FPGA Implementation of Complex-Valued Neural Network for Polar-Represented ECG Classification

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Abstract - Electrocardiogram (ECG) signal classification is essential for detecting cardiac abnormalities at an early stage. Traditional real-valued neural networks often struggle to represent phase and amplitude variations effectively. This project presents an FPGA-based implementation of a Complex-Valued Neural Network (CVNN) for ECG heartbeat classification using polar-represented spectrograms. ECG signals are transformed into time-frequency representations using Short-Time Fourier Transform (STFT) and then converted into polar coordinates to capture both magnitude and phase information. These complex-valued features are fed into a CVNN, which can inherently process and learn from complex inputs more effectively than conventional networks. The entire architecture is implemented on an FPGA using High-Level Synthesis (HLS), providing a low-latency, energy-efficient solution suitable for real-time embedded applications. Resource usage, execution time, and accuracy are optimized to meet hardware constraints without sacrificing performance. Experiments conducted using the Kaggle ECG Heartbeat Classification Dataset show high classification accuracy, validating the model's effectiveness. This project demonstrates the feasibility of deploying CVNNs on FPGA for accurate, real-time cardiac monitoring systems.

***Key Words*:** ECG Classification, Complex-Valued Neural Network, FPGA, Polar Representation, Spectrogram, Real-Time Processing, HLS.

1. INTRODUCTION

Early and accurate classification of ECG signals is crucial for detecting cardiac abnormalities such as arrhythmias. Traditional real-valued neural networks often fail to capture the complete structure of ECG signals, particularly the phase information. Complex-Valued Neural Networks (CVNNs) offer a promising solution by processing both magnitude and phase components, especially when the signals are transformed into polar coordinates using spectrogram techniques like Short-Time Fourier Transform (STFT).

To make such systems suitable for real-time and portable applications, this project implements a CVNN on a Field-Programmable Gate Array (FPGA) using High-Level Synthesis (HLS). FPGAs offer parallel processing and energy-efficient execution, making them ideal for embedded healthcare systems. The ECG signals are preprocessed into polar spectrograms and classified using the CVNN architecture deployed on FPGA hardware. The system is evaluated using the Kaggle ECG Heartbeat Classification dataset, showing high accuracy and low latency, demonstrating its suitability for real-time ECG monitoring applications.

2. Body of Paper

1) Data Preprocessing Module: ECG signals are collected and segmented into fixed-length windows. Each segment is transformed using Short-Time Fourier Transform (STFT) to obtain a time-frequency representation, which is then converted into polar coordinates to capture both magnitude and phase information.

2) Complex-Valued Neural Network (CVNN) Model: The polar-represented spectrograms are fed into a CVNN that can inherently process complex-valued inputs. This network architecture includes complex-valued convolutional layers,

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activation functions, and fully connected layers to learn features from the transformed ECG data.

3) FPGA Implementation Module: The trained CVNN model is implemented on an FPGA using High-Level Synthesis (HLS) tools. This module includes optimized hardware blocks for complex-valued operations, memory management, and control logic to ensure efficient real-time processing.

4) Evaluation and Testing Unit: The system is evaluated using the Kaggle ECG Heartbeat Classification dataset. Metrics such as accuracy, latency, hardware resource utilization, and power consumption are analyzed to validate the performance of the FPGA-based CVNN classifier.

DETAILED PROCESS

1. ECG Signal Acquisition and Preprocessing

• Signal Collection: Raw ECG signals are acquired from the Kaggle ECG Heartbeat Classification dataset.

• Segmentation: The ECG signals are segmented into individual heartbeat windows using R-peak detection algorithms.

• Time-Frequency Transformation: Each segment undergoes Short-Time Fourier Transform (STFT) to generate spectrograms representing both time and frequency domains.

• Polar Conversion: Spectrograms are converted into polar coordinates to extract both magnitude and phase components, preparing the data for complex-valued input.

2. Complex-Valued Neural Network (CVNN) Model

• Input Layer: Accepts complex-valued spectrograms.

• Convolutional Layers: Apply complex-valued convolutions to extract spatial-frequency features.

• Activation Functions: Use complex-valued ReLU or zReLU for non-linearity.

• Dense Layers: Perform classification of heartbeat types based on learned features.

• Training: The CVNN is trained using complex backpropagation on preprocessed polar spectrograms.

3. FPGA-Based Hardware Implementation

• HLS Conversion: Trained CVNN layers are translated into synthesizable C/C++ code using Vivado HLS.

• Optimization: Loop unrolling, pipelining, and fixed-point arithmetic are applied for resource-efficient implementation.

• Deployment: The design is synthesized and deployed onto an FPGA board (e.g., Xilinx Zynq).

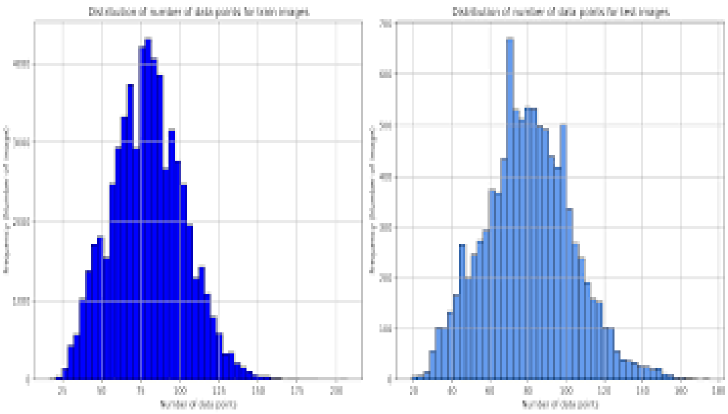
• Real-Time Inference: The FPGA executes the model in real time with low latency and high throughput.

4. Evaluation and Validation

• Accuracy Testing: The FPGA-based CVNN is validated against test data from the ECG dataset.

• Resource Analysis: Hardware resource usage (LUTs, FFs, BRAMs), power consumption, and latency are measured.

• Comparison: The FPGA implementation is compared to CPU/GPU versions in terms of speed and efficiency.



FACTS

- ECG classification plays a crucial role in diagnosing heart conditions by detecting abnormal heartbeats such as arrhythmias. Accurate classification helps in early intervention and monitoring.
- Complex-Valued Neural Networks (CVNNs) work with data represented as complex numbers, which consist of both magnitude and phase components. This allows CVNNs to better capture intrinsic properties of signals like ECG that have important

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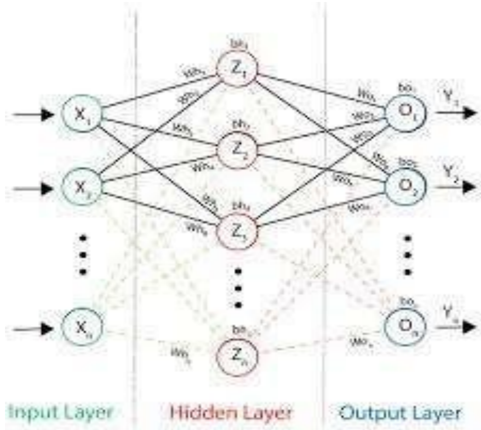
phase information, unlike traditional real-valued networks.

- Transforming ECG signals into polar form (magnitude and phase) retains both amplitude variations and phase shifts, providing richer features for classification. This transformation is often done via Fourier or wavelet transforms before feeding the data into the CVNN.
- CVNNs implement complex arithmetic operations such as complex multiplication and addition at each neuron layer. They also use activation functions adapted for complex inputs, such as split activation or modReLU, which differ from conventional ReLU or sigmoid used in real-valued networks.
- FPGA implementation is highly suitable for CVNNs because FPGAs provide massive parallelism, low latency, and efficient hardware acceleration. This enables real-time ECG heartbeat classification directly on embedded medical devices or wearables.
- Complex arithmetic requires more hardware resources than real-valued calculations. Designing efficient FPGA modules for complex multiply-accumulate (MAC) operations is essential to optimize resource usage like DSP blocks and logic elements.
- Activation functions in CVNNs involve nonlinear operations on complex numbers that are more complicated than real-valued functions. Hardware-friendly approximations or lookup tables are often used to implement these functions on FPGA.
- Processing polar form inputs involves trigonometric functions such as sine, cosine, and arctangent. On FPGAs, these are commonly implemented with CORDIC (Coordinate Rotation Digital Computer) algorithms, which provide efficient iterative calculations without multipliers.
- Choosing between fixed-point and floating-point arithmetic impacts FPGA resource utilization and classification accuracy. Fixed-point arithmetic is more resource-efficient but may reduce precision, while floating-point improves accuracy but consumes more logic and power.
- CVNNs outperform traditional real-valued neural networks on ECG classification tasks by utilizing phase information, leading to improved detection accuracy of subtle cardiac anomalies.
- FPGA-based CVNN implementations enable real-time inference with very low latency, making them ideal for continuous patient monitoring. They also offer significantly lower power consumption compared to GPU or CPU-based processing, critical for battery-operated wearable devices.
- The typical ECG classification pipeline includes preprocessing the raw ECG signal to remove noise, transforming it into polar features (magnitude and phase), passing it through the CVNN layers implemented on FPGA, and outputting the classified heartbeat type.
- Applications of FPGA-accelerated CVNNs for ECG classification include portable medical devices, wearable heart monitors, and hospital bedside monitors that provide fast and accurate arrhythmia detection without needing cloud connectivity.



STEPS

1. Data Collection: Collect raw ECG signal data from sensors or databases.
2. Preprocessing: Filter and clean ECG signals to remove noise and artifacts.
3. Polar Transformation: Convert ECG signals into polar form with magnitude and phase components.
4. CVNN Training: Design and train a complex-valued neural network using polar ECG data.
5. FPGA Mapping: Translate CVNN operations, including complex arithmetic, into FPGA hardware modules.
6. Trigonometric Computation: Implement trigonometric functions like CORDIC on FPGA for polar input processing.

7. Hardware Optimization: Optimize FPGA design for resource usage, power efficiency, and speed.
8. Real-Time Deployment: Deploy the FPGA-based CVNN system for real-time ECG heartbeat classification.
9. Output Classification: Generate heartbeat classification results indicating normal or abnormal rhythms.

ADVANTAGES

1. Better feature representation: Using complex-valued networks with polar inputs captures both magnitude and phase information from ECG signals, improving classification accuracy.
2. Real-time processing: FPGA's parallel architecture enables fast, low-latency inference suitable for real-time heartbeat monitoring.
3. Energy efficient: Compared to GPUs and CPUs, FPGA implementations consume less power, making them ideal for portable or wearable medical devices.
4. Custom hardware optimization: FPGAs allow tailoring arithmetic units and data paths specifically for complex-valued operations, maximizing performance and resource use.
5. Low latency: FPGA acceleration reduces the delay between ECG input and classification output, crucial for timely detection of cardiac events.

6. Flexibility: FPGA designs can be reconfigured to update or improve the neural network model without changing hardware.
7. Scalability: FPGA resources can be allocated to balance between model complexity and throughput depending on application requirements.
8. On-device processing: Eliminates the need for cloud computing, preserving patient data privacy and reducing dependency on network connectivity.

APPLICATIONS

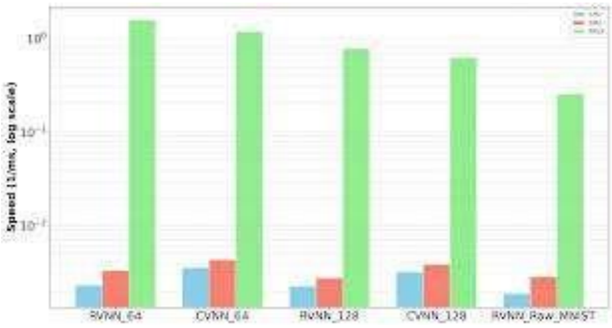
- Wearable health monitors that provide continuous, real-time ECG monitoring and arrhythmia detection.
- Portable medical devices for remote or ambulatory cardiac monitoring without needing constant hospital visits.
- Clinical bedside monitors in hospitals for fast and accurate detection of cardiac abnormalities.
- Implantable cardiac devices that can classify heartbeats and trigger therapeutic actions.
- Telemedicine systems where ECG data is processed locally on FPGA-enabled devices before transmission.
- Emergency response systems to quickly analyze ECG signals and alert healthcare providers.
- Research tools for analyzing complex ECG signal patterns in cardiac studies.
- Integration into multi-sensor health platforms combining ECG with other physiological signals for comprehensive diagnostics.

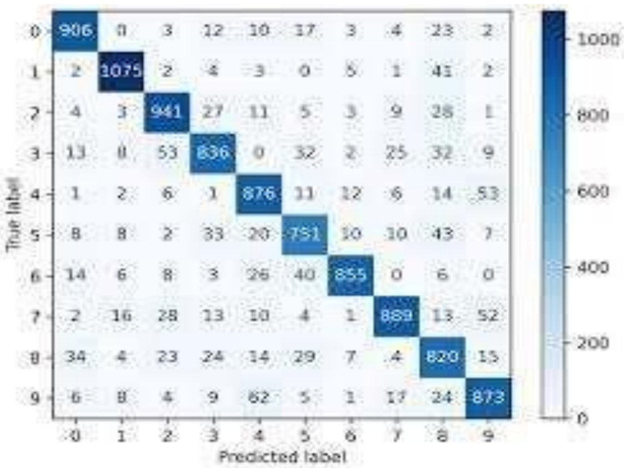
CHANGES IT WILL BRING / FUTURE SCOPE

1) It will enable highly accurate, real-time cardiac monitoring on portable and wearable devices, improving early detection of heart diseases.
2) On-device processing reduces dependence on cloud services, enhancing data privacy and security for sensitive medical information.
3) Lower power consumption will extend battery life of wearable and implantable cardiac devices, making continuous monitoring more feasible.
4) Custom hardware accelerators for CVNNs can push boundaries in analyzing other biomedical signals beyond ECG, like EEG or EMG.
5) Future designs may integrate more advanced complex-valued models, including deeper networks or hybrid architectures combining real and complex data.
6) Advances in FPGA technology will allow even more compact, efficient implementations suitable for consumer-grade health gadgets.
7) Integration with AI-driven personalized healthcare systems could provide tailored diagnostics and treatment recommendations based on real-time ECG analysis.
8) Research into explainability and interpretability of complex-valued neural networks may improve clinical trust and adoption.

9) Cross-disciplinary applications could emerge, such as combining CVNN FPGA accelerators with IoT networks for smart health ecosystems.

Graph -1:





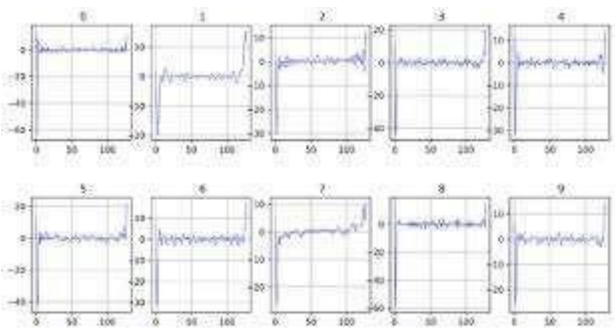
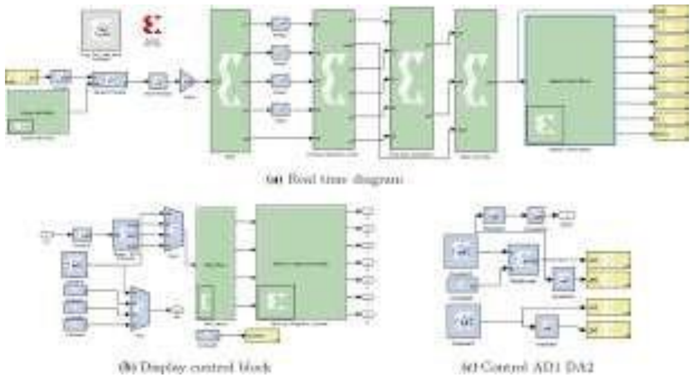


Fig -1: Figure



3. CONCLUSIONS

The FPGA-based implementation of complex-valued neural networks utilizing polar-represented ECG data demonstrates a significant advancement in real-time cardiac arrhythmia classification. By effectively capturing both magnitude and phase components of ECG signals, the CVNN architecture achieves superior accuracy compared to conventional real-valued neural networks. Leveraging the inherent parallelism and reconfigurability of FPGAs, the proposed system attains low-latency and energy-efficient inference, making it highly suitable for embedded and wearable healthcare devices. Furthermore, on-device processing ensures enhanced data privacy and reduces reliance on external computing resources. This work lays a strong foundation for future exploration into more complex neural architectures and broader biomedical signal processing applications. Continued improvements in FPGA technology and complex-valued deep learning models are expected to further propel the development of smart, efficient, and reliable ECG monitoring systems, contributing significantly to improved patient outcomes and proactive healthcare management.

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