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A Comparative Study of VLSI-Based ECG Detection Systems: Advancing Real-Time Cardiac Monitoring

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ABSTRACT: Cardiovascular diseases (CVDs) are among the leading causes of death worldwide, with arrhythmias posing significant risks if not detected early. Modern healthcare emphasizes real-time, portable solutions for continuous monitoring, and VLSI-based ECG detection systems are key to achieving this goal. This paper provides an extensive comparative analysis of various VLSI approaches for arrhythmia detection, with a focus on the Data-Shifting Neural Network (DSNN) proposed in the base study. By utilizing a unique data-shifting mechanism and a convolutional neural network (CNN)-based architecture, DSNN achieves 97.17% accuracy with minimal power consumption (0.75 mW) and an ultra-compact design (0.619 mm²). In contrast, traditional methods such as Naive Bayes classifiers and Support Vector Machines (SVMs) offer simplicity and lower power consumption but compromise accuracy and scalability. Other CNN-based architectures provide higher accuracy but demand larger chip areas and power resources. This review emphasizes DSNN's strengths while identifying future challenges and research directions in wearable healthcare technologies.

KEYWORDS: DSNN, Neural networks, Convolution neural networks, Naive Bayes Classifier, Support vector machines.

I. INTRODUCTION

The detection of cardiac arrhythmias is essential for diagnosing life-threatening conditions such as ventricular fibrillation, atrial fibrillation, and premature ventricular contractions. These abnormalities, if detected in their early stages, can significantly reduce the risks associated with sudden cardiac death and improve patient outcomes. Electrocardiograms (ECGs) remain the gold standard for monitoring the heart's electrical activity, but their integration into portable and wearable devices requires innovations in hardware design. This is where Very Large-Scale Integration (VLSI) technology has emerged as a transformative tool for developing low-power, compact, and real-time monitoring systems. [1]

Among recent advancements, the Data-Shifting Neural Network (DSNN), as proposed in the base study, is a groundbreaking architecture that combines a data augmentation strategy with deep learning for real-time arrhythmia detection. Its design is optimized for hardware implementation, making it highly efficient and well-suited for wearable devices. This architecture demonstrates the potential to bridge the gap between accuracy, power efficiency, and compactness—key parameters for next-generation healthcare devices. [1]

Other referenced approaches, including Naive Bayes classifiers, Support Vector Machines (SVMs), and alternative CNN-based architectures, also contribute significantly to the evolution of ECG-based arrhythmia detection. While these methods demonstrate specific strengths, they often fall short in achieving the balance of accuracy and efficiency required for portable applications. This paper systematically evaluates these methodologies, providing insights into their performance, design trade-offs, and practical implications for real-world healthcare scenarios.

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II. METHODOLOGY

2.1 DATA-SHIFTING NEURAL NETWORK (DSNN) APPROACH

The Data-Shifting Neural Network (DSNN) is an innovative method developed to enhance the accuracy and reliability of detecting heart-related conditions, such as arrhythmias, from ECG signals. It employs a unique data-shifting technique, which generates an additional version of the input ECG signal by slightly altering its data points. This approach effectively doubles the dataset available for training and testing the network. By increasing the diversity of the data, the network benefits in two significant ways. First, it enables the network to learn a broader range of features, improving its ability to generalize and perform accurately on unseen data. Second, processing both the original and shifted versions of the signal makes the network more robust to noise and real-world variations in ECG recordings, ensuring reliable performance even in less-than-ideal conditions.

The architecture of DSNN is composed of several specialized layers designed to process ECG signals effectively and includes a voting system to enhance decision-making. At its core are convolutional layers, which are tasked with identifying critical patterns within the ECG data. These three layers progressively extract features, with the initial layers focusing on smaller patterns like peaks and dips, while the later layers detect larger trends such as repetitive abnormalities. The convolutional filters are carefully optimized to strike a balance between pattern detection and computational efficiency. Following these are max-pooling layers, which simplify the data by retaining only the most important features. These layers reduce the size of the data after each convolutional operation, which lowers computational requirements without compromising the quality of the extracted information.

Once the features are extracted, they are passed to fully connected (FC) layers, where the network maps the features to specific classification labels. These layers take the flattened outputs of the earlier layers and learn to associate them with various heart conditions. Techniques like dropout are applied within the FC layers to minimize overfitting, ensuring that the network performs well on both training and unseen datasets.

The DSNN is not only innovative in its software design but also highly optimized for hardware implementation, making it suitable for energy-efficient devices such as wearables. A key feature of its hardware design is the use of shared resources, where a single Multiply-Accumulate (MAC) unit is utilized across all layers.

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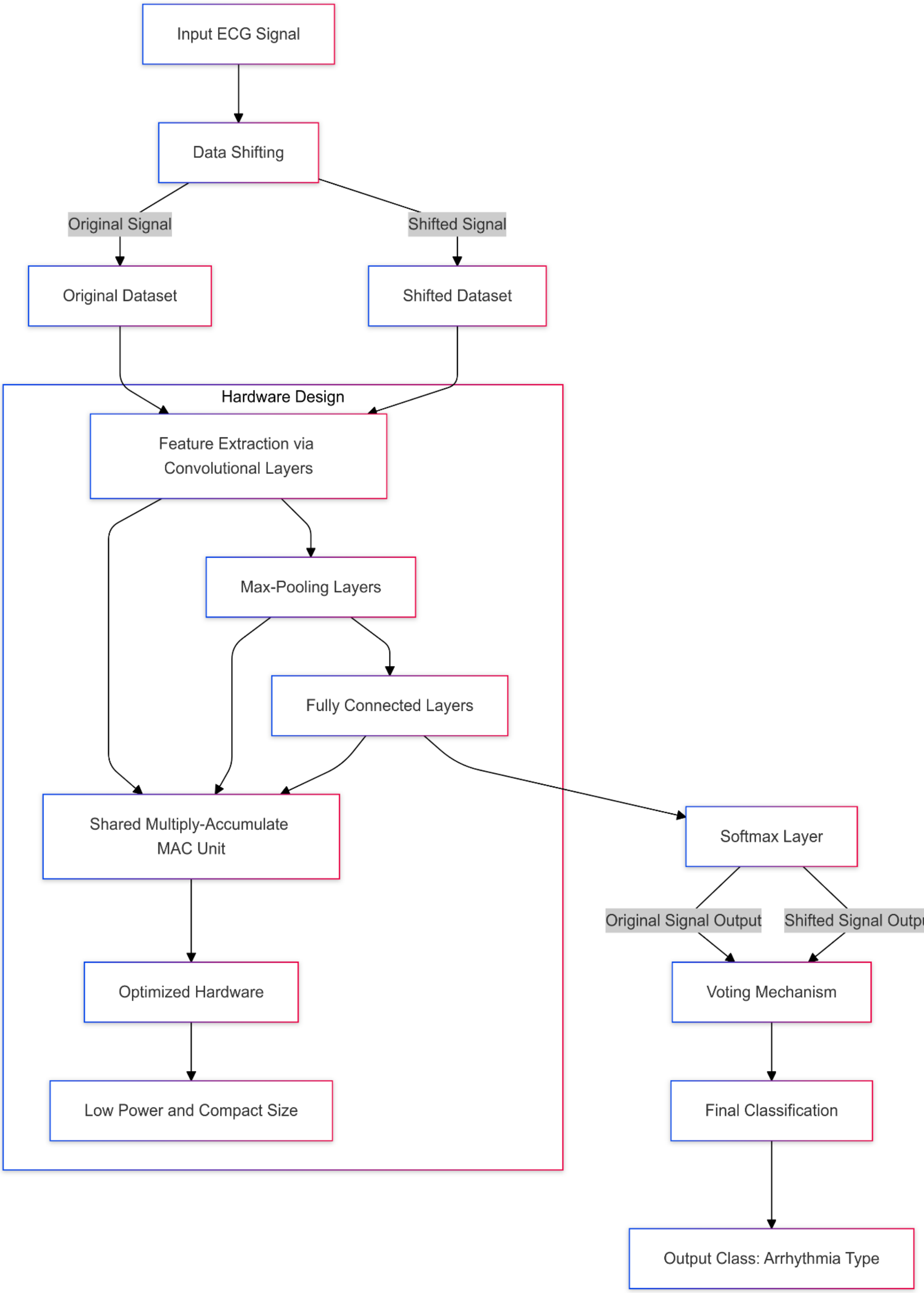

Figure1. Flowchart for Data Shifting (DSNN) approach

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REFERENCED APPROACHES

2.2 Naive Bayes Classifier ([2])

The Naive Bayes classifier is a simple yet effective method widely used for detecting arrhythmias in ECG signals. It operates on a probabilistic framework, calculating the likelihood of each possible class, such as normal or arrhythmic heartbeats, based on pre-defined features extracted from the ECG signal. These features typically include critical aspects such as the amplitude of specific signal peaks, the timing between beats, or the frequency of certain repetitive patterns. By using these handcrafted features, the Naive Bayes classifier can quickly estimate the probability of a signal belonging to a particular class and make classification decisions accordingly.

One of the major advantages of the Naive Bayes classifier is its lightweight and efficient design. The algorithm requires minimal computational power, making it ideal for resource-constrained systems. Additionally, its simple implementation allows it to function efficiently on basic hardware platforms, ensuring it can be deployed in low-cost systems. This efficiency is particularly beneficial in environments with limited access to computational resources, such as remote monitoring devices or low-cost medical equipment.

However, the method is highly feature-dependent, meaning it relies heavily on the quality and relevance of the features selected by experts. The success of the classifier is determined by how well the chosen features represent the underlying characteristics of the ECG data. This dependence on handcrafted features requires significant domain expertise and limits the adaptability of the method, as it struggles to generalize across varying datasets or evolving signal patterns.

Despite its simplicity, the Naive Bayes classifier has notable limitations, particularly in its accuracy. With a modest accuracy of 86%, it often fails to detect more complex or subtle arrhythmias, especially those involving intricate ECG signal variations. This restricted performance makes it less suitable for applications where high precision and reliability are critical. Nonetheless, its low cost, simplicity, and efficiency make it a reasonable choice for applications where computational power is very limited, and high accuracy is not the primary requirement. It serves as a pragmatic solution for entry-level ECG analysis systems or as a baseline for comparison against more advanced techniques.

2.3 Support Vector Machines ([3])

Support Vector Machines (SVMs) are a popular and robust choice for analysing ECG signals, owing to their ability to handle large datasets with high-dimensional features. The primary working principle of SVMs is to create a boundary, known as a hyperplane, that effectively separates normal heartbeats from arrhythmic ones. This boundary is designed to maximize the margin between different classes in the data, ensuring accurate classification even in cases with overlapping or closely related features.

One of the significant strengths of SVMs is their ability to handle complex data. ECG signals, which often contain numerous features and intricate patterns, are well-suited for analysis by SVMs due to their ability to work efficiently in high-dimensional spaces. This flexibility allows SVMs to classify a wide range of arrhythmias by utilizing detailed, feature-rich datasets.

However, SVMs are not without their challenges. Their performance heavily relies on the selection of the appropriate kernel function, which determines how the data is transformed into a higher-dimensional space. Choosing the wrong kernel can significantly reduce the model's effectiveness, making kernel selection a critical and often complex task. Additionally, SVMs are static models, meaning they cannot adapt dynamically to new patterns or changes in the dataset. This lack of adaptability limits their utility in real-time applications, where the nature of the input data can evolve over time.

In terms of accuracy, SVMs provide moderate performance, achieving classification rates of around 90%. While this is an improvement over Naive Bayes classifiers, SVMs are still outperformed by modern deep learning approaches such as Convolutional Neural Networks (CNNs). Unlike SVMs, CNNs can automatically learn features from raw ECG data, eliminating the need for manual feature engineering and significantly improving performance.

Despite these limitations, SVMs remain a reliable and efficient choice for ECG analysis, particularly in scenarios where computational resources are constrained, and dynamic adaptability is not a primary concern. Their structured approach

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to handling high-dimensional data ensures robust performance in a range of classification tasks, but their moderate accuracy and lack of adaptability make them less appealing for cutting-edge, high-performance ECG analysis systems. SVMs are best suited as intermediate solutions or as components of hybrid systems that combine multiple techniques for improved results.

2.4 Convolutional Neural Networks ([3] & [4])

Convolutional Neural Networks (CNNs) have brought about significant advancements in ECG signal classification by enabling models to learn directly from raw data. Unlike traditional methods that rely heavily on predefined features selected by domain experts, CNNs have the ability to automatically extract and discover patterns within the ECG signals. This autonomous feature-learning capability allows CNNs to identify intricate details in the data, making them highly effective at detecting arrhythmias, including subtle or complex abnormalities that might elude feature-based methods.

One of the key advantages of CNNs is their remarkable high accuracy, which can reach up to 96.7%. This level of precision makes CNNs among the most reliable models for ECG classification tasks. Their ability to generalize across different types of arrhythmias and datasets further enhances their utility in real-world applications. CNNs achieve this by leveraging multiple layers in their architecture to capture a hierarchy of features. The initial layers focus on simple and localized patterns, such as signal peaks and troughs, while deeper layers analyse broader and more abstract trends, including recurring irregularities or prolonged deviations in the ECG waveform. This hierarchical feature extraction enables CNNs to adapt to a wide range of ECG patterns, making them suitable for analysing both simple and complex arrhythmias.

However, while CNNs excel in accuracy and adaptability, they face several challenges when implemented in hardware, particularly for wearable and portable devices. One of the most pressing issues is their high-power consumption. CNNs require substantial computational resources to process data, which translates into significant energy usage. Hardware implementations of CNNs often consume more than 2 mW of power, far exceeding the requirements for energy-efficient wearable devices. This limitation is critical, as wearable devices typically depend on battery-powered operation, where minimizing power consumption is essential to ensure long battery life and consistent performance.
Another major challenge is the large chip size required to implement CNNs in hardware. Due to the complexity of their architecture, which includes multiple convolutional, pooling, and fully connected layers, CNN-based systems typically occupy substantial physical space. The chip area for such systems often exceeds 1.5 mm^2, which can be problematic for compact wearable devices. The large size not only limits integration into small-scale devices but also increases fabrication costs, making CNN-based designs less practical for cost-sensitive or space-constrained applications.

Despite these challenges, CNNs remain a powerful tool for ECG analysis, particularly in applications where power and space constraints are not critical. They are well-suited for larger systems, such as cloud-based diagnostic platforms or high-performance medical equipment used in clinical environments. In these contexts, CNNs provide unparalleled accuracy and adaptability, ensuring reliable detection of arrhythmias across diverse patient datasets. For wearable healthcare devices, further hardware optimizations are required to address the power and size limitations of CNN implementations. Strategies such as resource sharing, efficient memory management, and the use of low-power fabrication technologies hold promise in making CNNs more viable for portable and energy-constrained systems.

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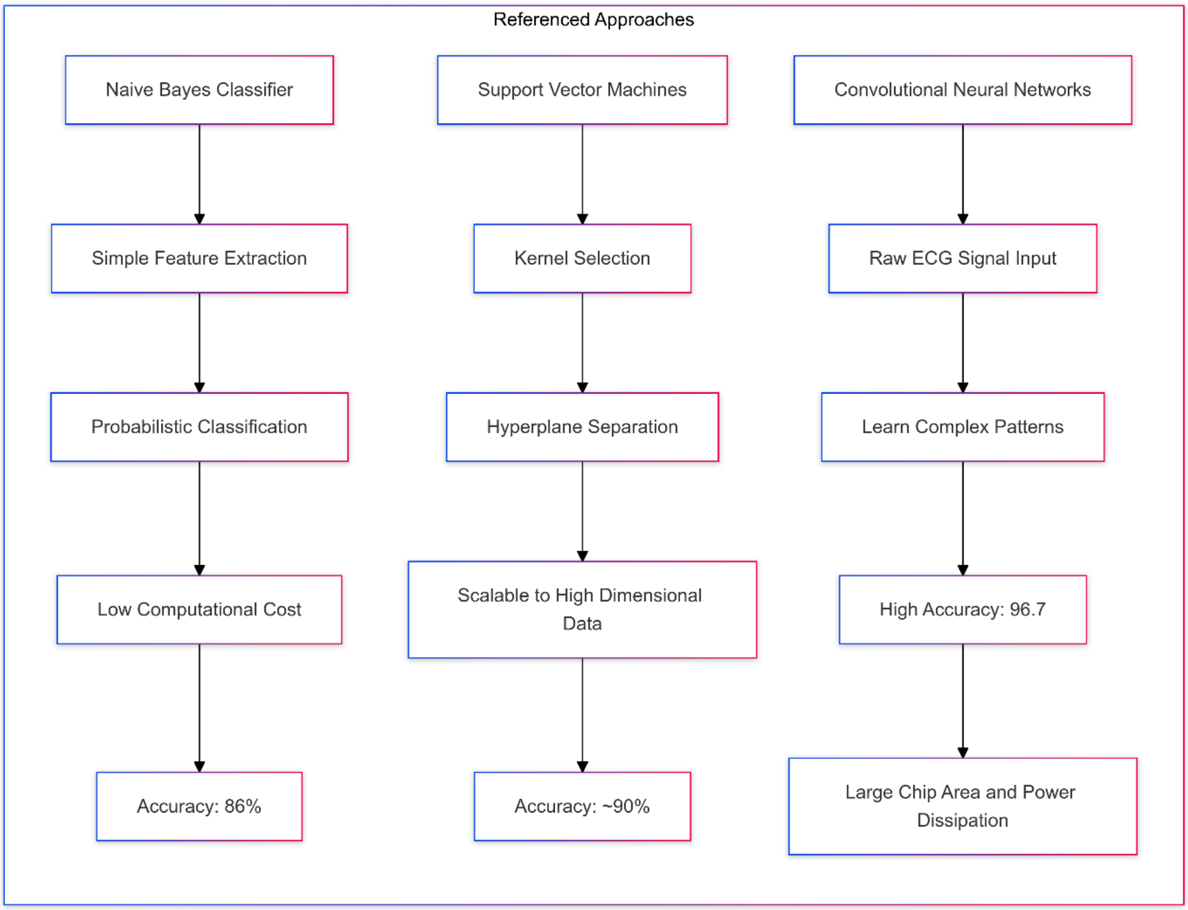

Figure 2: An image showing the referenced approaches

III. RESULTS AND DISCUSSION

3.1 Performance Analysis

The DSNN outperforms all referenced approaches in terms of accuracy, achieving 97.17% compared to 86% for Naive Bayes and 90% for SVMs. Its data-shifting mechanism enhances its ability to detect subtle arrhythmia patterns, ensuring robustness against noise and signal variability. CNN-based systems, while competitive in accuracy, fail to match DSNN's energy efficiency and compactness. *(Base Paper: [1], References: [2,3,4])*

Table1: Results and Discussions of DSNN Compared to Other Approaches

Metric	*DSNN*	*Naive Bayes*	*SVM*	*CNN-Based Systems*	*Discussion*
Accuracy	***97.17%***	*86%*	*90%*	*96.7%*	*DSNN achieves the highest accuracy, benefiting from the data-shifting mechanism for robust feature extraction and noise handling.*
Power Dissipation	***0.75 mW***	*~0.1 mW*	*~0.2 mW*	*>2 mW*	*DSNN provides significantly lower power dissipation than CNNs, making it ideal for wearable applications while maintaining high accuracy.*

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Metric	*DSNN*	*Naive Bayes*	*SVM*	*CNN-Based Systems*	*Discussion*
Chip Area	***0.619 mm²***	*~0.5 mm²*	*~0.6 mm²*	*>1.5 mm²*	*DSNN's compact design demonstrates efficient resource utilization, balancing performance with minimal area requirements.*
Robustness to Noise	***High***	*Low*	*Medium*	*Medium*	*The data-shifting mechanism gives DSNN a clear advantage in handling noisy and variable ECG signals.*
Hardware Complexity	***Moderate***	*Low*	*Low*	*High*	*DSNN optimizes hardware complexity through resource-sharing techniques, maintaining energy efficiency while outperforming simpler models.*
Adaptability	***High***	*Low*	*Low*	*High*	*While CNNs also adapt well to complex data, DSNN combines this adaptability with superior efficiency and compactness.*
Suitability for Wearables	***Ideal***	*Moderate*	*Moderate*	*Limited*	*DSNN strikes a balance between accuracy, efficiency, and size, making it highly suitable for wearable healthcare devices.*

3.2 Hardware Efficiency

The DSNN's compact chip design (0.619 mm²) and low power dissipation (0.75 mW) make it ideal for wearable applications. In contrast, traditional CNNs occupy larger areas and consume more power due to their deeper architectures and lack of resource-sharing optimizations. Naive Bayes and SVMs, while more efficient in terms of hardware, compromise on accuracy and adaptability, limiting their applicability in high-performance scenarios. *([1], References: [2], [3])*

3.3 Implications for Wearable Devices

Wearable devices require ultra-low-power operation, compact designs, and high accuracy to ensure prolonged battery life and reliable performance. The DSNN meets these criteria, offering an optimal balance of performance and efficiency. Its design demonstrates the feasibility of integrating advanced deep learning models into resource-constrained environments, paving the way for next-generation healthcare technologies. *(Base Paper: [1], Reference: [2])*

IV. CONCLUSION

The integration of VLSI technology with advanced machine learning models has transformed the field of ECG-based arrhythmia detection. Among the methodologies analysed, the DSNN stands out as a superior architecture, achieving a unique balance of accuracy, energy efficiency, and compactness. Its innovative data-shifting mechanism, combined with a robust CNN architecture and optimized hardware design, sets a new benchmark for real-time ECG monitoring systems.

Compared to traditional approaches, such as Naive Bayes and SVMs, the DSNN demonstrates a significant improvement in accuracy, adaptability, and scalability. While Naive Bayes offers simplicity and low hardware costs, its limited accuracy and reliance on handcrafted features restrict its application in modern healthcare. Similarly, SVMs, despite their computational efficiency, are outperformed by CNN-based methods in handling complex and evolving datasets.

The referenced CNN-based systems showcase the potential of deep learning in ECG classification but fall short in energy efficiency and hardware compactness, critical factors for wearable devices. The DSNN addresses these challenges by leveraging resource-sharing techniques and a voter mechanism, achieving superior performance without compromising efficiency.

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Future research should focus on enhancing the DSNN's noise resilience and expanding its adaptability to diverse patient populations. Exploring hybrid architectures that combine the strengths of multiple methodologies could further advance the state-of-the-art in real-time cardiac monitoring. Additionally, integrating multi-lead ECG data and developing solutions for real-world deployment, such as motion artifact handling and long-term signal stability, are essential steps toward making these systems more practical and reliable.

This comparative analysis underscores the transformative potential of DSNN and similar architectures in revolutionizing cardiac healthcare. As technology advances, the continued convergence of VLSI design and machine learning will undoubtedly drive innovations that save lives and improve the quality of care.

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