Sustainable Deep Learning-Based Fault Detection for Next-Generation 6G Networks

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***Abstract*—Tech advances like 6G and Industry 4.0 have transformed data processing, communication, and industrial automation. Real-time problem detection is difficult due to the rising complexity of heterogeneous data environments across sectors. Many industries are undergoing this shift, requiring reliable fault detection technologies. This research provides a deep learning framework for fault identification in Industry 4.0 scenarios driven by 6G infrastructure using advanced neural networks and improved processing techniques. The framework uses data from sensors, IoT devices, and industrial machines to improve problem identification accuracy, scalability, and energy efficiency. A hybrid deep learning model uses CNNs and LSTMs to extract spatial and temporal patterns from data. Fusing helps the system to investigate complex fault characteristics while optimizing computational resources. The framework balances resource allocation with detection accuracy to create a dependable and intelligent fault management solution. Simulation findings show that the proposed approach is efficient and suitable for industrial use. These findings can improve fault management tactics and help build resilient, smart, and sustainable Industry 4.0 systems.**

***Index Terms*—6G, Industry 4.0, Deep learning, Fault detection, Convolutional Neural Networks, Long Short-Term Memory, sustainability, IoT**

I. Introduction

THE swift advancement of industrial technology, propelled by the integration of 6G networks and Industry 4.0, has led to significant changes in production, automation, and data processing. The concept of Industry 4.0 encompasses the amalgamation of cyber-physical systems, Internet of Things-connected devices, artificial intelligence, and data analytics. This integration leads to the creation of industrial ecosystems characterized by high levels of interconnectivity and intelligence. The deployment of 6G technology enhances connectivity by providing communications that are remarkably swift and exhibit minimal latency, while also facilitating the seamless integration of diverse devices and data sources [1], [2]. While the advantages of 6G and Industry 4.0 are clearly evident, these developments also introduce a considerable array of challenges, especially concerning system reliability, fault identification, and sustainability. Identifying faults plays a crucial role in maintaining the operational efficiency, safety, and longevity of production systems. In standard industrial environments, systems for detecting problems rely on established rules and thresholds. The existing limitations may be inadequate for addressing the complexity and dynamism inherent in contemporary smart factories [3], [4]. The process of identifying faults is further complicated by the diverse characteristics of the data produced by Industry 4.0. The characteristics encompass sensor readings, machine logs, image data, and time-series signals. The vast array and multitude of data sources necessitate intricate processing techniques. It is essential for these methods to accurately identify faults in real time, while also reducing the occurrence of false positives and optimizing resource utilization [5].

This study aims to introduce a deep learning system that is sustainable and effectively tackles the challenges associated with fault detection in 6G-enabled Industry 4.0 settings. The framework combines advanced neural networks with resource-efficient processing methods to enhance the accuracy and speed of problem identification across diverse data scenarios. To uncover patterns in spatial and temporal data, we employ a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. The system aims to enhance resource allocation, thereby minimizing computational overhead and energy usage while preserving the efficacy of problem detection [6], [7]. This work aims to enhance the creation of fault detection systems that are precise, resilient, sustainable, and scalable for future applications in industrial environments.

The integration of cutting-edge digital technology is the key factor propelling the notable shift known as Industry 4.0, marking a profound transformation in industrial practices. Technologies such as the Internet of Things (IoT), cloud

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computing, big data analytics, and machine learning enable the development of smart factories. These technologies enhance operational efficiency and empower decision-making by automating processes and enabling data exchange. The notion of cyber-physical systems (CPS) is fundamental to Industry 4.0. These systems link physical equipment to computational models via Internet of Things (IoT) sensors, facilitating real-time data collection and analysis [8], [9]. With the advent of the sixth generation of wireless connectivity, or 6G, a significant transformation of the fourth industrial revolution, or Industry 4.0, is anticipated. The emergence of ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and extensive machine-type communication (mMTC) will represent significant advancements that 6G will bring to the foundations laid by 5G. These characteristics are expected to enable the implementation of new capabilities in industrial settings. To effectively handle the vast quantities of diverse data produced in smart factories, which are outfitted with numerous sensors and devices that constantly track industrial processes, the bandwidth and speed of 6G are essential. Challenges emerge due to the intricate nature stemming from the variety of the data. When handling data from diverse sources, including industrial sensors, cameras, and machine logs, it is essential to employ effective processing techniques to guarantee the prompt detection of flaws and the reliability of the system. The importance of sustainable solutions is underscored by the need to handle large volumes of data while minimizing the strain on processing resources [10] - [12].

To ensure operational efficiency, minimize downtime, and avert expensive breakdowns, fault detection plays a crucial role in industrial systems. To pinpoint discrepancies from the standard performance of the system, traditional fault detection techniques, including model-based methods, depend on either statistical approaches or physical representations of the system. While these strategies may yield positive results in straightforward or simplistic systems, they often fall short in effectively addressing the complexity and variability inherent in contemporary industrial environments. The diverse range of data and the need for immediate analysis demand the creation of more advanced techniques capable of identifying errors across different contexts [13], [14]. Recent years have seen a growing interest in methodologies that are more adaptive for fault identification, including machine learning (ML) and deep learning (DL). The ability of these models to identify patterns directly from the data allows for adaptation to the constantly evolving dynamics of the system, eliminating the necessity for explicit rules or models. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks represent significant advancements in deep learning models, recognized for their proficiency in understanding spatial and temporal relationships within data. Image-based fault detection is a prevalent application of convolutional neural networks (CNNs), which have shown proficiency in identifying visual patterns linked to machine defects or anomalies [15]. LSTMs excel at processing time-series data, making them well-suited for identifying problems in systems that utilize sequential data, like sensor readings or machine logs. Hybrid models can be developed by combining CNNs and LSTMs, effectively tackling challenges related to both spatial and temporal defect detection [16], [17]. It is possible to create hybrid models through the integration of CNNs and LSTMs. The diverse range of data available in scenarios associated with Industry 4.0 presents unique challenges for identifying defects. Data can be presented in multiple forms, such as organized sensor data, unstructured text logs, photographs, and videos. The presence of this diversity necessitates that fault detection algorithms be highly adaptable and proficient in analyzing multiple data formats concurrently [18]. Delays in identifying or addressing flaws can result in expensive system failures, making real-time processing essential for fault detection in Industry 4.0. Delays in recognizing or addressing defects can result in significant issues. The vast volume of data produced by Internet of Things devices, combined with the rapid connectivity enabled by 6G, necessitates defect detection systems that are both precise and capable of efficient, scalable computation [19]. Several frameworks for deep learning have been put forward as a promising approach for identifying faults in industrial environments. One example illustrates the use of convolutional neural networks (CNNs) for detecting anomalies in manufacturing processes through visual inspection. Conversely, LSTM networks have demonstrated their capability in tracking time-series data from industrial sensors. Conversely, these techniques typically concentrate on particular data types and do not possess the flexibility required to handle the diverse data sources present in systems associated with Industry 4.0. Concerns about sustainability emerge due to the energy-intensive nature of deep learning models, especially in resource-constrained environments [20], [21].

A major challenge confronting modern industrial systems is the need to guarantee the sustained effectiveness of deep learning models over time. This is particularly relevant in contexts such as Industry 4.0, where access to computational resources is often restricted. This holds particularly true in situations where the availability of resources is limited. In systems necessitating real-time data processing at scale, the energy consumption associated with the training and operation of deep learning models is substantial. This holds particularly in systems lacking scale. To maintain the viability of smart factories in their operations, enhancing the energy efficiency of deep learning models is crucial [22], [23]. The proliferation of 6G technology will lead to an enhancement in the capacity of industrial networks for data processing. Recent investigations conducted within the frameworks of Industry 4.0 and 6G have explored and analyzed various alternative defect detection algorithms. A CNN-based model was implemented to detect surface imperfections in manufacturing processes. This was achieved by employing image data analysis techniques. The aim of performing sensor data analysis for predictive maintenance in industrial machinery was achieved by employing LSTM networks. The tests revealed that deep learning serves as a highly effective approach for fault identification [24], although they also highlighted the limitations associated with data diversity and resource requirements. Incorporated into the ongoing projects aimed at tackling these challenges are hybrid models that combine various deep learning methodologies to effectively handle diverse data sources. The implementation of these models facilitates the management of diverse data sources. A CNN-LSTM hybrid model was utilized to assess both visual and time-series data throughout the analysis process. Enhancements in fault identification performance were noted across various data modalities, as demonstrated by the results of this performance evaluation. Conversely, these models face challenges regarding sustainability, especially when applied in large industrial environments that require real-time data processing [25]. This paper contributes to the advancement of previous studies by establishing a framework for deep learning that aligns with sustainability principles. This framework improves the precision of defect detection in diverse data scenarios while also incorporating resource-efficient algorithms, thereby minimizing energy consumption. Our framework leverages the ability of 6G to handle large volumes of diverse data while optimizing computational resources for sustainable operation. This capability enables 6G to handle a substantially greater volume of data compared to conventional networks.

II. METHODOLOGY

Within the context of G-enabled Industry diverse data settings, this part presents a sustainable deep learning methodology for defect detection. The framework handles important challenges such as the heterogeneity of data, real-time processing, and resource optimization, which ensures that the framework is accurate and sustainable during its implementation. In order to efficiently manage the numerous data streams that are generated in environments that are part of Industry 4.0, the framework that has been presented incorporates a number of different deep learning components. In order to take advantage of both the spatial and temporal characteristics of the data, the design makes use of a hybrid deep learning model that blends Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. The framework's major objective is to facilitate precise problem detection while simultaneously reducing the amount of computing overhead and energy consumption, with the end goal of enhancing the scalability and sustainability of the system [26].

In order to promote fault detection in real time, management of resources, and effective communication among the multiple devices that comprise the ecosystem, the components that are a part of the Industry 4.0 ecosystem collaborate with one another. In environments that are a part of Industry 4.0, it is vital to have efficient data preparation because of the different features that the data possesses. This makes it simpler for the deep learning model to interpret and analyze a wide range of inputs, which is a significant benefit. It is the responsibility of the Data Preprocessing Unit to manage a wide range of data types, including structured data from sensors connected to the Internet of Things, unstructured logs, picture data from cameras, and time-series data from machine logs. The unit is responsible for a variety of activities, including normalization, standardization, and the arrangement of the data into formats that are appropriate for input into the hybrid deep learning model [27].

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are both utilized in the suggested system, which is based on a Hybrid Deep Learning Model. This model incorporates the advantages of both types of neural networks. This hybrid model is designed to manage both geographical and temporal data patterns, which makes it suited for a wide variety of data sources in the industrial sector. Convolutional Neural Networks, often known as CNNs, are applied for the purpose of analyzing image data, which also includes photographs of production lines and machinery. The ability of convolutional neural networks (CNNs) to recognize spatial elements, such as patterns and anomalies in visual data, is essential for spotting problems in industrial equipment, such as fractures, deformities, or surface flaws. They are able to capture temporal relationships, which enables the model to recognize emerging patterns or anomalies over time. For example, strange temperature changes or odd vibration patterns in equipment are examples of such types of patterns.

The capability of the hybrid architecture to do simultaneous analysis of image and time-series data makes the model highly flexible to the different data contexts that are associated with the industrial sector. This is because the hybrid architecture is able to perform simultaneous analysis of both types of data. During the first phase of the procedure, information is gathered from a wide range of sensors that are dispersed throughout the surrounding region. Deep learning allows for the identification of system failures and the triggering of alarms that tell the monitoring system of Industry 4.0 of the problems that have been found. This is performed through the application of deep learning. In order to effectively manage heterogeneous data, this system incorporates three distinct deep learning architectures into a single configuration. The long short-term memory for time series, the convolutional neural network for images, and the graph convolutional neural network for graph data are the three types of neural networks that are included in these designs. Different kinds of data are handled by each of these designs, which are built to handle them. This research study introduces a one-of-a-kind Branch-and-Bound optimization strategy with the intention of achieving hyper-parameter tweaking in a variety of deep learning models. One of the objectives of this strategy is to achieve the best possible performance from the models. In order to analyze the enumeration tree and carry out a methodical investigation of the hyper-parameter space, the method makes use of a heuristic approach rather than applying exhaustive search methods. This is carried out in order to accomplish the aforementioned goals. A clear representation of the model that was developed as a result of this research is shown in Figure 1, which can be viewed by anyone interested in the topic.

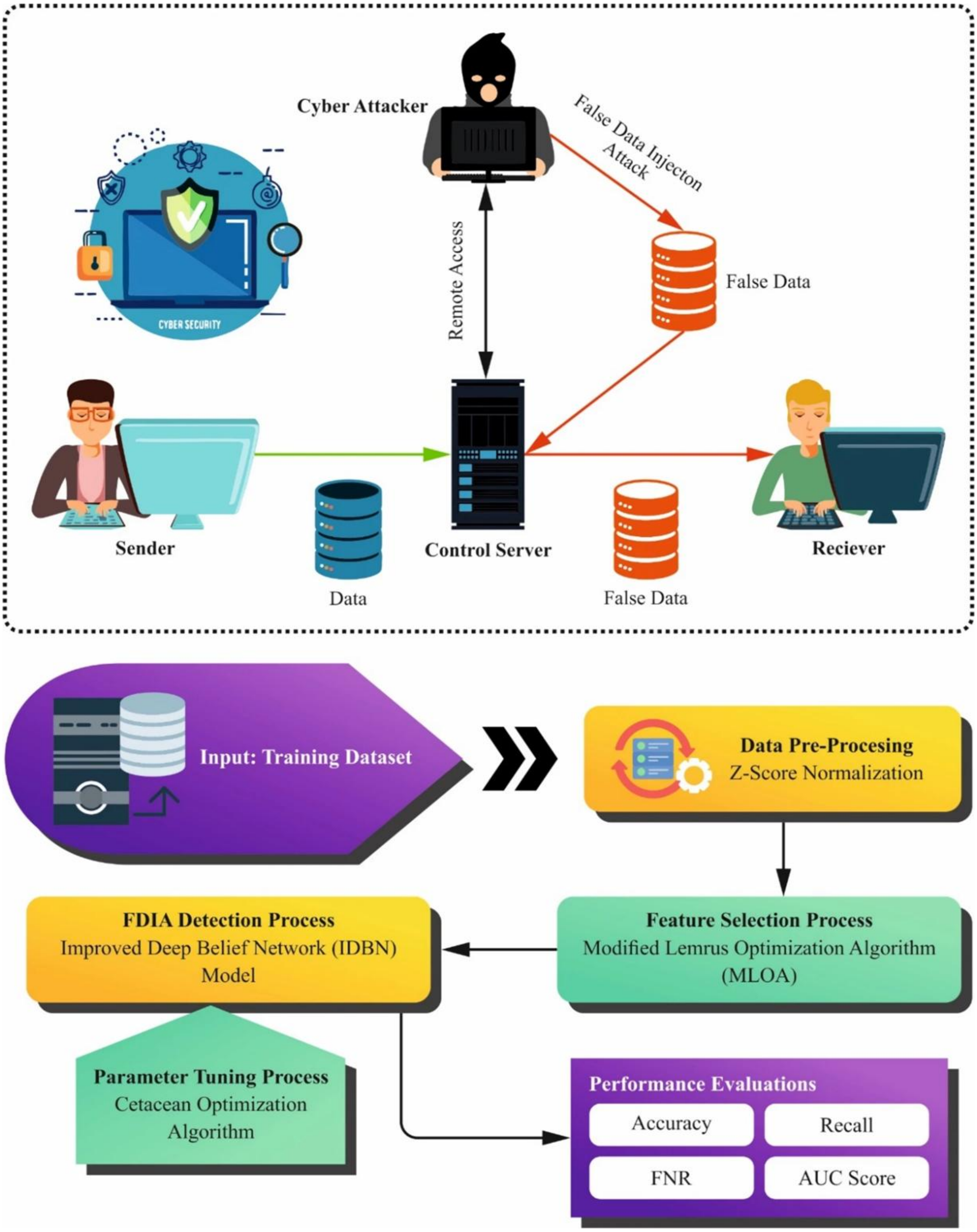

Fig. 1. Simplified representation of DL

In terms of continuously monitoring and diagnosing issues in real time, the Fault Detection Module is an extremely vital component that plays a significant role. After obtaining processed data from the hybrid deep learning model, the system then recognizes irregularities from the standard operating settings in order to identify potential problems. This procedure is repeated until the system identifies potential issues. The module is responsible for classifying defects, which permits the production of tailored responses that are in accordance with the degree and kind of the problem that has been identified. On the other hand, if there are significant issues, the system might be forced to shut down automatically in order to prevent any further damage from occurring by [28]. There is a possibility that alarms for preventive maintenance or other precautionary measures could be triggered by minor deviations. The defect detection module has been developed to attain a high level of precision while simultaneously reducing the number of instances in which it yields a false positive result. Consequently, this guarantees that true faults can be recognized with total reliability while industrial processes continue to function without interruption.

Being an essential part of the system, the Resource Optimization Engine is responsible for ensuring that the system is both scalable and sustainable. This is accomplished through its position as a vital component. The efficacy of the computational resources that are utilized by deep learning models and tasks that entail data processing is improved by the engine through the application of the following tactics, which are as follows:

When models are reduced and quantified, this is the process. Quantization, which needs a reduction in computational precision, and model pruning, which involves the removal of neurons and weights that are not required, are two strategies that can be applied to accomplish the objective of reducing the complexity of deep learning models. These tactics not only lower the amount of energy that is consumed but also the amount of memory that is utilized in an effective manner. Computing duties are distributed between central servers and devices situated at the edge of the network as a result of the incorporation of computers at the edge of the network. The amount of stress that is imposed on central systems is decreased, and the amount of data transfer that is necessary is also reduced. This is because jobs that are not critical for important operations can be carried out at the periphery of the network. In order to reduce the amount of latency and energy consumption in large-scale industrial contexts, this is an essential necessary step to take.

Scaling adaptive models to a larger scale The amount of data that is currently being processed and the requirements for fault identification can both be taken into consideration when adjusting the size and complexity of deep learning models. During periods in which the system is experiencing low levels of activity, it is possible to implement a simplified model in order to increase the efficiency with which resources are utilized. On the other hand, when the situation is extremely critical, the complete model is applied in order to carry out an in-depth investigation. Taking this approach to resource optimization ensures that the defect detection system performs with energy efficiency while also efficiently managing the huge data volumes that are typical of situations that are associated with Industry 4.0 and 6G.

A low-latency data transmission can take place between the various components of the framework in a speedy and effective manner thanks to the 6G Communication Layer, which makes it possible for this connection to take place. The fault detection system is able to assess data in real time from a broad variety of devices, sensors, and machines that are located on the premises thanks to this layer, which is part of the Industry 4.0 framework. It is possible for the framework to accommodate a large number of connected devices while simultaneously ensuring the speed and stability of the connection [29]. This is accomplished by utilizing the properties of URLLC (Ultra-Reliable Low Latency connection) and mMTC (Massive Machine Type Communication) in 6G. In order to reduce the amount of energy that is consumed and the carbon footprint that is associated with industrial processes, the framework combines a number of different sustainability components. This is done in order to decrease the carbon footprint. This bundle has the following goods, which are included in it:

In order to lessen the amount of computational resources that are necessary for training deep learning models from the ground up, the framework makes use of transfer learning and fine-tuning approaches. This is done in order to develop theories and models for energy conservation. The energy efficiency of the system is greatly improved as a result of this.

The process of cognitive data filtration comprises the selective processing and management of information with the goal of improving decision-making and promoting cognitive efficiency. This is accomplished through the utilization of selective processing and management. The technique in question necessitates the sifting through of extraneous data in order to preserve the information that is vital for the goal of carrying out an in-depth analysis and interpretation. In order to ensure that only pertinent information is processed, preprocessing units eliminate duplicate or irrelevant data. This, in turn, decreases the amount of computer resources that are required for tasks that are not absolutely necessary. The Adaptive Resource Allocation optimization engine is in charge of dynamically allocating resources in response to the demands that are being placed on the system in real time. This guarantees that energy is utilized in an efficient manner, particularly in situations that entail computation at the edge of the network. These components are incorporated into the deep learning framework that has been supplied in order to offer a full solution for fault identification in environments that are part of the 6G Industry 4.0. A balance is achieved between performance and sustainability through the use of this approach.

III. Results and Discussion

This section presents a summary of the findings derived from our evaluations that juxtapose the Advanced Deep Learning Framework for Fault Diagnosis in Industry 4.0 (ADL-FDI4) with the leading fault detection techniques. The assessment centers on three essential metrics: the fault detection rate, computational efficiency (quantified by the time required for operation), and energy consumption levels. Experiments were carried out in a simulated setting representative of Industry 4.0, incorporating a diverse range of data inputs. The data inputs comprised sensor time-series, visual data, and network graph topologies. ADL-FDI4 has demonstrated exceptional capabilities in fault detection across various data formats, particularly excelling in scenarios involving heterogeneous data. The system demonstrated an efficient capability to handle a diverse range of data types, leveraging the integration of Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Graph Convolutional Networks (GCN). This led to enhanced precision in identifying faults. In comparison to conventional deep learning methods, the LSTM module exhibited superior accuracy in detecting time-series sensor data. The ADL-FDI4 framework demonstrated a superior detection rate for faults when compared to the existing LSTM-based techniques. This framework effectively identified patterns in temporal sequences. The CNN component of ADL-FDI4 enabled precise defect identification in visual data sourced from industrial systems, proving especially beneficial for monitoring machinery and equipment. The detection rate of image-based fault detection surpasses that of competing CNN-based models. One of the crucial factors to evaluate when trying to identify errors in real-time industrial scenarios is the efficiency of the computation. The experimental results indicate that ADL-FDI4 markedly decreased the time needed for both training and inference in comparison to other models.

The primary parameters of the deep learning models employed in this study include the number of epochs, the learning rate, and the batch size. By employing the Branch-and-Bound optimization technique in every execution, comprehensive analyses have been conducted to assess these hyper-parameters. The batch sizes are modified from [start] to [end] in increments of [step], the epochs are altered from [start] to [end] in increments of [step], and the learning rate is revised from [start] to [end] in increments of 0.1. All of these modifications are implemented in increments of [step]. To identify the optimal parameters for each dataset, Branch-and-Bound conducts an exploration of the hyperparameter space. An overview of the optimal parameter values can be obtained by examining Table 1. In the subsequent two sections, we will evaluate our model against prominent models using these four benchmark datasets, focusing on accuracy and execution time. This comparison utilizes the optimal values of each hyper-parameter employed by our model.

TABLE 1
OPTIMAL PARAMETERS OF ADL-FDI4

Dataset	Epochs	Learning rate	Batches
Microsoft Azure Predictive Maintenance	54	0.66	15
NASA Milling	66	0.46	31
Preventive to Predictive Maintenance	74	0.53	9
CWRU Bearing	32	0.77	17

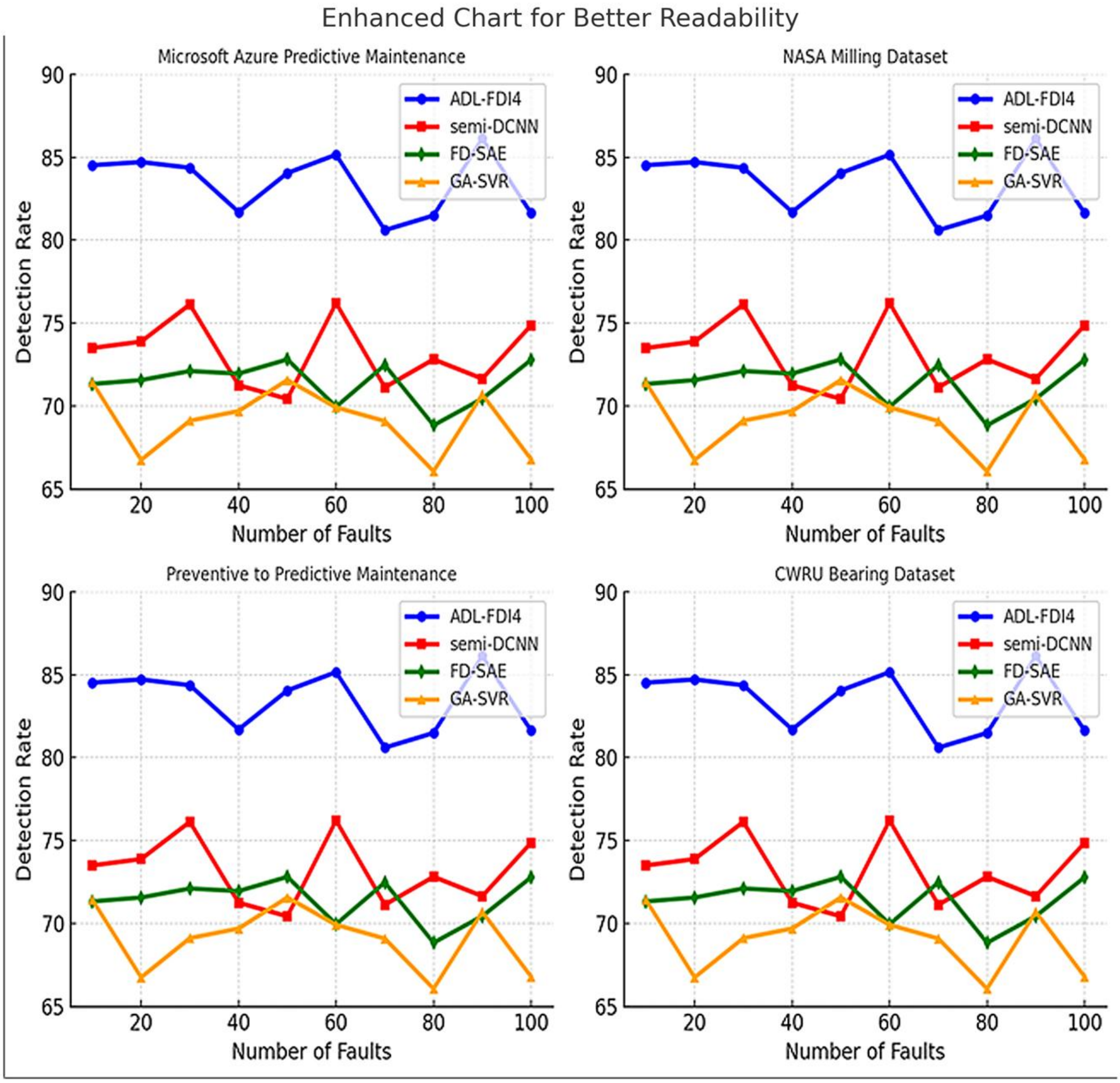

Fig. 2. ADL-FDI4 Accuracy in Comparison to Top-Notch Fault Diagnosis Systems

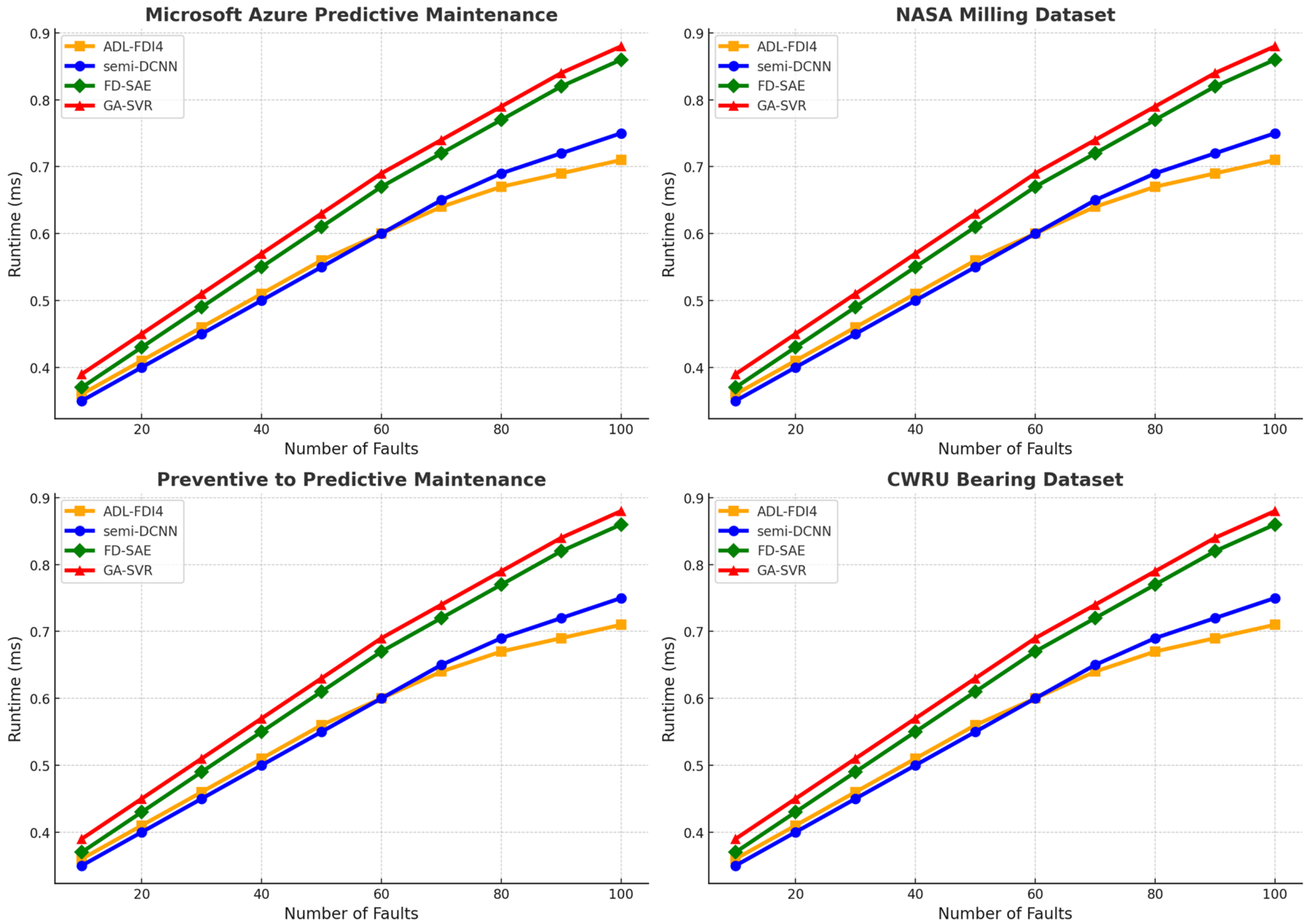

Fig. 3. The ADL-FDI4's runtime in comparison to the most cutting-edge fault diagnosis solutions

TABLE II
TRAINING EFFICACY OF THE ADL-FDI4 AND CONTEMPORARY FAULT DIAGNOSTIC METHODOLOGIES ON EXTENSIVE DATA SETS.

Dataset X 100	ADL-FDI4		semi-DCNN		FD-SAE		GA-SVR	
	CPU	Acc.	CPU	Acc.	CPU	Acc.	CPU	Acc.
Micro. Azure Pred. Maint.	1444	99	1433	97	898	93	905	90
NASA Mil. Data.	16334	96	1231	94	995	91	1075	89
Prev. Pred. Maint.	1550	98	1261	96	1122	95	999	92
CWRU Bear. Data.	1206	96	1005	97	878	94	975	93

Our objective was to assess the precision of ADL-FDI4 in comparison to the foundational fault diagnosis techniques, namely semi-DCNN, FD-SAE, and GA-SVR. The objective of our initial testing was to achieve this outcome. Employ the four datasets referenced previously in this conversation. Figure 2 illustrates that ADL-FDI4 exhibits superior performance in detection rate compared to the three baseline techniques. A method to demonstrate this distinction involves modifying the quantity of errors used as input. The ADL-FDI4 achieved a detection rate of 73% in its analysis of the Microsoft Azure predictive maintenance dataset. This was achieved to address challenges. In the course of addressing the identical situation, it has been noted that the detection rate for the alternative models falls below 691%. The successful integration of the Branch-and-Bound technique for fault identification with deep learning enabled the achievement of these results. The Branch-and-Bound method enables the effective optimization of hyperparameters across various deep learning models used in ADL-FDI4.

The second round of testing aimed to assess the performance of the ADL-runtime FDI4s against the baseline fault diagnostic solutions, which comprised semi-DCNN, FD-SAE, and GA-SVR. All of these experiments were conducted using the identical four datasets that were utilized in the previous set of tests.

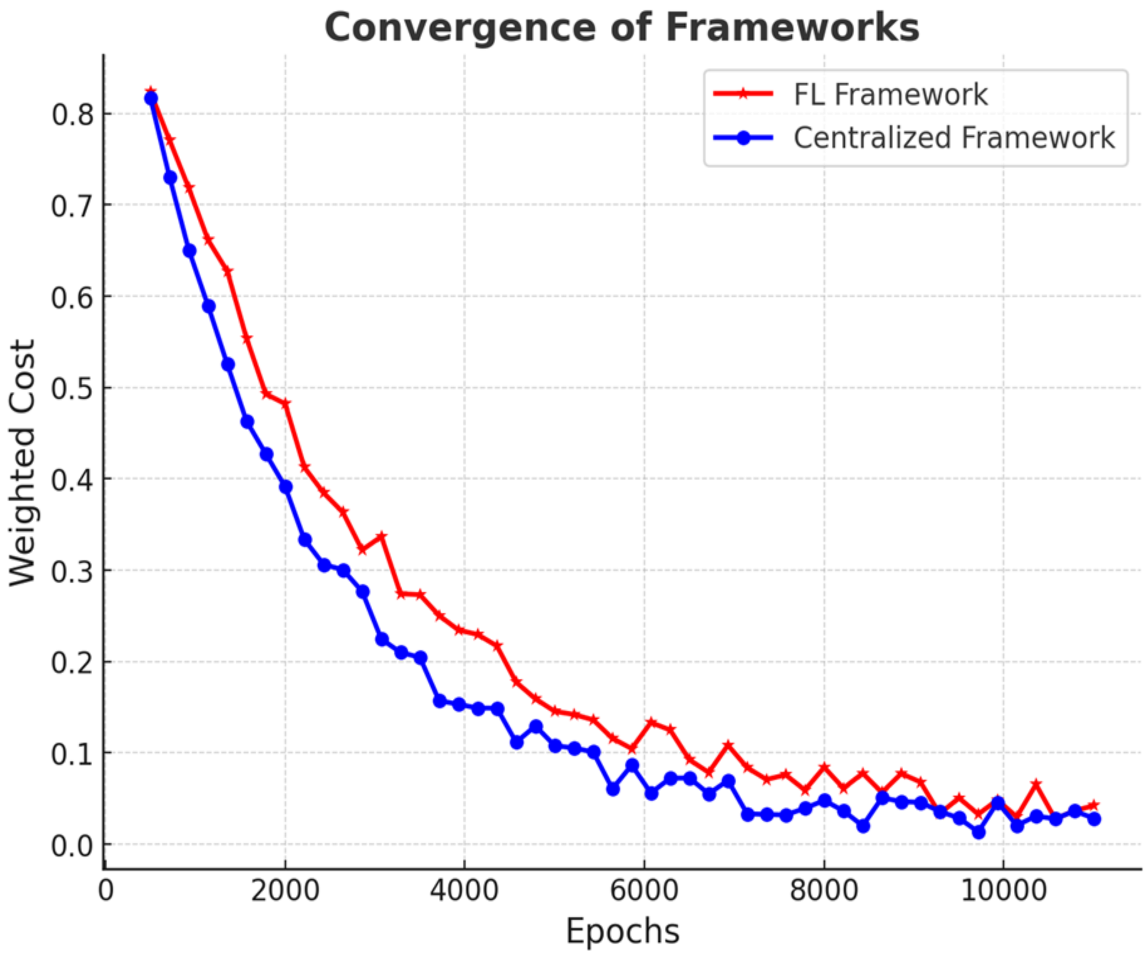

Fig. 4. Federated and centralized system performance

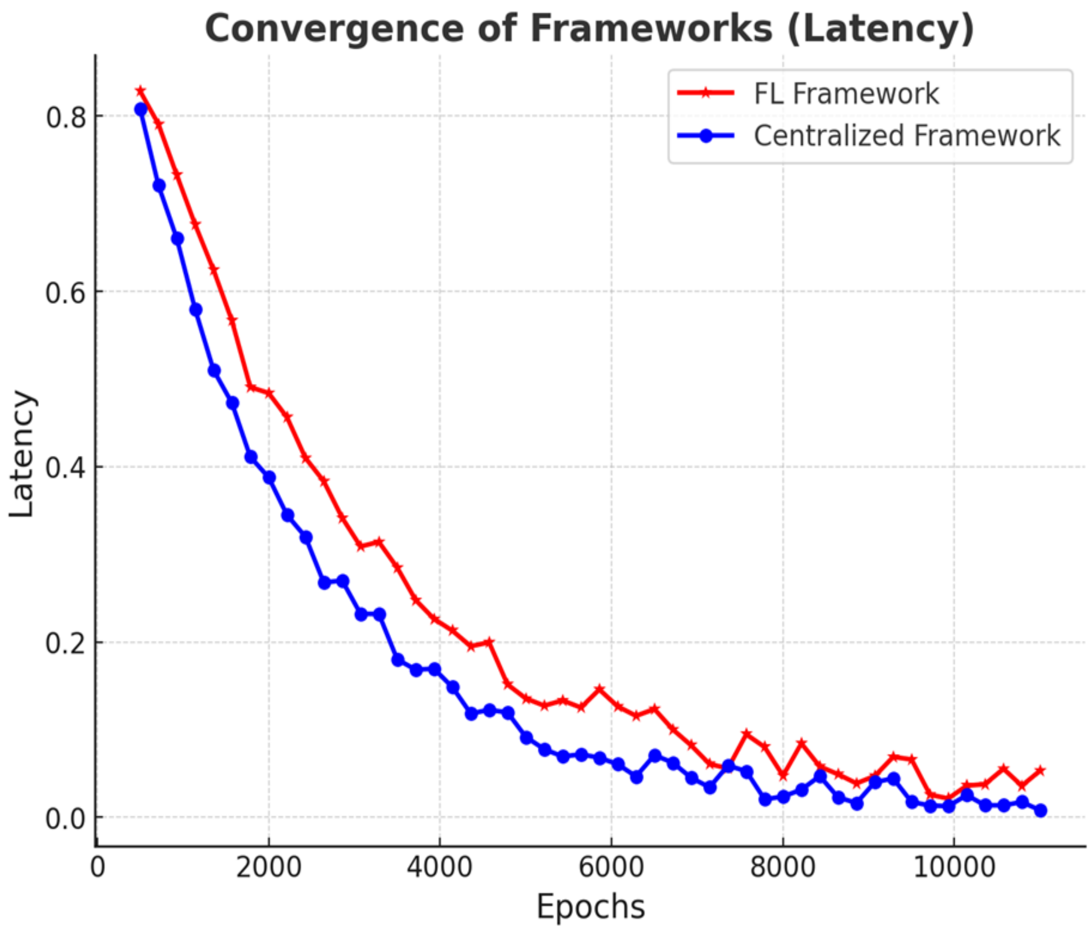

Fig. 5. Latency comparison of federated and centralized frameworks

The variability of the input fault count is illustrated in Figure 3, which shows that ADL-FDI4 achieves superior runtime performance when compared to the three baseline models. The dataset for Microsoft Azure Predictive Maintenance exhibits significant performance variation among the three models; however, it is considered insufficient in size. Conversely, the models for Azure exhibit a notable performance disparity.

The objective of the final experiment is to gain experience in Big Data by training the proposed framework. The effectiveness of the proposed solution compared to existing advanced solutions for managing the previously described data is illustrated in Table 2, which presents a summary of the training process results. The evaluation of training performance is conducted through the measurement of runtime in seconds and accuracy in percentages. The findings of this study demonstrate that, irrespective of the data employed, the proposed framework outperformed the alternatives in terms of accuracy. For instance, in comparison to other competing solutions, it attains a 99% accuracy rate with the Preventive to Predictive Maintenance dataset, while the other solutions struggle to exceed 95% accuracy with the same dataset and size. This outcome can be elucidated by the observation that the proposed framework demonstrates greater resilience compared to alternative frameworks, as it incorporates three distinct deep learning architectures. Moreover, the training accuracy can be enhanced by utilizing the Branch-and-Bound methodology to select hyper-parameters more effectively. Nonetheless, the training process for the proposed framework demands considerably more time compared to the alternatives. The utilization of three distinct designs instead of a single one, along with the duration needed for hyper-parameter tuning, are elements that lead to this conclusion.

With CAPs and IIoT devices counted as and, respectively, the overall system cost of the federated framework is shown in Figure 4, along with several iterations. After convergence, the performance of the suggested federated framework for efficient and flexible management of IIoT networks is comparable to that of the traditional centralized framework, according to comparisons with its performance. The federated framework and the traditional centralized framework both have the potential to experience a performance drop of around 0.1. On the other hand, compared to the traditional centralized framework, the federated one has a slower convergence speed. Performance in the traditional centralized framework and the federated framework both converge around the th Epoch. The federated and conventional centralized frameworks' system performances are shown in Figure 5, respectively, with the numbers of CAPs and IIoT devices set to and. Specifically, delay and energy use Figure 5 are related. The results of the federated system are comparable to those of the traditional centralized system, as seen by these two graphs. In particular, the two lines in Figure 5 show a performance drop from 0.11 to 0.05, while the two lines in Figure 5 show a performance drop from 0.11 to 0.05. In these numbers, though, the traditional centralized framework's performance converges more quickly than the federated one.

IV. CONCLUSION

The ADL-FDI4 architecture marks a notable advancement towards realizing effective and sustained fault detection within Industry 4.0 environments. To effectively handle diverse data within a unified computational framework, our approach integrates LSTM, CNN, and GCN models. This enables a reduction in energy consumption and simplifies the computations involved. Additionally, the Branch-and-Bound hyper-parameter optimization technique guarantees that ADL-FDI4 operates with a reduced computing load. This positions it as a scalable solution for the upcoming generation of intelligent industries driven by 6G technology. The objective is to enhance the scalability and adaptability of ADL-FDI4 for future projects by integrating reinforcement learning techniques, enabling real-time adjustments to evolving industrial contexts. Furthermore, we will investigate the potential for incorporating edge computing to reduce the latency encountered by defect detection systems and enhance their energy efficiency.

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