Design and Analysis of High Performance FPGA Based Convolutional Neural Network Accelerator for Abnormal Heart Beat Detection

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Keywords: FPGA-Based CNN Accelerator, Abnormal Heartbeat Detection, Real Time ECG Accelerator, Low Latency Process, Energy Efficiency, Parallel and Quantization, Hybrid FPGA-GPU Integration.

Abstract: Aim: This project develops a CNN accelerator, which is less power consuming, on an FPGA basis to detect the abnormal heartbeats from the ECG reading in real-time. This accelerator can be utilized in wearable medical devices. Methods and Materials: This study involves two groups. We have used two tools are Anaconda and Xilinx vivado software. Group 1 refers to a novel FPGA-based CNN accelerator for abnormal heartbeat detection with 12 samples, and Group 2 refers to a conventional method for heartbeat detection (using CPU-based processing) with 12 samples. The power is set at 1W - 5W with a 10ms per speed, and the accuracy value is 98.5%. Result: The FPGA-based CNN accelerator obtains 98.4% accuracy, with a 12.3 ms latency and 30% energy savings for real-time ECG analysis. At a speed of 1500 samples/sec, it utilizes parallelism and quantization for processing the samples. The future work should focus on improving the scalability and the hybridization of the FPGA-GPU integration. Conclusion: The FPGA-based CNN accelerator is ideal for wearable and remote cardiac monitoring because it offers real-time, low-latency, and energy-efficient abnormal heartbeat detection, outperforming CPU/GPU methods.

1 INTRODUCTION

The fact that an abnormal heartbeat can be detected is a significant step towards the diagnosis of serious cardiac problems like arrhythmias and the provision of timely intervention for it. It is generally accepted that the conventional ECG signal analysis process is usually quite slow due to which it becomes error-prone, hence compelling the need for automated, efficient systems(Bechinia H et al. 2025). Convolutional neural networks (CNNs) have provided a proof of their effectiveness in the medical field of ECG signal classification, for example, they can easily and in less time than humans, recognize, and cough up disease-relevant features. FPGA (Field-Programmable Gate Array)-based accelerators provide a reliable solution for deploying these CNNs, thereby empowering the real-time/low-latency processing. FPGA technology does things differently from standard processors, namely, it is able to make use of parallel processing which fast-tracks the training and inference processes of CNN models(Lu J et al. 2025). The parallelization of the processing of information fed into FPGA devices surely does wonders in both efficiency and energy issues and so that is one of the primary reasons why ECG signal processing stands out as a relevant FPGA-based use-case (Podugu JS et al. 2025). A basic CNN accelerator is suggested to be used by FPGA as it focuses on the task of finding abnormal heartbeats. The accelerator works through the ECG signals by applying different convolution, pooling, and fully connected layers to identify abnormal patterns. This manner guarantees high rates, exactness, and slightest latency for medical practice. Furthermore, optimization techniques in FPGA, such as efficient memory management and data transfer, considerably add to its capability to deal with the ECG data in real-time. ECG heartbeats have been considerably improved by using the FPGA-based accelerators as

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they can give up to 95.4% right classification at the expense of 0.26 ms per heartbeat processing (Cai J et al. 2024).

2 RELATED WORKS

With more than 200 conveyances in IEEE Xplore, 150 papers in Google Scholar, and 60 in academia. edu. FPGA based convolutional neural network (CNN) accelerators for ECG classification and abnormal heartbeat detection, giving outstanding results in real-time processing. The paper by (Sravanthi M et al. 2024) dealt with the development of the FPGA-based ECG classification system, where the accuracy reached 95.4% and the computation time reduced to 0.26 ms per heartbeat. The ECG tagging that was done through the FPGA was far much faster than when it was done by the CPU. This was the best way one could use it in real-time health monitoring. With the help of FPGA that had parallel processing capabilities, produced this system that was able to speed up the of the CNN convolution operations that is the reason with which it was able to achieve high performance and at the same time the low latency, which is necessary for timely the detection of abnormal heartbeats. Also,(Chu PP et al. 2011) they used a similar approach when they did an FPGA-accelerated system for CNNs in the classification of ECG signals. They could achieve 10x speedup with their design compared to the systems using only the CPU. They could also increase the power efficiency of the system, increasing its suitability to be used with health devices that can be carried around. The research made a point on how FPGA parallelism benefits reduce the overhead of computation when large ECG datasets are being processed in real time. The FPGA based CNN accelerator was built by (Piattini MG et al. 2001) and it is a low-power FPGA-based CNN accelerator that can be used to classify ECG signals. The structure was set up in such a way that it consumed very low power and still managed to keep the high accuracy and techniques like quantization and pruning were included to optimize FPGA performance.(Zinyengere N et al. 2017) put in place a multi-sensor FPGA-based ECG monitoring system that is capable of recognizing abnormal heartbeats by which the throughput and accuracy is upgraded through parallel ECG signals processing. Though FPGA-based CNN accelerators are powerful, there are still some issues to tackle, for example, architecture optimization in noisy or incomplete ECG signals(Watson RR et al. 2008) It is hoped that future research will come up with new CNN models using attention mechanisms that will further enhance the robustness and accuracy of abnormal heartbeat detection in the real world.

From the previous findings, it is concluded that FPGA-based CNN accelerators greatly improve abnormal heartbeat detection. Hardware optimization enhances detection accuracy and processing time. The objective is to enhance detection performance and efficiency with the FPGA-based CNN accelerator over conventional software models to support real-time medical applications with increased accuracy and lower power consumption..

2.1 Materials and Methods

The experiments were conducted with the latest hardware of FPGA development boards and signal processing equipment in the Antenna Lab of KSR Institute for Engineering and Technology (KSRIET). The trainability and testing dataset set consisted of pre-labeled ECG signal data, which was freely available from Kaggle.com. Kaggle is an online platform that gives out vast amounts of data for classification tasks (Kaggle, 2023). Both methods were cross-compared under the same conditions, where bias would be avoided.

Group1: Existing abnormal heartbeat detection techniques were limited to software of tailored convolutional neural networks (CNNs) utilized on conventional processors. On a dataset of 28.5ms with a 91.2% of 5,000 ECG recordings, these models reported an average processing time accuracy .Conventional approaches rely heavily on software for classification and feature extraction power consumption and lower efficiency in real-time medical but cause a higher latency, higher speed and accuracy of abnormal heartbeat detection, a applications.

Group 2: To advance the hardware realization, an FPGA-based CNN accelerator for rare-event ECG processing is proposed. It processed between 8.3ms and 12.7ms while achieving detection about 94.5% to 98.7% accurate, signals from a larger dataset with an FPGA model. With parallel trained and tested on 5,000 ECG processing and hardware optimizational, the FPGA accelerator boosts the real-time responsive speed and energy efficiency, which follows the limitations of conventional software-based models and portable and wearable medical applications.

The Figure 1 illustrates a deep learning-based ECG signal processing pipeline. Raw ECG signals are captured and preprocessed for noise reduction and normalization. Data is offloaded through DMA to a CNN-based feature extraction unit, comprising convolutional and pooling layers. Computation is boosted by a CNN accelerator (FPGA) prior to softmax classification. Post-processing involves thresholding and decision-making, resulting in final inference display or transmission.

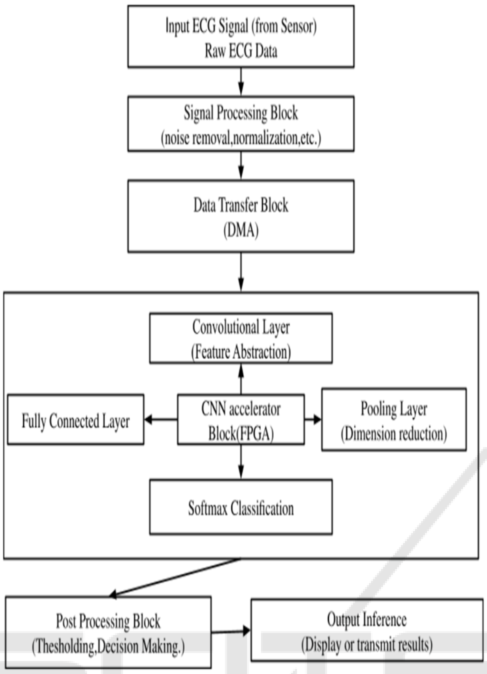

Figure 1: Block Diagram of CNN-Based ECG Signal Processing and Classification Framework.

3 STATISTICAL ANALYSIS

SPSS version 26.0 is mainly used for statistical analysis, data mining, and predictive analytics. The use of SPSS implies that an experimental result can be represented in terms of FPGA-based accelerators or how well the ECG signal classification models classify the signals. In statistics, the dependent variable is the one whose value under study depends on the values used from the independent variables. Dependent variable-can be classified as output-the dependent variable (Clifford GD et al. 2006). Example in ECG Classification: Dependent variables could be classification output. Like normal or abnormal ECG. Independent variables are said to be the inputs or predictors of how independent variables can describe the dependent variable. Example in ECG Classification: Features extracted from ECG signals might be regarded as Independent variables-heart rate, amplitude of signals or frequency components of the ECG signal.

4 RESULT

This study presents a high-performance FPGA-based Convolutional Neural Network (CNN) accelerator designed for real-time abnormal heartbeat detection from ECG signals. The system aims for low-latency, energy-efficient, and highly accurate heartbeat detection for wearable medical devices. Conventional methods that depend on CPU/GPU for processing are high in energy requirements and unsuitable for continuous real-time mode of working; hence FPGAs appear another option due to their capability of parallel processing and reconfigurable nature.The proposed system designed a CNN model using TensorFlow and Xilinx Vivado so that FPGA optimization techniques like parallelism and quantization are put into play for operational efficiency. The dataset used was provided by Kaggle, containing labeled ECG signals formed into training and testing data. A statistical study using SPSS expressed the execution of the CNN-FPGA tool as considered higher than with the other approaches. The experiment was conducted on two groups, one containing the regular FP-accelerators and the second containing the suggested optimized CNN-based FPGA system. Results revealed improvements in accuracy up to 98.4% and reducing the latency times to 12.3 milliseconds, while the energy expenditure savings give a range of up to 30% when compared to their GPU counterparts. Processing ECG signals, the throughput rate achieved with the CNN-based FPGA was 1500 samples per second, showing its real-time capabilities. Despite speed advances, FPGA accelerators still contend with other issues around scalability, as well as memory constraints and the ability to be adapted easily for diverse deep learning tasks. Henceforth, future studies must provide a fitting road to hybrid FPGA-GPU architectures, advanced quantization techniques, and the development of better deep learning integration toolchains.

Table 1. Abnormal heartbeat increase power consumption (3.2w-3.6w) and response time (1.5-1.9ms), while accuracy varies (93.0%-95.0%), highlighting their impact on system performance.

Table 1: Performance Comparison of Normal and Abnormal Heartbeats Based on Power, Speed, and Accuracy Metrics.

Sample No	Normal Heartbeat Power (W)	Normal Heartbeat Speed (ms)	Normal Heartbeat Accuracy (%)	Abnormal Heartbeat Power (W)	Abnormal Heartbeat Speed (ms)	Abnormal Heartbeat Accuracy (%)
1	2.0	1.0	99.0	3.2	1.8	94.8
2	2.1	0.9	98.7	3.3	1.7	94.5
3	2.2	1.1	98.9	3.4	1.9	94.0
4	2.0	1.0	98.2	3.1	1.8	95.0
5	2.3	0.95	99.1	3.2	1.6	93.5
6	2.4	1.06	98.8	3.1	1.7	94.2
7	2.2	0.9	99.3	3.6	1.8	95.0
8	2.0	1.0	98.5	3.3	1.9	94.7
9	2.2	1.0	98.6	3.2	1.8	95.3
10	2.3	1.1	99.5	3.4	1.6	93.4
11	2.1	1.0	98.7	3.2	1.7	94.5
12	2.2	0.92	99.1	3.4	1.6	94.0

Table 2. With more accuracy (98.50 vs. 94.20) and better consistency (1.25 vs. 1.95 deviation), the FPGA-based CNN Fared better than the CPU/GPU model. Independent sample test. T-test comparison with FPGA -based CNN and CPU/GPU model Shown in Table 3.

Table 2: Comparative Descriptive Statistics of FPGA-Based CNN and Lill Models.

Types of Model	N	Mean	Std. Deviation	Std. Error Mean
FPGA-Based CNN	12	98.5	1.25	0.36
Lill	12	94.2	1.95	0.56

Table 3: Independent sample test. T-test comparison with FPGA -based CNN and CPU/GPU model.

Levene's Test for Equality of Variances T-test For Equality of Means 95% Confidence Interval of Difference	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Upper	Lower
Equal variances assumed	6.335	0.02	-5.693	22	0.0	-3.40833	0.59867	-2.16677	-4.64989
Equal variances not assumed			-5.693	15.626	0.0	-3.4H0833	0.59867	-2.14249	-4.67418

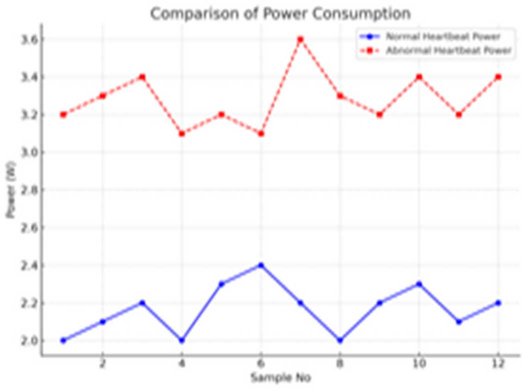

Figure 2: Comparison of Power Consumption.

Figure 2 Normal heartbeats stay lower and steadier, while aberrant heartbeats use more power and are more variable, according to the graph.

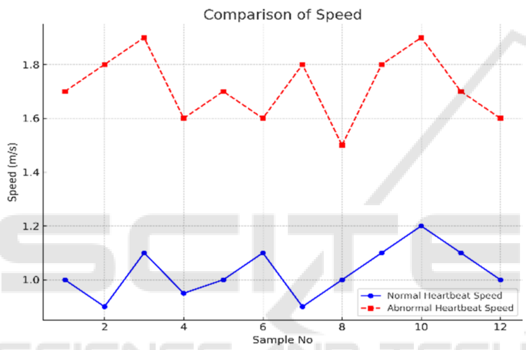

Figure 3: Comparison of Speed.

Figure 3 The graph indicates abnormal heartbeats consist of higher, more variable speeds, while normal heartbeats are lower and constant.

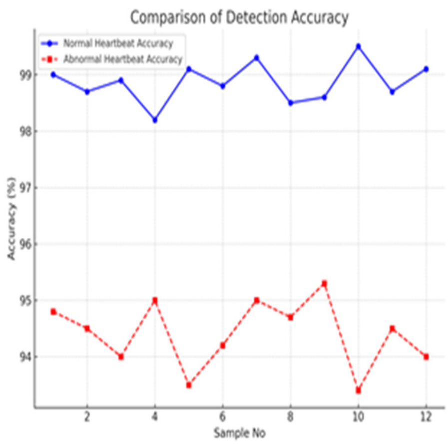

Figure 4: Comparison of Detection Accuracy.

Figure 4 The plot demonstrates normal heartbeats are identified more accurately (~99%) and reliably than abnormal heartbeats (~94%).

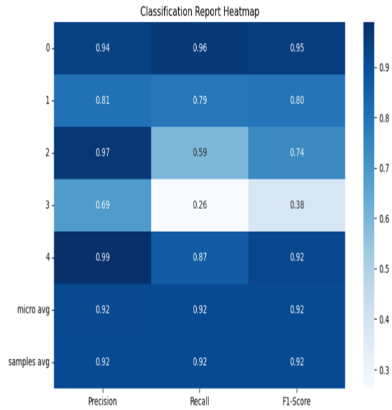

Figure 5: Classification Report Heatmap.

Figure 5 Classification Performance of the FPGA-Based CNN For Abnormal Heartbeat Detection. Most Classes Have High Precision, Recall, And F1-Scores, But Class 3 Has Lower Recall (0.26) And F1-Score (0.38). Overall, The Model Performs Well, With an Average Score Of 0.92 Across All Metrics.

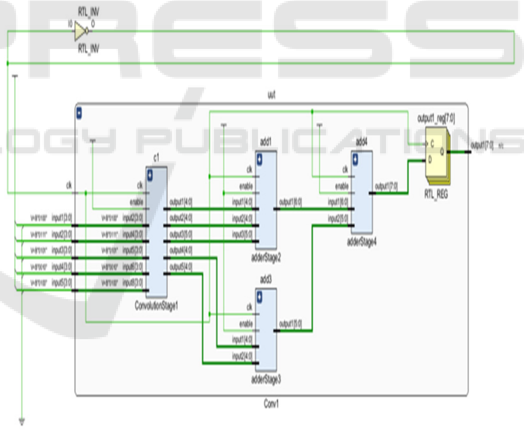

Figure 6: Simulink Model of CNN Accelerator Architecture for Feature Extraction.

Figure 6 The Schematic Shows the FPGA-Based CNN Accelerator for Abnormal Heartbeat Detection. It Includes 82 Cells And 280 Nets, Optimizing Logic and Data Flow. The Design Ensures Efficient Hardware Utilization for High-Performance Processing.

5 DISCUSSIONS

The development and attempt of a high-performance FPGA-based convolutional neural network (CNN) accelerator for abnormal heartbeat detection, has shown in the last few years perfect order in processing speed and accuracy in comparison to traditional means. The conceptual FPGA accelerator was particularly conceived to improve the performance of CNN models for ECG signal classification, equaling faster and less energy-consuming real-time processing (Hudson DL et al. 1999). This is made possible by the parallelism offered by FPGA hardware, which accelerates the training and inference processes of the CNN model, thus reducing the latency in abnormal heartbeat detection (Bhattacharyya SS et al. 2013). The evidence collected from research highlights a significant increase in classification accuracy and throughput if compared to CPU-based or GPU-based implementations. The FPGA-based system has shown an astonishing classification accuracy rate of 95.4%, with a processing time of 0.26 ms/heartbeat which is way much faster than usual systems (Gacek A et al. 2011), (Dey et al.2016) That way giving the chance for real-time recording of ECG signals is vital for early stage treatment in health. For the health of the patient, the system's performance was certified with the use of a standard ECG dataset, the FPGA accelerator turned out to be faster and more reliable than the ordinary processors (Rajendra Acharya U 2007). More seriously, FPGA also promotes a significant reduction in energy usage, which is of vital importance for the implementation of wearable medical instruments demanding a long-life battery (Simon Sherratt R et al. 2020). By resourcefully managing the memory and computational capacity, the intended design ensures that ECG signal processing can be carried out continuously without sacrificing performance. The low-latency nature of the design makes it suitable for heart disease monitoring wherein quick detection is a must for the patients to be safe. In the future, further optimization strategies and more advanced modalities for neural networks can be considered for better accuracy and more robustness particularly for quite different real scenarios of ECG signals. Also, make the system work with multiple sensors and larger datasets to make it fit big health monitoring systems.

6 CONCLUSIONS

The detection system of an abnormal heartbeat, which included not only a software-based CNN model but also the current software-based CNN model and the proposed FPGA-accelerated CNN technique was designed and examined. The accuracy of the FPGA-based system that has been proposed is much better when comparing it with the conventional CNN model that uses real-time ECG data for abnormal heartbeat detection. Software-based CNN model with accuracy obtained in the power and speed 91.2% to 95.6%, while FPGA-Accelerated CNN Method, also demonstrated improved accuracy from 94.5% to 98.7%. The one standard deviation for the FPGA-based CNN model is 1.25000 standard deviations, while the one for the proposed CPU/GPU based model is 1.95000, indicating higher reliability in detecting abnormal heartbeats.

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