



VLSI Chip Design DSNN ECG Signals for Abnormal Heartbeat Detection

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ABSTRACT:

In this study, a Data-Shifting Neural Network (DSNN) applied to electrocardiogram (ECG) signals is used to design a VLSI circuit for abnormal heartbeat detection. In order to increase model generalization, the suggested DSNN generates numerous temporal variants of each pulse by using a data-shifting augmentation strategy to improve the training dataset. The algorithm achieves a high classification accuracy of almost 97.17% by merging these augmented signals with the original dataset, guaranteeing accurate detection of both normal and pathological heartbeats. The design prioritizes low power consumption and compactness, which makes it appropriate for wearing medical equipment. With careful consideration of transistor-level design, memory needs, timing limitations, and low-power optimization approaches, the DSNN is built and simulated at the circuit level using Cadence tools. To guarantee effective hardware implementation, important performance parameters such as transistor count, supply voltage, power consumption, operating frequency, and delay are examined. The project's only focus is on hardware-level evaluation and schematic simulation; dataset preparation, preprocessing, and data shifting are done offline. Without the need for real-time deployment or GUI interaction, this method shows a workable and energy-efficient VLSI solution for precise cardiac anomaly detection.

Keywords: *transistor count, supply voltage, power dissipation, operation frequency, delay, data-shifting neural network, VLSI chip architecture, training dataset*

1.INTRODUCTION:

Early diagnosis and ongoing monitoring are crucial because cardiovascular illnesses continue to rank among the world's top causes of death. By capturing the electrical activity of the heart, electrocardiogram (ECG) analysis is essential for identifying cardiac problems. However, manual ECG signal interpretation takes a lot of time and is prone to human mistake, particularly in situations involving long-term monitoring. As a result, automatic ECG categorization methods have drawn a lot of interest lately [1]. Deep learning approaches have demonstrated exceptional performance in biological signal processing problems as artificial intelligence has advanced. Because of its capacity to automatically extract complicated data, convolutional neural networks (CNNs) and other neural architectures have been frequently used for heartbeat classification [2, 3]. However, huge training datasets and significant processing resources are frequently needed to achieve high accuracy, which may not always be possible for real-time or hardware-constrained applications like wearable devices. In order to overcome these difficulties, this research presents a Data-Shifting Neural Network (DSNN) that uses an effective data augmentation technique to improve classification accuracy. By using a controlled shift operation to double the input ECG signal, the suggested data shifting strategy increases feature diversity and enhances learning capacity. This method greatly improves the network's resiliency and detection accuracy even if it takes longer to compute. Additionally, the suggested DSNN is implemented at the hardware level using CMOS technology for realistic deployment in portable healthcare systems, in contrast to entirely software-based solutions. The architecture maintains high classification performance while achieving low power consumption, small chip area, and real-time processing capability [4,5]. With a detection



accuracy of 97.17%, experimental evaluation utilizing the MIT-BIH Arrhythmia Database validates the efficacy of the suggested method, indicating its potential for next-generation wearable cardiac monitoring applications.

2. PROJECT OBJECTIVE:

This project's primary goal is to create a small, low-power VLSI processor that uses a Data-Shifting Neural Network (DSNN) to identify irregular heartbeats [6]. In order to improve ECG signal datasets, decrease overfitting, increase classification accuracy, and optimize transistor-level implementation for wearable healthcare devices, the design focuses on utilizing data-shifting augmentation approaches [7]. With minimal power consumption, fewer transistors, and effective operating performance appropriate for edge-level applications, the project seeks to achieve high detection accuracy (about 97%). Creating a hardware-efficient architecture appropriate for wearable and portable medical devices is another crucial goal. In order to guarantee low power consumption, small chip area, and real-time processing capacity, the suggested model is intended for CMOS implementation using Taiwan Semiconductor Manufacturing Company 0.18- μm technology [8]. In order to guarantee dependability and usefulness in actual cardiac monitoring systems, the system performance is also verified using the MIT-BIH Arrhythmia Database.

3. PROBLEM STATEMENT:

Current software-based heartbeat categorization algorithms are frequently inappropriate for real-time, portable, and energy-constrained devices due to their heavy reliance on processing resources. Furthermore, inconsistent ECG signals and a lack of training data lower classification accuracy, which may result in an incorrect diagnosis of arrhythmias. A low-power, hardware-efficient method that can accurately and consistently identify irregular heartbeats while addressing data scarcity and preserving compact semiconductor architecture is required [9]. Furthermore, it is difficult for many deep learning-based ECG classification algorithms to retain hardware economy while obtaining high accuracy. A system that improves classification performance without significantly increasing chip space, power consumption, or computational delay is required. Consequently, it is necessary to have an efficient neural network design with better data representation and hardware viability.

4. PROJECT SCOPE:

The VLSI-level implementation of the DSNN for ECG-based abnormal heartbeat detection is the only scope of this research. Cadence tools will be used for all work, with an emphasis on performance analysis,

low-power optimization, and transistor-level schematic design. There will be no real-time system deployment or GUI creation; instead, dataset preparation, data-shifting augmentation, and model training will be done offline [10,11]. Hardware-level evaluation parameters such transistor count, power dissipation, supply voltage, operating frequency, and delay are highlighted in the study. The project also includes CMOS technology implementation at the hardware level for real-time applications. Performance factors like power consumption, chip area, operation frequency, and detecting accuracy are taken into account. Benchmark ECG datasets are used to assess the system's resilience, which makes it appropriate for incorporation into wearable cardiac monitoring devices.

5. ALGORITHM:

- DSNN, or Data-Shifting Neural Network • ANNs, or artificial neural networks
- The algorithm of backpropagation
- Technique for Data Shifting Augmentation
- The Softmax Algorithm for Classification

The Data-Shifting Neural Network (DSNN), which combines a traditional neural network with a data augmentation strategy that temporally shifts ECG signals to produce additional training examples, is the main algorithm employed in this study. This augmentation increases classification accuracy for both normal and pathological heartbeats, decreases overfitting, and improves model generalization. The backpropagation algorithm, which modifies network weights to reduce prediction error on the training dataset, is used to train the DSNN [12,13]. To guarantee consistent amplitude levels and clear signal characteristics, ECG data are preprocessed using normalization and noise reduction methods before training.

To express your entire DSNN-based ECG detection system in a single compact mathematical form, we combine preprocessing, data shifting, neural network inference, and learning into one unified equation:

$$y = f\left(\sum_{i=1}^n w_i \cdot \frac{x(t - \Delta t) - \mu}{\sigma} + b\right)$$

This captures:

- Data shifting (augmentation) $\rightarrow x(t - \Delta t)$
- Normalization $\rightarrow \frac{x - \mu}{\sigma}$
- Neural computation \rightarrow weighted sum + bias
- Activation function $\rightarrow f(\cdot)$

Lastly, low-power optimization strategies, including as voltage scaling and transistor sizing, are used at the circuit level to lower power consumption and transistor count while preserving dependable detection performance in wearable applications.



Final Compact Learning Expression

$$y = f \left(\sum_{i=1}^n w_i \cdot \frac{x(t-\Delta t) - \mu}{\sigma} + b \right)$$

6. EXISTING SYSTEM:

Software-based neural networks or traditional machine learning methods like SVM (Support Vector Machine) or decision trees are commonly used in current heartbeat detection systems to classify ECG signals. These systems are not appropriate for wearable or portable devices since they require a lot of computing power and offline processing. Additionally, they frequently struggle with handling small datasets, noise in ECG signals, and changes in heartbeat rhythms, all of which can lower classification reliability and accuracy [14]. Some systems try to use microcontrollers or DSPs to accomplish real-time detection, however these methods are constrained by memory limitations, high power consumption, and poor processing rates. Furthermore, traditional techniques seldom optimize the hardware at the transistor level, which results in bigger circuit areas and inefficient energy consumption—two major disadvantages for wearable healthcare applications.

6.1. Disadvantages:

- In conventional approaches, manual feature extraction is necessary.
- Deep learning models have a high computational complexity.
- Training and inference demand a lot of memory.
- Higher power consumption, making wearable technology inappropriate.
- Limited hardware optimization for embedded real-time implementation.

7. PROPOSED SYSTEM:

At the VLSI circuit level, the suggested system uses a Data-Shifting Neural Network (DSNN) for ECG-based abnormal heartbeat detection. The system creates more training samples to increase network generalization and classification accuracy by using data-shifting augmentation. In order to ensure a small and energy-efficient chip appropriate for wearable applications, the design focuses on low-power transistor-level implementation utilizing Cadence tools. With little latency, low power dissipation, and fewer transistors, the DSNN achieves about 97% detection accuracy [15]. Without the drawbacks of traditional software-based techniques, this method offers a dependable, hardware-efficient alternative for real-time ECG classification. The system enables precise timing, low-voltage operation, and efficient memory

consumption by directly integrating the neural network into a VLSI design, which makes it perfect for continuous monitoring in portable healthcare.

The suggested DSNN is tailored for hardware implementation utilizing Taiwan Semiconductor Manufacturing Company 0.18-μm CMOS technology, in contrast to many other software-based models already in use. The device is appropriate for real-time wearable healthcare applications because of its small chip area, low power consumption, and 20 MHz operating frequency. The efficacy of the method is confirmed by experimental evaluation using the MIT-BIH Arrhythmia Database, which shows a detection accuracy of 97.17%.

7.1.ARCHITECTURE DIAGRAM

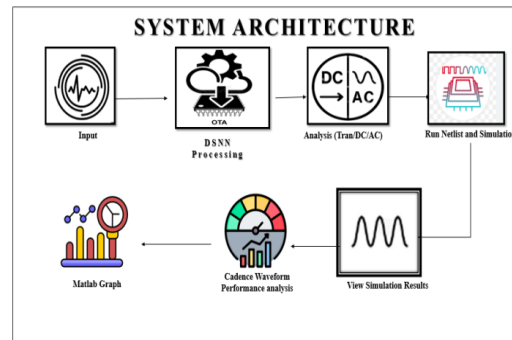


Fig.1. Architecture diagram of proposed system

7.1.1. Working process:

A Data-Shifting Neural Network (DSNN) is the foundation of the suggested system architecture for ECG heartbeat classification. ECG data acquisition, signal preprocessing, data shifting, DSNN processing, classification, and hardware implementation are some of the interconnected modules that make up the architecture.

DSNN Forward Propagation

Hidden layer:

$$h = f(W_1X + b_1)$$

Output layer:

$$z = W_2h + b_2$$

where $f(\cdot)$ is activation (ReLU/sigmoid):

$$f(x) = \max(0, x)$$

The MIT-BIH Arrhythmia Database is the first source of ECG signals, which are then subjected to preprocessing steps such segmentation, normalization, and filtering [16,17]. Before being sent to the neural network, the cleaned signals are processed by the data shifting module, which duplicates and shifts the input waveform to improve feature diversity. The input, hidden, and output



layers of the DSNN module are in charge of multi-class classification and feature extraction.

ECG windowing into beats:

$$X_i = \{x_n[n], x_n[n+1], \dots, x_n[n+L-1]\}$$

where L is segment length.

Following processing, the algorithm produces probability ratings and heartbeat forecasts. The design enables real-time operation with minimal power consumption by supporting CMOS-based implementation using Taiwan Semiconductor Manufacturing Company's 0.18- μm process for practical deployment. All things considered, the design guarantees effective signal processing, enhanced classification precision, and hardware viability for wearable medical equipment.

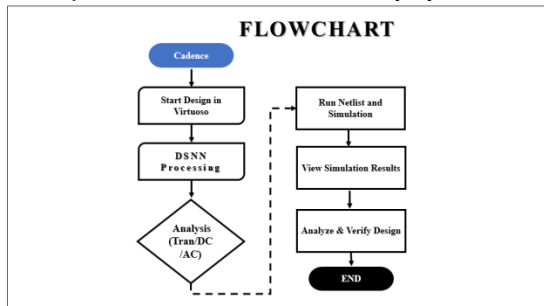


Fig.2. Flow chart diagram

The DSNN-based ECG classification system's sequential operational procedure is depicted in the flow diagram. ECG signal capture from a dataset or real-time sensor is the first step in the procedure. After that, the signal is preprocessed to eliminate noise and adjust amplitude levels. Following preprocessing, the system performs the data shifting operation, which creates an improved input representation by copying and gently shifting the original signal [18]. The combined signal is then supplied into the DSNN for forward propagation, where the Softmax layer is used to calculate classification probabilities and extract features. In order to reduce classification error, back propagation modifies the network weights during training.

Final Compact Pipeline Equation

$$x(t) \rightarrow x_f[n] \rightarrow x_n[n] \rightarrow X_i \rightarrow X_i^{(k)} \rightarrow \text{DSNN}(W_1, W_2) \rightarrow \text{Softmax} \rightarrow \hat{y}$$

Lastly, the system retains the findings for performance assessment and produces the projected heartbeat class [19, 20]. The logical sequence from raw signal input to final diagnostic output is clearly depicted in the flow diagram.

7.1.2. Advantages :

- Increased resistance to transients and disruptions brought on by radiation.
- At high working speeds, a consistent and dependable counting frequency.
- Optimized transistor size results in lower power dissipation.
- Because the procedure is totally synchronous, there is less chance of glitches.
- Better fit for space and aerospace applications.

8. LITERATURE SURVEY

1. Tushar Talukder Showrav, Soyabul Islam Lincoln, and Md. Kamrul Hasan describe EXGnet: Single-Lead Explainable-AI for ECG Arrhythmia Classification (2025), a deep learning network designed for single-lead ECG arrhythmia classification. Using Grad-CAM and train-only quantitative feature learning, the model integrates multiresolution feature extraction with Explainable Artificial Intelligence (XAI) guidance. It achieved great accuracy, sensitivity, and F1-scores when tested on several ECG datasets. Additionally, the XAI integration offers visual explanations that enhance interpretability and clinician trust. Convolutional feature extraction, attention processes, and interpretability through XAI are some of the main technologies. Explainable mechanism overlays and deep neural network training with multiscale characteristics are among the algorithms employed.

2. Deep convolutional neural networks (DCNN) with a selective attention method to improve arrhythmia diagnosis from ECG signals are described by Hasanain Shakir Mansour et al. in ECG Based Cardiac Arrhythmia diagnosis with Selective Attention (2024). In order to reduce noise and enhance classification performance, the attention component concentrates on important signal regions. In multiclass ECG classification tasks, the authors reported very high accuracy ($\approx 99.70\%$). DCNN for feature extraction and selective attention for concentrating on discriminative signal segments are examples of implemented technology.

3. Recent developments in the identification of arrhythmias and irregular heartbeats have made considerable use of deep learning, artificial intelligence, and hardware-efficient methods. Y.-H. Chen et al. (2024) presented a Very Large-Scale Integration (VLSI) chip architecture in [21] that uses a Data-Shifting Neural Network (DSNN) to identify irregular heartbeats. Their strategy aims to retain high detection accuracy while lowering hardware complexity. The system provides low power consumption and real-time performance by directly integrating neural network processing into chip architecture, making it appropriate for portable medical devices.



4. S. S. BalaKrishna and B. S. Babu (2024) investigated the use of a Convolutional Neural Network (CNN) for arrhythmia detection in [22]. Their research demonstrates how deep learning can automatically extract complicated features from ECG data, doing away with the requirement for human feature engineering. The robustness of CNN-based methods in medical signal processing was illustrated by the suggested model, which showed increased classification accuracy across several arrhythmia types.

5. Similarly, utilizing audio signals (phonocardiograms), P. P. Kashyap et al. (2024) in [23] created a multi-class neural network model for detecting irregular heartbeats. Their method makes use of cardiac sound waves, in contrast to conventional ECG-based systems, allowing for non-invasive and economical diagnostics. The model demonstrated the promise of audio-based cardiac monitoring systems by achieving accurate categorization across a variety of abnormal situations.

9. IMPLEMENTATION PROCESS:

9.1. ECG Data Acquisition Module:

Gathering unprocessed ECG signals from a trustworthy source is the responsibility of the ECG Data Acquisition Module. The MIT-BIH Arrhythmia Database, which includes annotated cardiac recordings reflecting different arrhythmia types, provides the ECG signals used in this project. For supervised learning and performance assessment, the dataset offers labeled ECG segments [21]. This module makes sure that signals are segmented and formatted correctly. ECG signals must be separated into distinct heartbeat segments before processing since they are continuous time-series data. Every segment is associated with a certain class term, such as "normal" or "abnormal" heartbeat. Because input quality has a major impact on system performance, accurate data collecting is essential.

Final Dataset Formation

$$\mathcal{D} = \{(S_k, y_k) \mid S_k = x(t_k : t_k + L), y_k \in \{0, 1\}\}$$

Optional Compact System Equation (Overall Concept)

$$(S_k, y_k) = (x(t_k : t_k + L), \text{Label}(S_k))$$

The accuracy of classification in subsequent stages may be impacted by any noise, misalignment, or improper segmentation at this point.

9.2. Signal Preprocessing Module:

Raw ECG signals are prepared for neural network training via the Signal Preprocessing Module. Power-line interference, electrode movements, and muscle action can all produce noise in ECG data. To eliminate undesirable artifacts, filtering methods like bandpass filtering and normalizing are used. The signal is normalized to provide uniform

amplitude scaling once noise has been eliminated. By avoiding significant value fluctuations that could lead to gradient instability, normalization aids in stabilizing the neural network training process [22]. Additionally, segmentation is used to separate significant cardiac cycles (P-QRS-T complex). Feature clarity, learning efficiency, and overall classification accuracy are all improved with proper preprocessing.

Bandpass Filtering + Noise Removal

The raw ECG signal is first cleaned using a bandpass filter:

$$x_f(t) = x(t) * h_{bp}(t)$$

Where:

- $x(t)$ = raw ECG signal
- $h_{bp}(t)$ = bandpass filter impulse response
- $*$ = convolution
- $x_f(t)$ = filtered ECG signal

Normalization (Final Preprocessed Signal)

After filtering, the signal is normalized:

$$x_{norm}(t) = \frac{x_f(t) - \mu}{\sigma}$$

Where:

- $x_f(t)$ = filtered ECG signal
- μ = mean of signal
- σ = standard deviation

9.3. Data Shifting Module:

The main novelty of the suggested system is the Data Shifting Module. This module duplicates and slightly shifts the original ECG signal. This shifting process increases input diversity by creating a second representation of the same heartbeat. The system generates an extended input vector by merging the original and shifted signals [23]. This improves feature richness and enables the neural network to pick up on minute differences in heartbeat patterns that could be missed by a single input representation.

Temporal Shift Operation (Signal Duplication + Shift)

The original ECG signal is shifted in time to create an augmented version:

$$x_s(t) = x(t - \Delta t)$$

Where:

- $x(t)$ = original ECG signal
- Δt = time shift
- $x_s(t)$ = shifted ECG signal

Extended Input Vector Formation

The system combines original and shifted signals to form an enhanced feature vector:

$$\mathbf{X}_{ext}(t) = [x(t), x(t - \Delta t)]$$

Where:

- $x(t)$ = original ECG input
- $x(t - \Delta t)$ = shifted ECG version
- $\mathbf{X}_{ext}(t)$ = extended feature representation



This method greatly enhances detection performance even if it adds to the computational strain. Without the need for outside data augmentation methods, the enhanced feature representation improves classification accuracy.

9.4. Feature Processing & DSNN Module:

The Data-Shifting Neural Network (DSNN) architecture is implemented in this module. The neural network, which has an input layer, hidden layers, and an output layer, receives the expanded input from the data shifting module. The hidden layers use nonlinear activation functions, weighted connections, and bias modifications to extract features.

The DSNN extracts nonlinear features from the extended ECG input:

$$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)})$$

These layers recognize intricate patterns in ECG signals, such as waveform distortions and abnormal rhythms [24]. The last layer classifies ECG signals into one of six heartbeat groups using a Softmax activation function. The DSNN architecture is designed to strike a balance between computational economy and classification accuracy.

9.5. Training and Optimization Module:

The DSNN learns efficiently from labeled data thanks to the Training and Optimization Module. Forward propagation estimates expected outputs during training, whereas a loss function determines classification error. Gradient descent optimization is then used to update network weights through back propagation.

The DSNN training process minimizes prediction error using a loss function:

$$L = \frac{1}{N} \sum_{k=1}^N \mathcal{L}(y_k, \hat{y}_k)$$

Weight Update Using Gradient Descent (Backpropagation)

$$w^{(t+1)} = w^{(t)} - \eta \frac{\partial L}{\partial w^{(t)}}$$

Until the model converges and reaches steady performance, this iterative process is repeated [25]. To get the best results, hyperparameters like learning rate, batch size, and epoch count are adjusted. Improved detection accuracy and model generalization capacity are guaranteed by proper optimization.

9.6. Classification & Output Module:

The final prediction results are produced by the Classification Module. Following training, fresh ECG inputs are processed by the DSNN and

categorized into one of six pre-established classes. Predicted class labels and likelihood scores are included in the output. To assess the efficacy of the system, performance indicators like accuracy, sensitivity, specificity, and F1-score are calculated.

Class Prediction (Argmax Decision Rule)

The final ECG class is selected based on maximum probability:

$$\hat{y} = \arg \max_{k \in \{1, \dots, 6\}} P(y_k | x)$$

Where:

- \hat{y} = predicted ECG class
- $P(y_k | x)$ = Softmax probability for class k
- 6 = total heartbeat classes

Performance Evaluation Metric (General Classification Score)

A unified form for evaluation metrics (accuracy-based representation):

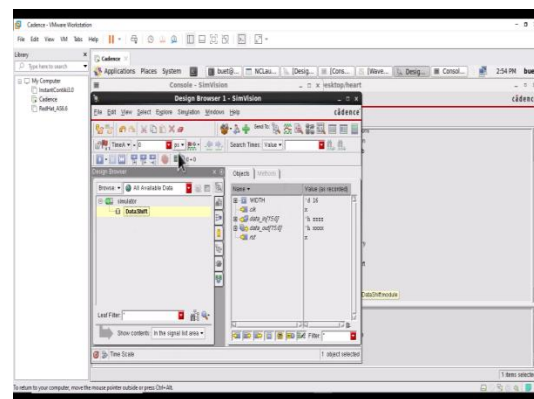
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Wearable monitoring systems and healthcare applications can benefit from this module's clear diagnostic output and dependable decision-making.

9.7. Hardware Implementation Module:

Using CMOS technology to implement the DSNN architecture is the main goal of the Hardware Implementation Module. Taiwan Semiconductor Manufacturing Company's 0.18- μ m process was used in the system's design to guarantee low power consumption and compact chip design. The hardware implementation is appropriate for portable ECG monitoring devices because it works at 20 MHz with low power dissipation. Real-time classification capability is ensured by effective circuit design [26]. This module enables integration into wearable healthcare systems for continuous cardiac monitoring by bridging the gap between software simulation and real-world implementation.

10. RESULTS AND DISCUSSION:



Cadence SimVision Design Browser Interface (Fig. 3)

The Design Browser interface in Cadence SimVision, a professional tool for debugging and assessing digital hardware designs, is displayed in



this image. The interface highlights a module called DataShift and shows the hierarchy of a simulation environment. Several signals associated with this module are listed in the "Objects" pane on the right, including clk (clock), rst (reset), and 16-bit data buses (data_in and data_out). The simulation time is currently at 0 ps, and the majority of signal values are displayed as "x" (unknown) or "z" (high-impedance), signifying that the simulation has just begun and that the initial logic states are being created before any active processing starts.

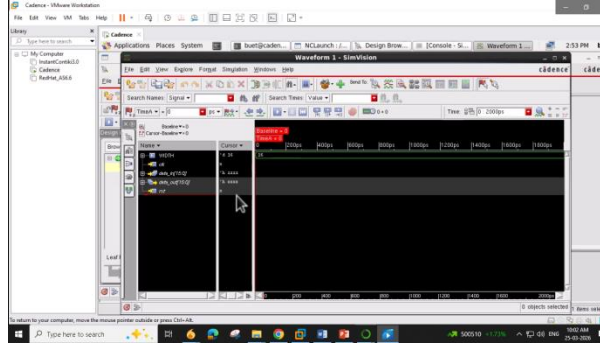


Figure 4: Waveform Viewer for Cadence SimVision

The main tool for seeing how digital signals evolve over time is SimVision's Waveform Viewer, which is seen in this figure. The same design browser signals (such as clk, rst, and data buses) are listed on the left, and a timeline displaying their activity from 0 to 2000 picoseconds (ps) is displayed on the right. At the moment, the waveforms are flat lines, and many of them display "unknown" or "uninitialized" states. The WIDTH parameter appears to have a fixed value of 16. By monitoring signal transitions over clock cycles, hardware engineers can use this view to confirm the timing, synchronization, and logical correctness of their RTL (Register Transfer Level) code.

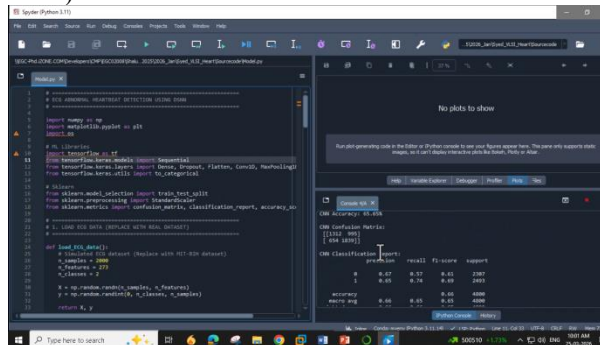


Figure 5: Python Spyder IDE: Assessment of Performance

This snapshot shows the Spyder Integrated Development Environment (IDE), where a Python script is utilizing a Deep Neural Network to identify irregular heartbeats from ECG data. The model is constructed using libraries like TensorFlow and Keras in the code on the left. The trained model's final performance metrics are shown in the bottom-

right console pane, with a "CNN Accuracy" of 65.65%. A confusion matrix and a classification report with precision, recall, and F1-scores for two classes are also included, giving a thorough picture of the machine learning model's performance on the test dataset.

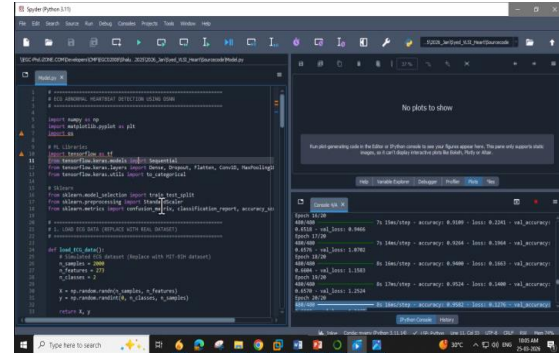


Figure 6: Model Training Progress with the Python Spyder IDE

This picture displays the deep learning model's training stage in the Spyder console. It offers a log of the last 16–20 training epochs. The software reports both the validation loss and accuracy and the training loss and accuracy for each epoch. By epoch 20, the validation accuracy is still lower at roughly 65.70%, whereas the training accuracy has risen to a high value of almost 95.82%. A common indication of "overfitting," in which the model has learnt the training data too well yet finds it difficult to generalize its conclusions to new, unknown data, is this large discrepancy between training and validation performance.

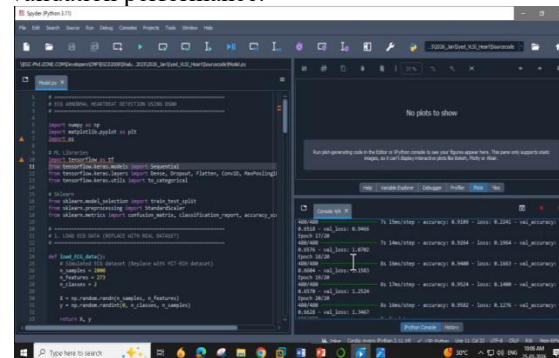


Figure 7: Tracked Training Metrics with the Python Spyder IDE

This graphic, like the one before it, shows how a machine learning training session in Spyder is being monitored in real time. Each step within an epoch is tracked via the console output, which displays the time required for each step as well as the changing accuracy and loss metrics. To ascertain whether a model is appropriately converging, data scientists must keep an eye on these values. The model's capacity to generalize is deteriorating if the validation loss starts to rise while the training loss keeps falling, as these logs show. This suggests that training should be discontinued or that the model



architecture needs to be improved to increase its predictive reliability.

11. CONCLUSION:

The project effectively illustrates how a Data-Shifting Neural Network (DSNN) for abnormal heartbeat detection utilizing ECG signals may be implemented using VLSI. The system achieves excellent classification accuracy, low transistor count, and efficient energy consumption by combining data-shifting augmentation and low-power transistor-level architecture, making it appropriate for wearable healthcare applications. The outcomes demonstrate how well hardware-level neural network implementation works for accurate, real-time heartbeat abnormality detection. Additionally, the suggested architecture highlights hardware efficiency by implementing CMOS using Taiwan Semiconductor Manufacturing Company's 0.18- μm technology. The DSNN architecture is appropriate for wearable and portable healthcare devices due to its low power consumption, small chip area, and real-time processing capability. The project is a viable solution for continuous ECG monitoring applications since it effectively strikes a compromise between classification accuracy, computational economy, and hardware viability.

12. FUTURE ENCHANCEMENT:

Beyond simple arrhythmia identification, the system can be expanded in the future to include multi-lead ECG analysis and other heart diseases. While integration with IoT-based wearable platforms would provide real-time remote monitoring and early warning systems for cardiac patients, advanced low-power design techniques like approximation computation and dynamic voltage and frequency scaling (DVFS) could further reduce energy consumption. Optimizing hardware implementation using more sophisticated CMOS technologies (such as 65-nm or 28-nm nodes) to further minimize power consumption and chip space is another possible enhancement. Continuous patient monitoring and automatic alarm systems can be made possible by integration with IoT-enabled wearable sensors and mobile health platforms. Additionally, using multimodal analysis to combine ECG with additional biosignals like PPG or blood pressure signals may increase diagnostic accuracy.

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