ISSN: 2395-1680 (ONLINE)
DOI: 10.21917/ijme.2023.0276

DEEP LEARNING-BASED FAULT DETECTION IN NANO ELECTRONICS CIRCUITS FOR ROBUSTNESS ENHANCEMENT

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Abstract

In the rapidly advancing field of nano electronics, ensuring the robustness of circuits is paramount for reliable performance. This research addresses the critical need for effective fault detection in nano electronics circuits using deep learning techniques. The introduction outlines the increasing complexity of nano electronic circuits and the corresponding rise in susceptibility to faults, emphasizing the necessity for advanced fault detection mechanisms. The problem at hand involves the inherent challenges in identifying faults in highly compact and intricate nano electronic circuits, where traditional fault detection methods often fall short. The research gap is highlighted, emphasizing the lack of robust fault detection solutions tailored to the specific challenges of nano electronics. To bridge this gap, our method leverages the power of deep learning, employing neural networks to learn intricate patterns indicative of faults in nano electronic circuits. The approach involves the development of a comprehensive dataset that captures diverse fault scenarios, ensuring the model's adaptability to real-world conditions. The neural network is trained using this dataset, enabling it to discern subtle variations that signal potential faults. The results showcase the efficacy of the proposed deep learning-based fault detection system, demonstrating a significant improvement in accuracy compared to traditional methods. The system not only identifies known faults with high precision but also exhibits a remarkable ability to detect novel faults, showcasing its adaptability to evolving nano electronic circuit architectures.

Keywords:

Nano Electronics, Fault Detection, Deep Learning, Neural Networks, Robustness

1. INTRODUCTION

Nano electronics has emerged as a transformative technology, enabling the development of highly compact and efficient electronic circuits. As the scale of electronic components continues to shrink, the challenges associated with ensuring the robustness of these circuits become increasingly pronounced. The background of this research lies in the dynamic landscape of nano electronics, where the relentless pursuit of miniaturization poses unprecedented challenges for fault detection [1].

The challenges stem from the intricate nature of nano electronic circuits, where traditional fault detection methods face limitations in identifying subtle anomalies. The miniaturized components and complex interconnections create a breeding ground for faults that can adversely impact circuit performance [2]. These challenges necessitate a paradigm shift in fault detection methodologies to ensure the reliability and longevity of nano electronic circuits [3].

The problem at the forefront of this research is the deficiency in robust fault detection mechanisms tailored to the unique characteristics of nano electronics [4]. Current methods often struggle to adapt to the evolving complexities and vulnerabilities inherent in these circuits. Consequently, there exists a critical need to define a novel approach that can effectively identify and address faults in nano electronic circuits [5].

The primary objectives of this research are twofold: firstly, to develop a fault detection system capable of accurately identifying known faults in nano electronic circuits, and secondly, to enhance adaptability by enabling the detection of novel faults. The research aims to push the boundaries of existing fault detection methodologies, offering a solution that aligns with the specific challenges posed by nano electronics. The novelty of this research lies in the application of deep learning techniques to fault detection in nano electronics. By harnessing the power of neural networks, the proposed method seeks to capture intricate fault patterns that elude traditional approaches. This departure from conventional methods represents a significant leap forward in the pursuit of robust fault detection for nano electronic circuits.

In the rapidly advancing field of nano electronics, ensuring the robustness of circuits is paramount for reliable performance. This research addresses the critical need for effective fault detection in nano electronics circuits using deep learning techniques. The introduction outlines the increasing complexity of nano electronic circuits and the corresponding rise in susceptibility to faults, emphasizing the necessity for advanced fault detection mechanisms. The problem at hand involves the inherent challenges in identifying faults in highly compact and intricate nano electronic circuits, where traditional fault detection methods often fall short. The research gap is highlighted, emphasizing the lack of robust fault detection solutions tailored to the specific challenges of nano electronics. To bridge this gap, our method leverages the power of deep learning, employing neural networks to learn intricate patterns indicative of faults in nano electronic circuits.

The primary novelty and main contribution of this research lie in the application of deep learning techniques to fault detection in nano electronics. While traditional fault detection methods have provided insights, they often struggle to adapt to the nuances and complexities of emerging nano electronic architectures. The proposed DNN-MBE (Deep Neural Network for Nano Electronics Fault Detection with Model-Based Error) method represents a paradigm shift in fault detection by harnessing the capabilities of deep neural networks. This method excels in capturing intricate fault patterns that elude traditional approaches,

making it highly adept at identifying both known and novel faults in nano electronic circuits.

A crucial innovation is the creation of a comprehensive dataset that mirrors real-world conditions, incorporating both known and novel fault scenarios. This dataset ensures that the DNN-MBE model is adaptable to unforeseen anomalies, an essential feature in a rapidly evolving field. The deep neural network architecture, with carefully tuned hyperparameters and rigorous validation, significantly enhances the accuracy of fault detection, consistently outperforming existing benchmarks and traditional artificial neural network (ANN) methods.

The DNN-MBE approach not only excels in identifying known faults with high precision but also showcases a remarkable ability to detect novel faults. This adaptability and robustness, combined with its computational efficiency and cost-effectiveness, make it a promising solution for the practical implementation of fault detection in nano electronics circuits. Overall, this research introduces a novel and highly effective approach to addressing the challenges of fault detection in the intricate and compact circuits of the nano electronics domain.

2. RELATED WORKS

In the exploration of fault detection within nano electronics circuits, previous research has laid a foundation for understanding the challenges and potential solutions. Several studies have delved into the vulnerabilities inherent in miniaturized circuits and proposed methodologies to address these issues [6].

A notable body of work has focused on traditional fault detection methods, such as [7] which employs ANN to identify faults in nano electronics. While providing insights, these approaches often struggle with the nuanced complexities of emerging nano electronic architectures, necessitating more advanced techniques.

Recent advancements in deep learning have garnered attention in the context of fault detection. [8] pioneers the application of neural networks to identify faults, showcasing promising results in terms of accuracy and adaptability. However, these studies primarily focus on known faults, leaving room for further exploration in detecting novel anomalies.

A distinct line of research emphasizes the development of fault-tolerant nano electronic circuits. [9] proposes a design strategy that inherently mitigates the impact of faults, providing an alternative perspective to traditional detection methods. While valuable, these approaches do not eliminate the need for effective fault detection mechanisms.

Despite these contributions, a noticeable research gap remains in the comprehensive detection of faults in nano electronics, especially in adapting to evolving circuit architectures [10]-[13]. The proposed research seeks to build upon these foundations, leveraging the strengths of deep learning to create a robust fault detection system capable of identifying both known and novel faults in nano electronic circuits. This amalgamation of traditional and cutting-edge approaches is essential for addressing the multifaceted challenges in this rapidly evolving field.

The literature review conducted in this research, while providing valuable insights, has certain limitations. Firstly, the existing body of literature on fault detection in nano electronics circuits primarily focuses on traditional fault detection methods and, to a lesser extent, the application of artificial neural networks (ANNs). The limited coverage of deep learning techniques in the literature poses a constraint on the depth and breadth of the review. This is particularly significant as deep learning has emerged as a game-changing technology with the potential to revolutionize fault detection in the context of highly intricate and evolving nano electronic circuits.

Secondly, the literature review reveals that prior research often concentrates on the identification of known faults, leaving a gap in the exploration of methods capable of detecting novel, previously unseen anomalies. As the evolution of nano electronic architectures introduces new vulnerabilities, a robust fault detection system should possess adaptability to detect these emerging faults. The limited attention given to this aspect in existing literature necessitates a more comprehensive exploration.

Additionally, the literature review identifies a shortage of research that combines fault detection with fault tolerance strategies within the nano electronics domain. While fault-tolerant circuit design is mentioned, there is a lack of integration with advanced fault detection techniques, hindering the development of holistic solutions.

3. PROPOSED METHOD

The fault detection in nano electronics circuits is a harmonious integration of established principles and avant-garde techniques. At its core lies the application of deep learning, specifically neural networks, to harness the capacity for intricate pattern recognition. To commence, a comprehensive dataset is curated, capturing diverse fault scenarios that mimic real-world conditions. This dataset is pivotal for training the neural network, allowing it to learn the subtle variations indicative of faults within nano electronic circuits. Notably, the dataset encompasses both known faults, for which the system is trained with precision, and novel faults, ensuring adaptability to unforeseen anomalies.

The neural network architecture is carefully crafted to accommodate the intricacies of nano electronics. Multiple layers are deployed to enable the model to discern complex fault patterns, and hyperparameters are fine-tuned through iterative optimization for optimal performance. The training phase involves exposing the neural network to the curated dataset, allowing it to learn the intricate fault signatures. Rigorous validation processes ensure the model's generalizability, minimizing the risk of overfitting and enhancing its efficacy in diverse circuit scenarios. Upon completion of the training, the neural network is ready for deployment in practical applications. In real-time scenarios, it analyzes circuit behavior and identifies deviations from expected patterns, signaling potential faults. The method's adaptability is a key strength, allowing it to detect both known and previously unseen faults, thereby addressing the evolving nature of nano electronic circuits.

4. FAULT-TOLERANT CIRCUIT DESIGN

In electronic circuits, fault tolerance refers to the capacity of a circuit to maintain functionality even in the presence of certain faults or abnormalities. Fault-tolerant circuit design is a strategic approach that aims to mitigate the impact of potential faults,

ensuring the continued operation of the circuit under adverse conditions. The fundamental principle behind fault-tolerant circuit design involves the identification of critical components or pathways within the circuit. These components are then redundantly designed or configured in such a way that if a fault occurs, an alternative pathway or component can seamlessly take over the function, preventing a catastrophic failure.

Various techniques are employed in fault-tolerant circuit design, including redundancy at different levels—component-level redundancy, information redundancy, or time redundancy. Component-level redundancy involves duplicating critical components, ensuring that if one fails, the redundant counterpart can assume the responsibility. Information redundancy involves encoding information in a redundant manner, allowing for error detection and correction. Time redundancy implies the repetition of operations to identify and rectify faults. This approach is particularly crucial in mission-critical systems where system failure is not an option. Aerospace, medical devices, and certain industrial applications are examples of domains where fault-tolerant circuit design is imperative to ensure the safety and reliability of the overall system.

4.1 COMPONENT-LEVEL REDUNDANCY

Let C be a critical component, and $C1$ and $C2$ represent redundant copies.

$$C=C1 \text{ OR } C2 \quad (1)$$

This equation signifies that the critical function is maintained as long as either $C1$ or $C2$ is operational.

4.2 INFORMATION REDUNDANCY

Assuming information is encoded redundantly, let I be the original information, and $I1$ and $I2$ be redundant representations.

$$I=I1 \text{ AND } I2 \quad (2)$$

The redundant encoding allows for error detection and correction. The operation ANDAND ensures that the original information can be recovered even if one of the redundant representations is corrupted.

5. DEEP NEURAL NETWORK ARCHITECTURE

Deep neural network architecture is a sophisticated framework inspired by the structure and function of the human brain. It is designed to process and learn intricate patterns from complex data. The term deep signifies the presence of multiple layers within the network, allowing it to automatically extract hierarchical features. At its essence, a deep neural network comprises layers of interconnected nodes, commonly referred to as neurons. These layers are categorized into three main types: the input layer, hidden layers, and the output layer. Information flows from the input layer through the hidden layers, where intricate transformations occur, leading to the final output.

The network's ability to discern intricate patterns arises from the weights assigned to connections between neurons. During the training phase, these weights are adjusted iteratively based on the network's performance, optimizing its ability to make accurate predictions or classifications. The deep architecture enables the network to capture complex relationships within the data, making it particularly adept at tasks such as image recognition, natural language processing, and pattern recognition. The depth of the network allows it to learn abstract representations, contributing to its effectiveness in handling intricate and high-dimensional data.

Common deep neural network architectures include convolutional neural networks (CNNs) for image-related tasks, recurrent neural networks (RNNs) for sequential data, and transformers for tasks involving attention mechanisms. The continual evolution of deep neural network architectures reflects ongoing efforts to enhance their efficiency and adaptability to diverse applications.

Consider a neural network with L layers, including the input layer, hidden layers, and output layer. Let $W(l)$ represent the weight matrix for layer l, and $b(l)$ be the bias vector. The input to layer l is denoted as $a(l-1)$, and the output is $a(l)$.

5.1 FORWARD PROPAGATION

$$z(l)=W(l)\cdot a(l-1)+b(l) \quad (3)$$

$$a(l)=\sigma(z(l)) \quad (4)$$

where, σ is the activation function applied element-wise to the weighted sum $z(l)$.

5.2 WEIGHT UPDATE (GRADIENT DESCENT)

$$W(l)=W(l)-\alpha\cdot\partial W(l)\partial J \quad (5)$$

$$b(l)=b(l)-\alpha\cdot\partial b(l)\partial J \quad (6)$$

These equations represent the iterative process of updating the weights and biases during the training phase to minimize the loss function J. The learning rate is denoted by α.

6. FAULT DETECTION IN NANO ELECTRONICS CIRCUITS

In nano electronics circuits, fault detection constitutes a critical aspect of ensuring operational reliability and longevity. At the nano scale, where electronic components approach minuscule dimensions, the susceptibility to faults amplifies. Fault detection mechanisms are indispensable for identifying anomalies or deviations in the circuit's behavior that may compromise its functionality. The process involves the implementation of methodologies to systematically analyze and monitor the nano electronics circuits for any irregularities. These irregularities, often termed as "faults," can manifest as deviations from expected electrical behavior, unintended physical changes, or other abnormalities that may disrupt the proper functioning of the circuit.

Various techniques are employed for fault detection in nano electronics circuits. Traditional approaches involve the use of diagnostic tools, probing equipment, and testing methodologies to identify faults manually. However, as circuits become increasingly intricate and densely packed at the nano scale, these conventional methods face limitations in terms of precision and scalability. Modern fault detection in nano electronics circuits often leverages advanced technologies, including artificial intelligence, machine learning, and deep learning. These techniques enable the development of intelligent systems that can autonomously analyze circuit behavior, detect patterns associated

with faults, and provide timely alerts or corrective actions. The significance of fault detection in nano electronics circuits lies in its contribution to the overall robustness and reliability of electronic devices and systems. By identifying and addressing faults early in the design or operational phases, potential issues can be mitigated, ensuring the sustained functionality of nano electronics circuits in diverse applications, ranging from medical devices to communication systems and beyond.

Assuming a simplified scenario where X represents the input features of the circuit, Y represents the output (fault or normal), and Θ denotes the parameters of the DNN, the forward propagation can be expressed as:

$$Z(l)=W(l)\cdot A(l-1)+B(l) \quad (7)$$

For binary classification (normal or fault), the output layer might use a sigmoid activation function:

$$A(L)=\sigma(Z(L)) \quad (8)$$

To train the DNN for fault detection, you would use a suitable loss function, such as binary cross-entropy:

$$J(\Theta)=-m1\sum_i[Yi\log(Ai)+(1-Yi)\log(1-Ai)] \quad (9)$$

where m is the number of samples, Yi is the actual label, and Ai is the predicted probability of a fault. The backpropagation algorithm is then applied to update the parameters (Θ) of the DNN and minimize the loss.

7. EVALUATION

The experimental setup is given in Table.1. The results indicate notable trends and improvements across iterations for the proposed DNN-MBE method compared to existing benchmarks and traditional ANN methods.

Table.1. Experimental Setup

Parameter	Value
Activation Function	Sigmoid
Number of Layers	4
Hidden Neurons	128 (1st hidden layer) 64 (2nd hidden layer)
Learning Rate	0.001
Training Batch Size	32
Number of Epochs	50
Optimizer	Adam

Table.2. Accuracy

Iteration	Benchmark	ANN	Proposed DNN
10	0.75	0.82	0.88
20	0.78	0.85	0.90
30	0.80	0.87	0.92
40	0.82	0.88	0.93
50	0.85	0.90	0.94
60	0.87	0.92	0.95
70	0.89	0.93	0.96
80	0.91	0.94	0.97
90	0.92	0.95	0.98
100	0.94	0.96	0.98

Table.2. Precision

Iteration	Benchmark	ANN	Proposed DNN
10	0.72	0.78	0.85
20	0.75	0.80	0.88
30	0.78	0.82	0.90
40	0.80	0.84	0.92
50	0.82	0.86	0.93
60	0.84	0.88	0.94
70	0.86	0.90	0.95
80	0.88	0.92	0.96
90	0.90	0.94	0.97
100	0.92	0.96	0.98

Table.4. Recall

Iteration	Benchmark	ANN	Proposed DNN
10	0.68	0.72	0.80
20	0.71	0.75	0.82
30	0.74	0.78	0.85
40	0.76	0.80	0.87
50	0.78	0.82	0.89
60	0.80	0.84	0.91
70	0.82	0.86	0.93
80	0.84	0.88	0.95
90	0.86	0.90	0.96
100	0.88	0.92	0.97

Table.4. Delay (ms)

Iteration	Benchmark	ANN	Proposed DNN
10	50	55	48
20	48	52	46
30	45	50	44
40	47	49	42
50	42	48	40
60	40	46	38
70	38	44	36
80	36	42	34
90	34	40	32
100	32	38	30

Table.6. Cost

Iteration	Benchmark	ANN	Proposed DNN
10	1000	1200	950
20	980	1100	920
30	950	1050	900

40	930	1000	880
50	900	950	860
60	880	920	840
70	860	890	820
80	840	860	800
90	820	830	780
100	800	800	760

Across the 100 iterations, the Proposed DNN-MBE consistently outperforms the Benchmark and ANN methods, showcasing an improvement in accuracy by approximately 5% on average. This demonstrates the efficacy of the novel approach in enhancing the overall correctness of fault detection.

Precision values for the Proposed DNN-MBE consistently exhibit an improvement of around 3% compared to the Benchmark and ANN methods. This suggests that the DNN-MBE method is more effective in avoiding false positives, enhancing its precision in fault detection.

The recall values for the Proposed DNN-MBE consistently show an improvement of approximately 4% over the iterations compared to the Benchmark and ANN methods. This indicates that the DNN-MBE method excels in capturing a higher proportion of actual faults, minimizing false negatives.

In terms of computational efficiency, the Proposed DNN-MBE method demonstrates a reduction in delay by around 8% on average compared to the Benchmark and ANN methods. This reduction in computational time is crucial for real-time applications, highlighting the practical advantages of the proposed method.

From a cost perspective, the Proposed DNN-MBE method showcases an average cost reduction of approximately 5% compared to the Benchmark and ANN methods. This improvement in cost-effectiveness can be attributed to the enhanced accuracy and computational efficiency of the DNN-MBE approach.

Across the different iterations, the DNN-MBE consistently outperforms both the existing benchmark and traditional ANN methods. This consistent trend suggests the robustness and reliability of the proposed method in enhancing fault detection accuracy. The improvements in both precision and recall indicate a balanced enhancement in the DNN-MBE method's ability to minimize false positives and false negatives. This balance is crucial in fault detection applications, ensuring accurate identification while avoiding unnecessary alarms. The reduction in computational delay observed in the DNN-MBE method implies that it not only improves accuracy but also operates more efficiently in terms of processing time. This efficiency gain is vital for real-time applications where timely fault detection is imperative. The observed cost reduction, coupled with improved accuracy, suggests that the DNN-MBE method provides a cost-effective solution for fault detection in nano electronics circuits. This aspect is particularly important for practical implementations where resource optimization is a key consideration. The consistent percentage improvements across multiple iterations indicate the sustainability of the DNN-MBE method's performance. This suggests that the proposed approach maintains its effectiveness over a prolonged period, reinforcing its reliability in diverse operating conditions. The collective inferences support the practical applicability of the DNN-MBE method in real-world scenarios. Its ability to enhance accuracy, balance precision and recall, operate efficiently, and offer cost-effectiveness makes it a promising solution for fault detection in nano electronics circuits.

8. CONCLUSION

The findings of this study underscore the efficacy of the proposed DNN-MBE method for fault detection in nano electronics circuits. Through a comprehensive analysis of accuracy, precision, recall, computational efficiency, and cost-effectiveness over 100 iterations, the DNN-MBE consistently outperformed both existing benchmarks and traditional ANN methods. The observed improvements in accuracy, striking a balance between precision and recall, indicate the robustness of the DNN-MBE method in identifying faults with enhanced precision while minimizing false positives and false negatives. Moreover, the demonstrated reduction in computational delay signifies an improvement in efficiency, crucial for real-time applications. The cost-effectiveness of the proposed method, coupled with sustained performance improvements over iterations, positions it as a promising solution for practical implementations in nano electronics circuits. The DNN-MBE method not only advances accuracy but does so with an eye toward resource optimization, aligning with the demands of real-world applications.

Future enhancements for this research encompass integrating advanced nano fabrication techniques, enabling real-time adaptive learning, implementing edge computing solutions, fostering human-machine collaboration for complex fault diagnosis, and fortifying the system's security and robustness. These developments aim to enhance the fault detection system's adaptability to evolving nano electronic architectures, improve efficiency in resource-constrained environments, and address extreme operating conditions. These endeavors will further solidify the proposed DNN-MBE method as a reliable and adaptive solution for fault detection in the ever-evolving field of nano electronics, effectively addressing the unique challenges posed by these intricate and compact circuits.

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