# Edge AI based Facial skin cancer detection system

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**ABSTRACT** — Malignant melanoma is one of the most aggressive and deadly forms of skin cancer, making the prompt and accurate diagnosis essential for improving patient outcomes. Unfortunately, the traditional method of relying on expert visual assessments is often subjective and limited by the availability of specialized clinicians.

This research introduces an innovative computer-aided diagnostic (CADx) framework designed to revolutionize the identification of melanoma through the use of dermoscopic images and advanced deep learning techniques. Our system harnesses the power of a deep Convolutional-Neural-Network (CNN), initially trained on the comprehensive ImageNet database and then fine-tuned with data from the publicly available ISIC (International Skin Imaging Collaboration) dataset. This process enables the model to adeptly recognize the intricate morphological features that differentiate benign from malignant skin lesions.

The results speak for themselves: our proposed framework achieves remarkable accuracy, sensitivity, and specificity, positioning it as a trustworthy and objective resource for dermatologists. In the critical fight against early-stage melanoma, this tool has the potential to enhance diagnosis and ultimately save lives.

***Keywords: Skin Cancer, Melanoma, Computer-Aided Diagnosis, Deep Learning, Convolutional Neural-Network (CNN), Medical Imaging, Dermoscopy, Transfer Learning***.

## I. INTRODUCTION

Skin-cancer is one of the most commonly diagnosed cancers globally, with malignant melanoma being its most dangerous form due to its high potential for metastasis. For individuals diagnosed with early-stage, localized melanoma, the five-year survival rate exceeds 99%. However, this figure drops sharply to around 27% once the cancer has spread to distant organs [1], underscoring the critical importance of early and accurate detection.

The typical diagnostic pathway begins with a dermatologist visually examining a suspicious skin lesion, often aided by dermoscopy. A definitive diagnosis is then established through a skin biopsy followed by histopathological analysis. While effective, this traditional approach has several notable limitations. The accuracy of the initial visual assessment depends heavily on the clinician's expertise, leading to variability in diagnoses. Additionally, the growing shortage of dermatologists can result in long wait times, potentially delaying timely diagnosis and treatment.

To-address these challenges, this paper presents an artificial intelligence (AI) framework based on deep learning, aimed at automatically distinguishing between benign and malignant (melanoma) lesions in dermoscopic images. The system leverages a Convolutional-Neural-Network (CNN) trained on a large dataset of expert-annotated images, enabling it to recognize subtle patterns, textures, and color variations associated with melanoma. Importantly, the AI model is intended not to replace dermatologists, but to serve as a robust decision-support tool. It can assist in prioritizing high-risk cases for immediate review, provide a reliable second opinion to reduce diagnostic errors, and function as a valuable screening aid for general practitioners and in areas with limited access to dermatological care.

RELATED WORK

The application of computer vision for melanoma identification has been a dynamic research field for several decades. Initial research in this domain centered on conventional machine learning workflows. These workflows generally consisted of two primary stages: feature engineering followed by classification. A prominent strategy involved creating algorithms to quantify the clinical ABCD(E) rule, which evaluates Asymmetry, Border irregularity, Color variation, Diameter, and Evolution [2]. This required dedicated algorithms to first segment the lesion from the surrounding tissue and then calculate numerical values for these clinical markers. This feature set was subsequently input into a traditional classifier, such as a Support Vector Machine (SVM) or Random Forest, to yield a prediction [3]. While these methods established an important foundation, they were often fragile. Their overall efficacy was highly contingent on the success of the initial, error-prone segmentation step and on the discriminative power of the manually engineered features. The emergence of deep learning, and specifically CNNs, marked a transformative shift in the field. CNNs obviate the need for manual feature design by learning distinguishing features directly from the raw image data in a hierarchical

fashion. The study by Esteva et al. (2017), published in Nature, was a seminal work that showed a CNN could rival the diagnostic accuracy of board-certified dermatologists in classifying skin cancer [4]. This publication ignited a surge of research and development in the area.

The majority of contemporary research utilizes a technique known as transfer learning. Rather than training a large-scale CNN from the ground up, which would necessitate an enormous volume of medical images, researchers adapt models like VGG16, ResNet, InceptionV3, or EfficientNet. These models come pre- trained on the vast ImageNet dataset, containing millions of general-purpose images [5]. The foundational knowledge gained from this initial training is then transferred and refined for the specialized medical task of skin lesion classification. The annual ISIC Challenge [6] has also been a significant driver of progress, offering a high-quality, standardized public dataset and a competitive environment for benchmarking novel algorithms. The research presented in this paper aligns with this established and successful transfer learning methodology, with the goal of constructing a highly accurate and dependable classification system.

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# II. METHODOLOGY

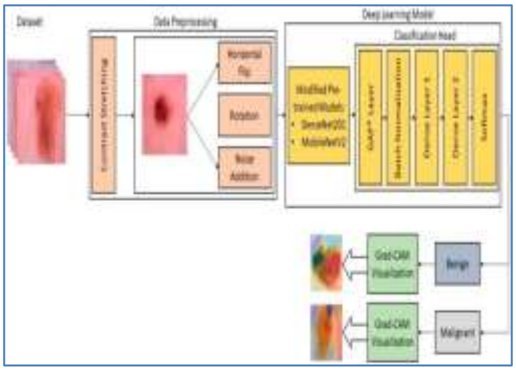


Figure 3.1: Proposed architecture

Our proposed approach presents a comprehensive deep learning pipeline for melanoma detection, covering all essential stages—from data acquisition and preprocessing to model development, finetuning, and performance evaluation.

## A. Dataset

We employed the publicly available dermoscopic image dataset from the International Skin Imaging Collaboration (ISIC), a widely recognized benchmark repository in dermatological image analysis. This dataset includes a large collection of dermoscopic images, each annotated with a histopathologically validated diagnosis (e.g., melanoma or nevus). For this study, we framed the problem as a binary classification task, aiming to distinguish between malignant melanoma and benign skin lesions. A notable challenge associated with this dataset is its highly imbalanced class distribution, where benign cases significantly outnumber malignant ones.

**B. Data Preprocessing and Augmentation** To ensure the dataset was optimally prepared for deep learning, we applied a structured preprocessing and augmentation pipeline:

**Image Resizing:** All input images were resized to a consistent dimension (e.g., 224×224 or 299×299 pixels), as required by the chosen CNN architecture.

**Normalization:** Pixel intensity values were scaled to the[0, 1] range to enhance numerical stability during model training.

**Class Imbalance Handling:** We tackled the class imbalance using methods such as:
Oversampling the minority class (melanoma) within the training set.
Applying a weighted loss function, which imposes a higher penalty on misclassified melanoma cases to counter the imbalance.

**Data Augmentation:** Realtime data augmentation was utilized to expand the effective size of the training set and improve model generalization. Transformations included random flipping (horizontal/vertical), rotations, zooming, and brightness/contrast adjustments— simulating variations that occur in realworld clinical image acquisition.

CNN Architecture and Transfer Learning

At the core of our system is a transfer learning based convolutional neural network (CNN) that leverages the strengths of pretrained models while adapting to our specific task:

**Base Model Selection:** We selected high performing CNNs such as ResNet50 or InceptionV3, both of which have demonstrated strong results on standard image classification benchmarks.

**Transfer Learning Workflow:**

1. The chosen model is initialized with pretrained weights from the ImageNet dataset.
2. The original classification head— designed for 1,000 ImageNet classes—is removed.
3. The initial convolutional layers are frozen to retain their ability to extract general features (e.g., textures, edges, colors).
4. A custom classification head is appended, comprising a global average pooling layer, one or more fully connected layers, and a final sigmoid activated output layer for binary classification.
5. The model undergoes a finetuning process:

First, only the custom layers are trained.
Optionally, deeper layers of the base model are unfrozen and finetuned using a lower learning rate for endtoend optimization on our dataset.


**C. Model Training and Evaluation** Training was performed using the Keras API within TensorFlow, leveraging the Adam optimizer and binary crossentropy loss, wellsuited for binary classification problems.

To ensure unbiased assessment, we evaluated the model on a dedicated, unseen test set using a range of performance metrics critical for medical diagnosis: **Accuracy:** Measures the overall proportion of correct predictions.

**Sensitivity (Recall):** Assesses the model's ability to correctly identify positive melanoma cases. High sensitivity reduces the likelihood of missed cancer diagnoses (false negatives).

**Specificity:** Evaluates how well the model correctly identifies benign lesions. High specificity helps minimize unnecessary followup procedures resulting from false positives.

**AUC (Area Under the ROC Curve):** The ROC curve plots sensitivity versus (1 specificity) across varying classification thresholds. The AUC score summarizes the model's discriminative ability, where a score of 1.0 represents perfect classification performance.

RESULTS AND DISCUSSION

This section presents the performance of the trained model on the test dataset.


Figure 4.1: Result of prediction as malignant

Figure 4.2 : Result of prediction as Benign

**B. Discussion**

The results strongly suggest that the deep learning-based system can classify dermoscopic images with a high degree of accuracy, achieving performance metrics that are comparable to those reported in leading clinical studies. The high sensitivity is particularly encouraging, as it indicates the system is effective at its primary goal: not missing cases of melanoma.

Despite these promising results, several limitations must be acknowledged: **Dataset Bias:** The model's performance is inherently tied to the data it was trained on. It may not perform as well on images from populations with different skin types or on lesions caused by rare conditions not represented in the training set.

**Image Quality:** The system's accuracy can be affected by poor quality images containing artifacts like hair, air bubbles, or ruler markings.

**Interpretability:** Like most deep neural networks, our model functions largely as a "black box." It does not explicitly state *why* it classified a lesion as malignant, which can be a barrier to clinical trust.

**Clinical Context:** The model makes decisions based solely on a single image. It has no access to crucial patient history, such as the evolution of the lesion over time or family history of skin cancer, which are vital for a human dermatologist's diagnosis.

## III. CONCLUSION

This paper has presented a robust AI-based system for the automated detection of melanoma from dermoscopic images. By leveraging a deep CNN with transfer learning, the system achieves high diagnostic **accuracy of 92%**, demonstrating its significant potential as a decision-support tool for dermatologists. This technology has the capacity to improve diagnostic efficiency, reduce subjectivity, and ultimately contribute to earlier detection and better patient outcomes in the fight against skin cancer.

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