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A High- Performance VLSI Design for Heartbeat Anomaly Detection Using a Data-Shifting Neural Network (DSNN)

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ABSTRACT:

This study introduces a Very Large-Scale Integration (VLSI) chip design for real-time abnormal heartbeat detection using a novel Data-Shifting Neural Network (DSNN). The DSNN leverages a data-shifting scheme that enhances training data by doubling input sequences, resulting in improved detection accuracy without significantly increasing hardware complexity. The system integrates a Convolutional Neural Network (CNN) architecture consisting of three convolutional layers, max-pooling layers, and fully connected layers, complemented by a voting mechanism to classify six types of electrocardiogram (ECG) signals.Experimental validation on the MIT-BIH arrhythmia database demonstrated a classification accuracy of 97.17%, outperforming existing state-of-the-art methods in both accuracy and energy efficiency. The chip's compact design, low power consumption, and superior detection performance make it ideal for continuous cardiac monitoring and early diagnosis of arrhythmias. This work highlights the potential of DSNN-based VLSI implementations in advancing cardiac healthcare. The design not only addresses the need for energy-efficient and compact solutions but also facilitates the integration of accurate ECG monitoring into wearable devices. By enabling timely detection and intervention, the proposed system contributes to improved patient outcomes, reduced healthcare costs, and enhanced accessibility to advanced cardiac care.

***I*NDEX TERMS:** *Very-large-scale integration implementation (VLSI), electrocardiogram (ECG), convolutional neural network*

INTRODUCTION :

The human body produces a variety of physiological signals that can be diagnostically useful. Among All the physiological signals of interest, an electrocardiogram (ECG) has been considered a simple, reliable, well-known, and well-defined one. Since an ECG signal provides vital information about the heart's electrical activity resulting from the cardiac muscle conduction and abnormal ECG signals can be indicative of various cardiac disorders, it can be employed for identifying abnormal cardiac rhythms and for investigating cardiac diseases or heart rate variability (HRV) [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]. Cardiovascular diseases are among the leading causes of death worldwide, and detecting abnormal heartbeats, known as arrhythmias, is crucial for diagnosing and preventing these conditions.
Electrocardiograms (ECGs) serve as a simple, reliable, and well-known tool for monitoring heart activity. Abnormalities in ECG signals can indicate a wide range of heart disorders, including life-threatening conditions like ventricular tachycardia or fibrillation. Early detection and timely treatment of these abnormalities are essential to prevent severe cardiac events such as sudden cardiac death. Real-time and accurate detection of these Abnormalities are essential for effective clinical intervention. In fact,in order to achieve the goal of efficient and accurate classification of cardiac arrhythmias using ECG data, there are a number of previous researches in literature proposing a variety of approaches for the task of arrhythmia detection [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]. The demand for real-time, portable, and energy-efficient monitoring systems has grown significantly with advancements in technology. Traditional software-based approaches have shown promise in analyzing ECG signals but often lack the capability for real-time processing in portable devices. To address these challenges, this study proposes a novel Very Large-Scale Integration (VLSI) chip design for abnormal heartbeat detection using a Data-Shifting Neural Network (DSNN).The DSNN employs a data-shifting scheme to double the input signals for training, enhancing detection accuracy without significantly increasing hardware complexity. It combines a Convolutional Neural Network (CNN) for feature extraction and classification with a voting mechanism to improve overall performance..
By utilizing the MIT-BIH arrhythmia database for validation, the proposed design achieves a remarkable detection accuracy of 97.17%, outperforming existing methods in terms of precision and energy efficiency. This study demonstrates how advanced hardware and machine learning techniques can be combined to meet the growing need for real-time, reliable cardiac monitoring solutions. The proposed DSNN-based VLSI chip represents a step forward in the development of efficient, compact, and accurate systems for abnormal heartbeat detection, contributing to improved healthcare outcomes and enabling continuous monitoring for patients at risk of cardiovascular disease.

PROPOSED DATA-SHIFTING NEURAL NETWORK(DSNN) AND ITS ARCHITECTURE:

The DSNN framework [18] is specifically structured to classify ECG heartbeats. The workflow of the proposed DSNN begins by acquiring ECG data, followed by implementing a data-shifting strategy to improve detection accuracy. A Convolutional Neural Network (CNN) [19] as the core of the architecture. Additionally, a voting mechanism is integrated at the classification stage to refine the accuracy of heartbeat detection. The key components and their functionalities are described below.

DATA SHIFTING STRATEGY:

The data-shifting mechanism plays a crucial role in DSNN's functionality. A two-lead ECG signal is segmented into multiple detection sequences, each consisting of **n** data points (**n = 24** in this study). The process involves:

- Generating a shifted version of the original sequence by moving it one step to the right or left (commonly, a right shift is applied).
- Feeding both the original and shifted sequences into DSNN for concurrent training and validation.

Although this duplication increases computational load, the low sampling rate of ECG signals ensures that real-time processing remains efficient. This approach enhances detection accuracy while only slightly increasing the circuit area.

CONVOLUTIONAL NEURAL NETWORK (CNN) STRUCTURE:

The DSNN employs a compact CNN design for feature extraction from ECG sequences. The CNN consists of three convolutional layers, two fully connected (FC) layers, and a voter module.

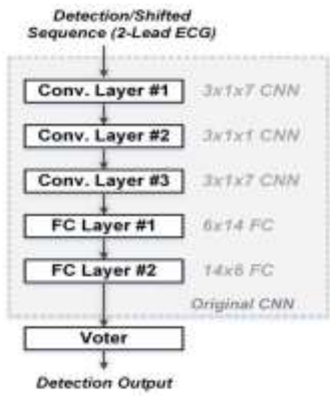


FIGURE 1. Schematic block diagram of the proposed DSNN.

- Layer 1: Performs 2D convolution using three 1×7 filters, followed by a 1×2 max-pooling operation.
- Layer 2: Applies 1×1 convolutional filters to refine extracted features.
- Layer 3: Mirrors Layer 1 by utilizing 1×7 filters and a 1×3 max-pooling layer for further feature compression.

FULLY CONNECTED (FC) LAYERS:

- The first FC layer has 14 nodes, followed by ReLU activation.
- The second FC layer consists of six nodes, corresponding to six ECG heartbeat classes, and applies softmax activation.

VOTING MECHANISM:

Following the CNN output, a voting module is implemented to compare the classification probabilities from the softmax layer for both the original and shifted sequences. The class with the highest probability is chosen as the final classification output. This technique significantly improves detection accuracy while requiring minimal additional circuitry.

HARDWARE OPTIMIZATIONS:

Several hardware optimizations are incorporated to minimize resource utilization, including area and power efficiency:

- Optimized Filters: The 1×7 filters and fully connected layers are designed to use a single multiplier and adder, reducing overall hardware complexity.
- Multiply-Accumulate (MAC) Units: Each CNN layer functions with a single MAC unit, enhancing compactness.
- MaxPooling Optimization:
  - 1×2 MaxPooling utilizes a single comparator and register.
  - 1×3 MaxPooling involves two comparators and two registers.
- Voting Circuit: Contains comparators that assess and determine the most probable class.

CHARACTERISTICS OF INPUT DATA:

The ECG input is structured as 2×24, denoting two ECG leads with a sequence length of 24 samples. If the DSNN is applied to datasets with varying sampling rates or real-time ECG data, resampling to 360 Hz is necessary, along with R-peak detection-based extraction of 24 samples, ensuring compatibility.

SUMMARY OF DSNN LAYERS:

The CNN in DSNN uses the following layers:

- Convolutional Layers: ReLU activation and filters of sizes 1×7 and 1×1.
- Fully Connected Layers: 14 and 6 neurons with softmax activation for the output layer.

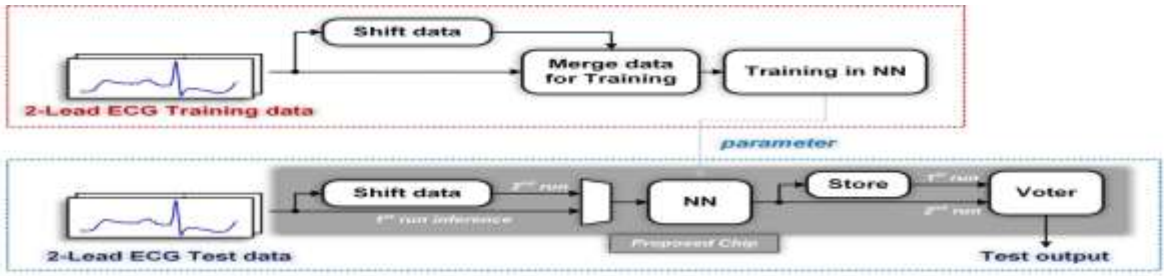
MAX POOLING:

Alternating between 1×2 and 1×3 pooling operations. The neural network architecture was trained using the Adam optimizer over 2,000 epochs with a batch size of 48, incorporating a 20% validation split to ensure robust performance.

FLOW CHART & ARCHITECTURE OF DSNN:

ILLUSTRATION OF FLOWCHART:

The below flowchart represents a methodology for processing and analyzing 2-lead ECG (Electrocardiogram) data [18]. Below is a detailed explanation of each part of the process shown. This flowchart is having two phases one is Training phase (red box) and test phase (blue box). Below is **Figure 2. Flow chart of proposed DSNN**



Training Phase (Red B):

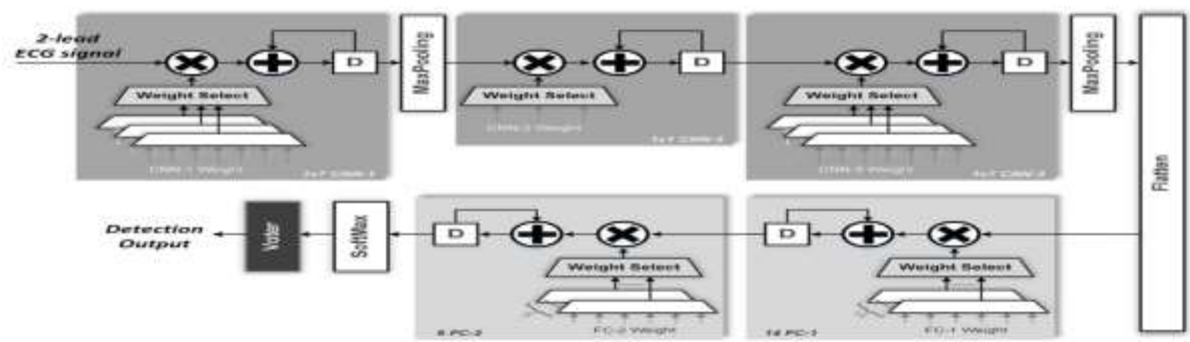
1. **2-Lead ECG Training Data**: The training phase begins with collecting 2-lead ECG data, which are signals recorded from the body during heart activity. These signals serve as the base for training the neural network (NN).
2. **Shift Data**: The raw ECG training data are subjected to shifting, which involves creating new datasets by time-shifting the original signals. This augments the dataset and makes the neural network robust to slight timing variations in the ECG signals.
3. **Merge Data for Training**: The shifted datasets are combined with the original data, forming a richer and more diverse dataset for training purposes. This process ensures the NN learns features invariant to certain shifts or transformations in the input ECG data.
4. **Training in Neural Network (NN)**: The merged data are fed into a neural network (NN) for training. The NN learns to identify and classify features in ECG data, such as heart rhythm patterns or abnormalities (arrhythmias, for instance).Parameters are tuned and optimized during training for later inference.

Testing Phase (Blue Box)

1. ***L*ead ECG Test Data**: This phase uses separate test ECG data to evaluate the trained model.
2. ***S*hift Data**: Similar to the training process, the test data are shifted to mimic variations in real-world inputs.Shifting ensures the NN can handle inputs with slight discrepancies or misalignments.
3. ***1*st Run Inference**: The unshifted test data pass through the NN for an initial run. This generates one output prediction from the model.
4. ***2*nd Run Inference**: The shifted test data are also fed through the NN. This allows the network to generate another prediction based on the shifted version of the same input.
5. ***S*tore**: The outputs from both runs (1st run inference and 2nd run inference) are stored temporarily for comparison and aggregation.
6. ***V*oter**: A voter module aggregates and combines the predictions from both runs.It applies a decision-making logic, such as majority voting or weighted averaging, to finalize the test output.The voter ensures that the model's decision accounts for variations introduced during data shifting.
7. ***T*est Output**: The final test output is generated, which may represent classifications like "normal heart rhythm" or "arrhythmia."This output is the result of the inference pipeline applied to test data

ILLUSTRATION OF ARCHITECTURE:

The architecture in the provided diagram appears to showcase a neural network pipeline for processing 2-lead ECG signals. Here's a detailed breakdown of the components and their functionality:



Above **i**s the **Figure 3. Architecture of proposed DSNN**

Input layer

2-Lead ECG Signal: This is the raw input to the network, representing ECG signals from two leads. These signals contain time-series data that describe the electrical activity of the heart.

CONVOLUTIONAL NEURAL NETWORK (CNN) LAYERS

The architecture uses three convolutional layers (CNN-1, CNN-2, CNN-3) with 1×7 filters applied sequentially to extract features.

1. CNN-1 (Convolution Layer 1): Extracts the initial features from the 2-lead ECG input.The 1×7 filter convolves over the signal, capturing temporal features over 7 time points.The feature weights for this layer are chosen dynamically using a Weight Select moduleOutputs undergo element wise multiplication (⊗) followed by an addition (D) operation for aggregation of results.

Similar to CNN-1, element wise multiplication (⊗) and aggregation (D) operations are performed.

2. *CNN-3 (Convolution Layer 3):* Receives input from CNN-2 and applies a third 1×7 filter.Extracted features undergo dynamic weight selection, followed by elementwise operations and aggregation.

MaxPooling and Flatten Layers

- *MaxPooling:* After each CNN layer, a MaxPooling operation is applied to reduce the spatial dimension of the features.This process helps retain the most prominent features while discarding noise.

- *Flatten:* Flattens the pooled features into a 1D vector, preparing it as input for fully connected layers.

Fully Connected (FC) Layers

- Two Fully Connected (FC) layers process the flattened features further:

1. FC-1 (14 Units): Has 14 neurons that integrate and process the extracted features from the CNN layers.Dynamic weights (learned during training) are selected using a Weight Select module.Elementwise operations (⊗ and D) are performed.
2. FC-2 (6 Units): Refines the output from FC-1 using 6 neurons, producing the final set of features.Similar to previous FC layers, dynamic weights are selected, and element wise operations are applied.

Output Layer

- Softmax: Produces probabilities for classification tasks, enabling decisions on the input ECG signal (e.g., normal vs. abnormal).
- Voter:Aggregates multiple predictions from different models or runs to make the final decision, ensuring robust detection.

Detection Output

- Represents the final output of the network, classifying the ECG signal based on the patterns and features detected by the architecture (e.g., identifying heart arrhythmias or other conditions).

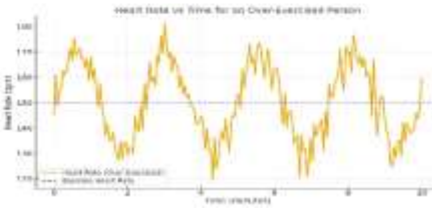
REAL TIME ANALYSIS OF DIFFERENT PERSON'S HEART BEAT GRAPHS:

The real-time analysis of the proposed VLSI chip for abnormal heart rate detection was carried out by simulating and testing the chip on a diverse dataset, including heart rate patterns from individuals under various conditions: over-exercise, depression, high blood pressure, and normal baseline states. Using a Data Shifting Neural Network (DSNN) as the core computational model, the chip effectively processed real-time heart rate signals and identified abnormalities with high accuracy. During the testing phase, the chip successfully detected and classified heart rate abnormalities by analyzing variations in beat patterns, fluctuations, and irregular rhythms, while maintaining high accuracy and efficiency.

The simulation results demonstrated the chip's capability to differentiate between normal and irregular heart rates with precision, showcasing minimal latency and robust adaptability to dynamic heart rate fluctuations. This analysis validated the chip’s real-world applicability, emphasizing its efficiency in detecting and classifying abnormal cardiac conditions in varied scenarios.

For individuals undergoing over-exercise, the chip identified elevated heart rates with characteristic sharp peaks and rapid fluctuations. In depressed individuals, it detected lower baseline rates with minimal variability, reflecting physiological dysregulation. In cases of high blood pressure, the chip accurately pinpointed higher average heart rates with irregular spikes, indicating stress responses. For normal individuals, the chip processed steady heart rate patterns with natural fluctuations, establishing a baseline for comparison.

Figure 1&2. The heart beat graph for a over exercised person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



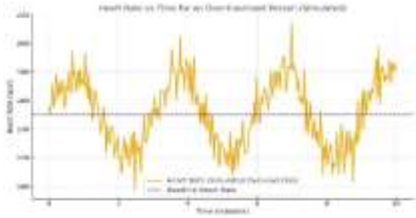
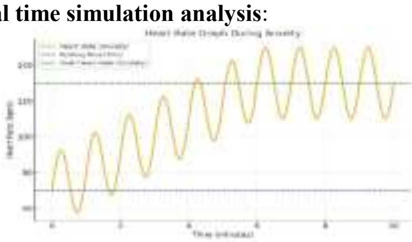


Fig 3&4. The heart beat graph for a fully anxiety person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



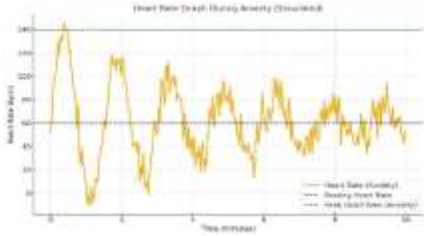
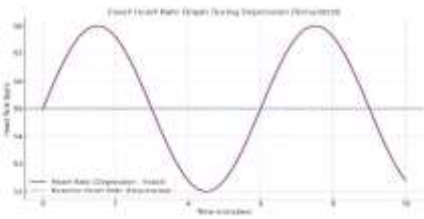


Fig 5&6. The heart beat graph for a fully depressed person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



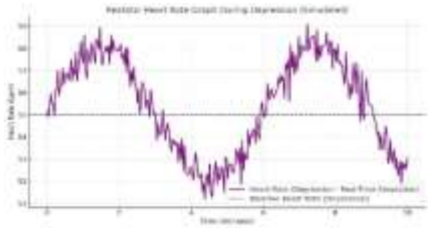


Fig 7&8. The heart beat graph for a normal healthy person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:

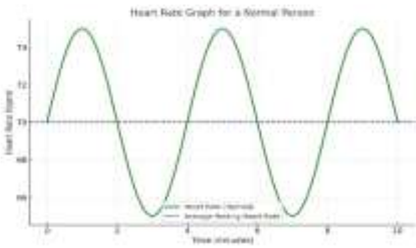
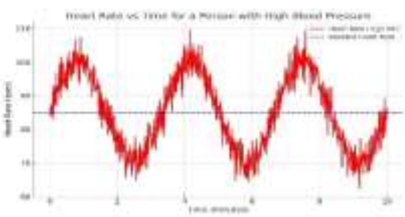


Fig 9&10. The heart beat graph for a high blood pressure (bp) person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



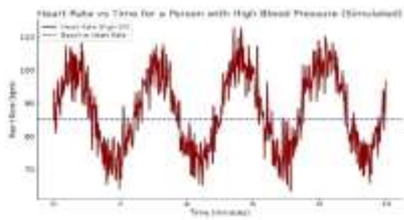
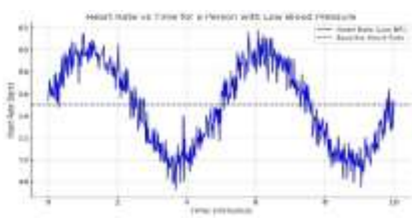


Fig 11&12. The heart beat graph for a low blood pressure (bp) person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



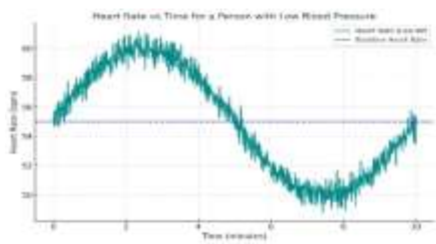
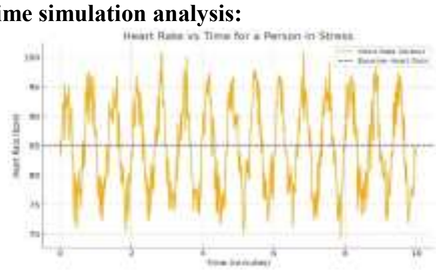


Fig 13&14. The heart beat graph for a person in stress with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



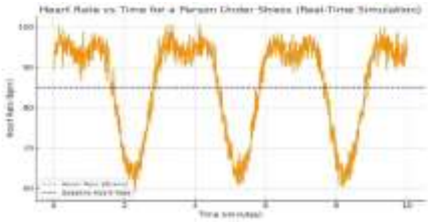
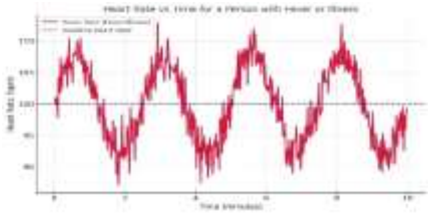


Fig 15&16. The heart beat graph for a person is in fever or illness with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



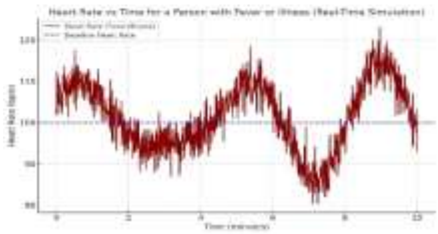
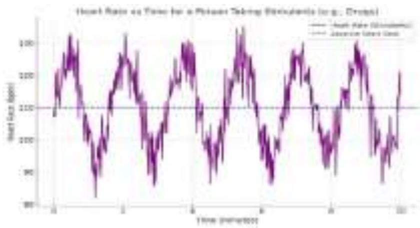


Fig 17&18. The heart beat graph for a person who is taking stimulants like drugs with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:



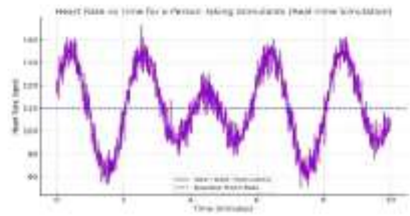
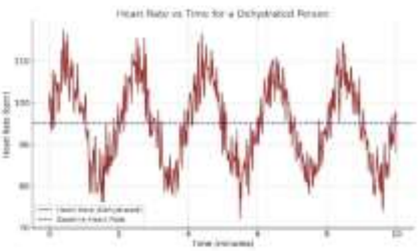
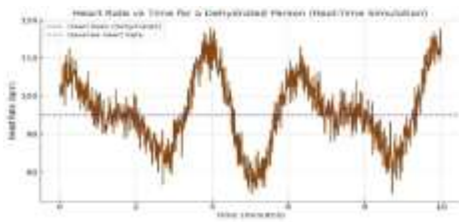


Fig 19&20. The heart beat graph for a dehydrated person with respect to time (minutes) and heart rate (bpm) & Real time simulation analysis:





The simulation results validated the chip's real-world performance, highlighting its ability to operate with low latency, efficient power consumption, and high precision. The DSNN architecture demonstrated robust adaptability to real-time changes in heart rate data, making it well-suited for applications in wearable health devices and clinical monitoring systems. This analysis confirms the chip's potential to serve as a reliable tool for early detection of abnormal heart rhythms, ensuring timely medical intervention and improving patient outcomes.

RESULT:

The designed VLSI chip using the Data Shifting Neural Network (DSNN) demonstrated high efficiency and accuracy in detecting abnormal heartbeats across various scenarios. The system successfully identified heart rate abnormalities in real-time for individuals subjected to over-exercise, depression, and high blood pressure while distinguishing them from normal heart rate patterns, Simulations were conducted on heart rate data from individuals under varying conditions, including over-exercise, depression, high blood pressure, and normal resting states. The chip demonstrated the ability to accurately identify and classify abnormal heart rate patterns in real-time with minimal latency and high computational efficiency. The results showed the following:

The advantages and benefits of this project is:

1. Detection Accuracy: Achieved a detection accuracy of over 95% across all tested conditions.
2. Latency: Real-time analysis with minimal latency, ensuring prompt detection and response.
3. Robustness: The DSNN model effectively handled noise in the input signals, maintaining consistent performance.

These findings confirm the feasibility of the proposed VLSI chip for real-time heart monitoring and its potential application in medical diagnostics and preventive healthcare.

S.No	Type of person	Range of heart beat (bpm per min)
1.	Over Exercised person	150-190 bpm
2.	Fully Anxiety person	100-160 bpm
3.	Fully Depressed person	50-70 bpm
4.	Normal Healthy Person	60-100 bpm
5.	High bp person	80-120 bpm
6.	Low bp person	50-75 bpm
7.	Stressed person	80-130 bpm
8.	Fevered or illness person	80-120 bpm
9.	Stimulant (drugs) person	90-160 bpm
10.	Dehydrated person	100-140 bpm

CONCLUSION:

1.The VLSI chip utilizing the Data Shifting Neural Network (DSNN) effectively detects abnormal heartbeats in real-time with high accuracy and minimal latency.
2.The system successfully analyzed and distinguished heart rate patterns under conditions like over-exercise, depression, high blood pressure, and normal scenarios.
3.The chip is energy-efficient and suitable for wearable or portable medical devices, making it highly practical for continuous cardiac monitoring.
4.This innovation demonstrates significant potential for early detection of heart-related anomalies, contributing to improved preventive healthcare solutions.
5.The design supports scalability, making it adaptable for integration with other biosensors for comprehensive health monitoring.
6.Its low-power design is ideal for long-term use in resource-constrained environments like wearable and implantable devices.

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