Panoramic Intelligent Monitoring of Power Equipment Using Dynamic Black Hole-Driven DCGAN Under New Power Systems

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Traditional ways of monitoring power systems do not offer sufficient real-time information on equipment status and do not sufficiently address various operational scenarios and parameters. To address these problems, a new method referred to as Dynamic Black Hole-driven Deep Convolutional Generative Adversarial Network (DBH-DCGAN) has been developed. This method utilizes the dynamic Black Hole mechanism that can adjust the flexibility and stability of the DCGAN model according to the power condition. The purpose of this study is to present and assess the novel DBH-DCGAN approach and its impact on improving the accuracy and efficiency of power plant monitoring. A large set of power equipment images was gathered that contains data regarding all the equipment. The images were then pre-processed using Histogram Equalization to improve the contrast of the images. To enhance the monitoring accuracy and flexibility in different power system situations, the proposed Dynamic Black Hole-driven Deep Convolutional Generative Adversarial Network (DBH-DCGAN) method was applied. Experimental results demonstrate that DBH-DCGAN effectively monitors power plants across different operating conditions, achieving performance metrics of recall (95.4%), accuracy (94.2%), and F1-score (96.3%). The study concludes that the DBH-DCGAN method significantly improves reliability and efficiency in power system management, thereby advancing intelligent monitoring technologies within the power grid.

Povzetek: Predlagana je nova metoda DBH-DCGAN za inteligentno spremljanje elektroenergetske opreme, ki prilagaja model glede na pogoje v omrežju in izboljšuje zanesljivost in učinkovitost nadzora.

1 Introduction

Electric power is crucial for the efficient operation of critical infrastructure and overall socioeconomic stability, significantly influencing both industrial and residential sectors. As connectivity advances, the capabilities of power grid monitoring systems are expanding, with increased emphasis on sophisticated technologies for real-time performance analysis and predictive maintenance [1]. The power grid's ability to operate safely and consistently is impacted by the security of its transformation and transmission equipment. Information system data from different kinds of equipment is required as additional assistance to do operations with the Internet of Things (IoT) for power transfer, transformation devices, and tracking devices. This is in addition to the necessity for remote monitoring of power transfer and transformation information [2]. It is challenging to promote power grid production procedures, safety supervision administration, and other company innovations and intelligent communication because power grid intelligent communication equipment technological maturity and system adoption are not high, and digital data platform and real mapping interaction ability are not enough [3].

A smart grid is an innovative type of power grid that combines modern sensor measurements, communication, data, computer, and control technologies with a physical power grid. It depends on the physical power grid and combines these technologies effectively [4]. It attempts to completely satisfy user demand for power while optimizing resource allocation; it also guarantees the security, dependability, and efficiency of the power supply; it corresponds with environmental regulations; it guarantees power quality; and it adjusts to the evolving power market. It provides consumers with additional benefits and a dependable, affordable, clean, and interactive power source. An electric energy meter that measures the power loss produced by a station during grid function or a substation's function and transmits that information to the user is known as an electric power distribution system [5].

The power sector, which is a crucial base industry for ensuring the long-term expansion of the national economy, has an extensive amount of knowledge about power equipment. A robust smart grid that can efficiently guarantee societal growth is built on transmission and transformation equipment, which is in excellent condition and operates consistently [6]. Numerous grid accidents, particularly in the past several years, have been brought through pollutants, icing, strong winds, and lightning. Building an effective control and administration system for smart grids is imperative to ensure the secure operation of the grid, accelerate emergency response times, and perform thorough and accurate tracking, diagnosis, and early signaling of the condition of power transformation and transmission equipment [7]. For monitoring power equipment in power systems, a novel approach based on a DBH-DCGAN is proposed.

Contribution of study:

- As power systems continue to evolve into more complex structures, advanced monitoring techniques are increasingly seen as necessary to guarantee the efficiency and dependability of power appliances. Because of the shortcomings of traditional methods, new panoramic monitoring tactics have been developed to provide more accurate and up-to-date information regarding the operational state of equipment.
- A new method called DBH-DCGAN, which stands for Dynamic Black Hole-driven Deep Convolutional Generative Adversarial Network, is created to solve these limitations. When it comes to steady performance under different operating situations and equipment characteristics, the dynamic Black Hole mechanism helps to further boost the DCGAN model's versatility.
- To prepare the image data for analysis, we compile a panoramic dataset and apply the histogram equalization technique. Python is used to implement the proposed approach.
- Various experimental results demonstrate the efficacy of the proposed DBH-DCGAN in monitoring power plants.

2 Related works

The study examined the condition-tracking system of power transfer and transforming devices were using panoramic information, and the data model was introduced into the power transfer IoT and transforming devices [8]. Simulation software was utilized to validate the efficacy and precision of the proposed structure, demonstrating its superiority over the conventional structure. The network safety of the power transferring structure was utilized and tends to build the fundamental model of power grid condition awareness [9]. It subsequently presented the fundamental architecture of the panoramic condition awareness technologies of the smart grid functioning state, which includes recognizing conditions, understanding conditions, and forecasting conditions. It is significant to develop a comprehensive condition monitoring system for smart grid operating status using a variety of technologies that could help decision-makers create well-informed decisions by accurately predicting the maximum risk assault path that the system might experience.

The panoramic condition monitoring strategy for typical environment applications was presented using an optical fiber composite power connection [10]. The proposed surveillance system plan facilitated the construction of the intelligent surveillance architecture for the modern power system and improved the functioning and servicing of electricity transmission lines. The researchers developed automated power transfer tower recognition by employing a modern deep learning system [11]. Compared to other methods, their method was more appropriate for application in power grid disaster investigation because it could consider both accuracy and speed. A miniature multirotor unmanned aerial vehicle (UAV) utilized for power grid inspection was established in the research [12]. The proposed solution incorporated mobile network communications and a smart robot. It offered benefits for power grid monitoring that were both effective and feasible, and it could be promoted and used. They examined reactive visualization approaches for multiple devices and Geographic information system (GIS)-based grid panoramic visualizing display techniques in the research [13]. Employing clustering techniques, the evaluations improved both the GIS rendering and the visualization components, hence increasing the visualization performance.

The study presented a Power system state estimation (PSSE) based on real-time data using a deep ensemble learning method [14]. The outcomes demonstrated that the proposed strategy performed better than the data-driven PSSE approaches. The study proposed an adaptive fault identification system and approach using GIS maps and IoT [15]. The procedure of panoramic presentation and reaction optimization that utilized GIS, as well as the phase of automatic defect detection and data evaluation based on IoT sensor information, were the main components of the technique. It increased productivity and offered a dependable and practical approach for smart address location and evaluation in power grid design. To improve power maintenance and operation, the study developed a set of servicing mechanisms for electrical devices using big data analytic technologies [16]. Big data utilization in electrical device maintenance and operation control leads to increased social and economic advantages as well as higher brand impact and better service for power supply companies. Table 1 presents the related works.

Table 1: Related works

Study	Method	Dataset	Key Results	Gaps in SOTA
[8] Power Transfer and Transforming Devices Monitoring	Panoramic information introduced into IoT-enabled power transfer and transforming devices	Simulated power transfer systems	Demonstrated superior efficacy and precision over conventional structures	No consideration of dynamic learning models or real-time condition updates
[9] Network Safety for Power Grid Condition Awareness	Power grid condition awareness model using fundamental panoramic condition architecture	Power grid condition data	Effective in recognizing, understanding, and forecasting grid conditions	Lacked integration of deep learning for enhanced predictive capabilities
[10] Optical Fiber-Based Power Connection Monitoring	Panoramic monitoring for typical environments using optical fiber connections	Optical fiber communication data	Improved power transmission monitoring and line maintenance	Limited application to specific environments and not scalable for diverse grid systems
[11] Deep Learning for Power Transfer Tower Recognition	Automated tower recognition using modern deep-learning techniques	Image data of power transfer towers	Suitable for disaster investigation due to high accuracy and speed	Did not address complex, evolving grid conditions in real time
[12] UAV for Power Grid Inspection	Unmanned Aerial Vehicle (UAV) with mobile network and smart robot communication	UAV flight data and power grid inspection data	Effective and feasible for grid inspection with high mobility	Limited scalability in large grid networks with frequent updates
[13] GIS-based Grid Panoramic Visualization	Reactive visualization and GIS-based visualization techniques for grid monitoring	GIS data and power grid sensor data	Improved GIS rendering and visualization performance using clustering	Lack of advanced predictive analytics or integration with AI
[14] PSSE Using Deep Ensemble Learning	Power system state estimation with real-time data using deep ensemble learning	Real-time power system data	Outperformed traditional PSSE methods in accuracy and speed	Not optimized for large-scale, dynamic grids requiring adaptive updates
[15] Adaptive Fault Identification with GIS and IoT	Fault identification and reaction optimization using GIS and IoT sensor data	GIS data and IoT sensor data	Increased productivity and offered reliable fault detection	Did not incorporate panoramic monitoring techniques or advanced learning algorithms
[16] Big Data for Electrical Device Maintenance	Big data analytics for improving power maintenance and operation	Big data from electrical devices	Increased social and economic advantages and improved service	No integration of deep learning or dynamic condition monitoring

3 Methodology

3.1 Data collection

This study was able to get 1495 images showing equipment faults. The internal components of the substation equipment were analyzed, and the results showed that the equipment could be classified into 3 categories (power cable, distribution equipment, and transformer), 18 components (insulator, bus, relay, etc.), 14 varieties of faults (oil leakage, burning, abnormal indication, screw loosening, crack damage, rust, silica gel discoloration, falling, etc.), and relevant measures and recommendations. After that, duplicate, unclear, and inconsistent images are manually filtered out of the gathered image data. Following screening, 896 excellent images are chosen to make up the first image set. These images are then similarly processed to have a resolution of 416 × 416 pixels.

3.2 Pre-Processed using histogram equalization

Through the redistribution of intensity values throughout the image, an approach known as histogram equalization is applied in image processing to enhance the general quality and contrast of the image. An image's dark and light areas may not have the best contrast, making features difficult to identify. Brighter parts become brighter and darker areas become darker as a result of histogram equalization spreading out the intensity levels.

When the intensity levels in a digital image fall inside range $[0, K-1]$, the histogram becomes a discrete function $g(q_l) = m_l$, where K represents the number of the level, q_l is the l^{th} intensity value, and m_l represents the number of pixels in the image with intensity q_l. A popular method for standardizing a histogram is to divide all of its fundamentals by the total amount of pixels in the image, symbolized by $N \times M$, where $N \, and \, M$ represent the image's column and row dimensions. We can obtain a normalized histogram using the Equation (1),

$$o(q_l) = \frac{m_l}{NM} for \; l = 0,1,2, \dots K-1 \quad (1)$$

Where $o(q_l)$ represents an approximation of the possibility that an image will include intensity level q_l, which is shown in Equation (2).

$$\sum_{l=1}^{K-1} o(q_l) = 1 \quad (2)$$

Let q represent the intensities of an image while considering the constant intensity values. q appears to be within range $[0, K-1]$. The focus is directed towards transformations, or intensity mappings, of the type $t = S(q)$ where $0 \leq q \leq (K-1)$generates an output intensity level t for each pixel in the input image given intensity.

3.3 DBH-DCGAN

An improved technique known as the DBH-DCGAN is a procedure for changing the panoramic tracking capabilities of power equipment in power systems. Developed from power system design and deep learning, the overview of a new method for monitoring and assessing power equipment tries to achieve higher accuracy and efficiency that has never existed before. DBH is employed to enhance the deep convolutional neural network structure by allowing the DBH-DCGAN. By integrating these two methods, the network can obtain high-quality images of the panoramic environment of power equipment faster, thereby improving the amount of monitoring and detailed evaluation.

The integration of DBH with DCGAN has several modifications: The DBH parameters are fine-tuned for each iteration, where several parameters like gravitational and black hole parameters are fine-tuned to optimally balance between exploration of solutions and exploitation of good solutions. This enables the network to escape from the local minima and achieve a global optimum. DBH is incorporated into the DCGAN structure to fine-tune the generator and discriminator networks, adjusting the weight of the networks in response to the generation of high-quality panoramic images and the identification of the anomalies present in the generated images. Although DBH-DCGAN is computationally expensive because of the real-time processing and iterative learning, real-time monitoring and early warning of possible problems justify its computational overhead, while dynamic optimization makes it capable of real-time monitoring of power equipment.

The method also helps in giving the right degree of accuracy when determining power equipment errors, problems, or even probable threats because of the learning capability of the method to look at certain trends and characteristics from a large data set. Consequently, the real-time assessment of the panoramic images indicates that the DBH-DCGAN can distinguish between the anomalies and the errors from the normal state. This enables it to offer warnings and in addition more recommendations on what can be done to prevent a breakdown. Additionally, incorporating dynamic optimization into the training process of the black hole will augment the functionality and performance of the network that is being trained as the parameters are being adjusted in training sessions. For instance, DBH-DCGAN can capture information from all the relevant information sources and adjust settings based on new conditions in the power system environment for this type of flexible optimization solution.

3.3.1 Deep convolutional generative adversarial network (DCGAN)

The Deep Convolutional Generative Adversarial Network (DCGAN) generates high-resolution images of power equipment faults. By training a generator and discriminator together, DCGAN improves anomaly detection and equipment monitoring, providing detailed and accurate insights into potential issues and fault conditions.

A system known as the DCGAN forms the foundation for the unsupervised learning portion of the analyzed model. DCGAN comprises two elements, the generator, and discriminator, which undergo training over each other in a minimax setting. The generator gains the ability to translate random distribution samples into output vectors of a given structure. An actual sample from a set of data or a generator output is the two inputs that the discriminator receives. The discriminator gains the ability to distinguish between created and real input.

A cross-entropy loss coefficient based on the number of inputs successfully identified as produced and the number properly categorized as real is used by the discriminator during training. The definition of the cross-entropy loss between forecasts $\hat{z}$ and true labels z is shown in Equation (3),

$$\mathcal{L}(x) = -\frac{1}{M}\sum_{m=1}^{M}[z_m \log \hat{z}_m + (1 - z_m)\log(1 - \hat{z}_m)] \quad (3)$$

Were,

M - Number of samples, and

x - Learned vector of weights.

Labels are expressed numerically in this computation as 1 for real and 0 for established. Next, the cross entropy for accurate actual forecasts reduces when $\hat{z}_q$ represents the discriminator's forecasts for all actual inputs as shown in Equation (4).

$$\mathcal{L}_q(x) = -\frac{1}{M}\sum_{m=1}^{M}\log \hat{z}_{q,m} \quad (4)$$

Since all of the correct forecasts in this instance are ones, likewise, if $\hat{z}_h$ stands for the discriminator's forecasts for every produced input, then the cross entropy for accurate forecasts of generated outputs reduces to Equation (5),

$$\mathcal{L}_e(x) = -\frac{1}{M}\sum_{m=1}^{M}\log\left(1 - \hat{z}_{h,m}\right) \quad (5)$$

Therefore, all zeros are the right forecasts in this particular instance. The discriminator's overall loss is determined by adding the prior two terms $\mathcal{L}_c = \mathcal{L}_q + \mathcal{L}_e$. The generator similarly makes use of a cross-entropy loss, but this loss is expressed as the number of created outputs that were mistakenly identified as real as shown in Equation (6).

$$\mathcal{L}_h(x) = -\frac{1}{M}\sum_{m=1}^{M}\log\left(\hat{z}_{h,m}\right) \quad (6)$$

As a result, the generator's loss decreases with increasing ability to generate outputs that the discriminator perceives as real. After adequate training phases, this causes the generator to finally create outputs.

3.3.2 Dynamic Black Hole Algorithm (DBH)

The Dynamic Black Hole (DBH) algorithm enhances the monitoring of power equipment by optimizing parameters iteratively. It balances exploration and exploitation to improve the network's ability to escape local minima and accurately detect anomalies in real-time equipment data. The DBH's primary stages were as follows,

i) Development of the initial population

The initial population of the black hole method, which was extensively utilized in adaptive algorithms, was generated at random. However, the computation results were affected by the possibility of assembling a large number of initial candidate solutions (CSs) in a small local space while utilizing this strategy. Consequently, several strategies for building a quality initial population have been proposed. In this research, the Small Region Creation Method (SRCM) was one of the strategies employed to generate an appropriate initial population. Using this strategy, the search range was initially consistently separated into several small zones equal to the size of the population. Subsequently, in every small location, a single original CS was generated at random. Consequently, the initial CSs might be dispersed equally over the search space utilizing the SRCM.

ii) The black hole algorithm included certain steps, such as those responsible for black hole choice, the motion of a star, star substitution, and black hole updating.

iii) Procedure for selection.

Enhanced random competition, with variable $\frac{m}{2}$, is an instance of an improved stochastic competition framework used for the selection process. This operation's fundamental steps are listed below,

It was believed that the population that occurred before the black hole updating process was the parent population, and that a new population was the offspring population. A union population was created by combining the parent and offspring populations. From the combined population the CSs whose total number of $\frac{m}{2}$ was chosen. The fitness values (FVs) of each CS w in the combined population were contrasted to those of the chosen CSs and the total amount of CSs whose FVs were higher than those of CS w was the CS ($w(w.score)$).

To modify a CS's score, a thickness measure of a certain kind might be included based on the restraining and stimulative response in an artificial immune mechanism. A CS's premature character was apparent if its thickness was large. Therefore, it is necessary to constrain a CS with a high thickness and increase the selection probability of a CS with significant fitness. The score of a CS was increased by the change depending on the CS's fitness and thickness, which was explained in Equation (7) as follows,

$$w'.score = w.score - 0.5.D.\left(1 - \frac{e(w)}{e_{max}}\right).w.score + 0.5.\frac{e(w)}{e_{max}}.w.score \quad (7)$$

Where D represented the thickness of a CS, which was the combined population as a whole divided by the number of people whose fitness was nearly identical to that of individual w.It was stated in the following Equation (8),

$$D = \frac{(0.9.e(w) \rightarrow 1.1.e(w)}{M} \quad (8)$$

Where M represents the union's entire population, $e(w)$ is the FV of a potential solution$w$, and e_{max} is the maximum FV of the union's population. The numerator was the sum of all the individuals whose fitness falls within $0.9^{*}e(w)$ and $1.1^{*}e(w)$. The CSs in the union population were sorted in descending order based on the scores of every CS; the first half was chosen for the subsequent iteration.

iv) *Termination criteria.*

Similar to the black hole algorithm, this process was carried out.

4 Result

Our proposed DBH-DCGAN approach was implemented on a Python 3.10 platform using an Intel i5 5th Gen laptop running Windows 11. This demonstrates the approach's feasibility on moderately powered hardware, highlighting its potential scalability and adaptability to more resource-constrained environments commonly found in real-world monitoring systems. We evaluate the performance of our proposed approach here by contrasting it with conventional approaches, including multi-scale dynamic graph convolutional network (D-GCN) attention [17], class-specific residual attention (CSRA) [17], and -Driven Dynamic Graph Convolutional Network (ADD-GCN) [17].

The precise nature of the data gathered, which guarantees an accurate understanding of the operation of the equipment, is referred to as accuracy. Loss is the measure of the difference between anticipated and actual values, which indicates ineffectiveness in the entire structure. This technology helps with preventive maintenance, which lowers delay and improves overall system dependability in the ever-changing world of contemporary power systems by decreasing loss and enhancing accuracy. Figure 1 displays the output of accuracy and loss.

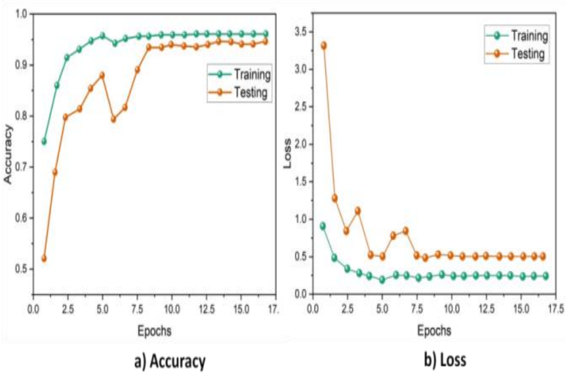

Figure 1: Output of a) accuracy and b) loss

The confusion matrix indicates the performance of the binary classification model as illustrated in the following Figure 2. It compares true labels (vertical axis) with predicted labels (horizontal axis) across four classes: The scale is made up of Normal, Slightly Abnormal, Moderately Abnormal and Severely Abnormal, with the values ranging from 3 to 10 and the darker shades of blue corresponding to higher qualities. For instance, the model successfully identified 10 instances of a specific class while at the same time, classified 6 instances of that class to another class. This tool can be used to assess the model's diagnostic accuracy and reliability and stresses that the model's performance in discriminating between various degrees of abnormality needs improvement.

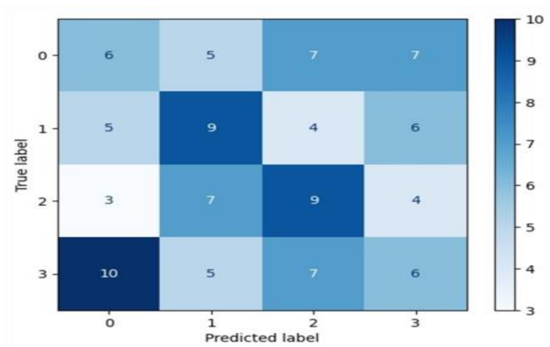

Figure 2: Confusion matrix

ROC curve evaluates the performance of a binary classifier in the context of our study. The curve plots True Positive Rate against False Positive Rate across different thresholds. The orange line represents the ROC curve, while the blue dashed line signifies random chance. With an Area Under the Curve (AUC) of 0.97, the model exhibits exceptional accuracy. This visualization is crucial for assessing the model's effectiveness in distinguishing between different fault conditions and equipment categories in our monitoring system.

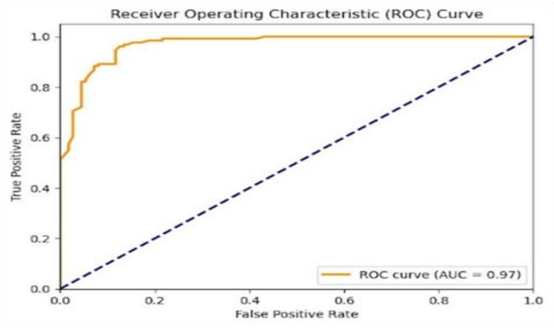

Figure 3: Result of ROC curve

Figure 4 presents the outcomes of the DBH-DCGAN method employed to estimate the health of the power equipment state. The mean precision is utilized to quantify the evaluations of four different equipment health conditions. Our proposed DBH-DCGAN method has a mean precision of health of 96.42%, and slightly abnormal values of 89.49%, whereas moderately abnormal and severely abnormal have results of 90.34% and 95.31%, respectively.

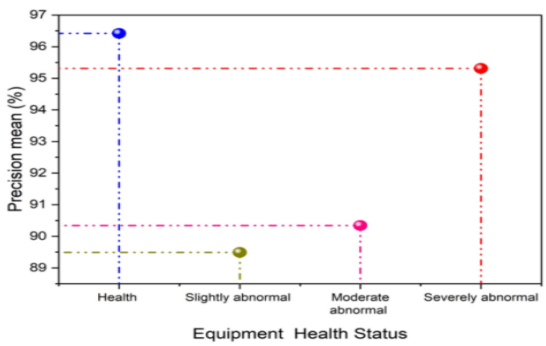

Figure 4: Evaluation outcomes of DBH-DCGAN technique for four states

The F1-score measures efficacy by balancing recall and precision. It assesses the model's capacity to accurately recognize abnormalities in power equipment tracking, providing an extensive evaluation of its efficacy in practical situations. The F1-score of the proposed DBH-DCGAN method is 96.3%, surpassing the F1-scores of the traditional ADD-GCN, CSRA, and Multi-scale D-GCN procedures, which are 81.1%, 80.3%, and 81.9%, as displayed in Figure 5.

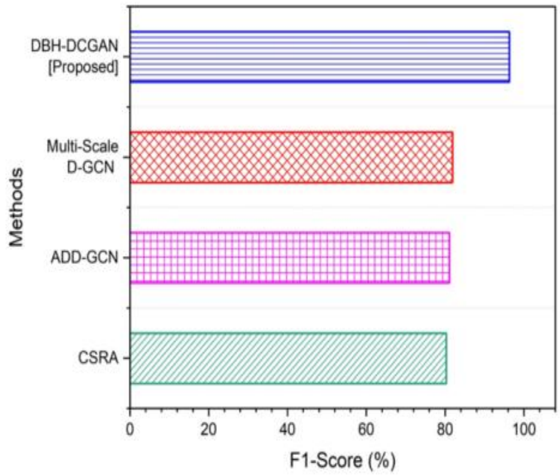

Figure 5: Result of F1-score

The recall evaluates the system's capacity to accurately recognize every pertinent occurrence of power equipment faults compared to the total number of actual problems to reduce missed detections and improve monitoring accuracy in the changing power system environment. With a recall rate of 95.4%, the proposed DBH-DCGAN strategy outperforms the traditional ADD-GCN, CSRA, and multi-scale D-GCN methods, which have recall rates of 78.9%, 75.8%, and 79.2%, correspondingly as shown in Figure 6.

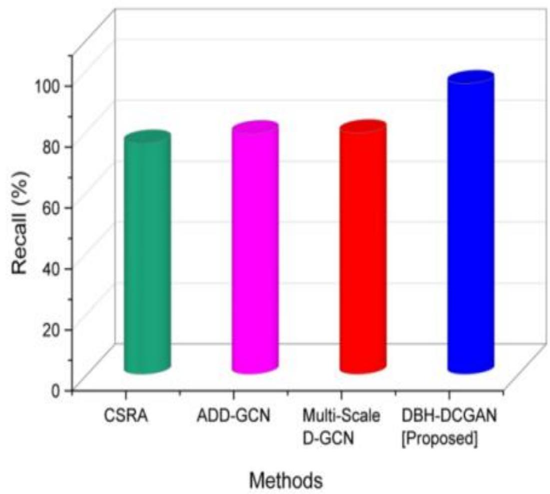

Figure 6: Output of recall

The precision evaluates the power equipment defects that are found and diagnosed, guaranteeing dependable and effective operation.

This measures the efficiency of the system and how well it is identifying and analyzing the abnormalities, reducing delay. In comparison to the existing methods including the ADD-GCN, CSRA, and Multi-scale D-GCN whose precision values are 83.3%, 85.3%, and 84.9% and the precisions of the proposed DBH-DCGAN approach are 94.2%, is shown in Figure 7. Table 2 shows the result of precision, recall, and F1-score.

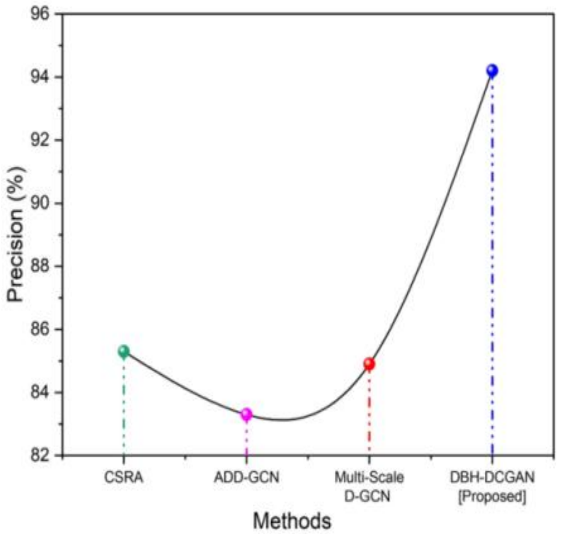

Figure 7: Result of precision

Table 2: Result of precision, recall, and F1-score

Methods	F1-score	Precision	Recall
CSRA	80.3%	85.3%	75.8%
ADD-GCN	81.1%	83.3%	78.9%
Multi-scale D-GCN	81.9%	84.9%	79.2%
DBH-DCGAN [Proposed]	96.3%	94.2%	95.4%

4.1 Discussion

CSRA [15] may be effective but they are not easily guaranteed to be understandable which makes it challenging for one to understand how a specific model arrived at a particular decision. This is important because interpretability is usually required for decision-making in a setting such as power equipment monitoring. ADD-GCN [16] may experience the greatest challenge when exposed to rapidly changing structures of the network or settings within the power system. It could be challenging to identify and respond to changes in the network topology.

Since there are strong interdependencies between characteristics in several dimensions, the multi-scale D-GCN [17] may be challenging to interpret. This means that there might be some challenges in identifying how data passes through the network and how all the factors affect the decision-making process, therefore making the monitoring system complex to understand. In contrast, **DBH-DCGAN** offers a promising alternative by addressing these challenges. The DBH-DCGAN model is designed to enhance the monitoring of power equipment by providing improved interpretability and adaptability. Its architecture is tailored to handle dynamic network structures more effectively, ensuring better performance in varying conditions. Additionally, the model's design simplifies the decision-making process, making it more accessible and understandable.

5 Conclusion

Specifically, the new environment of energy is based on the instant transition to distributed networks and renewable sources, whereas accurate monitoring technology constitutes a critical necessity. In this research, a novel approach based on a DBH-DCGAN is proposed for monitoring power equipment. We gathered the panoramic equipment image dataset. For training and inference, DBH-DCGAN frequently needs a large amount of computer power. The proposed method's efficiency is measured in terms of recall (95.4%), precision (94.2%), and F1-score (96.3%). It may be difficult to implement such models in continuous monitoring systems due to resource limits and computing efficiency, particularly in situations with limited resources. Future enhancements in effective training and implementation methodologies are essential. Handling computational limits will allow for simple incorporation into continuous monitoring systems, which is critical for applications that require limited resources.

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