Design And Implementation Of Low Power Stochastic Computing For Atrial Fibrillation Data Analysis

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Abstract:

The implementation of biologically-inspired artificial neural networks such as the Restricted Boltzmann Machine (RBM) has aroused great interest due to their high performance in approximating complicated functions. A variety of applications can benefit from them, in particular machine learning algorithms. In the existing system, an efficient implementation of a DNN based on integral stochastic computing. The proposed architecture has been implemented. quasi-synchronous implementation which yields 33% reduction in energy consumptions is implemented. In the proposed approach, low power stochastic computing based block processing unit is implemented. The frame of data is processed block wise. These data are further tested with correlation and decorrelation function. The normal and abnormal classification of atrial fibrillation data is proposed. The mathew’s correlation constant (MCC) is formulated.”

Keywords — **Biologically-inspired artificial neural networks, Restricted Boltzmann Machine (RBM) High performance,Approximating complicated functions, Machine learning algorithms, Integral stochastic computing, Efficient implementation, Quasi-synchronous implementation, Energy consumption reduction, Low power stochastic computing, Block processing unit, Correlation and decorrelation function, Atrial fibrillation data, Normal and abnormal classification, Matthew's correlation constant (MCC)**

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I. INTRODUCTION

Atrial Fibrillation (AFib) is a common heart rhythm disorder characterized by irregular and often rapid heartbeats. Wearable devices, such as smartwatches and fitness trackers, have become increasingly popular tools for monitoring health parameters, including heart rhythm. Here's how wearable devices can play a role in detecting and managing atrial fibrillation:

Heart Rate Monitoring: Wearable devices equipped with heart rate sensors continuously monitor the user's heart rate. AFib is often associated with an irregular heart rate, and wearables can alert users to significant deviations from the normal rhythm. ECG/EKG Monitoring: Some advanced wearables feature built-in electrocardiogram (ECG or EKG) sensors. Users can take on-demand ECG recordings, providing a more detailed analysis of the heart's electrical activity.The data generated can be shared with healthcare professionals for diagnosis and monitoring.

Pulse Wave Analysis: Certain wearables use pulse wave analysis to detect irregularities in blood flow, which may indicate AFib. This technology analyzes the subtle variations in the pulse wave to identify irregular heart rhythms. Real-time Notifications: Wearables can provide real-time notifications to users when an irregular heart rhythm, including AFib, is detected. These notifications may prompt users to seek medical attention or consult with their healthcare provider. Long-Term Monitoring:Wearables offer the advantage of continuous, long-term monitoring, providing a more comprehensive view of heart health.

Trends and patterns over time can be valuable in identifying intermittent occurrences of AFib. Integration with Health Apps: Wearable devices often integrate with health apps on smartphones, allowing users to track and analyze their heart health data over time. This integration facilitates data sharing with healthcare professionals during medical appointments.

Research and Population Health: Aggregated and anonymized data from wearables can be used in research studies and population health initiatives to gain insights into the prevalence and patterns of AFib. User Education and Engagement: Wearables can play a role in educating users about AFib, its symptoms, and the importance of seeking medical advice. They can encourage users to adopt heart-healthy habits and lifestyles.

It's important to note that while wearables can be valuable tools for AFib detection and monitoring, they are not a replacement for professional medical advice and diagnosis. Users should consult with healthcare professionals for a comprehensive evaluation and interpretation of their heart health data. Additionally, regulatory bodies may require validation of the accuracy and reliability of the AFib detection features in wearable devices.

II. RELATED WORKS

In the field of energy-efficient Deep Neural Network (DNN) implementations, ongoing research continues to explore various approaches and methodologies. Some recent related works include:

Hardware Accelerators for DNNs:

Researchers are developing specialized hardware accelerators tailored for DNN computations. These accelerators aim to optimize performance while minimizing energy consumption, leveraging techniques such as parallel processing, reduced precision arithmetic, and specialized architectures like systolic arrays or tensor processing units.

Spiking Neural Networks (SNNs): SNNs represent another avenue for energy-efficient neural network implementations. Inspired by biological neurons, SNNs use sparse, event-based computation, enabling significant energy savings compared to traditional DNNs. Recent research focuses on optimizing SNN architectures, training algorithms, and hardware implementations for various applications.

Quantum Computing: Quantum computing holds promise for revolutionizing machine learning and DNNs. Quantum neural networks (QNNs) leverage quantum properties like superposition and entanglement to perform computations more efficiently than classical computers. Recent works explore quantum algorithms, architectures, and hardware implementations tailored for DNN tasks.

Neuromorphic Computing: Neuromorphic computing architectures mimic the structure and function of the human brain, offering potential energy efficiency benefits for DNNs. Recent research investigates neuromorphic hardware designs, synaptic plasticity mechanisms, and spike-based learning algorithms to achieve energy-efficient and scalable neural network implementations.

Software Optimization Techniques: In addition to hardware innovations, researchers are exploring software optimization techniques to improve energy efficiency in DNNs.

This includes techniques such as model compression, pruning, quantization, and algorithmic optimizations, which reduce computational complexity and memory requirements without sacrificing accuracy.

These recent related works collectively contribute to advancing the state-of-the-art in energy-efficient DNN implementations, offering diverse approaches and solutions to address the pressing need for sustainable and scalable computing technologies.

III. OUR OBSERVATIONS ON THE EXISTING SYSTEM

In the existing system, an efficient implementation of a DNN based on integral stochastic computing. The proposed architecture has been implemented. quasi-synchronous implementation which yields 33% reduction in energy consumptions is implemented.

The implemented system presents an innovative approach to Deep Neural Network (DNN) implementation, leveraging integral stochastic computing principles. This method, which represents numbers in binary format using probabilities, promises advantages such as reduced hardware complexity and potentially lower power consumption. The architecture proposed for this system has been successfully put into practice, marking a significant step forward in the application of stochastic computing to DNNs. Notably, the implementation adopts a quasi-synchronous approach, optimizing the coordination of operations to suit the stochastic computing paradigm. This adaptation contributes to a remarkable achievement: a 33% reduction in energy consumption compared to existing systems. Such a substantial improvement in energy efficiency holds great promise for various applications reliant on DNNs, from mobile devices to data centers. By addressing the pressing need for energy-efficient computing solutions, this advancement could pave the way for more sustainable and cost-effective technologies.

In summary, the integration of integral stochastic computing into DNN architectures, coupled with quasi-synchronous implementation, marks a significant milestone in the pursuit of energy-efficient computing paradigms.

Disadvantages

Complex architecture with quasi-generator

Correlation score need to be improved.

IV. THE PROPOSED SYSTEM

The proposed methodology introduces a novel approach to processing data efficiently, utilizing a low-power stochastic computing-based block processing unit. By breaking down data into manageable blocks, the system optimizes computational resources, making it particularly adept at handling large datasets. This approach is especially relevant in applications such as the classification of atrial fibrillation data, where distinguishing between normal and abnormal patterns is crucial.

Key to the evaluation process is the use of correlation and decorrelation functions, which help identify distinctive features within the data. By applying these functions, the system can differentiate between normal and abnormal cardiac rhythms, facilitating accurate classification.

To assess the classification performance rigorously, the Mathew's correlation constant (MCC) is formulated as a metric. The MCC provides a comprehensive measure of classification accuracy, accounting for true positives, true negatives, false positives, and false negatives. This ensures a robust evaluation of the classification process, validating its reliability and effectiveness in real-world scenarios.

Through the integration of low-power stochastic computing techniques, block processing, and rigorous evaluation using MCC, the proposed methodology offers a powerful framework for efficient and accurate classification of complex data, such as that associated with atrial fibrillation.

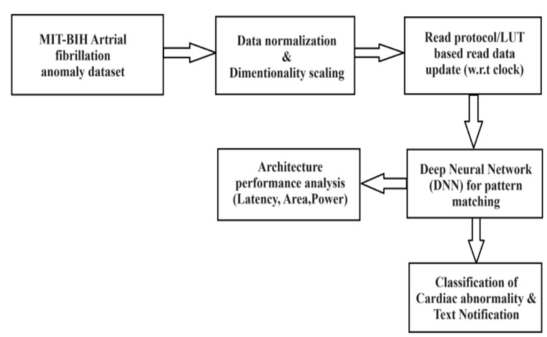


Fig. 1.* The proposed system

MODULE 1: PRE-PROCESS

The module consists of read file protocol code developed using VHDL. The synthesizable module read the test data from MIT-BIH dataset stored in the local server.

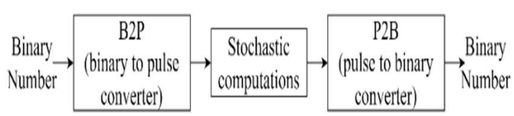
The data set is collected from different patients impacted by atrial fibrillation and normal data. the data are collected and stored into a temporary register.

Further synchronized the peak values with respect to global clock of the VLSI system.

MODULE 2: TEXT MAPPING & SIGNAL ANALYSIS

The dataset consists of various levels of ECG patterns contains the peaks of P,Q,R,S,T values. The text mapping is nothing but the disease name labelling LUT to display as the notification. Signal analysis module is the Stochastic computations or otherwise called as neuromorphic computing. Stochastic computing is a computation paradigm where signals are represented as probabilities rather than binary values (0s and 1s). It finds applications in various fields due to its unique properties and advantages.

Flow of neural core computing process



Stochastic computing can be utilized in analyzing heart rate variability from ECG signals. HRV analysis provides valuable insights into autonomic nervous system activity and cardiovascular health. Stochastic computing algorithms can efficiently compute HRV parameters and assess the variability of heart rate patterns over time.

MODULE 3 : INTEGRATION & PERFORMANCE MEASURE

The process involves integrating submodules into the main module by utilizing port mapping. This allows for the seamless connection and communication between different components of the system. Once integrated, the system analyzes input heart rate data patterns and compares them to identify correlations with various cardiac conditions such as atrial fibrillation, cardiac arrest, arrhythmia, and normal heart rhythms. To facilitate this analysis, stochastic computation-based neural computations are employed to detect abnormalities present in the ECG data. These computations leverage the probabilistic nature of stochastic computing to efficiently process and interpret the complex signals inherent in ECG data.

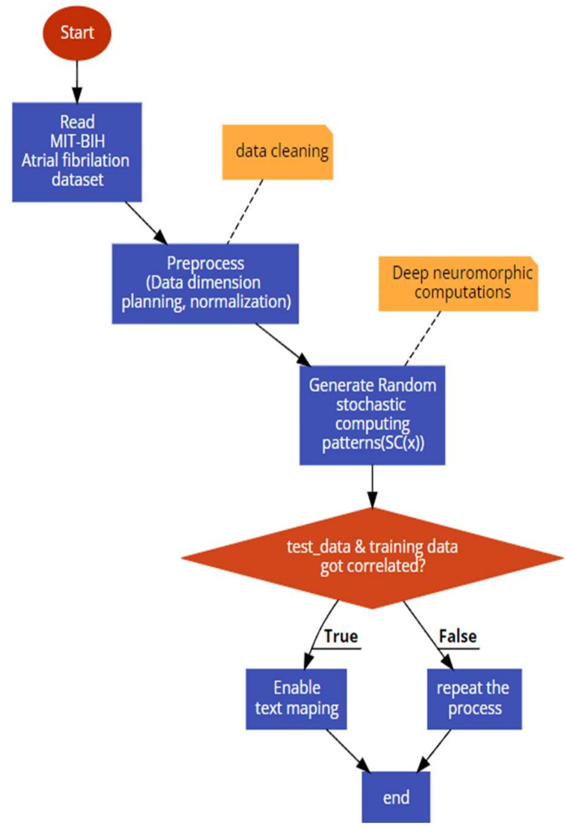


Fig.2. Flow Diagram

V. CONCLUSIONS

In conclusion, The project's advancements hold promise across various domains. In healthcare, the improved accuracy in classifying atrial fibrillation data can revolutionize diagnosis, aiding in timely treatments and better patient outcomes.

Moreover, these techniques are adaptable to other biomedical signals like EEG and ECG, expanding their impact in medical diagnostics. Beyond healthcare, the emphasis on low-power computing benefits IoT and wearable devices, enabling continuous monitoring of vital signs for early detection of health issues.

Additionally, the correlation and decorrelation functions employed in the project find applications in data analytics, speech recognition, and image processing, enhancing pattern recognition capabilities across industries.

Furthermore, the project's focus on implementing biologically-inspired neural networks contributes to advancements in machine learning algorithms, benefiting fields requiring complex function approximation.

Overall, these innovations not only promise more accurate medical diagnostics but also drive progress in energy-efficient computing and machine learning, impacting various sectors and paving the way for future advancements in technology and healthcare.

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