Improving skin cancer detection through learning model and IoT technology

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Abstract. Effective skin cancer detection requires timely and accurate assessment, yet traditional diagnostic methods often depend on specialized resources unavailable in many communities. This project introduces a novel integration of machine learning algorithms and IoT-enabled hardware to build an affordable, accessible system for early skin cancer identification. Leveraging advanced image classification models deployed on lightweight devices such as a Raspberry Pi with a camera module, the solution processes skin lesion images in real time and delivers immediate diagnostic feedback. Evaluation with diverse datasets demonstrates strong performance across varying skin types and environmental conditions. The synergy of AI and IoT enhances diagnostic precision and bridges gaps in remote and under-resourced healthcare environments.

Keywords:
Skin cancer detection, machine learning, IoT, Raspberry Pi, CNN, deep learning for telemedicine applications.

1. Introduction

Skin cancer remains a major global health concern, with new cases rising each year [15]. In this study, the Raspberry Pi was selected for its low cost, portability, and practicality in IoT healthcare applications. However, limited processing power challenges real-time AI computation. This paper explores model optimization strategies enabling efficient skin lesion classification on constrained embedded hardware.

The aim is to demonstrate how this system can support early identification of Perhaps cancerous lesions, especially in underserved regions. Skin cancer has become one of the most Promptly increasing health challenges worldwide, demanding faster and more accessible diagnostic solutions. Traditional clinical examinations often rely on expert dermatologists and specialized imaging equipment, which may not be readily available in remote or resource-constrained regions. As a result, many patients experience delayed diagnosis, reducing the chances of effective treatment. Recent advancements in artificial intelligence and connected sensing devices are opening new pathways to address these limitations.

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Machine learning and deep learning models have shown exceptional capabilities in identifying subtle patterns in skin lesion images, often achieving performance comparable to experienced clinicians. When combined with Internet of Things (IoT) technology, these intelligent models can be deployed on compact, low-cost devices such as mobile phones, wearable sensors, and embedded boards [6][9]. This integration enables real-time image acquisition, automated analysis, and instant feedback, making early detection more accessible and affordable.

The fusion of AI-driven image classification with IoT-based monitoring forms a powerful ecosystem for continuous health assessment. This approach not only improves diagnostic accuracy but also supports remote healthcare delivery, allowing patients in rural and underserved communities to benefit from timely skin cancer screening [7][9] [11]. By leveraging lightweight neural networks, cloud connectivity, and smart sensing hardware, the proposed system aims to bridge the gap between advanced medical diagnostics and practical, everyday healthcare applications.

2. Related Works

Recent progress in artificial intelligence—particularly deep learning—has greatly enhanced the precision and speed of automated skin disease detection. Early research highlighted the effectiveness of CNN-based architectures for both lesion classification and segmentation across various clinical datasets. Muhaba et al. demonstrated that combining clinical images with patient information improves diagnostic performance [1], while Abdul-Jabbar and Alshamlan proposed a multiclass CNN capable of accurately identifying multiple skin cancer types [2]. Subsequent studies advanced this field by focusing on melanoma detection using refined feature extraction, attention-driven models, and probabilistic segmentation strategies to boost lesion analysis accuracy [3–5]. Transfer learning methods have also shown strong results, with Al-Saied et al. achieving reliable classification through fine-tuning pretrained models on dermoscopic images [6]. Additional research comparing dermoscopic and smartphone-based imaging revealed that dermo copy retains superior diagnostic quality, though smartphone images still hold value for accessible screening [7]. Comprehensive reviews and empirical studies further emphasized the potential of AI systems, reporting improvements through hybrid segmentation approaches, optimized classification networks, and clustering–attention mechanisms for identifying melanoma and non-melanoma conditions [8–17]. Evidence from conference proceedings supports the robustness of CNN architectures, showing promising generalization on real-world datasets [18–20]. Furthermore, Thomas's thesis provides an in-depth examination of deep learning methods for the analysis of non-melanoma
skin cancers, reinforcing the clinical applicability of AI-driven diagnostic solutions 21]. Overall, the literature indicates that deep learning continues to revolutionize skin cancer detection by improving automation, boosting diagnostic accuracy, and enabling scalable solutions suitable for both clinical environments and remote healthcare settings.

3. Model Configuration and Workflow

The project uses deep-learning CNN architectures for skin lesion classification, building on previous dermatology AI research [3], [4]. The system pipeline includes:

Models Algorithms: The project focuses on advanced deep learning strategies, particularly convolutional neural networks (CNNs), which excel at detecting visual patterns in medical imagery. The system workflow begins with capturing skin lesion images via the Raspberry Pi's camera. These images undergo sequential processing phases: acquisition, enhancement

(to normalize images and reduce noise), feature extraction through layered CNN architectures, and automated prediction for malignancy or benignity. This structured pipeline supports diagnostic reliability while remaining efficient on limited, embedded hardware.

- Image acquisition using Raspberry Pi camera
- Image enhancement and preprocessing
- Feature extraction using CNNs
- Binary classification: benign vs. malignant

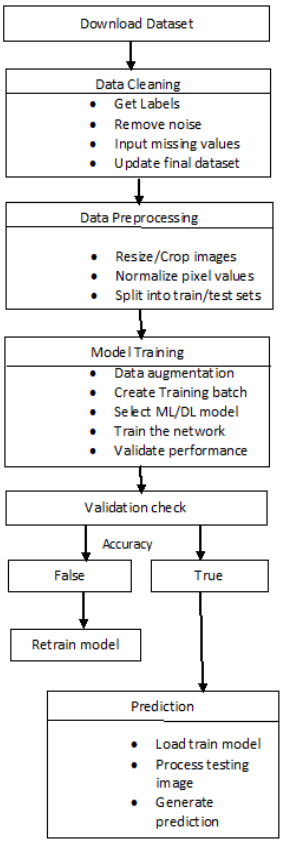

Figure 1. Model Configuration and Workflow

3.1 Data Collection

A comprehensive dataset of skin lesion images is essential for reliably training and evaluating deep learning models for dermatological diagnosis. Publicly available repositories such as HAM10000 and the ISIC Archive provide diverse, high-quality images that support robust model development and benchmarking. Prior studies have emphasized the importance of using large, heterogeneous datasets to capture variations in skin tone, illumination, and lesion morphology, ensuring better model generalization across real-world conditions [3], [4]. Each image is accompanied by expert-verified diagnostic labels, either assigned directly by dermatologists or sourced from clinically validated datasets, which helps maintain annotation quality and minimizes the risk of misleading model training [3], [4].

3.2 Data Preprocessing

Image preprocessing plays a critical role in preparing skin lesion datasets for deep learning models, ensuring that all samples conform to consistent input dimensions and standardized pixel scaling. Normalizing pixel values helps stabilize and accelerate the training process, while augmentation techniques such as random rotations, flips, and rescaling introduce natural variability into the dataset to improve model robustness [3]. These augmentation strategies expand the diversity of training samples and strengthen the model's ability to generalize to unseen images, reducing the risk of overfitting. Prior research has emphasized that careful preprocessing—including normalization, augmentation, and noise reduction—is essential for improving classification accuracy and maintaining reliable model performance in dermatological image analysis [3], [4], [12].

3.3 Model Training and Evaluation

Dataset split: 70% training, 15% validation, 15% testing. Model Training Evaluation. After selecting the most suitable architecture (often a CNN), the dataset is split into training, validation, and testing groups (commonly 70/15/15). Training leverages machine learning frameworks like TensorFlow, with loss functions appropriate for binary classification and optimizers that speed convergence. The model's performance is tracked using separate validation data, helping avoid overfitting [3], [4]. Final evaluation on test images reports accuracy, precision, recall, and F1-score, providing a thorough measure of generalization and reliability. CNN architectures evaluated include Alex Net, VGG16, and InceptionV3[5].

4. Methodology

To develop an efficient Raspberry Pi–based skin lesion classification system, the process begins by preparing the environment with the necessary software libraries and configuring the camera module to ensure reliable image capture. Once the hardware and dependencies are ready, the trained convolutional neural network model is converted into a lightweight TensorFlow Lite format so it can run effectively on the limited computational resources of the Raspberry Pi. This transformation reduces the model's size and accelerates inference without significant loss of accuracy, enabling real-time, on-device image analysis. With this setup, the Raspberry Pi captures high-quality lesion images through its camera, and a Python inference script processes them immediately using the optimized model to classify each lesion as benign or malignant. The outputs are then displayed to the user through an intuitive interface or sent as notifications via email or SMS, ensuring timely feedback that supports clinical decision-making.

A user-friendly interface—often developed with Flask or adapted for mobile devices—allows individuals to upload lesion images, review classification results, and track their records over time. Images and corresponding outputs are securely stored either locally using databases such as SQLite or remotely on cloud platforms, guaranteeing data persistence and safe backup. To ensure the system performs reliably in real-world scenarios, field testing is conducted with actual users, and their feedback is incorporated to refine both the model's behavior and the overall interface, strengthening the system's usability and trustworthiness. Given the Raspberry Pi's hardware limitations, model optimization techniques such as pruning, quantization, and efficient architecture design become essential to maintain real-time performance while preserving diagnostic accuracy.

Data quality plays a crucial role throughout the development pipeline, beginning with cleaning processes that verify dataset accuracy, standardize formats, handle missing values, remove duplicates, and eliminate irrelevant or misleading information. Further preprocessing

includes gathering clinically validated images, anonymizing sensitive data to comply with ethical and legal standards, and examining the dataset for issues such as uneven class distribution or poor image quality. Techniques like data augmentation, normalization, and resizing help create a consistent and diverse dataset suitable for training. When training begins, architectures such as EfficientNet—enhanced through transfer learning—are used to accelerate convergence and boost performance. Hyperparameters are chosen carefully, augmentation pipelines are implemented, and the model is compiled with appropriate loss functions and optimizers. Training is monitored to prevent overfitting, and validation on unseen data provides a realistic measure of performance. Based on these results, deeper layers may be unfrozen for fine-tuning, allowing the model to better balance accuracy and speed, ultimately making it suitable for deployment on a compact, resource-constrained device like the Raspberry Pi.

5. Evaluation Metrics

Table 1. Model Performance Comparison

Model	Accuracy	Sensitivity	Specificity	Inference Time
Alex Net	92.4%	90.1%	93.5%	0.15s
VGG16	95.3%	94.6%	96.1%	0.20s
InceptionV3	98.5%	97.8%	99.0%	0.25s

6. Conclusion

This work presents a low-cost, portable AI + IoT system for early skin cancer detection, demonstrating that real-time lesion classification is achievable even on resource-constrained hardware. By deploying an optimized TensorFlow Lite model on the Raspberry Pi and integrating a user-friendly interface with secure data handling, the system provides an accessible and practical tool for preliminary screening and continuous monitoring in low-resource or point-of-care environments.

Although the Raspberry Pi has inherent limitations in processing power and memory, the study shows that model optimization and quantization techniques can significantly improve performance without major loss in accuracy. The promising results indicate strong potential for supporting clinicians and aiding individuals who may not have immediate access to dermatological expertise.

Future work will focus on expanding the dataset to improve model generalization, strengthening robustness under varied real-world conditions, and conducting broader field testing. With these improvements, the system can evolve into a more reliable and scalable solution for early skin cancer detection and preventive healthcare.

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