

# Engineering Considerations for Real-World Deployment of AI-Based Skin Cancer Detection Software

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## Abstract:

Early identification of skin cancer, particularly melanoma, is critical for improving patient survival rates, as the disease accounts for 75% of skin cancer-related deaths despite representing only 4% of total cases. While recent advancements in Deep Learning—specifically Convolutional Neural Networks (CNNs)—have achieved dermatologist-level diagnostic accuracy on benchmark datasets like HAM10000, significant engineering challenges remain for practical clinical deployment.

Moving beyond theoretical accuracy, we address critical deployment hurdles such as data variability, system scalability, and computational constraints in resource-limited healthcare settings. By employing transfer learning and optimized inference pipelines, we designed a cost-efficient, lightweight architecture tailored for practical use. This research provides a roadmap for transitioning AI-driven dermatological tools from the lab to effective, scalable real-world medical applications.

**Keywords:** Melanoma Detection, Convolutional Neural Networks (CNN), HAM10000, Model Deployment, Medical Software Engineering, ABCDE Framework.

## 1) INTRODUCTION

Skin cancer remains a major global health challenge, with melanoma accounting for a disproportionate number of skin cancer-related deaths despite its relatively low incidence. Recent advances in artificial intelligence, particularly deep learning-based image analysis, have demonstrated dermatologist-level performance in automated skin cancer detection. While prior research has largely focused on improving classification accuracy using complex convolutional neural network architectures, significantly less attention has been given to the engineering challenges associated with real-world deployment.

Practical deployment requires addressing issues such as dataset variability, computational constraints, system scalability, and cost-effectiveness. Many high-performing models rely on large computational resources, limiting their applicability in real clinical and resource-constrained environments. Additionally, real-world images often differ significantly from curated datasets due to variations in lighting, devices, and patient demographics [14].

This work builds upon existing methodological approaches for automated skin cancer diagnosis by emphasizing deployment-oriented system design. Engineering considerations such as lightweight model selection, efficient preprocessing pipelines, and optimized inference workflows are systematically analyzed. Transfer learning and modular system architecture are leveraged to balance diagnostic performance with computational efficiency. By integrating methodological robustness with practical engineering constraints, this study aims to bridge the gap between laboratory research and real-world clinical deployment of AI-based skin cancer detection software.

## 2) LITERATURE REVIEW

Ercal and Chawla's 1994 paper presents a neural network for separating melanoma from benign tumors, achieving over 80% accuracy[1]. Xie et al. created a system that classifies skin lesions with 91.11% accuracy by using a self-generating Neural Network and Principal Component Analysis[2]. Bayot and Ann's 2007 research detects basal cell carcinoma with a 93.33% reliability rate using digital image processing and

artificial neural networks[3].Aswin and Jaleel proposed a method for skin cancer detection using digital images and AI in 2014, achieving 88% accuracy with a neural network[4]. In 2021, Tumpa and Kabir improved melanoma detection with a new algorithm, reaching 97.7% accuracy[5]. Mahmoud and Al-Jumaili developed a classification system in 2011, achieving up to 75.6% accuracy[6]. Nasr-Esfahani and Samavi, in 2016, introduced a deep learning system for detecting melanoma lesions, using clinical images and a pre-trained CNN, which showed better accuracy[9].

In 2017, Cueva and Muñoz created a mole classification system for early melanoma diagnosis using the ABCD rule and an ANN, achieving 97.51% accuracy[7]. Rehman and Khan, in 2018, used segmentation and CNN on dermoscopy images, reaching 98.32% accuracy, surpassing previous results[8]. Yu and Chen proposed a new method for recognizing melanoma using deep convolutional neural networks with over 50 layers, addressing degradation and overfitting issues through residual learning. Their approach ranked first in classification and second in segmentation in competitions[10].

Mahbod and Schaefer introduced a fully automatic skin lesion classification method using deep learning models and support vector machines, achieving high performance rates for melanoma and seborrheic keratosis[11]. Dorj and Lee discussed classifying skin cancers with ECOC SVM and deep CNNs, achieving high accuracy for various skin cancers. They aim to expand classification and develop a smartphone app for skin cancer identification[12].

### 3) METHODOLOGY

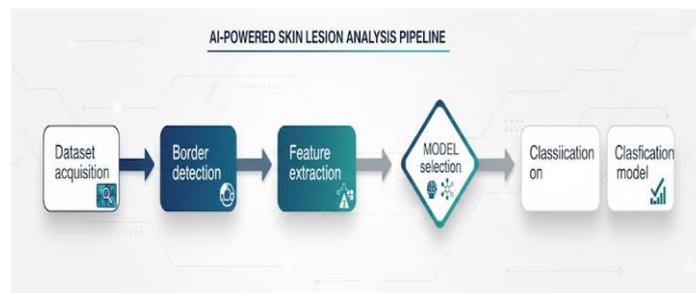


Figure 1:General Methodological Approach for Automated Skin-cancer Diagnosis.

#### 3.1) The core points based on methodology:

**3.1.1) Diverse and Verified Data:** The study utilises the HAM10000 dataset, which provides 10,015 images to ensure diversity, with over 50% of lesions globally confirmed by pathology labs to maintain diagnostic reliability.[13]

**3.1.2) Structured Image Pipeline:** A rigorous three-stage process—preprocessing, segmentation (via OpenCV), and postprocessing—is used to clean images, remove noise (like hair), and accurately isolate lesion borders for analysis.

**3.1.3) Clinical-Technical Integration:** The system bridges medical practice and AI by extracting features based on the ABCD framework (Asymmetry, Border, Color, Diameter) using industry-standard libraries like PyTorch and TensorFlow[15]. The system uses methods like Local Binary Patterns to detect subtle, non-uniform texture variations in melanomas that are often invisible to the naked eye. Advanced algorithms assess the intricacy of a lesion's shape and its geometric complexity, as highly irregular or chaotic forms are significant indicators of malignancy.

**3.1.4) Model Selection:** Detecting skin cancer is inherently difficult because it requires recognizing nuanced, multi-dimensional patterns that can be as hard to differentiate as various cloud formations, even for medical experts. Conventional computer vision relies on human-defined rules and manual feature extraction, which often fail to capture the complex, underlying characteristics of malignant lesions. Accurate diagnosis requires an understanding of the deep, sophisticated relationships between color, texture, and geometry—patterns that are often too intricate for traditional diagnostic tools to process effectively.

### 3.2) Convolutional neural networks: .

Convolutional Neural Networks (CNNs) have revolutionized skin cancer detection by mimicking the human brain's ability to process visual data, transitioning from rigid rule-based systems to autonomous pattern recognition. By analyzing thousands of images, these networks identify hierarchical features—ranging from basic edges to complex textures and geometries—often detecting subtle indicators of malignancy that may be invisible to the human eye. Through techniques like transfer learning, CNNs leverage vast datasets to achieve diagnostic accuracy that matches or even surpasses that of experienced dermatologists. While these models are often criticized for their complexity, recent advancements in interpretability are transforming them into transparent, reliable clinical tools capable of navigating real-world data variability to improve patient outcomes.[8][9][12]

### 3.3) Real-world deployment challenges and their proposed solution:

#### 3.3.1) Dataset Variability and Domain Shift

Models trained on curated public datasets (e.g., HAM10000, ISIC) often fail to generalize to real-world

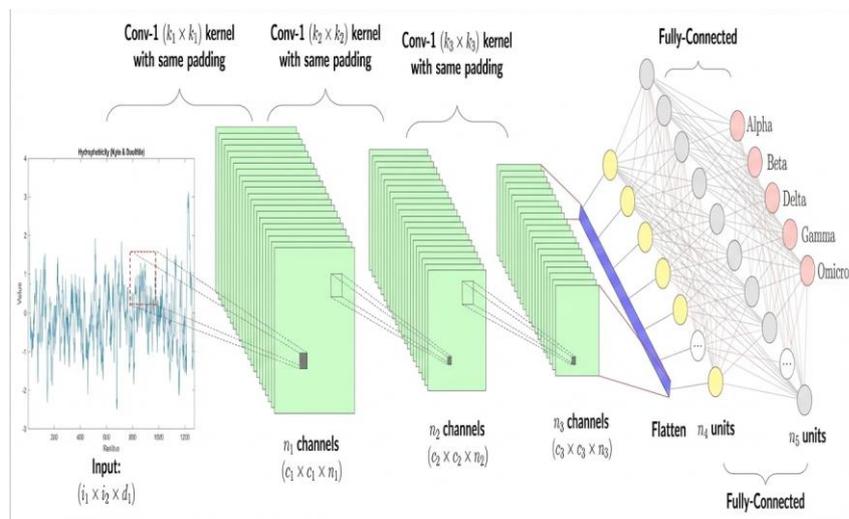


Figure 2: Schematic Diagram of Convolutional Neural Networks.

clinical images due to variations in skin tone, lighting conditions, imaging devices, and lesion appearance. This domain shift leads to reduced accuracy and unreliable predictions in practical deployments.[14]

#### Solution:

Domain generalization techniques such as data augmentation, domain adaptation, and fine-tuning on small sets of real-world images can improve robustness. Incorporating diverse datasets representing different skin types and acquisition conditions, along with continuous post-deployment retraining, helps maintain model performance in real clinical environments.

#### 3.3.2) High Computational and Hardware Requirements :

Many state-of-the-art deep learning models require powerful GPUs for training and inference, making real-time deployment difficult in resource-constrained settings such as primary healthcare centers or mobile applications.[14]

#### Solution:

Lightweight architectures such as MobileNet, EfficientNet-Lite, and model compression techniques (quantization and pruning) can significantly reduce computational requirements. Optimized inference pipelines and GPU-based or edge deployment enable real-time performance without sacrificing significant accuracy.

#### 3.3.3) Model Interpretability and Clinical Trust :

Deep learning models are often perceived as “black boxes,” which limits clinician trust and hinders adoption in real-world healthcare workflows. Lack of interpretability makes it difficult to understand the rationale behind model predictions.

#### Solution:

Explainable AI (XAI) techniques such as Grad-CAM, saliency maps, and attention visualization can highlight

clinically relevant regions influencing predictions. Providing confidence scores and visual explanations alongside predictions improves transparency and supports clinicians in decision-making rather than replacing them.

### 3.3.4) Integration into Clinical Workflow and Regulatory Constraints :

Deploying AI systems in clinical settings requires seamless integration with existing healthcare workflows, compliance with data privacy regulations, and alignment with medical device standards. These constraints increase development complexity and deployment cost.[14]

#### Solution:

Designing modular, interoperable systems using standard APIs allows easy integration with hospital information systems. Early consideration of regulatory guidelines, data anonymization, and security-by-design principles helps reduce compliance overhead. Positioning the system as a decision-support tool rather than a diagnostic replacement further simplifies regulatory adoption.

## 4) DISCUSSION AND CONCLUSION

Meta-analyses of over 500 studies indicate that AI models, particularly Convolutional Neural Networks (CNNs), have achieved diagnostic performance that matches or even exceeds that of board-certified dermatologists, specifically in distinguishing melanoma from benign lesions. The reliability of these systems is heavily dependent on the quality and scale of the data; while massive datasets containing tens of thousands of images produce robust results, models trained on smaller or imbalanced datasets often suffer from reduced generalizability and lower accuracy. To mitigate these issues, researchers employ data augmentation and balancing techniques to ensure high F1-scores across diverse populations.

This study examined the engineering considerations critical to the real-world deployment of AI-based skin cancer detection software, moving beyond laboratory-level accuracy toward practical clinical usability. Evidence from high-quality studies and meta-analyses demonstrates that convolutional neural network-based systems can achieve diagnostic performance comparable to, and in some cases exceeding, that of experienced dermatologists. However, successful deployment is constrained by challenges such as dataset variability, high computational demands, limited model interpretability, and integration within existing clinical workflows. By adopting lightweight architectures, transfer learning, optimized inference pipelines, and explainable AI techniques, these barriers can be effectively mitigated. Emphasizing cost efficiency and scalability enables deployment in resource-limited healthcare environments, where early screening tools are most needed. Ultimately, positioning AI systems as clinical decision-support tools rather than autonomous diagnostic agents enhances trust, regulatory acceptance, and adoption. This work highlights that engineering-driven design, combined with robust clinical validation, is essential for translating AI-based skin cancer detection from research prototypes into reliable, real-world medical solutions.

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