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Neural Network based ECG Anomaly Detection on FPGA

Mrs. SHARADA P N[1] Mr. Mahesh KT[2]
1. Assistant Professor, Department Of ECE, K.N.S.I.T Bangalore, India, sharadapatagupi@gmail.com
2. UG Student, Department Of ECE, K.N.S.I.T Bangalore, India, mkt1923@gmail.com

***Abstract*— This paper presents FPGA-based ECG arrhythmia detection using an Artificial Neural Network(ANN). The objective is to implement a neural network-based machine learning algorithm on FPGA to detect anomalies in ECG signals, with a better performance and accuracy, compared to statistical methods. An implementation with Principal Component Analysis (PCA) for feature reduction and a hybrid approach which include multi-layer perceptron (MLP) and Probabilistic neural network (PNN) for classification, proved superior to other algorithms. For implementation on FPGA, the effects of several parameters and simplification on performance, accuracy and power consumption were studied. Piecewise linear approximation for activation functions and fixed point implementation were effective methods to reduce the amount of needed resources. The resulting neural network with twelve inputs and six neurons in the hidden layer, achieved, in spite of the simplifications, the same overall accuracy as simulations with floating point number representation. An accuracy of 99.82% was achieved on average for the MIT-BIH database.**

Keywords—ECG classification; survey; preprocessing; neural network; mit-bih database; feature extraction; MLP;PNN

I. Introduction

An Electrocardiogram (ECG) tracks the electrical activity of the heart over time. It represents the physiological state of the heart and therefore is the most important method for diagnosing heart diseases [1]. Some of the major challenges to detect anomalies in ECG signal are: noise from measuring electrodes or loose contacts and mechanical disturbances; symptoms of anomalies might not show up all the time; taking measurements for long time may not be feasible. Advancement and efficiency of artificial neural networks (ANN) led to its habituation in various applications. Several different ANN models like multi-layer perceptron (MLP) [2], [3], [4], modular neural networks (MNN) [5], general feed forward neural networks (GFFNN) [5], [6], radial basis function neural networks (RBFNN) and probabilistic neural networks (PNN) [4] have been implemented for ECG classification. In addition to the neural network, the optimization of preprocessing and feature selection holds most potential for improvement. In [2], a combination of fuzzy C-means clustering and principal component analysis (PCA) was successfully implemented with significant improvement of accuracy and dimensionality reduction of the input vectors. For neural network-based ECG anomaly detection on FPGA, a low number of input and hidden-layer neurons is crucial for an effective implementation. Several successful implementations exist, including optimized designs[7]. As full implementations of ANN are computationally intensive, an optimized approach is needed for hardware implementation and is presented in this paper. It is of paramount importance to understand the impact of ANN parameters while designing the system.

This paper proposes optimization of neural network with piecewise linear approximated transfer functions and fixed point arithmetic. For selection of the most suitable fixed point precision, an extensive trade-off study was performed, discussing the merits and demerits of high/low precision datatypes, and detailing their influence on accuracy and required resources. The paper provides information on how to effectively reduce the amount of required resources implementing ANN on FPGA, for the task of ECG anomaly detection.

II. IMPLEMENTATION

For an FPGA implementation of an ANN, an architecture was developed which allows for a fast development process and high flexibility. Employing High Level Synthesis (HLS) offers the flexibility to study the effects of data type precision and size of the neural network.

A. System Architecture

Before presenting the used system architecture setup, we describe the basic steps and workflow involved in ECG anomaly detection. This includes basically three phases: feature extraction, principal component analysis (PCA), optimizing input data for processing and ANN for anomaly detection. Feature extraction involves detection of turning points in the ECG signal. To reduce the computational costs, the extracted feature set is reduced to a lower dimension using PCA and this data is provided to a multi-layer perceptron (MLP) and probabilistic neural networks (PNN) for anomaly detection. An MLP is a fully connected ANN, with each node connected to every node in the next and previous layers with at least one hidden layer. The hidden layers enable the MLP to perform a nonlinear mapping between an input vector and an output vector [8]. The whole data flow is presented in Figure 1
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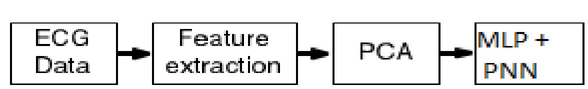

Fig. 1. Data flow for ECG anomaly detection

As shown in Figure 2 the data is preprocessed in MATLAB on the host PC and then transferred to the FPGA which implements the MLP and PNN. Training and testing of the neural network is entirely controlled by the spartan 3 FPGA board. Classification is performed by the hardware implementation of MLP and PNN.

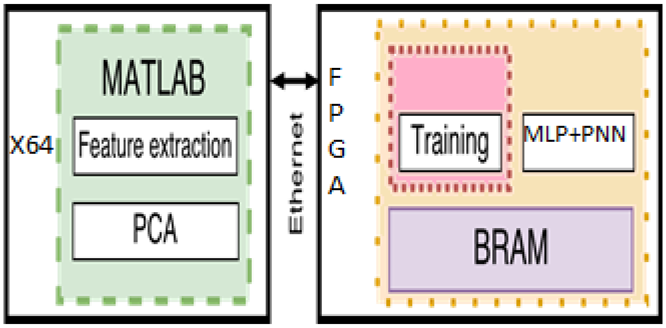

Fig. 2. Hardware/Software architecture, the feature vector is computed in MATLAB, transmitted via Ethernet onto the Zynq FPGA which implements the MLP and performs its training

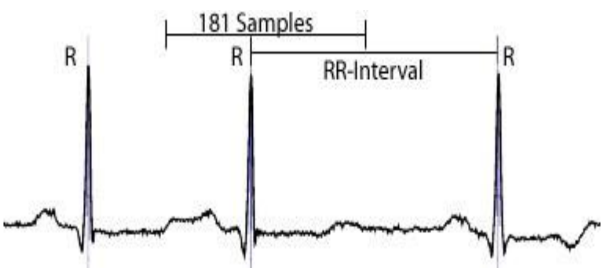

Fig. 3. For every heartbeat 181 Samples around the R-peak and RR-Interval lengths are used

Input and output of the entire process is controlled by a MATLAB GUI.

B. Dataset

For verification of the algorithm, the MIT-BIH arrhythmia database [9] was used. The database contains forty-eight 30-minute ambulatory ECG recordings, which include also less common but clinically significant arrhythmias. The Database is therefore suitable to evaluate performance and accuracy of the developed hardware for a wide spectrum of heart diseases [10]. For classification, a variety of feature vectors have been compared in terms of best classification accuracy. As illustrated in Figure 4, 181 samples around the R-peak were used. Additionally, for every heartbeat, the RR-intervals to the preceding and the succeeding beats were derived from the MIT-BIH arrhythmia database annotations files. To obtain the feature vector, the selected samples are reduced with Principal Component Analysis (PCA), a statistical procedure to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. Implementing Fuzzy clustering as in [2] did not prove efficient, as in this work the heartbeats were classified into only two classes.

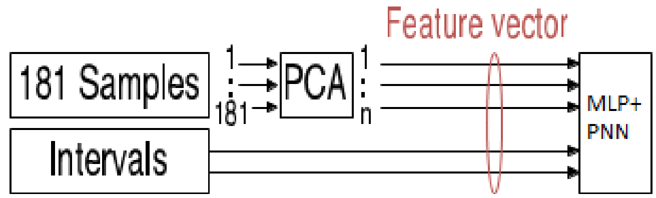

Fig. 4.The feature vector consists of n principal components and the RR-Interval lengths to the preceding and succeeding R-peaks

C. Hybrid approach

Hybrid approaches in the current context employ multiple classifiers which are fused at some level to perform a classification task. Hybrid Systems are computational systems which are based mainly on the integration of different soft - Computing techniques (like Fuzzy Logic, Neuro computing, evolutionary Computing, Probabilistic Computing) but which also allow a traditional symbolic interpretation or interaction with symbolic components (Knowledge Based Systems / Expert Systems) to classify the ECG signals. There are many different possible combinations among the Symbolic systems and Soft-Computing techniques, and also different ways to integrate them. As for example, Neural Networks can be combined with Fuzzy Logic. According to this author Multi-Layer Perceptron (MLP) and Fuzzy Clustering Neural Network(FCNN) he has got 98.9 to 99.9 percent accuracy. And R. U. Acharya et al [28]. According to this author ANN and Fuzzy Logic he has got 80 to 85 percent accuracy.

Before presenting the used system architecture setup, we describe the basic steps and workflow involved in ECG anomaly detection. This includes basically three phases: feature extraction, principal component analysis (PCA), optimizing input data for processing and ANN for anomaly detection. Feature extraction involves detection of turning points in the ECG signal. To reduce the computational costs, the extracted feature set is reduced to a lower dimension using PCA and this data is provided to a multi-layer perceptron(MLP) for anomaly detection. A MLP is a fully connected ANN, with each node connected to every node in the next and previous layers with at least one hidden layer. The hidden layers enable the MLP to perform a nonlinear mapping between an input vector and an output vector. As full implementations of ANN are computationally intensive, an optimized approach is needed for hardware implementation for that we use FPGA spartan 3 series.

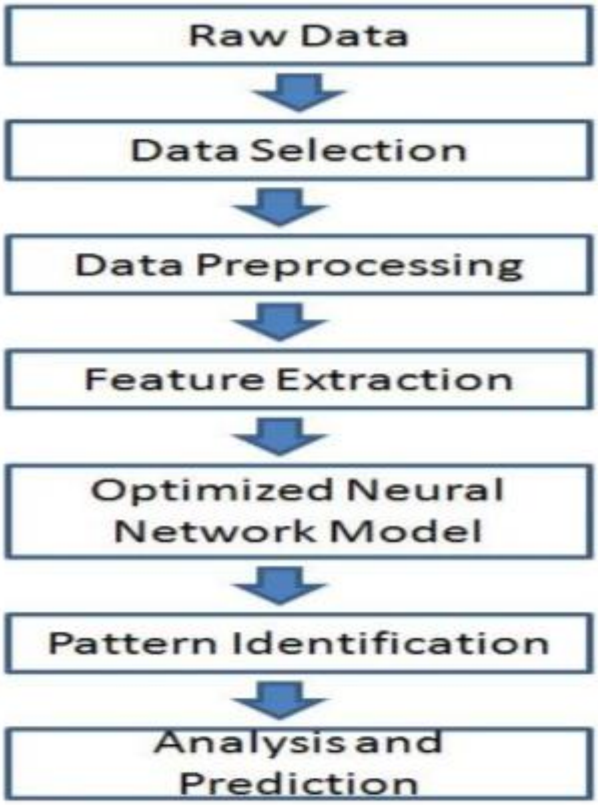

Fig 5. Proposed system architecture

D. Methodology

In today's world, an optimal and intelligent problem-solving approaches are required in every field, regardless of simple or complex problems. Researches and developers are trying to make machines and software's more efficient, intelligent and accurate. This is where the Artificial Intelligence plays its role in developing efficient and optimal solutions. Prediction is done with the help of available knowledge or previous values so accuracy in prediction is the main challenge. The artificial neural network (ANN) can use for pattern recognition, classification as well as prediction because it is based on biological neurons, an artificial neural network (ANN) is a self-adaptive trainable process that is able to learn to resolve complex problems based on available knowledge.

Hybrid Approach**:** Hybrid approaches in the current context employ multiple classifiers which are fused at some level to perform a classification task. There are many different possible combinations among the Symbolic systems and Soft-Computing techniques, and also different ways to integrate them. For example, Neural Networks can be combined with Fuzzy Logic. In this Multi-Layer Perceptron (MLP) is combined with Probabilistic Neural Network(PNN) to achieve maximum efficiency. Work flow involved in ECG anomaly detection system includes basically three phases:

Data Pre-processing: This includes operations applied to the data to prepare it for further analysis. Typical pre-processing operations include data cleaning to filter out noisy data elements, data interpolation to cope with missing values, data normalization to cope with heterogeneous sources, temporal alignment, and data formatting.

Feature Extraction: This includes operations for representing the data appropriately and selecting specific features from this representation. Feature extraction involves detection of turning points in the ECG signal like QRS duration, R-R interval, P-R interval, Q-T interval, R-wave Amplitude, P-wave Duration and T-wave duration. To reduce the computational costs, the extracted feature set is reduced to a lower dimension using PCA This stage is often called feature extraction and selection.

Optimized Neural Network Model: This stage also called as mining, applies knowledge discovery algorithms to identify patterns in the data. Modelling problems can be classified into six broad categories: anomaly detection to identify statistically deviant data, association rules to find dependencies and correlations in the data, clustering models to group data elements according to various notions of similarity, classification models to group data elements into predefined classes, regression models to fit mathematical functions to data and summarization models to summarize or compress data into interesting pieces of information.

Here, we are applying Optimized neural network using MLP and PNN for classification and prediction of anomalies' is a fully connected ANN, with each node connected to every node in the next and previous layers with at least one hidden layer. The hidden layers enable the MLP to perform a nonlinear mapping between an input vector and an output vector. For classification problems, we use probabilistic neural networks (PNNs) with straight forward and training independent designs to find out the smoothing factor which is a standard deviation of Gaussian kernel. The system is implemented on Xilinx spartan 3 FPGA board.

III. EXPERIMENTAL RESULTS

An ANN with twelve input neurons, one hidden layer with six nodes with PLA tanh as activation function and Ntanh for the output layer has been implemented on FPGA using the MATLAB and XILINX. With 24 bit data size this approach achieves 99.042% accuracy. Output windows are given below.

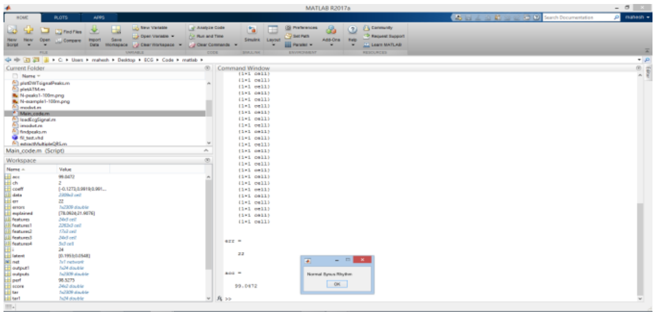

Fig 6: output window

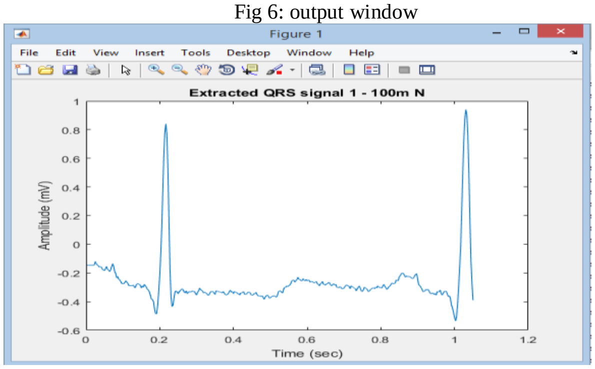

Fig 7: Extracted QRS Signal

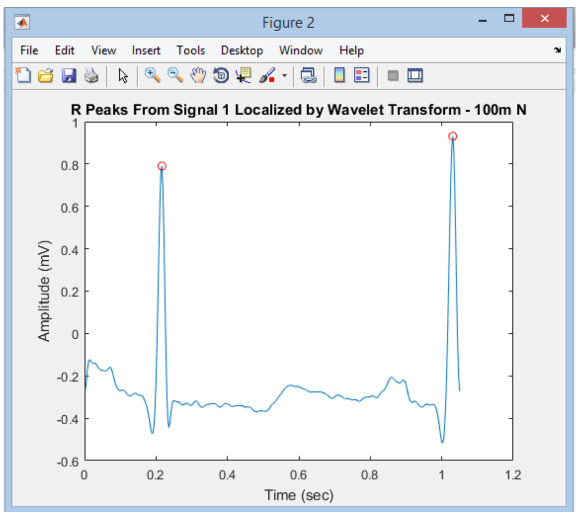

Fig 8: R peaks from extracted signal

IV. CONCLUSION

This paper presents a study of the impact of a NN architecture, activation functions, and fixed point precision on accuracy, performance, and area usage for FPGA implementations of an ECG anomaly detection algorithm. Piecewise linear approximation of activation functions was found an effective approach to reduce required resources and latency. The final implementation of a 12-6-2 24-bit multi-layer perceptron and Probabilistic Neural Network classifies the entire MIT-BIH database with 99.82% accuracy. Accuracy can be improved by increasing the number of inputs, hidden layer neurons and fixed point precision. All implementations were performed with High Level Synthesis, leaving potential for manual optimization.

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