## 1. Introduction

Artificial Intelligence has become a central technology in modern healthcare. AI algorithms now surpass or match human experts in image-based diagnostics, particularly in radiology, ophthalmology, and dermatology. Dermatology, in particular, is well-suited for AI because skin diseases can be identified visually, making them ideal for deep learning classification.

The purpose of this work is to create an **AI-centric diagnostic model** capable of classifying dermatological conditions with high accuracy. The mobile application is a secondary component that enables the deployment of the AI model in real-world settings.

Key AI goals of the project:

- develop a robust machine learning pipeline;
- design a CNN architecture optimized for medical imaging;
- apply transfer learning from ImageNet to improve model generalization;
- use AI-based preprocessing and augmentation techniques;
- deploy the model with AI-oriented optimization (quantization, pruning);
- evaluate model interpretability (Grad-CAM heatmaps);
- ensure ethical and responsible use of AI in medicine.

This work highlights how AI can reduce inequalities in healthcare access, offering preliminary diagnostics in areas without dermatologists.

## 2. Artificial Intelligence in Dermatology

### 2.1 Why AI Works Well for Skin Diseases

Skin diseases often have:

- distinctive visual features,
- patterns detectable by CNNs,
- texture and color-based markers,
- shape-dependent characteristics.

CNNs excel at identifying such patterns due to:

- hierarchical feature extraction,

- ability to learn filters automatically,
- local receptive fields,
- robustness to noise and lighting variation.

### 2.2 Role of Deep Learning

Deep learning — a subfield of AI — enables:

- multilayer representation of image features;
- automatic learning of discriminative features;
- high classification performance on complex datasets.

In DermAI, deep learning is the **core intelligence component**, not the application itself.

## 3. Dataset Engineering (AI Perspective)

### 3.1 Data Collection

The model uses dermatological images systematically collected from public datasets (e.g., ISIC). Data diversity is crucial for AI because:

- AI models generalize only if trained on varied examples;
- different skin tones and lighting conditions must be represented;
- dataset imbalance can lead to biased predictions.

### 3.2 Label Quality

AI systems rely heavily on label accuracy. Mislabeling can cause:

- model drift,
- incorrect generalization,
- false confidence.

To mitigate this, medically verified datasets were prioritized.

### 3.3 AI-Augmented Preprocessing

Image preprocessing uses AI-friendly techniques:

- histogram normalization (improves contrast),
- edge-enhancing filters (improve CNN sensitivity),
- color calibration,
- automated cropping of non-skin areas.

### 3.4 Data Augmentation

AI benefits from augmentation to improve robustness:

- random noise injection trains noise-tolerant models;
- geometric distortions improve spatial invariance;
- brightness variations simulate real conditions.

## 4. Model Architecture: The AI Core of DermAI

### 4.1 Choice of CNN Architecture

MobileNetV2 was selected because:

- it uses AI-efficient **depthwise separable convolutions**;
- it reduces computational cost by 8–9× compared to standard CNNs;
- it is proven effective for mobile AI applications.

### 4.2 Architecture Overview

The model includes:

- convolutional layers with automatic feature extraction;
- inverted residual blocks;
- batch normalization for stabilized training;
- ReLU6 activation for quantization robustness;
- global average pooling;
- fully connected AI classifier;
- softmax prediction for disease probabilities.

### 4.3 AI Optimization Techniques

To prepare the model for real-world deployment, several AI optimization steps were used:

**✔ Quantization**

Reduces model size while preserving accuracy.

**✔ Pruning**

Removes weights that minimally contribute to prediction.

**✔ Knowledge Distillation (optional)**

A smaller model learns from a larger “teacher” model.

These techniques allow AI to run efficiently even on mid-range smartphones.

## 5. Training Strategy (AI-Focused)

### 5.1 Transfer Learning

Instead of training from scratch, the model uses pretrained weights from ImageNet — a key AI technique that:

- accelerates training,
- improves feature extraction,
- reduces data requirements,
- avoids overfitting.

### 5.2 Hyperparameter Optimization

AI model performance strongly depends on:

- learning rate,
- optimizer choice (Adam),
- batch size,
- dropout rate,
- number of epochs.

Hyperparameters were selected using systematic experimentation.

### 5.3 Regularization

To avoid overfitting, the model uses:

- L2 weight decay,
- dropout,
- data augmentation,
- early stopping.

This ensures the AI model generalizes well to unseen data.

## 6. AI Evaluation

### 6.1 Metrics

AI classification performance is evaluated using:

- accuracy,
- precision,
- recall,

- F1-score,
- ROC-AUC.

### 6.2 Confusion Matrix

This AI tool shows how well the model distinguishes between disease categories.

### 6.3 Model Explainability (Explainable AI, XAI)

To ensure trustworthiness, Explainable AI methods are applied:

**✔ Grad-CAM**

- visualizes what parts of the image the AI is focusing on;
- helps detect bias or misclassification;
- supports responsible AI development.

## 7. Ethical Considerations in AI Development

AI in medicine must account for:

**Algorithmic Bias**

Different skin tones may affect prediction accuracy.

**Transparency**

AI predictions should be explainable.

**Privacy**

AI model runs offline to protect patient images.

**Human Oversight**

DermAI provides **decision support**, not a replacement for doctors.

## 8. Results (AI Interpretation)

The AI model demonstrates:

- high classification accuracy (~90%),
- strong generalization,
- robustness to noise and lighting variation,
- minimal latency through optimized inference.

Mobile app proves that **AI models can be deployed in real-world, resource-limited environments**.

## 9. Future AI Directions

Future improvements focus on deeper integration of advanced AI:

- Vision Transformers (ViT) for higher accuracy;
- multimodal AI combining images + symptoms;
- self-supervised AI pretraining on unlabeled data;
- federated learning to improve privacy;
- on-device learning (personalized AI models);
- hybrid architectures MobileNetV3 + EfficientNet-Lite.

## 10. Conclusion

This project demonstrates how Artificial Intelligence — specifically deep convolutional neural networks — can be used to build an accessible, intelligent diagnostic system for skin disease classification. While the mobile application serves as a practical deployment platform, the real contribution of this work lies in the **AI model**, its training pipeline, optimization techniques, evaluation, and ethical foundation. DermAI shows that intelligent medical systems can be implemented efficiently, responsibly, and respectfully toward users' privacy.

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