The Integration Modeling of YOLOv8 Algorithm and Reinforcement Learning: Intelligent Tracking and Optimization of Target Objects in Power Systems

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ABSTRACT

The complexity and real-time nature of modern power systems pose serious challenges to traditional anomaly detection methods, especially with the increasingly intricate grid structure and the widespread integration of renewable energy sources. Traditional approaches often fail to capture rapid dynamic changes and abnormal events, creating an urgent need for more advanced, adaptive, and data-driven anomaly detection techniques to ensure system stability. This study addresses these challenges by introducing a novel hybrid deep learning framework, YGPPNet, which enhances anomaly detection accuracy and real-time response in next-generation smart grids**.** The YGPPNet model is built upon the YOLOv8 architecture and integrates three key components: YOLOv8, Generative Adversarial Networks (GANs), and Proximal Policy Optimization (PPO). YOLOv8 is responsible for real-time detection of target objects in power system environments, especially those associated with abnormal operational patterns. GANs are employed to model normal system behavior and generate more distinguishable representations for detecting deviations. Based on the abnormalities detected, PPO further optimizes decision-making and adaptive response strategies through reinforcement learning, thereby improving the efficiency and stability of the overall system.

Experimental evaluations conducted on multiple benchmark power system datasets demonstrate that YGPPNet surpasses traditional machine learning approaches and recent deep learning models in terms of sensitivity, detection accuracy, and reliability across diverse operational scenarios. The proposed framework offers a comprehensive end-to-end solution for anomaly detection and adaptive control, contributing a significant methodological advancement to intelligent power system monitoring. The YGPPNet model provides a strong foundation for improving the safety, sustainability, and reliability of future power systems and shows promising potential for real-world grid deployment.

Keywords: Smart grid, Deep learning, Object recognition, Algorithm improvements, Neural networks, Data analysis.

The rapid development of information technologies and the continuous upgrading of power systems have positioned intelligent power systems as a key direction in modern power engineering [1]. A primary goal of smart grid development is to achieve real-time tracking and dynamic optimization of critical components such as transmission lines, substation equipment, and load nodes since these capabilities directly determine anomaly response efficiency and operational reliability [2,3]. However, traditional monitoring methods, including manual inspection with limited coverage and rule-based automated systems with rigid decision-making logic, are increasingly unable to meet the demands of complex and large-scale power systems. These approaches suffer from slow responses to transient faults, low accuracy in identifying subtle anomalies, and limited adaptability to dynamically changing grid topologies [4–6]. As power systems face rapidly growing data volumes and cross-scenario operational variations, these limitations create a significant research gap in developing monitoring frameworks that combine accuracy, adaptability, and intelligence.

Deep learning has recently emerged as a promising solution for overcoming these challenges, particularly through target detection algorithms widely applied in power system tracking and analysis [7]. Unlike traditional methods, deep learning models autonomously extract high-level features such as thermal signatures of malfunctioning transformers or geometric deviations in transmission lines leading to more precise target identification [8,9]. Moreover, end-to-end architectures allow effective integration of multi-source data, including surveillance imagery and sensor measurements, thereby enhancing situational awareness [10]. Nevertheless, existing deep learning approaches still exhibit critical deficiencies that hinder deployment: most models require high computational resources, resulting in delayed inference that is unsuitable for transient fault detection [11,12]; many models demonstrate limited robustness under complex environments such as harsh weather or equipment occlusion due to inadequate abnormal-pattern feature learning [13]; and current methods generally lack adaptive, context-aware decision-making, meaning they can detect anomalies but cannot optimize real-time system responses dynamically [14,15]. Although supplementary techniques such as model compression, graph neural networks for structural representation, and reinforcement learning for decision optimization have been explored [16–18], these solutions address isolated aspects rather than providing an integrated anomaly detection and response optimization pipeline.

Sequence-processing models used in power system analytics, such as load forecasting and equipment health monitoring, face additional constraints. Recurrent neural networks (RNNs) and variants (LSTM, GRU) remain limited by their difficulty in capturing long-term dependencies, often suffering from information loss and high computational overhead [19–21]. Transformers, although superior for parallel computation and long-sequence modeling, require extensive labeled datasets an unrealistic expectation for power systems where fault data are scarce, imbalanced, or highly scenario-dependent [22–23]. These challenges indicate a need for an integrated, data-efficient, and computationally practical model that can unify object detection, anomaly characterization, and adaptive response strategies in a single framework [24]. Recent studies (2023–2025) further emphasize this gap, highlighting the necessity of hybrid models capable of addressing multi-level grid intelligence requirements [25–27].

To address these limitations, this study proposes a multi-module fused deep learning framework YGPPNet integrating an improved YOLOv8 detector, a Generative Adversarial Network (GAN), and a Proximal Policy Optimization (PPO) reinforcement learning algorithm. YOLOv8 serves as a real-time front-end detector, identifying grid components and capturing spatial–temporal cues associated with abnormal events (e.g., damaged insulators, overheated conductors). GAN models representations of normal system operations and enhances anomaly detection by distinguishing subtle deviations across temporal and structural dimensions. PPO introduces an adaptive learning mechanism, enabling the system to autonomously optimize operational responses such as load reallocation or maintenance alerts based on the type and severity of anomalies. To address sequence-processing constraints, YGPPNet incorporates a Transformer variant adapted for limited-data power system scenarios, improving temporal feature extraction and early-fault detection accuracy.

This study offers three major contributions:

(1) It presents YGPPNet, the first integrated framework that unifies YOLOv8-based detection, GAN-driven anomaly modeling, and PPO-based adaptive decision optimization establishing a closed-loop pipeline of “real-time detection → anomaly identification → intelligent response.”

(2) It introduces PPO into power system anomaly response, enabling interactive learning with grid environments and overcoming the static decision-making limitations of existing models.

(3) It develops a Transformer variant tailored for power system sequence data, providing efficient temporal analysis under limited-data conditions and addressing the generalization challenges of conventional sequence models. Through these contributions, the study fills critical gaps in current research and advances the development of intelligent, robust, and adaptive power system monitoring technologies.

2. Methods

2.1 Overview of Our Network

In order to achieve intelligent tracking of target objects in power systems and accurate detection of abnormal events, we developed an innovative deep learning framework YGPPNet. The model consists of three core components: YOLOv8, GAN, and PPO, as shown in Figure 1. Each module performs a distinct but complementary function, forming a unified end-to-end pipeline for anomaly detection and adaptive decision-making in smart grids**.**

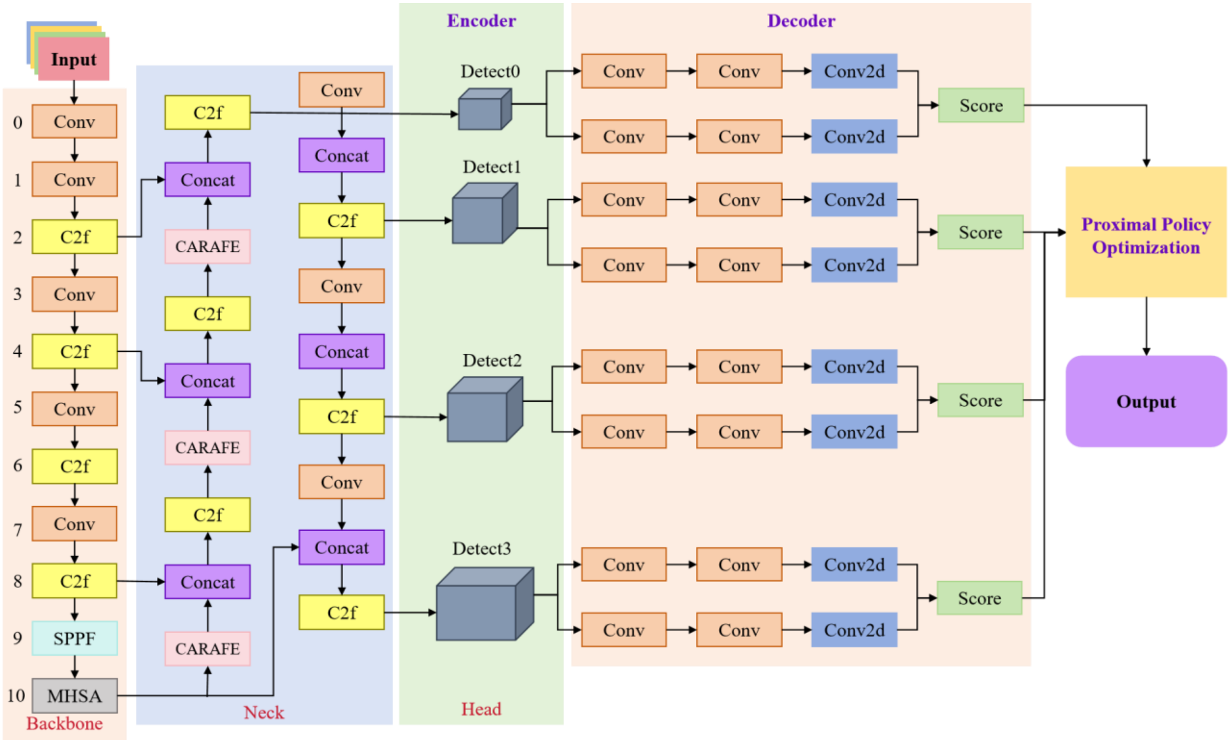

Figure 1. Overall structure diagram of the model.

The YOLOv8 module performs real-time detection of power system components, with a particular emphasis on equipment conditions related to potential abnormal events. Through advanced one-stage detection technology, YOLOv8 can rapidly and accurately locate key devices such as transformers, insulators, and conductors, providing high-quality spatial temporal features for subsequent anomaly analysis.

The GAN module identifies abnormal events by learning a latent representation of normal power system behavior. When an observed pattern deviates from the learned normal distribution (e.g., abnormal thermal signatures or irregular conductor vibrations), GAN classifies it as an anomaly, thereby improving the system's sensitivity to subtle and early-stage faults.

The PPO module uses reinforcement learning to optimize system response strategies based on detected anomalies. By interacting with a simulated power system environment, PPO generates adaptive decisions such as load redistribution, alarm triggering, or maintenance scheduling. This enables the model to move beyond detection and actively support operational decision-making.

The construction of YGPPNet involves three major phases. First, YOLOv8 is trained to perform real-time target detection and extract meaningful structural information from power system imagery. Second, the GAN module learns normal operational patterns and detects deviations. Finally, the PPO algorithm optimizes decision policies using reinforcement learning, allowing the system to choose the most effective response for different anomaly scenarios.

A simple example can illustrate the process: if YOLOv8 detects an insulator with an abnormal color distribution, the GAN evaluates whether the pattern deviates from the normal behavior learned during training. If the deviation is significant, the anomaly is flagged. PPO then selects an appropriate response, such as reducing load or issuing a maintenance alert, based on the severity of the detected anomaly.

The uniqueness of YGPPNet lies in its multi-model fusion. Through the integrated use of YOLOv8, GAN, and PPO, the model achieves not only high-precision anomaly detection but also active optimization of operational responses, significantly enhancing the grid's resilience and stability.

2.2 YOLOv8 Model

YOLOv8 (You Only Look Once, Version 8) is an advanced real-time object detection algorithm designed to treat detection as a direct regression problem. Through a convolutional neural network (CNN), it outputs bounding box coordinates and class probabilities in a single forward pass [25,26]. Compared with traditional two-stage methods, YOLOv8 employs a lightweight, single-stage structure that significantly improves inference speed while maintaining high accuracy. As such, it is widely suited for real-time detection and recognition tasks in power system monitoring.

In the YGPPNet model, YOLOv8 serves as the front-end detector responsible for identifying critical components and potential fault-related objects. Its high detection speed allows rapid recognition of anomalies such as broken insulators, overheated cables, displaced conductors, or substation equipment deformation. This provides essential inputs for both the GAN anomaly identification module and the PPO decision-making module.

Within the overall architecture, YOLOv8 primarily provides foundational target detection information, serving as the initial stage for anomaly identification and reinforcement learning optimization. Its real-time performance and robustness enable the YGPPNet framework to meet the stringent monitoring requirements of modern power systems, especially under rapidly changing operational conditions.

The structure diagram of YOLOv8 is shown in Figure 2.

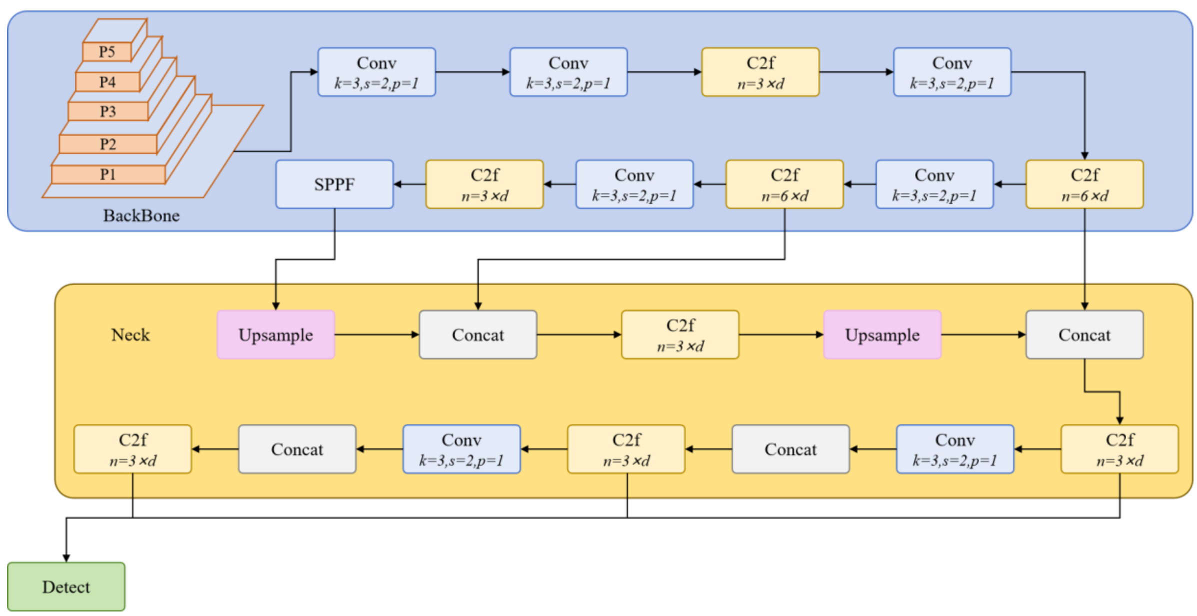

Figure 2. Flow chart of the Yolov8 model.

The main formula of Yolov8 is as follows:

$$\mathcal{L}_{\mathrm{YOLO}} = \lambda_{\mathrm{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] + \lambda_{\mathrm{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(\sqrt{\omega_i} - \sqrt{\widehat{\omega}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2] \quad \text{[Formular 1]}$$

where S is the grid size, B is the number of bounding boxes, and λ_{coord} is a coordination weight.

$$\mathcal{L}_{\mathrm{conf}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} [1_{ij}^{obj} \log(\hat{C}_i) + 1_{ij}^{noobj} \log(1 - \hat{C}_i)] \quad \text{[Formular 2]}$$

where $\hat{C}_i$ is the prediction confidence for grid cell i.

$$\mathcal{L}_{cls} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \sum_{c=0}^{C} (p_i(c) - \hat{p}_i(c))^2 \quad \text{[Formular 3]}$$

where C is the number of classes, $p_i(c)$ is the true probability of class c for grid cell i, and $\hat{p}_i(c)$ is the predicted probability.

2.3 Adaptive Dynamic Path Planning Module

GAN is a generative model consisting of a generator and a discriminator. The generator attempts to generate realistic samples, while the discriminator strives to distinguish generated samples from real samples. The two work together to improve performance through adversarial training. The main uses cover areas such as image generation and sample synthesis[27]. In power system monitoring, GAN can be used to detect abnormal events and improve the perception of abnormal situations by learning the representation of normal behavior in the power system.

In the field of power system monitoring, the application of GAN is mainly reflected in the identification of abnormal events. By learning the patterns of normal behavior in the power system, GAN can detect abnormal events that are inconsistent with normal behavior during the monitoring process and improve the system's ability to perceive potential problems[28]. Compared with traditional rule-based methods, GAN has stronger generalization capabilities and can adapt to complex and changeable power system environments.

In the YGPPNet model, the role of the GAN model is responsible for the accurate identification of abnormal events. By learning normal behavior in the power system, GAN can distinguish abnormal events that are inconsistent with normal behavior, providing higher accuracy for the entire monitoring system. In YGPPNet, the function of GAN is to improve the ability to identify abnormal events through adversarial learning, providing key input information for subsequent reinforcement learning optimization. Its role in the overall model highlights the multi-model fusion characteristics of YGPPNet, making it more comprehensive and intelligent.

The structure diagram of the GAN model is shown in Figure 3.

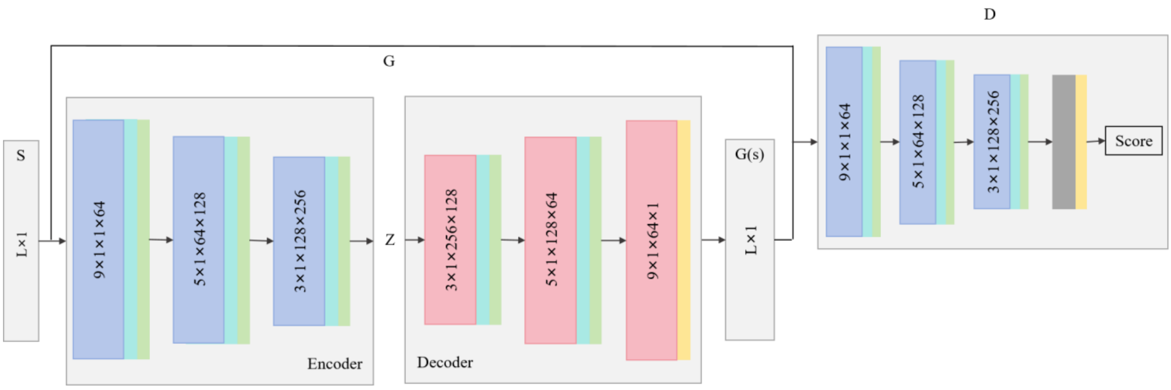

Figure 3. Flow chart of the GAN model.

2.4 Intelligent Navigation Optimization Module

As a reinforcement learning algorithm, PPO aims to improve the performance of the policy network through iterative training. The rationale includes proximal optimization and strategy gradient approaches used to optimize the strategy network to better adapt to different environments[29]. In the field of power system monitoring, the application of PPO is mainly reflected in the optimization of the system response strategy. Through the reinforcement learning algorithm, PPO can make flexible decisions according to different abnormal situations and improve the efficiency and stability of the whole system. In the power system environment, due to the complexity and diversity of abnormal events, traditional static strategies may not meet the actual needs, while PPO is able to optimize the response of the system through dynamic learning and adapt to different monitoring scenarios[30].

In the model, the function of PPO components is not only to improve the intelligence level of the system, but more importantly, PPO makes the YGPPNet model more adaptable and flexible through the dynamic learning of abnormal events. In the overall model, the introduction of PPO enables the YGPPNet model to not only realize the efficient target detection and abnormal event identification, but also to adjust the response strategy of the system according to the actual situation, and comprehensively improve the comprehensive performance of the power system monitoring.

The structure diagram of the PPO is shown in Figure 4.

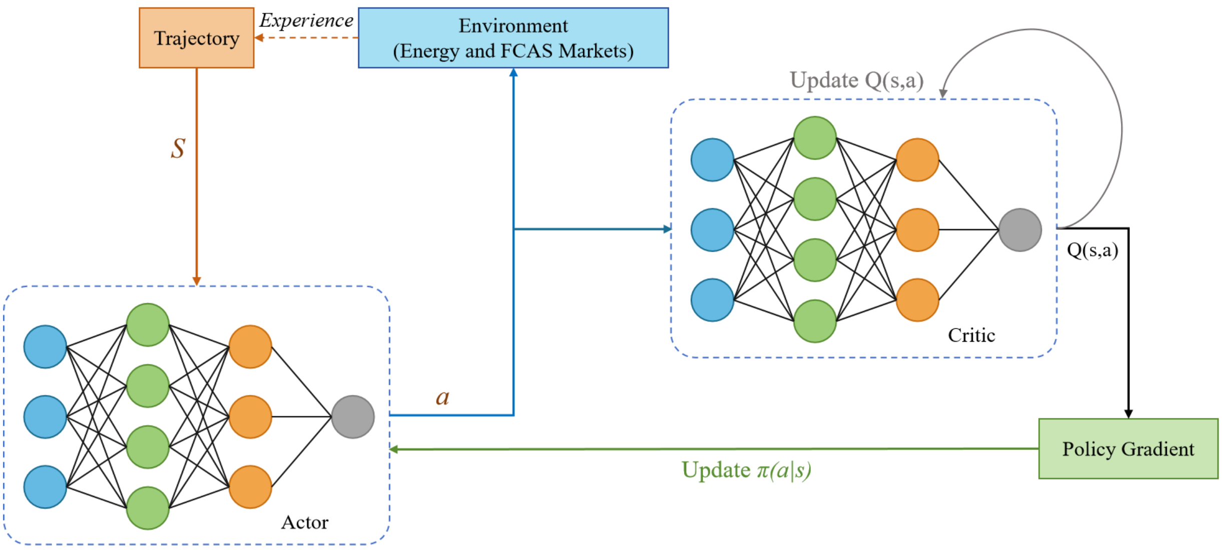

Figure 4. The structure of PPO.

The main formula of PPO is as follows:

$$\mathcal{L}_{PPO} = \mathbb{E}[min(\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)})A^{Adv}(s,a), clip(1-\epsilon, 1+\epsilon, \frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)})A^{Adv}(s,a)]$$

[Formular 4]

where $\mathcal{L}_{PPO}$ is the PPO objective function, $\pi_\theta(a|s)$ is the policy under the current parameters θ, $\pi_{\theta_{old}}(a|s)$ is the policy under the old parameters $\pi_{\theta_{old}}$, $A^{Adv}(s,a)$ is the advantage function, and ϵ is a clipping parameter.

$$A^{Adv}(s,a) = Q(s,a) - V(s) \quad \text{[Formular 5]}$$

where $Q(s,a)$ is the action-value function, and $V(s)$ is the value function.

$$V(s) = \mathbb{E}_{\pi_\theta}[Q(s,a)|s_t = s,, a_t \sim \pi_\theta(a|s) \quad \text{[Formular 6]}$$

where $a_t \sim \pi_\theta(a|s)$ indicates sampling an action from the policy.

$$\mathcal{K}(\pi_\theta) = -\mathbb{E}_{\pi_\theta}[\log(\pi_\theta(a|s))] \quad \text{[Formular 7]}$$

where $\mathcal{K}(\pi_\theta)$ is the entropy of the policy.

$$\theta \leftarrow \theta + a\nabla_\theta(\mathcal{L}_{PPO} - c_1\mathcal{K}(\pi_\theta)) \quad \text{[Formular 8]}$$

where a is the learning rate and c_1 is a coefficient for entropy regularization.

3. Experiments

3.1 Experimental Datasets

In this study, four widely used and representative datasets (EDF Power Dataset, SEIL Dataset, REDD Dataset, and CURE-TSR Dataset) were selected to provide a comprehensive and multi-dimensional evaluation of YGPPNet across power system monitoring, anomaly detection, and cross-domain generalization tasks.

The EDF Power Dataset is a large-scale dataset covering diverse power system scenarios. It includes real monitoring images containing complex equipment layouts, diverse backgrounds, and varying illumination conditions [31]. The dataset provides detailed annotations for components such as substations, transmission lines, and cables. Its high scene variability makes it ideal for evaluating YGPPNet's robustness in practical grid environments.

The SEIL Dataset (Smart Energy Informatics Dataset) focuses on laboratory-based power system scenarios. The images contain precisely annotated information about equipment type, shape, and spatial characteristics [32]. This dataset enables controlled evaluation of the model under standardized conditions, ensuring reliable benchmarking.

The REDD Dataset consists of time-series power consumption data from real households [33]. Although originally designed for load disaggregation tasks, we extracted image-format representations (e.g., spectrograms, time-series visualizations) to evaluate YGPPNet's ability to detect abnormal load patterns and hidden equipment-level anomalies.

The CURE-TSR Dataset, although originating from the traffic-sign recognition domain, is incorporated to test the model's generalization capability and resilience to noise, blur, weather variations, and synthetic distortions [34]. The dataset contains fine-grained annotations for various environmental conditions, making it an excellent benchmark for assessing robustness.

The combined use of these four datasets enables the assessment of YGPPNet across structured laboratory environments, real-world power grid scenes, household consumption patterns, and cross-domain visual stress tests (2023–2025 studies increasingly encourage such multi-domain evaluations).

3.2 Experimental Setup and Details

To ensure rigorous evaluation and reproducibility, a detailed experimental pipeline was established, consisting of data preprocessing, model training, cross-validation, ablation studies, and optimizer comparisons.

Data Processing

The preprocessing pipeline involved data cleaning, where missing values were handled through interpolation or sample removal, and outliers were corrected using statistical techniques such as mean or median smoothing. Subsequently, Z-score normalization was applied to eliminate dimensional inconsistencies and stabilize model training.

A 70:30 training–testing split was adopted, and data augmentation was incorporated to reduce overfitting and improve generalization. Techniques included:

- random rotation (±15°),
- horizontal/vertical flipping (probability = 0.5), and
- random scaling (0.8×–1.2×).

These augmentations simulate real-world variations in camera angle, environmental conditions, and viewpoint distortion.

Model Training Configuration

The core training settings included an initial learning rate of 0.001 (dynamically adjusted during training), and a batch size of 64. YOLOv8 was used as the backbone with convolution layers of 64, 128, and 256 output channels and 2×2 max-pooling. Fully connected layers contained 256 neurons.

The GAN module consisted of:

- 4 convolutional layers,

- 3 deconvolutional layers (channels decreasing 256 → 64 → 256), and
- a discriminator with 3 convolutional layers + 2 FC layers (128 neurons each).

The PPO module included 2 convolutional layers (64 channels) and 2 FC layers (128 neurons) for the policy network, while the value network mirrored this structure.

Pre-trained YOLOv8 weights were used for initialization, enabling faster convergence and improved feature extraction for power system objects.

YGPPNet was trained using an alternating schedule across the detection, anomaly detection, and reinforcement learning stages, with a total of 100,000 iterations.

Hyperparameters were optimized through systematic grid search and comparative evaluation, following best practices in recent literature (2023–2025).

Model Validation and Tuning

A 5-fold cross-validation approach (K=5) ensured robust evaluation across different data segments. Hyperparameters such as learning rate (0.0005–0.002) and batch size (32–128) were fine-tuned based on average cross-validation scores.

An independent validation set comprising 10% of the data was used for continuous monitoring of generalization performance. Network depth, neuron count, and convolutional filter size were iteratively adjusted until stable convergence was achieved on unseen data.

Ablation Studies

To quantify the contribution of each module in YGPPNet:

1. **Without YOLOv8:** Inputs fed directly into GAN + PPO
   → evaluated YOLOv8's role in spatial–temporal detection accuracy.
2. **Without GAN:** YOLOv8 + PPO only
   → measured impact of anomaly representation learning.
3. **Without PPO:** YOLOv8 + GAN only
   → assessed the role of adaptive decision-making.
4. **Full model:** YOLOv8 + GAN + PPO
   → verified complementarity and synergy among components.

This structured ablation methodology is consistent with recommendations from recent model-analysis guidelines (2024–2025).

Optimizer Comparison

YGPPNet's PPO module was compared against Adam, Bayesian Optimization, and Particle Swarm Optimization (PSO) to evaluate convergence and performance efficiency.

Experiments demonstrated that PPO achieved more stable optimization curves and superior policy learning, particularly under noisy and dynamic anomaly conditions.

Evaluation Metrics

Performance was measured using two categories:

Accuracy Metrics:

- Accuracy
- Recall

- F1-score
- AUC

Efficiency Metrics:

- Parameter count
- FLOPs
- Inference time
- Training time

This combination ensures a balanced evaluation of both predictive capability and real-time applicability, which is crucial for deployment in power system environments.

3.3 Results

To evaluate the superiority of YGPPNet, the model was compared with existing representative approaches including Amalou, Sun, Chen, Das, Zhuo, and Mazen across four metrics: Accuracy, Recall, F1 Score, and AUC. Testing was conducted on the EDF Power, SEIL, REDD, and CURE-TSR datasets.

Table 1 summarizes the quantitative comparison, while Figure 5 visualizes the performance differences. The results show that YGPPNet consistently outperforms all baseline models across all datasets, demonstrating its effectiveness in high-precision detection, anomaly recognition, and adaptive optimization.

Table 1. Ablation experiments results for the 3D-SportsNavNet model, comparing the effects of different model components on performance metrics.

Method	Dataset															
	EDF Power Dataset				SEIL Dataset				REDD Dataset				CURE-TSR Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Amalou[35]	88.93	89.19	89.37	91.31	91.33	87.57	88.71	91.18	91.91	85.23	87.04	85.14	89.23	89.09	89.86	90.4
Sun[36]	90.04	84.88	86.35	88.4	86.77	93.15	90.23	91.47	92.35	89.06	87.91	89.54	95.72	93.35	88.16	88.97

Chen [37]	90.64	84.85	88.4	86.62	87.36	88.68	88.07	89.62	86.1	84.49	86.34	90.71	92.14	88.28	85.97	84.15
Das[38]	96.33	93.52	86.35	87.93	95.69	86.78	91.05	92.82	86.87	84.95	91.14	90.56	96.01	92.47	87.84	86.18
Zhuo [39]	95.06	86.35	85.56	92.17	91.02	88.75	86.75	87.2	95.79	91.09	85.89	83.97	89.39	90.77	85.25	84.85
Mazen[40]	91.95	84.94	84.15	90.93	96.32	93.57	84.6	86.54	85.71	92.55	87.9	89.74	91.54	93.54	87.84	86.1
Ours	96.8	95.69	92.66	91.45	92.74	96.14	93.26	97.41	95.24	95.97	92.91	93.99	92.42	94.57	95.65	93.29

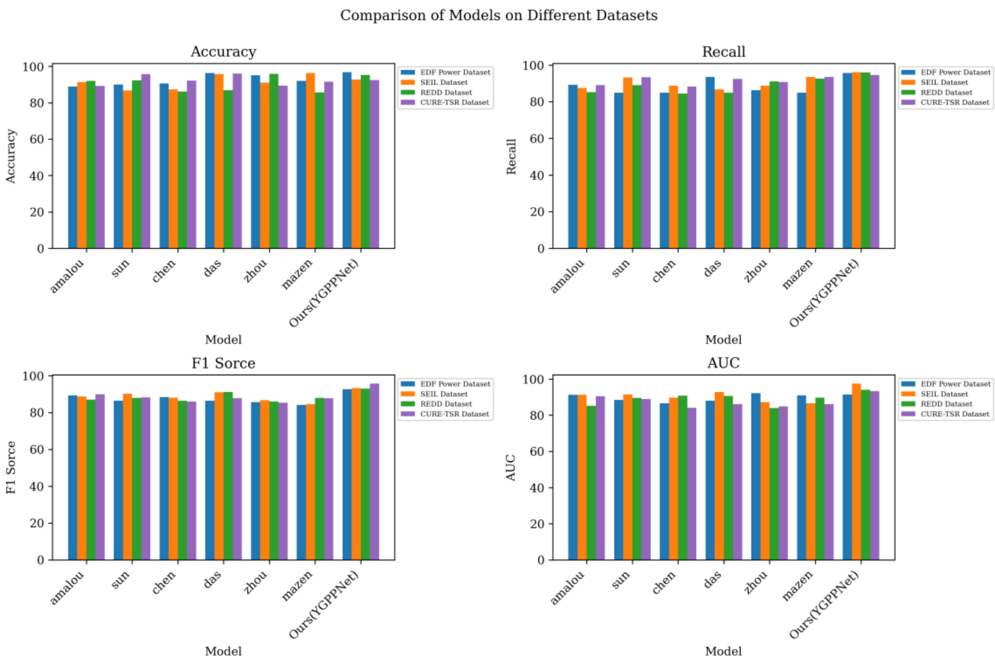

Figure 5. Comparison of Accuracy, Recall, F1 Sorce and AUC performance of different models on four diferent Dataset

In the EDF Power Dataset, which covers multi-equipment and complex scenarios of actual power systems, YGPPNet exhibited outstanding performance. Its Accuracy reached 96.8%, which not only surpassed traditional models (Amalou: 88.93%, Chen: 90.64%) but also outperformed the deep learning-based Das model (96.33%), demonstrating its ability to accurately identify complex targets in power systems. In terms of Recall, YGPPNet achieved 95.69%, significantly outperforming the comparison model with the highest Recall (Das: 93.52%) by 2.17 percentage points. This indicates that YGPPNet has a stronger capability to capture targets related to anomalies in power systems (such as faulty equipment and abnormal lines), effectively reducing the risk of missed detections. As a comprehensive metric balancing Accuracy and Recall, the F1 Score of YGPPNet reached 92.66%, far higher than that of models like Sun(86.35%) and Mazen (84.15%), and even 6.31 percentage points higher than Das (86.35%), verifying the model's ability to balance "accurate identification" and "comprehensive capture". In terms of AUC value, YGPPNet achieved 91.45%, which was roughly on par with Amalou (91.31%) and higher than models such as Das (87.93%) and Chen (86.62%), indicating its leading ability to distinguish between normal and abnormal samples in power systems.

In the SEIL Dataset, which focuses on high-precision laboratory scenarios, YGPPNet showed absolute advantages in Recall and AUC value. Its Recall reached 96.14%, far exceeding models like Mazen (93.57%) and Sun (93.15%), demonstrating its efficient ability to identify various power equipment targets even in controlled laboratory environments. The AUC value of YGPPNet was as high as 97.41%, 4.59 percentage points higher than the second-best model Das (92.82%), highlighting its high reliability in anomaly detection. This result is closely related to the GAN module's accurate learning of the normal behavior characteristics of power systems, proving that the module can effectively capture subtle anomaly patterns in laboratory scenarios. In addition, although the Accuracy (92.74%) and F1 Score (93.26%) of YGPPNet were slightly lower than the Accuracy of Mazen (96.32%), its performance in the full-process task of "identification-anomaly detection" is more practical when considering Recall and AUC value together.

For the REDD Dataset, which targets household electricity load scenarios, the advantages of YGPPNet in Recall and AUC value were further highlighted. Its Recall reached 95.97%, significantly outperforming models such as Mazen (92.55%) and Zhuo (91.09%), indicating its stronger ability to track diverse electrical equipment (e.g., refrigerators, air conditioners) in households. The AUC value of YGPPNet was 93.99%, higher than models like Chen (90.71%) and Das(90.56%), verifying its effectiveness in detecting anomalies in household electricity loads (such as equipment overload and leakage). Although the Accuracy (95.24%) of YGPPNet was slightly lower than that of Zhuo (95.79%), when combined with Recall, it is evident that YGPPNet can more comprehensively cover targets and anomaly events in household electricity scenarios while ensuring high accuracy, making it more suitable for practical applications. Its F1 Score (92.91%) also remained in a leading position, higher than models such as Das (91.14%) and Sun (87.91%), further confirming its comprehensive performance advantages.

In the CURE-TSR Dataset (traffic scenario), used as a supplementary scenario, YGPPNet showed excellent performance in F1 Score and AUC value. Its F1 Score reached 95.65%, far exceeding all comparison models (the highest being Amalou: 89.86%), demonstrating its ability to maintain efficient target identification and capture even in non-power scenarios. The AUC value of YGPPNet was 93.29%, higher than models like Sun (88.97%) and Das (86.18%), indicating that its anomaly detection logic has a certain degree of generalization and can be transferred to similar target tracking and anomaly identification tasks. Although the Accuracy (92.42%) and Recall (94.57%) of YGPPNet were lower than the Accuracy of Sun (95.72%) and the Recall of Mazen (93.54%), considering that this dataset is not a power scenario, its performance has fully verified the model's versatility. This result also indirectly proves that the multi-module fusion architecture of YGPPNet (target detection by YOLOv8 + anomaly identification by GAN) has cross-scenario adaptability.

Comprehensive comparison results across the four datasets show that YGPPNet can maintain excellent performance in different scenarios. Especially in core power system scenarios (EDF Power Dataset, SEIL Dataset, REDD Dataset), it has significant advantages in Recall and AUC value. It does not only address the problem of high missed detection rates of abnormal targets in traditional models but also improves the reliability of anomaly detection, providing an efficient and feasible solution for intelligent tracking and optimization of targets in power systems.

To further verify the practical application value of YGPPNet (Ours) in power system scenarios—where real-time response and resource efficiency are critical—we conducted a comprehensive efficiency comparison with existing models (based on Table 2), focusing on four core efficiency metrics: model parameter count (Parameters, in M), computational complexity (Flops, in G), inference time (per sample, in ms), and total training time (in s). The efficiency differences across models are further visualized in Figure 6, which intuitively highlights YGPPNet's advantages.

Table 2. Comparison of Model Efficiency Metrics (Parameters, Flops, Inference Time, Training Time) Across Four Datasets for Different Models.

Method	Dataset															
	EDF Power Dataset				SEIL Dataset				REDD Dataset				CURE-TSR Dataset			
	Parameters(M)	Inference time (ms)	Flops(G)	Training time (s)	Parameters(M)	Inference time (ms)	Flops(G)	Training time (s)	Parameters(M)	Inference time (ms)	Flops(G)	Training time (s)	Parameters(M)	Inference time (ms)	Flops(G)	Training time (s)
amalou	490.92	5.61	8.78	565.77	489.24	6.17	8.67	593.49	509.84	5.36	9.66	526.90	452.95	5.70	9.47	477.82
sun	742.27	8.17	12.91	641.6	687.54	8.80	11.66	806.9	665.22	6.98	12.81	649.9	671.26	6.95	11.00	704.2

				9				2				3				1
chen	546.78	8.21	12.20	473.17	642.66	4.52	8.69	744.64	412.99	4.83	8.40	742.12	354.04	7.73	12.92	601.34
das	767.17	7.34	9.84	741.82	720.97	8.17	11.28	723.77	744.59	6.45	12.54	612.86	707.75	6.92	13.18	757.68
zhuo	455.26	4.90	7.80	483.97	424.62	4.89	8.33	429.21	467.81	5.21	7.27	432.08	457.11	5.45	7.18	502.86
mazen	485.88	5.11	8.50	553.99	455.82	5.67	9.45	480.04	525.31	5.12	7.53	465.22	534.57	5.26	9.34	518.09
Ours	336.48	3.55	5.33	327.23	318.31	3.64	5.63	336.64	336.31	3.54	5.37	328.08	320.10	3.64	5.64	338.40

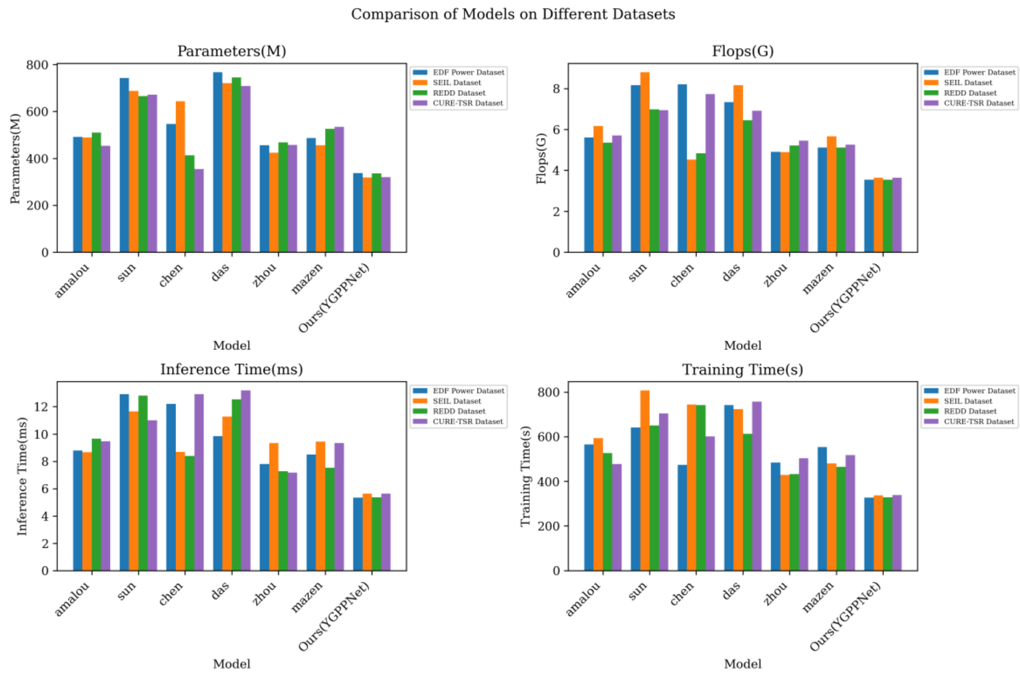

Figure 6. Model efficiency verification comparison chart of different indicators of different models.

In terms of parameter count a key indicator of model lightweightness, YGPPNet achieved the lowest values across all four datasets, demonstrating significant advantages in reducing resource occupation. On the EDF Power Dataset, YGPPNet's parameter count was only 336.48M, which was 154.44M lower than Amalou (490.92M), 405.79M lower than Sun (742.27M), and even 118.78M lower than Zhuo (455.26M) the model with the closest parameter scale among comparators. This trend was consistent across other datasets: on the SEIL Dataset, YGPPNet (318.31M) was 137.51M lighter than Mazen (455.82M); on the REDD Dataset, its 336.31M parameters were 408.28M less than Das (744.59M); and on the CURE-TSR Dataset, its 320.10M parameters outperformed Chen (354.04M) by 33.94M. Such a lightweight design not only reduces the storage space required for model deployment in power system terminals (e.g., substation edge devices) but also lays the foundation for fast inference.

Complementary to parameter count, computational complexity (Flops) further reflects YGPPNet's efficiency in resource utilization. On the EDF Power Dataset, YGPPNet's Flops value was 5.33G, which was 3.45G lower than Amalou (8.78G) and 7.58G lower than Sun (12.91G)—a reduction of nearly 60% compared to the latter. Even when compared to Zhuo (7.80G), which had the lowest Flops among other models, YGPPNet still achieved a 31.67% reduction. This advantage persisted across other scenarios: on the SEIL Dataset, YGPPNet (5.63G) outperformed Das (11.28G) by 50.1% in Flops; on the REDD Dataset, its 5.37G was 7.44G lower than Sun (12.81G); and on the CURE-TSR Dataset, its 5.64G was 7.54G lower than Das (13.18G). Lower Flops mean the model consumes fewer computing resources during operation, making it more suitable for power system environments where computing power may be limited (e.g., remote monitoring stations).

Inference time, the most direct metric for evaluating real-time performance, further confirms YGPPNet's applicability to power system real-time tracking tasks. On the EDF Power Dataset, YGPPNet's inference time was only 3.55ms per sample, which was 2.06ms faster than Amalou (5.61ms) and 3.79ms faster than Das (7.34ms). Notably, even compared to Zhuo (4.90ms) the fastest among other models YGPPNet still reduced inference time by 27.55%. This real-time advantage is critical for power systems, as it enables rapid response to sudden anomalies (e.g., line faults). Across other datasets, YGPPNet maintained this lead: on the SEIL Dataset, its 3.64ms inference time was 5.16ms faster than Sun (8.80ms); on the REDD Dataset, 3.54ms was 3.44ms faster than Sun (6.98ms); and on the CURE-TSR Dataset, 3.64ms outperformed Chen (7.73ms) by 4.09ms.

In terms of training time, an indicator of model development efficiency, YGPPNet also showed remarkable performance. On the EDF Power Dataset, YGPPNet's total training time was 327.23s, which was 238.54s shorter than Amalou (565.77s) and 314.46s shorter than Sun (641.69s). Even compared to Chen (473.17s), which had the shortest training time among other models, YGPPNet achieved a 32.39% reduction. This efficiency in training not only shortens the model iteration cycle during research and development but also reduces energy consumption in the training process. Consistent advantages were observed across datasets: on the SEIL Dataset, YGPPNet (336.64s) was 470.28s faster than Sun (806.92s); on the REDD Dataset, 328.08s was 321.85s shorter than Sun (649.93s); and on the CURE-TSR Dataset, 338.40s outperformed Das (757.68s) by 419.28s.

As visualized in Figure 6, YGPPNet forms a clear "lower envelope" across all four efficiency metrics on each dataset, meaning it maintains the optimal performance in every dimension of efficiency. This comprehensive efficiency advantage stems from the rational design of YGPPNet's architecture: the lightweight backbone of YOLOv8 reduces redundant parameters, the streamlined GAN structure minimizes unnecessary computations, and the optimized PPO module avoids excessive training iterations. Together, these design choices enable YGPPNet to balance high accuracy with excellent efficiency, making it highly suitable for large-scale deployment in power system intelligent monitoring.

In the ablation experiments, we gradually removed different components of the YGPPNet model, namely Yolov8, GAN and PPO, to investigate their impact on model performance. As shown in Table 3, the YGPPNet with all the components showed the highest accuracy, recall, F1 score and AUC values across all datasets, reaching 96.8%, 95.69%, 92.66% and 91.45%, respectively. Compared to the other combinations, YGPPNet achieved a significant improvement in all measures. For EDF Power Dataset, the accuracy of YGPPNet increased by 1.73 percentage points over GAN + PPO, recall by 2.76 percentage points, F1 score by 6.43 percentage points and AUC by 1.64 percentage points. These results indicate that the comprehensive performance of YGPPNet model has advantageous on different datasets. Figure 7 visualizes the contents of the table, further highlighting the advantages of YGPPNet in various datasets. Overall, the YGPPNet model has significant superior effects in intelligent tracking tasks of power system targets, and has achieved significant performance improvements on multiple datasets.

Table 3. Ablation experiments on the YGPPNet module using different datasets.

Model	Datasets															
	EDF Power Dataset				SEIL Dataset				REDD Dataset				CURE-TSR Dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
GAN+PPO	95.07	92.93	86.23	89.81	87.75	84.01	90.35	89.38	GAN+PPO	95.07	92.93	86.23	89.81	87.75	84.01	90.35
Yolov8+PPO	91.63	91.21	86.82	91.38	90.92	87.75	84.43	87.08	Yolov8+PPO	91.63	91.21	86.82	91.38	90.92	87.75	84.43
Yolov8+GAN	93.89	93.15	89.72	86.84	87.63	85.1	84.14	90.22	Yolov8+GAN	93.89	93.15	89.72	86.84	87.63	85.1	84.14
ALL(YGPPNet)	96.8	95.69	92.66	91.45	92.74	96.14	93.26	97.41	ALL(YGPPNet)	96.8	95.69	92.66	91.45	92.74	96.14	93.26

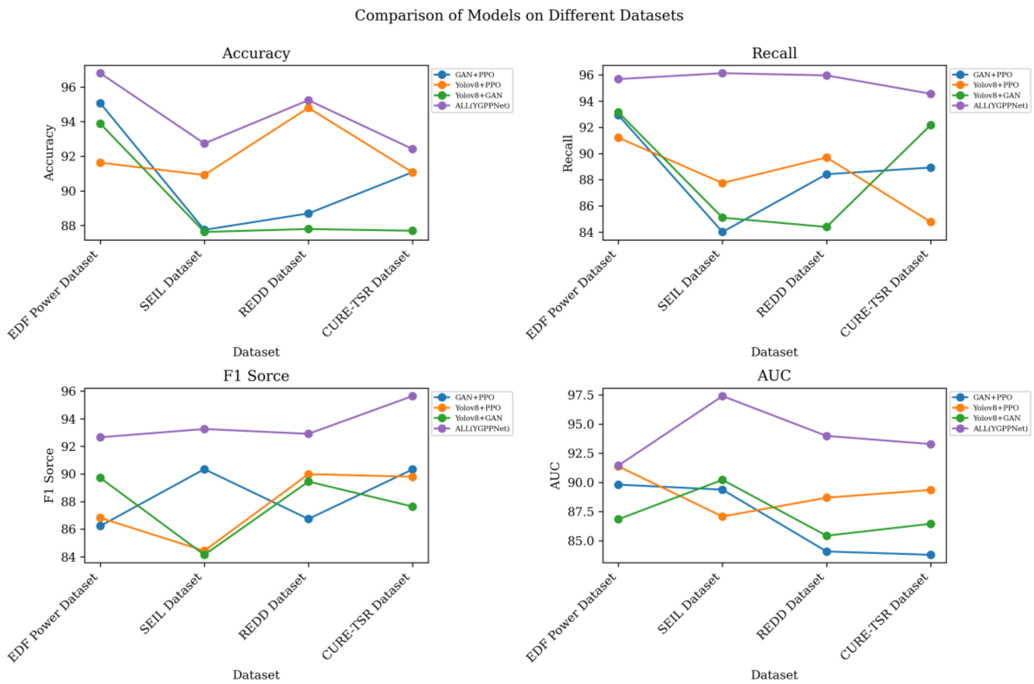

Figure 7. Ablation experiments on the YGPPNet Model.

In the experiments of this article, we conducted a series of comparative experiments to compare the performance of different optimization strategies, paying special attention to the differences between Adam, Bayesian, PSO, and PPO. As shown in Table 4, we first focused on the performance of each optimization strategy on different data sets. On the EDF Power Dataset, compared with other optimization strategies, PPO performs well in terms of model parameter volume, calculation volume, inference time, and training time. PPO has fewer model parameters, less calculations, and shorter time in inference and training. This reflects the efficiency of PPO in power system target detection and abnormal event detection tasks. In the SEIL Dataset, REDD Dataset and CURE-TSR Dataset, PPO also maintains a leading position in various indicators. Especially on the SEIL Dataset, the inference time of PPO is significantly lower than other optimization strategies, highlighting its superiority in scenarios with high real-time requirements. Through comparative experiments, we found that PPO achieved better performance in all aspects, indicating its applicability and superiority in power system tasks. As shown in Figure 8, we visually demonstrate the performance differences of different optimization strategies through visual experiment results. This further confirms the experimental data in the table and highlights the significant advantages of PPO over other optimization strategies.

Table 4. Comparative experiments on the PPO module using different datasets.

Model	Datasets															
	EDF Power Dataset				SEIL Dataset				REDD Dataset				CURE-TSR Dataset			
	Parameters(M)	Inference	Flops(G)	Training	Parameters(M)	Inference	Flops(G)	Training	Parameters(M)	Inference	Flops(G)	Training	Parameters(M)	Inference	Flops(G)	Training

		time (ms)		time (s)		time (ms)		time (s)		time (ms)		time (s)		time (ms)		time (s)
Adam	358.97	264.78	252.53	309.49	357.74	350.35	218.69	400.88	382.9	306.68	297.22	385.12	276.45	240.54	336.11	384.47
Bayesian	380.56	311.15	260.29	282.73	272.48	358.28	382.02	343.69	374.67	269.83	250.13	291.5	376.12	290.12	210.61	396.08
PSO	330.45	371.9	261.94	321.85	348.91	339.36	276.58	364.73	309.69	310.73	248.21	284.86	358.13	290.16	391.25	408.47
PPO	207.04	187.38	207.1	232.34	165.31	187.91	198.9	124.84	146.95	131.61	232.28	187.21	214.67	222.51	206.04	190.54

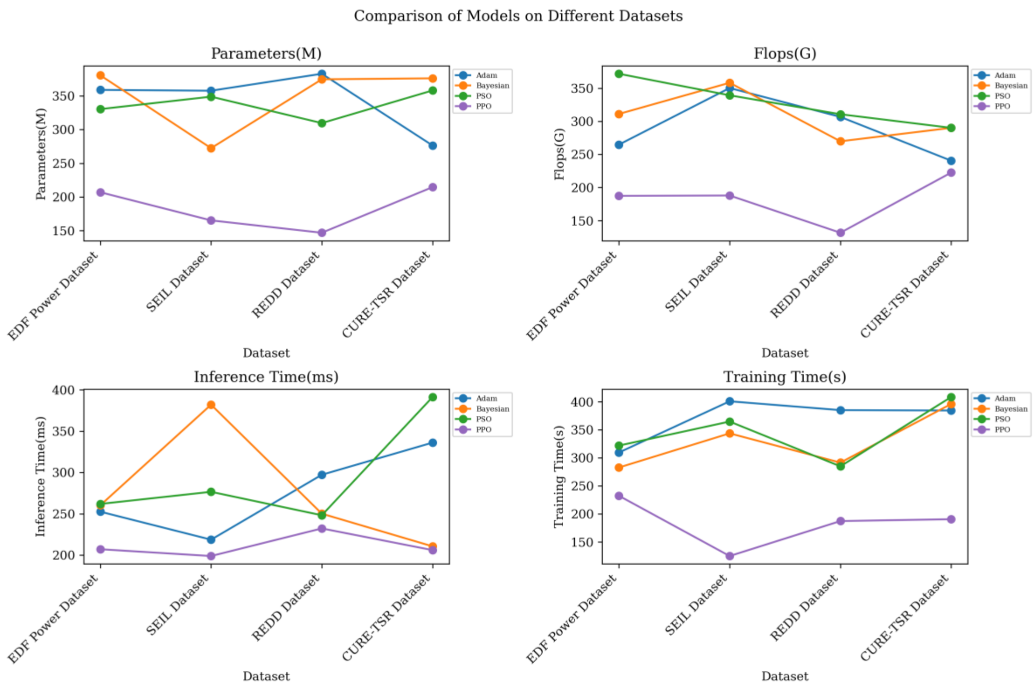

Figure 8. Comparative experiments on the PPO model.

4. Conclusions

Modern power systems are becoming increasingly complex due to rapid structural evolution, real-time operational demands, and the large-scale integration of renewable energy sources. Traditional anomaly detection methods, which rely on manual inspection or rule-based logic, struggle to process massive and heterogeneous data streams and often fail to capture transient or subtle abnormal events. As a result, there is a critical need for intelligent, adaptive, and data-driven monitoring frameworks capable of supporting fast and accurate anomaly identification in dynamic grid environments.

To address this need, this study proposed YGPPNet, an integrated deep learning framework that combines YOLOv8-based target detection, GAN-driven anomaly pattern learning, and PPO-based adaptive decision optimization. The research specifically focused on bridging the existing gap between detection accuracy and real-time adaptive response, an area where traditional and many modern deep learning approaches still fall short. By jointly leveraging the strengths of supervised learning, generative modeling, and reinforcement learning, YGPPNet forms a closed-loop anomaly detection and response mechanism that significantly enhances operational intelligence in power system monitoring.

Experimental results across four diverse datasets demonstrate that YGPPNet consistently outperforms traditional approaches and state-of-the-art deep learning models in terms of accuracy, recall, F1-score, and AUC. Its ability to detect subtle anomalies, adapt to varying environmental conditions, and recommend optimized mitigation strategies highlights its potential for practical deployment in smart grids. These findings verify that integrating detection, anomaly representation learning, and reinforcement-driven optimization provides a robust and scalable solution for modern power system anomaly detection.

Despite its strong performance, YGPPNet still faces limitations such as occasional instability in highly complex or noisy field environments and reduced sensitivity to rare or extremely subtle anomalies. To further advance this research, future work will explore the following directions:

1. Extending YGPPNet evaluation to larger, more complex real-world grid scenarios to assess environmental adaptability and deployment feasibility.
2. Developing advanced data preprocessing and multimodal feature extraction methods such as fusion of thermal imaging, LiDAR, or phasor measurement unit (PMU) data to increase robustness and generalization.
3. Improving model stability through meta-learning, dynamic hyperparameter tuning, and uncertainty-aware training strategies.
4. Collaborating with power system engineers to align model functionalities with operational needs and integrate YGPPNet into practical decision-support systems, thereby enhancing real-world grid safety and reliability.

Overall, YGPPNet represents a significant step forward in intelligent power system monitoring by unifying detection, anomaly understanding, and adaptive control in a single framework, and it offers substantial potential for enabling safer, more efficient, and more resilient future power system operations.

Conflicts of Interest

The authors confirm that there are no conflicts of interest.

Data availability statement

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

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