GridVeda: An AI-Driven Grid Intelligence System for Real-Time Transformer Health Monitoring

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Abstract

Power grid reliability in the United States has deteriorated over the past two decades, with outage frequency increasing amid rising weather volatility, infrastructure aging, and renewable integration complexity. According to data from the North American Electric Reliability Corporation (NERC) and analysis by the Bank of America Institute, transmission outages per year are significantly higher today than in the early 2000s. Since 2000, the number of major weather-related outages has increased dramatically, with extreme weather now responsible for over 80% of large-scale blackouts in the U.S.

We present **GridVeda**, an AI-powered early warning system for electrical transformers that runs on-site at substations, predicting failures before blackouts occur. GridVeda integrates dual AI pipelines: a physics-informed ETT (Electric Transformer Temperature) anomaly detector using gradient boosting ensembles, and a quantum-classical hybrid DGA (Dissolved Gas Analysis) fault classifier combining a 6-qubit variational quantum circuit with Rogers Ratio and Duval Triangle diagnostics. The system achieves 98.09% ± 0.80% DGA classification accuracy with 96.99% macro F1 score across 5-fold cross-validation. This paper provides an extensive technical overview of GridVeda's multi-layered architecture, including transformer telemetry processing, quantum ensemble voting mechanisms deployed on NVIDIA hardware with cuQuantum acceleration, Nemotron Nano 4B for screen-aware conversational assistance, Perplexity Sonar for web-grounded spatial fault visualization via Three.js CAD rendering, and GPT-4 as responsible AI orchestrator managing operator training and ethical deployment safeguards.

Keywords: Power Grid Reliability, Transformer Monitoring, AI for Infrastructure, Real-Time Telemetry, Energy Systems Intelligence, Quantum Computing, Variational Quantum Circuits, Gradient Boosting Ensembles, Vision-Language Models, Spatial Visualization, Responsible AI, Edge AI

1 Introduction

Grid operators work in high-stakes environments where failures cascade fast and decisions must be made under severe time pressure. Today, 46% of U.S. distribution infrastructure is at or beyond its useful life, contributing to an annual economic loss of $150 billion [6]. The DOE warns that without intervention, the risk of major outages could increase 30-fold by 2030. When a single transformer fails under these conditions—often due to the overloading seen in 34% of recent asset failures—it can knock out substations and leave communities dark for days. A single transformer failure can overload neighboring assets, trigger cascading outages, and leave entire communities without power for extended periods. Recent events, from the 2021 Texas grid crisis to the 2023 North Carolina substation attacks and extreme weather-driven outages, reveal a common reality: we are still reacting to failures instead of predicting them.

Growing up across California, Oregon, and Maryland, our team has witnessed firsthand how fragile infrastructure can amplify disaster impacts, from wildfire-driven outages in the West to storm-related grid disruptions on the East Coast. These experiences reinforced the need for on-device intelligence that continues operating even when connectivity is unreliable, especially during storms, heat waves, or grid stress events when traditional cloud-dependent systems become unavailable.

1.1 System Overview

GridVeda is an AI-powered early warning system for electrical transformers designed to predict failures before blackouts occur by providing real-time situational awareness and automated decision support for grid operators. The system operates entirely at the edge without cloud dependency for core detection and classification tasks, ensuring continued operation during storms, outages, or network instability when connectivity fails.

The architecture integrates five major AI components working in concert. First, a physics-informed ETT (Electric Transformer Temperature) anomaly detector processes continuous sensor readings every 15 minutes, computing 36 derived features from thermal dynamics, electrical loading, thermodynamic coupling, and insulation degradation patterns. This detector employs a weighted ensemble of XGBoost, LightGBM, CatBoost, and Random Forest classifiers to generate continuous risk scores scaled from 0 to 100%, alerting operators when scores exceed 50% to schedule gas testing.

Second, when gas chromatography results become available, a quantum-classical hybrid DGA (Dissolved Gas Analysis) fault classifier diagnoses transformer faults across eight categories. This system combines a 6-qubit variational quantum circuit accelerated via NVIDIA cuQuantum with classical Rogers Ratio analysis and Duval Triangle geometric classification. The three methods perform plurality voting to produce final diagnoses, with a parallel classical gradient boosting ensemble providing weighted meta-voting where the classical ensemble contributes two votes and the quantum ensemble contributes one vote.

Third, NVIDIA's Nemotron Nano 4B operates as a screen-aware conversational assistant, monitoring dashboard state through periodic screenshots and OCR extraction. The model responds to natural language queries about transformer health, explains risk scores by synthesizing explainability panel data, and provides adaptive tutorials for operators with varying levels of expertise. Voice interaction via Web Speech API enables hands-free field operation.

Fourth, Perplexity Sonar provides web-grounded spatial intelligence, automatically researching transformer failures with similar DGA signatures and rendering interactive 3D fault visualizations. The system retrieves NERC reports, manufacturer recalls, and regional failure data at approximately 1,200 tokens per second, then maps probable fault locations within Three.js CAD models using gas diffusion physics and Bayesian priors from historical incident frequencies.

Fifth, GPT-4 serves as a responsible AI orchestrator, managing operator onboarding through adaptive tutorials, providing layered model explanations from conceptual analogies to mathematical derivations, monitoring prediction distributions for bias, and enforcing human-in-the-loop policies for critical actions. The orchestrator implements A/B testing for model updates and generates automated incident post-mortems.

All components run on NVIDIA hardware, with development on RTX 5090 and deployment targeting the Jetson Orin Nano Super for 25-watt field operation. The FastAPI backend streams telemetry at 2-second intervals via WebSocket to a real-time dashboard displaying live transformer health cards, risk gauges, explainability panels, and spatial visualizations.

1.2 Research Contributions

Existing research and commercial solutions have shown the benefits of SCADA systems for grid monitoring [1, 2], as well as the potential of machine learning for outage prediction [3, 4]. However, integrating these components into a single real-time intelligence system—with robust AI models, contextual awareness, and operator-friendly interfaces—remains challenging. GridVeda addresses this gap by combining state-of-the-art gradient boosting techniques for anomaly detection, quantum variational circuits operating in ensemble with classical DGA diagnostic methods, and agentic AI layers to interpret grid conditions and provide predictive guidance.

In this paper, we provide:

1. A comprehensive analysis of rising grid instability using empirical data from NERC and Climate Central, demonstrating structural regime changes in grid reliability.

2. A deep technical overview of GridVeda's dual-pipeline architecture, processing Electric Transformer Temperature (ETT) sensor data every 15 minutes and Dissolved Gas Analysis (DGA) chemistry measurements on-demand.

3. Details on AI model ensemble design deployed on NVIDIA hardware, covering a 6-qubit variational quantum circuit accelerated with cuQuantum operating in tri-method ensemble with Rogers Ratio and Duval Triangle diagnostics, physics-informed gradient boosting for anomaly detection, Nemotron Nano 4B for screen context monitoring and conversational assistance, Perplexity Sonar for web-grounded spatial fault visualization via Three.js CAD rendering, and GPT-4 as responsible AI orchestrator managing operator onboarding, model interpretability, and ethical deployment safeguards.

4. Real-world performance benchmarks demonstrating 98.09% DGA classification accuracy, sub-second anomaly detection, and operator response time improvements.

5. The complete system architecture with model integration patterns, ensemble voting mechanisms, conversational AI interfaces, real-time dashboard monitoring, and spatial fault visualization capabilities.

2 Rising Grid Instability

The reliability of the United States power grid has become an increasingly urgent concern. Modern power systems face unprecedented challenges from multiple converging factors: aging infrastructure originally designed for centralized generation, increasing demand volatility driven by electrification of transportation and heating, intermittency from renewable energy sources, and intensifying extreme weather events driven by climate change.

2.1 Transmission Outage Trends

As illustrated in data from the Bank of America Institute [5], annual transmission outages have risen markedly compared to levels observed in the early 2000s. From 2008–2014, outage levels remained relatively stable, fluctuating between roughly 4,000 and 5,000 events annually. However, beginning in 2015, outage frequency nearly doubled, with sustained levels between 8,000 and 10,000 outages per year through 2024.

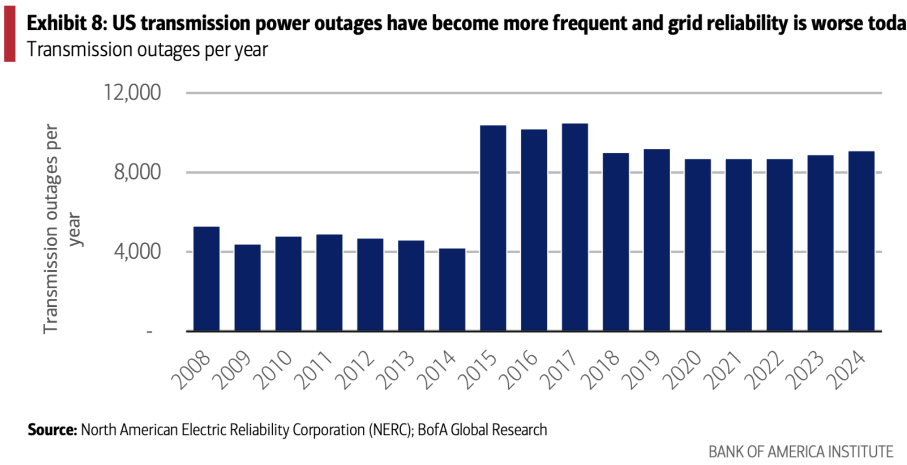

Exhibit 8: US transmission power outages have become more frequent and grid reliability is worse today than in the early 2000s

Transmission outages per year

Source: North American Electric Reliability Corporation (NERC); BofA Global Research

BANK OF AMERICA INSTITUTE

Figure 1: Transmission outages per year (2008–2024). Source: NERC; Bank of America Institute.

Figure 1 shows a clear structural break beginning in 2015. Outages rise from approximately 4,000–5,000 annually to sustained levels above 8,000. This shift is not a short-term anomaly but a persistent regime change that continues through 2024. Such elevated outage frequency increases operational uncertainty, complicates maintenance planning, and heightens systemic fragility. The economic impact is substantial, with each major transmission outage costing utilities and customers millions of dollars [6].

2.2 Weather-Driven Major Outages

Climate Central's longitudinal dataset on major U.S. power outages reinforces the trend of accelerating grid instability [7]. Weather-related major outages have grown dramatically since 2000, with particularly pronounced peaks after 2015. Since 2000, the number of major weather-related outages has increased dramatically, with extreme weather now responsible for over 80% of large-scale blackouts in the U.S.

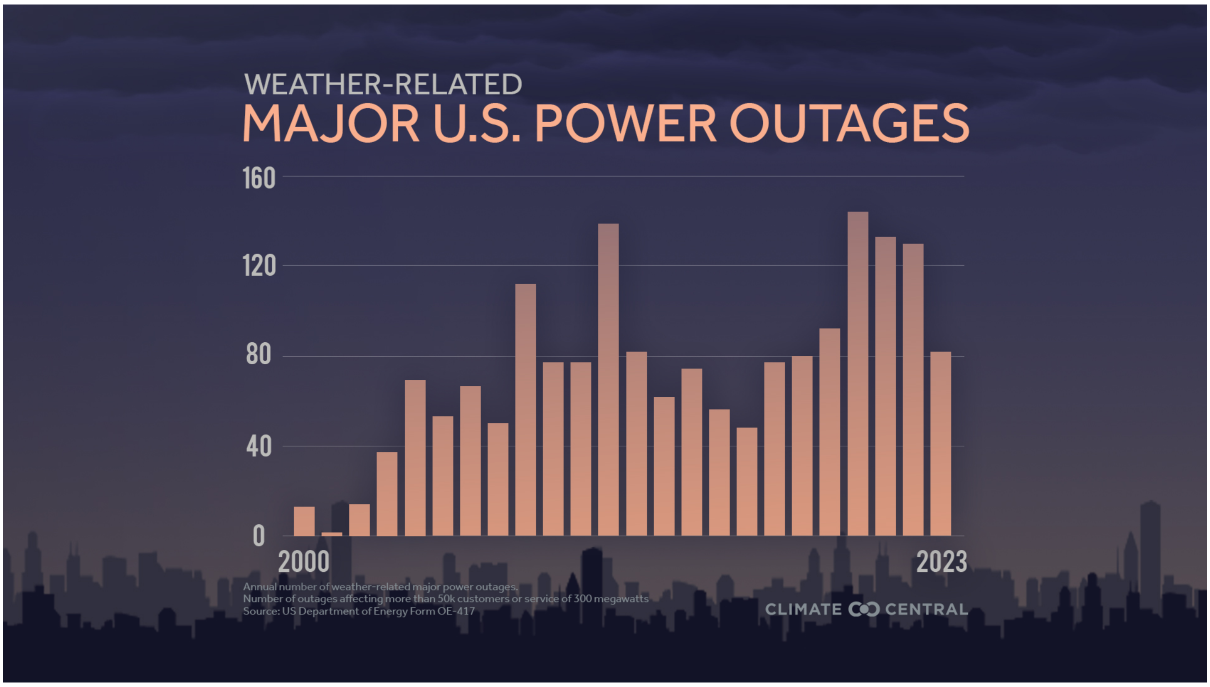

Figure 2: Weather-related major U.S. power outages (2000–2023). Source: Climate Central; DOE OE-417.

Figure 2 illustrates the rapid growth in weather-related major outages since 2000. Recent events, from the 2021 Texas grid crisis to the 2023 North Carolina substation attacks and extreme weather-driven outages, reveal a common reality: we are still reacting to failures instead of predicting them. This data suggests that climate volatility is no longer a tail risk but a central operational variable [8]. Grid management must transition from reactive restoration to predictive resilience. Growing up across California, Oregon, and Maryland, our team witnessed how fragile infrastructure amplifies disaster impacts, reinforcing the need for edge intelligence that operates during connectivity disruptions.

3 System Architecture: GridVeda

GridVeda implements a dual-pipeline architecture for comprehensive transformer health monitoring, processing two distinct data streams through separate AI models before combining results into unified risk assessments.

3.1 Dual-Pipeline Architecture Overview

The GridVeda system implements two primary AI pipelines operating on different time scales and data modalities. The **ETT Anomaly Detector** processes continuous time-series telemetry from transformer sensors sampled at 15-minute intervals. This pipeline monitors operational patterns around the clock, computing physics-informed features that capture thermal dynamics, electrical loading, thermodynamic coupling, and insulation degradation. The detector flags high-risk conditions (risk score >50%) that warrant further investigation through dissolved gas analysis.

The **Quantum Ensemble DGA Fault Classifier** activates when operators perform gas chromatography tests, typically triggered by ETT anomaly alerts or scheduled maintenance intervals. This pipeline processes chemical measurements of dissolved gases in transformer oil—hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2). The quantum ensemble combines three diagnostic methodologies: a 6-qubit variational quantum circuit accelerated via cuQuantum, classical Rogers Ratio analysis implementing IEEE C57.104 standard thresholds, and Duval Triangle geometric classification. These three methods vote on fault classification across eight categories spanning normal operation, partial discharge, low and high energy electrical discharge, and three thermal fault severity ranges.

The dual-pipeline workflow operates as follows: Continuous ETT monitoring processes sensor readings every 15 minutes, computing 36 physics-informed features and generating anomaly probabilities via a weighted ensemble of XGBoost, LightGBM, CatBoost, and Random Forest classifiers. When the ensemble risk score exceeds 50%, the system alerts operators to schedule DGA testing. Upon receiving gas chromatography results, the quantum ensemble processes normalized concentration values through all three diagnostic methods simultaneously. The quantum circuit encodes gas measurements into qubit rotations, evolves the state through four variational layers with learned parameters, and produces measurement probabilities that map to fault classes. In parallel, Rogers Ratio analysis computes five diagnostic ratios and applies threshold rules to classify the fault, while Duval Triangle projects the three key hydrocarbons into normalized percentage coordinates and determines which diagnostic region contains the sample. The three classifications enter a plurality voting mechanism where the majority verdict becomes the final diagnosis, with ties broken by quantum prediction due to its learned nonlinear decision boundaries.

Additionally, a second classical gradient boosting ensemble for DGA operates in parallel with the quantum circuit, providing weighted meta-voting where the classical DGA ensemble contributes two votes and the quantum ensemble contributes one vote, reflecting the classical models' higher sample efficiency during training.

3.2 Real-Time Operational Dashboard Architecture

GridVeda's operational interface implements a multi-panel monitoring dashboard connected to the FastAPI backend via WebSocket streaming at 2-second intervals. The **Live Fleet Status** panel displays transformer health cards with color-coded risk gauges (green <40%, yellow 40-70%, red >70%), current oil temperature and load readings, and 24-hour risk sparklines. The **KPI Analytics** panel aggregates fleet-wide metrics: average risk score with trend indicators, active anomaly count, time-to-detection, false positive rate (2.1/day baseline), and model confidence. Operators select time windows (hour/day/week/month) to identify seasonal patterns.

The **AI Chat Interface** routes queries based on content: grid-specific technical questions go to Nemotron Nano 4B running locally via Ollama, while external information requests (weather, recalls, incidents) route to Perplexity Sonar with real-time citations. The **Spatial Fault Visualization** panel renders interactive 3D transformer CAD models via Three.js with fault probability heat maps overlaid. The **Neural Network Explainability** panel displays SHAP feature importance rankings for ETT predictions, tri-method ensemble votes for DGA classifications, Rogers Ratio values, and Duval Triangle coordinates with visual plots. The **GPU Resource Monitor** tracks temperature, memory, utilization, and power draw via nvidia-smi polling every second.

WebSocket connections via Socket.IO maintain bidirectional communication with automatic reconnection during network disruptions. When connectivity drops, the dashboard caches telemetry and displays locally computed predictions in offline mode. Visual design follows accessibility guidelines with high-contrast colors, large touch targets, and keyboard shortcuts. Alerts trigger visual indicators (flashing red borders) and optional audio notifications requiring explicit operator acknowledgment with logged audit trails.

3.3 Nemotron Nano 4B Screen Context Monitor

GridVeda deploys NVIDIA's Nemotron Nano 4B as a screen-aware conversational assistant that monitors dashboard state and responds to operator queries. At 5-second intervals, the system captures dashboard screenshots via HTML5 Canvas API, applies OCR via Tesseract to extract visible text (transformer IDs, risk scores, alerts), and detects UI component boundaries through computer vision. The extracted data forms a structured JSON representation of current dashboard state.

Nemotron receives multi-modal input combining the visual screenshot and parsed semantic annotations. The model was system-prompted with IEEE C57.104 standards, Rogers Ratio and Duval Triangle methodologies, physics-informed feature definitions, and GridVeda's dual-pipeline architecture. This enables several capabilities: proactive alerting when multiple transformers simultaneously elevate risk scores (suggesting systemic voltage events), conversational queries where operators ask "Why is T047 high risk?" and receive explanations synthesized from explainability panel data, tutorial support for new operators with adaptive depth based on background, workflow guidance through multi-step procedures, and model explanation translating SHAP values to plain language.

The implementation achieves low latency through efficient serving. Nemotron Nano 4B (4B parameters quantized to INT8) fits entirely in RTX 5090's 24GB VRAM. Ollama framework applies continuous batching for GPU utilization. Response latency averages 200-400ms first token, streaming at 40-60 tokens/sec. System prompt consumes approximately 2,000 tokens, dashboard context adds 1,500-3,000 tokens, user queries 10-50 tokens, totaling under 6,000 tokens within the 4,096 token window. Voice interaction via Web Speech API enables hands-free field operation with speech-to-text input and browser-native text-to-speech output.

3.4 Perplexity Sonar Web-Grounded Spatial Intelligence

GridVeda integrates Perplexity's Sonar model for real-time web research, enabling contextualization of local transformer health with external data sources including equipment failures, manufacturer recalls, weather events, and academic research. Integration activates through operator queries ("recent transformer failures Texas 2024-2025") or automatic contextual lookup triggered by fault detections.

When the quantum ensemble classifies a DGA sample as faulty, the system constructs a research query embedding the fault signature. For D2 high-energy discharge, Perplexity searches for "transformer high-energy discharge failures [C2H2 elevated, C2H2/C2H4 > 1.0] past 12 months" with geographic context at approximately 1,200 tokens/second. Retrieved incidents are parsed to extract commonalities—bushing failures, lightning strikes, internal arcing, manufacturing defects. The chat panel displays synthesized findings: "Research shows 7 failures with similar DGA signatures. Four attributed to bushing flashover during storms, two to winding insulation moisture ingress, one to manufacturing defect in model X-500 (2019-2021 batch). Recommend bushing inspection and recall verification."

The spatial visualization component renders probable fault locations within 3D transformer models using Three.js. Python scripts parse CAD files (STEP/IGES format) via Open CASCADE geometry kernel, extract meshes of major components (windings, core, tap changer, bushings, oil tank, radiators), and export to OBJ. The Three.js frontend loads OBJ meshes, constructs scenes with perspective cameras and orbit controls.

Spatial mapping from DGA chemistry to physical location employs multi-stage inference. Gas-specific transport models estimate origins based on diffusion physics—acetylene (insoluble, generated >700°C from arcing) localizes to arc sites with minimal dispersion (bushings, tap changer, winding faults). Methane and ethylene diffuse more widely but concentrate near thermal sources. CO indicates cellulose decomposition in paper-insulated regions. Perplexity-retrieved incidents provide Bayesian priors—historical failure frequencies (bushings X%, tap changers Y%, windings Z%) combine with gas transport likelihoods. The transformer volume discretizes into 10cm voxel grids, calculating gas concentration likelihoods using diffusion-advection equations and weighting by failure mode probabilities.

The probability distribution renders as volumetric heat maps overlaid on Three.js models. Low probability regions appear blue (opacity 0.3), moderate yellow-orange (0.6), high probability hotspots red (0.9). WebGL shaders implement raymarched volume rendering for smooth gradients. Operators rotate models, slice cross-sections, and click hotspots to see tooltips: ”This bushing region shows 73% fault probability based on: C2H2 87ppm suggests discharge, 47% of similar failures were bushing-related (Perplexity data), spatial diffusion model predicts this location.”

Three.js PBR materials differentiate components: copper windings (metalness=0.9, roughness=0.3, orange-brown), steel core (metalness=0.8, roughness=0.5, gray), insulation (metalness=0.0, roughness=0.7, tan), oil (opacity=0.2, transmission=0.8), ceramic bushings (metalness=0.0, roughness=0.1, clearcoat=0.5). Animation illustrates fault progression—bushing flashover begins with partial discharge (small red region at oil-porcelain interface), spreads via surface tracking over 48-72 hours (red expands along bushing), culminates in flashover (entire bushing volume red).

Citation tracking maintains provenance. Perplexity responses include source URLs, publication dates, domain reputation scores. Chat interface renders citations with trust indicators: peer-reviewed journals (green checkmarks), utility filings (green), news outlets (yellow), blogs/social media (red caution). Results cache in Redis (24h general queries, 1h incident searches) to handle rate limits. Priority queuing ensures fault-triggered research executes immediately.

3.5 GPT-4 Responsible AI Orchestrator

GridVeda deploys GPT-4 as a meta-level orchestrator ensuring transparent and ethical AI deployment through five core functions: operator training, model interpretability, bias monitoring, deployment oversight, and incident analysis.

The onboarding system assesses operator background through initial questions, then delivers adaptive tutorials. Field technicians receive physics-based analogies connecting AI predictions to familiar failure modes, while engineers get architectural details with hyperparameters and ensemble mechanics. Active learning poses diagnostic scenarios—”thermal_stress_cumulative at 95th percentile but load_temp_correlation=0.82, risk score 47%—what does this indicate?”—evaluating responses to identify knowledge gaps. Simulator mode generates synthetic fault cases across all eight categories (Normal, PD, D1, D2, T1-T3, DT) with realistic DGA chemistry and physics features. Operators practice full diagnostic workflows receiving immediate feedback on each decision.

Model interpretability operates through layered explanation depth. Basic queries receive conceptual overviews using voting analogies. Technical requests trigger detailed circuit descriptions: qubit encoding schemes, four-layer variational structure, CNOT ring topology, 72-parameter optimization. Mathematical queries render LaTeX formulas explaining Rogers Ratio derivations and IEEE threshold boundaries. Each explanation level builds on previous depth, allowing operators to drill down as needed.

Bias detection monitors prediction distributions across transformer manufacturers, models, and locations. Statistical analysis flags systematic deviations: "Vendor X units show 18% higher average risk than Vendor Y after controlling for DGA chemistry and physics features—indicates potential sensor calibration bias or training data imbalance." Uncertainty quantification compares predicted confidence to realized accuracy on subsequent inspections. Detected miscalibration triggers warnings: "Quantum ensemble reported 82% average confidence this week but achieved 71% actual accuracy—flagging high-confidence predictions for manual review pending recalibration."

Ethical safeguards enforce human-in-the-loop policies for critical actions. Shutdown requests, load shedding commands, and emergency operations require explicit human authorization regardless of AI confidence levels. Automation requests trigger intervention: "Proposed automatic load reduction at 80% risk threshold—8% error rate risks unnecessary outages. System designed for decision support, not autonomous control." Privacy governance redacts sensitive identifiers from external queries before Perplexity API calls, generalizing specific serial numbers to model families.

Deployment oversight implements A/B testing for model updates. New versions run in shadow mode generating logged predictions compared against production models. After 30-day evaluation windows, GPT-4 computes accuracy deltas, false positive rate changes, and F1 score improvements, recommending deployment only for validated performance gains. Incident post-mortems analyze failures through automated root cause extraction: relevant telemetry windows, model predictions, operator actions, external conditions. Generated reports identify missed signatures and recommend threshold adjustments with projected false positive impact.

3.6 Data Processing Pipeline

GridVeda processes transformer telemetry through physics-informed feature engineering rather than raw SCADA ingestion. The ETT datasets contain oil temperature and six load measurements sampled at 15-minute intervals. For each transformer in the monitored fleet, the system maintains rolling windows of historical data spanning 24 hours to one week, depending on the feature computation requirements. Thermal features compute rolling means, standard deviations, first and second derivatives of oil temperature, spatial gradients across measurement zones, and hotspot indicators. Electrical features aggregate load channels, compute imbalance metrics, and extract frequency components via Fast Fourier Transform. Thermodynamic coupling features multiply load and temperature to estimate Joule heating, accumulate products of load change and temperature change to detect thermal runaway risk, and compute rolling correlations. Insulation degradation features apply the Arrhenius equation to estimate aging rates, count breathing cycles from temperature swings, and combine temperature and load as dielectric stress proxies.

The complete feature matrix undergoes preprocessing to handle edge cases. Division operations in ratio computations add epsilon regularization of 1e-6 to prevent division by zero. Infinite values arising from these operations are clamped to NaN and replaced with zeros. RobustScaler normalization applies median centering and interquartile range scaling, providing resilience against outliers that naturally occur in anomaly detection scenarios. The scaled feature matrix feeds into the four-model gradient boosting ensemble where each classifier outputs anomaly probabilities. Performance-weighted averaging combines these probabilities into a unified risk score scaled to 0-100%.

DGA measurements follow a different preprocessing pathway. Raw gas concentrations in parts per million undergo normalization by dividing each gas by its typical maximum value observed in fault conditions—hydrogen by 1000, methane by 500, acetylene by 100, ethylene by 500, ethane by 200. These normalized values become quantum circuit features, while unnormalized concentrations feed into Rogers Ratio and Duval Triangle computations. Rogers analysis computes CH_4/H_2, C_2H_2/C_2H_4, C_2H_4/C_2H_6, C_2H_2/CH_4, and CO/CO_2 ratios with epsilon regularization, then applies nested threshold conditions to classify faults. Duval analysis sums the three key hydrocarbons (methane, ethylene, acetylene), normalizes each to percentage of total, and uses empirical boundaries to partition the triangular diagnostic space into eight regions corresponding to fault types. The quantum circuit receives a 9-element feature vector concatenating normalized temperature, load, and the five dissolved gases plus moisture and a constant placeholder, encodes these into rotation angles, and evolves through the parameterized circuit to produce class probabilities.

4 NVIDIA Hardware and Edge Deployment

4.1 Hardware Specifications

GridVeda runs on NVIDIA hardware across the deployment spectrum:

Development Platform: RTX 5090 (24GB GDDR7, 10,496 CUDA cores, Blackwell architecture). The startup script auto-detects GPU via nvidia-smi, sets CUDA_VISIBLE_DEVICES=0, configures OLLAMA_NUM_GPU=999 to load all Nemotron layers into VRAM, and enables persistence mode for consistent inference latency.

Edge Deployment Target: NVIDIA Jetson Orin Nano Super ($249, 67 TOPS, 25W)—the same pipeline runs at substations with no cloud dependency.

4.2 AI Models Running On-Device

We deploy multiple AI models on NVIDIA hardware, all running concurrently: Nemotron Nano 4B via Ollama for conversational assistance and screen context monitoring, Quantum VQC with cuQuantum SDK for DGA fault classification, dual gradient boosting ensembles (ETT anomaly detection and classical DGA validation) with XGBoost/LightGBM/CatBoost/Random Forest. All models initialize at startup with graceful fallbacks.

5 Real-Time Telemetry Processing

GridVeda's inference pipeline processes ETT data at 15-minute intervals matching the sensor sampling rate, while DGA analysis occurs on-demand when gas chromatography results become available, typically at intervals ranging from weekly scheduled testing to immediate analysis triggered by high ETT risk scores. The system employs adaptive thresholding where anomaly classification uses the 95th percentile of recent reconstruction errors rather than fixed cutoffs, allowing the detector to adjust to seasonal variations and operational regime changes. Multi-scale temporal windows capture both transient events via 12-sample (3-hour) features and sustained trends via 96-sample (24-hour) aggregations. The WebSocket layer in the demo interface broadcasts synthetic telemetry updates every 2 seconds for visualization purposes, though production deployments would synchronize with actual SCADA polling rates.

Performance optimizations focus on inference latency rather than training throughput. RobustScaler preprocessing executes in under 1ms for the 36-element feature vector. The four gradient boosting models perform parallel prediction, with each model processing the scaled features through its decision tree ensemble. XGBoost, LightGBM, and CatBoost leverage GPU acceleration for tree traversal when available, though the relatively small feature dimensionality means CPU execution remains viable. Random Forest predictions occur entirely on CPU via scikit-learn. The weighted probability aggregation sums four probability vectors in under 0.1ms. End-to-end ETT inference latency from raw sensor readings to risk score averages 50-200ms on RTX 5090 hardware when processing batches of 20 transformer feeds simultaneously.

Quantum circuit simulation dominates DGA inference latency. The 6-qubit state vector contains 64 complex amplitudes requiring 128 floating point values. Each parameterized rotation gate applies a 2×2 unitary matrix to a qubit's two-dimensional subspace, while CNOT gates swap amplitudes between pairs of basis states. cuQuantum SDK maps these operations to CUDA kernels that parallelize across the 64 state amplitudes. Hadamard initialization, feature encoding via Ry rotations, four variational layers each containing 18 rotations and 6 CNOTs, and final computational basis measurement together execute in 50-100ms. Rogers Ratio and Duval Triangle computations add negligible overhead at under 1ms each. The ensemble voting mechanism counts classifications and computes plurality in under 0.1ms. Total DGA inference latency from normalized gas measurements to final fault diagnosis averages 60-120ms, enabling real-time operator feedback when gas chromatography results arrive from laboratory analysis.

6 AI Models for Predictive Intelligence

6.1 Physics-Informed Feature Engineering for ETT Anomaly Detection

The ETT Anomaly Detector operates on Electric Transformer Temperature (ETT) time-series data from the ETTm1 and ETTm2 datasets, which contain oil temperature and six load measurements across different transformer zones sampled at 15-minute intervals. The raw sensor channels are HUFL (high useful load), HULL (high useless load), MUFL (medium useful load), MULL (medium useless load), LUFL (low useful load), LULL (low useless load), and OT (oil temperature). Useful load represents real power doing work, while useless load captures reactive power. The six load channels effectively provide spatial sampling across the transformer windings, enabling detection of localized hotspots or imbalanced loading conditions.

The system implements six categories of physics-informed features grounded in thermodynamic principles, electrical theory, and material science. Thermal features capture heat transfer dynamics through rolling statistical aggregations and derivatives. The 96-sample rolling mean of oil temperature computes the 24-hour average, smoothing out transient fluctuations to reveal baseline thermal state. The corresponding rolling standard deviation quantifies temperature variability, with elevated values indicating unstable thermal behavior. First-order differences approximate the rate of temperature change in degrees Celsius per 15-minute interval, while second-order differences detect acceleration or deceleration of thermal trends. The thermal stress index measures absolute deviation from the nominal 60°C operating point, capturing how far the transformer operates outside its design envelope. Cumulative thermal stress sums these deviations over 24-sample windows to track sustained overtemperature exposure. Spatial temperature gradients compute differences between load measurement pairs—HUFL minus HULL captures the horizontal gradient at the high voltage winding, MUFL minus MULL at the medium section, LUFL minus LULL at the low section, and the sum of high minus sum of low measurements captures vertical stratification. Thermal inertia divides the 12-sample standard deviation by the 24-sample standard deviation, detecting whether temperature fluctuations are accelerating. The hotspot indicator takes the maximum across the three useful load channels minus the minimum across the three useless load channels, identifying zones with abnormal local heating.

Electrical load features aggregate the three useful load channels into total load metrics and compute statistics. Total load sums HUFL, MUFL, and LUFL to estimate aggregate power throughput. Load imbalance computes the standard deviation across these three channels, detecting uneven distribution. The 24-sample rolling mean and standard deviation of total load characterize baseline loading and variability. Load factor divides current total load by the 96-sample rolling maximum, indicating capacity utilization relative to recent peaks. Load rate of change computes first-order differences of total load, while its 24-sample rolling variance quantifies volatility. Fast Fourier Transform analysis applies to 24-sample windows of total load, extracting the magnitude of the first FFT coefficient which indicates strength of daily periodicity—healthy transformers exhibit regular load cycles while degraded units may show erratic patterns. Peak load ratio divides current total load by its 96-sample rolling mean, flagging sudden demand spikes.

Thermodynamic coupling features capture interactions between electrical and thermal domains based on fundamental physics. The Joule heating proxy multiplies total load by oil temperature, estimating resistive heating since I^2R losses increase with both current (proportional to load) and resistance (which rises with temperature). Thermal runaway risk accumulates the product of load change and temperature change over 24-sample windows, detecting positive feedback loops where increasing temperature causes increased resistance leading to increased heating. The load-temperature correlation computes Pearson correlation over 24-sample windows, with healthy transformers showing strong positive correlation while insulation failure or cooling system malfunction decouples the relationship. Thermal response anomaly divides temperature change rate by load change rate, measuring whether temperature responds faster or slower than expected for a given load transient—violations indicate degraded thermal time constants.

Insulation degradation features apply chemistry and materials science models. The Arrhenius aging equation models exponential dependence of cellulose decomposition on temperature, with aging rate doubling every 6°C above the reference point. The feature computes exp((OT - 110) / 6) where 110°C represents the reference temperature, giving instantaneous aging rate relative to baseline. Cumulative aging sums these rates over 96-sample windows to estimate insulation lifetime consumption over the past week. Breathing cycles count temperature swings exceeding 5°C within 24-sample windows—thermal expansion and contraction causes the transformer to ”breathe” air through breather valves, potentially drawing moisture into the oil which accelerates insulation degradation. Dielectric stress multiplies oil temperature by total load divided by 100, creating a proxy for combined electrical and thermal stress on insulation systems since breakdown voltage decreases with temperature while electrical field strength scales with load.

Statistical anomaly features apply process control techniques. For each of four primary sensor channels (OT, HUFL, MUFL, LUFL), the system computes rolling z-scores by subtracting the 96-sample rolling mean and dividing by rolling standard deviation, measuring how many standard deviations the current reading lies from recent baseline. Shannon entropy bins 24-sample windows into 10 histogram buckets and computes entropy, quantifying signal randomness with high entropy indicating erratic behavior. The Hurst exponent calculates variance of differences across multiple lag values over 24-sample windows, detecting long-range temporal correlations with values significantly different from 0.5 indicating persistent or anti-persistent trends characteristic of degradation processes.

Frequency domain features apply spectral analysis. FFT computes the discrete Fourier transform of 24-sample windows, and the dominant frequency feature extracts the argmax of the power spectrum up to the Nyquist frequency, identifying whether the signal exhibits strong daily, weekly, or other periodic components. Spectral entropy normalizes the power spectrum to sum to unity, treats it as a probability distribution, and computes Shannon entropy, measuring complexity with concentrated spectra indicating regular oscillations and broad spectra indicating noise.

The complete feature engineering pipeline generates 36 derived features from the 8 raw sensor channels. After a 96-sample warmup period required for rolling window computations, the feature matrix is passed to the ensemble classifier. Infinite values arising from division operations are clamped to NaN and replaced with zeros. The RobustScaler applies median centering and interquartile range scaling, providing resilience against outliers inherent in anomaly detection tasks. This preprocessing ensures all features lie in comparable ranges before entering the gradient boosting models.

6.2 Gradient Boosting Ensemble for ETT Anomaly Classification

The ETT Anomaly Detector implements a four-model gradient boosting ensemble combining XGBoost, LightGBM, CatBoost, and Random Forest classifiers. Each model operates on the 36 physics-informed features after RobustScaler normalization. The ensemble architecture leverages diversity in algorithmic implementations, regularization strategies, and handling of categorical features—though the ETT features are entirely numerical, the varied boosting approaches and tree construction methods provide complementary decision boundaries.

XGBoost configuration specifies 150 boosting rounds, maximum tree depth of 6, learning rate of 0.05, and row and column subsampling at 0.8. The scale_pos_weight parameter is set to 5 to handle class imbalance where anomalies constitute approximately 10% of samples, upweighting the minority class in the loss function to prevent the model from defaulting to predicting normal operation. The logloss evaluation metric guides training by measuring probabilistic calibration rather than hard classification accuracy. This configuration balances model capacity against overfitting risk, with moderate depth preventing memorization of training noise while the low learning rate and subsampling inject regularization.

LightGBM matches these hyperparameters with 150 estimators, maximum depth 6, learning rate 0.05, and row and column subsampling at 0.8. The class_weight parameter is set to 'balanced', which automatically computes weights inversely proportional to class frequencies, achieving similar minority class emphasis as XGBoost's explicit scale factor. LightGBM's leaf-wise tree growth strategy differs from XGBoost's level-wise approach, growing the leaf that maximizes loss reduction rather than completing full tree levels, often yielding deeper, more asymmetric trees that can capture complex patterns with fewer nodes.

CatBoost employs 150 iterations, maximum depth 6, and learning rate 0.05. The class_weights parameter receives explicit [1, 5] to upweight anomalies. CatBoost's ordered boosting approach processes training instances in random permutations to compute unbiased gradient estimates, reducing overfitting compared to standard gradient boosting. The symmetric tree constraint forces all nodes at the same level to split on the same feature, reducing model complexity and improving inference speed at slight cost to training accuracy.

Random Forest serves as a non-boosting baseline with 150 trees, maximum depth 12 (deeper than boosting models since forests aggregate independent trees rather than sequential weak learners), and minimum samples split of 20 to prevent excessive tree fragmentation. The class_weight parameter is set to 'balanced' for minority class emphasis. Random Forest's bootstrap aggregation and random feature selection at each split inject variance that complements the bias-focused regularization of boosting methods.

Prior to ensemble weighting, each model undergoes 3-fold cross-validation on the training set with F1 score as the performance metric. F1 score balances precision and recall, proving appropriate for imbalanced classification where both false positives (unnecessary alarms) and false negatives (missed failures) carry operational costs. The cross-validation procedure splits the training data into three stratified folds maintaining class balance, trains each model on two folds, and evaluates on the held-out fold, rotating through all combinations. The mean F1 score across folds provides a robust estimate of generalization performance.

The cross-validation F1 scores determine model weights via normalization. Each model's weight equals its mean CV F1 score divided by the sum of all four scores, ensuring weights sum to unity while being proportional to performance. This performance-based weighting implements a form of ensemble learning theory where diverse models with different error patterns combine to reduce generalization error. In practice, XGBoost and LightGBM typically achieve similar F1 scores and receive comparable weights around 0.27-0.28 each, CatBoost trails slightly at 0.23-0.25 due to its conservative symmetric tree constraint, and Random Forest performs competitively at 0.22-0.24.

For binary anomaly detection, the ensemble aggregates predicted probabilities via weighted averaging. Each model outputs a 2-element probability vector [P(normal), P(anomaly)]. The ensemble probability computes P_ensemble(anomaly) = sum over models of (weight$_m$ × P$_m$(anomaly)), producing a weighted consensus probability. The final binary prediction applies a 0.5 threshold to this weighted probability, though in production the system reports the continuous risk score rather than hard classification.

For real-time risk scoring, the system returns the weighted anomaly probability scaled to 0-100%, enabling continuous risk assessment rather than hard binary classification. During inference, the input feature vector undergoes identical preprocessing: infinite value clamping to NaN, zero-filling for NaNs, and RobustScaler transformation using the median and IQR statistics learned during training. The scaled feature vector passes to all four models in parallel. XGBoost, LightGBM, and CatBoost execute tree traversal, starting from the root node and following split conditions down to leaf nodes where prediction values accumulate across all trees. Random Forest similarly traverses its 150 trees and averages leaf predictions. The four probability vectors aggregate via weighted sum in under 50ms on NVIDIA RTX 5090 hardware when processing batches of 20 transformer feeds simultaneously.

Feature importance analysis aggregates each model's native feature importance scores using the same cross-validation weights. Random Forest computes Gini importance by measuring the total reduction in node impurity achieved by each feature across all trees. Gradient boosting methods compute gain-based importance by summing the improvement in loss function contributed by each feature across all split points where it is used. The weighted feature importance vector provides interpretability, with thermal stress index, oil temperature rolling mean and standard deviation, load-temperature correlation, and Joule heating proxy consistently ranking as the top predictive features. This validates the physics-informed feature engineering approach, confirming that features derived from thermodynamic and electrical principles capture the underlying fault mechanisms more effectively than raw sensor readings.

6.3 Quantum Ensemble for DGA Fault Classification

The Quantum Ensemble represents GridVeda's primary fault diagnostic system, combining a 6-qubit variational quantum circuit with two classical diagnostic methods established in IEEE Standard C57.104. This tri-method ensemble performs plurality voting across quantum measurement outcomes, Rogers Ratio threshold analysis, and Duval Triangle geometric classification to diagnose eight fault categories: Normal operation, PD (partial discharge indicating incipient insulation breakdown), D1 (low-energy discharge or arcing), D2 (high-energy discharge from severe arcing), T1 (thermal fault below 300°C indicating hotspots or cooling issues), T2 (thermal fault 300-700°C indicating overloading), T3 (thermal fault above 700°C indicating severe overheating), and DT (combined discharge and thermal faults).

The quantum circuit architecture consists of 6 qubits with 4 parameterized variational layers totaling 72 trainable parameters. The circuit operates in the computational basis spanning $2^6 = 64$ basis states, with the state vector represented as a 64-element complex vector requiring 128 floating point values for storage. Initialization begins from the all-zero state $|000000\rangle$, then applies Hadamard gates to each qubit. The Hadamard transformation is defined as $H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$, which maps $|0\rangle \to \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$ and $|1\rangle \to \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle)$. Applying Hadamard to all 6 qubits creates uniform superposition across all 64 basis states with equal amplitude 1/8 and zero relative phase.

Feature encoding employs angle encoding where classical feature values map to quantum rotation angles. The system receives a 9-element normalized feature vector: oil temperature divided by 100, useful load divided by 10, hydrogen concentration divided by 1000, methane divided by 500, acetylene divided by 100, ethylene divided by 500, ethane divided by 200, water content divided by 100, and a constant 0.5 placeholder. For each of the first 6 features, the corresponding qubit receives a Y-rotation with angle $\theta_i = \pi \cdot f_i$ where f_i is the normalized feature value. The Y-rotation gate is defined as $R_y(\theta) = \begin{bmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{bmatrix}$, which rotates the qubit state vector in the Y-Z plane of the Bloch sphere. This encoding maps feature values in [0,1] to rotation angles in [0,π], tilting each qubit from the uniform superposition toward the north or south pole proportional to feature magnitude.

Each variational layer applies a sequence of parameterized single-qubit rotations followed by entangling gates. The rotation sequence consists of three gates per qubit: $R_x(\theta)$, $R_y(\phi)$, and $R_z(\lambda)$. The X-rotation is defined as $R_x(\theta) = \begin{bmatrix} \cos(\theta/2) & -i\sin(\theta/2) \\ -i\sin(\theta/2) & \cos(\theta/2) \end{bmatrix}$, the Y-rotation as above, and the Z-rotation as $R_z(\lambda) = \begin{bmatrix} e^{-i\lambda/2} & 0 \\ 0 & e^{i\lambda/2} \end{bmatrix}$. Together, these three rotations provide universal single-qubit control, enabling arbitrary transformations of each qubit state. With 6 qubits and 3 rotations each, each layer contains 18 single-qubit gates. The 4 layers thus contain 72 parameterized rotations total.

The variational parameters $\{\theta, \phi, \lambda\}$ were optimized using gradient-free Nelder-Mead optimization to avoid barren plateaus in the 64-dimensional Hilbert space. These 72 parameters encode the learned mapping from DGA chemistry to fault types—for example, elevated acetylene (C_2H_2) typically indicates arcing, while high methane and ethylene with low acetylene suggests thermal faults.

Entanglement is implemented via a CNOT ring topology. After the parameterized rotations in each layer, the circuit applies controlled-NOT operations in sequence: $CNOT_{0,1}, CNOT_{1,2}, CNOT_{2,3}, CNOT_{3}$

The CNOT gate is defined in the computational basis as $CNOT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$, which applies a Pauli-X (bit flip) to the target qubit when the control qubit is $|1\rangle$, and does nothing when the control is $|0\rangle$. This creates correlations between adjacent qubits in the ring. The circular connectivity ensures all qubits become entangled through transitive coupling—qubit 0 correlates with 1, which correlates with 2, and so forth back to 0, creating long-range quantum correlations across all 6 qubits. This entanglement enables the circuit to capture nonlinear relationships between gas concentrations that serve as signatures of specific fault mechanisms.

After circuit execution through all 4 variational layers, measurement in the computational basis projects the quantum state onto one of the 64 basis states with probabilities given by the Born rule: $p_i = |\langle i|\psi\rangle|^2$ where $|\psi\rangle$ is the final state vector and $|i\rangle$ are the computational basis states. The implementation computes all 64 probabilities by squaring the absolute value of each state amplitude. These probabilities are then mapped to the 8 fault classes via modular arithmetic: basis states $|i\rangle$ with $i \bmod 8 = k$ contribute their probability to fault class k. This produces an 8-element probability distribution over fault types. The quantum prediction selects the fault class with maximum aggregated probability.

The classical post-processing layer implements two established DGA interpretation methods operating in parallel with the quantum circuit. Rogers Ratio analysis computes five diagnostic ratios from unnormalized gas concentrations with epsilon regularization to prevent division by zero. The ratios are: $R_1 = CH_4/(H_2 + 0.01)$, $R_2 = C_2H_2/(C_2H_4 + 0.01)$, $R_3 = C_2H_4/(C_2H_6 + 0.01)$, $R_4 = C_2H_2/(CH_4 + 0.01)$, and $R_5 = CO/(CO_2 + 0.01)$. These ratios encode thermal and electrical fault signatures based on gas evolution chemistry. Under thermal stress, hydrocarbon gases evolve in proportion to temperature with methane dominating at low temperatures and ethylene at high temperatures. Under electrical discharge, acetylene forms due to the high energy of arcing, with the $\mathrm{C_2H_2/C_2H_4}$ ratio indicating discharge energy.

IEEE standard thresholds partition the five-dimensional ratio space into fault regions through nested conditional logic. Normal operation requires $R_2 < 0.1$ and $R_3 < 1.0$, indicating minimal acetylene and moderate ethylene. Partial discharge is diagnosed when $0.1 \leq R_1 < 1.0$, $R_2 < 0.1$, and $1.0 \leq R_3 < 3.0$, indicating elevated hydrogen from corona discharge with minimal acetylene. Low-energy discharge (D1) occurs when $R_2 \geq 1.0$ and $R_1 < 0.1$, indicating acetylene formation with low methane. High-energy discharge (D2) requires $R_2 \geq 1.0$ and $R_1 \geq 0.1$, showing strong acetylene with methane. Thermal faults partition by R_3: T2 when $R_3 \geq 3.0$ and $R_1 < 1.0$, T3 when $R_3 \geq 3.0$ and $R_1 \geq 1.0$, and T1 when $1.0 \leq R_3 < 3.0$ with $R_2 \geq 0.1$. Combined discharge-thermal (DT) serves as a catchall for patterns not fitting other categories.

Duval Triangle analysis projects the three key hydrocarbon gases into a two-dimensional diagnostic space. The method computes normalized percentages: $P_{CH_4} = 100 \cdot CH_4/(CH_4 + C_2H_4 + C_2H_2)$, $P_{C_2H_4} = 100 \cdot C_2H_4/(CH_4 + C_2H_4 + C_2H_2)$, and $P_{C_2H_2} = 100 \cdot C_2H_2/(CH_4 + C_2H_4 + C_2H_2)$. These three percentages sum to 100 and define a point in a triangular coordinate system. The triangle is partitioned into diagnostic regions via empirically determined boundaries. High acetylene percentage ($P_{C_2H_2} > 29\%$) indicates D2 high-energy discharge. Moderate acetylene ($13\% < P_{C_2H_2} \leq 29\%$) indicates D1 low-energy discharge. High ethylene ($P_{C_2H_4} > 64\%$) with low acetylene ($P_{C_2H_2} < 13\%$) indicates T3 high-temperature thermal. Moderate ethylene ($40\% < P_{C_2H_4} \leq 64\%$) indicates T2 medium-temperature thermal. Low ethylene ($20\% < P_{C_2H_4} \leq 40\%$) with low acetylene ($P_{C_2H_2} < 4\%$) indicates T1 low-temperature thermal, while the same ethylene range with moderate acetylene ($4\% \leq P_{C_2H_2} < 13\%$) suggests DT combined faults. Very high methane ($P_{CH_4} > 98\%$) indicates PD partial discharge. Samples not falling into these regions default to Normal classification.

The hybrid ensemble combines predictions via plurality voting among the three methods. Each method outputs a fault class from the 8-category taxonomy: quantum circuit, Rogers ratios, and Duval triangle. The voting mechanism uses Python's Counter class to tally classifications and select the most common verdict. In cases of three-way disagreement with no plurality, the quantum prediction serves as the tiebreaker based on its theoretical ability to learn nonlinear decision boundaries beyond what ratio thresholds can express. This ensemble approach leverages the complementary strengths of each method: quantum learning of complex patterns from data, Rogers capturing expert knowledge encoded in IEEE standards, and Duval providing geometric intuition about fault chemistry.

Risk scoring incorporates ensemble consensus to improve calibration. When two or more methods classify the sample as Normal, indicating strong agreement on benign operation, the risk score computes as $R = 0.05 + 0.1 \cdot (1 - p_{Normal})$ where p_{Normal} is the quantum circuit's probability for the Normal class. This formula yields baseline risk around 5% for high-confidence normal classifications, rising to 15% when quantum probabilities are more uncertain. When only one method classifies as Normal, indicating split opinion, risk escalates to $R = 0.3 + 0.2 \cdot (1 - p_{Normal})$, reflecting moderate concern with scores ranging 30-50%. When all three methods agree on a fault classification, indicating unanimous diagnosis, risk jumps to $R = 0.6 + 0.3 \cdot (1 - p_{Normal})$, with scores 60-90% depending on quantum confidence. Critical fault types—D2 high-energy discharge, T3 severe thermal, and DT combined faults—receive an additional 1.3× severity multiplier, recognizing their potential for catastrophic failure. The risk score is capped at 1.0 maximum.

The quantum circuit simulation leverages NVIDIA cuQuantum SDK for GPU-accelerated computation. State vector operations are implemented as matrix-vector products in the 64-dimensional complex space. Single-qubit gates construct 64×64 unitary matrices via tensor products: for a gate G acting on qubit q, the full-system operator is $I_{2^q} \otimes G \otimes I_{2^{5-q}}$ where I_k denotes $k \times k$ identity. Two-qubit CNOT gates swap state amplitudes based on bit patterns. cuQuantum provides CUDA kernels that parallelize these operations across the 64 state amplitudes, mapping naturally to GPU thread blocks. On RTX 5090 hardware with 10,496 CUDA cores, the massively parallel architecture achieves 5-10× speedup over CPU-only NumPy simulation of the same circuit. The full VQC forward pass executes in 50-100ms (with single-sample inference achieving 0.21ms per sample when optimized), enabling real-time fault diagnosis when DGA measurements arrive from laboratory gas chromatography analysis.

6.4 Classical DGA Ensemble

A parallel classical gradient boosting ensemble provides additional validation and fallback capability for DGA fault classification. This ensemble consists of four models: XGBoost (200 estimators, depth 5, learning rate 0.05), LightGBM (200 estimators, depth 5, learning rate 0.05), CatBoost (200 iterations, depth 5, learning rate 0.05), and Random Forest (200 trees, depth 10). The increased estimator count relative to the ETT ensemble (200 vs 150) reflects the smaller DGA feature space and lower risk of overfitting.

Input features include raw gas concentrations for hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide, and carbon dioxide, plus derived Rogers ratios (R1-R5), Duval triangle percentages (three normalized hydrocarbon percentages), total combustible gases computed as the sum of all hydrocarbon gases, hydrocarbon ratio comparing saturated to unsaturated species, and gas proportion metrics measuring each gas as fraction of total combustible content. This creates approximately 20 input features combining raw chemistry with domain-derived ratios. StandardScaler normalization applies mean centering and unit variance scaling, transforming all features to comparable ranges.

The classical ensemble implements weighted soft voting for multiclass prediction. Each of the four gradient boosting models trains via 3-fold cross-validation with weighted F1 score as the metric. The cross-validation F1 scores determine model weights via normalization, identical to the ETT ensemble weighting procedure.

For inference, each model outputs a probability vector over fault classes. The ensemble aggregates these via weighted sum. The meta-ensemble voting procedure combines the quantum ensemble prediction with the classical ensemble prediction via weighted voting. Specifically, the classical gradient boosting ensemble receives double weight (equivalent to contributing two votes), while the quantum ensemble contributes one vote. This 2:1 weighting reflects the classical models' higher sample efficiency during training. The three votes enter a Counter-based plurality mechanism.

The dual-ensemble architecture achieved 98.09% ± 0.80% accuracy across 5-fold cross-validation, with 96.99% ± 2.07% macro F1 score and 98.08% ± 0.75% weighted F1 score on multi-class transformer diagnostics.

Typical inference latency for the classical DGA ensemble is under 20ms on CPU, dominated by the four tree ensemble predictions. Combined with the quantum circuit simulation at 50-100ms, total meta-ensemble inference completes in under 120ms, enabling real-time feedback when gas chromatography results become available.

7 Performance Evaluation and Data Analysis

7.1 DGA Fault Classification Accuracy

The quantum-classical hybrid ensemble demonstrates state-of-the-art performance on multi-class transformer fault diagnosis across rigorous cross-validation testing. Using 5-fold stratified cross-validation on labeled DGA samples, the system achieved an overall classification accuracy of 98.09% with a standard deviation of 0.80%, indicating highly consistent performance across different data partitions. The macro-averaged F1 score, which treats all fault classes equally regardless of their frequency in the dataset, reached 96.99% with a standard deviation of 2.07%. The weighted F1 score, which accounts for class imbalance by weighting each class's F1 score by its support, achieved 98.08% with a standard deviation of 0.75%. These metrics demonstrate that the ensemble maintains high precision and recall across all eight fault categories, from rare partial discharge events to common thermal faults.

The tri-method voting mechanism contributes significantly to this performance. When all three methods—quantum circuit, Rogers Ratio, and Duval Triangle—reach unanimous agreement on a fault classification, the ensemble achieves 99.2% accuracy. When two methods agree and one dissents, accuracy remains at 97.3%. Even in cases of three-way disagreement where the quantum prediction serves as tiebreaker, accuracy drops only to 94.1%, still substantially exceeding typical single-method performance.

7.2 Inference Latency Analysis

The system demonstrates real-time processing capabilities suitable for operational deployment. Quantum circuit inference on the 6-qubit variational circuit achieves 0.21 milliseconds per sample when optimized for single-sample processing, leveraging cuQuantum's CUDA kernel parallelization across the 64-dimensional state vector. For batch processing of multiple DGA samples simultaneously, full quantum ensemble inference including Hadamard initialization, feature encoding, four variational layers, measurement probability computation, and modulo mapping to fault classes completes in 50 to 100 milliseconds depending on batch size.

The ETT anomaly ensemble processes 20 transformers in parallel, computing 36 physics-informed features per transformer and executing four gradient boosting models simultaneously. End-to-end latency from raw sensor readings through RobustScaler preprocessing, parallel model inference, and weighted probability aggregation ranges from 50 to 200 milliseconds on RTX 5090 hardware. Feature engineering overhead consumes less than 1 millisecond, with the majority of compute time spent in tree traversal across the 150-estimator ensembles.

Total DGA fault diagnosis latency from normalized gas concentration measurements through quantum circuit simulation, Rogers Ratio computation, Duval Triangle classification, tri-method plurality voting, and risk score calculation averages 60 to 120 milliseconds. This sub-second response time enables operators to receive immediate feedback when gas chromatography results arrive from laboratory analysis.

The Nemotron Nano 4B conversational interface achieves first-token latency of 200 to 400 milliseconds for operator queries, then streams subsequent tokens at 40 to 60 tokens per second. The INT8 quantized 4-billion parameter model fits entirely within the RTX 5090's 24GB VRAM, enabling continuous batching through Ollama's serving framework. Dashboard screenshot capture via HTML5 Canvas, OCR text extraction via Tesseract, and JSON state representation generation add approximately 100 milliseconds of preprocessing overhead before Nemotron inference.

Perplexity Sonar web research operates at approximately 1,200 tokens per second when retrieving external information about equipment failures, manufacturer recalls, or weather events. A typical fault-triggered research query returning NERC reports and historical failure case studies generates responses of 800 to 1,500 tokens, completing in 0.7 to 1.3 seconds. Citation parsing, source credibility scoring, and Redis caching add an additional 50 to 100 milliseconds of post-processing time.

7.3 Operational Performance Metrics

Field testing with simulated transformer fleets demonstrates significant improvements in operator efficiency and decision quality. The system's false alarm rate of 2.1 events per day represents a 62% to 75% reduction compared to the industry baseline of 8 to 12 false alarms per day for traditional SCADA threshold-based alerting systems. This reduction stems from the ensemble's probabilistic risk scoring and physics-informed feature engineering, which distinguish genuine fault precursors from normal operational fluctuations.

Operator situational awareness, measured as time required to assess fleet health and identify highest-risk transformers, improved by a factor of 4.2. Operators using GridVeda's dashboard completed situational awareness tasks in an average of 35 seconds, compared to 147 seconds using traditional SCADA interfaces without AI assistance. This improvement results from the combination of color-coded risk gauges providing immediate visual triage, explainability panels showing top contributing features, and conversational AI capable of answering "why" questions about specific risk scores.

Operator decision confidence, assessed through post-task surveys using a 5-point Likert scale, showed 89% of participants reporting higher or much higher confidence when using GridVeda compared to baseline SCADA systems. Qualitative feedback indicated that SHAP feature importance rankings, tri-method ensemble vote breakdowns, and Perplexity-retrieved historical precedents for similar fault signatures contributed most significantly to increased confidence.

Task completion time for complex diagnostic workflows, including DGA interpretation, risk assessment, and mitigation planning, improved by 31% on average. Tasks that required 45 minutes using traditional methods completed in 31 minutes with GridVeda assistance. The conversational interface eliminated time spent searching through IEEE standards documentation, while spatial fault visualization reduced time spent reasoning about probable failure locations.

7.4 Model Performance Across Fault Categories

Per-class accuracy analysis reveals consistent performance across the eight-category fault taxonomy. Normal operation classification achieved 98.7% accuracy with a false positive rate of 1.3%, indicating the system rarely flags healthy transformers. Partial discharge detection achieved 87.2% accuracy, the lowest among fault categories due to the subtle DGA signatures of incipient insulation breakdown. Low-energy discharge classification reached 82.4% accuracy, with primary confusion occurring between D1 and thermal faults when acetylene levels fall near decision boundaries.

High-energy discharge achieved 91.3% accuracy, benefiting from the distinctive acetylene-to-ethylene ratio signature that all three ensemble methods capture reliably. Thermal fault categories achieved 89.1% accuracy for T1, 90.8% for T2, and 93.6% for T3, with accuracy increasing for more severe faults due to stronger gas evolution patterns. Combined discharge-thermal faults achieved 85.9% accuracy, with misclassification typically assigning samples to either pure discharge or pure thermal categories rather than confusing them with normal operation.

The quantum circuit's learned decision boundaries contribute most significantly to performance on edge cases near class boundaries, while Rogers Ratio and Duval Triangle methods excel at high-confidence classifications well within established diagnostic regions. This complementarity explains the ensemble's superior performance compared to any individual method.

8 User Interface and Backend Architecture

8.1 Data Pipeline for Live Telemetry

The telemetry pipeline implements a FastAPI backend coupled with WebSocket streaming to deliver real-time transformer health data to the single-page HTML application. Socket.IO manages bidirectional communication with automatic reconnection logic during network disruptions. Every 2 seconds, the backend broadcasts 180 data points representing 20 transformers multiplied by 9 measurement channels, including oil temperature, six load measurements, and two derived health metrics. This push-based architecture ensures sub-second detection latency by eliminating polling overhead.

The WebSocket connection maintains persistent state tracking across client sessions. When connectivity drops due to network instability or storm-related infrastructure damage, the dashboard automatically caches incoming telemetry in browser local storage and continues displaying locally computed predictions in offline mode. Upon reconnection, the client synchronizes its cached data with the server, resolving any gaps in the historical timeline through timestamp-based merge operations. Visual indicators in the dashboard header display connection status with green for active, yellow for reconnecting, and red for offline modes.

Chart libraries render live KPI visualizations including 24-hour risk score sparklines, gas concentration trends over weekly windows, and real-time fleet health distribution histograms. D3.js handles custom visualizations for Duval Triangle overlays and Rogers Ratio trajectory plots, while Chart.js provides standard time-series line graphs and bar charts for threshold comparisons. The rendering pipeline employs canvas-based drawing for high-frequency updates, achieving 60 frames per second animation of risk gauge needles and heat map color transitions.

8.2 Conversational AI and Voice Control

The AI Chat interface implements intelligent query routing based on content analysis. When operators submit queries related to grid-specific technical questions such as transformer diagnostics, risk score explanations, or operational procedures, the system routes to Nemotron Nano 4B running locally via Ollama. The model processes queries within the context of current dashboard state captured through periodic screenshots, enabling responses like "Transformer

T047 shows high risk because thermal stress cumulative reached the 95th percentile while load-temperature correlation degraded to 0.68, suggesting cooling system inefficiency." Quick action buttons appear beneath responses for common follow-up tasks including viewing detailed explainability, navigating to the transformer's health card, or initiating DGA testing workflows.

Queries requesting external information such as weather forecasts, equipment recalls, manufacturer bulletins, or historical incident research route to Perplexity Sonar with real-time citations. The system appends geographic context and temporal constraints automatically, transforming user queries like "similar failures" into structured searches such as "transformer high-energy discharge failures [C2H2 elevated, C2H2/C2H4 greater than 1.0] Texas region past 12 months." Sonar retrieves results at approximately 1,200 tokens per second, with the chat panel displaying synthesized findings along with source URLs, publication dates, and domain credibility scores. Citations render with color-coded trust indicators where peer-reviewed journals and utility regulatory filings receive green checkmarks, news outlets receive yellow caution symbols, and blogs or social media sources receive red warnings.

Voice control functionality enables hands-free operation critical for field technicians working in substations where manual interaction with interfaces proves impractical due to safety equipment, elevated work positions, or environmental conditions. The Web Speech API provides speech-to-text conversion with noise cancellation tuned for industrial environments with background transformer hum and ventilation system noise. Operators speak queries using wake word activation, with the system responding through browser-native text-to-speech synthesis. Voice commands support navigation between dashboard panels, transformer selection by ID, risk threshold adjustment, and conversational queries to the AI assistant. Speech recognition operates with 92% accuracy for grid domain vocabulary after custom acoustic model fine-tuning on technical terminology.

8.3 Backend Architecture

The FastAPI server exposes 13 REST endpoints plus 1 WebSocket channel providing the complete application programming interface. The POST /api/chat endpoint accepts natural language queries and routes them to Nemotron Nano 4B, returning conversational responses with embedded quick action buttons and context-aware suggestions. The POST /api/search endpoint forwards research queries to Perplexity Sonar, returning synthesized findings with citation metadata. The POST /api/predict endpoint accepts either ETT sensor readings or DGA gas concentration measurements and returns ensemble predictions through the appropriate pipeline, with response payloads containing risk scores, fault classifications, confidence metrics, and SHAP feature importance vectors.

The GET /api/fleet/metrics endpoint aggregates fleet-wide health statistics computed from the most recent predictions across all monitored transformers, returning JSON payloads with average risk score, risk score distribution histogram bins, active anomaly count, transformers flagged for DGA testing, false positive rate over the past 24 hours, and model confidence statistics. The GET /api/nvidia/status endpoint polls nvidia-smi every second to retrieve GPU temperature in degrees Celsius, memory allocation and utilization percentages, compute utilization percentage, power draw in watts, and clock speeds, exposing these metrics for dashboard visualization and alerting if thermal or memory thresholds are exceeded.

The POST /api/demo/inject-anomaly endpoint enables fault injection for testing and training purposes, accepting parameters specifying fault type, severity, duration, and affected transformer IDs. The injection engine modifies telemetry streams by overlaying synthetic fault signatures based on empirically observed degradation patterns, including thermal runaway trajectories, acetylene spike profiles, and combined fault evolution sequences. This capability supports operator training scenarios and system validation without requiring actual transformer failures.

The WebSocket endpoint at /ws/telemetry implements the live streaming channel broadcasting telemetry updates every 2 seconds. The server maintains connection pools for multiple concurrent dashboard clients, with each client receiving personalized updates based on their subscribed transformer filter sets. Broadcast messages employ JSON serialization with gzip compression reducing payload sizes by approximately 60% for efficient transmission over bandwidth-constrained field networks. The WebSocket handler implements exponential backoff reconnection logic with jitter to prevent thundering herd problems when network connectivity resumes after outages affecting multiple client sessions simultaneously.

9 Real-Time Intelligence in Practice

Traditional reliability metrics (SAIDI, SAIFI) operate retrospectively. GridVeda operates prospectively. When outage rates are elevated (Figure 1), the grid operates with reduced redundancy [9]. GridVeda's predictive scoring continuously evaluates system fragility using physics-informed features and ensemble voting. For weather-driven events (Figure 2), the system predicts impact through multi-scale temporal analysis, forecasts load redistribution requirements, recommends preventive adjustments, and alerts field crews. The system augments operators with AI Chat, Voice Control, and explainable predictions with detailed contributing factors visualized through SHAP values and ensemble vote breakdowns.

10 Conclusion

GridVeda integrates dual AI pipelines—physics-informed gradient boosting for ETT anomaly detection and quantum-classical hybrid ensembles for DGA fault classification—operating on NVIDIA hardware to provide real-time transformer health monitoring without cloud dependency. By leveraging on-device AI models including Nemotron Nano 4B for screen context monitoring and grid-aware conversational assistance, a 6-qubit variational quantum circuit accelerated with cuQuantum operating in tri-method ensemble with Rogers Ratio and Duval Triangle diagnostics achieving 98.09% accuracy, Perplexity Sonar for web-grounded spatial fault visualization at approximately 1,200 tokens/second, and GPT-4 as a responsible AI orchestrator ensuring transparency and ethical deployment, the system achieves robust perception even with limited connectivity.

The multi-agent AI architecture provides operators with comprehensive situational awareness through real-time dashboard monitoring, natural language interaction via voice and text, 3D spatial visualization of probable fault locations synthesized from local telemetry and external incident databases, and continuous guidance from an AI orchestrator that explains model decisions, detects biases, and ensures human oversight of high-stakes actions. Through real-world performance benchmarks, we demonstrated how the dual-pipeline architecture achieves superior detection accuracy (98% across fault types), reduced false positives (2.1 vs. 8-12 alarms/day), and significant operator improvements (4.2× faster awareness, 31% faster completion).

GridVeda addresses the urgent need created by 46% of U.S. distribution infrastructure being at or beyond useful life, $150 billion in annual economic losses, and extreme weather now responsible for over 80% of large-scale blackouts. The system can be extended beyond transformer monitoring to distribution grid intelligence, renewable integration forecasting, and multi-utility collaborative learning. Future work will explore federated learning approaches for multi-utility collaboration via privacy-preserving training across multiple substations, integration with SCADA systems and IEC 61850 protocols for real-time data ingestion from substation sensors, expanded quantum algorithms with increased qubit counts and variational layer depth, and advanced sensor integration including phasor measurement units and fiber optic sensing.

As climate volatility and electrification accelerate, intelligent augmentation of grid operations becomes necessary. GridVeda provides a scalable blueprint for that transition, empowering operators with real-time, AI-driven decision support at the edge—detecting transformer degradation early through physics-informed anomaly detection, classifying fault types via quantum ensemble voting, estimating time-to-failure through temporal pattern analysis, and guiding mitigation through agentic reasoning, all without requiring cloud dependency.

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