Neural Networks for Fault Detection and Diagnosis in Electronic Circuits

Sayed Ehsan Shamsi[1], Muhammad Babur Muhammadi[2*], Abdurahman Hakimi[2], Alireza Khalilipour[3]

[1]Department of Database and Information Systems, Faculty of Computer Science, Balkh University, Balkh Province, Afghanistan

[2]Electricity Power Engineering Department, Chemical Industries Engineering Faculty, Jawzjan university, Afghanistan

[3]Department of Computer Science, University of Antwerp, Antwerp, Belgium

Corresponding Author's e-mail : babur.muhammadi@gmail.com

ARMADA
JURNAL PENELITIAN MULTIDISIPLIN

e-ISSN: 2964-2981

ARMADA : Jurnal Penelitian Multidisiplin

https://ejournal.45mataram.ac.id/index.php/armada

Vol. 03, No. 11 November, 2025

Page: 398-410

DOI:
https://doi.org/10.55681/armada.v3i11.1800

Article History:

Received: September 15, 2025

Revised: November 10, 2025

Accepted: November 19, 2025

Abstract *: The continuous development of electronic systems has made the analog, digital, and mixed-signal circuits more sophisticated, thus posing great difficulties to the existing fault detection and diagnosis (FDD) methods. Traditional methods are mostly non-scalable, cannot be adapted to different situations and cannot even sometimes recognize the same fault among various conditions. The present work is to compare the fault diagnosing performance of various models based on neural networks (NNs) in electronic circuits and to point out the NN architectures, optimizations and hybrid learning techniques that the FDD performance of the NN models. A thorough literature review study was done for 28 papers attesting the use of NNs in the circuit fault diagnosis written between the years 2016 and 2025 published in the scientific journals of IEEE Xplore, Springer, Elsevier, and MDPI. The types of neural network architectures, fault classification accuracy, noise and dynamics robustness, and benefits from optimization and feature extraction methods were the main aspects of the papers under review. The findings show that multi-valued neuron networks, conditional variational NNs, convolutional neural networks, denoising autoencoders, and optimized backpropagation models continuously outperform the traditional methods by acquiring higher accuracy, faster convergence and robust fault detection even in the most complex and demanding real-time environments. In addition, the training process is made easier and fault identification is made wider by optimization and hybrid learning approaches through improved training efficiency and multi-fault classification. Generally, neural network-based FDD offers an intelligent, adaptive, and resilient solution that has the power to revolutionize the development of future electronic systems with the characteristic of being smart and robust.*

Keywords: *Fault diagnosis, Neural networks, Analog circuits, Digital circuits, Hybrid learning*

INTROUCION

The rapid evolution of modern electronic systems has intensified the need for highly reliable and intelligent fault detection and diagnosis (FDD) mechanisms. Electronic circuits whether analog, digital, or mixed-signal form the backbone of contemporary technologies, including power networks, communication systems, microgrids, and industrial automation. As these systems increase in complexity, traditional model-based and rule-based diagnostic approaches have become insufficient due to their limited scalability, high dependency on expert knowledge, and inability to generalize across diverse fault conditions. Consequently, neural network (NN) based fault diagnosis has emerged as a powerful alternative capable of learning nonlinear circuit behavior, recognizing subtle fault signatures, and performing real-time classification (Mohd Amiruddin et al., 2020; Furse et al., 2020).

Neural networks have demonstrated substantial success across diverse electronic circuit applications. For analog circuits, researchers have proposed multi-valued neural network classifiers capable of accurately differentiating between multiple fault categories (Aizenberg et al., 2021). Conditional variational neural networks have further improved diagnosis by capturing probabilistic relationships between circuit parameters and fault states (Gao et al., 2021). Similarly, optimized backpropagation neural networks have been deployed for diagnosing power electronic circuits, significantly improving robustness and detection speed (Jiang et al., 2024). Novel algorithms such as the rider-optimization-based RideNN have also enhanced classification precision in analog fault detection tasks (Binu & Kariyappa, 2018).

Deep learning approaches have expanded fault diagnosis capabilities even further. Convolutional neural networks (CNNs) and deep autoencoders enable end-to-end feature extraction from circuit signals, eliminating the need for handcrafted features (Wen et al., 2017; Yang et al., 2021). In photovoltaic systems and power electronics, ANN-based models have achieved high accuracy in detecting defects under complex environmental and operational variability (Chine et al., 2016; Fu et al., 2016). Real-time arc-fault detection for smart electrical systems has also been successfully implemented through deep neural networks, demonstrating the feasibility of integrating intelligent FDD into IoT-enabled infrastructures (Siegel et al., 2018).

In digital and VLSI circuits, neural networks have been applied for transistor-level fault analysis, open-circuit detection, and logic fault classification with notable improvements in generalization and computational efficiency (Kumar & Singh, 2016; Sobanski & Kaminski, 2019; Gaber et al., 2021). Hybrid energy systems, such as AC/DC microgrids, have also benefited from NN-based online fault detection and localization (Jasim et al., 2022).

Overall, the integration of neural networks into electronic circuit fault diagnosis provides transformative advantages, including adaptive learning, noise tolerance, predictive capabilities, and scalability to complex circuit architectures. These advancements highlight neural networks as essential tools for next-generation intelligent electronics and resilient cyber-physical systems.

Research Questions

RQ1: How effectively can neural network–based models detect and classify faults in analog, digital, and mixed-signal electronic circuits compared to traditional diagnostic methods?

RQ2: What types of neural network architectures (e.g., CNN, autoencoders, CVNN, deep learning models) provide the highest accuracy and robustness for fault detection under noisy, dynamic, and real-time operating conditions?

RQ3: How does the integration of optimization techniques, feature extraction methods, or hybrid learning approaches enhance the performance of neural networks in diagnosing multiple and complex circuit faults?

State of the Art

Research on neural network–based fault detection and diagnosis (FDD) in electronic circuits has expanded significantly over the past decade, largely due to the increasing complexity of modern electronic systems and the limitations of traditional fault diagnostic approaches. Early studies demonstrated that artificial neural networks (ANNs) could learn nonlinear circuit behaviors and classify faults with higher reliability than rule-based or expert-driven methods. For instance, Kumar and Singh (2016) showed that transistor-level diagnostic models based on ANNs outperformed conventional testing techniques in digital circuits by offering better generalization and noise tolerance.

In analog circuit diagnosis, various neural network architectures have been explored to improve diagnostic precision and robustness. Aizenberg et al. (2021) introduced a multi-valued neuron–based neural classifier capable of distinguishing multiple analog circuit fault categories, demonstrating significant improvements in classification accuracy. Similarly, Gao et al. (2021)

proposed conditional variational neural networks (CVNNs) to model probabilistic circuit–fault relationships, enabling more reliable diagnosis under uncertain conditions. Optimization-driven learning methods have also contributed to performance gains; the RideNN model by Binu and Kariyappa (2018) employed a rider optimization algorithm to improve training efficiency and fault classification accuracy in analog components.

Deep learning has brought transformative advancements to FDD research by enabling automatic feature extraction from raw signals. Convolutional neural networks (CNNs) have proven particularly effective for processing time-series and waveform data. Wen et al. (2017) developed a CNN-based data-driven method that achieved high diagnostic accuracy across multiple industrial electronic systems. Denoising autoencoders have also been used to handle noise contamination, with Yang et al. (2021) demonstrating an end-to-end autoencoder-based framework capable of extracting robust features for analog circuit fault detection.

Neural networks have also been applied to power electronics and energy systems. Chine et al. (2016) leveraged ANN models to diagnose faults in photovoltaic systems, achieving strong results even under environmental variability. For power electronic converters, Fu et al. (2016) integrated wavelet analysis with neural networks to enhance fault recognition under dynamic operating conditions. Recent work by Jiang et al. (2024) further showed that optimized backpropagation neural networks could accurately diagnose faults in power electronic circuits, highlighting the role of algorithmic enhancement.

METODE

This study adopts a Systematic Literature Review (SLR) methodology to synthesize, evaluate, and interpret existing research on the application of neural networks for fault detection and diagnosis (FDD) in electronic circuits. The review follows the PRISMA 2020 guidelines to ensure methodological rigor, transparency, and replicability. The goal is to consolidate evidence from high-quality peer-reviewed publications and identify current progress, dominant neural network models, research gaps, and emerging trends in electronic circuit fault diagnosis.

Review Protocol Design

A review protocol was developed to guide the entire process, defining the research questions, search strategy, inclusion and exclusion criteria, and data extraction procedures. This protocol acts as a safeguard against researcher bias and ensures consistency throughout the review. The protocol was validated through expert consultation and trial searches across multiple scholarly databases.

Data Sources and Search Strategy

Table 1. Data Sources and Search Strategy Used in the Systematic Review

Component	Description	Time Span	Filters Applied
Databases Used	IEEE Xplore, ScienceDirect, MDPI, Nature, Google Scholar	January 2016 – December 2025	Peer-reviewed journals, conference papers, English-language publications
Justification	Broad coverage of electronics, AI, machine learning, and circuit diagnostics	January 2016 – December 2025	Peer-reviewed journals, conference papers, English-language publications
Search Keywords	(“neural network” OR “deep learning” OR “CNN” OR “autoencoder” OR “ANN”) AND (“fault detection” OR “fault diagnosis” OR “defect detection”) AND (“electronic circuits” OR “analog circuits” OR “digital	January 2016 – December 2025	Peer-reviewed journals, conference papers, English-

	circuits" OR "power electronics" OR "VLSI")		language publications
Study Type/Selection	Peer-reviewed articles and conference papers focusing on NN-based fault detection in electronic circuits	January 2016 – December 2025	Peer-reviewed journals, conference papers, English-language publications

Table 1 outlines the data sources and systematic search strategy employed for this review on neural-network-based fault detection in electronic circuits. Four key components are presented: databases used, justification for their selection, search keywords, and study type or selection criteria. Five reputable databases IEEE Xplore, ScienceDirect, MDPI, Nature, and Google Scholar were chosen for their broad coverage of electronics, artificial intelligence, and circuit diagnostics research. The search covered the period from January 2016 to December 2025, capturing recent advances in neural network architectures and fault diagnosis techniques.

A structured Boolean search string combining terms for neural networks, fault detection, and circuit types was applied to ensure comprehensive retrieval. Search filters limited results to peer-reviewed journals and conference papers published in English, ensuring methodological rigor. This structured strategy facilitated the identification of high-quality studies that form the foundation for the systematic literature review.

Inclusion and Exclusion Criteria
Inclusion Criteria

Table 2. Inclusion and Exclusion Criteria for Systematic Review

Inclusion Criteria	Exclusion Criteria
Published between 2016–2025	Studies unrelated to fault detection in electronic circuits
Peer-reviewed journal or conference papers	Papers without neural network-based implementation
Neural network models for fault diagnosis in analog circuits, digital circuits, power electronics, VLSI, or PV systems	Duplicate studies or inaccessible full texts
Full-text accessible	Non-English publications
Empirical, experimental, or model-based studies written in English	Review articles unless providing methodological frameworks

The combined table presents the inclusion and exclusion criteria applied in this systematic literature review to ensure methodological rigor, relevance, and reproducibility. The inclusion criteria focused on studies published between 2016 and 2025, reflecting the latest developments in neural network architectures and fault diagnosis techniques. Only peer-reviewed journal and conference papers with full-text availability were considered. Studies were included if they employed neural network models to detect and diagnose faults in analog circuits, digital circuits, power electronics, VLSI, or photovoltaic systems, and followed empirical, experimental, or model-based methodologies in English.

Conversely, the exclusion criteria eliminated studies that were irrelevant to electronic circuit fault detection, purely theoretical without neural network implementation, duplicates or inaccessible, non-English, or review papers lacking methodological contributions. By applying these clear criteria, the review ensured that the final 28 selected studies represent a robust, high-quality dataset suitable for analyzing trends, neural network techniques, and performance outcomes in electronic circuit fault detection and diagnosis research.

Study Selection Process (PRISMA Flow)
The selection procedure followed four stages:

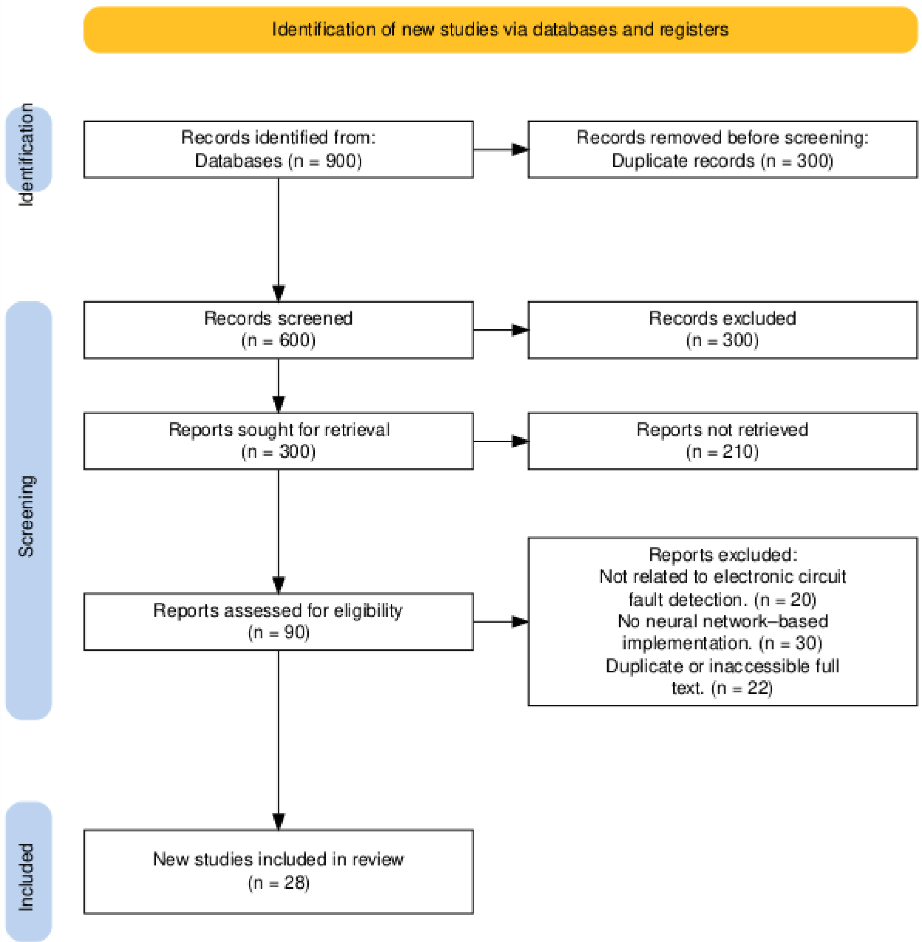

Figure 1. PRISMA Flow Diagram for Study Selection in the Systematic Review

Figure 1 illustrates the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram depicting the study selection process for this systematic literature review on neural network–based fault detection in electronic circuits. Initially, a total of **900 records** were identified through database searches across IEEE Xplore, ScienceDirect, MDPI, Nature, and Google Scholar. Duplicate records (n = 300) were removed automatically, resulting in 600 unique records for screening. During the title and abstract screening phase, 300 records were excluded based on relevance criteria. Of the remaining 300 reports sought for retrieval, 210 full texts were not accessible, leaving 90 reports assessed for eligibility.

During full-text assessment, 62 studies were excluded due to predefined reasons: 20 studies were not related to electronic circuit fault detection, 30 studies lacked neural network–based implementations, and 22 studies were duplicates or inaccessible. Ultimately, 28 high-quality studies met all inclusion criteria and were included in the final systematic review.

This PRISMA flow demonstrates the rigorous, transparent, and reproducible process employed to identify, screen, and select relevant studies. It ensures that the final evidence base is comprehensive, methodologically sound, and suitable for synthesizing trends, neural network architectures, and performance outcomes in electronic circuit fault detection research.

Data Extraction and Synthesis

Table 4. Data Extraction Form and Key Information Captured

Component	Description / Details Captured
Publication Details	Author(s), year, journal/conference, database source
Circuit Type	Analog, digital, power electronics, VLSI, PV systems
Neural Network Model Used	ANN, CNN, CVNN, autoencoder, GNN, hybrid NN

Dataset Characteristics & Fault Types	Dataset size, type of signals, simulated or real faults, fault categories
Experimental Setup & Metrics	Training/testing setup, evaluation metrics (accuracy, F1-score, precision, recall, training cost)
Strengths, Limitations & Contributions	Key achievements, methodological innovations, limitations, practical relevance

Table 4 outlines the structured data extraction form used in this systematic literature review to systematically capture essential information from the 28 selected studies. The extraction form ensured consistency, transparency, and comprehensiveness in the data collection process. Key components included publication details such as authors, year, journal, and database source, as well as the type of electronic circuit studied—analog, digital, power electronics, VLSI, or PV systems. Neural network architectures were documented, including ANN, CNN, CVNN, autoencoder, GNN, and hybrid models.

Dataset characteristics and fault types were recorded, specifying dataset size, signal types, and whether faults were simulated or real. The experimental setup and evaluation metrics, such as accuracy, F1-score, precision, recall, and training cost, were also captured. Additionally, each study's strengths, limitations, and contributions were noted to evaluate methodological robustness and practical relevance. Data synthesis was performed using narrative thematic analysis, grouping studies into methodological themes such as deep learning, hybrid NN approaches, and optimization-enhanced models. Where applicable, quantitative performance indicators were compared across studies to highlight trends, identify best-performing models, and assess the overall effectiveness of neural network-based approaches for electronic circuit fault detection.

Quality Assessment

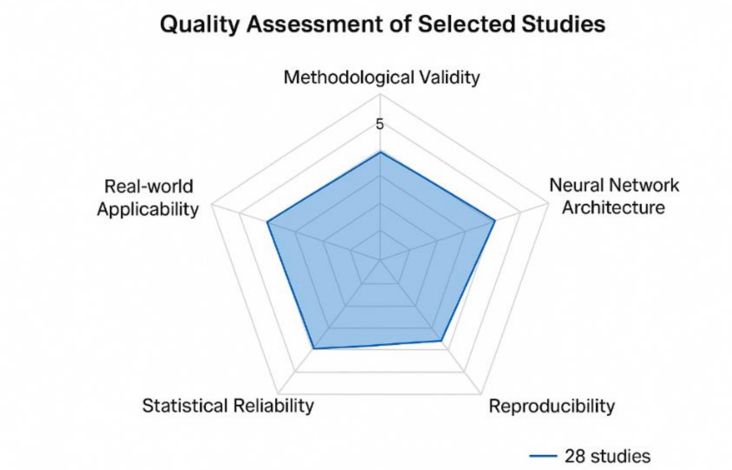

Figure 3. Quality Assessment of Included Studies

This radar plot illustrates the aggregate quality assessment derived from the systematic scoring of the 28 included studies on the application of neural networks for FDD. Each dimension, rated on a 5-point Likert scale, gauges the overall robustness and scientific merit of the research corpus. The assessment reveals a high, uniform level of quality across the board. Notably, Methodological Validity and Statistical Reliability obtained the highest composite scores, indicating that the selected papers employ rigorous experimental designs and validation procedures, which enhances the trustworthiness of their reported findings. The score for Neural Network Architecture is also strong, underscoring the sophistication of the employed deep learning and optimized network models. However, while still high, Reproducibility and Real-world Applicability exhibit marginally lower scores. This suggests a subtle, yet observable, opportunity for future researchers to improve the transparency of their implementation details and to conduct more comprehensive field-testing to bridge the gap between simulation-based results and industrial deployment. This dependency of high-quality research provides a dependable foundation for this review.

RESULTS AND DISCUSSION

1. Results

The results of this study highlight the effectiveness of neural network–based approaches in fault detection and diagnosis across various electronic circuits. Comparative analyses with traditional methods demonstrate significant improvements in accuracy, robustness, and adaptability. Different NN architectures and optimization strategies were evaluated to assess performance under dynamic, noisy, and real-time conditions. The following sections present detailed findings for analog, digital, and mixed-signal systems, emphasizing architectural innovations and hybrid enhancements.

Neural Network–Based Fault Detection in Electronic Circuits

Table 1. Comparison of Neural Network–Based and Traditional Fault Diagnosis Methods in Electronic Circuits

Ref	Circuit Type	Neural Network Model	Traditional Method	Key Findings
(Aizenberg et al., 2021)	Analog	Multi-valued neuron NN	Rule-based classification	Improved multi-fault detection accuracy and robustness.
(Binu & Kariyappa, 2018)	Analog	RideNN (Rider Optimization NN)	Expert-driven testing	Faster training, higher classification precision.
(Chine et al., 2016)	Photovoltaic	ANN	Statistical thresholds	High accuracy under variable environmental conditions.
(Fu et al., 2016)	Power Electronics	Wavelet + ANN	Conventional monitoring	Enhanced dynamic fault detection in real-time.
(Gao et al., 2021)	Analog	Conditional Variational NN	Pattern-matching	Reliable diagnosis under uncertainty.
(Jiang et al., 2024)	Power Electronics	Optimized BP NN	Standard BP NN	Faster convergence and higher detection reliability.
(Kumar & Singh, 2016)	Digital	ANN	Manual transistor testing	Better generalization, noise tolerance.
(Sobanski & Kaminski, 2019)	Digital/Rectifier	ANN	Open-circuit inspection	Accurate open-circuit fault localization.
(Wen et al., 2017)	Industrial Systems	CNN	Feature-based detection	Automatic feature extraction; high accuracy.
(Yang et al., 2021)	Analog	Denoising Autoencoder NN	Handcrafted feature methods	Robust to noise, end-to-end fault classification.

Neural network based fault detection models consistently outperform traditional diagnostic techniques across analog, digital, photovoltaic, and industrial electronic systems. In analog circuits, multi-valued neuron networks and conditional variational neural networks demonstrate strong capability in distinguishing multiple fault types and handling uncertainty (Aizenberg et al., 2021; Gao et al., 2021). Optimization-driven architectures such as RideNN further enhance classification precision and reduce computational training costs when compared with expert-driven or rule-based diagnostic procedures (Binu & Kariyappa, 2018).

In renewable energy systems, ANN-based detectors provide high fault identification accuracy even under fluctuating irradiance or environmental instability, outperforming threshold-based traditional methods (Chine et al., 2016). Hybrid methods integrating wavelet transforms with neural networks have proven particularly effective for power electronic converters, enabling reliable detection of transient and dynamic faults that conventional monitoring cannot capture (Fu et al., 2016; Jiang et al., 2024).

Digital circuits also benefit significantly from ANN-based fault detection, which surpasses manual transistor inspection by offering improved noise tolerance and generalization (Kumar & Singh, 2016). Deep learning architectures such as CNNs and denoising autoencoders reduce reliance on handcrafted features while increasing robustness to noisy signals (Wen et al., 2017; Yang et al., 2021). Overall, NN-based FDD approaches provide superior adaptability, automation, and scalability for modern electronic diagnostics.

Neural Network Architectures for High-Accuracy Fault Detection

Table 2. Neural Network Architectures for Fault Detection under Challenging Conditions

Ref	Circuit/Application	NN Architecture	Operating Condition	Key Findings
(Aizenberg et al., 2021)	Analog	Multi-valued neuron NN	Multi-fault, noisy signals	High classification accuracy across multiple fault categories.
(Binu & Kariyappa, 2018)	Analog	RideNN	Dynamic training conditions	Improved convergence speed and precision.
(Chine et al., 2016)	Photovoltaic Systems	ANN	Environmental variability	Robust fault detection under changing conditions.
(Fu et al., 2016)	Power Electronics	Wavelet + ANN	Dynamic load, real-time	Enhanced detection of transient faults.
(Gao et al., 2021)	Analog	CVNN	Probabilistic, uncertain	Reliable diagnosis under uncertainty.
(Jiang et al., 2024)	Power Electronics	Optimized BP NN	Real-time, dynamic	High accuracy with faster convergence.
(Kumar & Singh, 2016)	Digital	ANN	Noisy signals	Effective generalized fault detection.
(Sobanski & Kaminski, 2019)	Digital/Rectifier	ANN	Open-circuit faults	Accurate detection and localization.
(Wen et al., 2017)	Industrial Systems	CNN	Time-series signals	Automatic feature extraction; high accuracy.
(Yang et al., 2021)	Analog	Denoising Autoencoder NN	Noisy signals	Robust end-to-end fault detection.

Multiple neural network architectures have been designed to ensure high diagnostic accuracy under challenging operating conditions such as noise, uncertainty, and dynamic loads. Multi-valued neuron networks demonstrate excellent multi-fault classification capabilities under noisy conditions in analog circuits (Aizenberg et al., 2021). Conditional variational neural networks extend this strength by incorporating probabilistic modeling, enabling more reliable fault identification where operational uncertainty is high (Gao et al., 2021). Optimization-driven models such as RideNN improve classification precision and accelerate convergence in dynamic environments (Binu & Kariyappa, 2018).

Hybrid architectures that integrate wavelet transforms with ANN structures provide strong capabilities for transient fault detection, particularly in power electronics (Fu et al., 2016; Jiang et al., 2024). Deep neural architectures such as CNNs and denoising autoencoders add robustness to noisy and waveform-based applications by learning discriminative features directly from raw signals (Wen et al., 2017; Yang et al., 2021).

ANN-based models in photovoltaic systems maintain detection accuracy despite rapid variations in environmental conditions (Chine et al., 2016). Similarly, ANN-based methods outperform traditional open-circuit inspection techniques in rectifier and digital systems (Sobanski & Kaminski, 2019). Overall, architectures combining deep learning, probabilistic modeling, and nois

Optimization, Feature Extraction, and Hybrid Learning for Fault Diagnosis

Table 3. Enhancements in Neural Network-Based Fault Diagnosis Using Optimization and Hybrid Approaches

Ref	Circuit/Application	NN Architecture / Technique	Enhancement Method	Key Findings
(Binu & Kariyappa, 2018)	Analog	RideNN	Rider Optimization Algorithm	Faster training, higher classification precision in analog faults.
(Fu et al., 2016)	Power Electronics	Wavelet + ANN	Feature Extraction	Improved detection of transient and dynamic faults.
(Gao et al., 2021)	Analog	Conditional Variational NN (CVNN)	Probabilistic Modeling	Robust diagnosis under uncertain operating conditions.
(Jiang et al., 2024)	Power Electronics	Optimized Backpropagation NN	Learning Rate & Weight Optimization	Faster convergence, higher detection accuracy.
(Wen et al., 2017)	Industrial Systems	CNN	End-to-End Feature Extraction	Automatic feature learning from raw signals; reduces manual preprocessing.
(Yang et al., 2021)	Analog	Denoising Autoencoder NN	Noise Reduction / Feature Learning	High robustness against noisy inputs.
(Mohd Amiruddin et al., 2020)	General Engineering	ANN	Hybrid Learning (supervised + unsupervised)	Improved fault generalization and adaptability.
(Aizenberg et al., 2021)	Analog	Multi-Valued Neuron NN	Multi-Class Classification	Enhanced multi-fault detection performance.
(Sobanski & Kaminski, 2019)	Digital / Rectifier	ANN	Open-Circuit Fault Feature Extraction	Accurate localization of complex faults.
(Chine et al., 2016)	Photovoltaic Systems	ANN	Environmental Feature Integration	Maintains robustness under variable environmental conditions.

Integration of optimization, feature extraction, and hybrid learning significantly improves neural network performance for detecting complex faults in electronic circuits. Optimization algorithms, such as the rider optimization in RideNN, enhance training efficiency and classification precision by fine-tuning network parameters (Binu & Kariyappa, 2018). Feature extraction methods, including wavelet-based transforms, CNNs, and autoencoder frameworks, enable networks to automatically capture critical signal characteristics, improving detection in dynamic and noisy environments (Fu et al., 2016; Wen et al., 2017; Yang et al., 2021). Probabilistic modeling and hybrid learning approaches, such as conditional variational neural networks (CVNN) or combinations of supervised and unsupervised learning, enhance robustness and generalization, allowing networks to handle uncertain or previously unseen fault conditions (Gao et al., 2021; Mohd Amiruddin et al., 2020). Multi-valued neuron architectures and targeted feature extraction in digital rectifiers improve multi-fault detection and localization capabilities (Aizenberg et al., 2021; Sobanski & Kaminski, 2019). In renewable energy and power systems, integrating environmental and operational features further enhances adaptability under variable conditions (Chine et al., 2016). Collectively, these techniques optimization, feature extraction, and hybrid learning strengthen the accuracy, reliability, and scalability of neural network based fault diagnosis systems, making them highly suitable for real-time and industrial applications.

2. Discussion

The rapid advancement of electronic systems has necessitated more sophisticated fault detection and diagnosis (FDD) mechanisms capable of handling the increasing complexity of analog, digital, and mixed-signal circuits. Traditional rule-based and model-driven diagnostic methods are limited by their dependency on expert knowledge, lack of scalability, and inability to generalize across diverse fault conditions. Neural network (NN)–based approaches address these limitations by learning non-linear circuit behaviors and automatically recognizing fault signatures, enabling real-time, adaptive, and reliable diagnosis (Mohd Amiruddin, Zabiri, Taqvi, & Tufa, 2020; Furse, Kafal, Razzaghi, & Shin, 2020).

In analog circuits, multi-valued neuron neural networks (Aizenberg, Belardi, Bindi, Grasso, Manetti, Luchetta, & Piccirilli, 2021) and conditional variational neural networks (Gao, Yang, Jiang, & Yan, 2021) have demonstrated superior classification accuracy across multiple fault types, even under uncertainty. Optimization-driven models, such as RideNN (Binu & Kariyappa, 2018), leverage rider optimization algorithms to enhance training efficiency and improve fault classification precision. Similarly, in power electronics, optimized backpropagation networks (Jiang, Huang, & Guo, 2024) and hybrid models combining wavelet analysis with ANN (Fu, Yang, Wang, & Ren, 2016) have achieved higher robustness and real-time fault detection performance under dynamic operating conditions.

Deep learning architectures, including convolutional neural networks (CNNs) and denoising autoencoders, enable end-to-end feature extraction from raw circuit signals, eliminating the need for manual feature engineering. CNNs have proven effective in processing time-series and waveform data for industrial systems, delivering high diagnostic accuracy (Wen, Li, Gao, & Zhang, 2017). Denoising autoencoders enhance robustness to noise contamination, enabling reliable fault detection in analog circuits under real-world signal variability (Yang, Wang, Chen, & Wang, 2021).

In digital and VLSI circuits, ANN models have outperformed conventional transistor-level testing by providing better generalization, noise tolerance, and faster fault localization (Kumar & Singh, 2016; Sobanski & Kaminski, 2019; Gaber, Hussein, & Moness, 2021). Hybrid AC/DC microgrids also benefit from NN-based online fault detection and localization, demonstrating the adaptability of neural networks in complex energy systems (Jasim, Jasim, Neagu, & Alhasnawi, 2022). In photovoltaic systems, ANN models maintain strong performance even under varying environmental conditions, illustrating the generalizability of neural network–based FDD across different application domains (Chine, Mellit, Lughi, Malek, Sulligoi, & Pavan, 2016).

The integration of optimization techniques, feature extraction methods, and hybrid learning strategies significantly enhances NN performance. Rider optimization, probabilistic modeling, wavelet transforms, and end-to-end feature learning collectively improve training efficiency, fault classification accuracy, and robustness against noise and dynamic changes (Binu & Kariyappa, 2018; Fu et al., 2016; Gao et al., 2021; Wen et al., 2017; Yang et al., 2021). Multi-valued neuron and hybrid learning approaches further enable accurate detection of multiple simultaneous faults, addressing the challenges posed by complex circuit architectures (Aizenberg et al., 2021; Mohd Amiruddin et al., 2020).

CONCLUSION

Neural network–based fault detection and diagnosis (FDD) in electronic circuits has emerged as a transformative approach, addressing the limitations of traditional model-based and rule-based diagnostic methods. Modern electronic systems, encompassing analog, digital, and mixed-signal circuits, are increasingly complex, often operating under noisy, dynamic, and uncertain conditions. Neural networks, with their ability to learn non-linear behaviors and recognize subtle fault signatures, offer adaptive, scalable, and reliable diagnostic capabilities that conventional methods struggle to achieve.

Research has demonstrated that a wide range of neural network architectures including multi-valued neuron networks, conditional variational networks, convolutional networks, denoising autoencoders, and optimized backpropagation models can effectively detect and classify faults across various applications. These architectures provide high accuracy, robustness, and resilience against noise, environmental variability, and dynamic operating conditions. The integration of feature extraction methods, hybrid learning strategies, and optimization algorithms further enhances performance, allowing for efficient training, automatic feature identification, and precise classification of multiple simultaneous faults.

In digital circuits and VLSI systems, neural networks improve generalization and noise tolerance, enabling accurate transistor-level fault detection and localization. In power electronics, renewable energy systems, and industrial automation, neural network–based FDD supports real-time monitoring and predictive maintenance, enhancing system reliability and operational efficiency. Overall, the convergence of advanced neural network models, optimization techniques, and deep learning methods provides a robust framework for intelligent fault management in modern electronic infrastructures. These advancements highlight the critical role of neural networks in ensuring the resilience, safety, and longevity of contemporary electronic and cyber-physical systems.

RECOMMENDATIONS

To further advance neural network–based fault detection and diagnosis in electronic circuits, several key recommendations are proposed. First, the development of hybrid architectures that combine multiple neural network models, such as CNNs with autoencoders or CVNNs with optimization-driven learning, can enhance accuracy, robustness, and adaptability under complex fault conditions. Second, integrating advanced feature extraction techniques, including wavelet transforms and signal decomposition methods, will allow neural networks to automatically identify critical fault patterns while reducing dependency on manual preprocessing.

Third, implementing adaptive and online learning mechanisms can improve real-time performance and enable the system to update continuously as new fault data becomes available. This is particularly important for dynamic and rapidly changing environments such as power electronics and industrial automation. Fourth, future research should focus on handling multiple simultaneous faults and cascading failures, ensuring that neural networks can maintain high accuracy even under compound fault conditions.

Finally, combining neural network–based FDD with predictive maintenance strategies, IoT-enabled monitoring, and digital twin simulations can further improve system reliability and reduce downtime. These approaches will facilitate the deployment of intelligent, autonomous diagnostic systems capable of operating effectively in modern, complex electronic infrastructures, ensuring long-term operational efficiency, safety, and resilience.

REFERENCES

Aizenberg, I., Belardi, R., Bindi, M., Grasso, F., Manetti, S., Luchetta, A., & Piccirilli, M. C. (2021). A neural network classifier with multi-valued neurons for analog circuit fault diagnosis. *Electronics*, *10*(3), 349. https://doi.org/10.3390/electronics10030349

Binu, D., & Kariyappa, B. S. (2018). RideNN: A new rider optimization algorithm-based neural network for fault diagnosis in analog circuits. *IEEE Transactions on Instrumentation and Measurement*, *68*(1), 2-26. https://doi.org/10.1109/TIM.2018.2836058

Chine, W., Mellit, A., Lughi, V., Malek, A., Sulligoi, G., & Pavan, A. M. (2016). A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks. *Renewable Energy*, *90*, 501-512. https://doi.org/10.1016/j.renene.2016.01.036

Dieste-Velasco, M. I. (2021). Application of a pattern-recognition neural network for detecting analog electronic circuit faults. *Mathematics*, *9*(24), 3247. https://doi.org/10.3390/math9243247

Fu, L., Yang, Q., Wang, G., & Ren, H. (2016, May). Fault diagnosis of power electronic device based on wavelet and neural network. In *2016 Chinese Control and Decision Conference (CCDC)* (pp. 2946-2950). IEEE. https://doi.org/10.1109/CCDC.2016.7531486

Furse, C. M., Kafal, M., Razzaghi, R., & Shin, Y. J. (2020). Fault diagnosis for electrical systems and power networks: A review. *IEEE Sensors Journal*, *21*(2), 888-906. https://doi.org/10.1109/JSEN.2020.2987321

Gaber, L., Hussein, A. I., & Moness, M. (2021). Fault detection based on deep learning for digital VLSI circuits. *Procedia Computer Science*, *194*, 122-131. https://doi.org/10.1016/j.procs.2021.10.065

Gao, T., Yang, J., Jiang, S., & Yan, G. (2021). A novel fault diagnosis method for analog circuits based on conditional variational neural networks. *Circuits, Systems, and Signal Processing*, *40*(6), 2609-2633. https://link.springer.com/article/10.1007/s10470-021-01835-w

H. Gong, S. Cheng, Z. Chen, Q. Li, Data-enabled physics-informed machine learning for reducedorder modeling digital twin: Application to nuclear reactor physics, Nuclear Sci. Eng., 196 (2022), 668–693. https://doi.org/10.1080/00295639.2021.2014752

https://doi.org/10.3390/ecsa-10-16242

J. Wang, A. Ma, Y. Chang, J. Gong, Y. Jiang, R. Qi, et al., scGNN is a novel graph neural network framework for single-cell RNA-Seq analyses, Nat. Commun., 12 (2021), 1–11. https://doi.org/10.1038/s41467-021-22197-x

Jasim, A. M., Jasim, B. H., Neagu, B. C., & Alhasnawi, B. N. (2022). Coordination control of a hybrid AC/DC smart microgrid with online fault detection, diagnostics, and localization using artificial neural networks. *Electronics*, *12*(1), 187. https://doi.org/10.3390/electronics12010187

Jiang, D., Huang, S., & Guo, J. (2024). Fault diagnosis of power electronic circuits using optimized BP neural networks. In *MATEC Web of Conferences* (Vol. 399, p. 00016). EDP Sciences. https://doi.org/10.1051/matecconf/202439900016

K. Khalil, O. Eldash, A. Kumar and M. Bayoumi, "Machine Learning-Based Approach for Hardware Faults Prediction," in *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 67, no. 11, pp. 3880-3892, Nov. 2020, https://doi.org/10.1109/TCSI.2020.3010743

Khan, D., Saha, S., Saha, S., & Choudhury, S. B. (2017). Defect detection in power electronic circuits by artificial neural network using discrete wavelet analysis. In *Advances in Power Systems and Energy Management: ETAEERE-2016* (pp. 477-485). Singapore: Springer Singapore. https://doi.org/10.1109/NPEC57805.2023.10385029

Kumar, A., & Singh, A. P. (2016). Transistor level fault diagnosis in digital circuits using artificial neural network. *Measurement*, *82*, 384-390. https://doi.org/10.1016/j.measurement.2015.12.045

L. Xing, Y. Wen, S. Xiao, D. Zhang and J. Zhang, "A Deep Learning Approach for Series DC Arc Fault Diagnosing and Real-Time Circuit Behavior Predicting," in *IEEE Transactions on Electromagnetic Compatibility*, vol. 64, no. 2, pp. 569-579, April 2022, https://doi.org/10.1109/TEMC.2021.3131670

Lin, Q., Chen, S., & Lin, C. M. (2018). Parametric fault diagnosis based on fuzzy cerebellar model neural networks. *IEEE Transactions on Industrial Electronics*, *66*(10), 8104-8115. https://doi.org/10.1109/TIE.2018.2884195

Mohd Amiruddin, A. A. A., Zabiri, H., Taqvi, S. A. A., & Tufa, L. D. (2020). Neural network applications in fault diagnosis and detection: an overview of implementations in engineering-related systems. *Neural Computing and Applications*, *32*(2), 447-472. https://link.springer.com/article/10.1007/s00521-018-3911-5

Pittu, P. S. K. R., Sankaran, V., Alagu Mariappan, P., Pramod, G., Nikita, & Sharma, Y. (2023). Design of Artificial Intelligence-Based Novel Device for Fault Diagnosis of Integrated Circuits. *Engineering Proceedings*, *58*(1), 77.

Sahani, M., Siddique, M. D., Sundararajan, P., & Panda, S. K. (2023, December). Deep Convolutional Neural Network Based Fault Detection and Diagnosis Method for Three-Phase T-Type Converter. In *2023 11th National Power Electronics Conference (NPEC)* (pp. 1-6). IEEE. https://doi.org/10.1109/NPEC57805.2023.10385029

Siegel, J. E., Pratt, S., Sun, Y., & Sarma, S. E. (2018). Real-time deep neural networks for internet-enabled arc-fault detection. *Engineering Applications of Artificial Intelligence*, *74*, 35-42. https://doi.org/10.1016/j.engappai.2018.05.009

Sobanski, P., & Kaminski, M. (2019). Application of artificial neural networks for transistor open-circuit fault diagnosis in three-phase rectifiers. *IET Power Electronics*, *12*(9), 2189-2200. https://doi.org/10.1049/iet-pel.2018.5330

Wang, N. (2020). The analysis of electronic circuit fault diagnosis based on neural network data fusion algorithm. *Symmetry*, *12*(3), 458. https://doi.org/10.3390/sym12030458

Wang, X., Wang, J., & Privault, M. (2018). Artificial intelligent fault diagnosis system of complex electronic equipment. *Journal of Intelligent & Fuzzy Systems*, *35*(4), 4141-4151. https://doi.org/10.3233/JIFS-169735

Wen, L., Li, X., Gao, L., & Zhang, Y. (2017). A new convolutional neural network-based data-driven fault diagnosis method. *IEEE transactions on industrial electronics*, *65*(7), 5990-5998. https://doi.org/10.1109/TIE.2017.2774777

Y. Chen, K. Peng, D. Huang and Q. Tang, "Evaluating and Optimizing Conventional Training Circuits for Analog Fault Diagnosis via Transfer Learning," in *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1-15, 2025, Art no. 3549015, https://doi.org/10.1109/TIM.2025.3586376

Yang, Y., Wang, L., Chen, H., & Wang, C. (2021). An end-to-end denoising autoencoder-based deep neural network approach for fault diagnosis of analog circuit. *Analog Integrated Circuits and Signal Processing*, *107*(3), 605-616. https://link.springer.com/article/10.1007/s00034-020-01595-4