PROJECT ABSTRACT

Skin Lesion Classification using CNN

A convolutional neural network classifying dermatoscopic skin lesions into the seven HAM10000 categories with transfer learning, real ABCD analysis, a live demo and viva kit. An educational prototype, not a medical device. Delivered built-to-order with report, PPT and Q&A.

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01. Title

Skin Lesion Classification using CNN

02. Introduction / Background

Skin cancer is the most common cancer worldwide, and dermatoscopy — magnified imaging of pigmented lesions — is how dermatologists triage them. Deep learning reached dermatologist-level classification on the HAM10000 benchmark (Tschandl et al., Harvard / Medical University of Vienna): 10,015 dermatoscopic images across 7 diagnostic categories with histopathology ground truth. This project reproduces that pipeline with transfer learning: an ImageNet-pretrained EfficientNet-B0 fine-tuned on HAM10000, with class weights handling the heavy imbalance toward benign nevi.

03. Problem Statement

Student medical-AI projects often train tiny CNNs from scratch on a few hundred images, claim unrealistic accuracy, and never state clinical limits — a dangerous combination for a medical topic. This project addresses that with the standard HAM10000 benchmark, transfer learning, honest per-class metrics, and explicit educational-prototype scoping throughout: the live demo computes the real dermatological ABCD rule from the photo's pixels and states plainly that it cannot diagnose.

04. Objectives

- Fine-tune EfficientNet-B0 (ImageNet init) on HAM10000 with class-weighted loss.
- Implement real ABCD analysis (Otsu segmentation, asymmetry, border, color, diameter).
- Build a live lesion-analyzer demo with transparent ABCD scoring.
- Evaluate with balanced accuracy, per-class metrics and the confusion matrix.
- State the educational-prototype limitation explicitly in demo, report and page.
- Deliver the complete student kit: notebook, model, demo, report, PPT and viva Q&A.

05. Proposed Methodology

The pipeline has four stages. (1) Data: HAM10000 images are stratified-split, normalized and augmented (rotation, flip, color jitter). (2) Modelling: EfficientNet-B0 with ImageNet weights is fine-tuned with a 256-unit dense head, dropout 0.4 and class-weighted cross-entropy against the nv majority. (3) Evaluation: the held-out split is scored once for balanced accuracy, per-class precision/recall/F1, top-2 accuracy and the confusion matrix. (4) Demo: an uploaded photo is segmented by Otsu thresholding on the brown-pigment channel; asymmetry is measured by mirror non-overlap, border by compactness, color by distinct quantized clusters, diameter by lesion extent; the clinical ABCD rule combines them with published weights and bands.

06. System Architecture / Working

The training notebook produces the fine-tuned EfficientNet plus preprocessing parameters. The single-file web demo has three views: the Lesion Analyzer (photo upload, Otsu segmentation, live ABCD measurements, triage score and the educational-prototype disclaimer), the ABCD Lab (each rule letter explained with its exact computation), and the System Report (CNN architecture, HAM10000 facts and design-target metrics with the scope limit).

07. Hardware / Software Requirements

- Python 3, TensorFlow/Keras (EfficientNet), NumPy, OpenCV, scikit-learn
- Jupyter Notebook (training & evaluation)
- HAM10000 dataset
- HTML5 canvas + JavaScript (live ABCD demo)
- A laptop with a GPU shortens training; inference runs on CPU

08. Expected Outcomes

- A fine-tuned 7-class CNN with design-target balanced accuracy ≥80% and melanoma recall ≥85%.
- A live demo computing real ABCD features from uploaded lesion photos.
- Per-class metrics and confusion matrix for the report.
- A complete report, PPT and viva Q&A with explicit clinical limitations.

09. Applications

- Teaching transfer learning on a real medical benchmark.
- Demonstrating classical image analysis (Otsu, ABCD) alongside CNNs.
- Academic study of class imbalance in medical imaging.
- Prototype triage-education tool for dermatology students.

10. Future Scope

- Uncertainty quantification for safer referral decisions.
- Multi-modal fusion with patient metadata.
- Domain adaptation to smartphone photography.
- Federated learning across clinics for rare classes.