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Smart Trafo: A Random Forest and LLM-Based Decision Support System for Power Transformer Fault Diagnosis via Dissolved Gas Analysis

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ABSTRACT *– Manual management of Dissolved Gas Analysis (DGA) data for power transformers at PT. PLN (Persero) UPT Manado has been identified as a critical operational bottleneck, with existing spreadsheet-based workflows susceptible to human error, poor historical traceability, and limited scalability. Prior studies on DGA-based transformer diagnosis have been predominantly confined to standalone classification models without integration into operational management systems, leaving a significant gap in practical field deployment. This research contributes a novel integrated Decision Support System named Smart Trafo, which is the first to combine a Random Forest classification model, Duval Pentagon visualization, historical trending analysis, and an LLM-based conversational assistant (Volty AI) within a unified full-stack web platform. The Random Forest model was trained on 375 DGA samples across six fault classes using five gas parameters conforming to IEEE C57.104, achieving an overall accuracy of 84% and a macro-average F1-score of 0.83. Feature importance analysis revealed Hydrogen (H_2) as the dominant diagnostic indicator at 26.2%. The system successfully automates DGA fault classification, eliminates manual calculation errors, and provides real-time technical recommendations, thereby enabling more efficient and data-driven preventive maintenance decisions at PT. PLN (Persero) UPT Manado.*

Keywords *– Decision Support System; Dissolved Gas Analysis; Large Language Model; Power Transformer; Random Forest*

Smart Trafo: Sistem Pendukung Keputusan Berbasis Random Forest dan LLM untuk Diagnosis Gangguan Transformator Daya melalui Dissolved Gas Analysis

ABSTRAK *– Pengelolaan data Dissolved Gas Analysis (DGA) transformator daya di PT. PLN (Persero) UPT Manado secara manual telah teridentifikasi sebagai hambatan operasional kritis, di mana alur kerja berbasis spreadsheet rentan terhadap kesalahan manusia, keterbatasan keterlacakan historis, dan skalabilitas yang rendah. Penelitian-penelitian sebelumnya tentang diagnosis transformator berbasis DGA umumnya terbatas pada model klasifikasi tersendiri tanpa integrasi ke dalam sistem manajemen operasional, sehingga meninggalkan kesenjangan signifikan dalam penerapan di lapangan. Penelitian ini berkontribusi pada pengembangan Sistem Pendukung Keputusan terintegrasi bernama Smart Trafo, yang merupakan sistem pertama yang menggabungkan model klasifikasi Random Forest, visualisasi Duval Pentagon, analisis tren historis, dan asisten percakapan berbasis LLM (Volty AI) dalam satu platform web full-stack. Model Random Forest dilatih menggunakan 375 sampel DGA pada enam kelas gangguan dengan lima parameter gas sesuai standar IEEE C57.104, menghasilkan akurasi keseluruhan 84% dan macro-average F1-score sebesar 0,83. Analisis feature importance mengidentifikasi Hidrogen (H_2) sebagai indikator diagnostik dominan sebesar 26,2%. Sistem ini berhasil mengotomatisasi klasifikasi gangguan DGA, mengeliminasi kesalahan perhitungan manual, dan memberikan rekomendasi teknis secara real-time, sehingga mendukung pengambilan keputusan perawatan preventif yang lebih efisien di PT. PLN (Persero) UPT Manado.*

Kata Kunci *– Dissolved Gas Analysis; Large Language Model; Random Forest; Sistem Pendukung Keputusan; Transformator Daya*

1. INTRODUCTION

Electrical energy is a fundamental necessity supporting industrial operations and modern society [1]. In the transmission system, the Power Transformer is the most critical and highly valuable asset, where functional failures can result in significant financial losses and widespread power supply disruptions [2], [3]. To prevent sudden failures, transformer condition monitoring must be conducted periodically. One of the primary diagnostic methods used is Dissolved Gas Analysis (DGA), which detects internal faults such as overheating, partial discharge, and arcing by analyzing the concentration of dissolved gases — including Hydrogen (H_2), Methane (CH_4), and Acetylene (C_2H_2) — in the insulation oil [4], [5], [6]. Interpretation of DGA results generally refers to strict international standards such as IEEE C57.104 and the Duval Triangle, requiring high precision in analyzing gas ratios [7], [8], [9].

Based on observations at PT. PLN (Persero) UPT Manado, DGA test data management still relies on manual spreadsheet documents, making it difficult for technicians to rapidly track transformer health history and prone to human error when handling large datasets.

Several studies have attempted to address this issue through machine learning. Risatayn et al. [10] applied Random Forest for transformer fault classification using Duval Triangle and Pentagon, but the model existed as a standalone classifier without any operational system integration. Hidayat et al. [11] employed K-Nearest Neighbors and Artificial Neural Networks for DGA-based diagnosis, yet similarly lacked a centralized data management interface. Suwarno et al. [12] proposed a multi-method framework combining classifiers to reduce misclassification, but their approach remained a research prototype not designed for field deployment. Dladla and Thango [13] conducted a systematic review of DGA-based machine learning approaches and consistently noted the absence of integrated platforms that combine automated classification with historical data management and user interaction. These limitations reveal a critical gap: no prior work has delivered a unified operational platform integrating machine learning-based DGA diagnosis, standardized visualization, historical trending, and intelligent user interaction within a single deployable system.

This research addresses that gap through the following novel contributions: (1) development of Smart Trafo, the first full-stack web-based Decision Support System integrating Random Forest DGA classification, Duval Pentagon visualization, and historical trending within a single operational platform; (2) integration of an LLM-based conversational assistant (Volty AI) to bridge automated technical analysis with natural language user interaction — a scientifically motivated design choice to reduce the expertise barrier for field technicians interpreting complex diagnostic outputs; and (3) empirical evaluation of the system on real-world DGA data from PT. PLN (Persero) UPT Manado [1], [2]. The rest of this paper is organized as follows: Section II reviews related literature, Section III describes the research method, Section IV presents results and discussion, and Section V concludes the paper.

2. LITERATURE REVIEW

Dissolved Gas Analysis (DGA)

DGA is widely recognized as one of the most effective methods for detecting internal faults in power transformers, analyzing dissolved gas concentrations in insulation oil to identify thermal faults, partial discharge, and arcing in accordance with IEEE C57.104 and Duval Pentagon standards [7], [8], [9].

Machine Learning for Transformer Diagnosis

Risatayn et al. [10] demonstrated Random Forest effectiveness for transformer damage classification using Duval Triangle and Pentagon. However, their work was limited to a classification experiment without a management system or user interface for field technicians. Hidayat et al. [11] applied K-Nearest Neighbors and Artificial Neural Networks for DGA-based fault diagnosis, but their system also lacked integration with historical data management or an operational dashboard. Suwarno et al. [12] proposed a multi-method machine learning framework combining multiple classifiers to reduce misclassification; however, the approach remained a research-level prototype without practical deployment considerations. Dladla and Thango [13] further confirmed through a systematic literature review that existing machine learning approaches for DGA are predominantly confined to classification accuracy studies, with none providing a complete operational platform suitable for field use.

Web-Based System Development

React.js provides a stable ecosystem for component-based Single Page Applications [14], [17], while Python FastAPI outperforms Flask in automatic data validation and machine learning model deployment [18], [19]. Supabase enables centralized and scalable cloud-based data management for operational systems [3], [4].

Large Language Model in Technical Systems

LLMs integrated via APIs such as Groq demonstrate significant potential for enhancing user interaction and providing intelligent recommendations in technical systems [20], [21]. Critically, for DGA-based systems, where diagnostic outputs require domain expertise to interpret, an LLM-based assistant serves a scientifically important role: it democratizes access to complex diagnostic knowledge, enabling field technicians without deep expertise to understand and act on system recommendations without requiring specialist intervention.

Research Gap and Novelty

The convergence of the above limitations establishes a clear research gap. No prior study has: (a) combined Random Forest-based DGA classification with Duval Pentagon visualization and historical trending, (b) within a production-ready full-stack web platform, (c) augmented with an LLM-based assistant for natural language diagnostic interaction. Smart Trafo is positioned as the first integrated operational system addressing all three dimensions simultaneously.

3. RESEARCH METHOD

This research employs an Agile software development methodology, selected for its iterative nature enabling close collaboration with end-users at PT. PLN (Persero) UPT Manado and dynamic adjustments based on stakeholder feedback across development sprints.

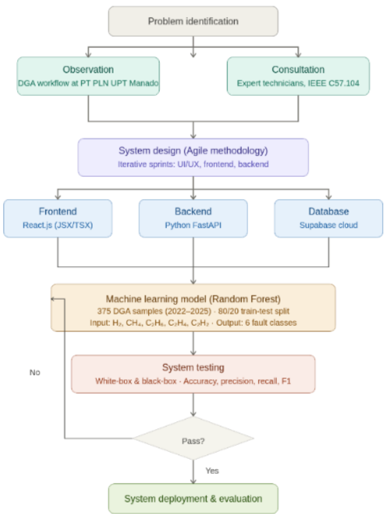

Figure 1. Methodology Flowchart

Figure 1 illustrates the overall research workflow following the Agile methodology, consisting of five iterative stages: requirements gathering, system design, implementation, testing, and deployment. The iterative loop between testing and implementation reflects the sprint-based development cycle conducted in collaboration with field technicians at PT. PLN (Persero) UPT Manado, ensuring each system module met operational requirements before proceeding to the next development phase.

System Requirements

Requirements were gathered through two methods [15]: (1) direct observation of the existing DGA workflow, which revealed manual spreadsheet-based processes with significant limitations in error prevention, historical tracking, and scalability; and (2) consultation with expert field technicians to understand IEEE C57.104 boundary values, Duval Pentagon methodology [8], [9], and end-user automation expectations.

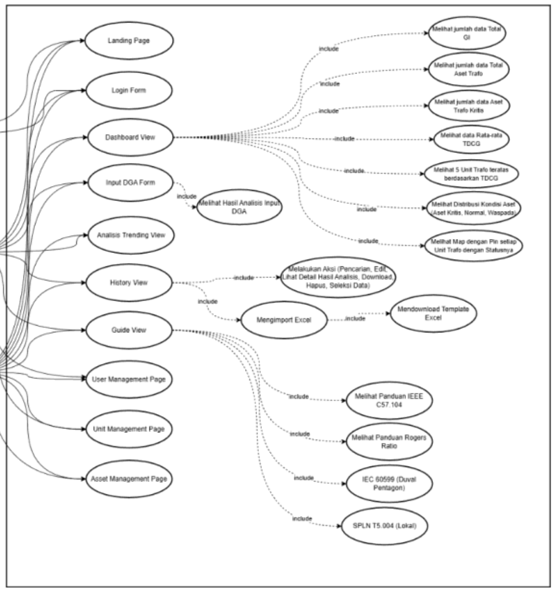

Figure 2. Usecase Diagram

Figure 2 presents the system use case diagram depicting interactions between three actor roles: Administrator, Technician, and Supervisor. Technicians are assigned primary access to DGA data input and diagnostic result viewing, while Supervisors have read-only access to historical trending and reporting features. Administrator privileges cover user and asset management. This role-based access design ensures data integrity and appropriate authorization levels for each user category in the field environment.

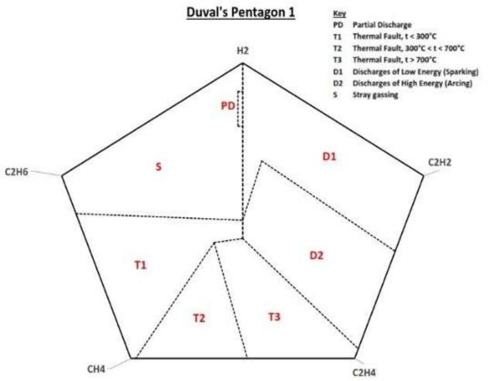

Figure 3. Duval Pentagon

Figure 3 shows the Duval Pentagon visualization method used as one of the two diagnostic engines in Smart Trafo. The Pentagon maps the relative concentrations of five key gases (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2) into a geometric region corresponding to a specific fault zone. Unlike the simpler Duval Triangle which uses only three gases, the Pentagon provides finer fault discrimination — particularly between thermal and electrical fault subtypes — making it more appropriate for the six-class classification scheme adopted in this research.

System Architecture

The system follows a full-stack architecture separating frontend and backend layers. The frontend was built using React.js for component-based Single Page Application development [14], [17]. The backend was implemented using Python FastAPI, chosen for its superior performance over Flask and native support for machine learning model deployment [18], [19]. Centralized data management is handled via Supabase cloud database. An additional integration layer connects to the Groq API to support the Volty AI conversational assistant [20], [21].

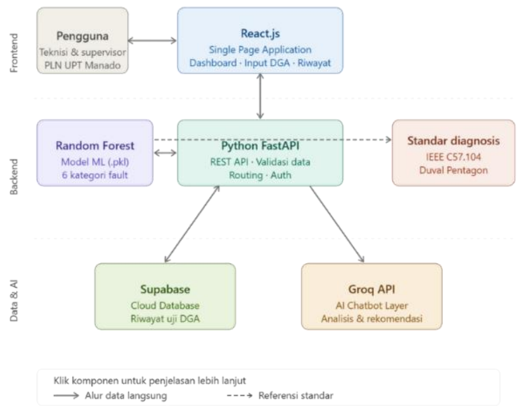

Figure 4. System Architecture

Figure 4 depicts the three-tier system architecture of Smart Trafo. The frontend layer (React.js) communicates with the backend layer (Python FastAPI) via RESTful API calls. The backend handles two parallel processes: ML inference using the trained Random Forest model, and natural language processing via the Groq API for the Volty AI assistant. The data layer (Supabase) stores all DGA test records, user accounts, and asset information in a centralized cloud database. This architecture ensures separation of concerns between presentation, business logic, and data persistence, supporting scalability and maintainability.

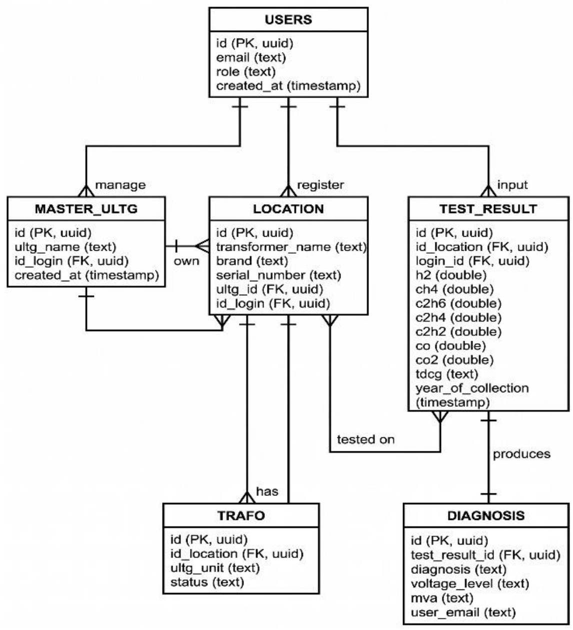

Figure 5. Entity Relationship Diagram

Figure 5 illustrates the database schema of Smart Trafo, comprising four primary entities: User, Asset (transformer unit), DGA Test Record, and Diagnosis Result. The one-to-many relationship between Asset and DGA Test Record enables historical trending per transformer unit, which is a key capability absent in prior standalone classification approaches. The Diagnosis Result entity stores both the Random Forest prediction output and the corresponding Duval Pentagon coordinates, enabling audit trails for each diagnostic event.

Machine Learning Model

Random Forest was selected as the core diagnostic algorithm based on three evidence-based criteria: (1) its demonstrated superiority over K-Nearest Neighbors and Artificial Neural Networks specifically for imbalanced DGA datasets [10], [11]; (2) its resistance to overfitting, which is critical given the limited real-world DGA sample availability; and (3) its built-in feature importance mechanism, which provides interpretable diagnostic insights consistent with domain knowledge (e.g., H_2 dominance in DGA theory).

The dataset comprises 375 DGA samples obtained from two sources: real-world test records from PT. PLN (Persero) UPT Manado covering the 2022–2025 period, supplemented by publicly available DGA datasets based on international standards, to address the limitation of available field data and improve model generalizability.

The dataset was split 80:20 for training (300 samples) and testing (75 samples) with stratified sampling to preserve class distribution across splits. Hyperparameter configuration used: n_estimators = 100 decision trees, max_features = 'sqrt', and default sklearn RandomForestClassifier settings. No feature engineering or normalization was applied, as Random Forest is inherently scale-invariant. Class imbalance was addressed implicitly through Random Forest's bootstrap aggregation; however, certain minority classes (notably Spark Discharge with only 10 test samples) were identified as candidates for future SMOTE-based augmentation..

Table 1. Dataset Features and Classification Categories

Type	Parameters/Categories
Input Features (Gas)	H2, CH4, C2H6, C2H4, C2H2
Output Fault Classes	Condition 1, Condition 2, Condition 3, General Overheating, Arcing, Spark Discharge

Model performance was evaluated using four metrics: accuracy, precision, recall, and F1-score, defined as follows:

$$F1 = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (1)$$

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (2)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (3)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (4)$$

System Testing

System testing used both white-box testing (verifying internal logic of the ML inference pipeline and API endpoints) and black-box testing (validating functional correctness from the user perspective). Feedback from field technicians and supervisors was integrated iteratively across development sprints.

4. Result and Discussion

Machine Learning Model Performance

The Random Forest model achieved an overall accuracy of 84% on the 75-sample test set, with a macro-average F1-score of 0.83, indicating consistent performance across the six fault classes. Detailed per-class results are presented in Table 2.

Table 2. Classification Performance Of The Model

Class	Precision	Recall	F1-Score	Support
Arcing (High Energy)	0.85	0.69	0.76	16
General Overheating	0.70	1.00	0.82	14
Kondisi 1	0.96	0.96	0.96	27
Kondisi 2	1.00	1.00	1.00	2
Partial Discharge (Corona)	1.00	0.67	0.80	6
Spark Discharge	0.67	0.60	0.63	10
Accuracy			**0.84**	**75**
Macro Avg	0.86	0.82	0.83	75
Weighted Avg	0.85	0.84	0.84	75

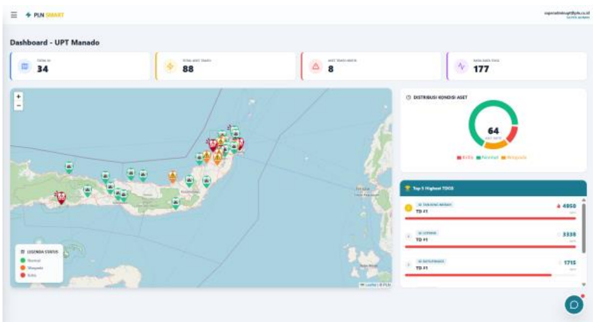

Figure 6. Dashboard Page

Figure 6 presents the main dashboard of Smart Trafo, which provides a real-time overview of transformer fleet condition at PT. PLN (Persero) UPT Manado. The dashboard displays the total number of registered transformer units, distribution of current diagnostic conditions (normal, warning, critical), and the most recent DGA test entries. This centralized overview directly replaces the previously fragmented spreadsheet-based monitoring, enabling supervisors to assess the overall health status of all managed transformers in a single interface without manually aggregating data from separate documents.

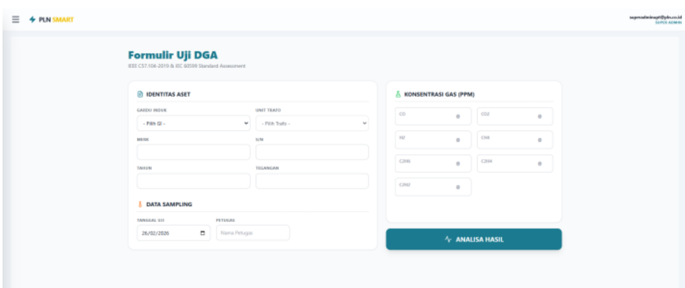

Figure 7. Input Form Page

Figure 7 shows the DGA data input form where technicians enter the five gas concentration values (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2) along with the associated transformer unit and test date. Figure 8 presents the resulting diagnostic output, which includes: the Random Forest fault classification result, the corresponding Duval Pentagon coordinate mapping with the identified fault zone highlighted, and a natural language recommendation generated by Volty AI. The integration of these three output components in a single result view is a key usability contribution of Smart Trafo, enabling technicians to obtain a complete diagnostic picture — classification, visualization, and recommendation — from a single data submission without requiring separate tools or manual interpretation.

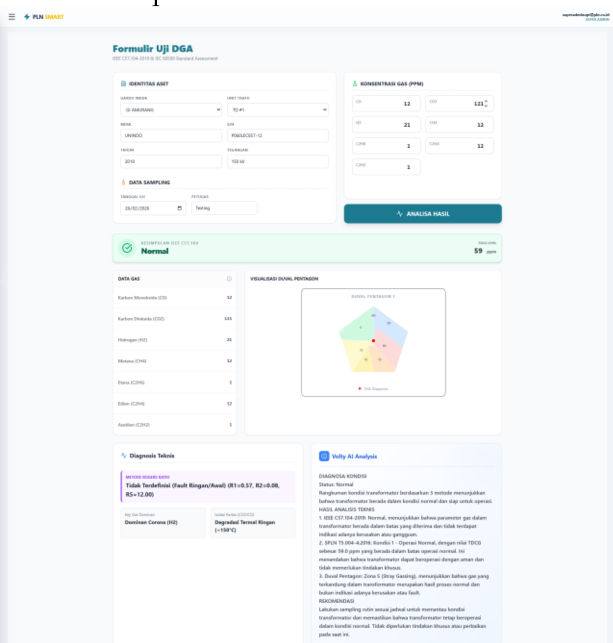

Figure 8. Input Form Result

Based on Figure 8, the image presents a web-based Dissolved Gas Analysis (DGA) diagnostic system interface called *PLN Smart*, designed to analyze the condition of power transformers using gas concentration data. The system allows users to input transformer identity information, gas measurement values such as hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), acetylene (C_2H_2), and carbon monoxide (CO), as well as sampling details. After processing the data, the system displays the transformer health status, which in this case is categorized as "Normal" with a confidence score of 59%. The interface also visualizes DGA interpretation through graphical representation and provides technical diagnosis results, including fault classification and analytical recommendations. Additionally, the platform integrates an AI assistant feature named *Volty AI Analytics* that generates automated explanations and maintenance suggestions based on the analyzed transformer data, supporting decision-making in transformer monitoring and preventive maintenance.

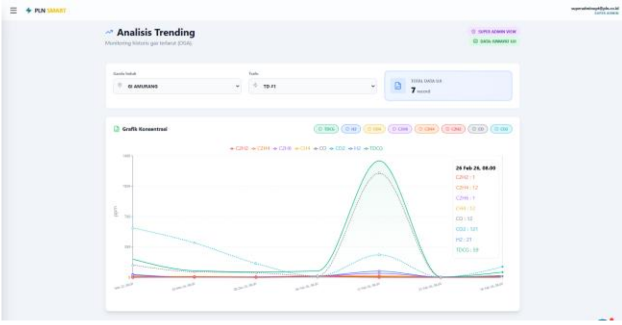

Figure 9. Trending Page

Figure 9 displays the historical trending view for individual transformer units, plotting gas concentration values across successive DGA test dates. This feature directly addresses one of the primary limitations identified in the prior manual system: the inability to rapidly track transformer health trajectory over time. The trending visualization enables early detection of deteriorating conditions — for example, a progressive increase in H_2 or C_2H_2 concentration across multiple tests may indicate developing fault conditions before they reach critical thresholds, supporting proactive rather than reactive maintenance decisions.

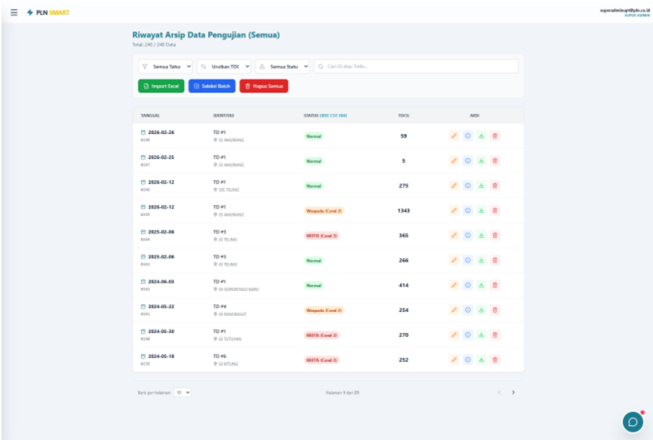

Figure 10. History Page

Figure 10 shows the test history page, which provides a chronological log of all DGA tests conducted for each transformer unit. Each record displays the input gas values, diagnosis result, test date, and the responsible technician. This centralized audit trail replaces the previously dispersed spreadsheet records and provides accountability tracking, enabling supervisors to review historical decisions and verify diagnostic consistency over time.

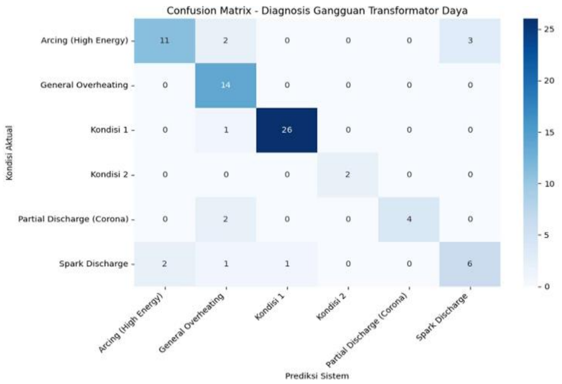

Figure 11. Confusion Matrix

Figure 19 presents the confusion matrix of the Random Forest model evaluated on the 75-sample test set. The matrix reveals that Condition 1 (normal state) was classified with near-perfect accuracy, consistent with its largest sample support and distinct gas profile. The most notable misclassification pattern occurs between Spark Discharge and Arcing (High Energy), where 4 out of 10 Spark Discharge samples were incorrectly predicted as Arcing — reflecting the known similarity in gas signatures between these two electrical fault subtypes. General Overheating showed 4 false positive predictions from adjacent classes, explaining its lower precision (0.70) despite perfect recall. These misclassification patterns confirm that class boundary ambiguity, rather than model weakness, is the primary source of error, suggesting that additional discriminating features or expanded datasets would yield the most significant accuracy improvements.

Interpretation of Results

Condition 1 (normal transformer state) achieved the highest F1-score of 0.96, which is expected given its largest sample support (27 test samples) and its distinct gas signature. Condition 2 achieved perfect classification (F1 = 1.00); however, with only 2 test samples, this result should be interpreted cautiously as statistically insufficient for generalization.

General Overheating achieved perfect recall (1.00) but lower precision (0.70), indicating the model tends toward over-prediction of this class — likely due to overlapping gas signatures with adjacent fault types, a pattern consistent with findings in [12].

Arcing (High Energy) shows relatively low recall (0.69), meaning 31% of actual arcing events were misclassified. This is operationally significant as arcing represents a high-severity fault; underdetection could delay preventive intervention. This class warrants priority attention in future dataset expansion.

The Spark Discharge class recorded the lowest F1-score (0.63), attributable to its limited test support (10 samples) and the inherent similarity of its gas ratios to Arcing. This finding is consistent with known challenges in DGA interpretation [13] and suggests SMOTE-based augmentation as a necessary future step.

Feature importance analysis identified H_2 as the most influential diagnostic feature (26.2%), followed by C_2H_2 (21.8%) and C_2H_4 (19.9%). This ranking aligns strongly with established DGA theory: H_2 is produced across virtually all fault types and serves as a universal stress indicator, while C_2H_2 is the primary marker for high-energy arcing [7], [8]. The model's feature weighting thus demonstrates domain validity beyond mere statistical optimization.

Table 3. Feature Importance of Gas Parameters in Random Forest Model

Feature	Importance Score
H_2 (Hidrogen)	26,2%
C_2H_2 (Asetilena)	21,8%
C_2H_4 (Etilena)	19,9%
CH_4 (Metana)	17,2%
C_2H_6 (Etana)	15,0%
Total	**100%**

Technical System Evaluation

White-box testing confirmed the correctness of the ML inference pipeline, API endpoint responses, and database read/write operations. Black-box testing validated that DGA input submitted through the web interface produces correct IEEE C57.104-compliant classifications and corresponding Duval Pentagon coordinate mapping. System testing with field technicians confirmed that the diagnostic output format, historical trending view, and Volty AI conversational interface align with practical operational requirements.

The integration of rule-based IEEE C57.104 classification with the Random Forest model provides complementary diagnostic coverage: the rule-based layer ensures regulatory interpretability, while the ML layer captures complex multi-gas interaction patterns that rigid threshold rules cannot detect. This dual-layer approach represents a technical advantage over prior single-method implementations [10], [11].

The Volty AI assistant serves a measurable functional role beyond cosmetic enhancement: it translates classifier outputs and Duval Pentagon coordinates into natural language explanations, reducing the expertise requirement for frontline technicians. This is particularly significant at facilities like PT. PLN (Persero) UPT Manado where DGA interpretation expertise is limited to a small number of specialists.

Discussion

From a discussion perspective, the integration of the IEEE C57.104 standard, the Duval Pentagon method, and the Random Forest machine learning model provides a more comprehensive diagnostic approach compared to using a single method alone. Each approach contributes differently: rule-based standards ensure interpretability and compliance with industry practices, while machine learning enhances pattern recognition and predictive capability, consistent with findings from previous studies [10], [11], [12].

However, the accuracy of the system remains dependent on the quality and completeness of the input data. Inaccurate or noisy data may lead to deviations in both rule-based and machine learning results. The Spark Discharge class recorded the lowest F1-score of 0.63, which can be attributed to the limited number of samples in that class (10 samples), suggesting the need for additional data collection or oversampling techniques such as SMOTE in future development.

Despite its advantages, the system still has certain limitations, particularly in terms of scalability and real-time data integration. Currently, data input is still performed manually, meaning the system is not yet fully automated. Future development can focus on integrating IoT-based sensors for real-time data acquisition and applying more advanced machine learning or deep learning techniques to further improve predictive accuracy.

Overall, the digitalization of DGA analysis combined with machine learning significantly improves efficiency, accuracy, and speed in transformer condition diagnosis. The Smart Trafo system has strong potential for broader implementation in the electrical power industry, especially in supporting preventive maintenance and more informed decision-making at PT. PLN (Persero) UPT Manado.

5. CONCLUSION

This research successfully developed Smart Trafo, a novel web-based Decision Support System that, for the first time, integrates Random Forest-based DGA fault classification, Duval Pentagon visualization, historical trending, and an LLM-based conversational assistant (Volty AI) within a unified operational platform for power transformer condition monitoring. This integration constitutes the primary novelty of the research, addressing the critical gap identified in prior work where machine learning approaches for DGA diagnosis remained confined to standalone classifiers without operational system context [10], [11], [12], [13]. The Random Forest model trained on 375 real-world DGA samples from PT. PLN (Persero) UPT Manado achieved 84% overall accuracy and macro-average F1-score of 0.83, with H_2 confirmed as the dominant diagnostic feature (26.2%), validating both model performance and domain alignment. The system's dual-layer architecture combining IEEE C57.104 rule-based analysis with machine learning classification provides superior diagnostic coverage compared to single-method approaches. The system presents several limitations that define the scope of its current applicability: (1) data input remains manual, meaning the system is not yet capable of real-time automated acquisition; (2) the Spark Discharge class is underrepresented in the dataset (10 test samples), limiting classification reliability for this fault type; (3) the dataset is derived from a single facility (PT. PLN UPT Manado), which may limit generalizability to transformers with different operating characteristics or oil types; and (4) the LLM assistant depends on third-party API availability (Groq), introducing an external dependency that affects system reliability. Future development should prioritize: expanding the DGA dataset with additional historical records and applying SMOTE to address class imbalance; integrating IoT-based sensors for real-time automated data acquisition; validating the system across multiple PLN regional facilities; and exploring local LLM deployment to eliminate external API dependency.

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