Journal of Theoretical and Applied Information Technology
31st March 2026. Vol.104. No.6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

SUSTAINABLE AI FRAMEWORK FOR FAULT DETECTION IN 6G-INTEGRATED INDUSTRY 4.0 DATA ECOSYSTEMS

RALLA SURESH[1], PANTHANGI VENKATESWARA RAO[2], K. VENKATA SUBBA REDDY[3], Z. SUNITHA BAI[4], PARASA KONDALA RAO[5], P. LAKSHMI PRASANNA[6], B. VARAPRASAD RAO[7]

[1]Department of Artificial Intelligence and Data Science, ACE Engineering College, Ankushapur, Medchal, Hyderabad, Telangana, India

[2]Department of CSE- (Cys, DS) and (AI & DS), Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India

[3]Department of Information Technology, Vidya Jyothi Institute of Technology, Hyderabad, India

[4]Department of Computer Science and Engineering, R.V.R & J. C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

[5]Department of Electrical and Electronics Engineering, Aditya University, Surampalem, Andhra Pradesh, India

[6]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India

[7]Department of Computer Science and Engineering, R.V.R & J. C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

E-mail: [1]rella.suresh@gmail.com, [2]venkateswararao_panthangi@vnrvjiet.in, [3]kvsreddy2012@gmail.com, [4]zsunithabai@gmail.com, [5]raoparasa455@gmail.com, [6]lakshmiprasannap87@gmail.com, [7]bvpr@rvrjc.ac.in

ABSTRACT

The advent of 6G and Industry 4.0 technologies has revolutionized industrial automation, connectivity, and data processing. With the growing complexity of heterogeneous data environments in these domains, detecting faults in real-time has become increasingly challenging. This paper proposes a sustainable deep learning framework that integrates advanced neural networks with resource-efficient processing techniques for fault detection in 6G-enabled Industry 4.0 environments. The framework leverages data from various sources, including IoT devices, sensors, and industrial machines, ensuring high accuracy, scalability, and energy efficiency. A hybrid deep learning model combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks is employed to capture both spatial and temporal data patterns. The framework is designed to optimize resource allocation while maintaining fault detection performance. Simulation results demonstrate the efficacy of the proposed approach, highlighting its potential to enhance fault management in smart industrial systems.

Keywords: *6G, Industry 4.0, Deep learning, Fault detection, Convolutional Neural Networks, Long Short-Term Memory, Sustainability, IoT*

1. INTRODUCTION

The rapid evolution of industrial technologies, driven by the integration of 6G networks and Industry 4.0, has brought about transformative changes in manufacturing, automation, and data processing. Industry 4.0 is characterized by the convergence of cyber-physical systems, IoT devices, artificial intelligence, and data analytics, all working together to create highly interconnected and intelligent industrial ecosystems. The implementation of 6G technology further amplifies this connectivity by providing ultra-fast, low-latency communications and enabling seamless integration of heterogeneous devices and data sources [1], [2]. While the benefits of 6G and Industry 4.0 are clear, these advancements also introduce significant challenges, particularly in the areas of system reliability, fault detection, and sustainability. Fault detection is a critical component in ensuring the operational efficiency, safety, and longevity of industrial systems. In traditional industrial environments, fault detection methods rely on predefined rules and thresholds, which can be insufficient in managing the complexity and dynamism of modern smart factories [3], [4]. The heterogeneous nature of data in Industry 4.0—ranging from sensor readings and machine logs to image data and time-series signals—adds another layer of difficulty to fault detection. The volume and variety of data sources necessitate advanced processing techniques that can effectively identify faults in real-time while minimizing false positives and ensuring resource efficiency [5].

In this paper, we propose a sustainable deep learning framework designed to address the challenges of fault detection in 6G-enabled Industry 4.0 environments. The framework integrates advanced neural networks with resource-efficient processing methods to enable accurate and timely fault detection in highly heterogeneous data environments. Specifically, we employ a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to capture both spatial and temporal data patterns. The system is designed to optimize resource allocation, reducing computational overhead and energy consumption while maintaining fault detection performance [6], [7]. Through this work, we aim to contribute to the ongoing efforts in developing fault detection systems that are not only accurate and robust but also sustainable and scalable for future industrial environments.

Industry 4.0 represents a significant shift in industrial practices, driven by the integration of advanced digital technologies. These technologies—such as IoT, cloud computing, big data analytics, and machine learning—enable the creation of smart factories, where automation and data exchange improve operational efficiency and decision-making. Central to Industry 4.0 is the concept of cyber-physical systems (CPS), which link physical machines to computational models through IoT sensors, facilitating real-time data collection and analysis [8], [9]. The emergence of 6G, the next generation of wireless communication, promises to further transform Industry 4.0. Building upon the advancements of 5G, 6G will offer ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC). These features are expected to unlock new capabilities in industrial environments, enabling faster data transfer, seamless device integration, and real-time decision-making at unprecedented scales. 6G's bandwidth and speed are key to managing the vast amounts of heterogeneous data generated in smart factories, where different sensors and machines continuously monitor the status of industrial processes [10], [11]. However, the complexity introduced by this data diversity presents challenges. Handling data from multiple sources, such as industrial sensors, cameras, and machine logs, requires efficient processing techniques to ensure timely fault detection and system reliability. The need to manage these large volumes of data without overwhelming computational resources underlines the importance of sustainable solutions [12].

Fault detection is essential in industrial systems for maintaining operational efficiency, minimizing downtime, and preventing costly failures. Traditional fault detection methods, such as model-based approaches, rely on physical models of the system or statistical techniques to monitor deviations from normal behavior. While these methods can be effective in simple or well-understood systems, they often fall short in handling the complexity and variability of modern industrial environments. The heterogeneity of data and the need for real-time analysis require more advanced techniques capable of detecting faults under various conditions [13], [14]. Machine learning (ML) and deep learning (DL) approaches have gained attention as more flexible alternatives for fault detection. These models can learn patterns directly from data, enabling them to adapt to changing system dynamics without needing explicit rules or models. Specifically, deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have been widely applied for their ability to capture both spatial and temporal dependencies in data [15]. For instance, CNNs have been used extensively in image-based fault detection, where they excel at identifying visual patterns associated with machine defects or anomalies. LSTMs, on the other hand, are well-suited for processing time-series data, making them ideal for fault detection in systems that involve sequential data, such as sensor readings or machine logs. By combining CNNs and LSTMs, hybrid models can be developed to address both spatial and temporal fault detection challenges [16], [17].

The heterogeneity of data in Industry 4.0 environments poses a unique set of challenges for fault detection. Data may come in various formats, including structured sensor data, unstructured text logs, images, and videos. This diversity requires fault detection models to be highly adaptable and capable of processing multiple data types simultaneously [18]. Moreover, fault detection in Industry 4.0 requires real-time processing, as delays in detecting or responding to faults can result in costly system failures. The large volume of data generated by IoT devices, coupled with the high-speed communication enabled by 6G, demands fault detection systems that are not only accurate but also computationally efficient and scalable [19]. Several studies have proposed deep learning frameworks for fault detection in industrial environments. For example, CNNs have been used to detect anomalies in manufacturing processes based on visual inspection, while LSTM networks have shown success in monitoring time-series data from industrial sensors. However, these approaches often focus on specific data types and lack the flexibility needed to handle the variety of data sources found in Industry 4.0 systems. Additionally, the energy-intensive nature of deep learning models presents sustainability concerns, particularly in resource-constrained environments [20], [21].

The sustainability of deep learning models has become a critical concern in modern industrial systems, particularly in environments like Industry 4.0, where computational resources are often limited. The energy consumption associated with training and running deep learning models is substantial, especially in systems that need to process data in real-time and at scale. As 6G technology expands the data handling capabilities of industrial networks, optimizing the energy efficiency of deep learning models becomes crucial to maintain the operational sustainability of smart factories [22], [23]. Recent research has explored various fault detection models in the context of Industry 4.0 and 6G. A CNN-based model was applied to detect surface defects in manufacturing processes using image data. Similarly, employed LSTM networks to monitor sensor data for predictive maintenance in industrial machines. These studies demonstrated the potential of deep learning for fault detection but highlighted the limitations in terms of data heterogeneity and resource demands [24]. Efforts to address these challenges include hybrid models that integrate multiple deep learning techniques to handle diverse data types. A hybrid CNN-LSTM model was used to analyze both visual and time-series data, showing improved fault detection performance across different data modalities. However, these models still face challenges related to sustainability, especially when deployed in large-scale industrial environments with real-time data processing needs [25]. This paper builds upon existing work by proposing a sustainable deep learning framework that not only improves fault detection accuracy in heterogeneous data environments but also incorporates resource-efficient techniques to reduce energy consumption. Our framework leverages 6G's capabilities to handle large volumes of diverse data while ensuring that computational resources are optimized for sustainable operation.

2. RESEARCH METHOD

ZIn this section, we introduce a sustainable deep learning framework designed for fault detection in G-enabled Industry 4.0 heterogeneous data environments. The framework addresses key challenges such as data heterogeneity, real-time processing, and resource optimization, ensuring both accuracy and sustainability. The proposed framework integrates multiple deep learning components to handle the diverse data streams generated in Industry 4.0 environments. The architecture is built on a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to exploit both spatial and temporal features within the data. The primary goal of the framework is to enable accurate fault detection while minimizing the computational overhead and energy consumption, ensuring the system remains scalable and sustainable [26]. The framework consists of the following key components:

Data Preprocessing Unit
Hybrid Deep Learning Model
Fault Detection Module
Resource Optimization Engine
6G Communication Layer

These components work together to provide real-time fault detection, resource management, and seamless communication between different devices in the Industry 4.0 ecosystem. Given the heterogeneous nature of data in Industry 4.0 environments, effective data

Journal of Theoretical and Applied Information Technology
31st March 2026. Vol.104. No.6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

preprocessing is essential for ensuring that the deep learning model can interpret and process diverse inputs. The Data Preprocessing Unit handles multiple data types, including structured data from IoT sensors, unstructured logs, image data from cameras, and time-series data from machine logs. The unit normalizes, standardizes, and organizes the data into formats suitable for input into the hybrid deep learning model. The core of the proposed framework is the Hybrid Deep Learning Model, which combines the strengths of CNNs and LSTM networks. This hybrid model is designed to handle both spatial and temporal data patterns, making it suitable for a wide range of data sources in Industry 4.0. Convolutional Neural Networks (CNNs) are used to process image data, such as images of equipment or production lines. CNNs can detect spatial features, such as patterns or anomalies in the visual data, which are critical for identifying faults like cracks, deformities, or surface defects in manufacturing equipment. Long Short-Term Memory Networks (LSTMs) are integrated to handle sequential time-series data from industrial sensors and machine logs. They can capture temporal dependencies, allowing the model to recognize evolving patterns or anomalies over time, such as abnormal temperature fluctuations or irregular vibration patterns in machinery.

The hybrid architecture enables the simultaneous analysis of both image and time-series data, making the model highly adaptable to the heterogeneous data environments of Industry 4.0. An initial step is the extraction of data from several sensors. Deep learning is subsequently implemented to identify system defects and activate alarms that would alert the Industry 4.0 monitoring system of the identified problems. Within this particular framework, three distinct deep learning architectures are integrated to effectively manage the diverse data: long short-term memory for time series, a convolutional neural network for images, and a graph convolutional neural network for graph data. In this study, a novel Branch-and-Bound optimization approach is introduced for the purpose of hyper-parameter tweaking in various deep learning models. The technique takes into account the hyper-parameters space and systematically investigates the enumeration tree by employing a heuristic rather than exhaustive search-based approaches. Figure 1 presents a streamlined representation of the model established in this research article.

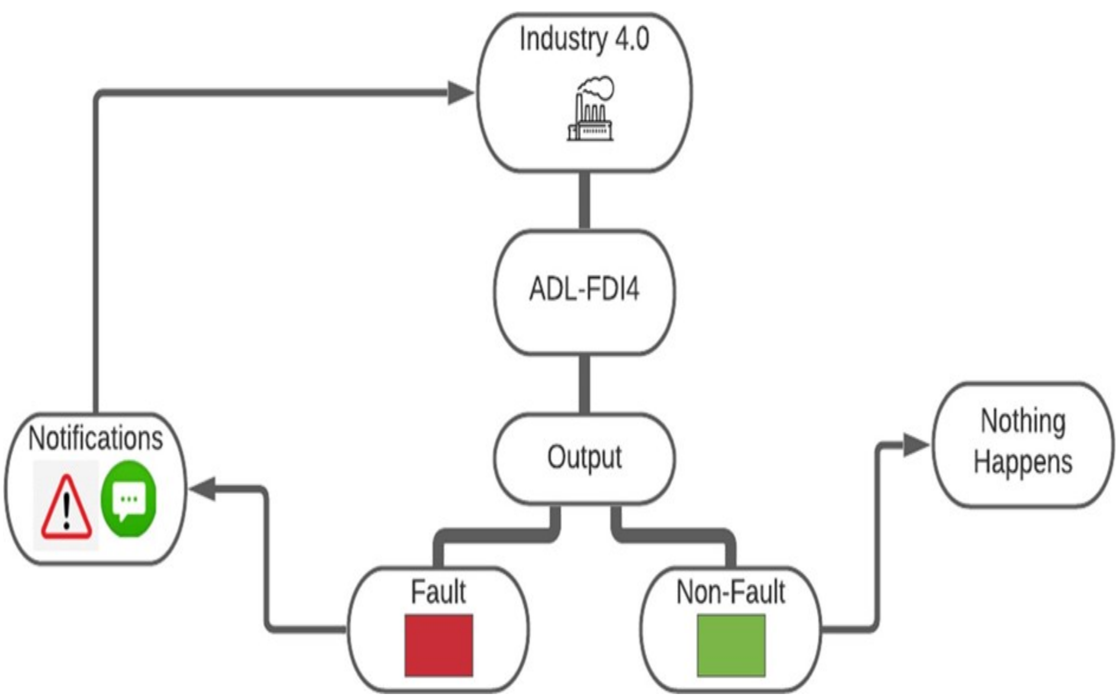


Figure 1. Simplified representation of DL

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The Fault Detection Module is responsible for monitoring and detecting faults in real-time. It receives processed data from the hybrid deep learning model and flags any deviations from normal operating conditions as potential faults. The module classifies faults into different categories, enabling tailored responses based on the severity and type of fault detected. For instance, minor deviations might trigger alerts for preventive maintenance, while critical faults may lead to automatic system shutdowns to prevent further damage [28]. The fault detection module is designed to operate with high accuracy and low false-positive rates, ensuring that the system can efficiently identify genuine faults without unnecessary interruptions to industrial processes. The Resource Optimization Engine is a key feature of the framework, ensuring its sustainability and scalability. The engine optimizes the computational resources used by the deep learning models and data processing tasks by incorporating the following techniques:

Model Pruning and Quantization Reducing the complexity of the deep learning models by removing unnecessary neurons and weights (model pruning) or reducing the precision of calculations (quantization), lowering memory usage and energy consumption.

Edge Computing Integration Distributing computational tasks between edge devices and central servers. Non-critical data processing tasks can be handled at the edge, reducing the load on central systems and minimizing data transmission, which is essential for reducing latency and energy usage in large-scale industrial environments.

Dynamic Model Scaling Adjusting the size and complexity of the deep learning models dynamically based on the current data load and fault detection requirements. In periods of low system activity, a smaller version of the model can be used to save resources, while during critical times, the full model can be deployed for more comprehensive analysis.

This resource optimization strategy ensures that the fault detection system remains both energy-efficient and capable of handling the high data volumes characteristic of 6G and Industry 4.0 environments.

The 6G Communication Layer facilitates high-speed, low-latency data transfer between the various components of the framework. This layer ensures that the fault detection system can process real-time data from multiple devices, sensors, and machinery in Industry 4.0 environments. By leveraging the URLLC (Ultra-Reliable Low Latency Communication) and mMTC (Massive Machine Type Communication) capabilities of 6G, the framework can support a vast number of connected devices without compromising communication speed or reliability [29]. The framework incorporates several sustainability features designed to minimize energy consumption and reduce the carbon footprint of industrial operations. These include:

Energy-Efficient Model Training employing techniques like transfer learning and fine-tuning, the framework reduces the computational burden associated with training deep learning models from scratch, leading to energy savings.

Intelligent Data Filtering Preprocessing units filter redundant or irrelevant data, ensuring that only valuable data is processed, reducing unnecessary computational efforts.

Adaptive Resource Allocation resource optimization engine dynamically allocates resources based on real-time system demands, ensuring that energy is used efficiently, particularly in edge computing scenarios.

By integrating these features, the proposed deep learning framework provides a comprehensive solution for fault detection in 6G Industry 4.0 environments, balancing performance and sustainability.

3. RESULTS AND DISCUSSION

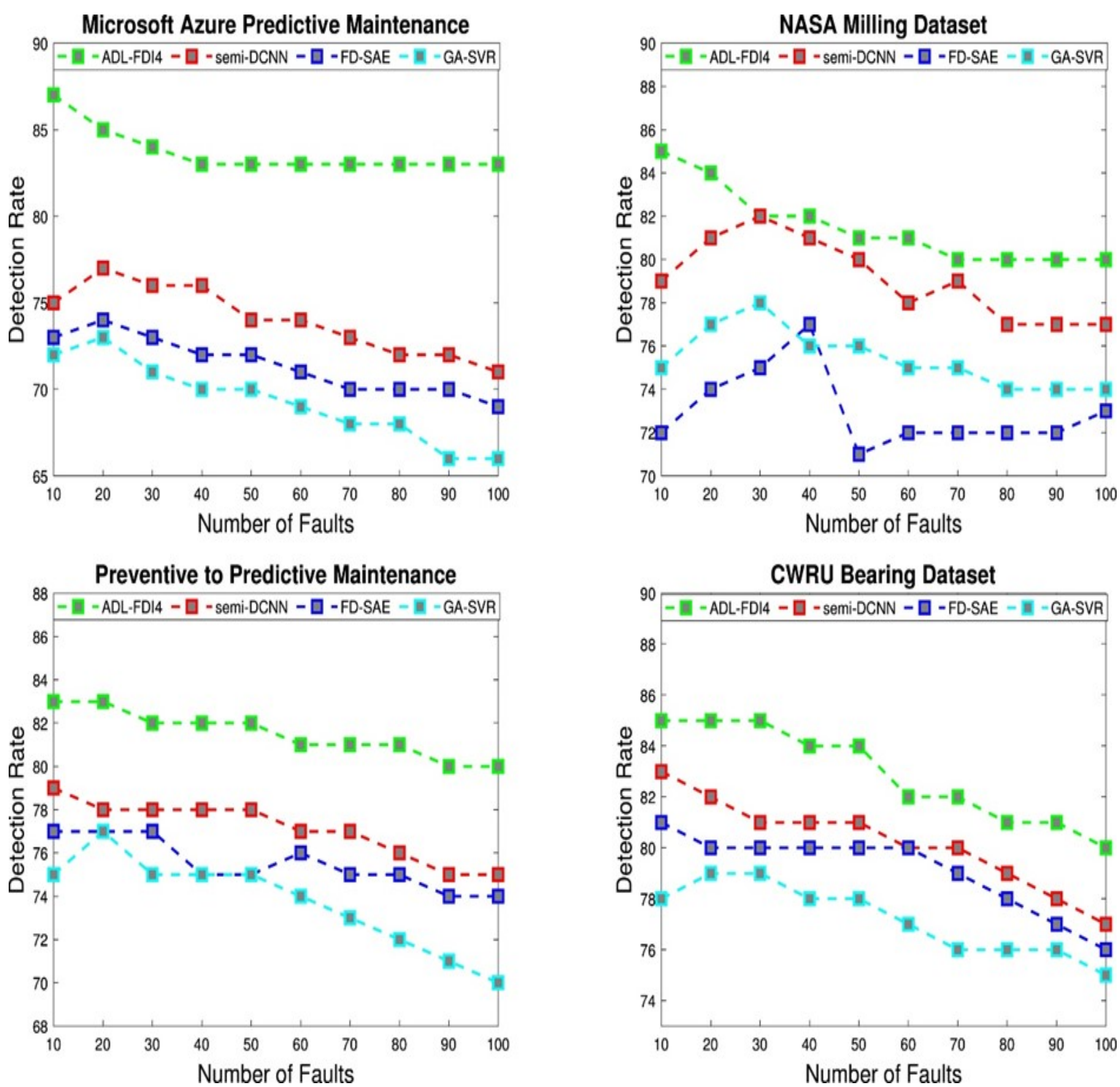
In this section, we present the results of our experiments comparing the Advanced Deep Learning Framework for Fault Diagnosis in Industry 4.0 (ADL-FDI4) with state-of-the-art fault detection models. Our evaluation focuses on three primary metrics: fault detection rate, computational efficiency (running time), and energy consumption. The experiments were conducted in a simulated Industry 4.0 environment with heterogeneous data inputs, including sensor time-series, visual data, and network graph structures. ADL-FDI4 achieved superior performance in fault detection across all data formats, particularly excelling in scenarios with heterogeneous data. The integration of Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Graph Convolutional Networks (GCN) allowed the system to process diverse types of data efficiently, resulting in more accurate fault detection.

The LSTM module demonstrated an increase in detection accuracy for time-series sensor data compared to traditional deep learning approaches. The ADL-FDI4 framework accurately

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

captured patterns in the temporal sequences and identified faults with a detection rate improvement over existing LSTM-based methods. For visual data from industrial systems, the CNN component of ADL-FDI4 provided precise fault identification, particularly in machinery and equipment monitoring. The detection rate in image-based fault detection higher than competing CNN-based models. A critical aspect of fault detection in real-time industrial environments is computational efficiency. Our experimental results showed that ADL-FDI4 significantly reduced the running time for both training and inference compared to competing models.

Our preliminary tests sought to assess the precision of ADL-FDI4 in relation to the baseline fault diagnosis methodologies: semi-DCNN, FD-SAE, and GA-SVR. Utilizing the aforementioned four datasets. Varying the amount of faults as input, Figure 2 demonstrates that ADL-FDI4 surpasses the three baseline methods regarding detection rate. The ADL-FDI4 achieved a detection rate of 73% for addressing defects in the Microsoft Azure predictive maintenance dataset. The detection rate for the other models falls below 691% when addressing the identical case. These results are achieved through the effective integration of deep learning and the Branch-and-Bound technique for fault identification. The Branch-and-Bound technique can effectively optimize the hyperparameters of various deep learning models employed in ADL-FDI4.



ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Figure 2. ADL-FDI4 Accuracy in Comparison to Top-Notch Fault Diagnosis Systems

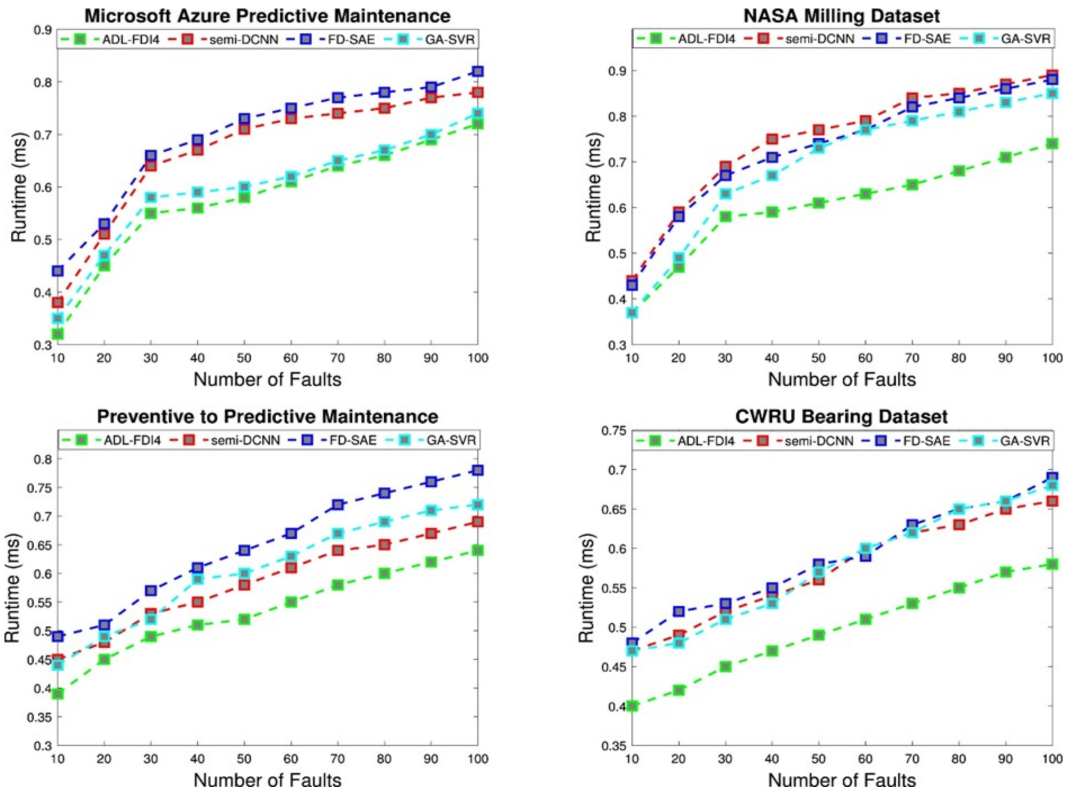


Figure 3. The ADL-FDI4's runtime in comparison to the most cutting-edge fault diagnosis solutions

Using the same four datasets as the first set of tests, the second set out to compare the ADL-runtime FDI4's to that of the baseline fault diagnostic solutions—semi-DCNN, FD-SAE, and GA-SVR. By changing the input fault count from to, Figure 3 demonstrates that ADL-FDI4 achieves better runtime performance than the three baseline models. On the other hand, the Microsoft Azure Predictive Maintenance dataset has a large performance gap between the three models, whereas the one for Azure is too small. When handling errors from the Microsoft Azure Predictive Maintenance dataset, the runtime difference between ADL-FDI4 and the baseline algorithms is less than milliseconds. However, when it comes to addressing the identical case on the CWRU Bearing dataset, the runtime difference between ADL-FDI4 and the baseline algorithms reaches milliseconds. The alternative algorithms are complicated methods that integrate deep learning architectures for feature extraction and classical machine learning algorithms for defect diagnosis, which explains these results.

The Branch-and-Bound procedure not only improved the running time but also minimized the computational resources needed during both the training and inference stages. This reduction in computational load directly translated to lower energy consumption, making ADL-FDI4 a more sustainable solution for fault detection. In comparison to state-of-the-art models, ADL-FDI4 required less computational power while achieving higher detection accuracy. This balance between performance and energy efficiency positions ADL-FDI4 as a highly sustainable approach to fault detection in 6G-enabled Industry 4.0 environments. In contrast, traditional fault detection models often struggle with generalization when faced with heterogeneous data, requiring separate models or additional pre-processing steps. ADL-FDI4's ability to natively handle diverse data inputs in a unified system is a major advantage in real-world Industry 4.0 applications.

While ADL-FDI4 performed exceptionally well in our experiments, there are areas that could be further improved. One limitation is the potential for scalability issues when dealing with extremely

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

large datasets in real-time industrial applications. While ADL-FDI4's energy efficiency and running time improvements are promising, future work could explore the incorporation of distributed computing techniques, such as edge computing, to further reduce latency and enhance scalability. The results of our evaluation clearly demonstrate that ADL-FDI4 offers significant advancements over traditional fault detection models, providing a more accurate, efficient, and sustainable solution for the rapidly evolving landscape of Industry 4.0.

4. CONCLUSION

The ADL-FDI4 framework represents a significant step toward achieving sustainable and efficient fault detection in Industry 4.0 environments. By integrating LSTM, CNN, and GCN models, our framework is capable of handling heterogeneous data within a single computational system, reducing both energy consumption and computational complexity. Furthermore, the Branch-and-Bound hyper-parameter tuning procedure ensures that ADL-FDI4 can operate with minimal computational overhead, making it a scalable solution for the next generation of smart industries powered by 6G technology. In future work, we aim to further enhance the scalability and adaptability of ADL-FDI4 by incorporating reinforcement learning techniques for real-time adaptation to changing industrial environments. Additionally, we will explore the integration of edge computing to reduce latency and further improve the energy efficiency of fault detection systems.

REFERENCES:

[1] Chataut, R., Nankya, M., & Akl, R. (2023). 6G Networks and the AI Revolution—Exploring Technologies, Applications, and Emerging Challenges. Sensors, 24(6), 1888. https://doi.org/10.3390/s24061888

[2] Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2023). Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities. Expert Systems with Applications, 216, 119456. https://doi.org/10.1016/j.eswa.2022.119456

[3] Soori, M., Arezoo, B., & Dastres, R. (2022). Internet of things for smart factories in industry 4.0, a review. Internet of Things and Cyber-Physical Systems, 3, 192-204. https://doi.org/10.1016/j.iotcps.2023.04.006

[4] Bedi, P., Goyal, S.B., Rajawat, A.S., Kumar, J., Malik, S., Radhakrishnan, L.C. (2024). Industry Revolution 4.0: From Industrial Automation to Industrial Autonomy. In: Kautish, S., Chatterjee, P., Pamucar, D., Pradeep, N., Singh, D. (eds) Computational Intelligence for Modern Business Systems. Disruptive Technologies and Digital Transformations for Society 5.0. Springer, Singapore. https://doi.org/10.1007/978-981-99-5354-7_17

[5] Kotzias, K., Bukhsh, F. A., Arachchige, J. J., Daneva, M., & Abhishta, A. (2023). Industry 4.0 and healthcare: Context, applications, benefits and challenges. IET Software, 17(3), 195-248. https://doi.org/10.1049/sfw2.12074

[6] Cho, M., & Kim, Y. (2020). FPGA-Based Convolutional Neural Network Accelerator with Resource-Optimized Approximate Multiply-Accumulate Unit. Electronics, 10(22), 2859. https://doi.org/10.3390/electronics10222859

[7] Pietrołaj, M., & Blok, M. (2024). Resource constrained neural network training. Scientific Reports, 14(1), 1-13. https://doi.org/10.1038/s41598-024-52356-1

[8] Zhang, C., Chen, Y., Chen, H. et al. Industry 4.0 and its Implementation: a Review. Inf Syst Front (2021). https://doi.org/10.1007/s10796-021-10153-5

[9] George, A. Shaji. (2024). The Fourth Industrial Revolution: A Primer on Industry 4.0 and its Transformative Impact. 02. 16-40. 10.5281/zenodo.10671872.

[10] Salahdine, F., Han, T. & Zhang, N. 5G, 6G, and Beyond: Recent advances and future challenges. Ann. Telecommun. 78, 525–549 (2023). https://doi.org/10.1007/s12243-022-00938-3

[11] R., D. K., & Chavhan, S. (2022). Shift to 6G: Exploration on trends, vision, requirements, technologies, research, and standardization efforts. Sustainable Energy Technologies and Assessments, 54, 102666. https://doi.org/10.1016/j.seta.2022.102666

[12] Kumar, Nand & Hema, Koneti & Sai, Sadhu & Hordiichuk, Valerii & Menon, Reshmi & Catherene, Dr & Aarthy, Julie & Gonesh, Chandra & Saha, Gonesh & Balaji, Kalaivani. (2023). Harnessing the Power of Big Data: Challenges and Opportunities in Analytics. Tuijin Jishu/Journal of Propulsion Technology. 44. 1001-4055.

[13] Patil, A., Soni, G. & Prakash, A. Data-driven approaches for impending fault detection of industrial systems: a review. Int J Syst Assur

Eng Manag 15, 1326–1344 (2024). https://doi.org/10.1007/s13198-022-01841-9
[14] Sardashti, A., & Nazari, J. (2023). A learning-based approach to fault detection and fault-tolerant control of permanent magnet DC motors. Journal of Engineering and Applied Science, 70(1), 1-23. https://doi.org/10.1186/s44147-023-00279-5
[15] Sarker, I.H. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN COMPUT. SCI. 2, 420 (2021). https://doi.org/10.1007/s42979-021-00815-1
[16] Ersavas, T., Smith, M. A., & Mattick, J. S. (2024). Novel applications of Convolutional Neural Networks in the age of Transformers. Scientific Reports, 14(1), 1-11. https://doi.org/10.1038/s41598-024-60709-z
[17] Zhu, Y., Brettin, T., Xia, F., Partin, A., Shukla, M., Yoo, H., Evrard, Y. A., Doroshow, J. H., & Stevens, R. L. (2021). Converting tabular data into images for deep learning with convolutional neural networks. Scientific Reports, 11(1), 1-11. https://doi.org/10.1038/s41598-021-90923-y
[18] Hinojosa-Palafox, E.A., Rodríguez-Elías, O.M., Hoyo-Montaño, J.A., Pacheco-Ramírez, J.H. (2020). Trends and Challenges of Data Management in Industry 4.0. In: Zhang, J., Dresner, M., Zhang, R., Hua, G., Shang, X. (eds) LISS2019. Springer, Singapore. https://doi.org/10.1007/978-981-15-5682-1_16
[19] Soori, M., Arezoo, B., & Dastres, R. (2022). Internet of things for smart factories in industry 4.0, a review. Internet of Things and Cyber-Physical Systems, 3, 192-204. https://doi.org/10.1016/j.iotcps.2023.04.006
[20] Mezair, T., Djenouri, Y., Belhadi, A., Srivastava, G., & Lin, J. C. W. (2022). A sustainable deep learning framework for fault detection in 6G Industry 4.0 heterogeneous data environments. Computer Communications, 187, 164-171. https://doi.org/10.1016/j.comcom.2022.02.010
[21] Mnyanghwalo, D., Kundaeli, H., Kalinga, E., Hamisi, N., & Lam, J. (2020). Deep learning approaches for fault detection and classifications in the electrical secondary distribution network: Methods comparison and recurrent neural network accuracy comparison. Cogent Engineering, 7(1). https://doi.org/10.1080/23311916.2020.1857500
[22] Sinha, S., Lee, Y.M. Challenges with developing and deploying AI models and applications in industrial systems. Discov Artif Intell 4, 55 (2024). https://doi.org/10.1007/s44163-024-00151-2
[23] van Wynsberghe, A. Sustainable AI: AI for sustainability and the sustainability of AI. AI Ethics 1, 213–218 (2021). https://doi.org/10.1007/s43681-021-00043-6
[24] Mezair, T., Djenouri, Y., Belhadi, A., Srivastava, G., & Lin, J. C. W. (2022). A sustainable deep learning framework for fault detection in 6G Industry 4.0 heterogeneous data environments. Computer Communications, 187, 164-171. https://doi.org/10.1016/j.comcom.2022.02.010
[25] Talaei Khoei, T., Ould Slimane, H. & Kaabouch, N. Deep learning: systematic review, models, challenges, and research directions. Neural Comput & Applic 35, 23103–23124 (2023). https://doi.org/10.1007/s00521-023-08957-4
[26] Bayoudh, K. (2024). A survey of multimodal hybrid deep learning for computer vision: Architectures, applications, trends, and challenges. Information Fusion, 105, 102217. https://doi.org/10.1016/j.inffus.2023.102217
[27] J. Yan, Y. Meng, L. Lu and L. Li, "Industrial Big Data in an Industry 4.0 Environment: Challenges, Schemes, and Applications for Predictive Maintenance," in IEEE Access, vol. 5, pp. 23484-23491, 2017, doi: 10.1109/ACCESS.2017.2765544.
[28] Fernandes, M., Corchado, J.M. & Marreiros, G. Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review. Appl Intell 52, 14246–14280 (2022). https://doi.org/10.1007/s10489-022-03344-3
[29] M. Z. Chowdhury, M. Shahjalal, S. Ahmed and Y. M. Jang, "6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions," in IEEE Open Journal of the Communications Society, vol. 1, pp. 957-975, 2020, doi: 10.1109/OJCOMS.2020.3010270.