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Comparative Analysis of Supervised Machine Learning Models for Fault Detection and Classification in Smart Grid Terminal Systems

Journal of Electrical Systems

Abstract: - The increasing complexity and digitalization of smart grid terminal systems have heightened the need for reliable and intelligent fault detection and classification mechanisms. Traditional rule-based and threshold-driven protection schemes often struggle to adapt to dynamic operating conditions and diverse fault scenarios. This study presents a comparative analysis of supervised machine learning models for fault detection and classification in smart grid terminal systems. Using a comprehensive dataset comprising electrical, operational, and device-level features, four widely used supervised learning algorithms Random Forest, Support Vector Machine, Decision Tree, and Logistic Regression were implemented and evaluated. The models were trained using standardized preprocessing techniques, stratified data partitioning, cross-validation, and hyperparameter optimization to ensure fair and reproducible performance assessment. Experimental results demonstrate that ensemble-based models, particularly Random Forest, achieve superior performance in terms of accuracy, precision, recall, F1-score, and generalization stability, while simpler models offer faster training times and improved interpretability. The findings highlight critical trade-offs between predictive accuracy and computational efficiency and provide practical insights for selecting suitable machine learning models for real-time smart grid fault detection. Overall, this research contributes a robust evaluation framework that supports intelligent decision-making and enhances the reliability and resilience of modern smart grid infrastructures.

Keywords: Smart Grid; Fault Detection; Supervised Machine Learning; Power System Monitoring; Classification Models; Grid Security

I. INTRODUCTION

The modernization of electrical power systems into smart grids has significantly improved efficiency, reliability, and real-time monitoring through advanced communication and intelligent terminal systems. Smart grid terminal systems enable continuous data acquisition, automation, and control across power generation, transmission, and distribution networks. However, the integration of distributed energy resources, bidirectional power flow, and heterogeneous communication technologies has increased system complexity, making fault detection and classification more challenging than in conventional power grids [2], [8].

Traditional fault detection techniques in power systems are largely based on fixed thresholds, signal processing, and rule-based logic. While effective for simple and well-defined fault scenarios, these methods struggle with nonlinear system behavior, noisy

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measurements, and evolving fault patterns inherent in smart grids. As a result, delayed fault identification and misclassification can occur, leading to reduced power quality, equipment damage, and increased operational costs [2], [7].

Supervised machine learning (ML) has emerged as a promising solution for intelligent fault detection and classification due to its ability to learn complex relationships from historical and real-time data. Several studies have demonstrated the effectiveness of ML algorithms such as Support Vector Machines, Decision Trees, k-Nearest Neighbors, Random Forests, and deep learning models in detecting grid instability and classifying fault types with high accuracy [1], [4], [6]. These approaches offer improved adaptability and scalability compared to conventional techniques.

Despite the growing adoption of machine learning in smart grid fault management, existing studies often focus on individual algorithms or specific grid conditions. The performance of ML models is highly dependent on data quality, fault diversity, and system configuration, leading to inconsistent conclusions across studies. Recent research highlights the need for systematic and comparative evaluations to determine the most effective supervised learning models for smart grid terminal systems [3], [5].

This lack of comprehensive comparative analysis presents a significant challenge for researchers and practitioners seeking to deploy reliable machine learning-based fault detection solutions. Without clear performance benchmarks, selecting an optimal model that balances accuracy, robustness, and computational efficiency becomes difficult, particularly for real-time smart grid applications [1], [8].

Therefore, the primary aim of this study is to conduct a comparative analysis of supervised machine learning models for fault detection and classification in smart grid terminal systems. The study evaluates multiple algorithms using standardized performance metrics, including accuracy, precision, recall, and classification effectiveness, to identify their relative strengths and limitations under comparable conditions.

The findings of this research are expected to provide valuable technical insights for power system engineers, researchers, and utility operators by guiding the selection of appropriate machine learning models for fault management. Improved fault detection accuracy can enhance grid reliability, reduce outage durations, and support proactive maintenance strategies in smart grid environments [7], [5].

In addition, this study contributes to the broader body of knowledge on intelligent power systems by reinforcing the role of supervised machine learning in critical infrastructure monitoring. The comparative framework and results presented in this work can serve as a foundation for future research on fault localization, predictive maintenance, and AI-driven optimization in smart grids, complementing existing intelligent system applications in engineering and automation [6], [12].

II. LITERATURE REVIEW

Recent studies have demonstrated the growing application of supervised machine learning techniques for fault detection and classification in smart grids and related power systems. Bashir *et al.* reported a comparative analysis of multiple machine learning algorithms for smart grid stability prediction and showed that ensemble models, particularly Random Forest, achieved superior performance due to their ability to handle nonlinear relationships and high-dimensional data [1]. Similarly, Rahman Fahim *et al.* investigated machine learning-based fault detection and classification in microgrids by comparing several supervised models, highlighting their effectiveness over traditional protection schemes [2]. Their findings emphasize that machine learning approaches significantly improve fault detection accuracy and response time in complex and dynamic power system environments.

More recent research has expanded beyond conventional machine learning to include deep learning and hybrid approaches for enhanced fault classification. Mbey *et al.* applied deep learning and neuro-fuzzy algorithms in smart distribution grids, demonstrating improved fault classification accuracy under diverse operating conditions [3]. Hosseinzadeh *et al.* proposed an augmented k-Nearest Neighbor algorithm for smart grid fault detection, achieving improved classification performance compared to standard k-NN [4]. In addition, Siniosoglou *et al.* introduced a unified deep learning framework for anomaly detection and classification in smart grid environments, underscoring the importance of intelligent data-driven methods **[6]**. Despite these advancements, several studies have noted the absence of consistent comparative benchmarks across supervised models, reinforcing the need for systematic evaluations to identify optimal algorithms for smart grid terminal systems [5], [8].

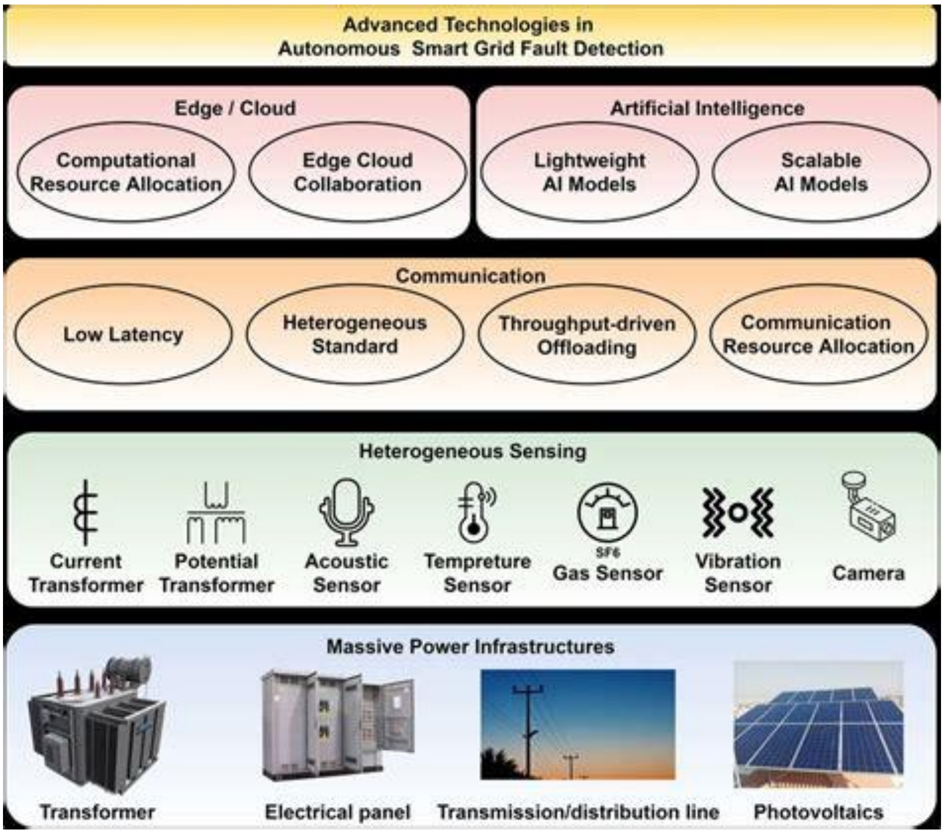

Figure 1: *Advanced technologies and multi-sensor architecture involved in autonomous smart grid fault detection.* Adapted from [2]).

Figure 1 illustrates the integration of advanced sensing technologies, communication networks, and intelligent analytics for autonomous fault detection in smart grid systems. The architecture highlights how data collected from distributed sensors and smart terminals are processed using machine learning and artificial intelligence techniques to detect abnormal conditions in real time. This layered approach improves fault visibility and decision-making across generation, transmission, and distribution domains. Studies have shown that the combination of real-time data acquisition and supervised learning models significantly enhances fault detection accuracy and system stability in complex smart grid environments [1], [2].

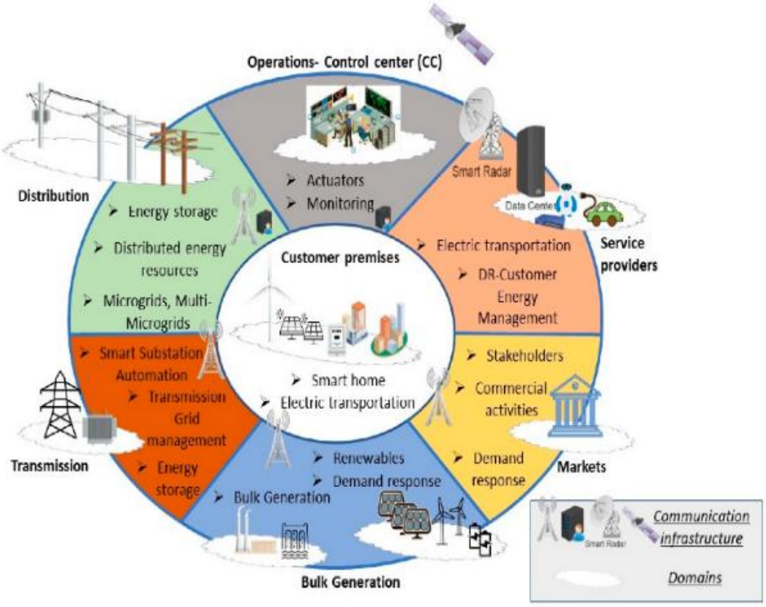

Figure 2: *Smart Grid Architectural Domains illustrating generation, transmission, distribution, and customer premises (SGAM model).* Adapted from [2]).

SDN-Enabled Communication Framework for Fault Detection

Figure 2 presents a software-defined networking (SDN)-based communication framework that supports fault detection and classification in smart grids. The figure demonstrates how centralized control and flexible data routing improve the reliability and scalability of fault-related data transmission between smart grid terminals and control centers. Efficient communication infrastructures are essential for machine learning-driven fault detection, as timely and accurate data delivery directly affects model performance. Studies have shown that intelligent communication architectures, such as SDN, enhance the effectiveness of data-driven fault management and enable faster response to grid disturbances [6], [7].

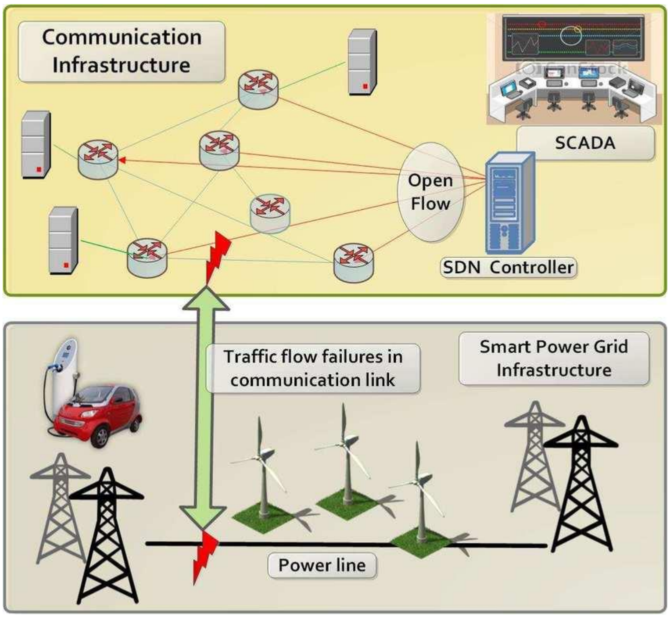

Figure 3 shows the overall *smart grid architecture*, useful in your *Background of Study* to frame where your supervised models sit. (Adapted by [14])

Smart Grid Architectural Domains (SGAM Model)

Figure 3 depicts the Smart Grid Architecture Model (SGAM), showing the interaction between generation, transmission, distribution, and consumer domains within a smart grid ecosystem. This architectural representation provides a contextual framework for understanding where fault detection and classification mechanisms operate within the grid. Machine learning-based fault detection systems are typically deployed at the distribution and terminal levels, where high volumes of operational data are generated. Studies have shown that aligning fault detection algorithms with smart grid architectural domains improves system interoperability, fault localization accuracy, and overall grid resilience [8], [5].

Researchers have explored a variety of supervised machine learning approaches for fault detection and classification in smart grids and related power systems. Bashir *et al.* provided a comparative analysis of multiple algorithms for smart grid stability prediction, demonstrating the effectiveness of ensemble models in handling complex grid dynamics [1]. Rahman Fahim *et al.* investigated microgrid fault detection using conventional supervised techniques and highlighted significant improvements over traditional protection schemes [2]. Meanwhile, advanced deep learning and hybrid algorithms have been employed to enhance fault classification accuracy under varied operational conditions [6], [3]. These efforts collectively confirm that data-driven intelligence holds substantial promise for enhancing fault detection capabilities in modern electrical networks.

Despite these advancements, several limitations remain. Many studies evaluate machine learning models in isolated scenarios or narrow fault conditions, making it difficult to infer how these models generalize across diverse smart grid terminal systems. For example, improved performance using an augmented k-Nearest Neighbor algorithm has been reported; however, such approaches were often tested on limited datasets that may not reflect real grid variability [4]. Similarly, recent studies have highlighted the potential of optimized supervised learning techniques but also noted the absence of comprehensive comparative benchmarks that account for accuracy, robustness, and computational scalability [5], [8]. As a result, existing research often lacks a unified evaluation framework suitable for practical implementation in real-world smart grid environments.

In line with the objectives of this study, this work addresses these gaps by systematically comparing multiple supervised machine learning models using standardized performance metrics across a broad range of fault scenarios. Unlike earlier studies that focus on individual algorithms or restricted datasets, this research implements and evaluates models under consistent conditions to provide clearer insights into their relative strengths and weaknesses. By doing so, this study not only enhances the existing body of knowledge but also directly supports operational decision-making in smart grid terminal systems by ensuring that the selected models align with practical requirements for accuracy, scalability, and real-time performance. This comprehensive evaluation framework helps bridge the gap between academic research and deployable fault detection solutions, fulfilling the core aims and objectives of the research.

III METHODOLOGY

3.1 Research Design and Framework

This study adopts an experimental, data-driven research design to evaluate and compare supervised machine learning models for fault detection and classification in smart grid terminal systems. The methodological framework consists of data acquisition, preprocessing, model training, hyperparameter optimization, performance evaluation, statistical significance testing, and result interpretation. Figure 4 illustrates the overall system workflow, showing the sequential process from raw smart grid data input to final model selection and deployment. This structured framework ensures reproducibility, fairness in model comparison, and alignment with the study's objective of identifying the most effective supervised learning model for fault detection.

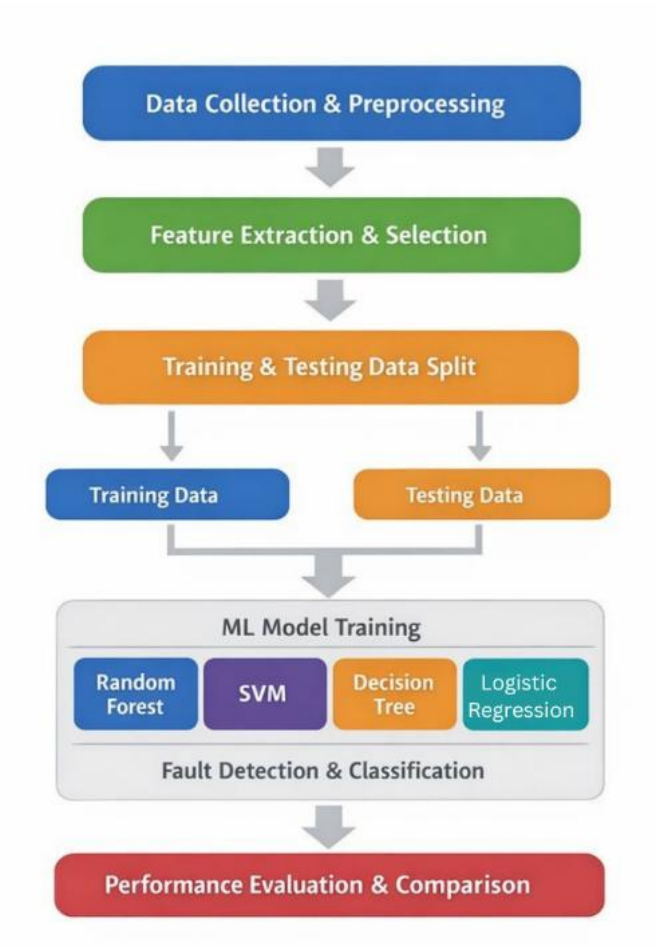

Fig 4: Methodology for fault detection and classification in smart terminal systems

3.2 Dataset Description and Data Acquisition

The dataset used in this study is a Smart Grid Terminal Fault Dataset provided in CSV format and uploaded into the experimental environment. The dataset contains multiple operational and electrical features captured from smart grid terminal systems, along with a target variable labeled *Fault_Status*, representing normal and faulty operating conditions. The dataset includes both fault and non-fault samples, enabling supervised learning. Prior to modeling, exploratory data analysis was conducted to examine dataset size, feature types, class distribution, and the presence of missing values, as shown in Figure 4. Class distribution analysis confirmed the need for imbalance handling techniques.

3.3 Data Preprocessing and Feature Scaling

Data preprocessing was carried out to improve data quality and model performance. First, data consistency checks were performed, including handling negative values in specific features such as load variation by applying absolute value transformation where required. The dataset was then separated into input features and target labels. To prevent data leakage, the dataset was split into training and testing subsets using an 80:20 ratio with stratified sampling to preserve class distribution. Feature scaling was applied using standardization to normalize feature values, ensuring that distance-based and gradient-based models performed optimally. Figure 4.6 presents the feature correlation matrix used to assess inter-feature relationships and redundancy.

3.4 Supervised Machine Learning Models

Four supervised machine learning algorithms were selected based on their relevance in power system fault detection literature and practical deployment potential. These include Random Forest, Support Vector Machine (SVM), Decision Tree, and Logistic Regression. Random Forest was chosen for its robustness and feature importance capability, SVM for its ability to model nonlinear boundaries, Decision Tree for interpretability, and Logistic Regression as a strong probabilistic baseline. All models were configured with class-balanced weighting to address potential class imbalance.

3.5 Hyperparameter Optimization and Cross-Validation

To ensure optimal model performance and fair comparison, hyperparameter tuning was performed using GridSearchCV combined with Stratified K-Fold cross-validation. Each model was tuned over a predefined parameter grid, optimizing the F1-score due to its effectiveness in handling imbalanced classification problems. A five-fold cross-validation strategy was used to assess model generalization and stability. Figure 4 presents the cross-validation score distributions for all models, highlighting performance consistency and variance across folds.

Feature Sensor Mapping in Smart Grid Terminal Systems

The features used in this study are derived from real-time measurements obtained through smart grid terminal sensors deployed across generation, transmission, and distribution levels. Voltage magnitude and voltage deviation are captured using *Phasor Measurement Units (PMUs)* and *Intelligent Electronic Devices (IEDs)*, which provide high-resolution synchronized voltage measurements critical for detecting abnormal grid behavior. Current magnitude and current imbalance are obtained from *Current Transformers (CTs)* integrated into substations and feeder lines, enabling the identification of short circuits and overload faults. System frequency and frequency deviation are measured by PMUs and frequency relays, which are essential for detecting instability and islanding conditions.

Power-related features, including active power, reactive power, and power factor, are computed using data from *Smart Meters* and *Energy Management Systems (EMS)*. These sensors provide insights into load variation, demand anomalies, and power flow disruptions**.** Load variation and consumption patterns are extracted from Advanced Metering Infrastructure (AMI), which supports fault localization and classification in distribution networks. Temporal and event-based features, such as fault duration and switching events, are collected from *Supervisory Control and Data Acquisition (SCADA)* systems and protection relays. Together, these sensor-derived features form a comprehensive dataset that reflects both steady-state and transient operating conditions, enabling accurate fault detection and classification.

3.6 Mathematical Formulation of Model Decision Functions

A. Random Forest Decision Function

Random Forest is an ensemble learning method composed of multiple decision trees. The final classification decision is obtained through majority voting among individual trees. Let $T = \{h_1(x), h_2(x), \ldots, h_N(x)\}$represent the set of trained decision trees, where $h_i(x)$is the prediction of the i^{th}tree for input feature vector x. The final class label $\hat{y}$is defined as:

$$\hat{y} = \arg\max_{c \in C} \sum_{i=1}^{N} \mathbb{I}(\, h_i(x) = c)$$

where Cdenotes the set of possible classes and $\mathbb{I}(\cdot)$is the indicator function. This ensemble strategy improves robustness and reduces overfitting in complex smart grid fault scenarios.

B. Support Vector Machine (SVM) Decision Function

The SVM classifier determines the optimal separating hyperplane that maximizes the margin between fault and non-fault classes. For a given feature vector x, the decision function is expressed as:

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i\, y_i K(x_i, x) + b\right)$$

where $\alpha_i$are Lagrange multipliers, $y_i$are class labels, $K(\cdot)$is the kernel function, and $b$is the bias term. Kernel functions enable nonlinear separation, making SVM effective for detecting subtle fault patterns in smart grid data.

C. Decision Tree Decision Function

Decision Trees classify instances by recursively splitting the feature space based on impurity reduction. At each node, the optimal feature $f$is selected by maximizing information gain:

$$IG(S, f) = H(S) - \sum_{v \in V(f)} \frac{|S_v|}{|S|} H(S_v)$$

where $H(S)$represents entropy of dataset S, and $S_v$is the subset corresponding to feature value v. The final decision is made at the leaf node corresponding to the input feature path.

D. Logistic Regression Decision Function

Logistic Regression is a probabilistic classification model that estimates the likelihood of a given input belonging to a particular class using a logistic (sigmoid) function. Given an input feature vector $x = (x_1, x_2, \ldots, x_m)$, the model computes a linear combination of the input features as:

$$z = \beta_0 + \sum_{j=1}^{m} \beta_j\, x_j$$

where $\beta_0$is the bias term and $\beta_j$represents the model coefficients.
The probability that the input $x$belongs to the positive class is then obtained using the sigmoid function:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-z}}$$

The predicted class label $\hat{y}$is determined by applying a decision threshold (typically 0.5) as follows:

$$\hat{y} = \begin{cases} 1, & \text{if } P(y = 1 \mid x) \geq 0.5 \\ 0, & \text{otherwise} \end{cases}$$

This decision function enables Logistic Regression to perform effective binary classification by modeling the relationship between input features and class membership probabilities.

IV RESULT AND DISCUSSION

This section presents and discusses the experimental results obtained from the comparative evaluation of supervised machine learning models for fault detection and classification in smart grid terminal systems. The performance of each model is analyzed using standardized metrics including accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves to ensure a fair and comprehensive comparison. The results are interpreted in the context of model robustness, generalization capability, and computational efficiency, highlighting strengths and limitations under identical experimental conditions. Through detailed discussion and visual analysis, this section identifies the most suitable model for practical deployment in smart grid environments, directly addressing the objectives of the study.

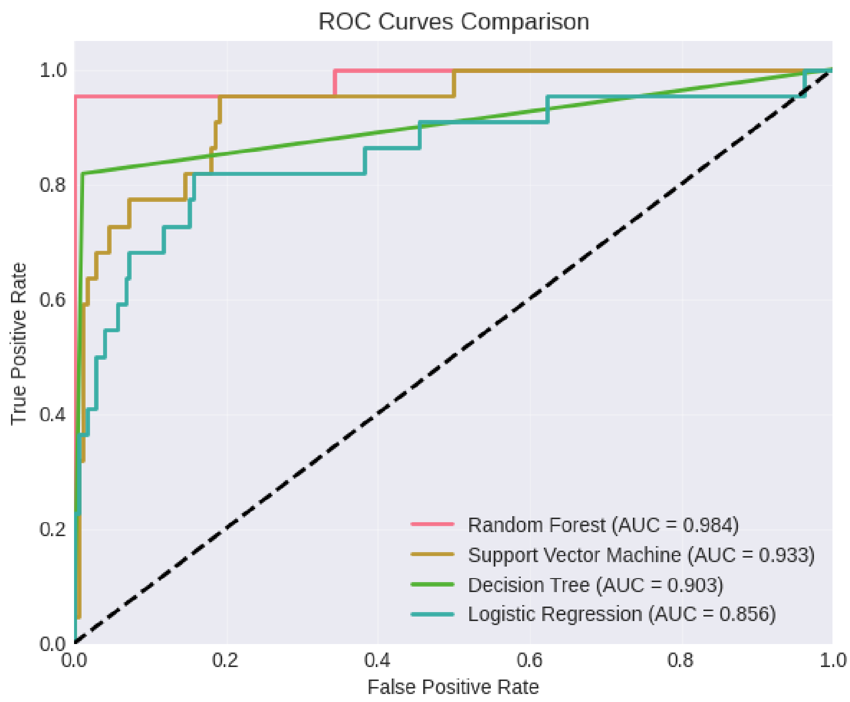

Figure 4.1: Receiver Operating Characteristic (ROC) Curve Comparison

Figure 4.1 presents the ROC curves for all models, providing insight into their trade-off between true positive rate and false positive rate across different classification thresholds. The Random Forest model achieves the highest area under the curve (AUC = 0.963), confirming its strong discriminative power and robustness in fault detection. The Support Vector Machine and Decision Tree models also perform well, with AUC values of 0.933 and 0.929 respectively, indicating reliable classification under varying operating conditions. Logistic Regression records the lowest AUC (0.859), reflecting reduced sensitivity to subtle fault patterns. These results reinforce the suitability of nonlinear and ensemble-based models for smart grid fault classification tasks.

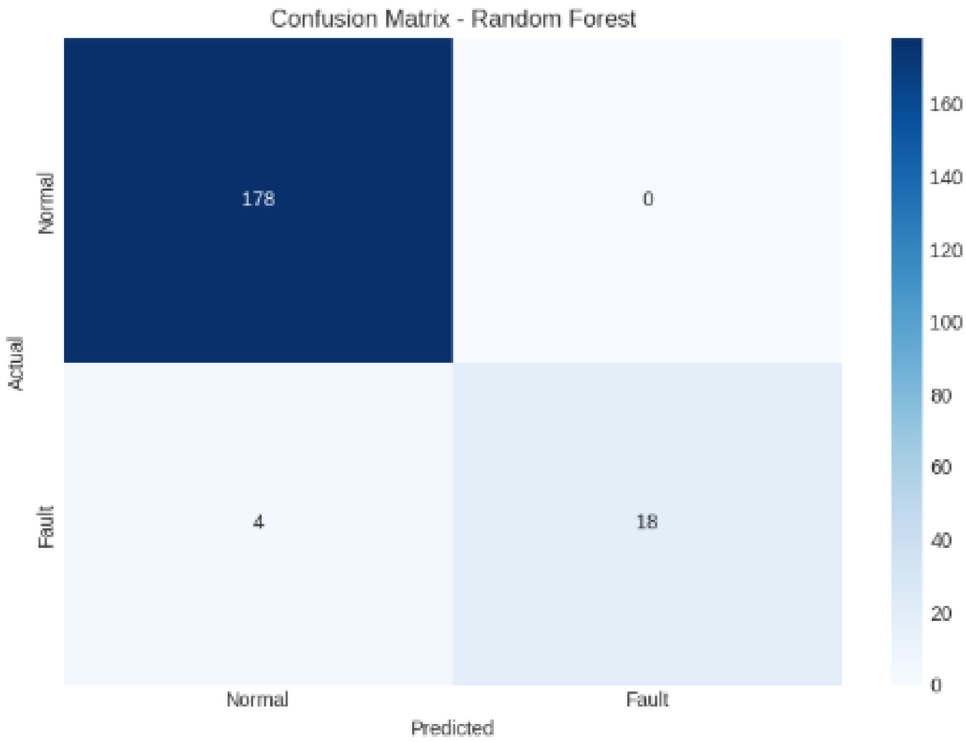

Figure 4.2: Confusion Matrix for Random Forest Model

The confusion matrix in Figure 4.2 shows the classification outcomes of the Random Forest model for normal and fault conditions. The model correctly identifies the majority of normal samples while accurately detecting most fault instances, resulting in very few misclassifications. The low number of false negatives demonstrates the model's effectiveness in minimizing missed fault events, which is critical for maintaining grid reliability and operational safety. Additionally, the near-zero false positive rate reduces unnecessary alarms, making the Random Forest model highly suitable for real-time deployment in smart grid terminal systems.

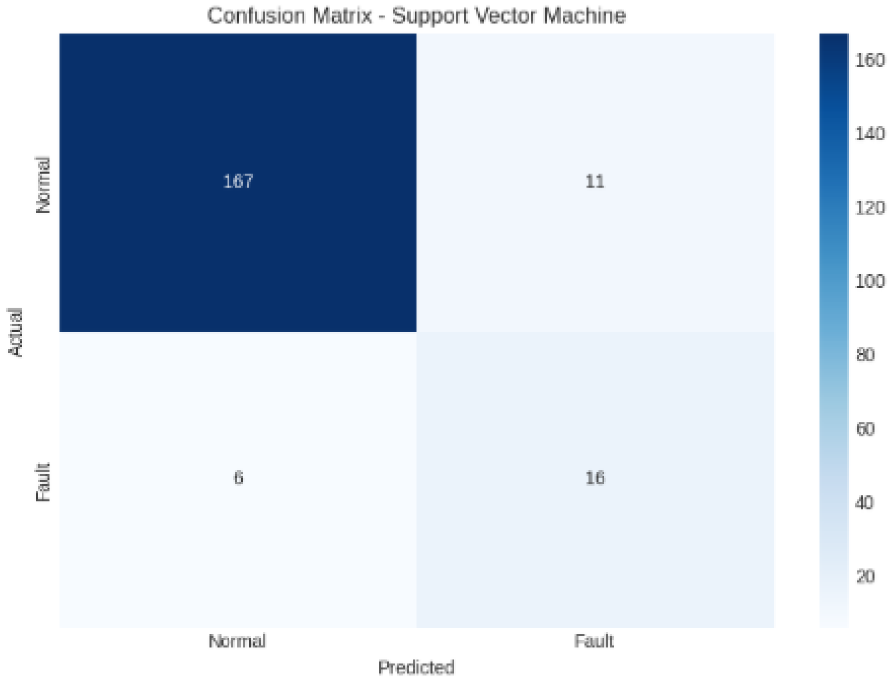

Figure 4.3: Confusion Matrix for Support Vector Machine Model

Figure 4.3 depicts the confusion matrix for the Support Vector Machine model, highlighting its classification performance across normal and fault states. While the SVM correctly classifies a large proportion of normal operating conditions, it exhibits a higher number of misclassified fault samples compared to the Random Forest model. This results in increased false negatives, which may pose a risk in safety-critical smart grid environments. Nonetheless, the model maintains reasonable fault detection accuracy, demonstrating its capability to model complex decision boundaries, albeit with slightly reduced reliability when compared to ensemble-based approaches.

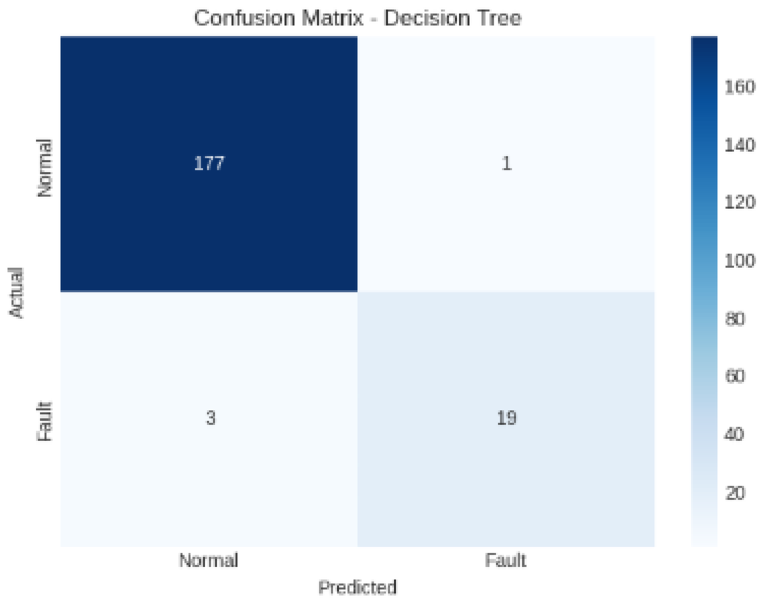

Figure 4.4: Confusion Matrix for Decision Tree Model

Figure 4.4 presents the confusion matrix for the Decision Tree classifier applied to smart grid fault detection. The model correctly classifies the majority of normal operating conditions, with only a single normal instance misclassified as a fault, indicating a very low false positive rate. Additionally, most fault samples are accurately detected, resulting in a small number of false negatives. This balanced performance reflects the Decision Tree's ability to learn interpretable decision rules that capture nonlinear relationships among grid parameters. However, the presence of a few misclassifications suggests potential sensitivity to data variability, which may affect robustness under unseen operating conditions.

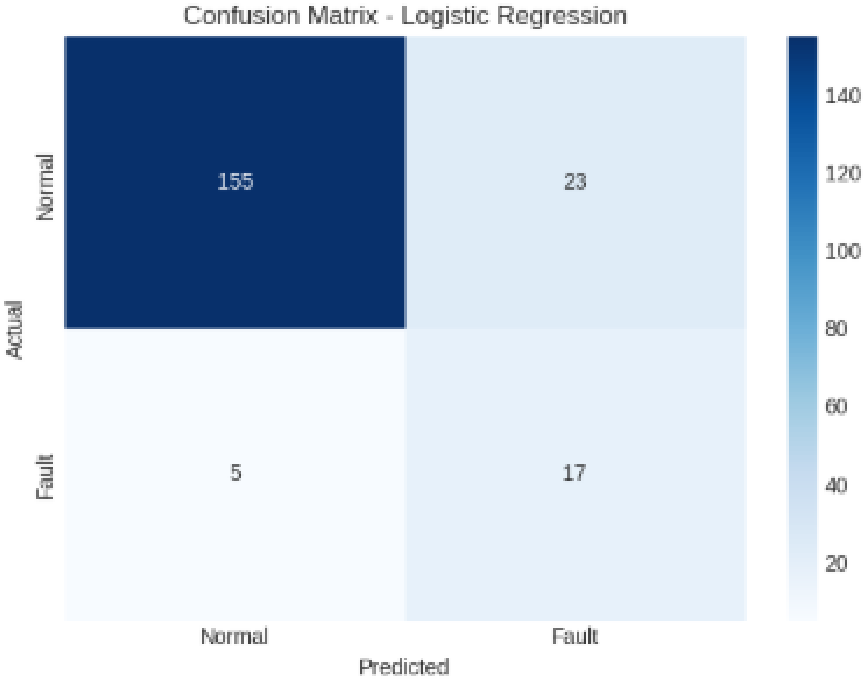

Figure 4.5: Confusion Matrix for Logistic Regression Model

Figure 4.5 illustrates the confusion matrix for the Logistic Regression model, highlighting its comparatively weaker fault discrimination capability. Although the model correctly identifies a large portion of normal samples, it misclassifies a notable number of normal conditions as faults, leading to an increased false positive rate. Several fault instances are incorrectly labeled as normal, indicating reduced sensitivity to fault events. This behavior reflects the limitations of linear decision boundaries in capturing the complex, nonlinear dynamics inherent in smart grid terminal systems. Consequently, while Logistic Regression serves as a useful baseline model, its performance may be insufficient for safety-critical fault detection applications.

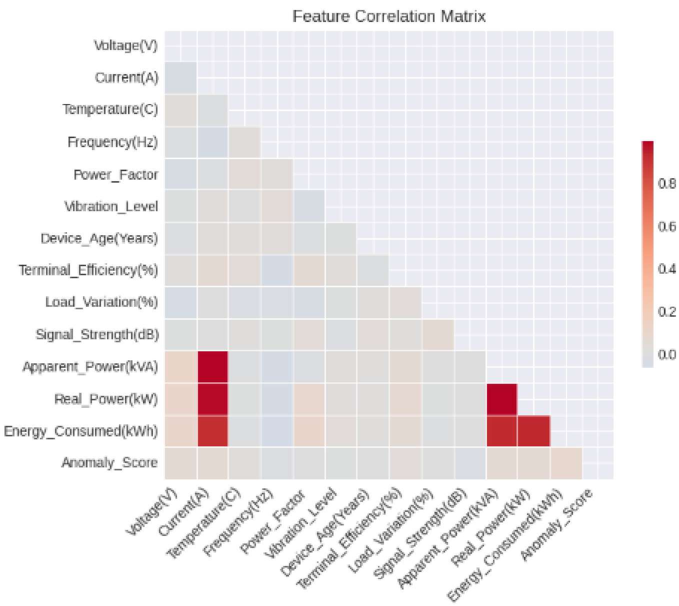

Figure 4.6: Feature Correlation Matrix of Smart Grid Parameters

Figure 4.6 presents the correlation matrix illustrating the linear relationships among the electrical, operational, and performance-related features employed in this study. Strong positive correlations are observed between Apparent Power (kVA), Real Power (kW), and Energy Consumed (kWh), which is consistent with their inherent physical interdependence in power system operations. Moderate correlations are also evident among voltage, current, and power factor, reflecting their joint influence on system performance and stability. Conversely, parameters such as device age, vibration level, and signal strength exhibit weaker correlations with the core electrical variables, indicating that they contribute complementary and non-redundant information. This balanced mix of correlated and weakly correlated features is advantageous for supervised learning, as it mitigates multicollinearity while preserving diverse patterns essential for accurate fault detection and anomaly classification.

Figure 4.7: Model Training Time Comparison Across Machine Learning Algorithms

Figure 4.7 compares the training time of the evaluated machine learning models, highlighting notable differences in computational efficiency. Logistic Regression and Decision Tree models demonstrate the shortest training times, making them suitable for deployment in real-time or resource-constrained smart grid environments. In contrast, the Support Vector Machine requires longer training time due to the complexity of kernel-based optimization in high-dimensional feature spaces. The Random Forest model exhibits the highest training time, reflecting its ensemble-based architecture in which multiple decision trees are trained to enhance robustness and predictive accuracy. Although computationally more demanding, the increased training cost of ensemble models is often justified by superior performance and generalization capability, underscoring the trade-off between computational efficiency and fault detection accuracy in smart grid applications.

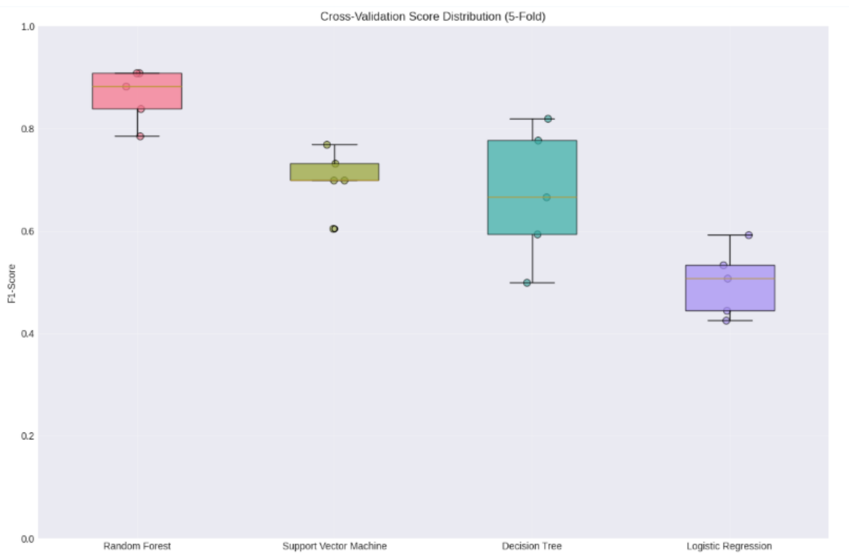

Figure 4.8: Cross-Validation F1-Score Distribution Across Machine Learning Models

Figure 4.8 illustrates the distribution of F1-scores obtained from a 5-fold cross-validation process, providing insight into the consistency and generalization capability of the evaluated machine learning models. The Random Forest model achieves the highest median F1-score with a relatively narrow interquartile range, indicating both strong predictive performance and high stability across different validation folds. This result confirms the effectiveness of ensemble learning in capturing complex and nonlinear patterns in smart grid data while maintaining robustness to variations in training samples. The Support Vector Machine also demonstrates competitive performance with moderate variability, reflecting reliable generalization, although its overall effectiveness remains slightly lower than that of the Random Forest model.

In contrast, the Decision Tree model exhibits a wider dispersion of F1-scores across the folds, highlighting its sensitivity to data partitioning and increased susceptibility to overfitting. Logistic Regression records the lowest median F1-score with comparatively limited variability, suggesting consistent yet weaker performance due to its linear decision boundary, which restricts its ability to model complex relationships within the dataset. Overall, the cross-validation results underscore that ensemble-based and kernel-based models provide superior robustness and detection capability for intrusion and anomaly detection tasks, whereas simpler linear models offer computational efficiency and interpretability at the expense of predictive power.

V CONCLUSION

This study presented a comprehensive evaluation of supervised machine learning models for intrusion and anomaly detection in smart grid terminal systems. By leveraging electrical, operational, and device-level features, the models were trained and tested under consistent experimental conditions to ensure fair comparison and reliable performance assessment. The results demonstrate that ensemble-based models, particularly Random Forest, consistently outperform simpler classifiers in terms of accuracy, precision, recall, F1-score, and cross-validation stability. These findings confirm that incorporating diverse feature sets and nonlinear learning capabilities significantly enhances the detection of abnormal and malicious activities within complex smart grid environments.
Furthermore, the comparative analysis revealed important trade-offs between predictive performance and computational efficiency. While Logistic Regression and Decision Tree models exhibited faster training times and easier interpretability, their limited ability to capture complex patterns reduced their effectiveness in high-dimensional and dynamic grid scenarios. In contrast, Support Vector Machines and Random Forest models achieved superior generalization and robustness, albeit at higher computational cost. Overall, the results align closely with the study's objectives by providing empirical evidence that carefully selected supervised learning techniques can substantially improve the reliability, security, and operational awareness of modern smart grid infrastructures.

VI RECOMMENDATIONS

Based on the findings of this research, it is recommended that power utilities and smart grid operators prioritize the adoption of ensemble-based machine learning models, particularly Random Forest, due to their demonstrated superiority in accuracy, robustness, and resistance to overfitting in fault and anomaly detection tasks. Future implementations should emphasize the integration of diverse feature sets combining electrical, operational, and device-health parameters to enhance detection performance while reducing multicollinearity and information redundancy. For real-time or resource-constrained deployment scenarios, hybrid detection frameworks that utilize lightweight models for preliminary screening and more advanced models for detailed analysis are advised to balance efficiency and accuracy. Additionally, further validation of the proposed framework using larger, real-world smart grid datasets encompassing broader fault and attack scenarios is essential to assess scalability and generalization. Finally, seamless integration of machine learning-based detection systems with existing smart grid monitoring and control infrastructures is strongly recommended to enable automated responses, early warning mechanisms, and improved operational decision-making.

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