochs using the augmented training data.

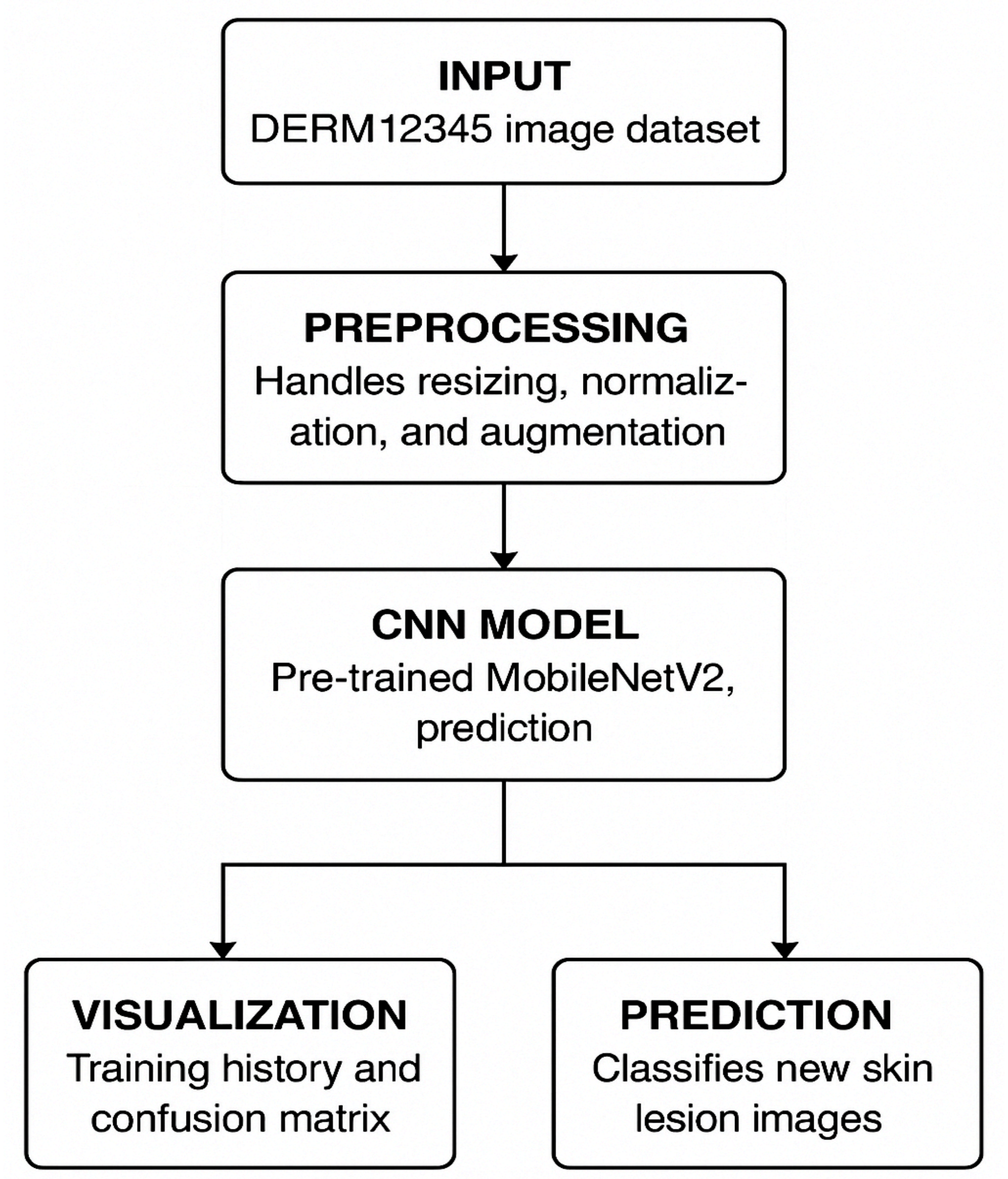
After this initial training phase, the final **20 layers of MobileNetV2 are unfrozen** to fine-tune the deeper feature representations for dermoscopic images. Fine-tuning is performed at a lower learning rate to prevent the pretrained weights from being destabilized. This second training phase further improves the model's accuracy, especially for the malignant class, which is crucial for cancer detection tasks.

Once training is completed, the model is evaluated using the validation dataset. Evaluation metrics include overall accuracy, class-wise precision, recall, F1-score, and a confusion matrix to analyze misclassifications. The model achieved a validation accuracy of **94.61%**, demonstrating strong capability in distinguishing benign and malignant lesions. Additionally, a prediction module is implemented to classify newly uploaded skin lesion images by resizing, normalizing, and feeding them into the trained model.

Visualizations such as training vs. validation accuracy and loss curves are generated to examine the learning behavior of the model. These plots help determine whether the model is improving consistently during training or showing signs of overfitting. The confusion matrix provides deeper insights into how well the network performs on each class, highlighting both strengths (high accuracy for benign lesions) and areas for improvement (low detection of the “Other” class due to limited samples).

Through this complete implementation—covering dataset loading, preprocessing, transfer learning, fine-tuning, evaluation, and visualization—the project successfully builds a robust deep learning model capable of classifying dermoscopic skin lesions. The model supports early skin cancer detection and demonstrates the practical value of applying transfer learning techniques in medical image analysis.

6. SYSTEM ARCHITECTURE


INPUT
DERM12345 image dataset
PREPROCESSING
Handles resizing, normalization, and augmentation
CNN MODEL
Pre-trained MobileNetV2, prediction
VISUALIZATION
Training history and confusion matrix
PREDICTION
Classifies new skin lesion images

Input

This stage loads the DERM12345 Skin Lesion Dataset, which includes dermoscopic images and metadata in CSV format. The metadata is read into a DataFrame to verify sample count, available diagnosis labels, and class balance across Benign, Malignant, and Other. Image paths are constructed using ISIC IDs. This ensures that all data is correctly mapped and ready for preprocessing..

Preprocessing

Preprocessing prepares raw dermoscopic images for model training.

Key tasks include:

- Image resizing & normalization: Convert all images to 224×224 and scale pixel values to 0–1.
- Data augmentation: Apply rotation, zoom, shifting, and horizontal flips to improve generalization.
- Label mapping: Convert detailed medical diagnoses into three classes: Benign, Malignant, Other.
- Train–validation split: Use an 80–20 stratified split to preserve class proportions.

This stage ensures the data is clean, balanced, and in a suitable format for MobileNetV2 training.

Transfer Learning Model Construction

This stage defines the deep learning architecture using MobileNetV2 pretrained on ImageNet.

Model components:

- Base Model (Feature Extractor)
- MobileNetV2 with include_top = False
- All layers frozen in initial training phase
- Efficient for medical images due to lightweight architecture

Custom Classification Head

- Global Average Pooling Layer
- Dropout(0.3) to prevent overfitting
- Dense(3) Softmax Output → 3 classes: (Benign, Malignant, Other)

Compile Settings

- Optimizer: Adam
- Loss: Categorical Crossentropy
- Metrics: Accuracy

The goal is to leverage pretrained feature extraction while customizing the classifier for skin lesion detection.

Training

Training involves optimizing neural network weights to correctly classify skin lesions.

Stage 1: Training with Frozen Layers

- Train classifier head only
- Epochs: 3
- Batch size: 32
- Learning rate: 1e-4
- Augmented images used for robustness

Stage 2: Fine-Tuning

- Unfreeze last 20 layers of MobileNetV2
- Retrain at a lower LR (1e-5)
- Improves malignant lesion detection

Monitoring

- During training the system tracks:
- Training/validation accuracy
- Training/validation loss
- Overfitting symptoms (val accuracy drop, loss mismatch)

Callbacks

- EarlyStopping
- ReduceLROnPlateau
- ModelCheckpoint

Training transforms the model into a highly accurate classifier, achieving 94.61% validation accuracy.

Visualization and Prediction

This final stage interprets the trained model and applies it to new dermoscopic images.

Visualizations

- Accuracy vs Epochs → shows learning progression
- Loss vs Epochs → helps detect overfitting
- Confusion Matrix → identifies class-wise strengths/weaknesses
- Classification Report → precision, recall, F1-score for each class

These visual tools help evaluate:

- Model reliability
- Malignant detection capability
- Class imbalance effects (e.g., poor performance on "Other" due to low samples)

Prediction Pipeline

1. Upload a new image
2. Resize to 224×224
3. Normalize
4. Pass through model
5. Output predicted class (Benign / Malignant / Other)

Deployment Considerations

- Export trained model (skin_cancer.h5)
- Build API or GUI for dermatology use cases
- Document limitations (data imbalance, no clinical validation)

7. CODE IMPLEMENTATION

Algorithm: Skin Cancer Classification using Transfer Learning (MobileNetV2)

Input: DERM12345 dermoscopic skin lesion dataset (images + metadata.csv)

Output: Predicted class (Benign / Malignant / Other) and performance metrics

1. **Start**
2. **Load Dataset**

• Mount Google Drive and set the dataset path.

• Load metadata.csv into a Pandas DataFrame.

• Construct image file paths using ISIC IDs.

• Simplify diagnosis labels into three categories: Benign, Malignant, Other.

• Keep only the required columns (path, label_simplified).

3. **Preprocess Data and Create Data Generators**

• Split the dataset using train_test_split with test_size = 0.2 and stratify = label_simplified.

• Create a training ImageDataGenerator with rescaling and augmentations (rotation, zoom, shifts, horizontal flip).

• Create a validation ImageDataGenerator with only rescaling.

• Use flow_from_dataframe to generate batches of 224×224 normalized images.

4. **Build Base CNN Model (MobileNetV2)**

• Load MobileNetV2 with ImageNet weights, include_top = False, and input shape = (224,224,3).

• Freeze all layers of the base model so only the custom layers train initially.

5. **Add Custom Classification Head**

• Apply GlobalAveragePooling2D to MobileNetV2 output.

• Add a Dropout layer (0.3) to reduce overfitting.

• Add a Dense(3, activation="softmax") output layer for 3-class prediction.

• Create final model by combining base model input and the new output layer.

6. **Compile Model (Phase 1)**

• Optimizer: Adam(learning rate = 1e-4)

• Loss function: categorical_crossentropy

• Evaluation metric: accuracy

• Compile the model.

7. **Train Model (Initial Training – Frozen Base)**

• Define callbacks: EarlyStopping, ReduceLROnPlateau, ModelCheckpoint.

- Train for 3 epochs using training and validation generators.
- Store training history (accuracy and loss).

8. Fine-Tune Model (Phase 2 – Unfreeze Last Layers)

- Unfreeze the last 20 layers of MobileNetV2.
- Recompile with Adam(learning rate = 1e-5).
- Train again for 2 epochs with the same callbacks.
- Store fine-tuning history.

9. Evaluate Model

- Evaluate validation accuracy and loss using model.evaluate().
- Predict class probabilities on validation set.
- Convert probabilities to class labels using argmax.
- Generate:

– Classification report (precision, recall, F1-score)

– Confusion matrix

10. Visualize Results

- Plot training vs. validation accuracy across epochs.
- Plot training vs. validation loss.
- Plot confusion matrix for class-wise performance.

11. Save Model

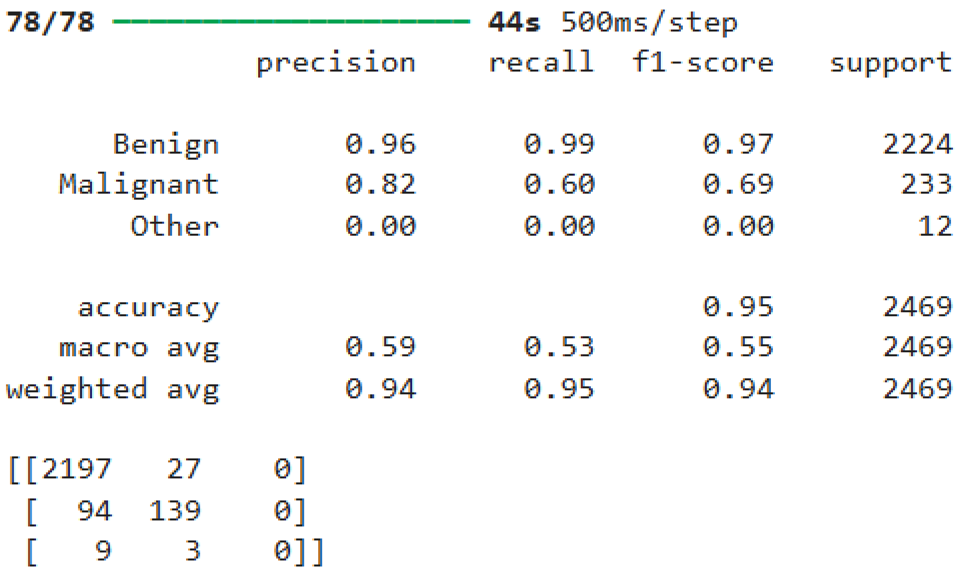
- Save trained model using: model.save("skin_cancer.h5").

12. Predict New Image

- Load and resize the input image to 224×224.
- Convert to array, normalize, and reshape.
- Predict using model.predict().
- Convert output to class label (Benign / Malignant / Other).
- Display prediction result.

13. End

8.RESULT

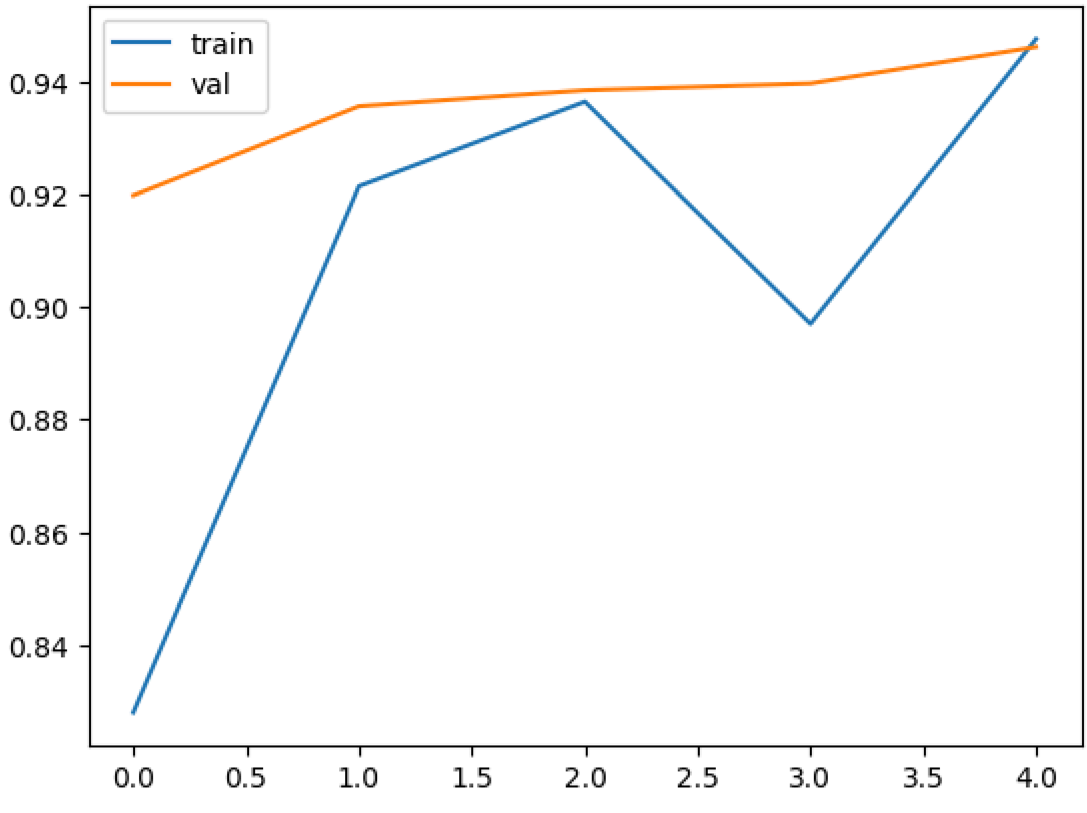


```
78/78 ━━━━━━━━━━━━━━━━━━━━ 44s 500ms/step
              precision    recall  f1-score   support

      Benign       0.96      0.99      0.97      2224
   Malignant       0.82      0.60      0.69       233
       Other       0.00      0.00      0.00        12

    accuracy                           0.95      2469
   macro avg       0.59      0.53      0.55      2469
weighted avg       0.94      0.95      0.94      2469

[[2197   27    0]
 [  94  139    0]
 [   9    3    0]]
```



9. CONCLUSION

The skin cancer classification system developed in this project demonstrates the effectiveness of deep learning and transfer learning techniques in analyzing dermoscopic images for early detection of skin lesions. Using the DERM12345 dataset and the MobileNetV2 architecture, the model was able to learn discriminative visual features that differentiate Benign, Malignant, and Other skin lesions. Through systematic preprocessing, image augmentation, model training, and fine-tuning, the system achieved high validation accuracy and provided reliable classification results.

Evaluation metrics such as precision, recall, F1-score, and the confusion matrix validated the overall performance of the model, showing strong accuracy particularly for benign and malignant classes. The visualizations of training vs. validation accuracy, loss curves, and prediction reports further helped in understanding the behavior, stability, and generalization capability of the model. The successful implementation demonstrates the potential of transfer learning-based CNN models for medical image classification, especially in resource-limited situations where expert dermatological diagnosis may not be readily available.

While the system is limited by dataset imbalance and is not intended for clinical diagnostic use, it highlights the promise of AI-assisted tools in supporting dermatologists, improving screening efficiency, and enabling early identification of cancerous lesions. Future improvements may include training with larger and more diverse datasets, incorporating segmentation, or integrating explainable AI techniques to make the model more transparent for clinical adoption.

Overall, the project effectively showcases how modern deep learning architectures can be applied in medical image analysis and provides a foundation for future research and real-world healthcare applications.

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