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Review Article

AI-Driven Predictive Maintenance for High-Voltage Equipment in Saudi Power Systems

Mohammed Javeed[1]*
[1]Research Scholars

***Corresponding Author**
Mohammed Javeed
Research Scholars

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Abstract: High-voltage assets are central to the reliability of modern power systems, yet their maintenance remains difficult because failures are rare, degradation is heterogeneous, and operational data are distributed across transformers, gas-insulated switchgear, circuit breakers, protection systems, and inspection platforms. This review examines how artificial intelligence can support predictive maintenance for high-voltage equipment in Saudi power systems. A structured review of literature published from 2020 to 2025 was conducted in line with PRISMA 2020 reporting principles. The evidence base comprises twenty-eight peer-reviewed studies and two official Saudi energy-sector reports covering dissolved gas analysis, partial-discharge recognition, thermal imaging, mechanical-state prediction, health indexing, remaining-life estimation, digital twins, anomaly detection, and deployment governance. The synthesis finds that artificial intelligence creates the greatest operational value when it combines multi-source condition data with asset context, uncertainty estimates, and maintenance decision rules rather than operating as an isolated fault classifier. Transformer applications are the most mature, particularly for dissolved gas analysis and health-index estimation, while gas-insulated switchgear and circuit-breaker applications show strong diagnostic accuracy but weaker evidence on long-term field generalisation. Saudi deployment conditions add specific requirements: extreme heat and dust, rapidly expanding transmission infrastructure, renewable-energy integration, large geographical service territories, and a strategic shift toward digital operations. The paper proposes a five-layer framework linking sensing, trusted data engineering, hybrid analytics, risk-based decision support, and continuous learning. It also identifies practical priorities for utilities, including asset-specific baselines, physics-informed models, explainability, cybersecurity, model-drift monitoring, and phased field validation. The review concludes that AI-driven predictive maintenance can strengthen reliability and lifecycle value in Saudi high-voltage networks, but its success depends more on data governance, engineering integration, and accountable maintenance workflows than on algorithmic accuracy alone.

Keywords: Artificial Intelligence, Predictive Maintenance, High-Voltage Equipment, Power Transformers, Gas-Insulated Switchgear, Saudi Arabia, Condition Monitoring.

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1. INTRODUCTION

High-voltage equipment performs the switching, transformation, insulation, measurement, and protection functions that keep electricity networks stable. Power transformers, gas-insulated switchgear, circuit breakers, instrument transformers, surge arresters, cables, and associated control systems operate under interacting electrical, thermal, mechanical, chemical, and environmental stresses. Their failures can interrupt supply, damage adjacent assets, create safety hazards, and require long replacement lead times. Conventional maintenance has therefore relied on scheduled inspection, manufacturer recommendations, periodic testing, and expert interpretation. These practices remain necessary, but they can lead to unnecessary interventions on healthy equipment while failing to identify rapidly developing defects between inspection intervals. Predictive maintenance seeks to reduce this gap by estimating the current health state, detecting abnormal degradation, forecasting future condition, and recommending the most appropriate maintenance action before functional failure occurs (Zonta *et al*., 2020; Theissler *et al*., 2021).

Artificial intelligence is increasingly used to interpret the large, heterogeneous datasets generated by digital substations and online condition-monitoring systems. Machine-learning models can detect complex relationships that are difficult to represent through fixed thresholds, especially when multiple weak indicators precede a fault. Deep learning can automatically extract features from waveforms, images, and time series, while probabilistic models can express uncertainty and health-state probabilities. Digital twins can connect these data-driven capabilities with physical representations of equipment and operational context (van Dinter *et al*., 2022). However, high reported classification accuracy does not automatically translate into safer or more economical maintenance. Utility applications must cope with scarce failure examples, imbalanced labels, changing equipment populations, sensor noise, cybersecurity threats, and the need to explain recommendations to engineers responsible for critical infrastructure.

Transformers currently represent the most developed application area. Dissolved gas analysis, oil quality, thermal condition, insulation response, partial discharge, winding measurements, tap-changer behaviour, and loading history can be combined to estimate fault type and asset health. Recent reviews show that no single test provides a condition picture and that online monitoring should complement established diagnostic practice (Jin *et al*., 2022; Abbasi, 2022; Jin *et al*., 2023). AI methods have improved the interpretation of dissolved-gas patterns, particularly where traditional ratio rules produce ambiguous results. They have also supported health-index estimation and remaining-life analysis. Similar approaches are emerging for gas-insulated switchgear through ultra-high-frequency partial-discharge sensing, for circuit breakers through coil-current, travel, vibration, and gas-pressure signals, and for substation components through infrared imaging.

The Saudi context makes this field especially important. The national power system is expanding to serve rising demand, industrial development, new urban projects, and renewable-energy integration. Saudi Electricity Company reported record capital investment in 2024, extensive digital transformation activity, smart-grid enhancement, and continued expansion of regulated assets (Saudi Electricity Company, 2025). The National Industrial Development and Logistics Program also reported major renewable-energy projects intended to increase the share of renewables in the generation mix (NIDLP, 2025). These changes increase the number, diversity, and operational criticality of high-voltage assets. They also create new duty cycles, bidirectional power flows, switching patterns, and maintenance demands. Extreme ambient temperatures, dust, salinity in coastal areas, and long travel distances between sites further strengthen the case for remote, condition-based decision support.

This paper reviews AI-driven predictive maintenance for high-voltage equipment with explicit attention to Saudi power systems. Its aim is not to identify a single best algorithm. Instead, it evaluates the relationship among sensing, data quality, model design, asset risk, and maintenance execution. The review addresses four questions: which equipment and data types have the strongest evidence; which AI methods are most suitable for different diagnostic tasks; what barriers prevent field deployment; and how should a Saudi utility organise a scalable predictive-maintenance architecture? The contribution is a cross-asset synthesis and a practical framework that connects research findings with utility governance, reliability objectives, and lifecycle management.

2. REVIEW METHODOLOGY

The review followed a structured evidence-synthesis process guided by the PRISMA 2020 principles of transparency, reproducibility, and explicit selection criteria (Page *et al*., 2021). Searches focused on publications from January 2020 through December 2025 because this period captures rapid developments in deep learning, transfer learning, digital twins, edge analytics, and explainable predictive maintenance. Search concepts combined terms for high-voltage assets with terms for condition monitoring, predictive maintenance, machine learning, artificial intelligence, anomaly detection, health index, remaining useful life, dissolved gas analysis, partial discharge, thermal imaging, and circuit-breaker diagnostics. Priority was given to peer-reviewed journal articles in electrical engineering, energy systems, reliability, measurement, and industrial artificial intelligence.

Studies were included when they addressed equipment condition, fault diagnosis, degradation prediction, or maintenance decision support and reported a defined method, dataset, application, or review synthesis. General predictive-maintenance studies were included only when their findings were directly relevant to high-voltage deployment, such as data scarcity, interpretability, digital twins, anomaly detection, and model governance. Publications were excluded when they focused only on protection operation without a maintenance dimension, used data unrelated to physical asset condition, or lacked sufficient methodological detail. Official Saudi reports were included to contextualise network investment, digitalisation, and renewable integration. The final evidence set contained twenty-eight peer-reviewed publications and two sector reports.

A narrative synthesis was selected because the studies differed substantially in equipment type, sample size, fault taxonomy, sensor configuration, validation protocol, and performance metric. Direct meta-analysis would therefore create misleading comparisons. Each study was coded by asset, signal source, analytical task, model family, reported strength, and deployment limitation. Evidence was then grouped into four functional categories: diagnosis, health assessment, prognosis, and maintenance decision support. Greater weight was assigned to work using field data, multiple assets, realistic noise, unknown faults, or external validation. Laboratory accuracy was treated as evidence of technical feasibility rather than proof of operational effectiveness. This distinction is important because utility maintenance decisions depend on false-alarm cost, missed-failure risk, lead time, repeatability, and integration with engineering procedures, not merely classification accuracy.

3. High-Voltage Asset Degradation and Maintenance Needs

Predictive maintenance begins with the physical mechanisms that create measurable evidence of degradation. In oil-immersed transformers, thermal faults, electrical discharges, insulation ageing, moisture, winding deformation, bushing deterioration, cooling-system problems, and on-load tap-changer wear can evolve at different rates. Dissolved gas analysis is widely used because gases generated by thermal and electrical processes provide early information on internal defects. Yet gas concentrations depend on oil volume, loading, temperature, fault energy, sampling practice, and previous maintenance. Consequently, diagnosis based on a single sample or rigid ratio rule can be uncertain. Reviews by Jin *et al*., (2022), Abbasi (2022), and Zhang *et al*., (2022) show why multi-parameter interpretation and trend analysis are more reliable than isolated thresholds.

Health assessment converts diverse measurements into an interpretable condition state. Foros and Istad (2020) linked transformer health indices with failure probability and remaining lifetime, demonstrating the managerial value of integrating technical condition with risk. Barkas *et al*., (2023) combined adaptive algorithms and deep learning for dissolved-gas-based condition assessment, while Islam *et al*., (2023) used a deep generative framework with multiple diagnostic attributes to classify transformer health. These approaches move beyond fault labels toward prioritisation. Nevertheless, health indices can hide uncertainty when weighting schemes are fixed, data are missing, or different failure modes are aggregated into one score. A credible system should retain the underlying indicators, confidence intervals, and reason codes so that engineers can understand why an asset moved from one condition category to another.

Gas-insulated switchgear presents a different diagnostic problem. Insulation defects can generate partial discharges whose phase-resolved patterns, frequency content, and temporal structure vary with defect type and measurement environment. Liu *et al*., (2021) showed that a convolutional neural network combined with long short-term memory could capture spatial and temporal features in partial-discharge signals. Zheng *et al*., (2022) used time-frequency features and an improved convolutional network, while Tuyet-Doan *et al.,* (2020) demonstrated one-shot learning for small datasets. These studies are valuable because utilities rarely possess large labelled datasets for every switchgear design and defect. Deep ensemble methods can also help identify unknown classes rather than forcing every observation into a known fault category (Tuyet-Doan *et al*., 2021). Unknown detection is operationally important: an uncertain alarm should trigger expert review, not a confident but incorrect diagnosis.

High-voltage circuit breakers are dominated by mechanical and operating-mechanism failure modes, although insulation and gas conditions also matter. Coil current, contact travel, opening and closing time, vibration, motor current, operation count, and sulfur-hexafluoride pressure can reveal degradation. Chen *et al*., (2023) applied improved deep learning to vibration-based fault monitoring and reported strong diagnostic performance. Zheng *et al*., (2023) combined long short-term memory prediction with support vector machine classification to forecast mechanical state. Bezerra *et al*., (2023) used wavelets and machine learning to predict filling pressure from operational circuit-breaker data. Together these studies show that predictive maintenance should not treat the circuit breaker as a single signal source. Mechanical, electrical, environmental, and gas variables should be aligned by operation event and equipment identity.

Other high-voltage components can be monitored through visual, thermal, acoustic, and electrical inspection. Ullah *et al*., (2020) used infrared images and learned features to identify thermal defects in high-voltage equipment. Hussain *et al*., (2020) addressed adaptive denoising for online partial-discharge monitoring, highlighting the importance of signal quality in active substations. Such techniques are particularly relevant for Saudi sites, where solar heating, high ambient temperature, dust deposition, and long outdoor exposure can complicate interpretation. Models should therefore compare equipment against asset-specific and weather-adjusted baselines rather than applying the same absolute thermal or leakage-current threshold across all locations and seasons.

Table 1: Evidence map for AI-driven predictive maintenance of high-voltage assets

Asset	Core condition data	Suitable AI tasks	Main operational risk
Power transformers	DGA, oil quality, loading, temperatures, bushings, PD, insulation tests	Fault diagnosis, health index, anomaly detection, remaining-life estimation	Ambiguous labels and sensor/operating-condition dependence
Gas-insulated switchgear	UHF/TEV/acoustic PD signals, PRPD patterns, switching and environmental context	Few-shot classification, time-frequency recognition, unknown-class detection	Laboratory-to-field domain shift and electromagnetic noise
Circuit breakers	Coil current, travel, timing, vibration, motor current, operation count, SF6 pressure	Mechanical-state classification, signal forecasting, leak/pressure prognosis	Sparse event history and inconsistent event synchronisation
Outdoor substation equipment	Infrared images, visual inspection, load, ambient temperature, peer-phase comparison	Thermal anomaly detection, image classification, inspection prioritisation	Solar loading, emissivity, weather and viewpoint variability
Cross-asset fleet	Asset registry, age, manufacturer, work orders, failures, spares and consequence data	Risk ranking, peer comparison, maintenance optimisation	Weak asset identity and incomplete feedback from field work

4. Data and Sensing Foundation

The strongest predictive-maintenance systems are built on a disciplined data architecture. High-voltage data arrive at different sampling rates and levels of reliability. Supervisory control and data acquisition systems provide loading, temperature, alarms, switching states, and environmental variables. Dedicated monitors provide dissolved gases, moisture, bushing leakage current, partial discharge, vibration, acoustic emission, travel curves, and gas pressure. Inspection systems add infrared images, visible images, test certificates, maintenance findings, and technician observations. Enterprise systems contribute asset age, manufacturer, design family, work history, spares, outage consequence, and cost. An AI model can only produce meaningful predictions when these sources are associated with the correct asset, timestamp, operating state, and measurement quality.

Data quality problems are not minor preprocessing issues; they directly affect safety. Sensor drift can imitate slow degradation. A changed sampling method can create an artificial trend. Missing values may reflect communication failure rather than healthy equipment. Maintenance can reset some indicators without resetting others. Equipment replacement may leave historical records attached to the wrong serial number. Online partial-discharge data can be contaminated by radio-frequency interference and switching noise, which motivated adaptive denoising research (Hussain *et al*., 2020). A utility data pipeline should therefore include calibration status, sensor-health indicators, data lineage, engineering units, quality flags, and automated checks for impossible values. Raw data should be retained so that transformations and model outputs remain auditable.

Label quality is equally important. Fault labels are often derived from inspection conclusions, laboratory results, or post-failure analysis, but these labels can be broad, uncertain, or inconsistent across teams. A model trained on inaccurate labels may learn organisational habits rather than physical degradation. Semi-supervised methods are useful because they can exploit large quantities of unlabelled normal data alongside a smaller set of confirmed faults. Kim *et al*., (2020) demonstrated a semi-supervised autoencoder for transformer dissolved-gas data, and Mao *et al*., (2022) used transfer learning to address heterogeneous and incomplete fault experience. Wang *et al*., (2021) used Gaussian-process multiclass classification to provide probabilistic outputs. These methods are attractive for utilities, but they still require carefully defined label hierarchies: observation, suspected defect, confirmed defect, failure mode, intervention, and verified outcome should not be treated as identical categories.

Data imbalance is a structural property of reliable power systems because severe failures are uncommon. Wu *et al*., (2020) used adaptive synthetic oversampling in a deep parallel diagnostic model, while Liu *et al*., (2020) applied correlation-based density clustering to dissolved-gas patterns. Synthetic balancing can improve learning, but it can also create unrealistic examples if physical constraints are ignored. A safer strategy combines several methods: anomaly detection trained on healthy behaviour; cost-sensitive classification for known faults; transfer or few-shot learning for rare classes; physics-based simulation for plausible degradation scenarios; and expert review of synthetic samples. The evaluation dataset must remain untouched by oversampling and should be separated by asset, site, or time to prevent information leakage.

Contextualisation is essential in Saudi power systems. Transformer loading is affected by seasonal air-conditioning demand, major industrial loads, and project commissioning. Outdoor equipment experiences large daily thermal cycles, intense solar radiation, dust, humidity variation, and coastal salt exposure. Renewable integration changes power flow, voltage control, switching frequency, and reactive-power behaviour. The 2024 Saudi energy reports describe rapid infrastructure investment, digitalisation, and renewable project development (Saudi Electricity Company, 2025; NIDLP, 2025). Predictive models should therefore include ambient temperature, solar irradiance where available, load profile, switching duty, geographic zone, and equipment design. Without this context, normal summer operation may be mistaken for degradation, while abnormal performance relative to comparable assets may be missed.

A practical data platform should organise information into three time horizons. The real-time horizon supports alarms and event detection at seconds or minutes. The operational horizon aggregates trends over days and weeks for maintenance planning. The strategic horizon evaluates health, risk, and replacement needs over months and years. Edge processing is suitable for waveform filtering, feature extraction, and local anomaly detection where bandwidth is limited. Central platforms are better for fleet benchmarking, model training, digital-twin simulation, and cross-site learning. The architecture should allow degraded operation when communications fail and should never prevent conventional protection or local control from functioning independently.

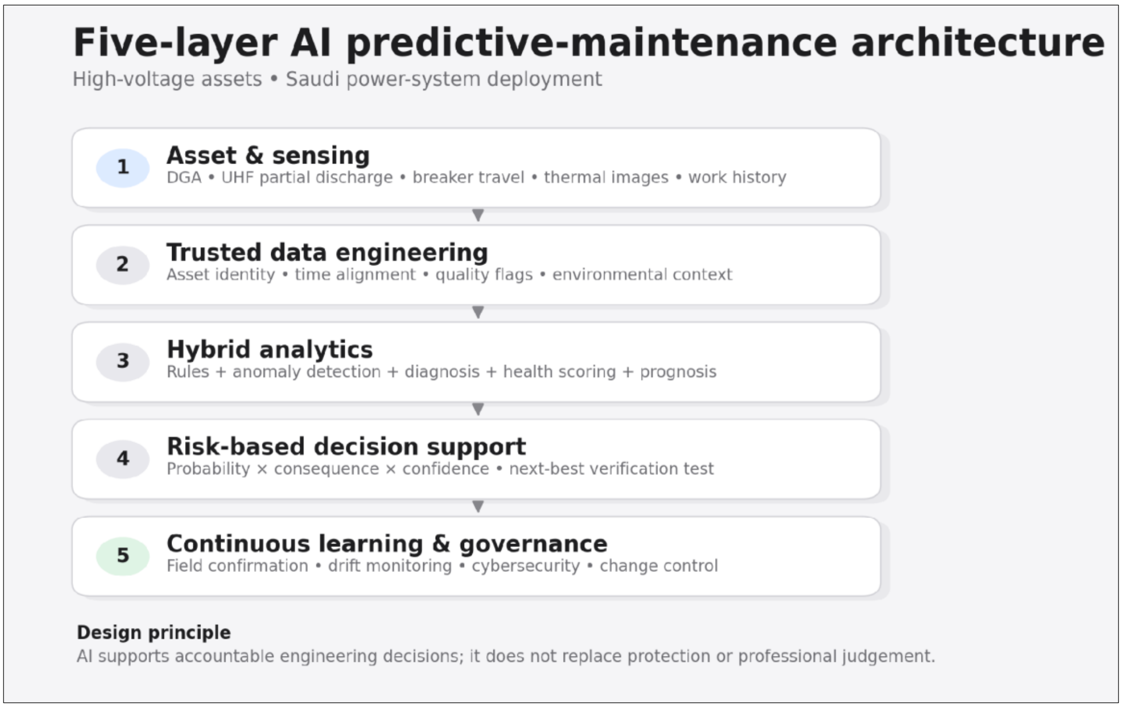

Figure 1: Proposed five-layer architecture linking high-voltage sensing to governed maintenance decisions

5. Artificial-Intelligence Methods and Evidence

AI methods for high-voltage maintenance can be organised by task rather than by algorithm. The first task is anomaly detection: identifying behaviour that differs from an asset's normal operating envelope. Autoencoders, one-class methods, clustering, and statistical change detection are useful when fault labels are scarce. Roelofs *et al*., (2021) illustrated how autoencoder reconstruction can be extended toward anomaly root-cause analysis. For power equipment, an anomaly model can learn relationships among load, temperature, gas generation, vibration, and ambient conditions. The advantage is early sensitivity to unfamiliar degradation. The limitation is that operational changes, sensor faults, and maintenance actions can also appear anomalous. Root-cause ranking and contextual rules are therefore necessary before work orders are generated.

The second task is fault diagnosis. Supervised classifiers including support vector machines, random forests, neural networks, convolutional networks, and ensemble models map measurements to known failure modes. Transformer dissolved-gas studies show a progression from engineered ratios toward learned feature spaces. Wu *et al*., (2020), Kim *et al*., (2020), Wang *et al*., (2021), and Mao *et al*., (2022) reported improvements through deep feature extraction, semi-supervised learning, probabilistic classification, and transfer learning. Nanfak *et al*., (2023) combined evolutionary clustering with gas subsets, reflecting the continuing value of domain-informed feature selection. For GIS, CNN-LSTM, time-frequency convolutional models, one-shot learning, and unknown-class ensembles address the structure and scarcity of partial-discharge data (Liu *et al*., 2021; Tuyet-Doan *et al*., 2020; Tuyet-Doan *et al*., 2021; Zheng *et al*., 2022).

The third task is health assessment. Health models aggregate multiple indicators into a condition category or continuous score. Their usefulness lies in fleet prioritisation and trend monitoring. Islam *et al*., (2023) demonstrated high classification performance using a generative model and real transformer test data. Barkas *et al*., (2023) integrated dissolved-gas evaluation with adaptive and deep-learning methods. A health score should not be interpreted as a direct probability of failure unless the model has been calibrated against failure outcomes. Utilities should separate three outputs: condition, probability of failure within a defined horizon, and consequence of failure. Combining these outputs creates risk, which is the appropriate basis for maintenance prioritisation.

The fourth task is prognosis, including remaining useful life and future condition prediction. Prognosis is more difficult than diagnosis because degradation trajectories are partially observed and maintenance alters them. Foros and Istad (2020) proposed systematic estimates of health, risk, and remaining lifetime, while Zheng *et al*., (2023) predicted future circuit-breaker mechanical signals before classifying state. Bezerra *et al*., (2023) forecast sulfur-hexafluoride pressure using wavelet-derived time delays and machine learning. Tusher *et al*., (2024) showed that transformer lifetime predictors can be vulnerable to false-data injection and proposed adversarial training. These studies indicate that a prognostic output should include an uncertainty range, forecast horizon, data sufficiency indicator, and sensitivity to assumed future loading.

Deep learning is attractive because it can learn features from raw signals, but it is not always the best operational choice. Small or tabular datasets may favour gradient boosting, random forests, Gaussian processes, or support vector machines. Complex waveforms and images may justify convolutional or recurrent networks. Theissler *et al*., (2021) observed that many predictive-maintenance studies depend on labelled data and that interpretability and data availability remain persistent challenges. Model selection should therefore consider maintainability, inference speed, calibration, uncertainty, and explanation quality. A slightly less accurate model that is stable, interpretable, and easy to validate can be preferable to a deep network whose errors cannot be understood.

Digital twins offer a way to combine data-driven models with engineering knowledge. A twin can represent equipment design, loading, thermal state, insulation ageing, maintenance history, and sensor observations. The systematic review by van Dinter *et al*., (2022) found that digital twins can support predictive maintenance but face computational, data-variety, and model-complexity challenges. For high-voltage assets, a useful twin does not need to reproduce every physical detail. It should answer maintenance questions: whether an observed temperature is plausible for the current load, how gas generation compares with expected thermal behaviour, how a breaker mechanism is drifting, and how risk changes under alternative operating scenarios. Hybrid models can constrain machine-learning outputs using thermal, electrical, mechanical, or chemical relationships.

Explainability must be designed around engineering decisions. Feature importance can indicate which measurements influenced a prediction, but it may not explain whether the relationship is physically credible. Local explanations should be translated into maintenance language, such as rising acetylene with increasing rate, abnormal phase-resolved discharge pattern, delayed opening time, or thermal deviation from comparable phases. Explanations should also show missing data and contradictory evidence. For high-consequence recommendations, the system should provide the measurement trend, peer comparison, model confidence, likely failure modes, and suggested verification test. Human review remains essential, particularly for novel anomalies, safety-critical switching, and replacement decisions.

Evaluation should reflect operational value. Random train-test splits can overstate performance when samples from the same asset appear in both sets. Better validation separates assets, substations, time periods, or equipment designs. Metrics should include precision, recall, false alarms per asset-month, detection lead time, calibration error, and cost-weighted risk. An AI alarm that detects every fault but produces frequent nuisance alerts will not be trusted. Conversely, a model with high overall accuracy may miss the rare severe class. Field trials should compare AI-supported decisions with existing practice and document whether the system changed inspections, prevented failures, reduced unnecessary maintenance, or improved outage planning.

6. Proposed Framework for Saudi Power Systems

The proposed framework has five connected layers. The first is the asset and sensing layer, which includes online monitors, protection records, operational measurements, inspection devices, and laboratory tests. Sensor selection should follow failure-mode-and-effects analysis rather than technology availability. Critical transformers may justify online dissolved-gas, moisture, bushing, and thermal monitoring, whereas lower-risk assets may rely on periodic tests and fleet comparison. Circuit breakers should capture operation-synchronised coil current, travel, timing, vibration, motor current, and gas condition where applicable. GIS monitoring should combine partial-discharge sensing with environmental and switching context.

The second layer is trusted data engineering. It provides asset identity, time synchronisation, quality flags, calibration records, environmental context, and integration with work management. A common asset model should connect each measurement to its subcomponent and location. Data validation should detect sensor freeze, drift, impossible rates of change, duplicate events, and communication gaps. Saudi utilities should preserve regional context because equipment in coastal, desert, industrial, and urban environments may require different baselines. Data access should be role-based, logged, and aligned with critical-infrastructure cybersecurity requirements.

The third layer is hybrid analytics. It combines rules and standards, anomaly detection, supervised diagnosis, health scoring, and prognosis. Rules provide transparent protection against obvious limit violations. Anomaly models identify unfamiliar behaviour. Supervised models classify known faults. Health models aggregate evidence, and prognostic models estimate future conditions. Physics-informed constraints reject impossible outputs, while uncertainty estimation distinguishes reliable predictions from cases requiring additional testing. Model libraries should be organised by equipment family and sensor configuration rather than assuming one national model can represent all manufacturers and ages.

The fourth layer is risk-based decision support. Model outputs are converted into actions using probability, consequence, confidence, and available maintenance options. A high-confidence abnormality on a redundant low-consequence asset may justify planned inspection, while moderate evidence on a critical transformer serving a major industrial or urban load may justify immediate verification. The system should recommend the next best test, not merely a fault label. For example, an uncertain transformer diagnosis could recommend confirmatory dissolved-gas sampling, infrared inspection, acoustic localisation, or electrical testing. Decision records should capture whether engineers accepted, modified, or rejected the recommendation and why.

The fifth layer is continuous learning and governance. Confirmed findings, maintenance actions, replaced components, and post-maintenance behaviour are returned to the dataset. Model performance is monitored by equipment group, region, season, and fault type. Drift triggers review rather than automatic retraining. Governance should define model ownership, approval authority, change control, validation frequency, and fallback procedures. Cybersecurity testing is particularly important because corrupted condition data can influence maintenance and asset-availability decisions, as demonstrated by Tusher *et al.,* (2024). The framework therefore treats predictive maintenance as a controlled engineering system, not a standalone analytics project.

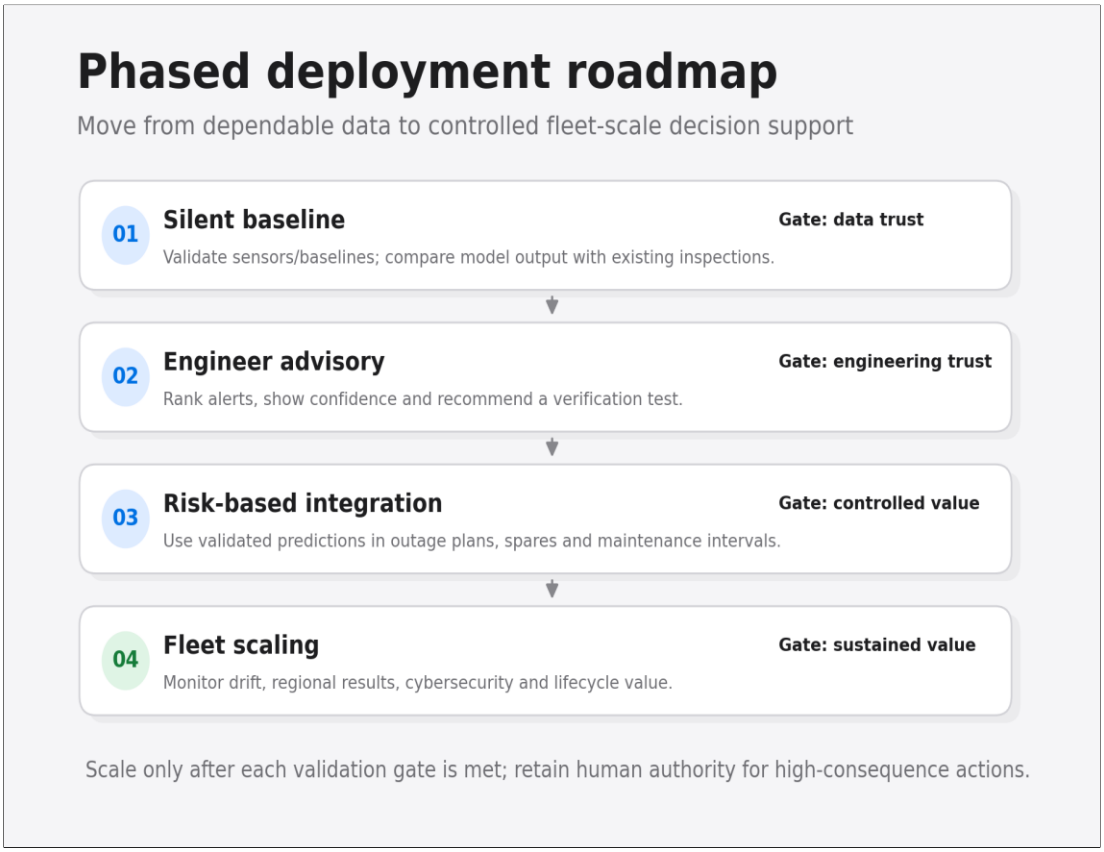

Figure 2: Phased roadmap for progressing from silent analytics to fleet-scale predictive maintenance

Table 2: Saudi implementation and governance roadmap

Phase	Scope	Validation gate	Key indicators
1. Silent baseline	Run models without changing maintenance decisions	Stable sensor quality and realistic seasonal baselines	Coverage, missingness, nuisance alarms, asset-level validation
2. Engineer advisory	Rank alerts and recommend verification tests	Engineers understand evidence, confidence and limitations	Precision, recall, false alarms per asset-month, acceptance rate
3. Controlled operational use	Inform outage plans, spares and maintenance intervals	Documented benefit under authorised engineering review	Detection lead time, avoided emergency work, changed decisions
4. Fleet scaling	Expand by equipment family, region and criticality	Governance, cybersecurity and drift controls remain effective	Regional calibration, drift, lifecycle cost, sustained reliability value

7. Implementation Priorities and Discussion

Implementation should begin with a limited number of high-value use cases. Transformer dissolved-gas trending, breaker mechanical-condition analysis, and infrared anomaly detection are suitable starting points because the physical indicators are established and the reviewed literature is relatively mature. Pilot assets should represent different ages, manufacturers, climatic zones, and criticality levels. The initial objective should be dependable data capture and workflow integration, not maximum model complexity. A baseline period is needed to learn normal seasonal behaviour and to compare AI alerts with existing engineering assessments.

A phased programme can move from advisory analytics to controlled operational use. In the first phase, models run silently and their outputs are compared with inspections and maintenance findings. In the second phase, engineers receive ranked alerts and recommended verification tests. In the third phase, validated predictions influence outage planning, spare allocation, and risk-based maintenance intervals. Automatic work-order generation should be reserved for well-defined low-risk actions with clear thresholds and strong validation. High-consequence actions must remain subject to authorised engineering review.

Economic evaluation should include avoided failure cost, reduced emergency work, deferred replacement, fewer unnecessary tests, improved outage coordination, and reduced travel to remote sites. Benefits should be compared with sensor installation, communications, data-platform, cybersecurity, model-validation, and change-management costs. The business case will vary by asset class. Online monitoring is most defensible where failure consequence is high, replacement lead time is long, or access is difficult. Fleet analytics may provide greater value for numerous lower-cost assets by identifying outliers and prioritising inspections. This alignment also supports transparent investment decisions across regional and national asset portfolios.

Several research gaps remain. Most studies evaluate one equipment type and one dataset, which limits transferability. Few report false alarms over long field periods, maintenance lead time, or post-intervention outcomes. Saudi-specific datasets are limited, especially for dust, heat, salinity, and mixed renewable-grid operating conditions. Future studies should develop benchmark datasets with anonymised field measurements, standard fault taxonomies, and asset-level train-test separation. Federated learning may allow utilities and manufacturers to improve models without pooling sensitive raw data. Hybrid digital twins, uncertainty-aware forecasts, and explainable root-cause analysis are promising directions, but they should be tested against maintenance outcomes rather than only laboratory accuracy.

The central finding of this review is that predictive maintenance is a socio-technical capability. Algorithms matter, but they operate inside a chain of sensors, communications, databases, engineering standards, maintenance teams, and governance. Weakness at any link can negate model performance. For Saudi power systems, the opportunity is substantial because infrastructure growth and digital investment can support modern asset management from the outset. The most credible path is to combine established diagnostic practice with AI, deploy gradually, measure operational value, and maintain clear human accountability.

8. CONCLUSION

AI-driven predictive maintenance can improve the reliability, safety, and lifecycle management of high-voltage equipment in Saudi power systems. Evidence is strongest for transformer dissolved-gas interpretation and health assessment, with promising results for GIS partial-discharge recognition, circuit-breaker mechanical prediction, gas-pressure forecasting, and thermal inspection. The reviewed studies also reveal persistent barriers: scarce and imbalanced fault data, sensor noise, limited external validation, model uncertainty, cybersecurity exposure, and weak integration with maintenance decisions. A successful deployment should therefore combine multi-source sensing, trusted data engineering, hybrid physics-and-data analytics, risk-based recommendations, and continuous governance. Saudi Arabia's expanding grid, renewable integration, harsh operating environment, and digital-transformation agenda create both urgency and opportunity. Predictive maintenance will deliver durable value when AI outputs are explainable, validated by field evidence, connected to engineering workflows, and used to support accountable decisions rather than replace professional judgement.

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