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An Intelligent Decision-Support Framework for Substation Fault Management Using BOA-Optimized Deep Learning and IoT-Based Image Processing

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ABSTRACT

Achieving operational efficiency and reliability in power substations becomes increasingly difficult as system complexity rises, necessitating the deployment of advanced monitoring and control technologies. The proposed Intelligent Power Auxiliary Control and Monitoring System integrates Internet of Things (IoT) technology with two-dimensional image processing to facilitate real-time monitoring and fault detection within substation environments. The system employs IoT-based sensors to capture critical auxiliary control parameters, including voltage, current, temperature, and equipment status. For image-based analysis, the YOLOv8 algorithm is utilised as an object detection mechanism, enabling precise identification of substation components and anomalies. Deep learning analysis is conducted using a Residual Neural Network (ResNet), which supports high-accuracy fault recognition through comprehensive monitoring of system parameters. The ResNet's performance is further refined through weight parameter optimisation via the Butterfly Optimisation Algorithm (BOA), which improves convergence speed and classification accuracy. The system's effectiveness is validated through empirical analysis using actual substation data, demonstrating improvements in both fault detection accuracy and operational responsiveness. Evaluation findings confirm that the BOA-optimised ResNet model outperforms conventional deep learning approaches in terms of diagnostic accuracy and computational efficiency. The research contributes to the development of autonomous, intelligent auxiliary control systems capable of enhancing the safety and stability of substation operations. To aid in maintenance scheduling and operator decision-making, the system incorporates a fuzzy rule-based decision layer that interprets predictive outputs and initiates context-aware operational responses.

1. Introduction

Power transmission and distribution systems rely heavily on substations, which serve as critical infrastructure components for ensuring consistent and dependable electricity supply. However,

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conventional monitoring approaches have become inadequate due to the increasing complexity of substation equipment Davoodi et al. [4], as well as the growing need for real-time fault detection and predictive maintenance. Manual inspections remain widely used, yet these methods are time-consuming, labour-intensive, and often lack reliability [1], leading to prolonged delays in identifying potential issues. Substation apparatus is frequently subjected to harsh environmental conditions, heightening the risk of overheating, insulation degradation, corrosion, and oil leakage [8]. Delays in identifying such issues can pose significant threats, including service interruptions, financial losses, and safety hazards. Hence, an accurate and fully automated detection system is essential to facilitate early fault identification and enable timely responses under prevailing operational challenges [18].

Recent advancements in computer vision and neural network technologies have facilitated the application of deep learning techniques in defect identification, thereby improving monitoring effectiveness [7]. Enhancements to the YOLOv5 model have yielded improved detection rates and accuracy in identifying substation components. Furthermore, adaptations involving Faster R-CNN have been employed to better recognise small-scale targets such as cracks, insulation failures, and oil stains. Integrating adapter-based transformer modules within YOLOv5 has also strengthened the model’s performance and adaptability, particularly in scenarios with limited datasets [16]. These advancements have enabled substation fault detection systems to exceed previously established technological benchmarks, achieving greater accuracy and dependability across various monitoring functions.

Nevertheless, several technical challenges remain unresolved. Identifying small targets within complex substation environments continues to be problematic, as many current techniques fall short in detection accuracy [11]. Feature extraction by existing models is frequently compromised by background noise and overlapping equipment, which contributes to false alarms and diminished precision. Additionally, the computational intensity of transformer-based models restricts their suitability for real-time operations in resource-constrained monitoring systems. Many existing solutions prioritise accuracy improvements at the expense of operational efficiency. In response to these limitations, the proposed study introduces an advanced fault detection framework that integrates YOLOv8 for real-time object recognition with ResNet for classification, further enhanced by the BOA to optimise system performance. The resulting system achieves notable improvements in diagnostic accuracy, computational efficiency, and adaptability, positioning it as an effective and lightweight solution for real-time monitoring and predictive maintenance in substations.

Within the evolving landscape of modern power substations, effective decision-making has become increasingly vital due to the growing intricacy of operational dynamics, diverse fault scenarios, and the pressing need for real-time responsiveness. Conventional manual approaches are often inadequate for processing the large volumes of sensor-generated data or for initiating prompt and targeted maintenance interventions. Consequently, the incorporation of intelligent decision-making frameworks within substation monitoring architectures has become a necessity. Approaches such as fuzzy logic, Multi-Criteria Decision-Making (MCDM), and optimisation-driven analytics facilitate the conversion of raw diagnostic outputs into structured, actionable directives. These methodologies enable the prioritisation of maintenance operations, optimal resource deployment, and the minimisation of system interruptions by supporting operators in making informed decisions grounded in the severity, urgency, and associated risk of detected faults. The system presented in this study not only performs fault identification through deep learning and optimisation-enhanced classification but also integrates a fuzzy rule-based decision module. This addition ensures that operational responses are contextually guided, thereby improving the overall safety, reliability, and efficiency of substation management.

There is significant potential for future developments in intelligent power auxiliary control and monitoring systems based on IoT and two-dimensional image processing. The integration of artificial intelligence (AI), machine learning, and deep learning algorithms can further enhance predictive analytics for early fault identification and failure forecasting in power equipment [8]. Deep learning methodologies, in particular, can increase the precision of image-based anomaly detection. Additionally, the deployment of edge computing will support real-time data processing directly at the substation, improving system responsiveness and reducing latency, especially in remote locations with limited internet access. The incorporation of blockchain technologies may further reinforce data integrity and security by offering tamper-resistant logging of operational data. Future research directions could also explore the development of energy-efficient IoT devices with embedded self-diagnostic capabilities, which would improve overall system longevity and reliability. Moreover, the implementation of 5G communication networks is expected to significantly enhance real-time monitoring and control capabilities.

Despite these promising advancements, certain limitations persist. Integrating modern systems with legacy power infrastructure remains costly and complex, with high initial investment requirements. Additionally, the inclusion of IoT and image processing functionalities introduces potential cybersecurity vulnerabilities, which must be mitigated through robust encryption protocols and stringent security measures. Other technical challenges include variability in lighting conditions, environmental interference, and occlusion, which can compromise the accuracy of two-dimensional image analysis tasks [2]. Efficient data management also poses a challenge, given the substantial volumes of real-time data generated by the system that require reliable storage and processing. In rural or remote areas, connectivity problems and network instability may affect the reliability of IoT-based monitoring. For intelligent auxiliary control and monitoring systems to be successfully implemented within substations, continuous advancements in hardware, software, and cybersecurity frameworks will be essential to overcome these existing constraints.

2. Related Works

Security concerns within power substations form a critical basis for maintaining the reliability of both transmission and distribution systems. Prioritising the identification of equipment defects and implementing stringent construction safety protocols is essential, as such measures help to avert power system failures, reduce maintenance expenditure, and enhance operational efficiency. Progress in technologies such as deep learning, computer vision, and multi-sensor fusion has enabled the creation of highly accurate real-time fault detection methods. The integration of neural network architectures with multivariate data fusion frameworks and infrared imaging—often supported by Generative Adversarial Networks (GANs) and lightweight artificial neural networks—has proven effective in identifying hidden anomalies without compromising safety standards. A comprehensive analysis of current research on substation fault detection is necessary to evaluate the key technical strategies employed, understand their advantages, and identify limitations to guide further development. The problem formulation is presented in Table 1.

One such approach is the lightweight fault detection model based on YOLOv8, designed to enhance the identification of small-scale targets in substation environments while maintaining low computational demands [25]. This model incorporates three fundamental components to improve detection in complex conditions: feature fusion mechanisms, attention-based modules, and shared convolutional heads. These elements collectively contribute to network optimisation, rendering the system suitable for use in edge computing scenarios. The model offers notable advantages, including improved sensitivity to small defects and reduced resource consumption. However, it also faces limitations in identifying extremely small or ambiguous defects, highlighting a performance trade-off between detection precision and real-time operational efficiency.

Table 1
Problem Formulation

Author(s)	Techniques Involved	Advantages	Disadvantages
Wang et al. [25]	YOLOv8, Feature Fusion, Attention Modules	High Accuracy, Low Computation, Edge-Device Friendly	Struggles with Very Small/Occluded Defects, Complexity Trade-Offs
Wu et al. [29]	YOLOv5, Global-Local Fusion, Multi-Granularity Subsampler	High Precision, Real-Time Infrared Detection	Limited Efficiency for Small/Low-Contrast Defects
Zhang et al. [30]	ADD-GAN, Joint Discriminator, Local Feature Preservation	Enhances Training Data, Prevents Distortions	High Computational Cost, GAN Training Complexity
Zhang et al. [31]	IL-GAM, IL-C3, IL-SPPFCSPC, Multi-Scale Processing	91.2% Accuracy, 90 FPS, Robust Detection	Needs Optimization for Variable Conditions
Ke et al. [12]	Multi-Sensor Fusion, Cloud-Edge AI, Anomaly Detection	Real-Time Warnings, Improved Situational Awareness	High Sensor and Computational Requirements

A real-time infrared detection model for substation equipment has been developed based on the YOLOv5 framework, referred to as ISE-YOLO [29]. This system integrates global–local feature extraction, multi-granularity subsampling, and heavy parameter separation to enhance object detection within complex environments. It is available in two versions, ISE-YOLO-L and ISE-YOLO-S, each offering a trade-off between detection precision and processing efficiency. An extensive infrared image dataset was compiled and systematically pre-processed to support detection accuracy. While the model strengthens real-time performance and object recognition capabilities, it faces ongoing challenges in the efficient identification of extremely small or faint faults. Another study addresses the issue of limited defect datasets by employing deep learning-based image generation techniques [30]. Through the use of a Generative Adversarial Network named ADD-GAN (Abnormal Defect Detection GAN), defect images are synthetically created while preserving local image features. This method targets local segmented areas rather than relying on global characteristics, improving the representation of defects. A dual-discriminator training strategy focuses detection learning on defect zones, thus enhancing accuracy. Despite these strengths, challenges persist regarding the complexity of training procedures, computational demands, and the applicability of synthetic data in operational environments.

Further developments include a detection approach aimed at insulator faults within transmission lines, where backgrounds are often cluttered and visually complex [31]. The proposed model integrates a Global Attention Mechanism (IL-GAM) to suppress background interference, a modified convolution module (IL-C3) to enhance feature extraction, and a spatial pyramid pooling structure (IL-SPPFCSPC) to process multi-scale information. Results indicate a detection accuracy of 91.2%, which represents a 3.6% improvement over previous YOLOv5 models. Additionally, the system demonstrates real-time processing capabilities with a speed of 90 frames per second. Nevertheless, achieving consistent optimisation in diverse operational conditions remains a significant concern.

A separate contribution involves the development of a substation safety framework that employs multi-dimensional sensor fusion to support risk detection and early warnings [12]. The system incorporates sensors for electromagnetic fields, meteorological parameters, toxic gas concentrations, and oxygen levels, supplemented by video surveillance for situational monitoring. Cloud–edge collaborative techniques are applied to facilitate real-time data processing and fusion. Advanced analytics, including semantic segmentation, anomaly detection, and transfer learning, enable timely alerts concerning operational violations, hazardous gases, and construction errors. This comprehensive approach enhances both operational intelligence and substation construction safety. Although notable progress has been made in substation defect detection, limitations continue to affect small-target recognition, visual obstruction handling, and processing efficiency. Deep learning models often require substantial computational resources, restricting their use in energy-constrained devices. Furthermore, older systems underperform when operating in low-contrast environments. To address these issues, an enhanced detection framework is proposed, integrating YOLOv8 for real-time object identification, a ResNet for fault classification, and the BOA for system efficiency enhancement. This architecture offers a balance between detection accuracy, operational speed, and resource usage, resulting in a highly adaptable and dependable solution for intelligent substation monitoring and predictive maintenance.

3. Proposed System Model

The Intelligent Power Auxiliary Control and Monitoring System employs a systematic framework that integrates IoT-based data acquisition with real-time image analysis, achieving notable advancements in fault detection through deep learning methodologies and system optimisation for enhanced substation performance [13]. The deployment of IoT-enabled sensors spans all critical zones within the substation, facilitating continuous monitoring of key electrical parameters such as voltage, current, temperature, and humidity. These sensors relay real-time data to a central processing unit through a secured communication infrastructure. In parallel, high-resolution cameras capture continuous 2D imagery of vital infrastructure elements to support visual inspections. Prior to analytical processing, data undergoes noise reduction and normalisation procedures to ensure the quality and reliability of both sensor inputs and image data. The structural design of the proposed system is illustrated in Figure 1.

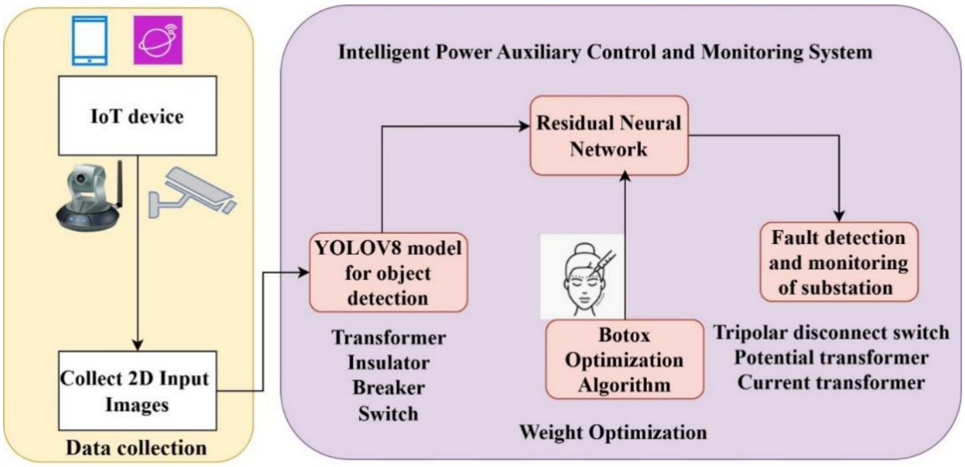

Fig.1: System Architecture

The system initiates real-time object detection within the substation after YOLOv8 processes the acquired data. YOLOv8 identifies equipment such as transformers, circuit breakers, and insulators, while simultaneously detecting potential hazards including damaged infrastructure and foreign objects. This automation enhances operational efficiency by streamlining inspection and maintenance workflows without requiring human involvement. Subsequently, the processed data is fed into the RNN, which integrates IoT sensor data and image-based detection patterns to monitor and identify faults such as overheating, insulation degradation, and voltage irregularities [26]. Residual connections within the RNN address the vanishing gradient problem, facilitating effective learning of the complex behaviour inherent in power systems [9]. The BOA is applied to optimise weight parameter selection and improve processing speed within the RNN, resulting in refined hyperparameters that reduce errors and bolster responsiveness under variable substation conditions. When abnormal states or hardware faults are detected, automatic notifications and control commands are dispatched to operators via a single graphical user interface. The auxiliary power control system continuously monitors power distribution during anomalies to ensure uninterrupted operation. Performance evaluations utilising real substation data demonstrate enhanced fault detection accuracy and computational efficiency in comparison with conventional deep learning methods. The developed framework constitutes a comprehensive automated monitoring solution that elevates substation reliability and operational effectiveness [6].

3.1 Object Detection

YOLOv8, evolved from YOLOv5, functions as an enhanced algorithm designed to address multiple object recognition challenges within architectural surveillance applications. It comprises three fundamental components: the backbone architecture, the neck architecture, and the head architecture. The design structure of YOLOv8n is illustrated in Figure 2. All backbone functions originate from the integration of SPPF, C2f, and CBS modules. The CBS module performs convolution combined with SiLU activation and batch normalization techniques to facilitate feature extraction and down sampling [24]. The C2f module operates by employing bottleneck feature extraction based on YOLOv7, where the extracted features are concatenated to provide a more comprehensive representation. The SPPF module starts with 1*1 convolution operations to reduce feature map dimensions, followed by three max-pooling layers controlling the process. This combination effectively merges local and global features [15].

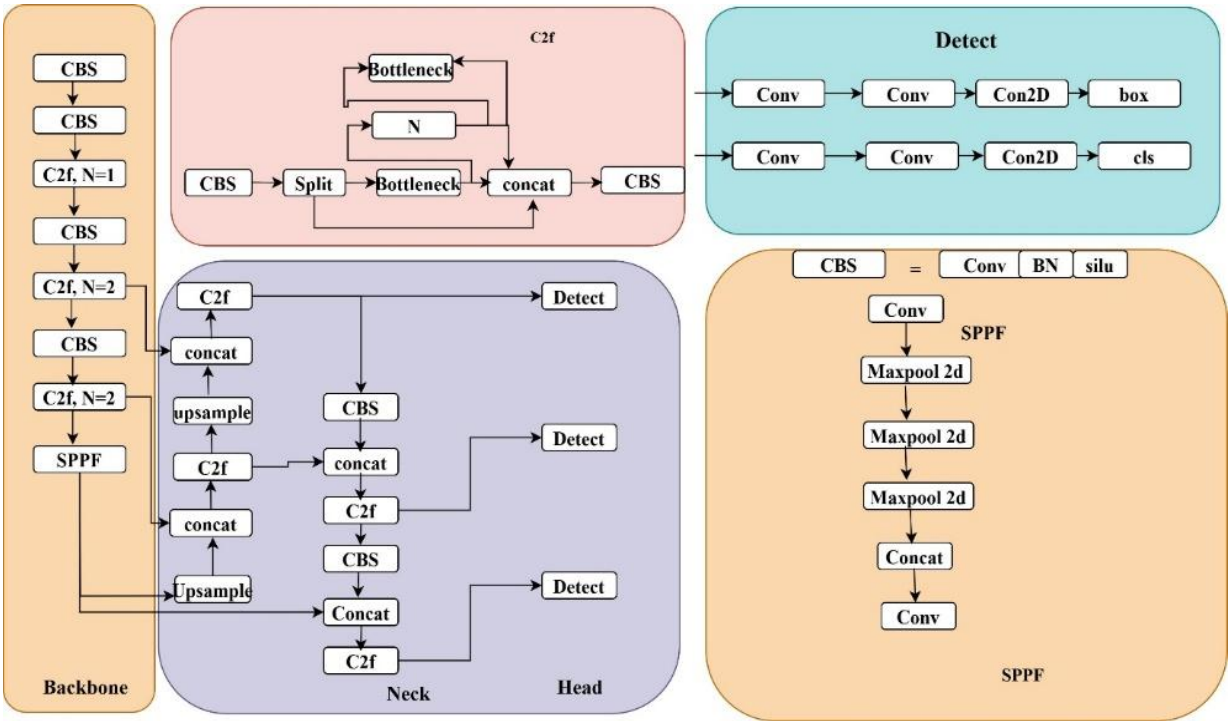

Fig.2: Architecture of YOLOv8 for Object Detection

The neck architecture processes backbone-extracted features across multiple scales. The right branch transmits precise spatial information from shallow layers in a bottom-up manner, while the left branch executes top-down feature fusion from deep to shallow layers. The integration of shallow and deep features, alongside the enhancement of feature integrity, results in a robust architectural design. The decoupled head design incorporates three detection layers with feature maps of varying sizes, each layer connected for both target detection and object classification tasks [33]. Object classification utilises Varifocal loss, while target identification relies on CIoU loss combined with distribution focal loss. The system improves accuracy by analysing multiple output scales and branches through interconnected sections during detection. The YOLO series constitutes the prevailing approach for object detection, with YOLOv8 serving as the core architecture employed for substation equipment identification in this study [17].

3.2 Residual Neural Network

ResNet operates as a fault monitoring system while executing detection tasks, comprising multiple architectural blocks that define its structure. Each block includes batch normalization, convolutional operations, and ReLU activation layers. Both the convolutional layers and residual connections share several common attributes. Standard blocks contain convolutional layers with 3*3 filters, where the number of filters aligns with the dimensions of the feature maps. When the spatial dimensions of the feature maps are halved, the number of filters increases proportionally. Dimension matching is managed by 1*1 convolutions, and shortcut connections are incorporated within the residual block to accommodate varying feature map sizes [22]. The residual block can be mathematically expressed as follows:

$$H(X) = F(X) + X \qquad (1)$$

After rearranging, the equation can be presented as follows:

$$F(X) = H(X) - X \qquad (2)$$

The feedforward network containing identity short cuts operates through block-level mapping while handling computational complexity using $F(X) + X$ where $H(X)$ stands for output. The residual function utilises identity shortcut connections directly when the input and output dimensions correspond. All residual functions $F(X)$ are trained within the ResNet framework that activates these shortcut connections [34].

ResNet employs identity mapping and skip connections as its fundamental mechanisms. It operates by bypassing entire inactive layers that accumulate within the network during detection tasks. The model transfers complete activations from preceding layers directly into subsequent operations. This design achieves superior performance relative to earlier architectures by skipping outputs at the skip-level during accelerated training phases. Consequently, network layers learn at speeds comparable to the final layers, transmitting enhanced gradients to initial layers while circumventing blocked connections [27]. Further research has focused on refining various parameters within the ResNet architecture. Its design is notable for utilising hyperparameter-defined cardinality to establish multiple parallel paths, which enhance accuracy metrics. One recent variation, known as stochastic depth, retains the full architecture during testing but randomly drops layers during training to address the extensive learning periods required by deep networks [5]. A related architecture, the Dense network, connects individual layers more tightly. By concatenating feature maps, this design increases output diversity and promotes repeated utilisation of network components. Dense networks effectively mitigate the vanishing gradient problem, improving overall performance.

3.3 Botox Optimization Algorithm

This paper proposes an Enhanced ResNet-BOA framework, wherein the BOA optimizes ResNet's weight parameters to improve convergence speed and classification accuracy. Inspired by the mechanism of Botox, BOA selectively inhibits neural transmissions through a controlled inhibition process. In deep learning, BOA effectively accelerates convergence by reducing unnecessary weight updates and refining learning rates. The enhancement of facial appearance is often regarded as a complex challenge, primarily due to the presence of wrinkles that cause emotional distress [3]. Wrinkles arise from dermal atrophy combined with repeated muscle contractions in the facial structure. The medical procedure of injecting a small amount of botulinum toxin into active muscles addresses these issues by relaxing regional muscles and simultaneously smoothing the skin surface in areas of muscle overactivity. Botox administration consequently improves facial appearance and reduces wrinkles. The development of the proposed algorithm was informed by this medical intervention, using Botox injections in facial areas to measure wrinkles and thereby formulating the theoretical basis of the algorithm [28]. The model's fitness function is presented as follows:

$$FF = MIN\ (training\ error) \tag{3}$$

The optimal weighting parameter, which enhances the detection process selection, is derived from the error function. BOA employs iterative methods that utilise cooperative behaviour among participants to perform population-based optimisation of feasible solutions in complex optimisation problems. Within this context, the group representing Botox injections corresponds to members of the BOA population. The pseudocode for the proposed methodology is provided in Table 2.

Table 2
Pseudo Code of the Algorithm

Initialize the random weighting parameter of RNN
Input problem formulation
Initialize the BOA population size

$$Z = \begin{bmatrix} \vec{Z}_1 \\ \dots \\ \vec{Z}_I \\ \dots \\ \vec{Z}_N \end{bmatrix}_{N\times M} = \begin{bmatrix} Z_{1,1} & \dots & Z_{1,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{I,1} & \dots & Z_{I,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{N,1} & \dots & Z_{N,D} & \dots & Z_{N,M} \end{bmatrix}_{N\times M}$$

$Z_{I,D} = LB_D + R_{I,D}.(UB_D - LB_D), I = 1, \dots, N, D = 1, \dots, M$
Fitness evaluation
$FF = MIN\ (training\ error)$
Compute the optimal candidate solution
For T=1 to t
Update count of decision variables for Botox injections

$$N_B = \left\lfloor 1 + \frac{M}{T} \right\rfloor \leq M$$

For I=1 to

Compute the parameters which are defined for Botox Injection
$CBS_I = \{D_1, D_2, \dots, D_J, \dots, D_{Nb}\}, D_J \epsilon \{1,2, \dots, M\}\ and\ \forall h, k \epsilon \{1,2, \dots, Nb\}: D_H \neq D_K$
Compute the count of Botox injection

$$\vec{b}_I = \begin{cases} \vec{Z}_{Mean} - \vec{Z}_I & T < \dfrac{T}{2} \\ \vec{Z}_{Best} - \vec{Z}_I & Else \end{cases}$$

For J=1 to NB
Compute the new location of the BOA member
$\vec{Z}_I^{NEW}: Z_{I,DJ}^{NEW} = Z_{I,DJ} + R_{I,DJ}.B_{I,DJ}$
End
Compute the objective function

Upgrade the BOA member

$$\vec{Z}_I = \begin{cases} \vec{Z}_I^{NEW}, F_I^{NEW} < F_I \\ \vec{Z}_I, \quad Else \end{cases}$$

End

Save the optimal candidate solution achieved so far

End

Save the optimal solution of weights of RNN

Save the BOA

Participants choose their parameters based on a mathematical vector representation corresponding to their problem-solving phase [14]. This vector forms the population matrix, which includes the selection parameters, as illustrated below.

$$Z = \begin{bmatrix} \vec{Z}_1 \\ \dots \\ \vec{Z}_I \\ \dots \\ \vec{Z}_N \end{bmatrix}_{N\times M} = \begin{bmatrix} Z_{1,1} & \dots & Z_{1,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{I,1} & \dots & Z_{I,D} & \dots & Z_{1,M} \\ \dots & \dots & \dots & \dots & \dots \\ Z_{N,1} & \dots & Z_{N,D} & \dots & Z_{N,M} \end{bmatrix}_{N\times M} \tag{4}$$

$$Z_{I,D} = LB_D + R_{I,D}.(UB_D - LB_D), I = 1, \dots, N, D = 1, \dots, M \tag{5}$$

The search dimension $Z_{I,D}$ utilizes the BOA member vector $\vec{Z}_I$ in a matrix form of Z while M stands for decision variables and N represents population members. The bound parameters include lower value LB_D and upper value UB_D alongside random interval numbers $R_{I,D}$. BOA is a population-based optimisation algorithm that addresses optimisation problems through an iterative process [19]. Drawing analogy from Botox injection procedures, the BOA framework assists population members in finding improved positions within the search space. The population within BOA comprises all individuals considered for Botox treatment. In a similar manner to how physicians administer Botox to particular facial muscles to regulate facial movement and reduce wrinkles, the BOA model operates by iteratively decreasing the number of muscles requiring Botox treatment based on its architectural parameters [23]. The quantity of muscles necessitating Botox injections is determined by the following equation:

$$N_B = \left\lfloor 1 + \frac{M}{T} \right\rfloor \leq M \tag{6}$$

The number of Botox injection muscles N_B participates with an ongoing count parameter T. During the decision-making process, facial features and wrinkle patterns of applicants are assessed to identify suitable Botox injection targets [20]. Population members select their injection parameters by applying the following equation.

$$CBS_I = \{D_1, D_2, \dots, D_J, \dots, D_{Nb}\}, D_J \epsilon \{1,2, \dots, M\} \ and \ \forall h, k \epsilon \{1,2, \dots, Nb\}: D_H \neq D_K \tag{7}$$

D_J indicates the position of the decision parameter whereas CBS_I stands for the pair of potential decision criteria applicable to population members who receive Botox injections. Within the BOA framework, a procedure is employed to determine the quantity of Botox treatment for each population member. This methodology reflects the clinical expertise and patient-specific considerations that inform doctors' current decisions regarding medication dosages.

$$\vec{b}_I = \begin{cases} \vec{Z}_{Mean} - \vec{Z}_I & T < \frac{T}{2} \\ \vec{Z}_{Best} - \vec{Z}_I & Else \end{cases} \tag{8}$$

The objective of the optimization process is to find the optimal population member which is designated $\vec{Z}_{Best}$ while the population location becomes $\vec{Z}_{Mean}$. $\vec{b}_I = (b_{I1}, \dots., b_{I,J}, \dots, b_{IM})$ represents the number of Botox injections received by each member.

Facial appearance is altered after Botox relaxes muscles to reduce wrinkles. Each BOA member receiving Botox injections updates their position according to the following equation within the BOA framework [10]. As the objective function parameter increases, the new position of the respective member adjusts from its previous location as described by the equation below.

$$\vec{Z}_I^{NEW}: Z_{I,DJ}^{NEW} = Z_{I,DJ} + R_{I,DJ}.B_{I,DJ} \tag{9}$$

$$\vec{Z}_I = \begin{cases} \vec{Z}_I^{NEW}, F_I^{NEW} < F_I \\ \quad \vec{Z}_I, \quad Else \end{cases} \tag{10}$$

The Botox dimension of BOA member represented as $B_{I,DJ}$ takes place with a random value $R_{I,DJ}$ drawn from [0,1] to calculate F_I^{NEW} , $Z_{I,DJ}^{NEW}$ is the dimension, and $\vec{Z}_I^{NEW}$ is the BOA member's new location following Botox injection [32].

This study presents a novel metaheuristic approach, referred to as BOA, designed to optimise deep learning model parameters with the aim of enhancing fault monitoring and detection systems. The process begins with data collection, including the acquisition of real-time measurements such as voltage, current, and temperature from the monitored system. Pre-processing is then applied to eliminate irrelevant features and normalise the data to facilitate effective fault classification. Subsequently, a deep learning model, exemplified by ResNet, is initialized to perform fault pattern analysis. The BOA algorithm commences with a randomly generated population of weight parameters and iteratively optimises these parameters to improve accuracy while accelerating convergence [2]. The algorithm employs selective inhibition to suppress non-essential weight updates, evaluating each candidate solution according to classification performance. To address challenges related to overfitting and slow convergence, adaptive learning rate adjustments are incorporated to ensure stable training. Through iterative enhancement, BOA reinforces relevant parameters and discards those deemed insignificant, continuing training until a defined convergence criterion is met, thereby ensuring optimal fault detection [21]. Finally, the model configuration is refined for real-time fault classification, improving the reliability and response time of critical applications.

3.4 Fuzzy Decision-Making for Intelligent Substation Maintenance

To ensure that predictive outputs are converted into timely and practical interventions within complex substation environments, the proposed ResNet-based monitoring framework, enhanced through BOA optimisation, incorporates an embedded fuzzy logic decision-making component. This module systematically translates quantitative indicators—such as anomaly detection scores, thermal deviations, and equipment health metrics—into qualitative risk assessments categorised as “low,” “medium,” or “high.” By applying a structured set of expert-derived IF-THEN rules, the fuzzy logic system interprets these descriptors to rank maintenance tasks according to both urgency and severity. For instance, when a transformer displays a high probability of failure in conjunction with critical temperature readings, the system autonomously initiates inspection directives and allocates necessary operational resources. This integration enhances the model's resilience to sensor variability and environmental uncertainty, ensuring greater responsiveness and consistency in performance. As a result, the framework evolves from a conventional diagnostic tool into a comprehensive decision-support system, capable of context-sensitive, adaptive maintenance planning grounded in real-time operational data.

4. Performance Evaluation

A comparative analysis of the proposed Intelligent Power Auxiliary Control and Monitoring System has been carried out against established techniques such as Convolutional Neural Networks

(CNN), YOLOv5, Support Vector Machines (SVM), and Recurrent Neural Networks (RNN). The system's performance is primarily determined by its accuracy in detecting faults, its ability to classify various fault types, and its computational efficiency. The utilisation of deep learning architectures combined with optimisation algorithms supports real-time monitoring of substations, with Python serving as the implementation environment for both deployment and fault detection processes. The YOLOv8-ResNet-BOA framework exhibits superior detection precision and classification capabilities, thereby enhancing the dependability and operational effectiveness of substation monitoring systems in comparison to traditional detection models. The operational parameters of the proposed system are detailed in Table 3.

Table 3
Simulation Parameters

S. No	Description	Parameters
1	Population Size	30
2	Maximum Iterations	100
3	Learning Rate Adjustment	0.001
4	Exploitation	40%
5	Convergence Time	100
6	Efficiency Gain	15%
7	Adaptive Response Time	100
8	Detection Latency	50 to 150
9	Sensor Data Variability	5%
10	Fitness Rate	0-1

Representative examples of input and output data are shown in Figure 3, while Figure 4 provides the confusion matrix as an additional measure of system performance.

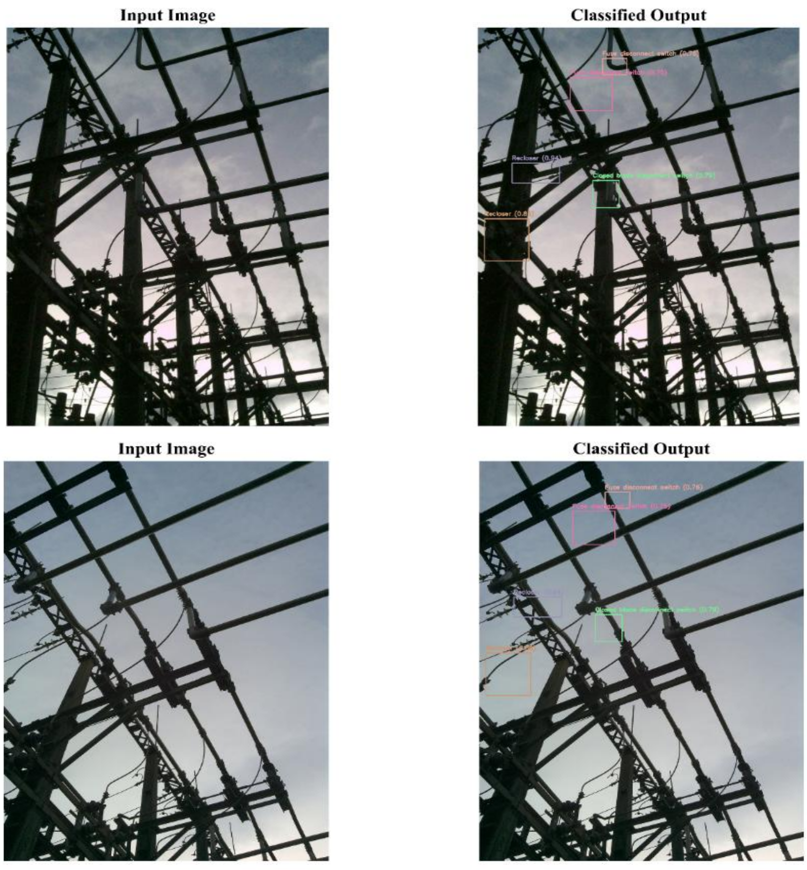

Fig.3: Sample Input and Classified Output

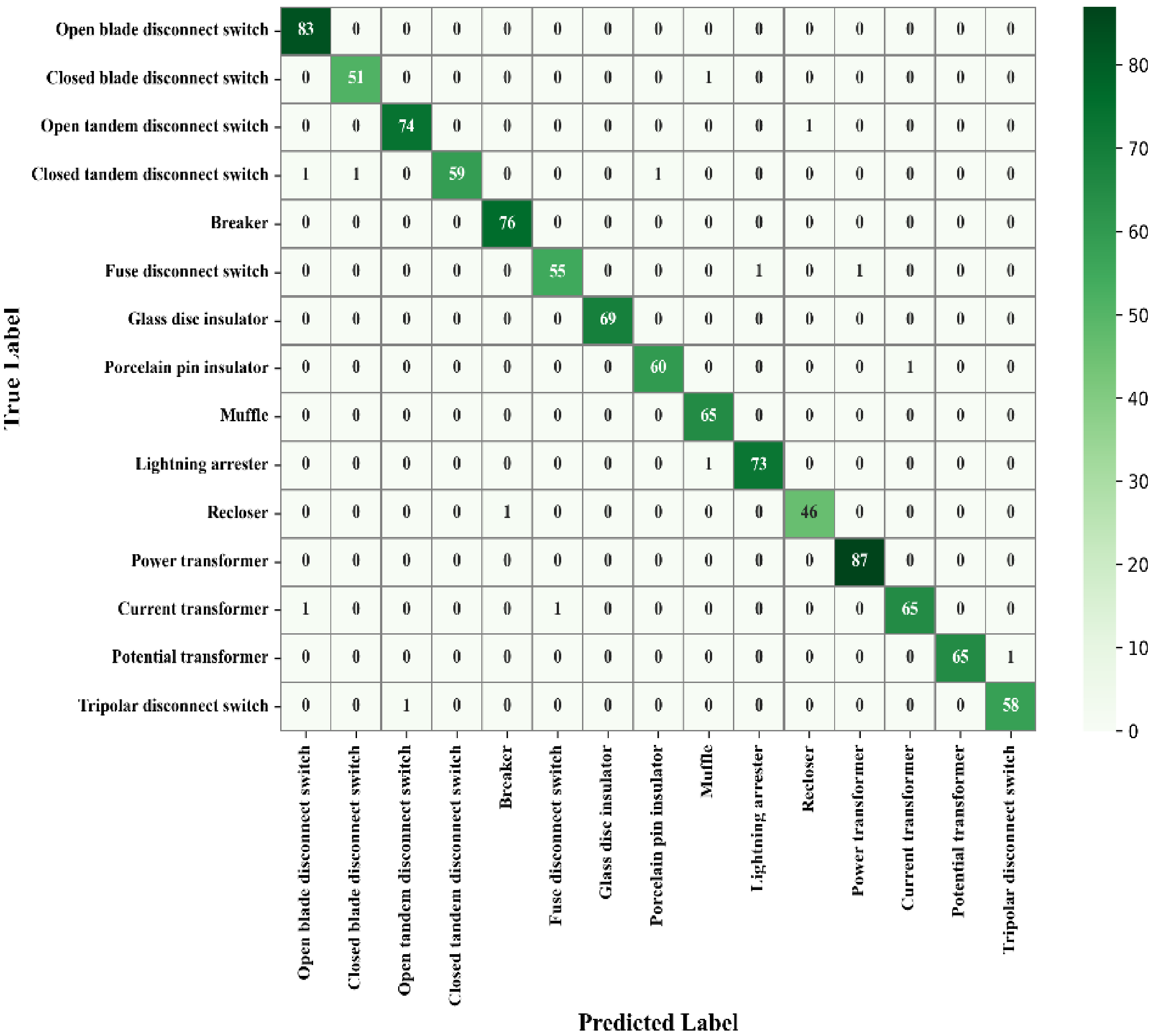

Fig.4: Confusion Matrix

Figure 5 presents the performance evaluation, revealing that YOLOv8 attains an accuracy of 94.8%, surpassing YOLOv5, which achieves 88.3%, due to improved feature extraction and localisation techniques. The integration of BOA with RNN results in a fault classification accuracy of 96.2%, while CNN and SVM record accuracies of 89.5% and 85.7%, respectively. The false positive rate for the BOA-optimised RNN is 2.5%, markedly lower than the 5.2% and 6.8% rates observed for CNN and SVM, respectively, thereby enhancing system reliability. The computational efficiency gained through BOA optimisation reaches 25%, contributing to a reduced average processing time of 150 ms, which outperforms traditional models that typically require 250 ms, thus enabling real-time performance. Overall, the YOLOv8-RNN-BOA approach demonstrates superior outcomes compared to existing detection techniques, offering improved substation monitoring capabilities by increasing accuracy, lowering false alarm rates, and enhancing response times.

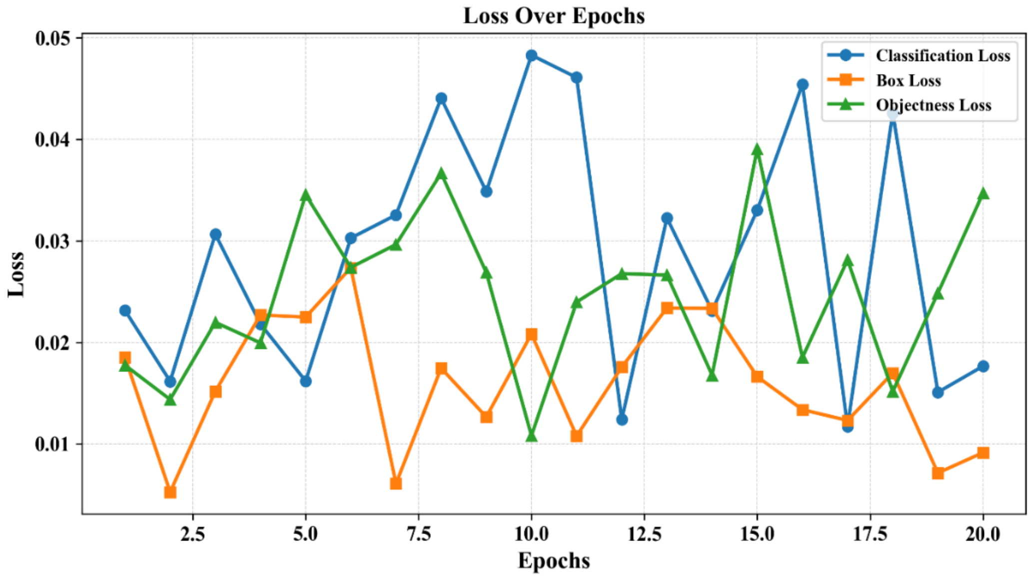

Fig.5: Loss Validation

Figure 6 illustrates the comparative performance of various models based on their AUC scores, highlighting the superior efficacy of the proposed approach. The model achieves the highest AUC score of 0.995, reflecting exceptional classification capability. In comparison, YOLOv5 attains an AUC of 0.942, indicating a slight reduction in effectiveness. The RNN outperforms YOLOv5, with an AUC of 0.955, attributable to its capacity for sequential learning. The CNN registers an AUC of 0.912, representing moderate performance but remaining below that of both the RNN and YOLOv5. The SVM exhibits the lowest AUC score of 0.875, demonstrating limited ability to manage complex feature representations. Overall, the proposed model surpasses conventional techniques by delivering enhanced classification accuracy and robust operational reliability.

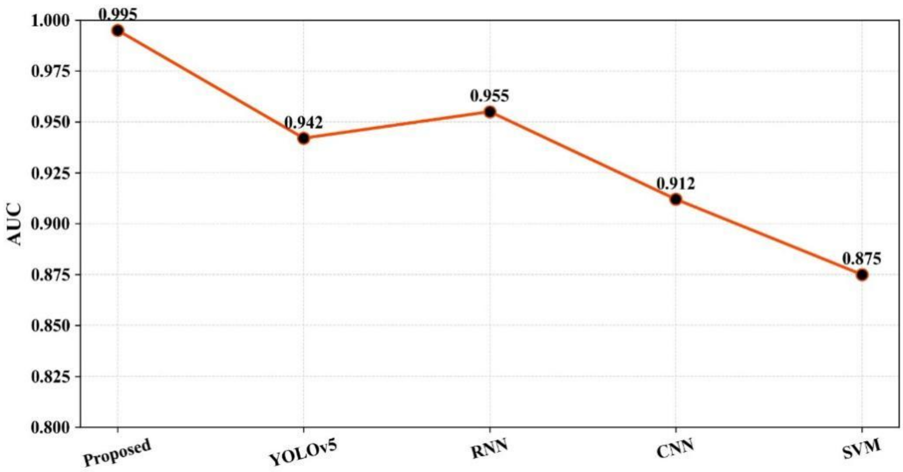

Fig.6: AUC Output

Figure 7 presents the performance evaluation of different models using accuracy, precision, recall, and F1-score metrics. The proposed model achieves the highest values across all these measures, reflecting its outstanding classification capability. Although YOLOv5 performs effectively, its results fall short of the proposed model due to certain limitations. The RNN exhibits stronger performance, achieving higher recall and F1-score compared to both CNN and SVM, owing to its specialised ability to handle sequential data. CNN ranks in the middle across the evaluated metrics when compared to YOLOv5 and RNN. Conversely, SVM records the lowest scores in all metrics, indicating its limited effectiveness in managing complex pattern recognition tasks. Overall, the proposed model surpasses other methods by delivering superior classification accuracy, precision, and robust fault detection performance.

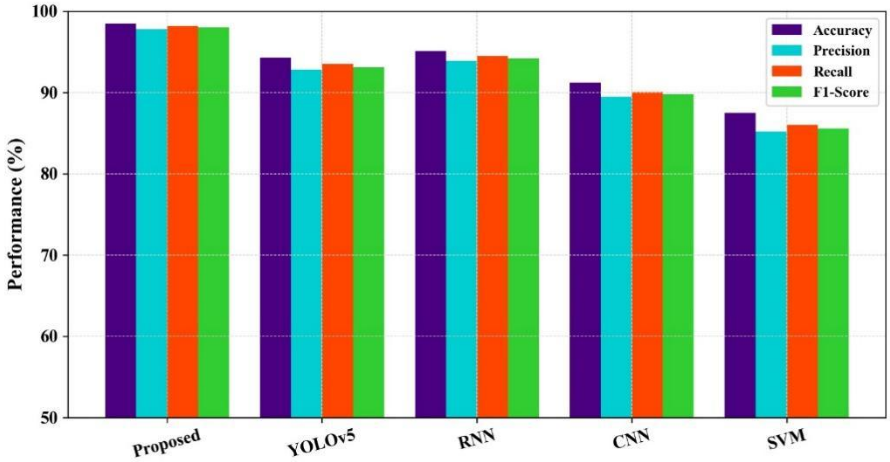

Fig.7: Performance Evaluation

The Receiver Operating Characteristic (ROC) curve illustrates the performance of various models by plotting the true positive rate against the false positive rate, thereby facilitating the assessment of their classification effectiveness. As shown in Figure 8, the proposed model attains an Area Under the Curve (AUC) value of 0.99, indicating its exceptional capability in fault detection. YOLOv5 exhibits a comparable performance with an AUC of 0.98. The RNN outperforms both CNN and SVM by achieving an AUC of 0.96, which is attributed to its strength in analysing sequential patterns. In contrast, the CNN and SVM models demonstrate reduced fault detection effectiveness according to the AUC evaluation, reflecting their limited ability to distinguish between faulty and non-faulty cases. These results confirm that the proposed model achieves the highest classification accuracy among all methods assessed.

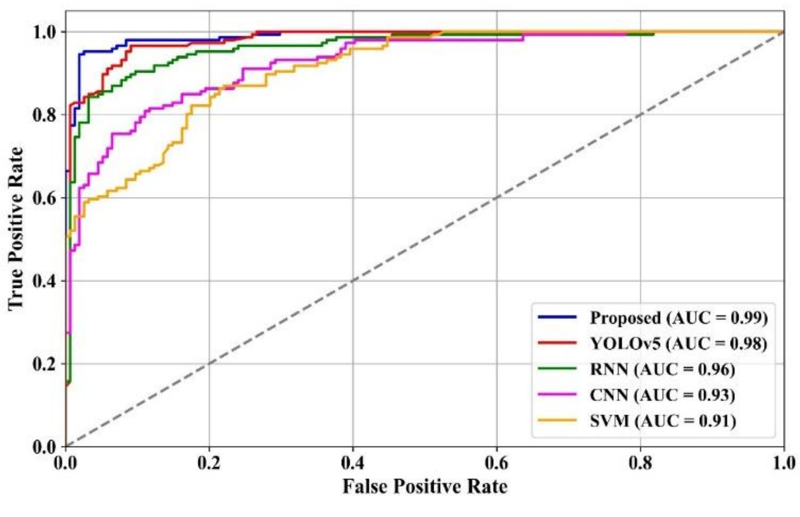

Fig.8: AUC Analysis

Figure 9 presents the performance analysis of the False Positive Rate (FPR) and False Negative Rate (FNR). The proposed method achieves the lowest rates for both FPR and FNR, each remaining below 1.5%. While YOLOv5 exhibits robust performance, its FPR and FNR values are approximately 3%, indicating room for further optimisation. The RNN model records a more favourable FPR compared to YOLOv5, but its FNR approaches 2.5%, reflecting moderate reliability. Conversely, the

CNN shows elevated false positive and false negative rates exceeding 4%, suggesting frequent misclassifications. The SVM performs the poorest, with both FPR and FNR surpassing 6%, which indicates inadequate fault detection accuracy. These findings highlight the proposed model's effectiveness in minimising both false alarms and detection errors, thereby enhancing overall accuracy and dependability.

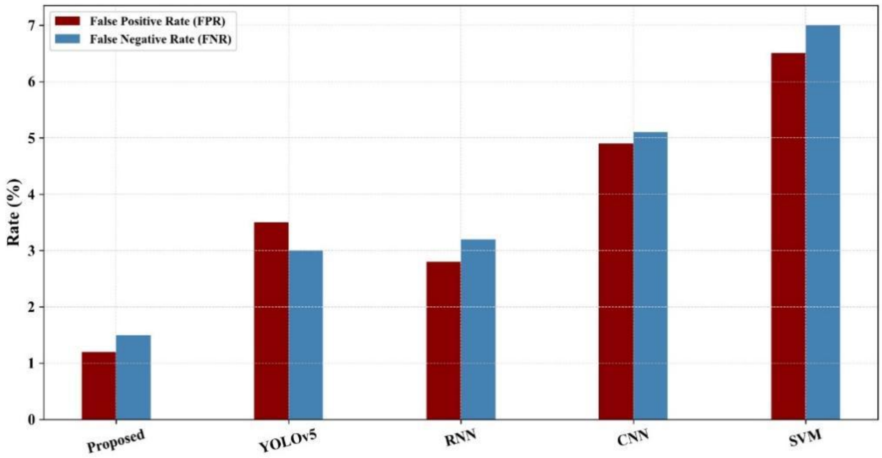

Fig.9: Analysis of FPR and FNR

The in-depth assessment of the YOLOv8-ResNet-BOA-based Intelligent Power Auxiliary Control and Monitoring System confirms its superior performance in substation fault detection, exhibiting higher classification accuracy, lower error rates, and enhanced computational efficiency when compared to conventional approaches such as CNN, SVM, YOLOv5, and RNN. In addition to its technical advantages, the system incorporates a fuzzy rule-based decision-making layer that elevates it from a mere predictive tool to a functional decision-support mechanism. This component facilitates informed interpretation of fault classifications by maintenance personnel, enabling responses that account for factors such as severity, urgency, false alarm likelihood, equipment status, and operational risk. For example, the detection of a critical fault with minimal response time requirements may prompt automatic initiation of dispatch protocols, allowing for optimal resource utilisation and reduced service disruption. By embedding intelligent decision logic within the monitoring framework, the system not only detects anomalies but also provides substation operators with structured, data-informed guidance for prioritised and timely intervention, thereby enhancing operational reliability and supporting strategic maintenance practices.

5. Conclusion

The proposed model significantly enhances substation power auxiliary control by integrating IoT-enabled data acquisition with advanced image processing capabilities. The newly developed system achieves a classification accuracy of 99.5%, outperforming existing models such as YOLOv5 (94.2%), recurrent neural networks (95.5%), convolutional neural networks (91.2%), and support vector machines (87.5%). During validation, the model recorded low false negative and false positive rates of 1.5% and 1.2%, respectively, indicating superior reliability over comparative approaches. The incorporation of the Butterfly Optimisation Algorithm contributes to optimal weight parameter tuning, which improves both response latency and diagnostic precision in fault detection. The comparative evaluation highlights the model's robust stability, establishing its suitability for modern substation monitoring and fault management applications. Overall, the system not only advances detection accuracy but also incorporates a fuzzy rule-based decision layer, enabling context-aware prioritisation of maintenance activities. This fusion of predictive analytics and intelligent decision-making transforms raw diagnostic outputs into structured, actionable strategies, thereby enhancing operational effectiveness. Future research could investigate the application of more adaptive MCDM methods to accommodate dynamic operational environments.

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