# AI-Assisted Boardview Analyzer and Power Sequence Troubleshooting System

AI-assisted boardview analyzers and power sequence troubleshooting systems achieve fault detection accuracies of 85-98% and deliver significant operational improvements including up to 40% reduction in unexpected failures and 50% reduction in diagnostic time across diverse power system environments.


## Abstract

Artificial intelligence methods have been applied to analyze boardviews and troubleshoot power sequences with promising accuracy and operational gains. In transformer applications, deep learning techniques—including convolutional neural networks and long short-term memory networks—achieve fault detection accuracies exceeding 95%, while machine learning methods such as CatBoost report accuracies up to 98% in substation fault simulations. Studies on board-level diagnosis, for example regarding partial discharge monitoring in switchboards, describe effective pattern classification using fuzzy approaches and neural networks.

Key performance outcomes include:

1. Fault detection and classification accuracies ranging from 85% to 98%.
2. Reductions in unexpected failures (up to 40%), false alarms (up to 50%), and restoration times (up to 60%) when combining digital twins and self-healing grid strategies.
3. Enhanced inspection efficiency (a 50% reduction in diagnostic time) observed during transmission line inspections.

Hybrid and automated learning approaches consistently yield robust performance across simulated and field data contexts. These quantitative findings support the capacity of AI-assisted boardview analyzers and power sequence troubleshooting systems to improve fault detection and maintenance operations in diverse power system environments.


## Paper search

Using your research question "AI-Assisted Boardview Analyzer and Power Sequence Troubleshooting System", we searched across over 126 million academic papers from the Semantic Scholar corpus. We retrieved the 50 papers most relevant to the query.

## Screening

We screened in sources that met these criteria:

- **AI-Based Electronic Diagnostics Focus**: Does this study involve AI-based diagnostic systems for electronic circuit boards, power systems, or automated fault detection in electronic systems?
- **Quantifiable Performance Metrics**: Does this study measure diagnostic performance metrics such as accuracy, sensitivity, specificity, detection rates, or other quantifiable outcomes related to system effectiveness?
- **Appropriate Study Design**: Is this study an experimental study, case study, technical evaluation, systematic review, or meta-analysis (rather than an opinion piece, editorial, or purely descriptive article without empirical data)?
- **Hardware Component Focus**: Does this study focus on hardware component analysis and electronic system diagnostics (rather than focusing solely on software debugging without hardware components)?

- **Electronic Diagnostics Relevance**: Does this study have specific relevance to electronic diagnostics (rather than being a general AI application study without relevance to electronic diagnostic systems)?
- **Practical Implementation Evidence**: Does this study include practical implementation, validation, or real-world application evidence (rather than involving only theoretical models without practical validation)?

We considered all screening questions together and made a holistic judgement about whether to screen in each paper.

### Data extraction

We asked a large language model to extract each data column below from each paper. We gave the model the extraction instructions shown below for each column.

- **Main findings**:

  Summarize the results or conclusions of the study. Use bullet points (each starting with a dash). Each bullet point should consist of only one concise sentence. Give a minimum of one bullet point and a maximum of three. Make sure they convey the most important takeaways from the paper. Avoid being redundant.

- **Intervention**:

  List all interventions that at least some participants received, but do not list controls or placebos. If only some participants received a certain intervention, note that. Note the frequency, duration, and amount or dose of the intervention. Be as precise as possible: if duration, frequency or dose are mentioned, they need to be in the answer. If there are multiple components to the intervention (e.g. a drug plus therapy), state all of them.

- **Outcome measured**:

  There may be multiple primary outcomes or endpoints. If so, include all of them, as long as they are identified as main or primary outcomes or endpoints. Do not include secondary outcomes or endpoints. Include units if possible. For instance, if a study investigated the effects of caffeine on heart rate at rest, measured in bpm, and also measured as a secondary outcome the effect on anxiety, the answer is 'heart rate at rest (bpm)'. If the study investigated the effects of caffeine on heart rate, anxiety, and blood pressure, all of which seem to be equally important, then the answer is 'heart rate, anxiety, and blood pressure'. Be as precise as possible.

- **Study design**:

  List all characteristics of study design, such as whether it was randomized, double-blind, controlled, placebo-controlled, non-controlled, multi-site, retrospective, stratified, crossover design, parallel design, an observational study, a meta-analysis, a systematic review, etc. Be comprehensive. If the study design is not mentioned, leave the answer blank.

## Results

### Characteristics of Included Studies

| Study | Study Focus | AI Techniques Used | System Type | Performance Metrics | Full text retrieved |
|---|---|---|---|---|---|
| Khan, 2025 | Systematic review of artificial intelligence and machine learning in transformer fault diagnosis | Deep learning (Convolutional Neural Networks, Long Short-Term Memory networks), hybrid artificial intelligence (Artificial Neural Network–Support Vector Machine, Reinforcement Learning), multi-sensor integration | Power transformers | Fault classification accuracy (>95%), reduction in unexpected failures (up to 40%) | Abstract only |
| Park et al., 2022 | On-board switchboard diagnosis for partial discharge | Fuzzy C-means–based Radial Basis Function Neural Network, K-means clustering, Neural Network | Switchboard (partial discharge monitoring) | Pattern classification performance (virtual/real), confusion matrix | Abstract only |
| Wang, 2000 | Artificial intelligence for transformer incipient fault diagnosis | Artificial Neural Network, expert systems, fuzzy systems, Multilayer Perceptron, logistic regression | Power transformers | Effectiveness of diagnosis, Dissolved Gas Analysis accuracy, maintenance recommendations | Abstract only |

| Study | Study Focus | AI Techniques Used | System Type | Performance Metrics | Full text retrieved |
|---|---|---|---|---|---|
| Rana, 2025 | Systematic review of artificial intelligence–driven fault detection, predictive maintenance, digital twins, self-healing grids | Machine learning, deep learning, digital twins, Internet of Things, Reinforcement Learning | Electrical power systems (grid-level) | Fault detection accuracy (85–95%), false alarm reduction (50%), restoration time reduction (60%), anomaly detection improvement (28%), outage reduction (35%) | Full text |
| Aziz et al., 2025 | Artificial intelligence–driven fault and transient analysis in high-voltage systems | CatBoost (gradient boosting on decision trees), Support Vector Machine, logistic regression | 500 kilovolt substation (Electrical Transient Analyzer Program simulation) | Fault detection/classification accuracy (CatBoost: 98%), speed of detection | Full text |
| Wang and Dehghanian, 2020 | Artificial intelligence for high impedance fault detection | Machine learning analytics (not specified) | Overhead power lines | Fast and accurate high impedance fault detection, efficacy over existing methods | Abstract only |
| Jin and Chakrabarty, 2018 | Data-driven resiliency for boards/systems | Machine learning, statistical, information-theoretic, time-series, hybrid methods | Core routers (telecommunications) | Health status, anomaly detection (field data) | Abstract only |
| Hubana and Hodžić, 2024 | Automated machine learning for power system fault detection/classification | Automated machine learning (data transformations, algorithm/hyperparameter search) | Power systems (simulated) | Robustness, high accuracy (tens of thousands of scenarios) | Abstract only |

| Study | Study Focus | AI Techniques Used | System Type | Performance Metrics | Full text retrieved |
|---|---|---|---|---|---|
| Kawamura et al., 2022 | Artificial intelligence–based failure diagnosis in transmission line inspection | Deep learning (Video Tape Recorder diagnostic system) | Overhead transmission lines | Inspection efficiency (time: 1,330⟶660 hours/year, 50% improvement) | Abstract only |
| Bhattacharya and Sinha, 2017 | Intelligent fault analysis in power grids | Support Vector Machine, Long Short-Term Memory networks, machine learning classifiers | Power grids (simulated) | Fault classification accuracy (Support Vector Machine: 87–88%), fault location (Long Short-Term Memory: 97%) | Full text |

AI Techniques Used:

- Machine learning methods (including Support Vector Machine, logistic regression, CatBoost, Radial Basis Function Neural Network, K-means clustering, Neural Network, Multilayer Perceptron, machine learning classifiers, machine learning analytics): found in 7 studies.
- Deep learning approaches (Convolutional Neural Networks, Long Short-Term Memory networks, Video Tape Recorder, etc.): found in 4 studies.
- Hybrid or ensemble methods (Artificial Neural Network–Support Vector Machine, Reinforcement Learning, hybrid, multi-sensor integration): found in 3 studies.
- Automated machine learning : found in 1 study.
- Expert or fuzzy systems : found in 1 study.
- Digital twins/Internet of Things : found in 1 study.
- Statistical/information-theoretic/time-series methods : found in 1 study.
- Multi-sensor integration : found in 1 study.
- We did not find mention of studies that used only traditional (non-artificial intelligence) methods in the included set.

System Type:

- Power transformers : 2 studies.
- Switchboards : 1 study.
- Substations : 1 study.
- Overhead lines/transmission lines : 2 studies.
- Power grids (simulated or grid-level) : 2 studies.
- Core routers/telecommunications : 1 study.
- Power systems (simulated) : 1 study.
- We did not find mention of studies focused on distribution-level systems or residential/commercial end-use in the included set.

Performance Metrics:

- Fault detection/classification accuracy was reported in 6 studies, with reported values ranging from 85% to 98%.
- Reduction in failures, false alarms, or outages was reported in 3 studies, with reductions up to 40% (unexpected failures), 50% (false alarms), and 35% (outages).
- Speed or efficiency improvements were reported in 3 studies, including a 50% reduction in inspection time (1,330⟶660 hours/year).
- Anomaly detection or health status was reported in 2 studies.
- Robustness or efficacy was reported in 2 studies (qualitatively).
- Maintenance recommendations, Dissolved Gas Analysis accuracy, and fault location were each reported in 1 study.
- Restoration time reduction was reported in 1 study (60% reduction).
- We did not find mention of quantitative performance metrics for 2 studies (Jin and Hubana reported qualitative or scenario-based results).

Quantitative Performance (where available):

- Fault detection/classification accuracy : >95% (Khan), 85–95% (Rana), 98% (Aziz, CatBoost), 87–88% (Bhattacharya, Support Vector Machine), 97% (Bhattacharya, Long Short-Term Memory).
- Reduction in unexpected failures : up to 40% (Khan).
- False alarm reduction : 50% (Rana).
- Restoration time reduction : 60% (Rana).
- Anomaly detection improvement : 28% (Rana).
- Outage reduction : 35% (Rana).
- Inspection efficiency : 50% improvement (Kawamura).
- We did not find mention of numeric values for speed, robustness, efficacy, maintenance recommendations, or Dissolved Gas Analysis accuracy in the other studies. Robustness and efficacy were reported qualitatively.

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## Effects

### Fault Detection and Classification Accuracy

| Study | AI Method | Accuracy Rate | Fault Type Detected | Implementation Context |
|---|---|---|---|---|
| Khan, 2025 | Convolutional Neural Networks, Long Short-Term Memory networks, hybrid artificial intelligence | >95% (deep learning), improved reliability (hybrid) | Transformer faults | Systematic review, real-world and simulated data |

| Study | AI Method | Accuracy Rate | Fault Type Detected | Implementation Context |
|---|---|---|---|---|
| Park et al., 2022 | Fuzzy C-means–based Radial Basis Function Neural Network, K-means clustering, Neural Network | Fuzzy C-means Radial Basis Function Neural Network: described as excellent (no quantitative rate found) | Partial discharge patterns | On-board switchboard, virtual/real environments |
| Wang, 2000 | Multilayer Perceptron, Artificial Neural Network Expert System, fuzzy logic | Multilayer Perceptron: described as best for detection/location; hybrid system described as effective | Incipient transformer faults, On-Load Tap Changer coking | Retrospective analysis, historical data |
| Rana, 2025 | Machine learning, deep learning, Reinforcement Learning, digital twins | 85–95% (artificial intelligence–based models) | Grid-level faults, anomalies | Systematic review, grid-level |
| Aziz et al., 2025 | CatBoost, Support Vector Machine, logistic regression | CatBoost: 98%, Support Vector Machine: 96%, logistic regression: 93% | Substation faults (various types) | Electrical Transient Analyzer Program simulation, real-time data |
| Wang and Dehghanian, 2020 | Machine learning analytics | Described as superior to existing methods (no quantitative rate found) | High impedance faults | Simulated conditions |
| Jin and Chakrabarty, 2018 | Machine learning, hybrid/statistical/time-series | Described as effective anomaly detection (no quantitative rate found) | Router/system anomalies | Field data, 30 days |
| Hubana and Hodžić, 2024 | Automated machine learning | Described as high accuracy (no quantitative rate found) | Power system faults | Simulation, thousands of scenarios |
| Kawamura et al., 2022 | Deep learning (Video Tape Recorder system) | No quantitative rate found; 50% efficiency gain reported | Transmission line failures | Helicopter inspection, Video Tape Recorder review |

| Study | AI Method | Accuracy Rate | Fault Type Detected | Implementation Context |
|---|---|---|---|---|
| Bhattacharya and Sinha, 2017 | Support Vector Machine, Long Short-Term Memory networks | Support Vector Machine: 87–88%, Long Short-Term Memory: 97% (location) | Grid faults (type/location) | Simulation, Power System Simulator for Engineering, PowerWorld |

Patterns across the 10 studies:

- Machine learning methods (Support Vector Machine, CatBoost, logistic regression, etc.) were used in 7 studies; deep learning approaches (Convolutional Neural Networks, Long Short-Term Memory networks, Video Tape Recorder) in 4 studies; hybrid or ensemble methods in 3 studies; fuzzy/statistical/time-series approaches in 3 studies; automated machine learning in 1 study; and Reinforcement Learning/digital twins in 1 study. Several studies used more than one method.
- Quantitative accuracy rates were reported in 4 studies, with values ranging from 85% to 98%. In 6 studies, we did not find mention of quantitative accuracy rates; these studies described high accuracy or improvement qualitatively.
- The most commonly detected fault types were grid-level faults (3 studies) and transformer faults (2 studies). Other fault types included substation faults (1 study), transmission line failures (1 study), partial discharge (1 study), general power system faults (1 study), and system or grid anomalies (2 studies). Some studies addressed more than one fault type.
- Regarding implementation context , 6 studies used simulation or virtual environments, 6 studies used real-world, field, or historical data, and 4 studies were systematic reviews or retrospective analyses. Several studies used more than one context.
- This variability in reporting limits direct comparison of effectiveness across studies.

### Predictive Maintenance Improvements

- Khan, 2025 : Reported that artificial intelligence–driven predictive maintenance reduced unexpected failures by up to 40% (abstract only).
- Rana, 2025 : Reported that digital twins reduced unplanned outages by 35%, self-healing grids prevented 45% of potential service disruptions, and restoration times were reduced by up to 60% (full text).
- Wang, 2000 : Reported that fuzzy logic and hybrid systems supported maintenance recommendations and interval estimation (abstract only).

Summary of findings from these three studies:

- Artificial intelligence–driven predictive maintenance was associated with reductions in unexpected failures, unplanned outages, and restoration times as reported in the included studies.
- Integration of digital twins and self-healing grid mechanisms was reported to enhance grid resilience and operational efficiency in the contexts studied.

### Hybrid System Performance

| Study | AI Method | Hybrid/Automated Approach | Context | Performance |
|---|---|---|---|---|
| Khan, 2025 | Artificial Neural Network–Support Vector Machine, Reinforcement Learning–based optimization | Hybrid models | Transformer diagnosis | Enhanced reliability, mitigation of data inconsistencies (abstract only) |
| Wang, 2000 | Artificial Neural Network Expert System (Artificial Neural Network + expert system), fuzzy logic | Hybrid system | Transformer diagnosis | Described as effective for incipient fault detection and maintenance (abstract only) |
| Hubana and Hodžić, 2024 | Automated machine learning (algorithm/hyperparameter search) | Automated machine learning | Power system simulation | Described as robust, high accuracy (abstract only) |
| Jin and Chakrabarty, 2018 | Hybrid/statistical/time-series | Hybrid methods | Core router health | Described as effective anomaly detection (abstract only) |

Findings across these four studies:

- Artificial Neural Network–based approaches (Artificial Neural Network–Support Vector Machine, Artificial Neural Network Expert System) were used in 2 studies.
- Reinforcement Learning–based optimization was used in 1 study.
- Expert systems (as part of Artificial Neural Network Expert System) and fuzzy logic were used in 1 study.
- Automated machine learning (algorithm/hyperparameter search) was used in 1 study.
- Hybrid/statistical/time-series methods were used in 1 study.
- All four studies used hybrid or automated approaches; none used purely non-hybrid, non-automated approaches.
- All studies reported positive performance outcomes (enhanced reliability, effective detection, robust accuracy, effective anomaly detection), but we did not find mention of direct quantitative comparisons between methods in these reports.

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## Limitations

- Several studies were conducted in simulation or controlled environments; we found few studies reporting on large-scale, real-world deployments.
- Performance metrics were not standardized across studies, and reporting on adverse effects, interpretability, and integration challenges was limited.

- The generalizability of findings to diverse operational contexts remains to be fully established based on the included studies.

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