International Journal of Reconfigurable and Embedded Systems (IJRES)
Vol. 15, No. 2, July 2026, pp. 281~290
ISSN: 2089-4864, DOI: 10.11591/ijres.v15.i2.pp281-290

Intelligent deep learning models for fault diagnosis in sixth generation industrial internet of things environments

Hareesha Dandamudi[1], Chenchu Punnarao Bandi[2], Simhadri Mallikarjuna Rao[3], Palacharla SVS Sridhar[4], Mythili Murugan[5], Srikanth Kilaru[6], Rama Krishna Paladugu[7]
[1]Department of Electronics and Communication Engineering, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada, India
[2]Analog and Mixed Signal Circuit designer for Memory Interfaces, Synopsys Inc., Boxborough, United States
[3]Department of Computer Science and Engineering, Vignan's Foundation for Science, Technology and Research, Guntur, India
[4]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[5]Department of Information Technology, M. Kumarasamy College of Engineering, Karur, India
[6]Department of Information Technology, Vignan's Nirula Institute of Technology and Science for Women, Guntur, India
[7]Department of Computer Science and Engineering, RVR and JC College of Engineering, Guntur, India

Article Info

Article history:

Received Oct 13, 2024
Revised Mar 20, 2026
Accepted May 30, 2026

Keywords:

6G
Convolutional neural networks
Deep learning
Industry 4.0
Internet of things
Long short-term memory

ABSTRACT

The integration of sixth-generation (6G) communication and Industry 4.0 technologies has transformed industrial automation, connectivity, and intelligent data analysis. However, the increasing volume and diversity of data generated from multiple industrial sources create significant challenges for accurate and real-time fault detection. This study presents a deep learning-based framework designed to improve fault identification in 6G-enabled Industry 4.0 environments. The proposed system processes heterogeneous data collected from internet of things (IoT) devices, monitoring sensors, and automated industrial equipment to ensure reliable and scalable fault analysis. A hybrid model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks is implemented to capture spatial features and temporal relationships within industrial datasets. The framework also focuses on optimizing computational resources while maintaining high detection performance. Simulation-based evaluations demonstrate that the proposed approach enhances fault detection accuracy and system reliability, making it suitable for advanced smart manufacturing and industrial monitoring applications.

Corresponding Author:

Hareesha Dandamudi
Department of Electronics and Communication Engineering
Prasad V Potluri Siddhartha Institute of Technology
Vijayawada, Andhra Pradesh, India
Email: hareeshashyam@gmail.com

1. INTRODUCTION

The rapid modernization of industrial operations has been strongly influenced by the emergence of Industry 4.0 along with the evolution of advanced wireless communication technologies. Industry 4.0 introduces a new manufacturing paradigm that integrates cyber-physical systems, internet of things (IoT) platforms, artificial intelligence, and advanced data analytics to develop intelligent and interconnected industrial environments. The arrival of sixth-generation (6G) communication technology is expected to further strengthen this transformation by enabling extremely high data transmission rates, ultra-low latency communication, and reliable connectivity among diverse industrial devices and networks [1], [2]. Although these advancements significantly improve industrial productivity and automation, they also introduce new challenges related to system dependability, fault identification, and efficient resource utilization. Fault detection plays a crucial role in ensuring the safe and efficient operation of industrial systems. In conventional manufacturing environments, fault diagnosis techniques often rely on mathematical modeling, signal threshold monitoring, or rule-based approaches. While these techniques can be effective in relatively stable and predictable systems, they often struggle to address the complexity and dynamic behavior of modern smart factories. Industry 4.0 environments generate highly diverse datasets originating from multiple sources such as sensors, machine operation logs, image-based monitoring systems, and time-series measurements. This heterogeneous nature of industrial data increases the difficulty of accurately detecting faults in real time while maintaining low false alarm rates and efficient computational performance [3]–[5].

To overcome these challenges, this study proposes an advanced deep learning framework for fault detection in 6G-supported Industry 4.0 systems. The proposed framework integrates sophisticated neural network architectures with optimized data processing strategies to improve fault identification accuracy in heterogeneous data environments. The model collects and processes data from various industrial sources, including IoT-enabled devices, embedded sensors, and automated manufacturing equipment. This integrated approach enables scalable and reliable fault detection across distributed industrial infrastructures. The proposed framework employs a hybrid deep learning architecture that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture both spatial and temporal characteristics of industrial data. Additionally, the framework incorporates efficient resource management mechanisms to minimize computational overhead while preserving fault detection performance [6], [7]. Industry 4.0 represents a significant shift in industrial design and operational strategies through the integration of digital technologies such as cloud computing, big data analytics, IoT connectivity, and machine learning. These technologies support the development of smart manufacturing facilities, where automated data exchange and intelligent decision-making improve operational efficiency and productivity. A key component of Industry 4.0 is the implementation of cyber-physical systems, which establish communication between physical industrial equipment and digital computational models using IoT sensors. This connection allows real-time monitoring, predictive maintenance, and performance optimization of industrial processes [8], [9]. The development of 6G wireless communication technology is expected to further enhance Industry 4.0 capabilities by providing ultra-reliable low-latency communication, enhanced broadband connectivity, and large-scale machine communication support. These communication features enable seamless data exchange between industrial devices, allowing real-time monitoring, and automated decision-making at unprecedented scales. The high bandwidth and speed offered by 6G networks are particularly beneficial for managing the enormous amount of heterogeneous data generated by smart industrial environments, where multiple sensors and automated machines continuously monitor operational conditions [10], [11]. However, the diversity and volume of this data create additional challenges in processing and analyzing information efficiently. Managing multiple data sources such as visual inspection images, sensor signals, and system logs requires advanced computational models capable of delivering timely fault detection while maintaining system reliability and operational efficiency [12].

Fault detection remains one of the most critical tasks in industrial system maintenance because it directly influences equipment reliability, operational continuity, and production cost reduction. Traditional fault diagnosis methods, including physics-based modeling and statistical monitoring techniques, and rely on predefined system parameters to identify abnormal behavior. Although effective in certain controlled environments, these methods often fail to handle the complexity, and variability present in Industry 4.0 systems. The need for real-time monitoring and adaptive analysis requires intelligent detection techniques capable of learning system behavior under varying operational conditions [13], [14]. Machine learning and deep learning techniques have emerged as powerful tools for addressing these complex fault detection challenges. Unlike conventional model-based methods, machine learning algorithms can learn system characteristics directly from historical and real-time data. Deep learning approaches, in particular, have demonstrated remarkable success in industrial monitoring applications due to their ability to process high-dimensional and unstructured data efficiently. CNNs are widely recognized for their capability to extract spatial features from data, making them suitable for image-based defect detection, pattern recognition, and anomaly identification in manufacturing systems [15]. In contrast, industrial systems frequently generate sequential data such as temperature measurements, vibration signals, and operational logs. LSTM networks, which belong to recurrent neural network architectures, are specifically designed to analyze temporal relationships in sequential datasets. LSTM models can retain historical information through memory units, enabling them to identify long-term dependencies in time-series data. These characteristics make LSTM networks particularly suitable for predictive maintenance and dynamic system monitoring applications [16], [17].

The integration of CNN and LSTM architectures into hybrid deep learning models provides a comprehensive solution for industrial fault detection. Hybrid models combine spatial feature extraction capabilities with temporal pattern learning, enabling accurate analysis of multimodal industrial datasets. Such approaches are especially useful in Industry 4.0 environments, where industrial data originates from multiple heterogeneous sources and requires integrated processing techniques [18]. The deployment of 6G communication infrastructure further enhances the performance of fault detection systems by enabling real-time data transmission between distributed industrial devices and centralized monitoring platforms. High-speed connectivity ensures faster data exchange and supports advanced industrial applications such as predictive maintenance and automated fault management. Additionally, 6G networks support communication paradigms such as ultra-reliable low-latency communication, enhanced mobile broadband, and massive machine connectivity, which are essential for large-scale industrial automation and monitoring [3]. Despite these advantages, the integration of deep learning models in industrial environments introduces computational and energy-related challenges. Training and deploying deep neural networks require significant processing power and memory resources, particularly in large-scale monitoring systems. Continuous data processing, real-time fault detection increase energy consumption, and operational costs highlighting the need for efficient resource management strategies in industrial fault detection frameworks [19], [20].

The importance of optimizing computational efficiency becomes more critical as 6G networks enable higher data throughput and increased connectivity across industrial platforms. Managing large volumes of heterogeneous industrial data without overloading computational resources requires advanced optimization techniques that balance detection accuracy and system efficiency. Several studies have explored deep learning-based fault detection models, including CNN-based visual defect detection and LSTM-based predictive maintenance systems. Although these approaches demonstrate strong detection performance, many of them focus on specific data types and lack adaptability to heterogeneous industrial data environments [19], [21], [22]. Hybrid deep learning models have been introduced to address these limitations by combining multiple neural network techniques to process diverse data sources. For example, CNN-LSTM hybrid architectures have demonstrated improved performance in analyzing both visual and sequential industrial datasets. However, existing hybrid models often face scalability challenges when deployed in large industrial environments requiring continuous monitoring and real-time processing [23]. To address these challenges, this study proposes a hybrid deep learning framework that enhances fault detection performance in heterogeneous Industry 4.0 data environments while improving computational efficiency. The proposed system leverages 6G communication capabilities to manage large-scale industrial datasets and ensures reliable data transmission across distributed industrial networks. By integrating CNN and LSTM architectures with optimized processing strategies, the framework provides accurate and scalable fault detection suitable for next-generation smart industrial applications.

2. METHOD

This section presents an advanced deep learning framework developed for fault detection in 6G-enabled Industry 4.0 environments characterized by heterogeneous data sources. The framework is designed to address major challenges including multimodal data processing, real-time monitoring requirements, and efficient resource utilization. The proposed architecture integrates multiple deep learning techniques to process diverse industrial datasets while maintaining high detection accuracy and system scalability. The framework employs a hybrid neural network model that combines CNNs and LSTM networks to capture both spatial and temporal characteristics of industrial data. The primary objective is to achieve reliable fault detection with reduced computational complexity and improved operational efficiency [24]. The overall system architecture consists of five major components: a data preprocessing unit, a hybrid deep learning module, a fault detection unit, a resource optimization engine, and a 6G communication layer. These components operate collaboratively to enable real-time monitoring, efficient resource management, and seamless communication among distributed industrial devices.

The data preprocessing unit plays a vital role in handling the heterogeneous nature of Industry 4.0 datasets. Industrial data is collected from multiple sources, including IoT-based sensors, machine-generated logs, visual monitoring systems, and time-dependent operational records. This unit performs data cleaning, normalization, standardization, and formatting processes to convert raw data into structured forms suitable for deep learning analysis. Proper preprocessing enhances model performance and ensures consistent feature representation across different data types. The core analytical component of the framework is the hybrid deep learning module, which integrates CNN and LSTM architectures. CNN models are utilized to extract spatial features from visual and high-dimensional datasets such as equipment images and production line monitoring systems. These models are highly effective in detecting physical defects including structural damage, cracks, surface irregularities, and manufacturing anomalies. In contrast, LSTM networks are incorporated to analyze sequential time-series data generated from industrial sensors and operational logs. LSTM networks possess memory capabilities that allow them to capture temporal dependencies and identify abnormal operational trends such as irregular temperature variations, unexpected vibration signals, and performance degradation patterns.

The hybrid architecture enables simultaneous processing of visual and sequential data streams, making the framework highly adaptable to complex industrial environments. Initially, data is continuously collected from multiple monitoring sensors and industrial devices. The deep learning model processes this information to identify abnormal system behavior and generate automated alert signals for industrial monitoring systems. To further enhance analytical capability, the framework incorporates multiple deep learning techniques, including LSTM networks for sequential data, CNN models for visual inspection data, and graph convolutional neural networks (GCNNs) for relational and network-based industrial data structures. Additionally, the framework introduces a Branch-and-Bound optimization strategy for hyperparameter tuning across deep learning models. This optimization approach systematically explores the hyperparameter search space using heuristic-based enumeration techniques, improving model performance while reducing computational search complexity compared to exhaustive optimization methods. Figure 1 illustrates the overall architecture and workflow of the proposed fault detection framework.

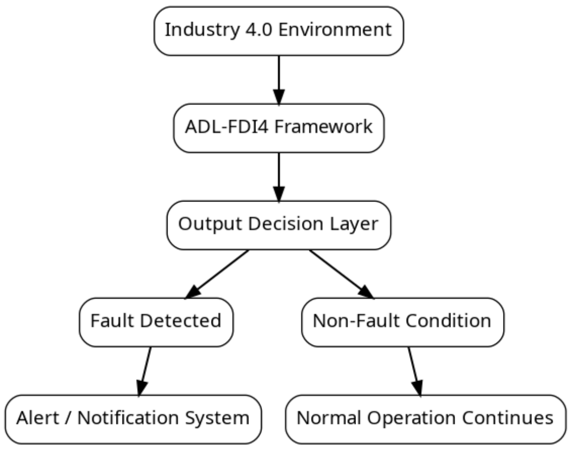

Figure 1. Simplified representation of DL

The design of the proposed framework is further motivated by recent advancements in big data analytics, Industry 4.0 technologies, and intelligent cybersecurity solutions. Large-scale industrial environments generate massive volumes of heterogeneous data that require efficient processing and analysis techniques for accurate decision-making and fault diagnosis. Recent studies have highlighted the importance of big data applications in industrial systems and healthcare domains, emphasizing the need for scalable data management and intelligent analytics frameworks [25]. Furthermore, Industry 4.0 enabling technologies have demonstrated significant potential in monitoring, prediction, and management of complex real-world phenomena through the integration of IoT, artificial intelligence, and advanced data-driven approaches [26]. In addition, the adoption of deep learning and meta-heuristic optimization techniques has shown promising results in enhancing cybersecurity and system reliability in critical infrastructures, supporting the use of intelligent learning models for robust fault detection and anomaly identification [27]. These findings provide a strong foundation for the development of the proposed hybrid CNN–LSTM-based fault diagnosis framework in 6G-enabled Industry 4.0 environments.

The fault detection module serves as the primary monitoring component responsible for identifying abnormal system behavior in real time. This module receives analyzed outputs from the hybrid deep learning framework and evaluates deviations from standard operating conditions. When abnormal patterns are detected, the module categorizes faults based on severity levels and operational impact. Such classification enables the implementation of appropriate response strategies. For example, minor irregularities may generate early warning notifications to support predictive maintenance, whereas severe faults can activate automated shutdown mechanisms to prevent equipment damage and operational hazards [28]. The module is carefully designed to achieve high detection precision while maintaining minimal false alarm rates, thereby preventing unnecessary disruptions in industrial operations and improving system reliability. A critical component supporting the efficiency of the framework is the resource optimization engine, which ensures scalability and efficient computational performance. This engine incorporates several optimization techniques to regulate resource utilization during data processing and deep learning inference. One of the primary techniques implemented is model pruning and quantization. Model pruning reduces neural network complexity by eliminating redundant connections and parameters that contribute minimally to prediction accuracy. Quantization further reduces computational overhead by lowering numerical precision during calculations, resulting in reduced memory consumption and lower energy usage.

Another significant optimization strategy involves the integration of edge computing technologies. In this approach, data processing tasks are distributed between edge devices and centralized processing units. Non-critical computations are performed at edge nodes close to data sources, which reduces communication delays and decreases the burden on central servers. This distribution of computational workloads is particularly important in large-scale industrial systems where real-time monitoring and rapid fault detection are required. By minimizing data transmission and processing delays, edge computing contributes to improved system responsiveness and operational efficiency. The framework also employs dynamic model scaling to enhance adaptability under varying industrial workloads. This mechanism adjusts the complexity of deep learning models according to real-time system requirements. During periods of low monitoring activity, simplified models are deployed to conserve computational resources. Conversely, during high-risk operational periods or abnormal system behavior, the framework activates more complex model configurations to improve analytical accuracy. This adaptive scaling strategy ensures efficient utilization of computational resources while maintaining high fault detection performance.

The 6G communication layer plays a vital role in enabling seamless data exchange among various components of the framework. This layer supports high-speed, low-latency communication between industrial sensors, monitoring devices, and centralized processing systems. By utilizing advanced 6G communication capabilities such as ultra-reliable low latency communication (URLLC) and massive machine-type communication (mMTC), the framework can manage extensive device connectivity while maintaining stable and reliable data transmission [29]. These communication features are essential for supporting real-time industrial monitoring applications involving numerous interconnected devices. Additionally, the framework incorporates several energy-aware operational strategies to improve overall system efficiency. Energy-efficient model training techniques such as transfer learning and model fine-tuning reduce the need for extensive training from initial stages, thereby lowering computational demands. Intelligent data filtering mechanisms eliminate redundant or low-value information before analysis, minimizing unnecessary processing overhead. Furthermore, adaptive resource allocation mechanisms dynamically assign computational resources based on real-time system demands, ensuring efficient energy utilization, particularly in distributed edge computing environments. By integrating advanced monitoring, optimization, and communication mechanisms, the proposed framework provides an effective and scalable solution for fault detection in 6G-enabled Industry 4.0 systems while maintaining balanced computational efficiency and operational reliability.

3. RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed advanced deep learning framework for fault diagnosis in Industry 4.0 (ADL-FDI4). The performance of ADL-FDI4 is compared against several state-of-the-art fault detection models, including semi-supervised deep convolutional neural network (semi-DCNN), fault diagnosis stacked autoencoder (FD-SAE), and genetic algorithm-support vector regression (GA-SVR). The evaluation focuses on three primary performance metrics: fault detection rate, computational efficiency (runtime), and energy consumption. Experiments were conducted in a simulated Industry 4.0 environment incorporating heterogeneous datasets, including time-series sensor signals, industrial image data, and graph-based network structures. The results demonstrate that ADL-FDI4 consistently outperforms baseline approaches across all evaluation metrics. The superior performance is primarily attributed to the hybrid integration of LSTM, CNNs, and graph convolutional networks (GCN), enabling effective processing of multimodal industrial data. Unlike conventional models that specialize in a single data format, ADL-FDI4 efficiently analyzes temporal, spatial, and relational data within a unified framework.

For time-series sensor data, the LSTM module significantly improved detection accuracy compared to traditional deep learning techniques. By effectively modeling temporal dependencies and long-term sequential patterns, ADL-FDI4 achieved a higher detection rate than standalone LSTM-based fault detection systems. The framework demonstrated strong capability in identifying evolving fault patterns in industrial signals, such as vibration anomalies and temperature fluctuations. In image-based fault detection tasks, the CNN component of ADL-FDI4 provided precise identification of defects in industrial equipment and production systems. The model achieved a detection rate of 73% on the Microsoft Azure predictive maintenance dataset, outperforming the baseline models, which achieved detection rates below 69% under the same experimental conditions. This improvement highlights the effectiveness of the hybrid architecture combined with the Branch-and-Bound hyperparameter optimization strategy. The optimization procedure systematically searched the hyperparameter space using heuristic-guided exploration, improving model configuration without excessive computational overhead.

The first set of experiments evaluated detection performance across four benchmark datasets while varying the number of injected faults. As illustrated in Figure 2, ADL-FDI4 consistently surpassed semi-DCNN, FD-SAE, and GA-SVR in detection accuracy. The unified processing of heterogeneous data allowed the proposed framework to maintain stable performance even as fault complexity increased. The second set of experiments focused on computational efficiency by comparing runtime performance under identical testing conditions. Figure 3 shows that ADL-FDI4 achieved faster training and inference times compared to baseline approaches. On the Microsoft Azure predictive maintenance dataset, the runtime difference between ADL-FDI4 and competing models was minimal, measured in only a few milliseconds. However, on the Case Western Reserve University (CWRU) Bearing dataset, the performance gap was more pronounced, with ADL-FDI4 demonstrating a substantially lower execution time. This difference is attributed to the architectural efficiency of ADL-FDI4, whereas baseline methods rely on complex multi-stage processing that combines deep feature extraction with separate classical machine learning classifiers.

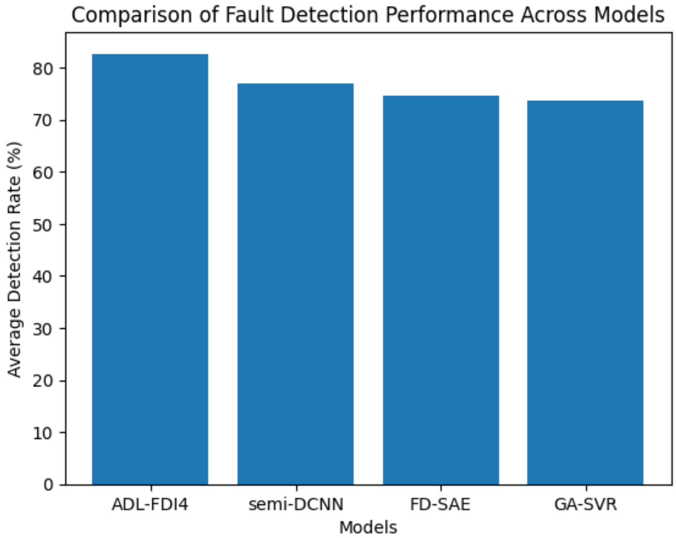

Figure 2. ADL-FDI4 accuracy in comparison to top-notch fault diagnosis systems

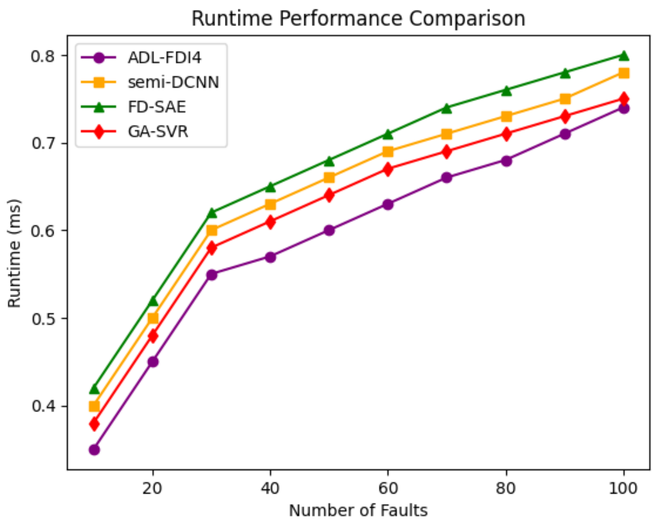

Figure 3. The ADL-FDI4's runtime in comparison to the most cutting-edge fault diagnosis solutions

The Branch-and-Bound optimization strategy played a significant role in reducing computational complexity. By efficiently tuning hyperparameters, the framework minimized redundant model configurations and accelerated convergence during training. This reduction in computational workload directly contributed to lower energy consumption during both training and inference stages. Energy efficiency analysis further confirmed that ADL-FDI4 required fewer computational resources compared to existing deep learning-based fault detection methods. The optimized architecture reduced memory utilization and processing cycles, leading to measurable energy savings. This balance between detection accuracy and computational efficiency makes ADL-FDI4 particularly suitable for large-scale 6G-enabled Industry 4.0 environments where continuous monitoring and real-time decision-making are essential. In contrast, traditional fault detection models often require separate pipelines for different data types, increasing system complexity and reducing scalability. ADL-FDI4's unified framework enables seamless integration of heterogeneous inputs without additional preprocessing modules, providing a practical advantage for real-world industrial deployments. Overall, the experimental results confirm that ADL-FDI4 delivers improved detection accuracy, reduced runtime, and enhanced energy efficiency compared to existing approaches, making it a robust and scalable solution for next-generation industrial fault diagnosis systems.

Although the ADL-FDI4 framework demonstrated strong performance across experimental evaluations, certain challenges remain that require further investigation. One notable limitation involves scalability when processing extremely large and continuously generated datasets in real-time industrial environments. While the proposed framework shows considerable improvements in computational efficiency and energy utilization, future enhancements could focus on integrating distributed processing mechanisms to support large-scale industrial deployments more effectively. The adoption of advanced distributed computing approaches, particularly edge and fog computing architectures, may help reduce processing latency and improve data handling capabilities by distributing computational workloads closer to data sources. Despite these limitations, the experimental findings confirm that ADL-FDI4 significantly outperforms conventional fault detection techniques in terms of detection accuracy, runtime efficiency, and optimized resource utilization. The ability of the framework to process heterogeneous data within a unified analytical structure makes it well-suited for complex smart manufacturing environments. Overall, ADL-FDI4 represents a reliable and efficient fault diagnosis solution capable of supporting the continuous technological evolution of Industry 4.0 systems.

4. CONCLUSION

The ADL-FDI4 framework marks a substantial advancement in developing efficient and reliable fault detection mechanisms for modern Industry 4.0 environments. By combining LSTM, CNN, and GCN architectures, the proposed system effectively processes heterogeneous industrial data within a unified analytical platform, thereby improving detection accuracy while reducing computational requirements. The incorporation of the Branch-and-Bound hyperparameter optimization strategy further enhances system performance by identifying optimal model configurations with reduced processing overhead. This optimization approach supports scalable deployment and makes ADL-FDI4 a suitable solution for emerging smart industrial infrastructures supported by advanced 6G communication technologies. Future research efforts will focus on improving the adaptability and scalability of the framework by integrating reinforcement learning techniques. Such integration would enable the system to dynamically adjust to changing industrial conditions and operational uncertainties. Additionally, the incorporation of edge computing strategies will be explored to distribute computational workloads closer to data sources, thereby minimizing communication delays and improving overall energy efficiency in large-scale industrial fault detection applications.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to their respective institutions for providing the necessary academic support, research facilities, and technical resources that made this research work possible. The authors also acknowledge the encouragement and guidance provided by their departments and research colleagues throughout the study. Their institutional support played a significant role in the successful completion of this research work.

FUNDING INFORMATION

The authors acknowledge that this research work was supported by their respective institutions through the provision of academic infrastructure and research facilities. No external funding was received for this study.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hareesha Dandamudi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chenchu Punnarao Bandi		✓				✓		✓	✓	✓	✓			
Simhadri Mallikarjuna Rao	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Palacharla SVS Sridhar	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	
Mythili Murugan	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Srikanth Kilaru	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Rama Krishna Paladugu	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this research work.

DATA AVAILABILITY

The data used to support the findings of this study are available from publicly accessible datasets. Additional data related to this research are available from the corresponding author upon reasonable request.

REFERENCES

[1] R. Chataut, M. Nankya, and R. Akl, "6G Networks and the AI Revolution—Exploring Technologies, Applications, and Emerging Challenges," *Sensors*, vol. 24, no. 6, p. 1888, Mar. 2024, doi: 10.3390/s24061888.

[2] Z. Jan *et al.*, "Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities," *Expert Systems with Applications*, vol. 216, p. 119456, Apr. 2023, doi: 10.1016/j.eswa.2022.119456.

[3] A. H. Sabry and U. A. B. U. Amirulddin, "A review on fault detection and diagnosis of industrial robots and multi-axis machines," *Results in Engineering*, vol. 23, 2024, doi: 10.1016/j.rineng.2024.102397.

[4] P. Bedi, S. B. Goyal, A. S. Rajawat, J. Kumar, S. Malik, and L. C. Radhakrishnan, "Industry Revolution 4.0: From Industrial Automation to Industrial Autonomy," in *Computational Intelligence for Modern Business Systems: Emerging Applications and Strategies*, 2024, pp. 321–356, doi: 10.1007/978-981-99-5354-7_17.

[5] K. Kotzias, F. A. Bukhsh, J. J. Arachchige, M. Daneva, and A. Abhishta, "Industry 4.0 and healthcare: Context, applications, benefits and challenges," *IET Software*, vol. 17, no. 3, pp. 195–248, Jun. 2023, doi: 10.1049/sfw2.12074.

[6] M. Cho and Y. Kim, "FPGA-Based Convolutional Neural Network Accelerator with Resource-Optimized Approximate Multiply-Accumulate Unit," *Electronics*, vol. 10, no. 22, p. 2859, Nov. 2021, doi: 10.3390/electronics10222859.

[7] M. Pietrołaj and M. Blok, "Resource constrained neural network training," *Scientific Reports*, vol. 14, no. 1, p. 2421, Jan. 2024, doi: 10.1038/s41598-024-52356-1.

[8] C. Zhang, Y. Chen, H. Chen, and D. Chong, "Industry 4.0 and its Implementation: a Review," *Information Systems Frontiers*, vol. 26, no. 5, pp. 1773–1783, Oct. 2024, doi: 10.1007/s10796-021-10153-5.

[9] A. S. George, "The Fourth Industrial Revolution: A Primer on Industry 4.0 and its Transformative Impact," *Partners Universal Innovative Research Publication*, vol. 2, no. 1, pp. 16–40, 2024, doi: 10.5281/zenodo.10671872.

[10] F. Salahdine, T. Han, and N. Zhang, "5G, 6G, and Beyond: Recent advances and future challenges," *Annals of Telecommunications*, vol. 78, no. 9–10, pp. 525–549, Oct. 2023, doi: 10.1007/s12243-022-00938-3.

[11] D. K. R. and S. Chavhan, "Shift to 6G: Exploration on trends, vision, requirements, technologies, research, and standardization efforts," *Sustainable Energy Technologies and Assessments*, vol. 54, p. 102666, Dec. 2022, doi: 10.1016/j.seta.2022.102666.

[12] N. Kumat. *et al.*, "Harnessing the Power of Big Data: Challenges and Opportunities in Analytics," *Tuijin Jishu/Journal of Propulsion Technology*, vol. 44, no. 2, pp. 363-371, Sep. 2023, doi: 10.52783/tjjpt.v44.i2.193.

[13] A. Patil, G. Soni, and A. Prakash, "Data-driven approaches for impending fault detection of industrial systems: a review," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 4, pp. 1326–1344, Apr. 2024, doi: 10.1007/s13198-022-01841-9.

[14] A. Sardashti and J. Nazari, "A learning-based approach to fault detection and fault-tolerant control of permanent magnet DC motors," *Journal of Engineering and Applied Science*, vol. 70, no. 1, p. 109, Dec. 2023, doi: 10.1186/s44147-023-00279-5.

[15] I. H. Sarker, "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," *SN Computer Science*, vol. 2, no. 6, p. 420, Nov. 2021, doi: 10.1007/s42979-021-00815-1.

[16] T. Ersavas, M. A. Smith, and J. S. Mattick, "Novel applications of Convolutional Neural Networks in the age of Transformers," *Scientific Reports*, vol. 14, no. 1, p. 10000, May 2024, doi: 10.1038/s41598-024-60709-z.

[17] Y. Zhu *et al.*, "Converting tabular data into images for deep learning with convolutional neural networks," *Scientific Reports*, vol. 11, no. 1, p. 11325, May 2021, doi: 10.1038/s41598-021-90923-y.

[18] E. A. Hinojosa-Palafox, O. M. Rodríguez-Elías, J. A. Hoyo-Montaño, and J. H. Pacheco-Ramírez, "Trends and Challenges of Data Management in Industry 4.0," in *LISS2019*, Singapore: Springer Singapore, 2020, pp. 213–225, doi: 10.1007/978-981-15-

5682-1_16.
[19] T. Mezair, Y. Djenouri, A. Belhadi, G. Srivastava, and J. C.-W. Lin, "A sustainable deep learning framework for fault detection in 6G Industry 4.0 heterogeneous data environments," *Computer Communications*, vol. 187, pp. 164–171, Apr. 2022, doi: 10.1016/j.comcom.2022.02.010.
[20] D. Mnyanghwalo, H. Kundaeli, E. Kalinga, and N. Hamisi, "Deep learning approaches for fault detection and classifications in the electrical secondary distribution network: Methods comparison and recurrent neural network accuracy comparison," *Cogent Engineering*, vol. 7, no. 1, Jan. 2020, doi: 10.1080/23311916.2020.1857500.
[21] S. Sinha and Y. M. Lee, "Challenges with developing and deploying AI models and applications in industrial systems," *Discover Artificial Intelligence*, vol. 4, no. 1, p. 55, Aug. 2024, doi: 10.1007/s44163-024-00151-2.
[22] A. van Wynsberghe, "Sustainable AI: AI for sustainability and the sustainability of AI," *AI and Ethics*, vol. 1, no. 3, pp. 213–218, Aug. 2021, doi: 10.1007/s43681-021-00043-6.
[23] T. T. Khoei, H. O. Slimane, and N. Kaabouch, "Deep learning: systematic review, models, challenges, and research directions," *Neural Computing and Applications*, vol. 35, no. 31, pp. 23103–23124, Nov. 2023, doi: 10.1007/s00521-023-08957-4.
[24] K. Bayoudh, "A survey of multimodal hybrid deep learning for computer vision: Architectures, applications, trends, and challenges," *Information Fusion*, vol. 105, p. 102217, May 2024, doi: 10.1016/j.inffus.2023.102217.
[25] K. Rahul, R. K. Banyal, and N. Arora, "A systematic review on big data applications and scope for industrial processing and healthcare sectors," *Journal of Big Data*, vol. 10, no. 1, 2023, doi: 10.1186/s40537-023-00808-2.
[26] A. G. Sheik *et al.*, "The role of Industry 4.0 enabling technologies for predicting and managing of algal blooms: Bridging gaps and unlocking potential," *Marine Pollution Bulletin*, vol. 212, 2025, doi: 10.1016/j.marpolbul.2024.117493.
[27] B. N. Bhukya, S. M. Kuchibhatla, N. K. Bhagavatham, T. L. Narayana, M. R. Chunduru, and B. K. Madhavi, "Implementation of meta-heuristic and deep learning algorithms for power system cybersecurity," *Bulletin of Electrical Engineering and Informatics*, vol. 15, no. 1, pp. 648–656, Feb. 2026, doi: 10.11591/eei.v15i1.8569.
[28] M. M. Rahman and A. K. Srivastava, "Detection, classification, and localization of faults and failures in photovoltaic arrays: A review, comparative analysis, and path forward," *Discover Energy*, vol. 6, 2026, doi: 10.1007/s43937-026-00136-5.
[29] Aarti, S. Gowroju, and S. I. Ansarullah, "A comprehensive review of developments and challenges in the 6G Internet of Things," *Discover Networks*, vol. 1, 2025, doi: 10.1007/s44354-025-00013-y.

BIOGRAPHIES OF AUTHORS

Hareesha Dandamudi is working as an Assistant Professor Department of Electronics and Communication Engineering, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada, Andhra Pradesh, India. Her research lines are communications and signal processing. She can be contacted at email: hareeshashyam@gmail.com.

Chenchu Punnarao Bandi currently is a Senior Architect at the Synopsys Inc., USA in R&D Engineering Solutions Group. His research interests low power high speed source synchronous interfaces which include memory interfaces MRDIMM, DDR, for high end computations like servers, data centres applications, and low power LPDDR for mobile and handheld devices, high band-width memory interfaces for graphic applications and die to die interconnects for multi die SoCs. He can be contacted at email: bpunnarao@gmail.com.

Dr. Simhadri Mallikarjuna Rao received the B.Tech. degree in Information Technology from Vignan in 2011, and the M.Tech. degree in Computer Science and Engineering from Andhra University in 2013. He successfully cleared the UGC-NET exam in December 2019 and joined as a full-time research scholar in 2020, subsequently earning their Ph.D. from ANU in 2025. With a rich academic career, they have served as both an Assistant Professor and Associate Professor across various reputed institutions. His primary research interests include machine learning, deep learning algorithms, cloud computing, and optimization techniques. He can be contacted at email: mallikarjun1254@gmail.com.

Palacharla SVS Sridhar currently is an Assistant Professor at the Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India. His research interests include machine learning and internet of things, computer science theory and methods, and software engineering. He can be contacted at email: psvssridhar@gmail.com.

Mythili Murugan presently is working as an Assistant Professor of the Department of Information Technology, M.Kumarasamy College of Engineering, Karur, Tamil Nadu, India. She has published the various papers in international journals and conferences. She is passionate about inspiring students through innovative teaching methods and fostering a strong learning environment. Her research interests are image processing, internet of things, artificial intelligence, and machine learning. She can be contacted at email: mythilimurugan7@gmail.com.

Mr. Srikanth Kilaru is an Assistant Professor in Department of Information Technology (IT) at Vignan's Nirula Institute of Technology and Science for Women, Peda Palakaluru, Guntur, Andhra Pradesh, India. His research interests are data mining, information retrieval systems, and software engineering. He can be contacted at email: sreekilaru@gmail.com.

Dr. Rama Krishna Paladugu is an Associate Professor in the Department of Computer Science and Engineering at R.V.R. and J.C. College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India. His research interests are machine learning, NLP, and information retrieval systems. He can be contacted at email: mails4prk@gmail.com.