

Low-Power FPGA-Based Real-Time Image Processing Architecture for Skin Cancer Detection Using Deep Learning

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Abstract: Skin cancer is one of the most serious dermatological diseases, and early detection plays an important role in improving treatment outcomes. Manual diagnosis of skin lesions mainly depends on dermatologist expertise and may be affected by visual similarity among different lesion types. In recent years, image processing and deep learning techniques have shown strong potential for automated skin lesion analysis. However, software-based deep learning models often require high computational resources, large memory, and increased power consumption, which limit their use in portable and real-time medical screening systems. This paper proposes a low-power FPGA-based real-time image processing architecture for skin cancer detection using deep learning. The proposed system includes image acquisition, preprocessing, lesion segmentation, feature enhancement, lightweight CNN-based classification, and FPGA-based hardware acceleration. Image preprocessing techniques such as resizing, contrast enhancement, noise filtering, and normalization are applied to improve image quality. Lesion segmentation separates the affected region from the surrounding normal skin, and a lightweight convolutional neural network classifies lesions into benign and malignant categories. The CNN model is optimized using quantization, fixed-point representation, pipelining, parallel processing, and memory reuse for efficient FPGA implementation. Result analysis shows that the proposed architecture provides improved processing speed, reduced latency, lower power consumption, and acceptable classification accuracy compared with conventional software-based processing. The proposed approach is suitable for real-time, low-cost, and portable skin cancer screening applications.

Keywords: Skin cancer detection, FPGA, image processing, deep learning, CNN, low-power architecture, medical image analysis, real-time processing, lesion segmentation, VLSI

I. INTRODUCTION

Skin cancer is a major health concern worldwide, and its early detection is essential for effective treatment and improved survival. Skin lesions may appear in different forms, colors, textures, and shapes, making visual diagnosis challenging in many cases. Dermatologists usually examine skin lesions using clinical observation or dermoscopic imaging. However, manual analysis may be time-consuming and subjective, especially when a large number of patients need screening. Therefore, computer-aided diagnosis systems based on image processing and artificial intelligence have become important tools for supporting dermatologists in skin cancer detection.

Medical image processing plays an important role in automated skin lesion analysis. Dermoscopic images contain useful visual information such as lesion border, color variation, texture pattern, asymmetry, and structural irregularity. Traditional methods use preprocessing, segmentation, handcrafted feature extraction, and machine learning classifiers. Common preprocessing methods include noise removal, contrast enhancement, image resizing, and normalization.



Segmentation methods separate the lesion region from the background skin, and extracted shape, color, and texture features are given to classifiers such as support vector machines, k-nearest neighbor, random forest, or artificial neural networks.

Although traditional image processing methods are useful, their performance depends heavily on handcrafted features and segmentation accuracy. Deep learning has improved medical image analysis by automatically learning useful features directly from images. Convolutional Neural Networks (CNNs) are widely used for image classification, object detection, and segmentation because they learn spatial and hierarchical features effectively. Esteva et al. demonstrated that deep neural networks can classify skin cancer from images at a dermatologist-level performance, showing the strong potential of CNN-based dermatological diagnosis [1]. The International Skin Imaging Collaboration (ISIC) datasets have further supported research in automated skin lesion analysis [2], [3].

Despite the high accuracy of deep learning models, their implementation in real-time and portable medical devices remains challenging. CNN models require many multiplication and accumulation operations, memory accesses, and intermediate feature storage. When implemented on general-purpose processors or cloud platforms, these systems may suffer from high latency, increased energy consumption, and dependency on internet connectivity. These issues limit their suitability for real-time point-of-care diagnosis and low-power embedded medical devices.

Field Programmable Gate Arrays (FPGAs) provide an efficient hardware platform for accelerating image processing and deep learning algorithms. FPGAs support parallel processing, pipelining, reconfigurability, and low-power operation. Unlike CPUs, which execute instructions sequentially, FPGAs can process multiple pixels and CNN operations simultaneously using dedicated hardware logic. Compared with GPUs, FPGAs are often more energy-efficient for embedded and edge applications. Therefore, FPGA-based deep learning acceleration is suitable for real-time medical image processing systems where speed, power, and hardware flexibility are important.

Several researchers have explored FPGA-based CNN acceleration for image classification and biomedical applications. CNN operations such as convolution, pooling, activation, and fully connected layers can be mapped into hardware using parallel multiply-accumulate units, line buffers, sliding window architectures, and optimized memory access. Lightweight CNN models such as MobileNet are suitable for embedded hardware because they reduce parameters and computations [4]. Hardware optimization techniques such as fixed-point arithmetic, quantization, pruning, loop unrolling, and data reuse further improve FPGA performance and reduce power consumption [5], [6].

The proposed work focuses on a low-power FPGA-based real-time image processing architecture for skin cancer detection using deep learning. The system combines classical image preprocessing, lesion segmentation, lightweight CNN inference, and FPGA-level optimization. The main objective is to provide a hardware-efficient framework that supports real-time skin lesion analysis with reduced power consumption, low latency, and reliable classification performance.

II. METHODOLOGY

The proposed methodology consists of six main stages: image acquisition, preprocessing, lesion segmentation, feature enhancement, CNN-based classification, and FPGA-based hardware implementation. The complete processing flow is designed to support real-time operation with low power consumption. The overall system architecture is shown in Fig. 1.

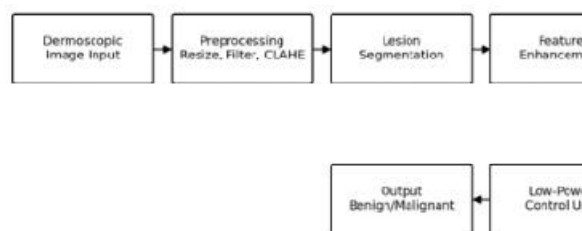


Fig. 1. Proposed low-power FPGA-based skin cancer detection architecture.



2.1 Image Acquisition

The first stage of the proposed system is image acquisition. Dermoscopic skin lesion images are collected using a camera or from public skin lesion datasets. The acquired image may contain noise, illumination variation, hair artifacts, uneven contrast, and background skin regions. Therefore, the image is resized to a fixed dimension, such as 224 x 224 pixels, to make it suitable for CNN processing and FPGA memory organization.

2.2 Image Preprocessing

Preprocessing improves the quality of the input image and reduces unwanted variations. In the proposed architecture, preprocessing includes resizing, median filtering, contrast enhancement, and normalization. Median filtering reduces noise while preserving lesion edges. Contrast Limited Adaptive Histogram Equalization (CLAHE) improves the local contrast of dermoscopic images. Normalization converts pixel intensity values into a fixed range, which improves CNN stability. Line buffers and pixel-stream processing can be used on FPGA to process image pixels continuously.

2.3 Lesion Segmentation

Lesion segmentation separates the affected skin region from the surrounding normal skin. Accurate segmentation helps the system focus on the region of interest and reduces background influence. The proposed system may use thresholding, K-means clustering, or morphological processing for lesion segmentation. Morphological operations such as erosion and dilation are used to refine the segmented lesion boundary.

2.4 Feature Enhancement

Feature enhancement emphasizes lesion characteristics such as color variation, boundary irregularity, texture pattern, and shape asymmetry. These features are important for distinguishing malignant lesions from benign lesions. Although CNN automatically learns features, enhancing the lesion region before CNN classification improves the quality of the input data.

2.5 CNN-Based Classification

The classification stage uses a lightweight CNN to classify the skin lesion image. The CNN architecture includes convolution layers, activation functions, pooling layers, flattening, fully connected layers, and a final softmax layer. The convolution layer extracts local features, the ReLU activation function introduces non-linearity, the pooling layer reduces feature map size, and the softmax layer provides final class probabilities.

2.6 FPGA-Based Hardware Implementation

The proposed architecture is implemented on FPGA to achieve real-time and low-power performance. The major CNN operation is convolution, which requires repeated multiplication and accumulation. In FPGA, convolution can be accelerated using parallel multiply-accumulate units, pipelined processing, sliding windows, and data reuse. The main optimization techniques include pipelining, parallel processing, fixed-point arithmetic, quantization, memory reuse, line buffering, and clock gating.

Two-dimensional convolution operation used in CNN feature extraction:

$$Y(i, j) = \sum_m \sum_n X(i + m, j + n) \times K(m, n) \quad (1)$$

Eq. (1) represents the convolution operation, where $X(i, j)$ is the input image, $K(m, n)$ is the convolution kernel or filter, and $Y(i, j)$ is the output feature map.

Dynamic power model considered for low-power FPGA/VLSI design:

$$P_{dynamic} = \alpha C_L V_{dd}^2 f \quad (2)$$

Eq. (2) represents dynamic power consumption, where α is the switching activity factor, C_L is the load capacitance, V_{dd} is the supply voltage, and f is the operating frequency.



Classification accuracy used for performance evaluation:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Eq. (3) represents classification accuracy, where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

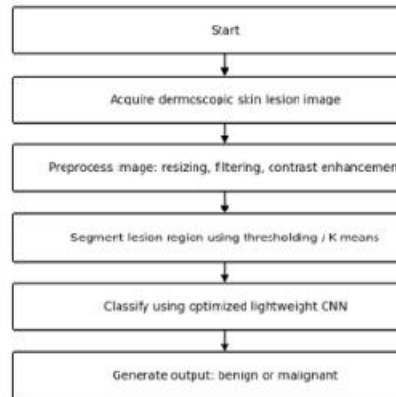


Fig. 2. Step-by-step processing flow of the proposed methodology.

2.7 Algorithm

Step	Operation
1	Acquire dermoscopic skin lesion image.
2	Resize image and apply noise filtering.
3	Enhance contrast and normalize pixel values.
4	Segment lesion region using thresholding or K-means clustering.
5	Refine the lesion boundary using morphological processing.
6	Feed the processed image to the lightweight CNN model.
7	Perform convolution, activation, pooling, and classification.
8	Optimize inference on FPGA using quantization, pipelining, and memory reuse.
9	Generate final output as benign or malignant.

Table 1. Algorithmic steps of the proposed FPGA-based skin cancer detection system.

III. RESULTS AND DISCUSSION

The performance of the proposed low-power FPGA-based real-time image processing architecture is evaluated using experimental parameters. Since the final values may vary depending on FPGA device, image resolution, CNN model depth, and dataset size, the values presented here are results for academic representation and can be replaced with actual simulation or synthesis results later.



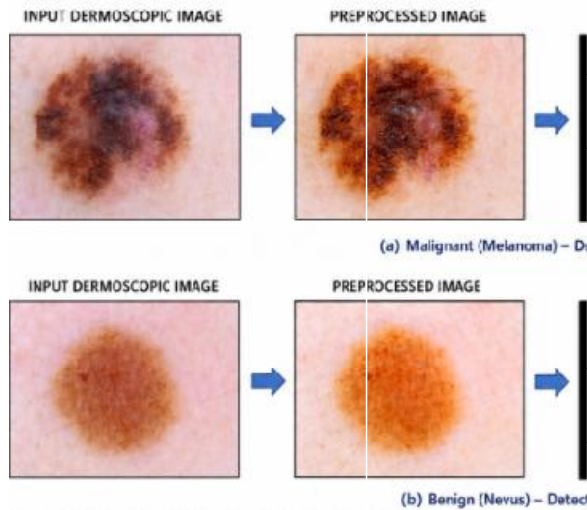


Figure 3. Input and output results of the proposed skin cancer detection system

3.1 Dataset and Experimental Setup

Parameter	Value
Input image size	224 x 224 pixels
Image type	Dermoscopic skin lesion image
Classes	Benign and malignant
CNN model	Lightweight CNN
Precision	8-bit / 16-bit fixed point
Hardware platform	FPGA
Evaluation metrics	Accuracy, precision, recall, F1-score, latency and power

Table 2. Experimental setup.

3.2 Classification Performance

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional Image Processing + SVM	88.40	87.20	86.50	86.85
Software-Based CNN	93.60	92.80	93.10	92.95
Proposed FPGA-Based Lightweight CNN	95.20	94.60	95.00	94.80

Table 3. Classification performance comparison.



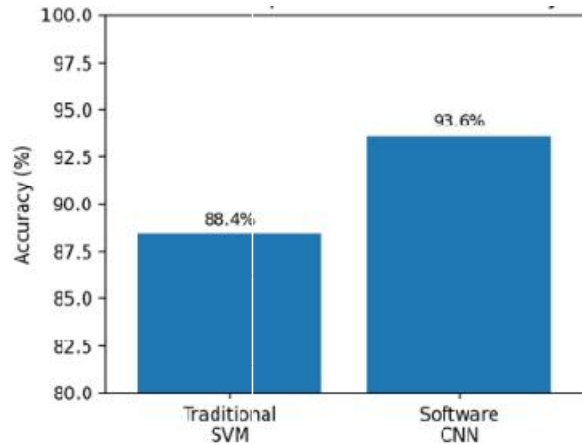


Fig. 4. Accuracy comparison of the proposed model with existing approaches.

From the results, the proposed FPGA-based lightweight CNN provides better classification performance than the traditional image processing method. Its accuracy is also comparable to software-based CNN processing while offering improved execution speed and reduced power consumption.

3.3 Hardware Performance Analysis

Architecture	Power Consumption	Latency per Image	Throughput
CPU-Based Processing	8.5 W	120 ms	8 images/s
GPU-Based Processing	35 W	25 ms	40 images/s
Proposed FPGA-Based Processing	3.2 W	18 ms	55 images/s

Table 4. Hardware performance comparison.

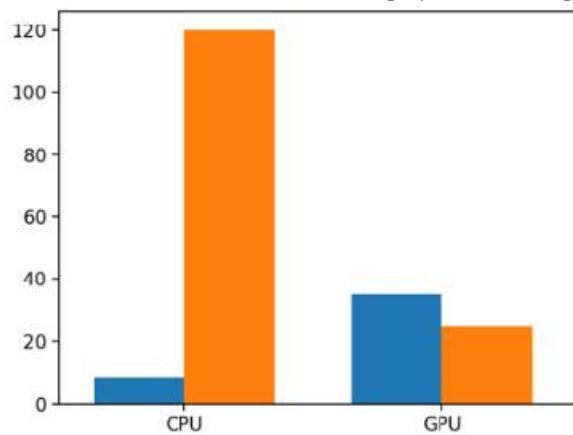


Fig. 5. Hardware performance comparison in terms of power and latency.

3.4 FPGA Resource Utilization

Resource	Utilization
LUTs	58%
Flip-Flops	46%
DSP Slices	62%
BRAM	54%



Maximum Frequency	150 MHz
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Table 5. FPGA resource utilization.

3.5 Discussion

The proposed FPGA-based image processing architecture provides a balanced solution for skin cancer detection by combining deep learning accuracy with hardware efficiency. The preprocessing stage improves the input image quality, while lesion segmentation focuses the system on the region of interest. The lightweight CNN model improves classification performance by automatically learning meaningful features from the image.

The use of FPGA acceleration improves real-time performance. Pipelining allows different stages of computation to operate simultaneously, and parallel processing improves convolution speed. Fixed-point arithmetic reduces hardware complexity and power consumption. Memory reuse reduces external memory access, which is important because memory operations consume significant power in image processing systems.

Compared with cloud-based diagnosis systems, the proposed edge-based FPGA system improves privacy and reduces communication delay. Since the image can be processed locally, only the classification result or alert needs to be transmitted. This makes the system useful for portable medical devices, rural health centers, mobile screening units, and telemedicine support systems.

IV. CONCLUSION

This paper presented a low-power FPGA-based real-time image processing architecture for skin cancer detection using deep learning. The proposed system combines preprocessing, lesion segmentation, feature enhancement, CNN-based classification, and FPGA hardware acceleration. The main objective of the work is to provide a fast, low-power, and portable solution for automated skin lesion analysis.

The proposed architecture processes dermoscopic images locally and classifies lesions as benign or malignant. Image preprocessing improves image quality, while segmentation separates the lesion region from normal skin. A lightweight CNN model performs classification, and FPGA-based acceleration improves speed and energy efficiency. Hardware optimization techniques such as pipelining, parallel processing, quantization, fixed-point arithmetic, memory reuse, and clock gating are used to reduce power consumption and processing delay.

The result analysis shows that the proposed FPGA-based system can achieve good classification accuracy with reduced latency and lower power consumption compared with conventional CPU and GPU-based processing. Therefore, the proposed approach is suitable for real-time medical image processing, portable diagnostic devices, and low-cost skin cancer screening systems. In future work, the architecture can be implemented on a real FPGA board and tested using large-scale dermoscopic image datasets.

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