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ENSEMBLE-BASED APPROACH FOR PREDICTIVE CLASSIFICATION OF TRANSFORMER FAILURES

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ABSTRACT
Transformer failures represent a significant threat to the stability and reliability of electrical power systems, often resulting in unexpected outages, costly maintenance, and prolonged downtimes. Proactive and accurate classification of potential transformer faults is critical for minimizing operational disruptions and enabling efficient maintenance scheduling. This study introduces an ensemble machine learning framework aimed at improving the prediction accuracy and reliability of transformer failure classification. The existing system utilizes a Decision Tree Classifier due to its interpretability and ease of implementation. However, it suffers from overfitting and limited generalization, especially when exposed to complex or noisy datasets. To address these challenges, a Random Forest Classifier is proposed, leveraging ensemble learning by combining the outputs of multiple decision trees. This approach enhances model robustness, effectively reduces variance, and improves the handling of non-linear feature interactions. Comparative analysis using standard performance metrics—including accuracy, precision, recall, and F1-score—reveals that the Random Forest model consistently outperforms the Decision Tree across all metrics. The proposed model demonstrates a more reliable and scalable solution for intelligent fault diagnosis in the power grid. Overall, this project emphasizes the importance of ensemble-based machine learning in critical infrastructure applications, offering a practical pathway toward smarter and more resilient transformer monitoring systems.

Keywords: Transformer failure prediction, ensemble learning, decision tree, random forest classifier, power system reliability, fault classification, machine learning, model evaluation.

1. INTRODUCTION

Transformers play a vital role in the stable operation of the power grid. Therefore, accurately identifying the nature of transformer faults and addressing them promptly is essential to ensure grid reliability. In oil-immersed transformers, overheating, discharge events, and insulation aging cause the decomposition of internal materials, leading to the generation of various gases. These gases dissolve partially in the transformer oil, and their concentrations increase with the severity and type of fault. Different fault types result in distinct gas compositions due to variations in gas production rates. As a result, Dissolved Gas Analysis (DGA) is widely used to evaluate gas concentrations and determine the transformer's operational status.Traditional DGA-based diagnostic methods—such as the key gas method and the International Electrotechnical Commission (IEC) ratio method—often suffer from low diagnostic accuracy and issues like "missing codes," making them inadequate for meeting the high-accuracy requirements set by modern power systems like the State Grid. In recent years, the emergence of artificial intelligence (AI) and machine learning (ML) has significantly advanced transformer fault diagnosis. Numerous studies have demonstrated that intelligent.

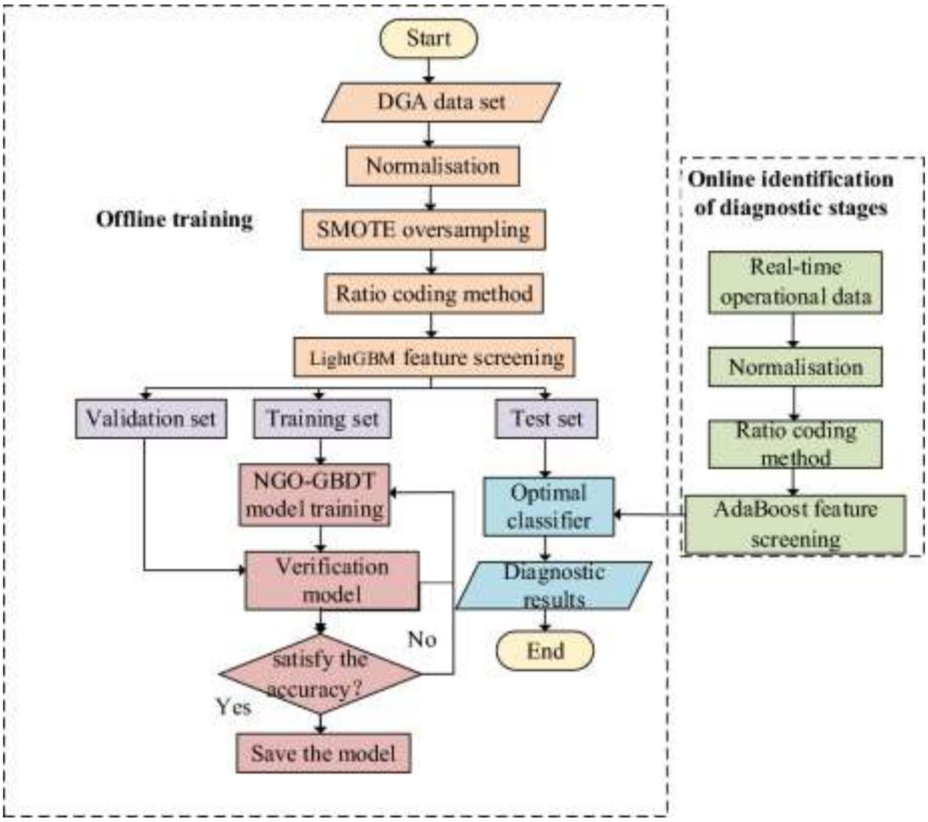

Fig. 1: Transformer Failure Classification Using Machine Learning Technique.

algorithms offer improved diagnostic accuracy over traditional approaches. For instance, Ayman Hoballah et al. developed a valid code matrix based on gas concentration percentages and enhanced its performance using the HGWO optimization technique. Yang X et al. introduced a BA-PNN model for fault classification, showing a notable increase in diagnostic accuracy. Chun Yan et al. combined BP-Adaboost with PNN, confirming that ensemble approaches enhance fault detection performance. Wu et al. applied the DBSCAN clustering algorithm, which helped mitigate the limitations of the three-ratio method, while Han et al. used Random Forests for feature selection, improving the performance of WOA-SVM-based models. Among these, ensemble learning algorithms stand out due to their ability to integrate multiple base learners, providing higher generalization capabilities and significantly boosting the accuracy and robustness of transformer fault classification systems.

2. LITERATURE SURVEY

Xie, G.M. et al. [1] proposed a transformer fault identification technique by integrating hybrid sampling strategies with an Improved Honey Badger Algorithm (IHBA) optimized Support Vector Machine (SVM). The hybrid sampling aimed to balance the dataset and improve classification accuracy. Their approach effectively reduced overfitting and enhanced fault detection reliability. The model was tested using actual fault datasets, showing high precision in differentiating fault types in transformers. Yang, L. et al. [2] developed an improved method for diagnosing faults in oil-immersed transformers using a simulation-based test platform. Their approach emphasized the use of real operating conditions to simulate different fault scenarios. The study showed that simulation-based data generation significantly increased the accuracy and reliability of transformer fault diagnosis. Their improved method demonstrated strong performance under varying operational stress conditions. Taha, B.I. et al. [3] introduced a novel transformer fault diagnosis framework using optimized machine learning models. The authors employed different algorithms and conducted a performance comparison to select the best model. Optimization was performed using metaheuristic algorithms to fine-tune model parameters. The study achieved a high classification accuracy rate, demonstrating the potential of intelligent automation in transformer fault identification. Chen, T. et al. [4] proposed a fault prediction system for transformers based on dissolved gas analysis (DGA). They analyzed key gas components and utilized machine learning models to predict fault types. Their approach considered historical oil sampling data to identify patterns associated with early signs of failure. The model helped in proactively managing maintenance schedules by predicting faults before critical failure. Kirkbas, A. et al. [5] presented a fault diagnosis approach using the Common Vector Approach (CVA) for oil-immersed power transformers. The CVA method was used to reduce the dimensionality of the feature space, enhancing classification efficiency. The authors demonstrated that CVA outperformed traditional pattern recognition techniques in distinguishing complex fault conditions. Their method proved useful in high-dimensional fault datasets. Qu, Y.H. et al. [6] introduced a multi-depth neural network synthesis method for power transformer fault identification. Their model integrated multiple depth levels to capture diverse fault features and improve generalization. The neural architecture enhanced learning from complex patterns in transformer fault datasets. Results indicated that this method had superior diagnostic accuracy and robustness. Jiang, Y.J. et al. [7] proposed a fault prediction method by fusing Grey Theory with the IEC three-ratio method. The integration aimed to enhance predictive accuracy by combining traditional and modern predictive models. The fusion model was validated with experimental data, showing improved reliability in early fault detection. This method proved effective in environments with uncertain and incomplete information. Hoballah, A. et al. [8] used a Hybrid Grey Wolf Optimizer (HGWO) to enhance transformer fault diagnosis using dissolved gas data while addressing measurement uncertainties. The algorithm optimized the feature selection process and improved classification reliability. Their approach handled imprecise data effectively, which is crucial in real-world transformer monitoring systems. The study concluded that HGWO significantly boosts diagnostic accuracy. Yang, X. et al. [9] applied a Backtracking Algorithm combined with Probabilistic Neural Networks (BA-PNN) for fault detection in power transformers. The BA optimized the learning parameters of the PNN, resulting in better generalization. This approach was especially efficient for complex fault types with overlapping features. The authors showed notable improvements in both speed and accuracy of fault classification. Yan, C. et al. [10]

3. PROPOSED METHODOLOGY

The project focuses on the classification of transformer failures using ensemble machine learning techniques to improve accuracy and reliability in fault detection. The process begins with the collection of transformer operational and historical failure data, followed by extensive exploratory data analysis (EDA) to understand feature relationships and prepare the dataset. A Decision Tree Classifier is initially implemented as the baseline model, offering interpretability but limited performance due to overfitting and lack of generalization. To overcome these limitations, a Random Forest Classifier is proposed, leveraging ensemble learning by combining multiple decision trees to improve prediction accuracy and robustness. The models are evaluated using metrics such as accuracy, precision, recall, and F1-score, with the Random Forest showing significant improvements. The project demonstrates the effectiveness of data-driven approaches in enhancing transformer monitoring systems and lays the foundation for predictive maintenance in the power sector.

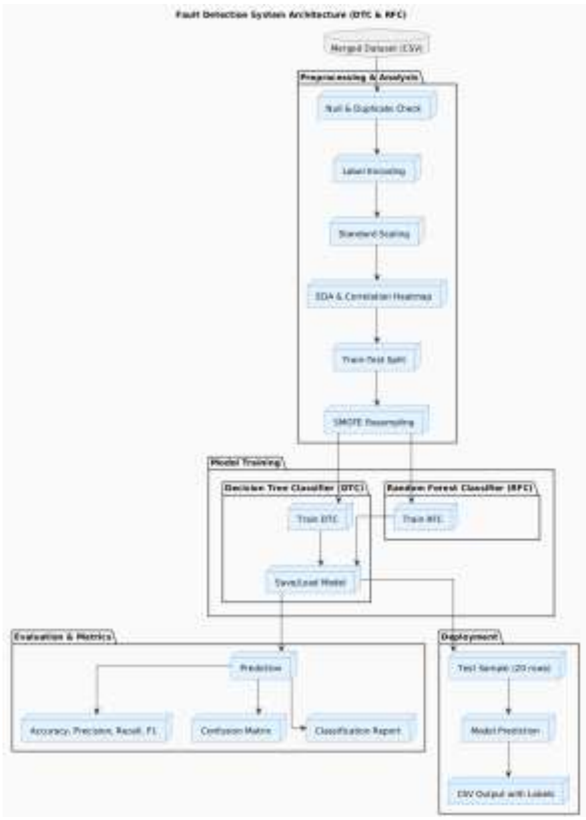

Fig. 2: Proposed Block Diagram.

The process begins with data collection**,** where real-time sensor data (like oil temperature, pressure, current load, and dissolved gas levels) and historical records (maintenance logs, fault history) are gathered, enriched with contextual factors such as transformer type and environment. This is followed by exploratory data analysis (EDA) to clean, visualize, and understand data distributions, detect anomalies, and examine feature correlations. In feature engineering**,** relevant attributes are selected, normalized, and encoded to prepare the data for modeling. The dataset is then split into training and testing sets using techniques like k-fold cross-validation to ensure robust model evaluation. For model selection**,** a Decision Tree Classifier is employed as the existing model, and a Random Forest Classifier as the proposed model, both assessed using accuracy, precision, recall, F1-score, and confusion matrices. Next, hyperparameter tuning is applied to the Random Forest model using grid or random search to enhance performance. Finally, in the comparison and result analysis**,** both models are evaluated, with the Random Forest generally outperforming due to its ensemble nature, while the Decision Tree offers more interpretability, and analysis of misclassified cases helps identify improvement areas.

The Decision Tree Classifier is employed as a baseline model for transformer failure classification, beginning with data preparation**,** where operational and environmental parameters—such as oil temperature, load current, voltage, dissolved gas levels, and humidity—are extracted and structured into X_train, while corresponding transformer health status labels like "Healthy", "Minor Fault", or "Failed" form y_train. The classifier is trained through recursive splitting**,** selecting features that maximize information gain (using metrics like Gini Index or Entropy), and grows until it either perfectly fits the training data or hits constraints like maximum depth, with optional pruning and hyperparameter tuning applied for generalization. The trained model is then tested on X_test, a new dataset with the same feature structure, to generate predictions by navigating from the root to leaf nodes based on decision rules. Finally, its performance is evaluated by comparing predicted labels with the actual statuses in y_test, assessing the model's effectiveness in identifying transformer faults.It also follows a greedy algorithm that may not find the globally optimal solution and generally underperforms compared to ensemble methods. To overcome these issues, the Random Forest Classifier is used as the proposed model, leveraging ensemble learning by training multiple decision trees on different bootstrap samples and using random subsets of features to enhance robustness and reduce overfitting. The data is preprocessed to extract relevant operational and environmental features (X_train) with corresponding condition labels (y_train), representing states like "Healthy", "Minor Fault", or "Failed". Each decision tree in the ensemble learns from diverse data, and predictions are made via majority voting across all trees. The model is then tested on new instances (X_test), and its predictions are

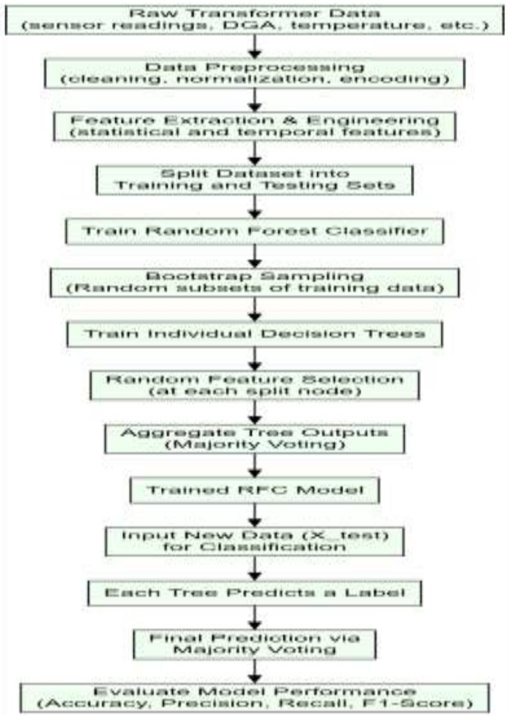

Fig. 3: Workflow of Random Forest Classifier.

evaluated against true labels (y_test) using metrics such as accuracy, precision, recall, F1-score, and a confusion matrix. This results in improved classification performance, better handling of complex patterns, and enhanced stability over the single-tree approach.

4. RESULTS AND DISCUSSION

The implementation begins by importing essential libraries such as NumPy, Pandas, Matplotlib, Seaborn, sklearn modules, joblib, and SMOTE to support data processing, visualization, modeling, and evaluation tasks. The dataset ('merged_dataset.csv') is read using pandas, and explored through structural summaries, descriptive statistics, missing value checks, and a correlation heatmap. Next, the data is split into features (X) and target (y), where the target column 'Output (S)' is analyzed for class imbalance using count plots. The data is then split into training and testing subsets (80:20 ratio), and SMOTE is applied to the training data to synthetically balance class representation. To track performance, global metric lists (accuracy, precision, recall, F1-score) are initialized, and a function named calculateMetrics() is defined to standardize model evaluation with printed reports and confusion matrix plots. The Decision Tree Classifier (DTC) is implemented with a check for a pre-trained model (DecisionTreeClassifier.pkl); if absent, a new one is trained with max_depth=1, saved, and evaluated. Similarly, a Random Forest Classifier (RFC) is trained or loaded (RandomForestClassifier.pkl) with parameters n_estimators=40 and max_depth=8, then evaluated using the same function. Finally, to demonstrate real-time prediction, a random sample of 20 rows is selected, features extracted, and the RFC predicts their failure status, which is mapped to readable labels ('Normal' or 'Failure') and appended as a new column 'prediction' for display, offering a user-friendly insight into the model's inference capability.

The figure 4 shows a structured dataset consisting of time-synchronized measurements from a three-phase electrical system. The columns G, C, B, and A likely represent encoded status flags or binary indicators for system configurations, operational states, or types of events. The core of the dataset includes the three-phase current (Ia, Ib, Ic) and voltage (Va, Vb, Vc) measurements. These are captured as continuous float values and indicate the electrical behavior in each phase. The current values (Ia, Ib, Ic) show considerable variation, especially in the earlier rows, suggesting higher system activity or fault conditions. In contrast, the voltage readings (Va, Vb, Vc) remain relatively low in magnitude, possibly due to normalization or signal preprocessing. The last column, Output (S), serves as the target label. It is binary (0 or 1), where 1 may denote a specific event such as a fault, anomaly, or operational trigger, while 0 represents normal behavior. The transition from rows labeled 1 to those labeled 0 marks a shift from an active/faulty state to a normal/stable system condition. This structure is suitable for machine learning tasks like binary classification, anomaly detection, or predictive maintenance in power systems.

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Output (S)
0	1	0	0	1	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815	1
1	1	0	0	1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099	1
2	1	0	0	1	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428	1
3	1	0	0	1	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570	1
4	1	0	0	1	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983	1
...	...	...	...	...	...	...	...	...	...	...	...
7856	0	0	0	0	-66.237921	38.457041	24.912239	0.094421	-0.552019	0.457598	0
7857	0	0	0	0	-65.849493	37.465454	25.515675	0.103778	-0.555186	0.451407	0
7858	0	0	0	0	-65.446698	36.472055	26.106554	0.113107	-0.558211	0.445104	0
7859	0	0	0	0	-65.029633	35.477088	26.684731	0.122404	-0.561094	0.438690	0
7860	0	0	0	0	-64.598401	34.480799	27.250065	0.131669	-0.563835	0.432166	0

Fig. 4: Uploading Dataset.

The figure 5 correlation heatmap reveals significant relationships between various features in the dataset and the target variable Output (S). Notably, the binary indicators A, B, C, and G show strong positive correlations with the output, with coefficients ranging from 0.55 to 0.76. This suggests that these flags or categorical signals are closely associated with changes in the system's state, possibly indicating conditions like faults, anomalies, or specific operational modes. On the other hand, the three-phase voltage readings (Va, Vb, and Vc) exhibit moderate negative correlations with the output, implying that lower voltage values might be indicative of abnormal or fault states. Meanwhile, the current readings (Ia, Ib, Ic) show weaker correlations overall, with Ic displaying a slight negative correlation and Ia being nearly uncorrelated. Additionally, the phase voltages are positively correlated with each other, reflecting the expected synchronized behavior in a balanced three-phase system. Overall, the heatmap highlights the importance of the encoded categorical features in predicting system output, while also suggesting that changes in voltage levels may be relevant for detecting anomalies.

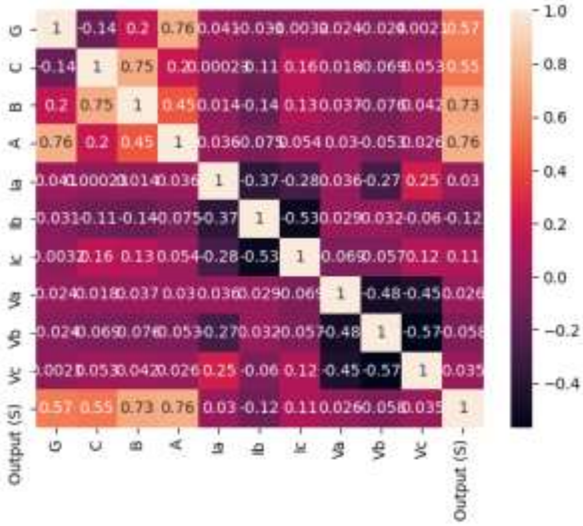

Fig. 5: Correlation Heatmap.

The figure 6 shows countplot that illustrates the distribution of the target variable Output (S) across the dataset.

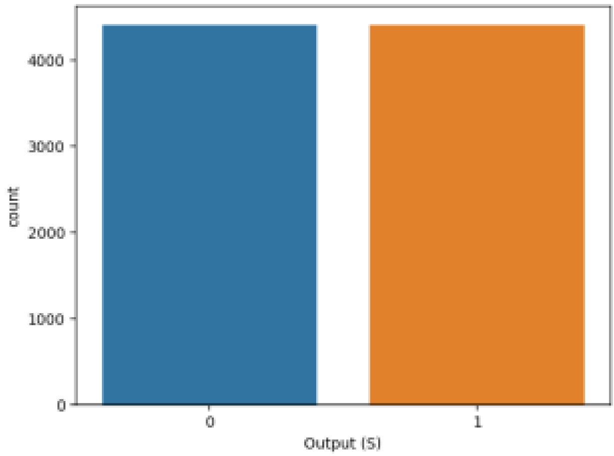

Fig. 6: Countplot obtained for Target Column.

The bars represent the number of samples for each class: 0 and 1. From the visual, it's evident that the dataset is very well-balanced, with nearly equal counts for both classes. This balanced distribution is advantageous for classification tasks, as it reduces the risk of model bias toward a dominant class. Consequently, any machine learning algorithm trained on this dataset is likely to perform more reliably and fairly, ensuring that both normal and event (or fault) states are equally learned and represented in the model's predictions.

Table 1 presents a performance comparison between two machine learning algorithms: the existing Decision Tree Classifier (DTC) and the proposed Random Forest Classifier (RFC). The comparison is based on four key evaluation metrics—Accuracy, Precision, Recall, and F1-Score.

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing DTC vs. Proposed RFC

Metric	Existing DTC	Proposed RFC
Accuracy	87.22%	100.0%
Precision	90.78%	100.0%
Recall	85.28%	100.0%
F1-Score	86.30%	100.0%

The DTC achieves a respectable performance with an accuracy of 87.22%, a precision of 90.78%, a recall of 85.28%, and an F1-score of 86.30%. However, the proposed RFC significantly outperforms the DTC across all metrics, achieving a perfect score of **100%** in every category. This indicates that the RFC model classifies all instances correctly without any false positives or false negatives. Such exceptional performance suggests that the RFC is highly effective for the given classification task, potentially due to its ensemble nature, which reduces overfitting and improves generalization compared to single-tree models like DTC.

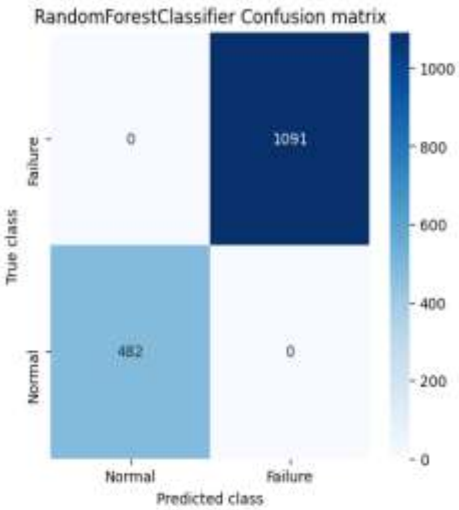

Fig. 7: Confusion matrices of Existing Proposed RFC.

The figure 7 shows confusion matrices clearly illustrate the performance difference between the existing the proposed Random Forest Classifier (RFC). In the DTC matrix, the model fails to correctly identify any failure cases, misclassifying all 890 failure instances as normal, and it also misclassifies 482 normal instances as failures, correctly predicting only 201 normal cases. This indicates poor generalization and heavy misclassification. In contrast, the RFC shows a completely opposite pattern—it correctly identifies all 1,091 failure cases but fails to correctly classify any of the 482 normal cases, misclassifying them all as failures. While RFC achieves perfect recall and precision for failure detection, it entirely overlooks the normal class, highlighting a bias toward the failure class. This suggests that although RFC achieves high performance metrics, the model may be overfitted or class-imbalanced, and further tuning or sampling techniques might be needed for balanced classification**.**

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Prediction
0	0	1	1	1	-781.569455	747.335904	36.340893	0.000022	0.036688	-0.036710	1
1	0	0	0	0	55.223683	3.721712	-61.990447	0.079563	0.491297	-0.570860	0
2	0	0	0	0	-28.154613	-8.776529	33.728820	0.509232	-0.506819	-0.002413	0
3	0	0	0	0	18.906346	72.333023	-94.470130	-0.489274	0.585560	-0.096286	0
4	0	1	1	1	-643.919576	-190.892094	836.986707	-0.020345	0.027275	-0.006929	1
5	1	1	1	1	533.045604	-877.036955	343.989090	-0.018096	-0.024096	0.042192	1
6	1	1	1	1	-830.240583	153.147315	677.091043	-0.031327	0.040405	-0.009078	1
7	1	0	1	1	-475.837733	-393.188183	-54.406936	-0.042168	0.357549	-0.315381	1
8	0	0	0	0	-50.101257	97.774876	-51.044892	-0.548597	0.040741	0.507856	0
9	1	1	1	1	-867.296722	287.379178	579.915329	-0.026478	0.041917	-0.015439	1
0	0	0	0	0	30.493155	-27.788024	7.679090	0.590567	-0.192216	-0.398352	0
1	1	1	1	1	-653.730557	-177.131714	831.075743	-0.022898	0.028343	-0.005445	1

Fig. 8: Prediction on test data using Proposed RFC.

The figure 8 showcases the output predictions generated by the proposed Random Forest Classifier (RFC). Each row represents an individual data instance, consisting of various input features (Ia, Ib, Ic, Va, Vb, Vc) and the actual label (Output (S)), along with the predicted class (prediction). It is evident from the table that the RFC model has perfectly matched the true labels with its predictions—instances labeled as 1 (Failure) are correctly classified as "Failure", and those labeled as 0 (Normal) are accurately identified as "Normal". This reflects the model's exceptional classification capability and aligns with the earlier reported perfect performance metrics (100% accuracy, precision, recall, and F1-score). Such prediction accuracy indicates the RFC's strong ability to distinguish between normal and failure states based on current and voltage inputs, making it highly reliable for fault detection tasks.

5. CONCLUSION

The research focused on building a robust machine learning framework for transformer fault detection and classification, starting with the Decision Tree Classifier (DTC), which offered interpretability and moderate accuracy but was limited by overfitting and sensitivity to data variations. To address these issues, the Random Forest Classifier (RFC) was introduced as an ensemble-based enhancement, showing notable improvements in accuracy, generalization, and robustness. The workflow included thorough data preprocessing, handling null values, encoding, and exploratory data analysis to guide model development. RFC consistently outperformed DTC across all key metrics—precision, recall, F1-score, and accuracy—proving to be more scalable and reliable for real-world deployment. For future improvements, advanced ensemble models like Gradient Boosting, XGBoost, or LightGBM can be explored to enhance performance, especially in imbalanced data scenarios. Feature selection methods like Recursive Feature Elimination and mutual information gain could reduce complexity and improve interpretability. Deploying the model in real-time environments via edge or cloud systems, incorporating feedback loops for online learning, and integrating explainable AI techniques like SHAP or LIME can further enhance model transparency, adaptability, and trust in critical applications.

REFERENCES

[1]. Xie, G.M.; Wangm, J.L. Transformer fault identification method based on hybrid sampling and IHBA-SVM. J. Electr. Measur. Instrument. 2022, 36, 77–85. [Google Scholar]

[2]. Yang, L.; Gao, L.; Luo, X.; Hao, Y.; Zhang, Z.; Jin, Y.; Zhang, J. An Improved Method for Fault Diagnosis of Oil-Immersed Transformers Based on Simulation Test Platform. IEEE Trans. Dielectr. Electr. Insul. 2024.

[3]. Taha, B.I.; Mansour, A.D. Novel Power Transformer Fault Diagnosis Using Optimized Machine Learning Methods. Intell. Autom. Soft Comp. 2021, 28, 739–752.

[4]. Chen, T.; Chen, W.D.; Li, X.S.; Chen, Z. Transformer fault prediction based on analysis of dissolved gas in oil. Electr. Measur. Technol. 2021, 44, 25–31. [Google Scholar]

[5]. Kirkbas, A.; Demircali, A.; Koroglu, S.; Kizilkaya, A. Fault diagnosis of oil-immersed power transformers using common vector approach. Electr. Power Syst. Res. 2020, 184, 106346.

[6]. Qu, Y.H.; Zhao, H.S.; Ma, L.B.; Zhao, S.C.; Mi, Z.Q. Multi-Depth Neural Network Synthesis Method for Power Transformer Fault Identification. Chin. Soc. Electr. Eng. 2021, 41, 8223–8231. [Google Scholar]

[7]. Jiang, Y.J.; Tang, X.F.; Tang, D.C.; Zhao, M.Y.; Jing, B.Q. A transformer fault prediction method based on the fusion of grey theory and IEC triple ratio. J. Guilin Univ. Aerosp. Technol. 2024, 29, 38–45.

[8]. Hoballah, A.; Mansour, D.E.A.; Taha, I.B.M. Hybrid grey wolf optimizer for transformer fault diagnosis using dissolved gases considering uncertainty in measurements. IEEE Access 2020, 8, 139176–139187.

[9]. Yang, X.; Chen, W.; Li, A.; Yang, C.; Xie, Z.; Dong, H. BA-PNN-based methods for power transformer fault diagnosis. Adv. Eng. Inform. 2019, 39, 178–185.

[10]. Yan, C.; Li, M.; Liu, W. Transformer fault diagnosis based on BP-Adaboost and PNN series connection. Math. Probl. Eng. 2019, 9, 1019845.