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Resource-Efficient FPGA Implementation for Real-Time Breast Cancer Classification Using Custom CNNs

Rashed Al Amin
Institute for Embedded Systems
University of Siegen
Siegen, Germany
rashed.amin@uni-siegen.de

Roman Obermaisser
Institute for Embedded Systems
University of Siegen
Siegen, Germany
roman.obermaisser@uni-siegen.de

***Abstract*—Field Programmable Gate Arrays (FPGAs) combined with deep learning algorithms exhibit exceptional efficiency in the field of medical imaging. Breast cancer is one of the most frequently diagnosed cancers and remains the leading cause of mortality among women worldwide. In recent years, convolutional neural networks (CNNs) have garnered significant attention for their effectiveness in breast cancer segmentation and classification. Nevertheless, CNNs demand substantial computational power to perform real-time classification tasks. To address these challenges, this paper proposes a hardware-software co-design for real-time breast cancer classification utilizing FPGAs. The software implementation has been implemented using TensorFlow, while the FPGA implementation, design, and verification are conducted using Vivado 2023.1. The proposed custom CNN architecture achieves 99.76% classification accuracy with the BUSI breast ultrasound dataset and maintains low resource utilization. Evaluated on the Xilinx ZCU102 FPGA board, the architecture delivers a throughput of 4949 frames per second (FPS) while consuming only 3.5W of power. The evaluation results underscore the efficacy and effectiveness of the proposed custom CNN architecture for breast cancer classification. Furthermore, the architecture holds potential for application in the classification of other types of cancer classification.**

***Keywords*—breast cancer, FPGA, CNN**

I. Introduction

Deep learning (DL) has made significant advancements over the years, with its popularity surging in the past decade due to the proliferation of powerful computing systems and the increased deployment of DL systems. CNN-based medical image processing applications have become crucial in this era, where they contribute to notable improvements in image quality and the extraction of valuable information from images. To leverage the high computational power of CNNs for real-time image classification tasks, they are often paired with hardware accelerators. A CNN-based hardware accelerator can be a viable solution for medical image processing, particularly for cancer detection and classification. FPGA-based hardware accelerators have emerged as promising platforms for various applications, including object detection [1], medical image processing [2], edge computing [3, 4], wave generation [5], hardware design [6], safety critical embedded system [7], advanced driver assistance systems [8], and accelerating CNNs [9], owing to their superior energy efficiency and reconfigurable nature.

Breast cancer is a leading cause of death among women globally. According to the World Health Organization (WHO), the number of breast cancer cases is projected to reach 20 million by 2025 [10]. Various DL techniques, such as CNNs [11], support vector machines (SVM) [12], and You Only Look Once (YOLO) [13], along with different imaging methods like mammography [14], magnetic resonance imaging (MRI) [15], and breast ultrasound [16], are employed to analyze images for potential cancer detection. While human specialists traditionally perform image analysis, computer-aided diagnostic tools offer faster and more accurate assessments. CNNs have shown promising results across multiple approaches for breast cancer classification. Due to the diverse approaches of CNNs, custom CNN architectures are necessary for breast cancer image classification to minimize computational complexity and achieve real-time classification. This paper proposes a hardware-software co-design approach to develop a domain-specific custom CNN architecture and evaluate its performance for real-time breast cancer classification using FPGAs. The key contributions of this paper are summarized as follows:

1. Design and development of a custom CNN architecture for breast cancer classification using TensorFlow.
2. Implementing Register Transfer Level (RTL) design of the proposed CNN architecture using Xilinx Vivado.
3. Evaluating the performance of the custom CNN based hardware accelerator through simulations in Xilinx and experimental testing on the Xilinx ZCU102 FPGA board.

II. Related Work

Gupta et al. [17] present an optimized fully resolution-CNN (FR-CNN) for breast tumor segmentation on the FPGA platform. The FPGA implementation of FR-CNN incorporates both fixed and floating-point operations to strike a balance between accuracy and hardware complexity. Typically, the FR-CNN network model necessitates numerous adder and multiplier units, leading to increased power consumption and area usage. To address this, an optimized Vedic multiplier utilizing a carry select adder with Simplified Sum-Carry Generation Logic has been introduced. Furthermore, the particle swarm optimization algorithm is employed to fine-tune the parameters in the network model. In experimental trials, the proposed model attained an accuracy of 96.89%, precision of 95.84%, F-score of 96.08%, specificity of 96.73% with mean absolute error of 0.87. Additionally, the FPGA implementation of the proposed model consumed only 0.6124W of power and utilized a Look-Up Table (LUT) count of 12,167. However, this method

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utilizes image resizing, which may lead to aspect ratio distortion, and there remains a need to improve the accuracy of this system.

Laxmisagar et al. [12] propose a pipelined architecture for a linear SVM classifier implemented in Verilog Hardware Description Language (HDL), using single-precision IEEE standard 754 number format to enable rapid processing. The study focuses on hardware resource utilization and timing analysis with the WBCD breast cancer datasets. Key performance metrics, including resource utilization, on-chip power consumption, and static timing analysis, are evaluated. Both software and hardware implementations are used to compute the accuracy rates for performance evaluation. The pipelined SVM architecture is designed using Verilog HDL and synthesized with the Vivado simulation tool, then implemented on the Xilinx KC705 Kintex-7 evaluation board. This study highlights the design of an SVM linear classifier with a pipelined architecture for FPGA implementation, leveraging FPGAs' advanced parallel computation capabilities for fast data classification, enabling the accuracy of 91.08% while consuming 1.17W power. However, the classification accuracy of this system is not adequate.

Kayalvizhi et al. [14] propose a custom CNN architecture aimed at reducing the number of parameters and computational complexity for hardware deployment. This method uses CNNs to classify breast carcinoma from digital mammogram images. The quantized neural network is accelerated using FPGAs to enhance detection speed and reduce power consumption while maintaining high accuracy. This approach offers a new tool to assist radiologists in diagnosing breast cancer from digital mammograms. Evaluations on benchmark datasets such as DDSM, MIAS, and INbreast show high classification rates, with an accuracy of 99.38% on the combined dataset. However, the proposed system utilizes very small datasets, and the throughput needs improvement to be viable for real-time image classification systems.

Maria et al. [18] propose an early breast cancer detection approach based on the BI-RADS score. This system uses a bespoke Digital Mammogram Diagnostic Convolutional Neural Network (DMD-CNN) model to categorize mammogram breast lesions. It employs PYNQ-based acceleration using the Artix 7 FPGA for the hardware acceleration of the DMD-CNN model, achieving a performance accuracy of 98.2%, outperforming current state-of-the-art methods. Comparative analysis shows a 4% increase in accuracy and a recognition rate of 96% over existing models. The system was tested using k-fold cross-validation, with reported accuracy scores of 96.2%, 97.5%, and 98.1%, respectively. Extensive testing on mammography datasets demonstrated improved performance. The FPGA-based solution optimizes resource utilization and reduces power consumption to 3.12 W compared to GPU acceleration with an classification throughput of 91 FPS. However, this method resizes images to 64×64 pixels, potentially causing aspect ratio distortion, and there is still a need for improvements in the system's accuracy.

Saeed et al. [11] introduced a CNN-based breast cancer classification algorithm tailored for FPGAs utilizing full-field digital mammography (FFDM) images. This method incorporates a Deep-learning Processing Unit (DPU) specifically designed for FPGAs to implement the CNN hardware. The CNN inference on the proposed platform yields a notable 1.6x speed-up factor and a remarkable 91.5% reduction in energy consumption compared to the traditional general-purpose multi-core Central Processing Unit (CPU). However, this technique involves resizing images to 100×100 pixels, which could potentially introduce aspect ratio distortion, and the consideration of system accuracy is not addressed.

The current state-of-the-art in FPGA-based breast cancer classification indicates a prevalent trend of resizing images to reduce computational complexity. However, various imaging modalities has been used for the early detection of breast cancer, including mammography, MRI, and ultrasound. Mammography, the most commonly used method, involves taking an X-ray of the breast. Nonetheless, mammograms possess limitations, particularly in sensitivity for young patients with denser breast tissue. In cases where abnormalities are detected on a screening mammogram, additional tests such as further mammograms or breast ultrasounds are often required to assess the likelihood of cancer. Ultrasound imaging is valuable for examining certain breast changes, particularly those that may be palpable but not visible on a mammogram. However, considering all above aspects, the proposed system in this study utilizes ultrasound images without resizing, resulting in highly accurate, resource efficient and fast breast cancer classification.

III. Implementation

The implementation process of the proposed custom CNN architecture for breast cancer classification commenced with both software and hardware implementation, with the overarching goal of establishing a robust and reliable classification system capable of accurately detecting breast cancer. Fig. 1 illustrates the overall architecture of the proposed system.

A. *Software Implementation*

1. *Dataset Preparation*

The Breast Ultrasound Images Dataset (Dataset BUSI) [19] comprises a comprehensive collection of 780 images, each with an average resolution of 500 × 500 pixels. This dataset, collected in 2018, features breast ultrasound images from women aged between 25 and 75 years, offering a broad age range for analysis. It includes both the original ultrasound images and their corresponding ground truth annotations, facilitating accurate and detailed image analysis. The dataset is meticulously categorized into three distinct classes: normal, benign, and malignant, providing a valuable resource for developing and testing machine learning algorithms aimed at breast cancer detection and classification. The dataset has been partitioned into three sections: training, validation, and

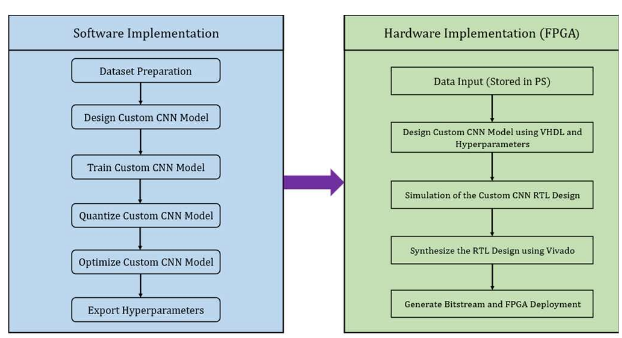

Fig. 1. Overall architecture of the proposed system.

TABLE I. CONFIGURATION OF THE PROPOSED CNN ARCHITECTURE.

Layer	Type	Activation Function	No. of Filters	Size/Stride	Output
0					500 × 500
1	Convolution	ReLU	8	3 × 3/1	498 × 498 × 8
2	Convolution	ReLU	8	3 × 3/1	496 × 496 × 8
3	Maxpool			2 × 2/2	248 × 248 × 8
4	Convolution	ReLU	16	3 × 3/1	246 × 246 × 16
5	Convolution	ReLU	16	3 × 3/1	244 × 244 × 16
6	Maxpool			2 × 2/2	122 × 122 × 16
7	Convolution	ReLU	16	3 × 3/1	120× 120 × 16
8	Maxpool			2 × 2/2	60 × 60 × 16
9	Convolution	ReLU	32	3 × 3/1	58 × 58 × 32
10	Convolution	ReLU	32	3 × 3/1	56 × 56 × 32
11	Maxpool			2 × 2/2	28 × 28 × 32
12	Convolution	ReLU	64	3 × 3/1	26 × 26 × 64
13	Convolution	ReLU	64	3 × 3/1	24 × 24 × 64
14	Maxpool			2 × 2/2	12 × 12 × 64
15	Convolution	ReLU	64	3 × 3/1	10 × 10 × 64
16	Maxpool			2 × 2/2	5 × 5 × 64
17	Flatten				1 × 1600
18	Fully Connected				
19	Fully Connected				
20	Fully Connected				

testing sets. For this study, 780 images from the BUSI dataset were utilized primarily for training purposes. Of these, 215 images were allocated to form the test set. This structured division ensures that the model can be effectively trained and subsequently validated on unseen data, thereby enhancing the robustness and reliability of the classification algorithm.

2. *Configuration of the Custom CNN*

The layers and parameters of the custom CNN architecture were configured within TensorFlow models' experimental setup, utilizing the Sequential class to construct the model. After extensive investigation and experimentation with various custom CNN models, the proposed CNN architecture has demonstrated the highest accuracy. This CNN configuration comprises 10 convolutional layers and 6 max pooling layers, followed by a single flattening layer. The architecture concludes with three densely connected layers, with the complete configuration and sequences detailed in Table 1.

The convolutional operation employs a 3×3×3 filter with a stride of 1 and uses the rectified linear unit (ReLU) activation function. This is followed by a max pooling operation with a 2×2 filter and a stride of 2. The CNN operation starts with the original 500×500 image as input, and through successive applications of convolution and max pooling layers, it reduces the dimensions to a final shape of 5×5×64. These output dimensions of 5×5×64 are then flattened and passed through a dense layer. By performing the necessary bias-weight computations and applying an argmax function, the model ultimately classifies the images into one of three categories: normal, benign, or malignant.

The model underwent training for 50 epochs, a duration deemed sufficient for achieving notable training performance. Following training, evaluation was conducted using test images from the BUSI dataset. Upon attaining satisfactory test results, the model underwent quantization, transitioning its precision from float32 to float16, a format more suitable for deployment on FPGA devices. Although some loss in accuracy occurred due to precision scaling, the model was retrained to mitigate this reduction. Subsequently, the quantized model underwent testing with the test dataset, and its accuracy was compared to that of the original model. The model hyperparameters were then converted from float16 to full integer format and saved as a model with a '.tflite' extension. Finally, the hyperparameters of the custom CNN model were extracted for hardware implementation.

B. *Hardware Implemetation*

The implementation process utilized Xilinx Vivado 2023.1 for hardware execution and subsequent evaluation on the Xilinx ZCU102 FPGA board. Each component within the CNN architecture, spanning convolutional layers, max pooling layers, flattening layers, and fully connected layers, was meticulously crafted to mirror the configuration set within the TensorFlow model. This custom architecture was strategically designed to enable concurrent computation across layers, ensuring efficient parallel processing while maintaining real-time responsiveness to incoming image data. All hyperparameters, including filters and weights derived from the trained model, were meticulously organized into arrays for each respective layer. Upon receiving sufficient input data, these layers executed convolution operations simultaneously, augmented by the ReLU activation function. However, the pooling layer, devoid of any trainable parameters, was individually configured based on its position within the architecture. Likewise, the flatten layer was engineered to serialize data, while the fully connected layers were tailored to align with the model specifications. Following meticulous design, configuration,

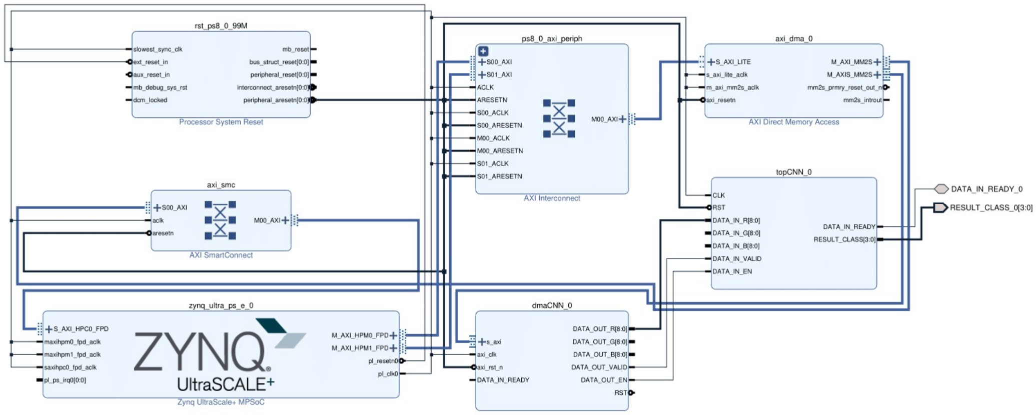

Fig. 2. Hardware implementation of the proposed CNN architecture in Vivado.

and validation of all architectural components, they were seamlessly integrated according to the prescribed model, with interconnections established among them.

Subsequently, the custom CNN IP was encapsulated to seamlessly interface with image data through AXI and DMA interfaces. The holistic design was synthesized and realized using the Vivado design suite, culminating in the generation of a bitstream file deployed to the FPGA board. Figure 2 illustrates the custom CNN architecture in the Vivado IDE.

IV. Result and Discussion

A. *Evaluation of the Proposed CNN Architecture*

The proposed CNN architecture underwent a thorough evaluation encompassing both software and hardware domains. Following an extensive training process spanning 50 epochs, meticulous analysis was conducted to scrutinize various performance metrics, including accuracy and loss. This multifaceted evaluation aimed to ascertain the efficacy and robustness of the trained model across diverse datasets and under varying conditions. By scrutinizing the model's performance over multiple epochs, insights were gleaned into its learning dynamics, convergence behavior, and potential areas for optimization. Additionally, this rigorous evaluation process provided valuable insights into the model's generalization capabilities and its suitability for real-world deployment scenarios. Through this comprehensive assessment, the effectiveness and reliability of the proposed CNN architecture were rigorously validated, laying the foundation for its potential application in real-world breast cancer detection systems.

Figures 2 and 3 represent the accuracy and loss curves of the proposed CNN architecture, respectively. Examination of these graphs reveals a consistent decrease of training losses as the epoch count advances during the training process. Additionally, the accuracy steadily improves with higher epoch counts for both the training and validation datasets. Notably, the accuracy reaches 0.9976 at the 50th epoch, signifying successful training and high performance of the CNN model.

For further evaluation, a confusion matrix has been constructed using 215 images drawn from the test dataset, encompassing three output classes (Normal, Benign, and Malignant). Fig. 5 illustrates this confusion matrix, where the horizontal axis delineates predicted classes and the vertical axis denotes actual classes of input images. Examination of the confusion matrix reveals that for both the Normal and Benign classes, all 55 and 68 images were

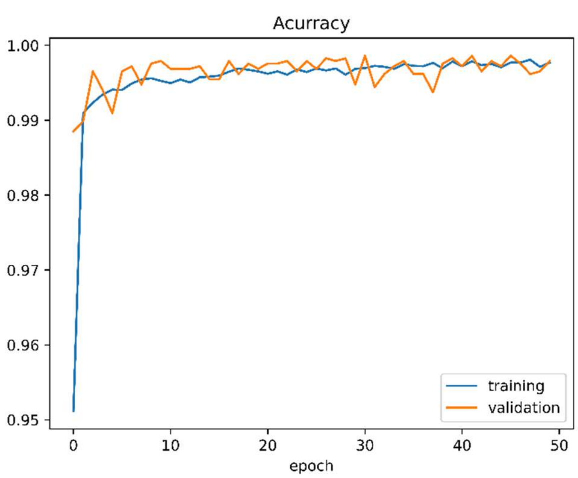

Fig. 3. Accuracy curve of the proposed system.

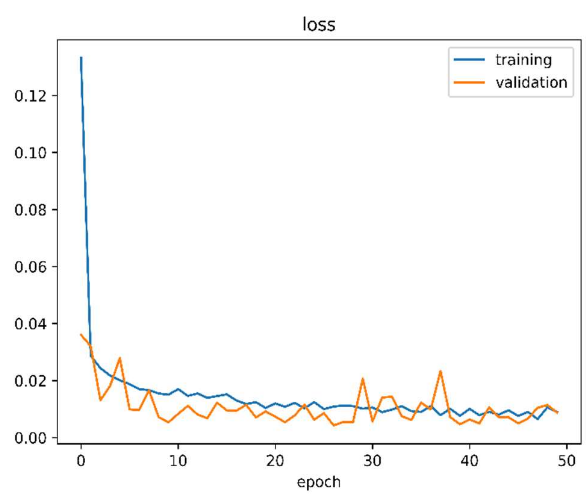

Fig. 4. Loss curve of the proposed system.

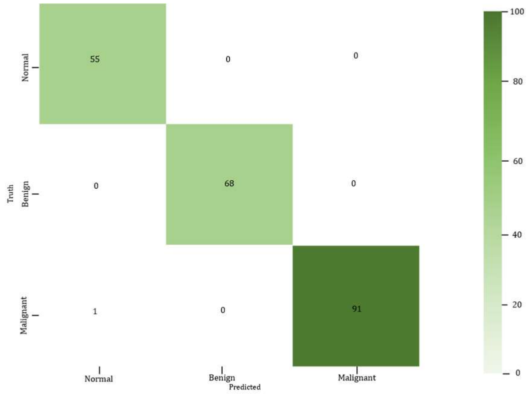

Fig. 5. Confusion matrix of the proposed system.

correctly classified. In the Malignant class, out of the 92 tested images, 91 was accurately classified while 1 was misclassified into the Normal class. This high level of accuracy across the classes underscores the robustness of the proposed custom CNN model in distinguishing between different breast cancer.

The hardware evaluation process entailed selecting few random image from each of the three classes and conducting comparisons after simulating these images. The simulation was performed using a meticulously designed test bench, which yielded results consistent with those obtained from the software implementation. Table 2 represents a concise summary of the simulation results for the proposed CNN architecture, highlighting key metrics such as accuracy, resource utilization, power consumption, and throughput. The proposed CNN architecture achieves an impressive throughput of 4949 FPS when processing input images of size 500×500 pixels, operating at a clock speed of 250MHz. Additionally, the power consumption of the proposed system was meticulously assessed using the Xilinx Power Estimator (XPE) and runtime measurement, yielding a value of 3.6 Watts.

B. Comparison with other Related Works

To assess the performance disparity between the architecture described in this paper and other state-of-the-art architectures, a comparative analysis was conducted by comparing the results of the proposed system with those of other pertinent studies reported in recent literature. This evaluation aimed to gauge the effectiveness of the system architecture delineated in this research. Table 3 presents the outcomes of breast cancer classification achieved by various systems, along with the results of the proposed CNN architecture. Table 3 clearly indicates the exceptional performance of the proposed CNN architecture, boasting the highest accuracy of 99.76% and the highest throughput among the compared state-of-the-art systems. Notably, the study by Guptha et al. [17] stands out for its minimal power consumption. It's noteworthy that since the proposed CNN architecture does not resize the input image, it requires slightly higher resources, resulting in 6X higher power consumption compared to the state-of-the-art system.

TABLE II. SUMMURY OF THE SIMULATION RESULTS.

Criteria	Output
Image Size	500 × 500
NN Model	Custom CNN
Clock (MHz)	125
LUT	41325
BRAM	1
DSP	81
Precision	16 bit
Accuracy (%)	99.76
Latency (ms)	202
Throughput (FPS)	4949
Power consumption (W)	3.5

Despite the higher power consumption, the remarkable accuracy and throughput achieved by the proposed CNN architecture highlight its effectiveness in breast cancer classification tasks. This suggests that the marginal increase in power consumption may be a justifiable trade-off considering the substantial gains in classification performance. Ultimately, these findings underscore the importance of considering multiple performance metrics, such as accuracy, throughput, and power consumption, to make informed decisions regarding the design and deployment of CNN architectures for medical imaging applications.

V. CONCLUSION AND FUTURE WORK

This paper delves into the exploration of designing, implementing, and evaluating a tailored CNN architecture optimized for FPGA platforms, with a primary objective of breast cancer classification. The developed system demonstrates substantial advancements in breast cancer image classification compared to existing works in the field, showcasing commendable attributes such as resource efficiency, accuracy, and throughput. This bespoke CNN architecture stands as a notable engineering feat in the realm of neural networks.

TABLE III. PERFORMANCE EVALUATION OF THE PROPOSED SYSTEM.

Author / Criteria	Guptha et al. [17]	Saeed et al. [11]	Maria et al. [18]	Kayalvizhi et al. [14]	Laxmisagar et al. [12]	This Paper
Year	2023	2023	2023	2023	2023	2024
NN Model	CNN	CNN	CNN	Custom CNN	SVM	Custom CNN
Hardware	Virtex 7	ZCU 104	Artix 7	PYNQ-Z2	KC705	ZCU 102
Accuracy (%)	96.89	-	98.2	99.38	91.08	99.76
Throughput (FPS)	-	2.4	91	75	-	4949
Power Consumption (W)	0.6	11.65	1.9	3	1.17	3.5

Future investigations could pivot towards augmenting the proposed system by integrating additional cancer classifications, thereby expanding its capabilities and applicability in real-time image classification systems within the biomedical domain. Such endeavors would not only enhance the system's versatility but also contribute to the ongoing evolution and refinement of AI-powered diagnostic tools in the medical field.

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