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Fault diagnosis in high-speed computing systems using big data analytics integrated evolutionary computing on the Internet of Everything platform

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Abstract: - The significance of high-speed computing systems is paramount for diverse applications. However, their intricate structure and rigorous operational prerequisites render them susceptible to malfunctions. The conventional fault diagnosis models need help managing the copious data produced by these systems, resulting in diagnostic procedures that are both time-consuming and ineffective. The research proposed an Internet of Everything (IoE) platform and big data analytics (BDA) based Fault Diagnosis System (IBFDS) in conjunction with evolutionary computing techniques. The system integrates a hybrid intelligent algorithm that amalgamates the advantages of evolutionary computing and machine learning to enhance the precision and effectiveness of fault diagnosis. The utilization of big data analysis methodologies facilitates the processing and examination of vast quantities of system data, thereby enabling the comprehensive detection and identification of faults. Furthermore, cloud services based on the IoE allow data storage, administration, and instantaneous cooperation among various parties involved.

Furthermore, a detection technique utilizing a Reduced Boltzmann Machine (RBoM) improves the precision of fault diagnosis. The efficacy of the proposed IBFDS was demonstrated through experimental evaluation using a high-speed computing system dataset. The results obtained were impressive, with a fault detection rate (94.11%), fault identification accuracy (93.76%), fault localization accuracy (93.71%), false positive rate (1.54%), and false negative rate (0.98%). The findings of this study make a valuable contribution to the advancement of fault diagnosis systems that are resilient and effective for high-speed computing systems. This facilitates proactive maintenance, enhances system reliability, and optimizes system performance.

Keywords: Fault Diagnosis, High-speed Computing Systems, Big Data Analytics, Internet of Everything, Evolutionary Computing

I. INTRODUCTION

The advent of high-speed computing systems has become a fundamental aspect of recent technological progress, transforming diverse sectors and stimulating innovative developments [1]. The methods can handle big data, perform intricate calculations at remarkable velocities, and have a long history spanning numerous decades [2]. The progression of high-speed computing systems, from early mainframe computers to contemporary supercomputers and high-performance computing clusters, has been driven by the growing need for expedited and more effective data processing. The systems hold significant importance in various domains, including scientific inquiry, financial analysis, meteorology, machine learning, and several other areas. The demand for rapid computing is driven by data's increasing magnitude and intricacy, in conjunction with the necessity for instantaneous analysis and decision-making. The systems demonstrate essential characteristics such as concurrent processing, fast interconnections, sophisticated memory administration, and customized architectures to enhance efficiency [3]. These systems are specifically engineered to manage computationally demanding tasks, utilizing state-of-the-art hardware and software advancements. High-speed computing systems possess specific attributes such as scalability, reliability, fault tolerance, and efficient processing of large-scale data sets [4]. The progression of these systems underscores the need for precise fault diagnosis and efficient management, which are essential to maintain uninterrupted performance and optimize system efficiency [5].

Identifying faults is critical to upkeep intricate systems, such as those in high-speed computing, to ensure their dependability and effectiveness. The process entails detecting and pinpointing anomalies or malfunctions in the system's constituent parts or functions. In the realm of high-speed computing systems, the issue of fault diagnosis assumes heightened importance owing to the substantial ramifications that faults can exert on the system's operational efficiency and overall efficacy [7-8]. Multiple factors prompt the requirement for fault diagnosis in high-speed computing systems. Initially, it should be noted that these systems can manage substantial quantities of data and perform intricate calculations, rendering them vulnerable to a range of hardware and software malfunctions. The prompt identification and diagnosis of malfunctions are crucial to reducing periods of inactivity, averting data loss, and guaranteeing continuous functionality.

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Moreover, high-performance computing systems are frequently employed for essential purposes such as scientific simulations, financial analysis, and rapid data processing. Malfunctions within these systems can result in significant monetary deficits, jeopardize the validity of research findings, or even present hazards to human well-being. Hence, it is imperative to have efficient fault diagnosis methods and systems to promptly detect and resolve faults, thereby facilitating timely corrective measures and upholding the dependability and efficiency of high-speed computing systems [9-10].

The efficacy of conventional fault diagnosis models in meeting the requirements of high-speed computing systems is hindered by various obstacles. The challenges associated with these systems pertain to their incapacity to effectively manage the vast and intricate data they generate, restricted scalability and real-time monitoring functionalities, insufficient precision in fault detection, and the absence of integration with nascent technologies. To address these obstacles, it is essential to incorporate the integration of Big Data Analytics (BDA) and the Internet of Everything (IoE) platform. BDA allows for the efficient processing and analysis of vast amounts of data from complex systems, thereby enabling the comprehensive identification and diagnosis of faults. The IoE platform capitalizes on the interconnectivity of various devices and systems, facilitating instantaneous monitoring, exchange of data, and cooperative identification of faults across diverse constituents of the high-speed computing system, thereby augmenting its fault diagnosis proficiency.

The IBFDS, which is based on IoE and BDA, offers the following principal contributions:

- The IBFDS system has been designed to integrate a hybrid intelligent algorithm that synergistically combines evolutionary computing and machine learning techniques. This integration has been shown to improve the accuracy and efficiency of fault diagnosis.
- The system employs big data analysis to effectively handle and scrutinize a vast amount of system data, thereby facilitating extensive identification and examination of faults.
- The IBFDS guarantees scalability, availability, and real-time monitoring of the high-speed computing system by including IoE-based cloud services, which enhances fault diagnosis capabilities.
- Utilizing a Reduced Boltzmann Machine (RBoM) based detection method in the system results in improved accuracy and efficiency of fault diagnosis in high-speed computing systems.

There are many uses for excessive-pace computing systems, but they often break down due to their complexity and traumatic operational wishes. These systems' huge records are too much for traditional fault analysis techniques, leading to inefficient and hard diagnostic techniques. A proposed strategy for this trouble is an IoE-primarily based Fault Diagnosis System (IBFDS) incorporating evolutionary computing strategies with huge facts analytics (BDA). Utilizing a hybrid intelligent set of rules, this system seeks to improve the accuracy and efficacy of defect diagnostics. Cloud offerings based totally on the Internet of Everything (IoE) make data storage, administration, and real-time collaboration less complicated, and the integration of massive statistics analytic methods permits thorough defect detection and diagnosis.

This research aims to create a complicated Fault Diagnosis System (IBFDS) for excessive-pace computing structures by combining the IoE platform, huge statistics analytics, and evolutionary computing techniques with the following objectives:

1.To increase and execute the IBFDS structure that improves fault prognosis through evolutionary computing and system learning.

2.The intention is to use large facts analytics strategies to thoroughly come across and identify errors by processing and studying huge quantities of gadget information.

3.Streamline information storage, administration, and collaboration with IoE cloud services.

4.To enhance the accuracy of disorder diagnosis, employ a Reduced Boltzmann Machine (RBoM) within the detection method.

5.This experimental validation seeks to assess the performance of the recommended IBFDS on a dataset from a high-velocity computing machine.

The following sections are organized in the given manner: The second section presents a comprehensive survey of the extant literature and investigations about fault diagnosis in high-speed computing systems. The third section of the paper outlines the structure and blueprint of the IBFDS. This proposed system amalgamates the IoE and BDA to augment the fault diagnosis capabilities of high-speed computing systems. The fourth section details the simulation analysis that was carried out to assess the efficacy and efficiency of the proposed IBFDS. The fifth section summarizes the primary discoveries and outcomes of the study, emphasizing the significance of the suggested IBFDS.

II. LITERATURE SURVEY AND ANALYSIS

The section on the literature survey presents a comprehensive analysis of prior studies on fault diagnosis in high-speed computing systems, covering diverse techniques, methodologies, and outcomes.

Ye et al. introduced a fault diagnostic network that utilizes deep learning techniques to address issues in secondary suspension systems of high-speed trains [11]. The methodology has been devised to exhibit immunity towards track irregularities and wheel wear, thereby augmenting the system's resilience. The findings indicate that the suggested method is proficient in precisely identifying malfunctions, exhibiting enhanced performance in detecting and categorizing faults. The results indicate that the approach has the potential to be implemented in practical settings, offering dependable fault diagnosis for secondary suspension systems in high-speed trains.

Ye et al. presented the Out-of-Order Network (OORNet), a deep-learning framework designed for onboard condition monitoring and fault diagnosis of out-of-round wheels in high-speed trains [12]. The method proposed in this study employs deep learning techniques to effectively identify and diagnose wheel faults that are out-of-round with a high degree of precision. The findings demonstrate the efficacy of OORNet in attaining elevated levels of accuracy and dependability in identifying defects. The results indicate that the approach has the potential for practical application, facilitating prompt identification and upkeep of non-circular wheels in high-velocity trains.

Imani et al. introduced an innovative approach in the time domain for detecting and categorizing faults in Voltage Source Converter High Voltage Direct Current (VSC-HVDC) transmission lines [13]. The system that has been put forth employs time-domain analysis techniques to detect and classify defects in VSC-HVDC transmission lines. The approach exhibits encouraging outcomes in terms of precision in identifying weaknesses and effectiveness in categorizing them. Even with its potential, the method's practical implementation requires addressing specific issues, such as computational complexity and sensitivity to parameter changes.

Cheng et al. have presented a methodology for detecting and diagnosing incipient faults in the running gear systems of high-speed trains, utilizing Slow Feature Analysis (SFA) [14]. The approach integrates SFA and data-driven methodologies to detect and analyze early-stage malfunctions in the locomotive's propulsion mechanisms. The findings suggest an enhancement in the precision of fault detection and diagnosis, demonstrating the efficacy of the proposed methodology. The results underscore the method's potential to improve the dependability and upkeep of high-speed train running gear systems.

Geng et al. presented an enhanced federated learning algorithm designed to bear fault diagnosis [15]. The method under consideration employs federated learning methodologies to train a fault diagnosis model using distributed data sources collaboratively. The findings indicate the efficacy of the enhanced federated learning algorithm in attaining precise bearing fault diagnosis. The results suggest that the approach can be practically implemented, facilitating collaborative and privacy-preserving fault diagnosis in bearing structures.

Xingxin et al. proposed an Artificial Intelligence (AI) based online fault detection tool for substation equipment [16]. The approach employs artificial intelligence methodologies to identify malfunctions in substation apparatus promptly. The findings indicate that the suggested tool is efficacious in detecting malfunctions, facilitating prompt upkeep, and diminishing operational inactivity. The results suggest that the approach can improve the dependability and efficiency of substation machinery. Notwithstanding, there could be possible obstacles concerning the accessibility of data and the integration of systems.

Zhu et al. proposed a novel approach for real-time fault diagnosis in Electric Vehicles (EVs) by integrating multilabel feature selection and sliding window control [17]. The method can improve the precision of fault diagnosis in electric vehicles, facilitating prompt identification and upkeep. The findings underscore the efficacy of the methodology in attaining precise fault identification in real-world situations. The results indicate that the approach has the potential to be practically implemented in improving the dependability and security of EV systems. Nevertheless, there are obstacles regarding selecting features and the intricacy of computations.

Wang et al. introduced a new approach for fault diagnosis in smart grids utilizing memory-spiking neural P systems [18]. The process considers the possibility of measurement tampering attacks and employs memory-based neural networks for fault diagnosis. The findings indicate the efficacy of the suggested approach in precisely identifying and diagnosing malfunctions in intelligent power grids while considering plausible security risks. The results indicate that the process can improve the security and dependability of smart grid systems. Nevertheless, there are difficulties with the intricacy of the model and the computational burden.

Ren et al. have introduced a novel approach called Layered Multimodal Convolutional Neural Network (LM-CNN), a cloud-edge collaborative method designed for adaptive fault diagnosis [19]. The process involves the expansion of the label sampling space as a means of enhancing the precision of fault diagnosis. The findings suggest the proposed method is efficacious in attaining adaptable fault diagnosis with improved accuracy. The results indicate that the system can facilitate cooperative fault identification and enhance the efficacy of fault diagnosis mechanisms. Even so, there are obstacles regarding the synchronization of data and allocation of resources between the cloud and edge nodes.

Aburakhia et al. presented a novel hybrid approach to monitor the condition and diagnose faults in rolling bearings with low system delay [20]. The approach under consideration amalgamates diverse strategies for specific fault prognoses, even concurrently reducing gadget latency. The findings indicate that the hybrid method is valuable in attaining expanded diagnostic precision while minimizing the time postponed. The consequences endorse that the process can enhance the dependability and performance of rolling bearing systems. Even so, there are boundaries concerning the intricacy of the model and the computational sources wanted for prompt execution. The literature evaluation affords a top-level view of diverse methodologies and techniques utilized for fault analysis throughout diverse domain names, demonstrating the progress and limitations encountered in this location of studies. The proposed device aims to triumph over the shortcomings of cutting-edge techniques by incorporating superior technology such as synthetic intelligence, deep learning, memory-based neural networks, and collaborative processes. This integration will convey superior precision, actual-time monitoring, heightened safety, and adaptable fault prognosis skills. Consequently, the device is expected to fulfil the demand for more inexperienced and effective fault analysis in complicated designs. There has been research on illness diagnostics in high-tempo PC systems; however, the blending of the IoE platform is lacking. To address this, the venture will use the Internet of Everything (IoE) to decorate the efficiency of disease evaluation through actual-time collaboration, statistics garage, and control. Extensive incorporation of big statistics analytics (BDA) strategies is lacking from numerous fault analysis models already in use. The proposed method should use the to technique and look at big volumes of device records to fill what is needed, considering extra correct fault detection and identification. Insufficient validation of disorder diagnostic models and the usage of actual-world datasets from excessive-pace computing systems may be determined within the scientific literature. The proposed research hopes to fill this know-how hole and offer practical insights into the IBFDS's effectiveness by doing experimental reviews on a dataset from high-speed computing devices.

This suggested method looks at objectives to fill these information gaps so that fault detection systems designed for excessive-pace computing settings can improve and offer better answers to the problems already referred to.

III. Proposed IoE and BDA-based Fault Diagnosis System

The IoE and BDA-based Fault Diagnosis System (IBFDS) is a suggested approach incorporating multiple essential elements to improve the fault diagnosis process in high-speed computing systems. The system integrates a hybrid intelligent algorithm combining rule-based reasoning, machine learning, and optimization methods to enhance precision. Using big data analysis capabilities facilitates the effective handling and examination of factual data, revealing concealed patterns and irregularities. Cloud services based on the IoE enable systems to monitor in real-time and proactively detect faults. The utilization of deep learning methods in a technique for identification based on RBoM enables the acquisition of intricate patterns, thereby augmenting fault diagnosis capabilities.

3.1 Fault Diagnosis Algorithm

The data-driven fault identification approach involves examining, extracting, and evaluating industrial data to identify and diagnose faults. The crux of this technique includes reworking complex, interrelated, and complex statistics units with excessive dimensions into more precise, uncorrelated, and more comprehensible information with lower dimensions. This technique allows the comprehension of the existing-day operational country of the gadget by the employees responsible for its preservation. The efficacy of a data-pushed method is contingent upon the calibre of the manner of information. Based on professional expertise, the diagnostic technique consists of engaging in a methodical evaluation of fuel turbine functioning and using clean and intentional descriptions to understand the simple cause of malfunctions and anticipated ability issues. Due to its straightforward functionality and strong identity capabilities, this method can diagnose gasoline turbine malfunctions through number one know-how and logical deduction. The gas turbine's early placed-on indicators can be detected through this generation, permitting well-timed and specific diagnostic information. This provides machine protection and operation engineers extra flexibility in scheduling protection and allows for greater scientifically knowledgeable gadget safety planning by using the manner of the plant earlier than device failure or extremely good harm. This method is appropriate for preliminary inspection of gas generators, as its knowledge coverage function is limited, impeding the powerful prognosis of elaborate faults. A hybrid fault identity model has been advanced to beautify the dependability of tool fault identification inside the context of big business statistics. IBFDS tool modelling involves the mixing of understanding engineering and facts-driven strategies. The primary method in fault detection is fact-driven, and fault analysis is achieved through knowledge engineering techniques. Collecting function information from tough systems, tool studying techniques, grouping, and choice bushes are applied for huge statistics mining. This technique establishes a professional expertise base to derive fault evaluation rules, improving the dependability of fault detection and evaluation. Figure 1 depicts the IBFDS fault diagnosis method.

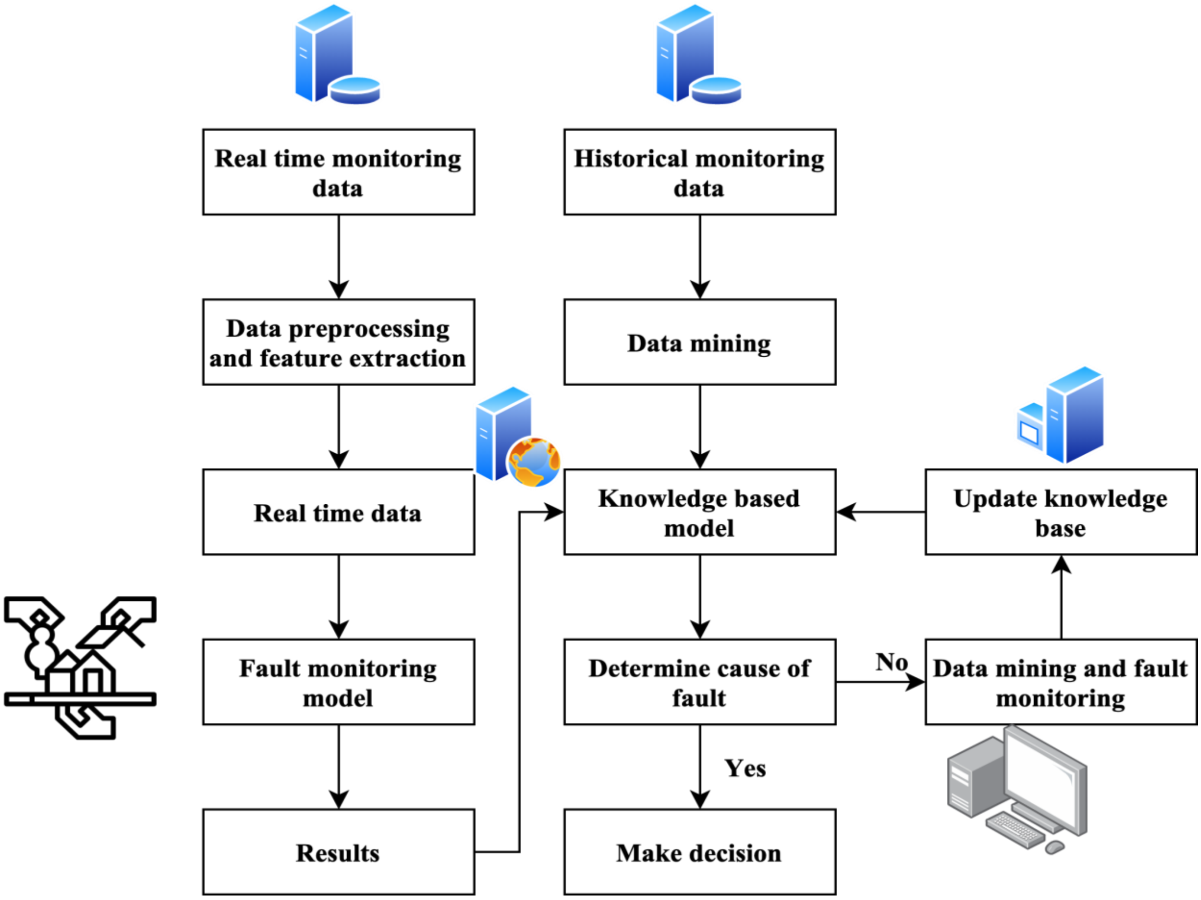

Figure 1. IBFDS fault diagnosis method

3.2 Big data analysis of equipment operation

By utilizing big data analysis technology for machine operation, proactive maintenance can be performed on equipment before equipment failure. This protection method is based upon circumstance monitoring and fault evaluation effects, representing a proactive and constructive technique to upkeep. Ensuring the renovation of unique, important equipment is of extreme significance, especially for people with a high utilization rate and whose failure can extensively obstruct production. Modern strategies for fault diagnosis in high-speed computing systems have emerged, along with the IoE and BDA-based Fault Diagnosis System (IBFDS). Improving the accuracy and efficiency of illness detection is the aim of IBFDS, which builds on the apex of the Internet of Everything (IoE) platform and carries advanced large information analytics (BDA) processes. The device's versatility and performance are superior, employing its one-of-a-type hybrid sensible algorithm, which combines evolutionary computing with machine mastering. Cloud services, which can be a part of the IoE platform, also make it easy to store data, control it, and work together in real time, all of which enhance the effectiveness of fault analysis. By including a Reduced Boltzmann Machine (RBoM) detection technique, IBFDS improves the accuracy of fault prognosis even further, making it a useful tool for increasing machine reliability and assuring proactive preservation in excessive-speed computing environments.

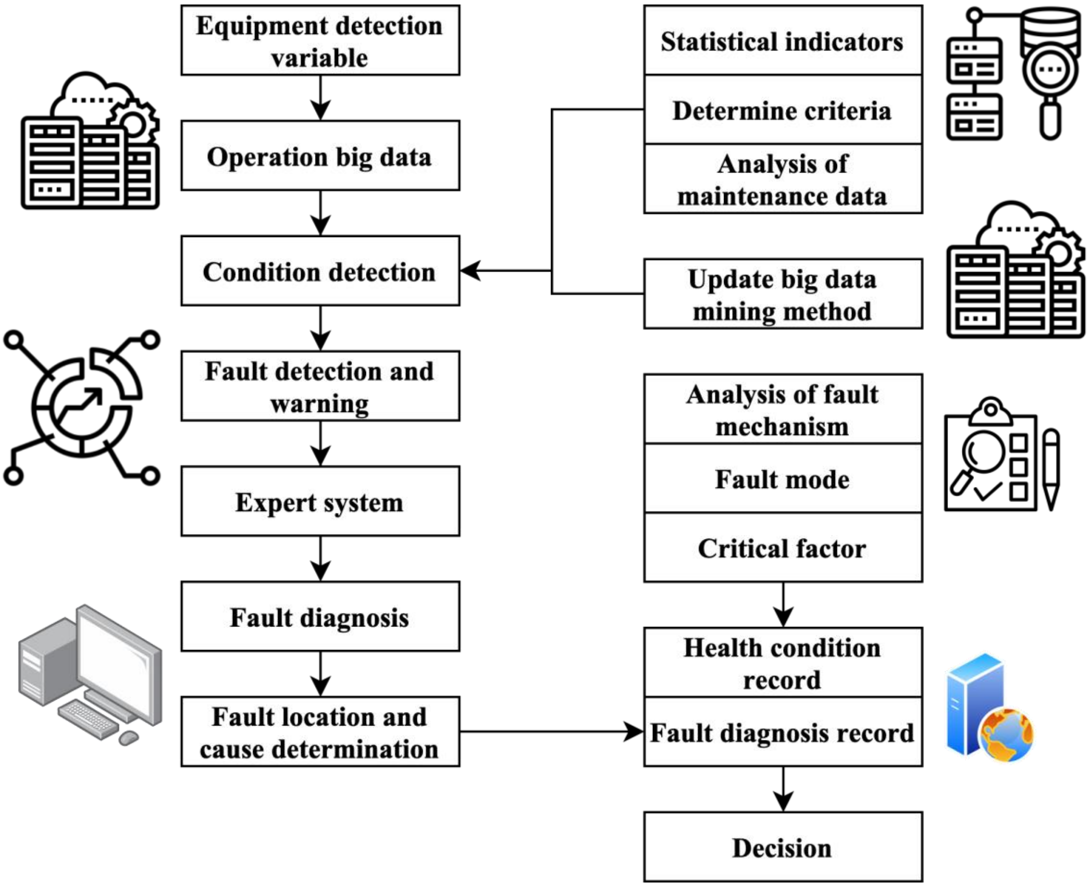

Figure 2. BDA-based fault diagnosis process

Figure 2 illustrates the process flow of big data analysis technology, which integrates categorizing big data drivers with the discrimination of specialist skill bases. A comprehensive fault diagnosis report is generated to serve as the foundation for resolving faults by combining fault mode and critical factor evaluation.

3.3 IoE-based cloud services

The IoE has found extensive application across various domains owing to its fundamental aspects: comprehensive awareness, stable delivery, and intelligent application. It provided a novel opportunity for surveillance and diagnosis of equipment, thereby expanding the scope of development in this area. The machinery's health scenario information is acquired collaboratively in real-time through detectors, data collection boxes, gadgets, and servers, which adhere to the agreed procedure rules. The acquired data is intelligently processed, and timely comments are provided. The resulting database is open, adaptable, adjustable, and reconfigurable, allowing real-time interaction. The dynamic, flexible feature component that represents the underlying reason for equipment failure has been extracted from the database. A novel monitoring and administration framework has been developed, incorporating features such as condition identification, fault forecasting, online tracking and evaluation, remote surveillance and evaluation, and remote management and upkeep.

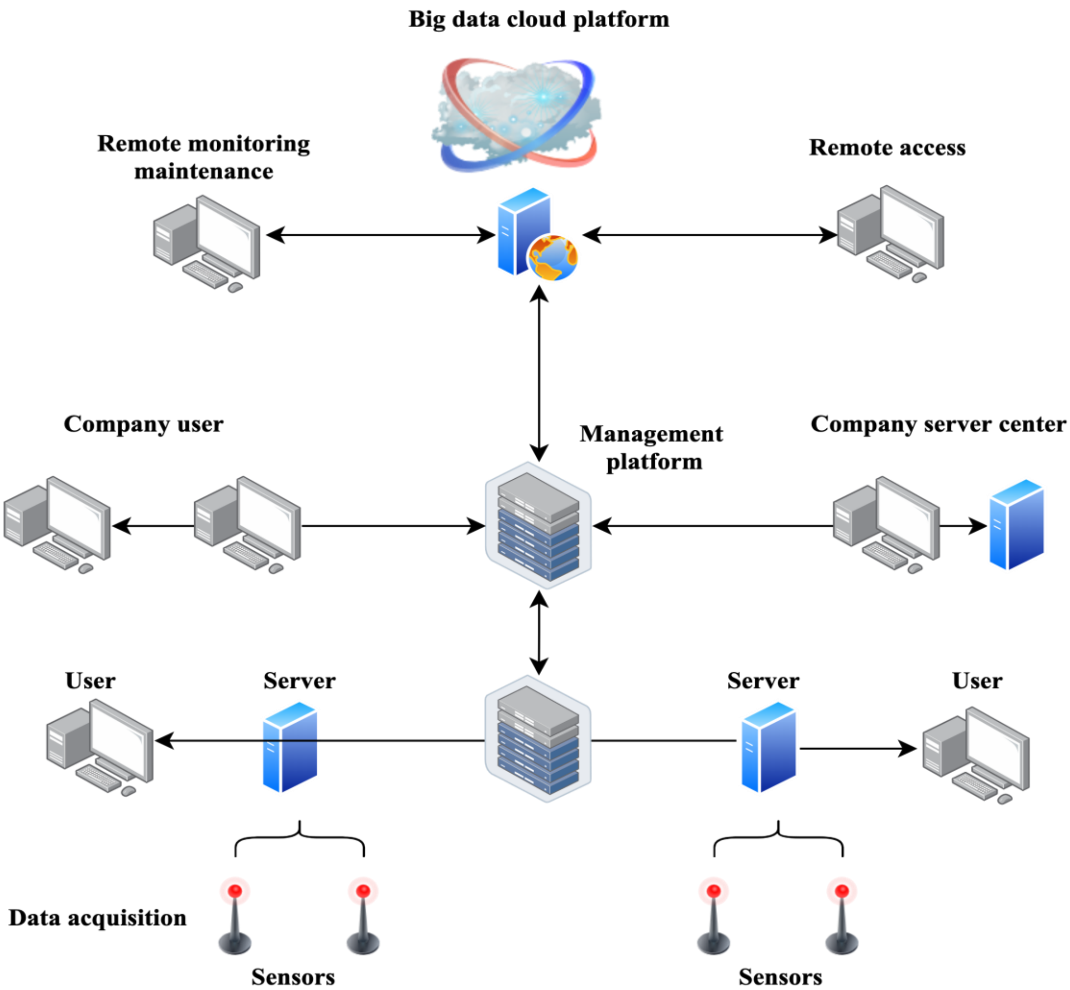

Figure 3. IBFDS fault identification system

Figure 3 depicts the IBFDS fault identification system that utilizes big data from the IoE. The system has incorporated information detecting, design, and intelligent computation technologies.

- The sensing layer employs the equipment's detector to gather data and utilizes short-range communication methods to transfer the details to the site entry point or host machine. This facilitates the collection and sending of data from the perceptual layer.
- The network layer facilitates the transmission of health monitoring signals and operational variable data from the equipment to the branch servers. These are subsequently published to the company's headquarters for centralized storage of the equipment's operating parameters and scenario data.
- The primary function of the application layer is to facilitate the examination of tracking signals, extraction of fault features, and provision of fault detection and forecasting capabilities. Initially, the data undergoes a sophisticated and advanced algorithm for pre-processing, which involves restructuring, extracting, and deducing information. The interface for human-machine interaction presents essential findings and insights to the users. The functional specifications for monitoring and diagnosing equipment wellness using the IoE concept have been fulfilled, resulting in intelligent administration, usage, and assistance.

Additionally, the system can retrieve data from the enterprise's Distributed Control Structure (DCS) to facilitate integrated administration. The software for managing machinery operation and upkeep, which utilizes the IoE, comprises management and surveillance. This software has successfully implemented various functions, such as sensing connect assistance, data analysis assistance, notification and measure service, map data assistance, operation data analysis assistance, network evaluation assistance, data query assistance, maintenance and operations records management, and user administration. The system furnishes manufacturing leadership, quality control, and maintenance and operations supervisors with fundamental data on equipment life-cycle, operation tracking value, functioning and upkeep specifics, precise fault position, prompt maintenance plan generations, competent assessment of data, and statistically analyzed chart reports as per requirements.

3.4 RBoM-Based fault diagnosis

The RBoM is a Markov Random Field (MRF) type that belongs to uncontrolled probabilistic graphical models. An undirected graph characterizes its Markov property. The visible layer indicates the discernible data, whereas the concealed layer is employed to pattern a distribution of the discerned variables. There is an absence of interconnections among any pair of nodes belonging to the identical layer.

The energy function for a specific RBoM block is formally specified in Equation (1).

$$P(u,k) = -\sum_{x=0}^{M-1} u \sum_{y=0}^{N-1} u\, W_{xy} k_{xy} \frac{u_x}{\propto_x} - \sum_{x=0}^{M-1} u \frac{(u_x - b_x)^2}{2{\propto_x}^2} - \sum_{y=0}^{N-1} u\, z_y k_y \quad (1)$$

The terms b_y and z_y represent the biases for noticeable and concealed units. W_{xy} indicates the weights of the connections between noticeable and concealed components. $\propto_x$ denotes the standard deviation of noticeable units u_x. Each block comprises noticeable real-value units u_x, where x ranges from 0 to m-1, and concealed binary units k_y, where y ranges from 0 to n-1. The units are fully connected. The RBoM block can process real-value information, as it is designed to handle the input u, which represents the sensed signals in actual situations and is expressed in real-value components.

The joint probability delivery can be derived from the energy function and MRF properties and shown in Equation (2).

$$E(u,k) = \frac{1}{C} exp\ exp\ (-P(u,k)) \quad (2)$$

The notation employed in the expression is such that u represents the observable layer, k means a concealed layer, and C is equivalent to the summation of the product of the visible layer and concealed layer, where the outline is taken over the range of u from 0 to $M-1$ and k from 0 to $N-1$. The mathematical expression denoted by $C = \sum_{u=0}^{M-1} u \sum_{k=0}^{N-1} u\ exp\ exp\ (-P(u,k))$ is commonly referred to as the partition operation. The marginal dispersion of u can be derived from the combined probability dispersion using Equation (3).

$$E(u) = \frac{1}{C} \sum_{k=0}^{N-1} u\ exp\ exp\ \left(-P(u,k)\right) \quad (3)$$

The probability is denoted $P(u,k)$, the hidden layer outcome is denoted C. The conditional independence of noticeable and concealed components allows for the expression of the Conditional Probability (CP) of $u\ and\ k$ in the following shapes, accordingly in Equations (4) and (5).

$$CP\left(k_y = 1|u\right) = func\left(z_y + \sum_{x=0}^{N-1} u\, w_{xy} \frac{u_x}{{\propto_2}^x}\right) \quad (4)$$

$$CP(u_x = u|k) = GP\left(u|b_x + \sum_{y=0}^{N-1} u\, h_y w_{xy}, {\propto_2}^x\right) \quad (5)$$

The notation $GP(*\ |i,j)$ represents the Gaussian Probability (GP) density function with an average of u and a variance of $\propto_2. In\ contrast, func()$ refers to the logistic sigmoid functioning. The concealed layer output is h_y, and the weight is denoted w_{xy}. The RBoM's methods for learning are founded on the principle of gradient ascent to optimize the log-likelihood $log\ log\ \left(L(\emptyset,u)\right)$. The gradient of the log-likelihood concerning a single training instance, denoted as u, can be expressed in Equation (6).

$$\frac{dloglog\ \left(L(\emptyset,u)\right)}{d\emptyset} = -\sum_{k=0}^{N-1} u\, E(k|u) \frac{dP(u,k)}{d\emptyset} + \sum_{u=0}^{M-1} u \sum_{k=0}^{N-1} u\, E(u,k) \frac{dP(u,k)}{d\emptyset} \quad (6)$$

The probability is expressed $P(u,k)$, gradient is denoted $d\emptyset$, and $E(k|u)$ represents the variable of RBoM. The development of learning methods for RBoM can be achieved by maximizing the log-likelihood gradient ascending.

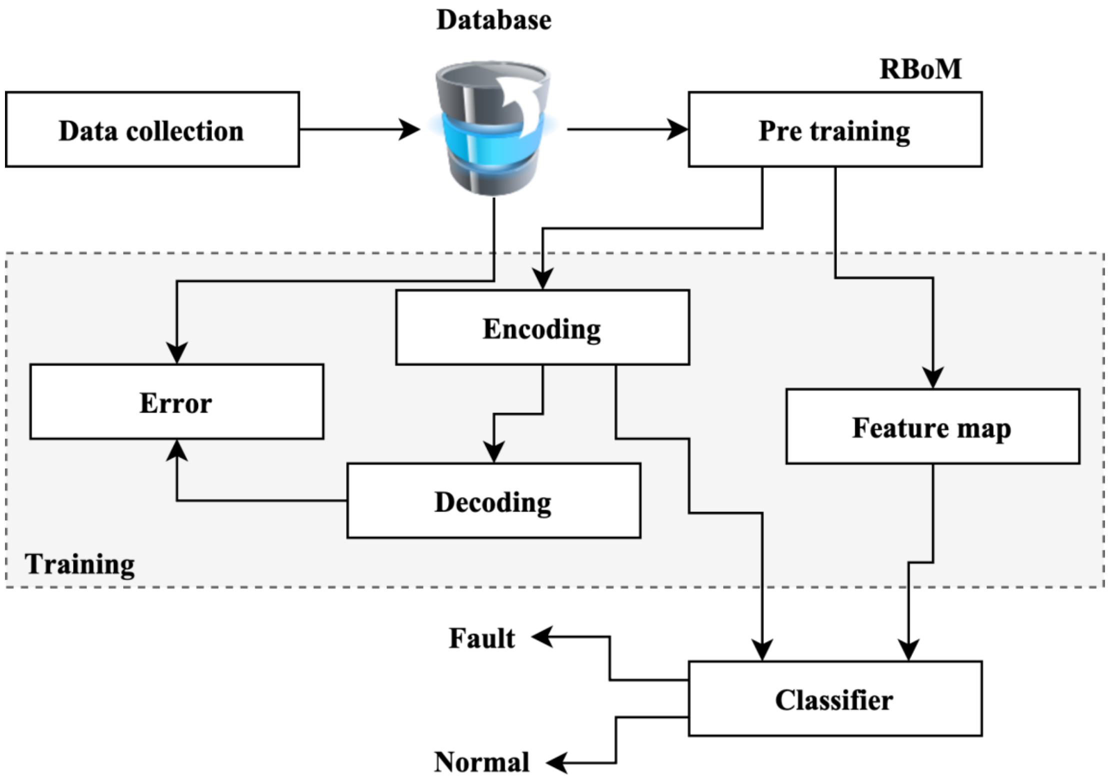

Figure 4. RBoM-based fault diagnosis model

Upon returning to Figure 3, it can be observed that a set of RBoMs were pre-trained. The pre-trained variables were utilized to initialize a deep autoencoder, a type of deep neural network. The encoder results of the RBoM-block might be represented as shown in Equation (7).

$$EO(u) = func\left(Z_y + \sum_{x=0}^{N-1} u\, w_{xy} \frac{u_x}{\propto_x{}^2}\right) \quad (7)$$

The weight is denoted w_{xy}, the output is denoted Z_y, the mean is denoted u_x, and the deviation is denoted $\propto_x$.

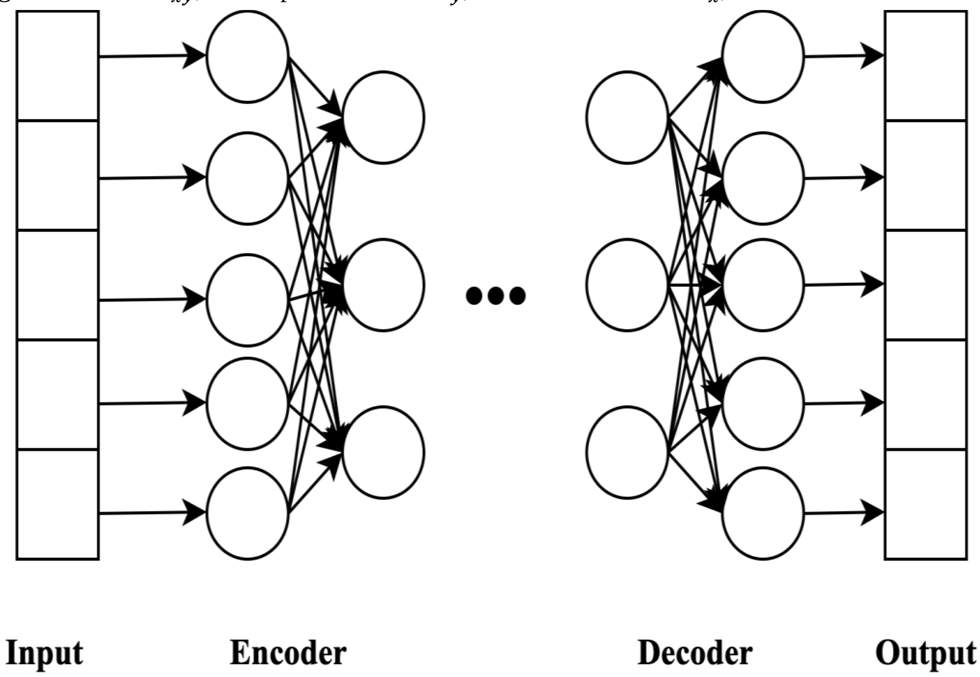

Figure 5. The architecture of the RBoM for fault diagnosis

The architecture of the RBoM for fault diagnosis is shown in Figure 5. The decoder's design exhibits symmetry with that of the encoder. The concealed layers' Deciphered Output (DO) can be formulated upon unwrapping using Equation (8).

$$DO(u) = func\left(Z'_y W^T_{xy} p(u)\right) \quad (8)$$

The output is denoted Z'_y, the weight is denoted W^T_{xy}, and the probability is denoted $p(u)$. In the fine-grained tuning phase, the backpropagation method maximizes reconstruction through a mean-square error (MSE) cost operation, as expressed by Equation (9).

$$E(D) = \frac{1}{M}\sum_{x=0}^{N-1} u\,(DO(u) - u\,)^2 \quad (9)$$

N represents the number of samples in the input set of information D, and the Decoded Output (DO) is mentioned as $DO(u)$. The mean input is denoted u. It is important to note that the primary objective of training an autoencoder is to recreate input data without utilizing any category label details. This characteristic renders the training procedure unsupervised. After the feature extraction process using RBoMs and autoencoder techniques, a softmax classification, consisting of two neurons, is incorporated downstream of the bottleneck layer.

The softmax classification is utilized to infer the likelihood that the input pertains to distinct categories, namely normal or faulty. The utilization of cross-entropy loss is ultimately adopted as the loss function $L(W_0, Z_0)$ is shown in Equation (10).

$$L(W_0, Z_0) = \frac{1}{M}\sum_{x=0}^{M-1} u\, q_x \, log\, log\left(q'_x(W_0, Z_0)\right) \quad (10)$$

The encoder networks in question are characterized by W_0 and Z_0. The labels used in this context are represented by q_x and q'_x for the actual and estimated values. Equation (10) is employed to quantify the detection error between the existing labels and the forecasted outcomes. The execution of variable optimization and categorization decisions can be achieved by reducing the loss function by utilizing the stochastic gradient descent and backpropagation methods. Since RBoM can handle real-valued information, RBoM-based deep neural networks are also suitable for processing such data. The IoE and BDA-based Fault Diagnosis System is a suggested technique that offers a combined strategy to enhance the fault diagnosis process in high-speed computing systems. The system achieves improved precision and effectiveness in fault detection and diagnosis by integrating a hybrid intelligent method, big data analysis, IoE-based cloud services, and RBoM-based techniques for detection. The approach utilizes sophisticated technologies to manage essential data, detect concealed patterns, and facilitate instantaneous monitoring.

IV. Simulation analysis and outcomes

The present study's simulation analysis section centres on assessing the efficacy of IBFDS, the proposed method, for fault diagnosis in high-speed computing systems. Other established techniques evaluate the effect by scrutinizing a range of metrics such as fault detection rate, fault identification accuracy, fault localization accuracy, false positive rate, and false negative rate. The simulation outcomes offer valuable perspectives on the exceptional efficiency of IBFDS and the capacity to transform fault identification in high-velocity computing systems.

MATLAB is a prevalent simulation software that provides a comprehensive platform for analysis and modelling [22]. The software offers extensive functions and toolboxes, empowering users to create and simulate intricate systems. MATLAB is a versatile software tool well-suited for analyzing vast datasets, implementing complex algorithms, and visualizing simulation outcomes across various domains. Its user-friendly interface, comprehensive mathematical functionalities, and compatibility with multiple data types make it an ideal choice for these purposes.

The Antarex HPC Fault Dataset is a comprehensive dataset that has been specifically developed to facilitate the investigation of fault diagnosis in High-Performance Computing (HPC) systems [21]. The aforementioned comprises a variety of characteristics and quantitative information pertinent to the analysis of faults in HPC. The dataset encompasses a range of metrics, including processor temperatures, memory utilization, network traffic, and power consumption, obtained from diverse HPC components. Furthermore, the system integrates fault labels denoting distinct fault categories that transpired during operation. The dataset is significant for creating and assessing fault diagnosis algorithms customized for HPC systems.

4.1 Fault Detection Rate

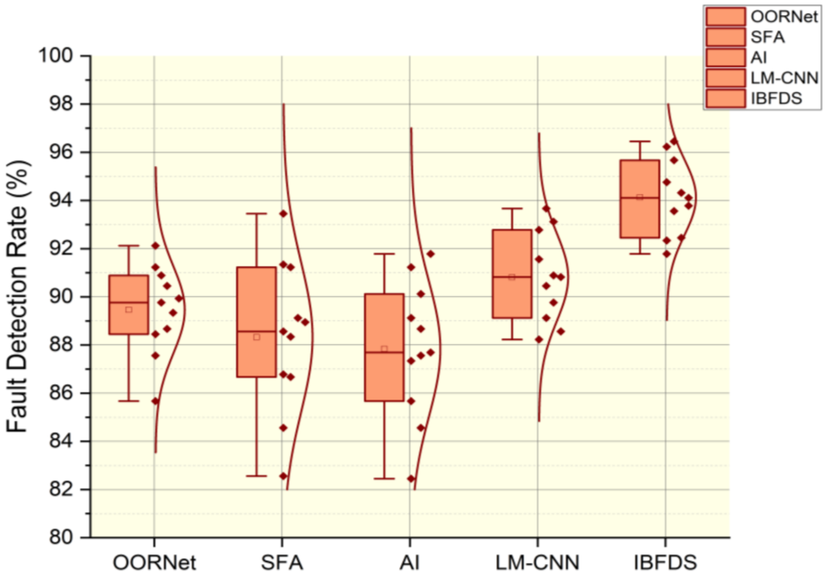

Figure 6. Fault Detection Rate Analysis

The metric known as fault detection rate quantifies the ratio of accurately detected faults in a given dataset. This is achieved by comparing the number of correctly identified faults with the total number of faults in the dataset. The efficacy of the suggested approach in identifying malfunctions in high-velocity computing systems is demonstrated. Figure 6 provides a concise overview of the Fault Detection Rate for several techniques, namely OORNet, SFA, AI, LM-CNN, and the proposed IBFDS, within the realm of rapid diagnosis in high-speed computing systems. The mean values for the strategies in the collection are 89.93%, 88.95%, 87.69%, 90.82%, and 94.11%. The findings suggest that the IBFDS technique plays higher than alternative techniques, as evidenced by its maximum common detection charge. This underscores its efficacy in exactly detecting faults in fast-paced computing structures. The discovered versions within the effects emphasize the uniformity and durability of the technique in terms of its effectiveness throughout numerous units of specimens. The IBFDS is well-known for its advanced implicit detection fee, substantiating its scalability in directly and exactly identifying malfunctions. These counterparts are the dependability and performance of systems in excessive-speed computing settings.

4.2 Fault Identification Accuracy:

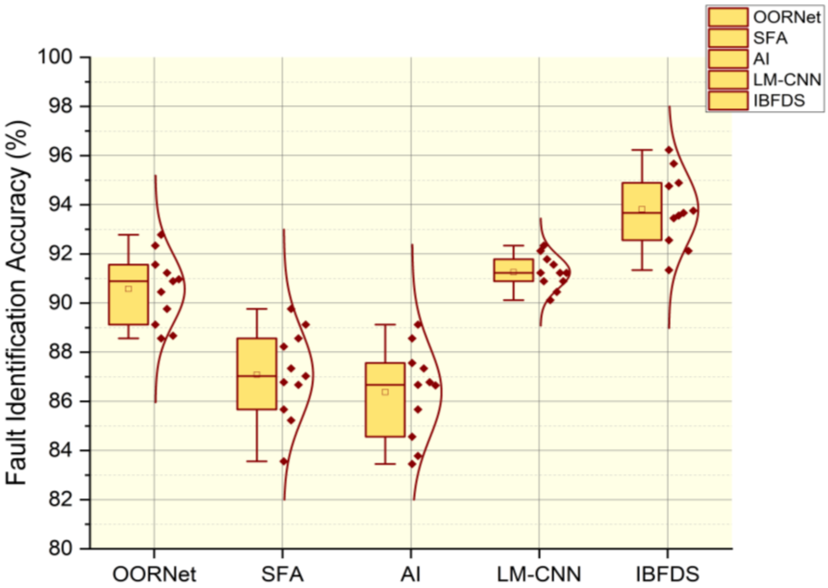

Figure 7. Fault Identification Accuracy analysis

The accuracy of fault identification is a metric that measures the degree to which the fault types in a given dataset have been correctly identified. The calculation compares the total number of identified faults and the number of adequately determined defects. This metric assesses the precision of the proposed approach in accurately detecting particular types of defects. Figure 7 presents the percentages of Fault Identification Accuracy achieved by various techniques, namely OORNet, SFA, AI, LM-CNN, and the suggested IBFDS, in the rapid diagnosis of high-speed computing systems. The mean values for the techniques are 90.97%, 87.03%, 86.65%, 91.23%, and 93.76%, correspondingly. The findings suggest that the IBFDS proposed in the study attains the most excellent mean identification precision, thereby exhibiting its efficacy in precisely detecting malfunctions in high-velocity computing systems. The discrepancies observed in the outcomes indicate the disparities in the performance of diverse samples. The higher average identification accuracy of the IBFDS highlights its ability to diagnose faults precisely, thus promoting efficient and reliable fault detection in high-speed computing systems.

4.3 Fault Localization Accuracy:

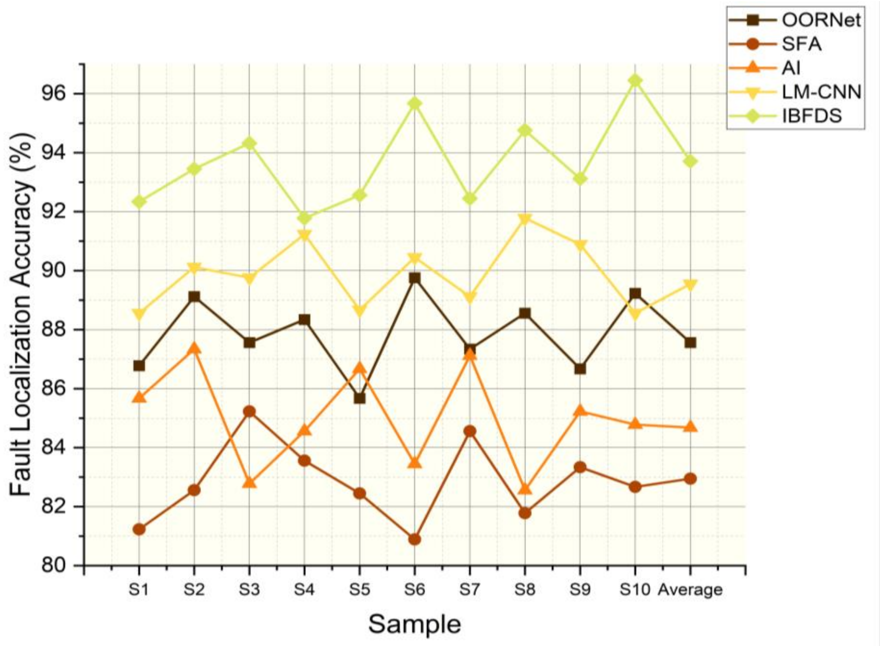

Figure 8. Fault Localization Accuracy analysis

The accuracy of fault localization in a system can be evaluated by assessing fault localization accuracy. The computation compares the count of accurately identified localized faults and the overall count of localized defects. The metric indicates the proposed technique's efficacy in determining the fault location in computing systems operating at high speeds. Figure 8 displays the outcomes of Fault Localization Accuracy for a range of techniques, such as OORNet, SFA, AI, LM-CNN, and the suggested IBFDS, within the domain of prompt diagnosis in high-speed computing systems. The mean values for the techniques are 87.56%, 82.95%, 84.68%, 89.55%, and 93.71% in sequence. The findings suggest that the IBFDS proposed in this study attains the most excellent mean precision in localization, demonstrating its proficiency in identifying malfunctions in high-speed computing systems. The observed discrepancies in the outcomes indicate the disparities in the efficacy exhibited by diverse sets of specimens. The IBFDS shows superior average localization accuracy, highlighting its accuracy in pinpointing faults. This, in turn, facilitates efficient and dependable fault localization in computing environments characterized by high-speed operations.

4.4 False Positive Rate:

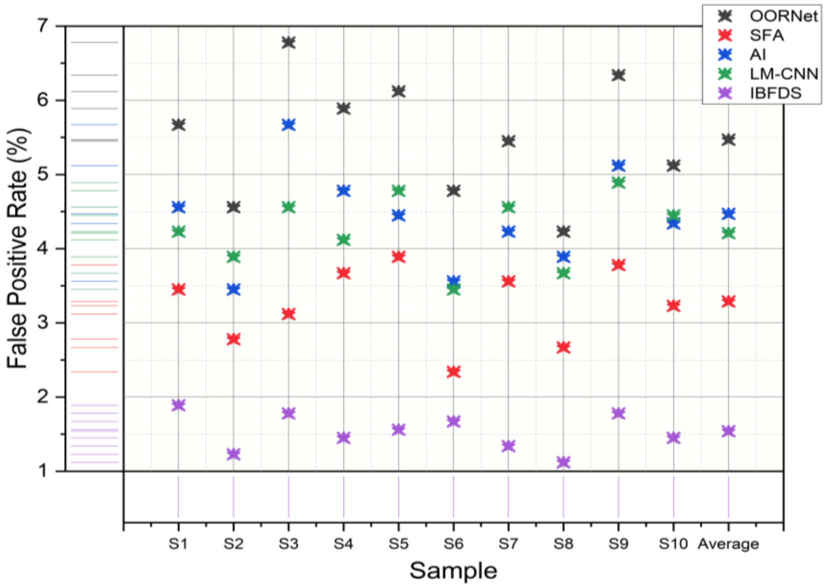

Figure 9. False Positive Rate Analysis

The metric of false positive rate quantifies the ratio of erroneously detected anomalies relative to the overall count of authentic non-anomalous occurrences present within the dataset. The efficacy of the proposed method in reducing false positive detections is demonstrated by its ability to evaluate false alarm frequency. Figure 9 displays the outcomes of the False Positive Rate for various techniques, namely OORNet, SFA, AI, LM-CNN, and the proposed IBFDS, within the domain of prompt diagnosis in high-velocity computing systems. The mean values for the techniques are 5.47%, 3.29%, 4.47%, 4.21%, and 1.54% in sequence. The findings suggest that the IBFDS proposed in this study performs better in reducing false positive fault detections in high-speed computing systems, as evidenced by its significantly lower average false positive rate. The observed discrepancies in the outcomes suggest the disparities in the occurrences of false positives among diverse sets of samples. The IBFDS significantly reduces the mean false positive rate, indicating its efficacy in mitigating false alarms and guaranteeing precise fault diagnosis in computing environments with high processing speeds.

4.5 False Negative Rate:

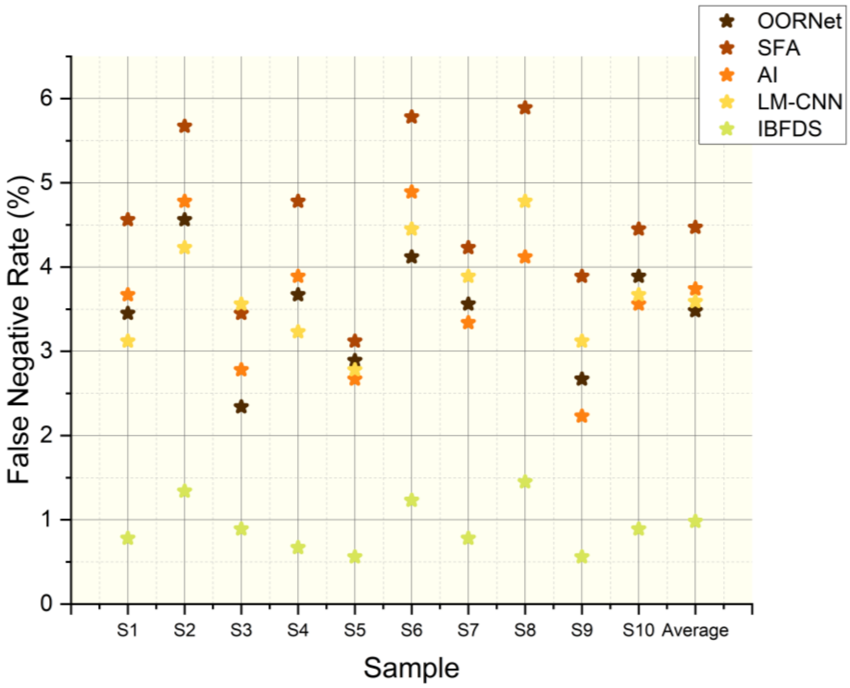

Figure 10. False Negative Rate Analysis

The false negative rate denotes the ratio of genuine errors that remain unnoticed or unobserved by the suggested approach within the given dataset. The metric quantifies the frequency of erroneous fault exclusions. It indicates the proposed method's efficacy in mitigating false negatives, guaranteeing heightened sensitivity in detecting faults. Figure 10 presents the outcomes of False Negative Rates about various techniques, namely OORNet, SFA, AI, LM-CNN, and the suggested IBFDS, within the domain of prompt diagnosis in high-velocity computing systems. In that order, the mean values for the strategies are 3.48%, 4.47%, 3.74%, 3.59%, and 0.98%. The findings propose that the IBFDS method has carried out the bottom mean fake negative price, thereby displaying its efficacy in detecting faults in excessive-pace computing structures and decreasing the chance of ignored detections. The observed discrepancies in the consequences underscore the disparities in the quotes of fake negatives among various samples. The IBFDS reveals a drastically decreased mean false negative charge, highlighting its dependability and precision in immediately figuring out faults. This feature guarantees effective fault detection and mitigates the possibility of undetected problems in computing environments that operate at high speeds.

The IBFDS exhibits superior performance compared to the comparison methods across all five metrics about fault diagnosis in high-speed computing systems. The proposed approach shows a noteworthy performance in fault diagnosis, as evidenced by its high fault detection rate (94.11%), fault identification accuracy (93.76%), fault localization accuracy (93.71%), and low false positive rate (1.54%) and false negative rate (0.98%). These results attest to the approach's effectiveness in swiftly and precisely detecting faults, positioning it as a viable solution for high-speed computing systems. The results may not apply to other industrial settings since the IBFDS assessment depends on a dataset from a particular high-speed computing machine. To make the system more useful, future studies should test it on more types of datasets. Several hyperparameters are involved in the IBFDS hybrid intelligence algorithm. The study might not investigate how the system reacts to various parameter settings. The best settings for different cases can only be determined with more research. It is possible that the research will not address how IBFDS can be adjusted to new standards and technologies in the future of high-speed computing. The system's continued usefulness depends on its ability to maintain its relevance and effectiveness throughout time.

Further study and development of the IBFDS can help address these constraints, making it more resilient and suitable for real-world high-speed computing settings. The IoE and BDA-based Fault Diagnosis System (IBFDS) found:

Better Fault Detection:

IBFDS has a 94.11% fault detection rate, 93.76% fault identification accuracy, and 93.71% fault localization accuracy. These measurements demonstrate the system's ability to find flaws in high-speed computing systems.

Lower false positive and negative rates:

With low false positive and negative rates (1.54% and 0.98%, respectively), the system was precise in defect diagnosis. Reduced alarms and accurate fault identification depend on this.

Effective Cloud Collaboration:

IBFDS used IoE cloud services for data storage, administration, and real-time collaboration. This cloud-based strategy improves efficiency, proactive maintenance, and performance, making high-speed computing systems more reliable.

V. Conclusion and findings

Fault diagnosis is essential in maintaining high-speed computing systems' dependable and effective functioning. The IBFDS approach aims to overcome the constraints of conventional models by utilizing the IoE, BDA, and hybrid intelligent algorithms. IBFDS has achieved significant improvements in fault detection rate (94.11%), fault identification accuracy (93.76%), fault localization accuracy (93.71%), false positive rate (1.54%), and false negative rate (0.98%) through the integration of a hybrid intelligent algorithm, big data analysis techniques, IoE-based cloud services, and RBoM-based detection.

The findings of this study indicate that IBFDS is a highly effective approach for swiftly and precisely diagnosing faults in high-speed computing systems. The implementation of proactive renovation helps improve system reliability and overall performance. The amalgamation of the IoE and BDA reduces all-inclusive scrutiny of huge amounts of information, resulting in improved detection and reputation of faults. Employing cloud services primarily based on the IoE allows the storage and control of records and facilitates real-time collaboration among numerous parties concerned. Furthermore, integrating RBoM-based total detection strategies improves the precision of fault identification.

Notwithstanding, certain limitations exist to scalability, real-time processing, and resource utilization optimization. Future research endeavours should prioritize the refinement of sophisticated algorithms, the mixing of on-the-spot monitoring methodologies, and the investigation of mechanized fault recuperation mechanisms. Future research will enhance excessive-overall performance computing systems' robustness and self-sustaining restoration functionalities, ensuring seamless capability in tough times.

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