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A Review of ECG Classification Techniques Based FPGA

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ABSTRACT: Electrocardiogram (ECG) signals are particularly used in the diagnosis and supervision of different cardiovascular diseases. The accurate and efficient classification of ECG signals is of critical importance in clinical applications. FPGA-based systems have been identified to offer an efficient solution to the implementation of real-time ECG signal classification systems because of their parallel processing, reprogrammable nature, and low power consumption. Thus, this review paper aims to explore the existing ECG classification techniques with a focus on FPGA implementation. The review discussed several classification methods, including adaptive algorithms and neural networks, which have been optimized for arrhythmia detection. Notably, Neural network techniques like ANN, CNN, and spiking neural networks are preferable due to their ability to provide superior accuracy. For instance, Mathias et al. developed a high-precision neural network with an impressive accuracy of 99.82%. Similarly, Arona et al. deployed a DCNN on FPGA, achieving accuracies reaching up to 99.67%. Researchers widely used the MIT-BIH dataset to evaluate ECG classification techniques, This paper presents new trends and focuses on future research prospects in this field. Hence, the findings of the present review can help researchers and engineers in developing effective and efficient FPGA-based ECG monitoring and diagnostic systems for clinical and healthcare applications.

Keywords: Electrocardiogram, Classification, Arrhythmia, Field Programmable Gate Arrays

1. INTRODUCTION

The human heart is a significant and substantial organ in the human body since it is accountable for pumping blood to all parts of the body via the circulatory system and it serves as the delivery system of oxygen and nutrients to the tissues of the body. It also eliminates waste products such as carbon dioxide their way out of the body. In the event of a heart malfunction, the body's well-being would be severely jeopardized, potentially leading to fatal consequences. Therefore, A healthy heart is critical for overall well-being [1]. An ECG is a vital signal measured by healthcare devices, It detects electrical activity from the heart, providing valuable real-time insights for diagnosing potentially life-threatening heart problems [2]. Moreover, ECG signals find widespread application in various areas, such as diagnosing cardiovascular diseases, identifying arrhythmias, detecting sleep apnea, and monitoring chronic patients [3-5]. Accurate identification of ECG fiducial points is essential for precise measurements of morphological and interval features of local waves (T-wave, P-wave, U-wave, QRS-complex) in ECG applications. These features include amplitude, duration, polarity, shape, QT -segment, PR -segment, ST-segment, and RR-interval [6-8]. Fig. 1. demonstrates the fiducial points of an ECG.

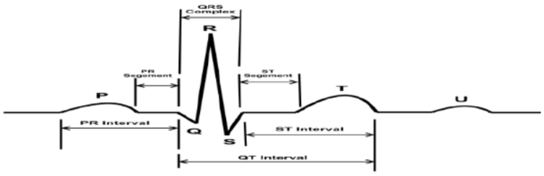

FIGURE 1. - ECG Signal showing fiducial points

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By examining the characteristics and relationships between these fiducial points, ECG signals can be classified into different rhythm types (e.g., sinus rhythm, atrial fibrillation, and ventricular tachycardia) or used for diagnosing specific cardiac conditions [9].

ECG classification requires real-time processing capabilities to analyze and interpret the electrical activity of the heart. Field-Programmable Gate Arrays (FPGAs) play a vital role in this domain due to their real-time processing capabilities, low power consumption, high performance, customizability, scalability, and hardware-level signal processing. FPGA is a programmable logic device programmed by a designer after manufacturing. An FPGA is made out of a large number of programmable logic blocks and a number of reconfigurable interconnection networks in a multitude of levels that can be implemented to produce certain digital circuits. These characteristics make FPGA-based systems well-suited for implementing efficient and accurate ECG classification algorithms, enabling timely diagnosis of cardiac abnormalities and improving patient care. Fig. 2 shows a basic structure of an FPGA. [10].

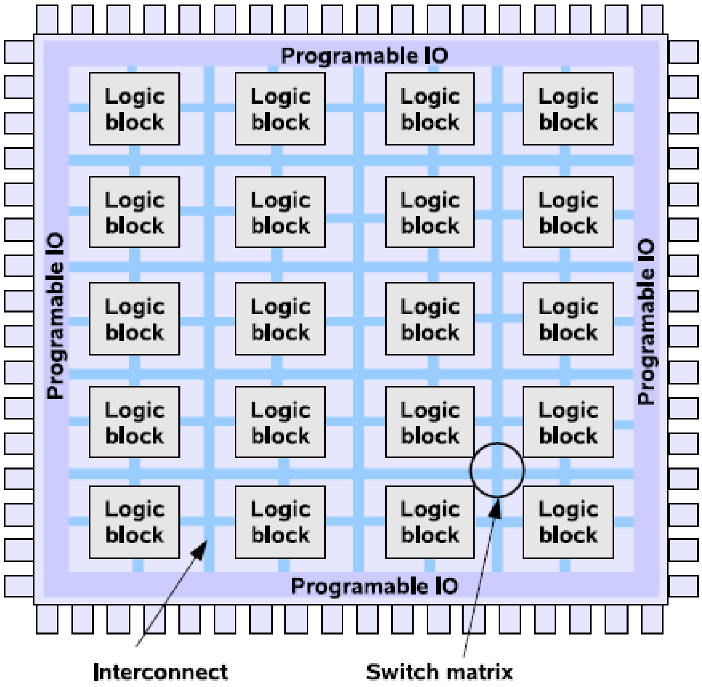


FIGURE 2. - Architectural layout of an FPGA

To enhance reader understanding throughout the paper, Table 1 summarizes the most recent literature on ECG classification techniques. These summaries provide a concise overview of relevant research.

This paper reviews various techniques for ECG classification, alongside a comparison between these methods. Additionally, the paper explores the current implementation of classification methods on FPGA, addressing challenges and optimization strategies. The key points of the contributions are outlined as follows:

1) The paper reviews ECG classification techniques, with a specific focus on FPGA implementation. It helps substantiate existing methods and their efficiency in the analysis of ECG signals.

2) Summarizes the existing literature on current practices of hardware acceleration for ECG classification and the proposed methodologies for FPGA design tools. Such information helps researchers and developers to orient themselves to the available resources and tools and design efficient hardware.

The following sections of this paper are organized as follows: Section 2 reviews the research work done in the literature closely related to the presentation of ECG classification-based FPGA employing various techniques. Section 3 goes further and presents the potentially rich study areas in ECG classification techniques based on the recent investigation of other researchers. Finally, Section 4 summarizes this article yet again.

Table 1. - A brief review of some of the recent literature reviews carried out on ECG classification techniques

[Refrence], Year	Real-Time processing	Main Findings
[10], 2018	✓	The paper reviewed various techniques for CNNs on FPGAs, emphasizing the importance of parallelism through methods like loop tiling and loop unrolling to enhance performance
[11],2020	×	The reviewed papers were categorized based on their focus on heart arrhythmias, the Deep Neural Networks (DNNs) used, and the variants of

		different DL methods applied for classification
[12],2021	×	Common machine learning methods for ECG classification include MLP, K-NN, SVM, CNN, and RNN. CNN and RNN achieve high accuracy.
[13],2023	×	CNN are the most commonly used models in the reviewed studies, accounting for 58.7% of the models.
[14],2024	×	• SNNs offer a low-power alternative, mimicking the human nervous system. • SNN-based methods achieve near-DNN accuracy with ultra-low-power performance, ideal for lightweight devices.
[15],2024	×	The paper emphasizes the importance of comprehensive comparisons between available techniques, aiming to bridge the gap in existing research and provide valuable insights for future studies in the field of ECG classification
[16],2024	✓	The review article discussed the effectiveness and efficiency of various methods used for analyzing ECG signals in real-time

2. LITERATURE REVIEW OF ECG CLASSIFICATION TECHNIQUES

This section delves into hardware-based approaches for ECG signal classification explored in research published from 2015 to 2024. It gathers relevant articles from credible sources like Elsevier, IEEE, Springer, and World Scientific. The review analyzes and compares these methods, highlighting key points used for classification (fiducial points) and the targeted cardiac issue. This comparison provides valuable insights for researchers developing hardware-based ECG classification systems.

Shuenn et al. [17] introduced a low-power collection and categorization setup for body sensor networks. It utilized a high-pass sigma-delta modulator for signal capture, a super-regenerative on-off keying transceiver for wireless transmission, and zinc-air batteries for extended operation. The system, with a body-end power consumption of 586.5 μW, demonstrated high accuracy in beat detection (99.44%) and ECG classification (97.25%) through wavelet transform-based digital signal processing.

Matthias et al. [18] implemented a highly accurate neural network-driven machine learning algorithm on FPGA for ECG anomaly detection. The algorithm outperformed other methods with an average accuracy of 99.82%. The utilization of PCA reduced features, while an MLP handled classification. The study examined the impact of parameters and simplifications on FPGA performance, power consumption, and accuracy. Techniques like piecewise linear approximation and fixed-point implementation reduced resource requirements while maintaining accuracy comparable to floating-point simulations.

Hassan, et al. [19] proposed an FPGA-based system for multi-heart disease classification, identifying eight different heart malfunctions based on standard ECG features. They introduced NVG-RAM and Threshold Decision (TD) weightless neural network classifiers for FPGA-based ECG signal analysis. The performance comparison of the TD and NVG-RAM classifiers was performed while emphasizing their application in the FPGA-based ECG classification system. Hence, this research was concerned with the identification of four attributes of the ECG signal including RR, PR, QT, and QRS intervals while designing a cardiac diagnostic system which was integrated into FPGA. The performance of the developed NVG-RAM classifier was excellent and the diagnosis of eight types of heart diseases was 100% accurate when new ECG signals were synthesized using Lab VIEW.

Syed et al. [20] introduced an SCA classification processor featuring a RSF5 feature extraction engine, a patient-specific threshold engine, and a real-time decision-making system for arrhythmia characterization. Achieving high accuracy, the system consumes minimal power, ensuring immediate response and continuous monitoring for SCA and NSCAs.

Omar et al. [21] created a system for classifying heart diseases using an FPGA kit. Their system utilized blocks from XSG to implement a classifier that analyzes ECG signals. To identify the QRS complex, a specific filter called approximate linear phase BLWDF was used on the ECG signal. The classifier was able to categorize ECG signals into four different heart disease classes: Normal, LBBB, LVH, and RBBB also were seen in the patients. To get the weights and biases for the classification, they utilized the Matlab toolbox hence training the neural network. Translating the models into VHDL code provided the capability to measure how much chip resources were consumed and decide on the maximum operating frequency.

Mariel et al. [22] put forward a new algorithm to automatically identify arrhythmias. This algorithm incorporated a continuous neural network and this structure was implemented on the FPGA based on fixed point arithmetics. Fivefold cross-validation was used on a large EKG signal database and the researchers recorded a sensitivity of 98% and an accuracy of 93. 80%. This work used CoNN for the first time as a real-time classifier and, therefore, can be considered one of the first attempts at directly using the EKG signals for arrhythmia classification.

Hadjer et al. [23] proposed a system for the recognition of arrhythmias which is based on ANN integrated into an FPGA chip. Their design aimed at minimizing the power consumption compared to classic software techniques and the size of the system. The working of the proposed system can be explained by the analysis of the ECG signal using wavelets, followed by feature classification using a multilayer perceptron neural network, and, subsequently, the decision about the type of arrhythmia. They built and tested their system on a Nexys4 Artix7 development kit and compared its performance to a software version running on MATLAB. This comparison showed that their fixed-point implementation on the FPGA was just as effective as the floating-point software but in a smaller and more power-efficient design, making it suitable for a mobile device for real-time patient monitoring.

Yanze et al. [24] proposed a real-time ECG classification model that uses discrete wavelet transform in combination with a support vector Machine algorithm. They implemented a versatile hardware system in Xilinx ZYNQ SoC for the acquisition of ECG signal, feature detection, and classification. They proposed a power-efficient DWT acceleration module to improve system performance. The system achieved a high accuracy of 98.7% and reduced classification time to 280 µs per heartbeat, meeting real-time requirements. On-chip power consumption was demonstrated to be 2.059 W, ensuring efficient operation.

Dongkyu et al. [25] designed the platform for evoking the diagnostic services and real-time processing of ECG data with the assistance of IoT edge servers. They developed the energy-efficient FPGA accelerator for the real-time analysis of the ECG data for better heart abnormalities' diagnosis. Their novel template-based ECG diagnosis algorithm was possible through a template approximate approach that availed personal learning; thus, there are enhanced detection rates with minimal learning time and low memory uses. The analysis of experimental results proved that the presented solution of hardware acceleration cuts the time of diagnosing ECG signals by 89.96% in comparison with software execution.

Jiahao, et al. [26] designed an efficient hardware system for the classification of ECG signals on wearable devices adopting the special CNN architecture. This system can conserve resources effectively because complex calculations are replaced by simpler ones in terms of processing, and there is a special design of the processing unit. Acquiring a high accuracy of 99. 1% of their approach proved to be three times more efficient when compared to standard methods for the classification of ECG beats.

Jiahao et al [27] deal with the issues of performing computations on power-demanding convolutional neural networks (CNNs) for ECG classification using wearable devices. They suggested a special accelerator to perform sparse CNNs, a case in which many weights are equal to zero. This accelerator's dataflow is optimized and it is using compressed storage to avoid useless calculations and it features two-level weight matching for a high processing rate. There was also a design of an elastic processing unit array. Using the proposed approach the efficiency of the simulation increased by 48% as compared to more conventional non-ultrasound approach which at the same time gave an accurate ECG classification rate of 98.99%.

Barıs et al. [28] developed an ANN-based ECG classifier with the ability to store raw input data in order to avoid loss of data while extracting features. For training and validation purposes, they used the MIT-BIH arrhythmia dataset to which they obtained an approximate accuracy of about 97%. They adopted a network architecture with the hidden nodes separated into two layers and the output nodes' layer for effective signal categorization of ECG signals. To ensure efficient mapping, they extracted network parameters as 32-bit floating-point numbers and converted them into 8-bit fixed-point numbers for FPGA implementation. The classifier was successfully implemented on Xilinx Zybo board using Verilog.

Dze et al. [29] analyzed common building blocks in an SNN and investigated spike-based plasticity for ECG classification. The behavior of STDP in a neuromorphic circuit was visually demonstrated, highlighting its application in ECG classification. Remarkably, they achieved state-of-the-art performance while utilizing only 1.058% of Zed board resources, showcasing efficient hardware resource usage.

Xing et al. [30] employed an ECG heartbeat classification technique based on a spiking neural network with a channel-wise attentional module. This enabled efficient real-time diagnosis on low-power wearable devices. The method used wavelet denoising and SNN layers with leaky integrate-and-fire neurons for energy efficiency. The attentional module automatically learned weights, capturing crucial ECG features.

Rohini et al. [31] proposed a simple prototype of arrhythmia classification based on using a PNN (Probabilistic Neural Network). Six ECG parameters were identified, which improved the differentiation of patients with arrhythmia: Using FPGAs implemented on an Artix-7 board, the accuracy was on an average of 98.27% in ECG classification. The rapidity of the classification time of 17 seconds demonstrated the efficiency of the proposed system in identifying the heart's arrhythmias. In particular, the early signs can be detected through the prototype system, so that timely actions are taken which in turn will benefit the patients with cardiac diseases.

Tiantai et al. [32] presented a highly efficient network for real-time multi-label ECG classification. They fashioned the hardware accelerator re-using data for repeated use and reducing power. In order to increase performance they were able to recycle the input/output/weight information to minimize the access time and costs. They proposed a cascaded processing strategy that adapts to the size of convolutions and increases the accelerator's performance.

Wei-Ting, et al. [33] made smart clothes that would detect heart disease from among people who are engaged in several activities. The clothes are made of special conductive material to analyze your heart rhythm in real-time. This analysis is based on ECG, a widely known tool used to read the health of your heart by conducting electrical tests on it.

Ming, et al. [34] proposed a high-performance AIA for arrhythmia classification on ECG using an efficient 1D-CNN with novel multiplicative behavioral and data reuse techniques. They introduced WS and IS approaches for low memory access in convolutional and fully connected layers, respectively. The AIA demonstrated high accuracy in software simulation classification on lab and MIT-BIH arrhythmia databases, achieving 97.3% and 98.3% accuracy, respectively. Hardware implementation on Xilinx PYNQ-Z2 operated at 10 MHz, consuming 0.131 W, enabling real-time, low-power arrhythmia classification with high accuracy. The proposed approach optimized memory access time by 29 times and latency by 22.5 times compared to a single MAC, showcasing significant performance improvements.

Aruna, et al. [35] presented an FPGA-Implemented DCNN for ECG classification. The DCNN architecture design had 3 layers of convolutional layers, 3 layers of pooling layers, and 3 layers of fully connected layers, which helped in categorizing the ECG signals as having more features. By leveraging MIT-BIH arrhythmia and PTB databases, they demonstrated the adaptability and strength of their approach, achieving remarkable classification accuracies of 98.6% and 99.67% respectively. The FPGA-based DCNN accelerator showcased efficiency and speed with low power consumption (0.45 mW), high operation frequency (185.426 MHz), and fast processing time (15 s).

Soumyashree, et al. [36] demonstrated a split 2D CNN for ECG beat classification on Xilinx's ZCU 104 FPGA, reducing parameters and resource utilization. She generated a customized FPGA IP using Vitis HLS, achieving 98.64% accuracy, 4.177W power, and 2.19E8ns latency in classifying arrhythmia. This addressed the need for automatic CVD diagnosis with resource-constrained edge devices, providing a solution for low latency, less complex, and energy-efficient FPGA architectures in real-time scenarios.

V.Ponniyin et al. [37] developed the High-Speed Extreme Learning Network (HSELN) for ECG signal monitoring, emphasizing efficiency and performance optimization for wearable devices through hardware-software co-design on Zynq-SoC families.

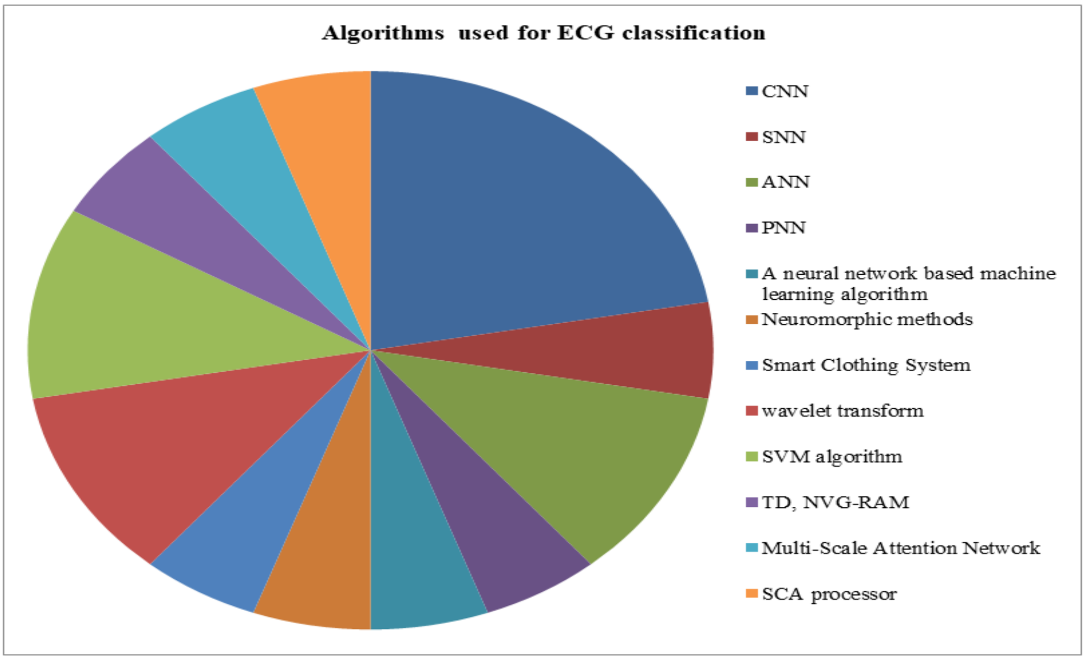
Marwa et al. [38] developed an optimized CNN architecture for enhanced ECG feature extraction and classification, aiding clinicians in quick and accurate diagnostics. The implementation on Pynq-Z2 achieved high accuracies of 98.39%, 98.61% , and 98.86%for training, validation, and test. A Hardware/Software Co-design leveraged FPGA parallel architecture, resulting in a 10x acceleration in time process compared to processor implementation, with significant resource savings.

Aditta et al. [39] explored classifying cardiovascular diseases using photoplethysmogram signals, achieving 93.48% accuracy for cerebral infarction, 96.43% for cerebrovascular disease, and 88.46% for diabetes, using support vector machines on Xilinx Zynq 7000 FPGA. The system utilizes 0.693W power and can be extended as a point-of-care cardiovascular disease detection system. Table 2 and Fig. 3 provide the summary of all the reviewed articles in term of which kind of ECG datasets were used, which Algorithm was used for ECG classification, and which kind of FPGAs were used for implementation.

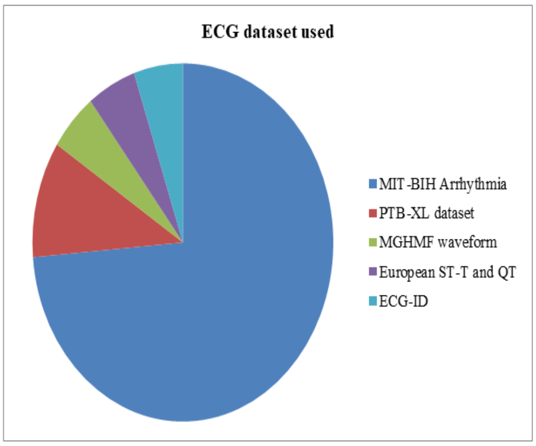
Table 2. - Overview of different methods for classifying ECG signals

[Refrence], Year	Dataset	Algorithm	FPGA Type
[17], 2014	MIT-BIH Arrhythmia	High-pass sigma-delta modulator, wavelet transform	Altera cyclone IV
[18], 2017	MIT-BIH Arrhythmia	A neural network based machine learning algorithm	Zynq
[19], 2018	MIT-BIH Arrhythmia	TD, NVG-RAM	Spartan 3AN
[20], 2018	ECG-ID, MIT-BIH Arrhythmia	SCA processor	FPGA
[21], 2019	European ST-T and QT	BLWDF	Spartan 6
[22], 2019	MIT-BIH Arrhythmia	Continuous Neural Network	Zynq
[23], 2019	Physiobank	ANN	Artix7
[24], 2020	MIT-BIH Arrhythmia	DWT and SVM	Zynq
[25], 2021	MIT-BIH Arrhythmia	Energy-Efficient FPGA Accelerator	AlveoU200
[26], 2021	MIT-BIH Arrhythmia	Convolutional Neural Network	Zynq
[27], 2022	N/A*	CNN	Zynq
[28], 2022	MIT-BIH Arrhythmia	ANN	Zybo
[29], 2022	MIT-BIH Arrhythmia	Neuromorphic methods	Zedboard
[30], 2022	MIT-BIH Arrhythmia	SNN	FPGA
[31], 2022	MIT-BIH Arrhythmia	PNN	Artix-7
[32], 2023	PTB-XL dataset	Multi-Scale Attention Network	Zynq
[33], 2023	MIT-BIH Arrhythmia, MIT-BIH AF, and MGHMF waveform	Smart Clothing System	Artix-7
[34], 2023	MIT-BIH Arrhythmia	1D-CNN	Pynq-Z2
[35], 2023	PTB, MIT-BIH Arrhythmia	DCNN	Virtex 4
[36], 2024	MIT-BIH Arrythmia	Convolutional Neural Network	ZCU 104
[37], 2024	N/A*	Hardware-Software Co-design techniques to deploy deep learning algorithms	Zynq
[38], 2024	MIT-BIH Arrhythmia	Convolutional Neural Network	Pynq-Z2
[39], 2024	N/A*	SVM algorithm	Zynq 7000

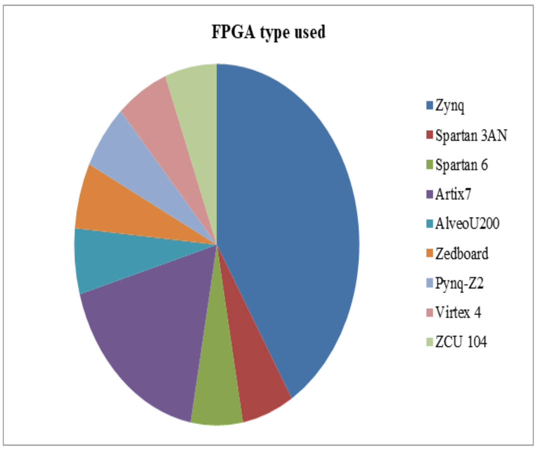
N/A*: Not Available



(a)



(b)



(c)

FIGURE 3. - **(a) Algorithms used for ECG classification; (b) ECG dataset used; (b) FPGA type used**

3. TREND DIRECTIONS OF RESEARCHERS

This part surveys a summary of the key trends noted by leading researchers in the area of ECG classification methodologies as an orientation and starting point for new scholars [40-50].

- An adaptive and effective SE-NLMS.
- Employing SVM for identifying arrhythmias.
- Accelerating CNN Inference .
- Efficient ECG Classification Techniques Based on Wavelet Transformation.
- Using machine learning models.
- 1-D convolutional deep residual neural network.
- Utilizing Convolutional Neural Networks and the STFT technique for deep transfer learning.
- LSTM-based recurrent neural networks.
- recurrent CNN with GWO.
- Spiking Neural Networks.
- ECG classification using DEA with LSTM.
- Binarized spiking neural network optimized for classification.

4. CONCLUSIONS

ECG signals have established their efficacy in accurately detecting cardiac abnormalities. This research paper offers an overview of ECG classification methods, which includes the implementation of an ECG classifier on an FPGA. The study showcases efficient resource utilization and a significant reduction in diagnosis time. Advancements in FPGA technology and algorithm design will contribute to enhanced ECG classification accuracy, real-time processing, and the creation of innovative medical devices for cardiac monitoring and diagnosis. The paper serves as a guide for researchers in navigating the extensive literature on ECG classification. Our survey encompasses a wide array of recently published ECG classification techniques, which are conveniently summarized in a table for straightforward comparison. An intriguing observation from the review is that the majority of researchers rely on the MIT-BIH database to evaluate their ECG classification techniques and Zynq board for implementation. The reviewed ECG classification techniques based on FPGA offer valuable insights for researchers and engineers involved in the development of medical devices, cardiac signal processing, and healthcare application.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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