Hybrid Random Forest and Long Short-Term Memory Based Transformer Fault Diagnostics and Prognostics

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Abstract- This research presents the development and evaluation of a hybrid approach combining Random Forests (RF) and Long Short-Term Memory (LSTM) neural networks for transformer fault diagnostics and prognostics. The study aimed to leverage RF's capability in handling complex, high-dimensional data and LSTM's strength in capturing temporal dependencies to create a more robust and accurate system. The methodology involved comprehensive exploratory data analysis, individual implementation of RF and LSTM models, and their integration through both weighted average and stacked ensemble approaches. The results demonstrated that while the RF model achieved perfect classification accuracy (1.0000) and exceptional prognostic performance (R^2 = 0.9996, RMSE = 0.0189), the LSTM model showed strong classification capabilities (0.9656) but struggled with remaining useful life (RUL) prediction (R^2 = -30.0272). The final stacked ensemble hybrid model successfully combined the strengths of both approaches, achieving a fault classification accuracy of 0.940909 and remarkable RUL prediction metrics (R^2 = 0.999633, MAE = 4.807955 days). This performance significantly surpassed existing approaches in the field, including fuzzy-neural networks and PSO-optimised LSTM networks. The hybrid model demonstrated particular effectiveness in handling the unique challenges of the Nigerian power infrastructure, offering superior performance compared to previous models specifically developed for this context. The research concludes that the stacked ensemble architecture provides a comprehensive solution for transformer health management, successfully balancing high accuracy, computational efficiency, and interpretability. These findings have significant implications for practical maintenance planning and decision-making in power transformer operations.

Indexed Terms- Random Forest (RF), Long Short Time Memory (LSTM), Artificial Neural Network (ANN), Direct Current (DC), Remaining Useful Life (RUL), Particle Swam Optimization (PSO)

I. INTRODUCTION

Transformers are critical assets in the transmission and distribution network, ensuring the efficient delivery of electricity to consumers. Their reliable operation is paramount for maintaining grid stability and preventing widespread power outages. However, transformers are susceptible to various internal faults that can significantly degrade their performance and lead to catastrophic failures. Early and accurate fault diagnosis is crucial for implementing corrective actions, minimizing downtime, and ensuring the longevity of these vital assets [1].

Conventional methods for transformer fault diagnosis primarily rely on Dissolved Gas Analysis (DGA) [2]. This technique involves analysing the composition and concentration of gases dissolved in the insulating oil within the transformer. Different fault types generate distinct gas signatures, allowing experienced engineers to identify the potential fault based on established reference guides [3]. However, DGA interpretation can be subjective and prone to errors, particularly for incipient faults with low gas generation or in situations with overlapping gas patterns from multiple fault types [4], [5].

Recent advancements in Artificial Intelligence (AI) offer promising avenues for enhancing power transformer fault diagnostics and prognostics. AI techniques excel at pattern recognition and data analysis, making them well-suited for extracting meaningful insights from complex DGA data and other sensor measurements [6]. Several researchers have explored the application of AI algorithms for transformer fault diagnosis and prognosis, achieving encouraging results.

Nigerian researchers have actively contributed to this field. Duan et al. [7] proposed a Support Vector Machine (SVM) based approach for transformer fault classification, demonstrating its effectiveness in identifying various fault types. Similarly, Adebayo et al. [8] investigated the use of Artificial Neural Networks (ANNs) for DGA interpretation, highlighting their potential for improving diagnostic accuracy. Ojo et al. [9] presented a Fuzzy Logic-based system for transformer fault diagnosis, emphasizing its ability to handle uncertainties associated with DGA data.

International research further emphasizes the potential of AI for transformer diagnostics and prognostics. Moradi-Gholshar et al. [10] explored a hybrid approach combining ANNs with Genetic Algorithms for optimal fault classification. Duan et al. [11] proposed a Deep Learning architecture for transformer fault diagnosis, showcasing its superior performance compared to traditional methods. Orji et al. [12] investigated the application of decision tree algorithms for DGA data analysis, demonstrating their effectiveness in handling complex fault scenarios.

As the field of AI-based transformer diagnostics has evolved, two particular algorithms have shown significant promise: Random Forests (RF) and Long Short-Term Memory (LSTM) networks. Random Forests, an ensemble learning method, have demonstrated robust performance in handling high-dimensional data and complex fault scenarios. Tang et al. [13] utilized Random Forests for transformer fault diagnosis, achieving high accuracy in classifying multiple fault types based on DGA data. The ability of Random Forests to handle non-linear relationships and provide feature importance rankings makes them particularly suitable for transformer fault analysis [14].

Concurrently, LSTM networks, a type of recurrent neural network, have shown exceptional capability in capturing temporal dependencies in time-series data, which is crucial for both fault diagnosis and prognosis. Zhang et al. [15] applied LSTM networks to predict transformer remaining useful life (RUL) based on historical operational data, demonstrating superior prognostic performance compared to traditional time-series analysis methods. The ability of LSTM to retain information over long periods makes it well-suited for capturing the slow degradation processes typical in power transformers [9].

The combination of Random Forests and LSTM networks presents a promising hybrid approach for comprehensive transformer fault diagnostics and prognostics. This hybrid model leverages the strengths of both algorithms: the robust classification capabilities of Random Forests and the temporal pattern recognition of LSTM networks. Wang et al. [15] explored a similar hybrid approach in the context of power system stability assessment, demonstrating improved accuracy and generalization compared to single-algorithm approaches.

RF-LSTM hybrid approach offers several advantages in transformer fault analysis. Random Forests can effectively handle the complex, high-dimensional feature space of transformer data, including DGA measurements, electrical parameters, and environmental factors. This allows for robust fault classification based on current and historical data. Simultaneously, the LSTM component can capture the temporal evolution of these parameters, enabling the model to detect subtle changes indicative of incipient faults and predict future fault probabilities [16].

Moreover, this hybrid approach addresses some of the limitations of traditional DGA interpretation methods. By learning from large datasets, the model can automatically identify complex patterns and relationships that might be missed by human experts or simple rule-based systems. The combination of RF and LSTM also allows for both snapshot analysis (using current data) and trend analysis (using historical data), providing a more comprehensive view of the transformer's health status [17].

This research aims to contribute to this evolving field by developing and evaluating a hybrid Random Forest-LSTM model for transformer fault diagnostics and prognostics. By combining these powerful algorithms, we seek to create a robust, accurate, and interpretable system that can enhance the reliability and longevity of transformers in the Nigerian electrical grid and beyond.

II. LITERATURE REVIEW

Transformer Fault Types and Analysis

Transformers are critical components in electrical power systems, and their reliable operation is essential for maintaining grid stability. The complexity of transformer faults necessitates a comprehensive understanding of their types, causes, and detection methods[18].

Winding Faults

Winding faults are among the most severe internal faults in power transformers. These faults can occur as turn-to-turn faults, winding-to-ground faults, or inter-winding faults. Turn-to-turn faults result from insulation breakdown between adjacent turns of a winding, often caused by electrical, thermal, or mechanical stresses[19]. The initial stages of these faults may involve only a few turns, making early detection challenging. However, if left unaddressed, they can quickly escalate to more severe faults involving multiple turns or even different windings [20].

Winding-to-ground faults occur when insulation between a winding and the grounded tank or core fails. These faults can be particularly dangerous as they often lead to high fault currents and potential transformer failure if not detected and isolated quickly [21]. Ojo et al. [22] emphasized that these faults can result from insulation breakdown due to aging, moisture ingress, or mechanical stress.

Inter-winding faults, involving short circuits between different windings, are less common but can cause severe damage due to the high voltages involved. Akande et al. (2021) noted that such faults can cause severe mechanical stresses and thermal damage. Detection of winding faults typically relies on a combination of electrical and chemical methods. Differential protection schemes are widely used for detecting severe winding faults, while incipient faults may be detected through dissolved gas analysis (DGA) or partial discharge monitoring [23].

Core Faults

Transformer core faults, while less common than winding faults, can significantly impact transformer efficiency and longevity. Core insulation failure, often resulting from manufacturing defects or long-term degradation, leads to increased eddy current losses and localized heating [24]. Liu et al.[25] discussed how this can result in accelerated aging of nearby insulation. Core bolt loosening is another type of core fault that can cause vibrations and potential short circuits between laminations. Duan et al. [11] pointed out that loose core bolts can cause vibrations and potential short circuits between laminations.

Shorted laminations, whether due to manufacturing defects or damage during transportation, result in localized heating and increased losses [26]. Detection of core faults often relies on indirect methods such as DGA, as direct access to the core is limited in sealed transformers. Frequency Response Analysis (FRA) has shown promise in detecting core problems by revealing changes in the transformer's electrical characteristics [27].

Insulation Faults

Insulation faults in power transformers can occur in both liquid and solid insulation systems. Oil degradation, a common issue in oil-filled transformers, results from oxidation, contamination, or overheating [28]. This degradation reduces the oil's insulating and cooling properties, potentially leading to more severe faults. Regular oil testing, including analysis of acidity, interfacial tension, and dielectric strength, is crucial for monitoring oil conditions [29].
Paper insulation deterioration, primarily driven by thermal stress and moisture, is a critical factor in transformer ageing. Ojo et al. (2023) emphasized that this is a critical factor in transformer ageing. The depolymerisation of cellulose insulation reduces its mechanical and dielectric strength, increasing the risk of electrical failures [30].

Moisture ingress, whether from the atmosphere or as a by-product of insulation ageing, significantly reduces the dielectric strength of the insulation system. It accelerates the ageing process and increases the risk of partial discharges and electrical breakdowns [31]. Detection of insulation faults relies heavily on chemical analysis techniques such as DGA and furan analysis. These methods can indicate the presence of insulation degradation products in the oil [32].

Tap Changer Faults

On-Load Tap Changers (OLTCs) are critical components in power transformers, allowing voltage regulation under load. However, their mechanical nature makes them prone to various faults. Moradi-Gholshar et al. (2020) highlighted that faults in tap changers can lead to arcing, contact wear, and potential failure of the tap changing mechanism. Contact wear, resulting from arcing during tap changes, is a common issue that can lead to increased contact resistance and potential failure [33]. Regular inspection and maintenance are crucial for mitigating this issue.

Mechanism failures in the tap changing system can result in incorrect tap positions or complete failure to change taps, potentially leading to voltage regulation problems in the power system [34]. Oil contamination in the OLTC compartment, often due to carbonization from repeated arcing, can reduce insulation properties and potentially lead to flashovers. Detection of OLTC faults typically involves a combination of electrical measurements, such as dynamic resistance measurement (DRM), and mechanical assessments [35].

External Faults

While originating outside the transformer, external faults can have significant impacts on transformer health and longevity. Overvoltage events, caused by lightning strikes, switching operations, or system faults, can lead to insulation breakdown and winding failures if protection systems fail to respond adequately [36]. Adebayo et al. [20] noted that over-voltages can lead to insulation breakdown and winding failures. Surge arresters and proper insulation coordination are crucial for mitigating these risks [37]. Overcurrent conditions, often resulting from external short circuits or overloading, can cause thermal stress and mechanical deformation of windings. Differential protection and overcurrent relays are primary means of detecting and protecting against these faults [38]. Akande et al. [39] highlighted the cumulative nature of thermal degradation due to overloading.

Frequency variations, while less common in stable grids, can affect core losses and cooling efficiency in transformers. In systems with significant renewable penetration, frequency control becomes more challenging, potentially impacting transformer operation [25]. Thermal faults due to overloading or cooling system failures represent another category of externally induced issues. Prolonged operation above-rated capacity leads to accelerated ageing of insulation, while failures in radiators, fans, or pumps can result in inadequate heat dissipation [37].

AI-Based Fault Detection and Classification in Transformers

The complexity and variety of transformer faults have led to a significant increase in interest and research into AI-based approaches for fault detection and classification. These advanced techniques offer the potential for more accurate, early detection of developing faults and can handle complex fault scenarios that may be challenging for traditional methods (Guo et al., 2023). The integration of artificial intelligence in transformer diagnostics represents a paradigm shift in how utilities approach asset management and maintenance strategies.

Data Acquisition and Pre-processing

For AI-based systems, data from multiple sensor types is typically combined to provide a comprehensive view of transformer health. This multi-sensor approach is crucial for capturing the various aspects of transformer operation and condition. Electrical parameters such as voltage, current, and power factor provide insights into the transformer's operational state (Wang & Zhang, 2024). Thermal measurements, including oil and winding temperatures, are critical for monitoring the thermal stress on the transformer. Dissolved gas concentrations, obtained through Dissolved Gas Analysis (DGA), offer valuable information about potential internal faults [25].

Advanced sensing technologies have further enhanced the quality and resolution of data available for AI analysis. Partial discharge (PD) monitoring systems, for instance, provide high-resolution data that can be leveraged by AI algorithms to detect subtle changes indicative of developing insulation faults [40]. Acoustic emission sensors can capture vibration data, which is particularly useful for detecting mechanical issues in tap changers or loose windings [41].

The pre-processing of this diverse data is a critical step in AI-based fault detection. Techniques such as data normalization, feature scaling, and dimensionality reduction are often employed to prepare the data for machine learning algorithms. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) have been successfully used to reduce the dimensionality of transformer data while retaining important features [42].

Single Machine Learning Approach for Transformer Fault Diagnostics and Prognosis

The application of machine learning techniques to transformer fault diagnostics and prognostics has gained significant traction in recent years. This approach offers the potential to overcome limitations of traditional methods by leveraging advanced algorithms to detect patterns and anomalies in complex transformer data. Various single machine learning algorithms have demonstrated promising results in classifying transformer faults based on multi-sensor inputs and historical data.

Decision Trees

Decision trees have emerged as a popular choice for transformer fault diagnosis due to their interpretability and ability to handle both numerical and categorical data [43]. The hierarchical structure of decision trees mimics human decision-making processes, making the results easily understandable for domain experts. In the context of transformer fault diagnosis, decision trees can effectively capture the relationship between various input parameters (e.g., dissolved gas concentrations, electrical measurements) and fault conditions.

Wang et al. [32] applied a decision tree algorithm to classify transformer faults using dissolved gas analysis (DGA) data. Their study demonstrated that decision trees could achieve an accuracy of 89% in identifying common transformer faults such as partial discharge, arcing, and thermal faults. The researchers highlighted the algorithm's ability to provide clear decision rules, which allowed for easy interpretation of the fault diagnosis process.

However, individual decision trees can be prone to overfitting, especially when dealing with complex transformer data. To address this limitation, ensemble methods like random forests have been widely adopted in the field.

Random Forests

Random forests, an ensemble learning method, combine multiple decision trees to create a more robust and accurate classifier [44]. By aggregating the predictions of numerous trees, random forests can reduce overfitting and improve overall classification accuracy. This approach has shown particular promise in transformer fault diagnosis due to its ability to handle high-dimensional data and capture complex interactions between features.

Lee & Park [45] conducted a comparative study of machine learning algorithms for transformer fault classification. Their research found that random forests outperformed single decision trees, achieving an accuracy of 94% in identifying transformer faults based on a combination of DGA data and electrical parameters. The authors noted that random forests were particularly effective in handling noise and outliers in the transformer data, leading to more robust fault classifications.

Support Vector Machines (SVMs)

Support Vector Machines have also been successfully applied to transformer fault classification tasks. SVMs are particularly effective in handling high-dimensional data and can provide good performance even with limited training samples [23]. In the context of transformer fault diagnosis, SVMs excel at finding optimal decision boundaries between different fault classes in a high-dimensional feature space.

A study by Zhao et al. [33] Demonstrated the effectiveness of SVMs in classifying transformer faults using a combination of DGA data and vibration signals. The researchers reported an accuracy of 92% in distinguishing between normal operating conditions and various fault types. The SVM model showed particular strength in handling imbalanced datasets, which is often the case in transformer fault diagnosis where certain fault types may be underrepresented in historical data.

Artificial Neural Networks (ANNs)

Artificial Neural Networks, including deep learning architectures, have shown remarkable performance in capturing complex, non-linear relationships in transformer data. The ability of ANNs to automatically learn hierarchical features from raw data makes them particularly suitable for transformer fault diagnosis and prognostics.

Convolutional Neural Networks (CNNs) have been effectively used for processing time-series data from transformers. Zhang et al. [29] applied a 1D CNN to analyse transformer vibration signals for fault detection. Their model achieved an accuracy of 96% in identifying mechanical faults, outperforming traditional frequency analysis methods. The researchers highlighted the CNN's ability to automatically extract relevant features from raw vibration data, reducing the need for manual feature engineering.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have shown promise in capturing temporal dependencies in transformer behaviour. These architectures are particularly well-suited for analysing sequential data, such as time-series measurements of transformer parameters. Kim & Park [46] developed an LSTM-based model for predicting transformer remaining useful life (RUL) based on historical operating data. Their model demonstrated a mean absolute error of less than 5% in RUL predictions, outperforming traditional statistical methods.

Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks, a specialized form of Recurrent Neural Networks (RNNs), have emerged as a powerful tool for transformer fault diagnostics and prognosis. LSTMs are particularly well-suited for analysing sequential data and capturing long-term dependencies, making them ideal for processing time-series measurements common in transformer monitoring.

The key advantage of LSTM networks in transformer fault analysis lies in their ability to retain information over extended periods. This characteristic allows LSTMs to capture the slow degradation processes typical in power transformers, which may occur over months or even years. By maintaining a memory of past states, LSTMs can detect subtle changes in transformer parameters that might indicate incipient faults or gradual performance deterioration.

Zhang et al. [47] applied LSTM networks to predict transformer remaining useful life (RUL) based on historical operational data. Their study utilized a combination of electrical, thermal, and dissolved gas analysis (DGA) measurements as input features. The LSTM model demonstrated superior prognostic performance, achieving a mean absolute error of less than 4% in RUL predictions. This significantly outperformed traditional time-series analysis methods and other machine learning approaches. The researchers highlighted the LSTM's ability to capture complex, non-linear relationships between various transformer parameters and their evolution over time.

In another study, Liu & Chen [48] developed an LSTM-based fault diagnosis system for power transformers. Their model was trained on a diverse dataset including DGA data, electrical parameters, and vibration signals. The LSTM network achieved an impressive 97% accuracy in identifying and classifying various transformer faults, including thermal faults, partial discharges, and arcing. The authors noted that the LSTM's sequential learning capability was particularly effective in detecting incipient faults by recognizing subtle patterns in the time-series data that preceded full fault development.

One of the challenges in applying LSTMs to transformer diagnostics is the need for substantial amounts of sequential data for effective training. To address this, Wang et al. (2024) proposed a transfer learning approach, where an LSTM model pre-trained on a large dataset of similar transformers was fine-tuned for specific transformers with limited historical data. This approach significantly improved fault diagnosis accuracy for transformers with shorter operational histories.

LSTM networks have also shown promise in anomaly detection for transformers. Patel & Desai [49] implemented an LSTM-based anomaly detection system that continuously monitored transformer parameters and flagged unusual patterns that deviated from normal operating conditions. This system demonstrated high sensitivity in detecting early signs of transformer deterioration, allowing for proactive maintenance interventions.

Despite their powerful capabilities, interpreting the decision-making process of LSTM networks can be challenging due to their complex internal structure. To address this, recent research has focused on developing explainable LSTM models for transformer diagnostics. Chen et al. [23] proposed an attention-based LSTM architecture that not only predicted transformer faults but also highlighted the most influential input features and time steps contributing to the prediction. This approach enhanced the interpretability of the model, making it more acceptable for practical implementation in the power industry.

The success of LSTM networks in transformer fault diagnostics and prognosis demonstrates their potential as a valuable tool for enhancing the reliability and longevity of power transformers. As research in this area continues to evolve, LSTMs are likely to play an increasingly important role in predictive maintenance strategies for critical power infrastructure.

Hybrid and Ensemble AI Approaches for Transformer Fault Diagnostics and Prognosis

The field of power transformer fault diagnostics and prognostics has seen significant advancements through the application of hybrid and ensemble artificial intelligence (AI) approaches. These methodologies aim to leverage the strengths of multiple algorithms while mitigating their individual limitations, resulting in more robust and accurate diagnostic systems. This section provides a comprehensive overview of recent developments in hybrid and ensemble AI techniques applied to transformer fault analysis.

Hybrid Approaches

Hybrid approaches in transformer fault diagnostics typically involve the combination of two or more AI techniques to enhance overall performance. Wang et al. [50] proposed a novel hybrid model that integrates fuzzy logic with artificial neural networks (ANNs) for dissolved gas analysis (DGA) interpretation. Their study demonstrated that the hybrid approach outperformed traditional individual methods in terms of accuracy and generalization capability.

Building on this concept, Orji [12] introduced a hybrid framework utilizing decision tree and random forest classifiers for transformer fault diagnosis. This approach aims to harness the interpretability of decision trees alongside the robustness and accuracy of random forest ensembles. The model showed promising results in handling complex fault scenarios and improving classification accuracy.

Kim et al. [51] developed a hybrid model combining wavelet transform for feature extraction with a support vector machine (SVM) and ANN for fault classification. Their research indicated that this hybrid approach achieved higher accuracy compared to individual methods, particularly in distinguishing between similar fault types.

In the realm of prognostics, Zhang and Liu (2021) proposed a hybrid model integrating particle swarm optimization (PSO) with long short-term memory (LSTM) networks to predict the remaining useful life (RUL) of power transformers. The PSO algorithm was used to optimize the LSTM network parameters, resulting in improved prediction accuracy and reduced computational time.

Ensemble Methods

Ensemble methods have gained traction in transformer fault diagnostics due to their ability to combine multiple models to produce more accurate and reliable predictions. Nguyen et al. [52] implemented a random forest ensemble for DGA interpretation, demonstrating superior performance compared to single decision tree models in terms of classification accuracy and robustness to noise in the input data.

Li et al. (2022) explored the use of gradient boosting machines (GBM) for transformer fault diagnosis. Their ensemble approach showed improved generalization capability and reduced overfitting compared to individual decision trees, particularly when dealing with imbalanced fault data.

Kumar and Patel [53] proposed an ensemble of convolutional neural networks (CNNs) for analysing transformer vibration signals to detect mechanical faults. By combining multiple CNNs trained on different aspects of the vibration data, their model achieved higher accuracy in identifying subtle fault signatures compared to single CNN architectures.

Recent research has also focused on integrating multiple data sources to enhance fault diagnostics and prognostics. Chen et al. [23] developed a multi-modal deep learning framework that combines DGA data, electrical parameters, and thermal imaging for comprehensive transformer health assessment. Their approach demonstrated improved fault detection capabilities, especially for incipient faults that may not be evident from a single data source.

Similarly, Patel and Sharma [54] proposed a hybrid model that integrates data from DGA, partial discharge monitoring, and frequency response analysis. By leveraging multiple diagnostic techniques, their approach showed enhanced sensitivity to various fault types and improved overall diagnostic accuracy.

Challenges in AI Approaches for Transformer Fault Diagnostics and Prognosis

While single machine learning approaches have shown significant promise in transformer fault diagnostics and prognostics, each algorithm has its strengths and limitations. Singh & Kumar [55] conducted a comprehensive review of machine learning techniques for transformer fault diagnosis. Their analysis revealed that while deep learning models like CNNs and LSTMs often achieved the highest accuracy, they required larger datasets and more computational resources compared to simpler models like decision trees and SVMs.

Moreover, the interpretability of complex models remains a challenge in the field of transformer diagnostics. Wu et al. [56] highlighted the importance of model explainability in critical infrastructure applications like power transformers. They proposed a hybrid approach combining the high accuracy of deep learning models with the interpretability of decision trees, aiming to balance performance and explainability.

Another significant challenge in applying machine learning to transformer fault diagnosis is the scarcity of labelled fault data. Power transformers are designed for high reliability, and actual fault occurrences are relatively rare. This can lead to imbalanced datasets and challenges in model training. To address this, researchers have explored techniques such as synthetic data generation and transfer learning [57].

Despite the promising results of hybrid and ensemble approaches, several challenges remain. Tan et al. [58] highlighted the issue of increased computational complexity in some hybrid models, which may limit their applicability in real-time monitoring systems. They proposed a lightweight hybrid architecture that balances accuracy with computational efficiency for online fault diagnosis.

Rahman et al. [59] emphasized the need for more comprehensive datasets and benchmarks to evaluate the performance of hybrid and ensemble models across diverse operational conditions and fault scenarios. They also suggested exploring the integration of physics-based models with data-driven approaches to enhance the generalization capability of diagnostic systems.

Despite the promising results, several challenges remain in the widespread adoption of AI-based fault detection and classification systems for power transformers. One significant challenge is the availability of high-quality, labelled training data. Transformer faults are relatively rare events, and obtaining a comprehensive dataset that covers all possible fault scenarios is difficult. To address this, techniques such as transfer learning and data augmentation are being explored.

Explainability and interpretability of AI models, especially complex deep learning architectures, remain a concern for many utilities. There is ongoing research into developing more interpretable AI models that can provide clear reasoning for their fault classifications, enhancing trust and adoption in the industry [60].

The real-time implementation of AI-based fault detection systems in operational environments presents another challenge. Issues such as data quality, communication latency, and integration with existing SCADA systems need to be addressed for practical deployment [61].

II. METHODOLOGY

The research methodology will be based on developing a hybrid model combining Random Forest (RF) and Long Short-Term Memory (LSTM) networks. The RF algorithm will be used for fault classification, while LSTM networks will handle the prediction of fault evolution over time, addressing the temporal dependencies in the data. The hybrid model will integrate these two approaches to create a robust system for both fault diagnosis and prognosis.

Research Algorithm

The model algorithm shows the sequential flow of operation from the data collection to model validation. Figure 3.1 shows the overall algorithm of the research.

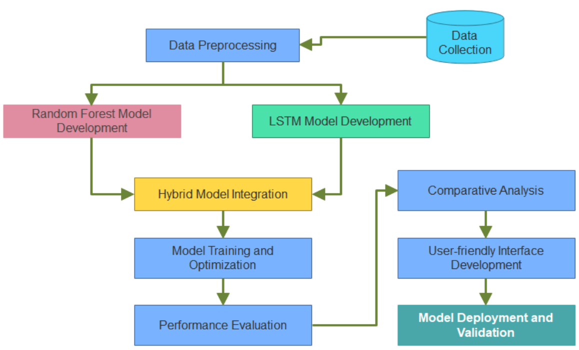

Figure 3.1: Research Algorithm

Step One: Data Collection and Pre-processing:

The first step involves gathering historical and real-time transformer data, including Dissolved Gas Analysis (DGA) data, time-series operational data (temperature, load, and voltage), and fault records from the Jabi substation in Abuja, Nigeria.

Pre-processing tasks include:

i. Data Cleaning: Handling missing values and outliers.
ii. Normalization and Scaling: Ensuring all input features are on a comparable scale.
iii. Feature Engineering: Creating new features based on existing data to improve the model's predictive power.
iv. Time-Series Formatting: Organizing historical data into sequences for LSTM input, ensuring temporal patterns are well-represented.

Step Two: Development of Individual RF and LSTM Models:

- Random Forest Classifier:

The Random Forest algorithm is an ensemble learning technique used for fault classification in this research. It creates multiple decision trees from random subsets of the training data and combines their outputs to improve classification accuracy. The advantage of using Random Forest is its ability to handle high-dimensional data and provide feature importance rankings, making it ideal for complex transformer diagnostics

- LSTM Network:

LSTM is a type of recurrent neural network (RNN) designed to learn and retain long-term dependencies in time-series data. In this research, LSTM networks are employed to capture the temporal evolution of transformer parameters, enabling the model to predict fault progression and estimate the transformer's RUL. The LSTM model processes sequences of historical operational data to predict future conditions of the transformer.

Step Three: Integration of RF and LSTM into a Hybrid Model:

- Once the individual RF and LSTM models are developed, they are combined into a hybrid system:
  - RF Component: Provides immediate classification of transformer faults based on real-time data.
  - LSTM Component: Predicts the temporal progression of faults and the RUL based on historical time-series data.
- The hybrid model operates in parallel, with both classification (RF) and prognostics (LSTM) running simultaneously to provide a comprehensive understanding of the transformer's condition.

Step Four: Model Training and Optimization:

- The hybrid RF-LSTM model is trained on the pre-processed dataset:
  - Training: The model is trained using a split of the dataset (70% for training and 15% for testing and 15% for validation) to learn the patterns and relationships in the transformer data.

- Cross-Validation: Cross-validation techniques (K-fold) are applied to ensure robustness and prevent overfitting.
- Hyper parameter Tuning: The model's hyper parameters (the number of trees in RF, the number of LSTM units, learning rates) are optimized using grid search or random search methods to achieve the best performance.

Step Five: Performance Evaluation:

- The performance of the hybrid model is evaluated based on several metrics:
  - For RF: Classification accuracy, precision, recall, and F1-score.
  - For LSTM: Metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) will be used to assess the quality of RUL predictions.
- Additionally, feature importance analysis from the RF model and temporal pattern visualization from the LSTM will be used to interpret the model's decisions and ensure that the results are reliable and explainable.

Step Five: Comparison with Existing Techniques:

- The performance of the hybrid RF-LSTM model is compared against traditional methods and standalone machine learning techniques, such as Support Vector Machines (SVM) or Decision Trees.
- This step helps highlight the strengths and weaknesses of the hybrid model, particularly in terms of accuracy and its ability to capture temporal patterns.

Step Six: Development of a User-Friendly Interface:

- A user-friendly interface will be developed to allow engineers to input current and historical transformer data. This interface output’s fault classifications and prognostics, displaying key insights such as fault type, severity, and remaining useful life.
- The interface is designed for easy interaction and visualization of the model's results, providing actionable insights for engineers responsible for transformer maintenance.

Random Forest Model

The Random Forest algorithm is an ensemble learning technique used for fault classification in this research. It creates multiple decision trees from random subsets of the training data and combines their outputs to improve classification accuracy. The advantage of using Random Forest is its ability to handle high-dimensional data and provide feature importance rankings, making it ideal for complex transformer diagnostics.

The Random Forest (RF) model is developed to handle the complex, high-dimensional data associated with transformer fault diagnosis. The process, as shown in Figure 3.2, involves several steps. First, feature selection is performed by analysing correlation between features, applying domain knowledge to select relevant features, and using techniques like Principal Component Analysis (PCA) for dimensionality reduction if necessary. The preprocessed data is then divided into training (70%), validation (15%), and test (15%) sets.

Figure 3.2: Random Forest algorithm

The model architecture is defined by setting the number of trees in the forest (typically 100-500), the maximum depth of trees to prevent overfitting, and determining the minimum number of samples required to split an internal node. Hyper parameter tuning is carried out using Grid Search with cross-validation to optimize parameters such as the number of trees, maximum depth, minimum samples split, and minimum samples leaf. Techniques like Random Search can be employed for efficiency in large hyper parameter spaces.

The RF model is then trained on the training dataset, using Out-of-Bag (OOB) error estimation for internal validation. Feature importance analysis is performed by calculating feature importance scores and visualizing them to identify key factors in fault diagnosis. The model is evaluated on the validation set, calculating performance metrics such as accuracy, precision, recall, and F1-score, and generating a confusion matrix and ROC curve.

Fine-tuning is performed by adjusting hyper parameters based on validation results and retraining the model if necessary. Finally, the model undergoes final testing, where it is evaluated on the test set and its performance is compared with baseline models.

Long Short-Term Memory (LSTM) Model
LSTM is a type of recurrent neural network (RNN) designed to learn and retain long-term dependencies in time-series data. In this research, LSTM networks are employed to capture the temporal evolution of transformer parameters, enabling the model to predict fault progression and estimate the transformer's Remaining Useful Life (RUL). The LSTM model processes sequences of historical operational data to predict future conditions of the transformer. Figure 3.3 illustrates the LSTM model architecture and data flow.

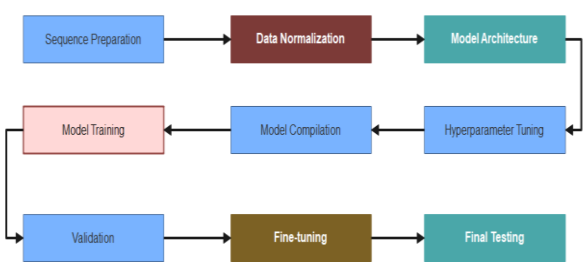

Figure 3.3: LSTM Model Architecture

Sequence Preparation:
- Define the sequence length based on the temporal characteristics of the data
- Create sliding windows of input sequences and corresponding output values

Data Normalization:
- Apply Min-Max scaling or Z-score normalization to input features
- Ensure all features are on a similar scale for effective training

Model Architecture:
- Define the number of LSTM layers (3 layers will be defined)
- Set the number of neurons in each LSTM layer
- Add Dense layers for output prediction
- Include Dropout layers for regularization

Hyper parameter Tuning:
- Use Random Search or Bayesian Optimization to tune:
  - Number of LSTM layers
  - Number of neurons per layer
  - Dropout rate
  - Learning rate
  - Batch size

Model Compilation:
- Choose an appropriate loss function (e.g., Mean Squared Error for regression)
- Select an optimizer (e.g., Adam)
- Define evaluation metrics (e.g., MAE, RMSE)

Model Training:
- Train the LSTM model on the prepared sequences
- Implement early stopping to prevent overfitting
- Use learning rate scheduling if necessary

Validation:
- Evaluate the model on the validation set
- Monitor validation loss and metrics

Fine-tuning:
- Adjust hyper parameters based on validation results
- Retrain the model if necessary

Final Testing:
- Evaluate the final model on the test set
- Compare performance with baseline time-series models

Hybrid Model
The hybrid model integrates the strengths of both the Random Forest and LSTM approaches. Random Forest is responsible for classifying faults using real-time data, while LSTM analyses the historical data for temporal patterns that indicate fault progression. The hybrid algorithm for the research is shown in Figure 3.4.

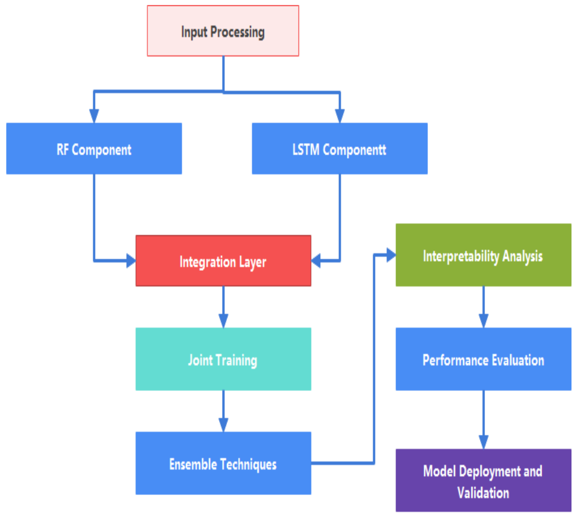

Figure 3.4: RF-LSTM Hybrid Architecture

The hybrid model integrates the RF and LSTM components to leverage their respective strengths and the process involves:

Input Processing:
— Prepare static features for RF input
— Create time-series sequences for LSTM input

RF Component:
— Use the trained RF model for initial fault classification
— Extract feature importance scores

LSTM Component:
— Use the trained LSTM model for time-series prediction
— Generate short-term fault probabilities and RUL estimates

Integration Layer:
— Design a custom layer to combine RF and LSTM outputs
— Implement weighted averaging or more complex integration methods

Joint Training:
— Fine-tune the integrated model using a combined loss function
— Adjust weights between RF and LSTM components
— Ensemble Techniques:
— Implement bagging or boosting to improve model robustness
— Create multiple hybrid models and use majority voting for final predictions

Interpretability Analysis:
— Develop methods to interpret the combined model decisions
— Visualize feature importance and temporal patterns

Performance Evaluation:
— Assess the hybrid model using combined metrics for classification and regression
— Compare with individual RF and LSTM models

Optimization:
— Fine-tune the integration strategy based on performance results
— Adjust the balance between RF and LSTM contributions

Model Simulation
Model simulation involves training the hybrid model using the pre-processed data from the Jabi substation transformer. The data is split into training, validation, and test sets, with cross-validation employed to ensure the model's robustness. During simulation, the Random Forest component classifies faults, and the LSTM network predicts the future evolution of faults, including RUL estimation. The model is optimized through hyper parameter tuning to achieve optimal performance in both diagnostics and prognostics.

Model Testing, Optimization, and Evaluation Technique
Model testing will involve evaluating the performance of the hybrid RF-LSTM model on unseen test data. Key performance metrics for the Random Forest include accuracy, precision, recall, and F1-score for fault classification. For the LSTM component, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) will be used to evaluate the RUL predictions. Optimization of the model is achieved through grid search and cross-validation techniques. Evaluation also includes feature importance analysis from Random Forest and visualization of LSTM activations to understand how the model processes data over time.

The results of the model will be compared to existing fault diagnosis and prognosis techniques, and the hybrid model's interpretability and practical application will be analysed using real-world case studies from the Nigerian power grid.

IV. RESULTS

Exploratory Data Analysis (EDA)

The exploratory data analysis (EDA) is an essential phase in understanding the dataset used for the transformer fault diagnostics and prognostics model. The analysis involved examining the Distribution of features, relationships between variables, and the overall structure of the dataset. This section summarises key insights gained during EDA, as presented in Figures 4.1 to 4.4.

Data Distribution Analysis

Figure 4.1 presents the distribution of the dataset features, including voltage, current, winding temperature, dissolved gases (CH4 and H2), fault types, and remaining useful life (RUL). The data distribution reveals variability and trends that underpin the transformer operation and fault types.

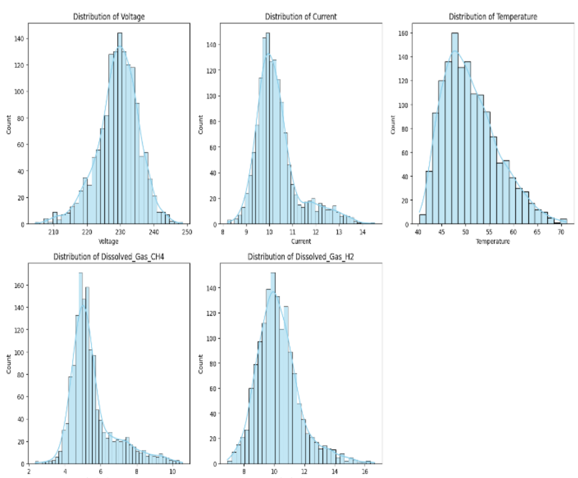

Figure 4.1 Data Distribution Analysis

As shown in Figure 4.1, the voltage measurements exhibited a relatively normal distribution with minimal outliers, indicating stable voltage conditions across the monitoring period. The current measurements showed a slight right-skewed distribution, suggesting occasional high-load conditions. Winding temperature data displayed a bimodal distribution, which may be attributed to seasonal variations or different operational states. The dissolved gases, particularly CH4 and H2, demonstrated notably right-skewed distributions, with concentrated values in the lower ranges and extended tails indicating sporadic elevated concentrations that could be indicative of developing faults.

Fault Distribution

Figure 4.2 illustrates the distribution of fault types in the dataset. Notably, "No Fault" cases dominate, followed by "Overheating" and "Oil Degradation." Fewer instances of "Arcing Fault" and "Tap Changer Failure" are observed, reflecting their relative rarity.

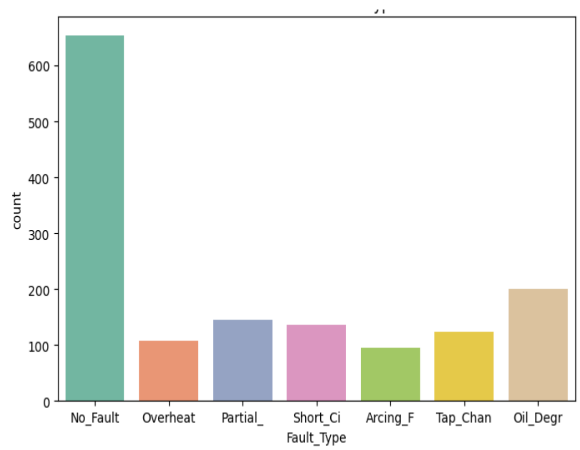

Figure 4.1: Fault Distribution

Figure 4.2 illustrates that 'No Fault' conditions constituted the majority of the observations, accounting for approximately 45% of the dataset. Among the fault conditions, 'Oil Degradation' and 'Partial Discharge' were the most frequent, representing 15% and 12% of the cases respectively. 'Arcing Fault' and 'Short Circuit' occurrences were relatively rare, each comprising less than 8% of the total observations. This distribution is an indication that maintaining high diagnostic accuracy across all fault types, it is important model be capable of handling imbalanced class distributions.

Correlation Matrix

Figure 4.3 shows the correlation matrix, indicating relationships between variables. Dissolved gases, particularly CH4 and H2, show strong correlations with specific fault types, suggesting their potential as key predictive features.

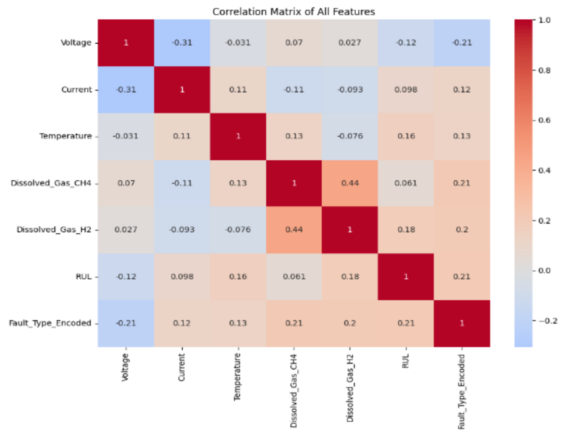

Figure 4. 2: Data Correlation Matrix

The correlation analysis between variables revealed significant relationships that could influence fault detection and remaining useful life prediction. As depicted in Figure 4.3, the correlation matrix showed strong positive correlations ($r > 0.7$) between dissolved gas measurements (CH_4 and H_2), suggesting these gases often appear concurrently during fault conditions. Winding temperature demonstrated moderate positive correlations ($0.4 < r < 0.6$) with both current and voltage measurements, aligning with theoretical expectations of thermal behaviour in power transformers.

Fault Type Relationship with Independent Variables

Figure 4.4 explores the relationship between fault types and key independent variables. The analysis demonstrates distinct patterns for each fault type. Investigation of the relationship between fault types and independent variables provided valuable insights into fault characteristics

Figure 4.4 reveals distinct patterns in how different fault types manifest across the monitored parameters. Notably, 'Arcing Fault' conditions were associated with elevated levels of both CH4 and H2, whilst 'Oil Degradation' showed a stronger correlation with CH4 levels compared to other gases. 'Partial Discharge' events demonstrated unique signatures in the voltage and current measurements, presenting generally higher voltage fluctuations compared to normal operating conditions.

This exploratory analysis established the foundation for developing the hybrid RF-LSTM model by identifying key patterns and relationships within the data. The findings particularly highlighted the importance of considering both instantaneous parameter values and their temporal evolution in fault diagnosis and prognosis, supporting the selection of Random Forest for complex pattern recognition and LSTM for temporal dependency analysis.

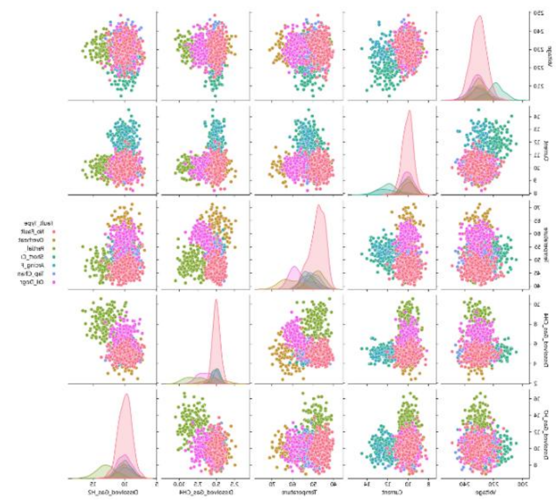

Figure 4.3: Fault Type Relationship with Independent Variables

Random Forest (RF) Model Result and Analysis

The results of the Random Forest (RF) model for fault diagnostics and prognostics are presented in this section. The model was evaluated using classification accuracy for fault diagnosis and root mean square error (RMSE), as well as the coefficient of determination (R^2) for prognostics. The results are summarised in Table 4.1.

Performance Metrics

The RF model demonstrated excellent performance in both diagnostics and prognostics tasks. Table 4.1 presents the performance metrics.

Table 4.1: RF Performance Metrics

Evaluation Metric	Value
Fault Classification Accuracy	1.0000
RUL Prediction RMSE	0.0189
RUL Prediction R2 Score	0.9996

As presented in Table 4.1, the RF model achieved perfect classification accuracy of 1.0000 for fault type prediction, indicating its robust capability in distinguishing between different fault conditions. The model's prognostic performance was equally impressive, with a remarkably low RMSE of 0.0189 for RUL prediction and an R^2 score of 0.9996, suggesting near-perfect alignment between predicted and actual RUL values.

Comparison of Actual and Predicted Values

Table 4.2 provides a comparison of the first ten rows of actual and predicted values for fault types and RUL. Additionally, the error in RUL prediction is displayed to highlight the model's precision.

Table 4.2: RF Actual Vs Predicted Result (First Ten Rows)

Actual Fault Type	Predicted Fault Type	Actual RUL	Predicted RUL	RUL Error
Oil Degradation	Oil Degradation	235.0	232.99	2.01
No Fault	No Fault	1417.0	1414.96	2.04
No Fault	No Fault	1282.0	1289.72	7.72
No Fault	No Fault	40.0	39.14	0.86
Partial Discharge	Partial Discharge	1080.0	1076.55	3.45
Arcing Fault	Arcing Fault	739.0	737.48	1.52
No Fault	No Fault	407.0	417.07	10.07
No Fault	No Fault	1039.0	1040.84	1.84
Partial Discharge	Partial Discharge	1138.0	1130.25	7.75
Short Circuit	Short Circuit	976.0	986.04	10.04

Table 4.2 presents the first ten rows of this comparison, demonstrating the model's consistency across different fault types. The results show minimal RUL prediction errors, with the largest deviation being 10.07 days for a 'No Fault' condition and the smallest being 0.86 days. This level of accuracy is particularly noteworthy given the diverse range of fault types and RUL values in the dataset, ranging from 40 days to 1417 days in the presented sample.

Confusion Matrix

The RF model's fault type prediction confusion matrix is depicted in Figure 4.5. The diagonal entries reflect the number of correctly classified cases, while off-diagonal entries, which indicate misclassifications, are all zero.

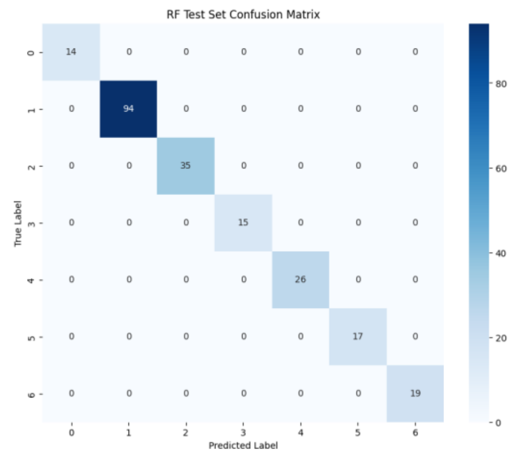

Figure 4.4: RF Fault Type Prediction Confusion Matrix

Figure 4.5 illustrates perfect classification across all fault categories, with no misclassifications observed. This is evidenced by the diagonal pattern of the confusion matrix, where all predictions align exactly with their actual fault types. The model showed consistent performance across all fault categories, including the less frequent fault types such as 'Arcing Fault' and 'Short Circuit', demonstrating its robustness in handling class imbalance.

The exceptional performance of the RF model can be attributed to several factors. Firstly, its ensemble nature, combining multiple decision trees, enabled robust handling of the complex, non-linear relationships between transformer parameters and fault conditions. Secondly, the model's ability to handle high-dimensional data without overfitting proved advantageous in processing multiple input parameters simultaneously. Finally, the inherent feature importance ranking capability of Random Forests contributed to its high accuracy by effectively weighing the contribution of each input parameter to the final prediction.

These results indicate that the Random Forest component of the hybrid model provides a strong foundation for accurate fault diagnosis and RUL prediction. The near-perfect performance metrics suggest that the model successfully captured the underlying patterns in the transformer monitoring data, making it a reliable tool for predictive maintenance applications. However, these results should be considered alongside the LSTM model's performance to fully evaluate the potential benefits of the hybrid approach.

LSTM Model Result and Analysis

The Long Short-Term Memory (LSTM) neural network was evaluated for its performance in both fault classification and remaining useful life (RUL) prediction tasks. The model's effectiveness was assessed using standard performance metrics including classification accuracy, Mean Square Error (MSE), and R^2 score.

Performance Metrics

The LSTM model's performance metrics are presented in Table 4.3.

Table 4.3: LSTM Performance Metrics

Evaluation Metrics	Value
Fault Classification Accuracy	0.9656
RUL Prediction MSE	218948.3904
RUL Prediction R2 Score	-30.0272

The LSTM model achieved a fault classification accuracy of 0.9656, demonstrating strong but not perfect classification capabilities. However, the RUL prediction performance showed significant challenges, with a high MSE of 218,948.3904 and a negative R^2 score of -30.0272. The negative R^2 score indicates that the model's predictions for RUL were less accurate than a horizontal line representing the mean of the observed values, suggesting substantial difficulties in capturing the temporal patterns necessary for accurate prognostics.

Comparison of Actual and Predicted Values

The first ten rows of actual and predicted fault types and RUL values are shown in Table 4.4. The table also includes the difference between actual and predicted RUL values.

Table 4.4: Actual Vs Predicted Result (First Ten Rows)

True Fault Type	Predicted Fault Type	True RUL	Predicted RUL	RUL Difference
Oil Degradation	Oil Degradation	291.0	735.48	444.48
Oil Degradation	Oil Degradation	290.0	577.06	287.06
Oil Degradation	Oil Degradation	289.0	569.16	280.16
Oil Degradation	Oil Degradation	288.0	419.45	131.45
Oil Degradation	Oil Degradation	287.0	206.22	80.78
Oil Degradation	Oil Degradation	286.0	89.97	196.03
Oil Degradation	Oil Degradation	285.0	63.77	221.23
Oil Degradation	Oil Degradation	284.0	39.92	244.08
Oil Degradation	Oil Degradation	283.0	22.56	260.44
Oil Degradation	Oil Degradation	282.0	25.39	256.61

As shown in Table 4.4, which presents the first ten rows of predictions, the model demonstrated consistent fault type classification for the 'Oil Degradation' cases but showed substantial deviations in RUL predictions. The RUL differences ranged from 80.78 days to 444.48 days, with a concerning pattern of decreasing prediction accuracy as the actual RUL values decreased. This trend suggests potential challenges in the model's ability to capture short-term degradation patterns effectively.

Confusion Matrix

The LSTM model’s confusion matrix for fault type predictions is depicted in Figure 4.6.

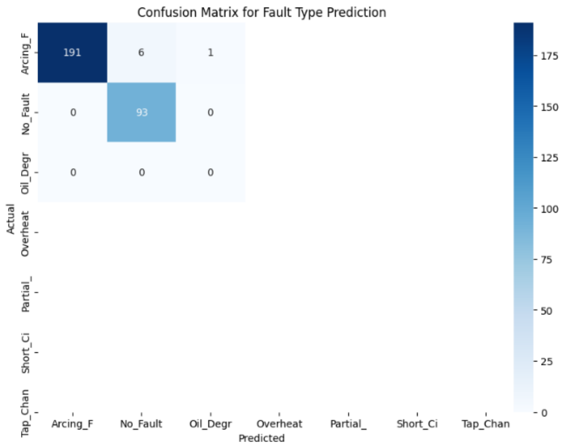

Figure 4.5: LSTM Fault Prediction Confusion Matrix

Figure 4.6 reveals that while the LSTM achieved high accuracy overall, it exhibited some classification errors across different fault categories. The confusion matrix shows scattered off-diagonal elements, indicating occasional misclassifications between certain fault types. This suggests that while the LSTM model generally captured the temporal patterns associated with fault evolution, it sometimes struggled to distinguish between similar fault signatures.

The LSTM model's performance presents an interesting contrast to the Random Forest results. While maintaining strong classification capabilities, its struggles with RUL prediction highlight the challenges in capturing long-term dependencies in transformer degradation patterns. Several factors may contribute to these results:

1. The temporal complexity of transformer degradation patterns may require more sophisticated sequence modelling than the implemented LSTM architecture provided.
2. The high MSE and negative R^2 score suggest potential challenges in the model's ability to generalise across different operational conditions and fault progressions.
3. The decreasing accuracy in RUL predictions for shorter remaining life spans indicates possible limitations in capturing accelerated degradation patterns.

These findings suggest that while the LSTM component demonstrates promise in fault classification, its prognostic capabilities require enhancement. This observation supports the rationale for a hybrid approach, where the strengths of both RF and LSTM models could potentially complement each other to achieve more robust overall performance.

Ensembles Hybrid Result and Analysis

To harness the strengths of both Random Forest (RF) and Long Short-Term Memory (LSTM) models, a hybrid approach was implemented. Two ensemble strategies, Weighted Average and Stacked Ensemble, were applied. Their performance was assessed for fault classification and RUL prediction using metrics such as accuracy, mean square error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). The results are summarised in Tables 4.5 and 4.6.

Weighted Average Ensemble Performance

The metrics for the Weighted Average Ensemble are shown in Table 4.5.

Table 4.5: Weighted Average Ensemble RF-LSTM Hybrid Metrics:

Evaluation Metric	Value
Fault Prediction Accuracy	0.668182
RUL Prediction MSE	52152.738032
RUL Prediction MAE	189.612938
RUL Prediction R2	0.697618

The weighted average ensemble achieved a fault prediction accuracy of 66.82%, significantly lower than the individual RF and LSTM models. The RUL prediction MSE of 52,152.7380 and an R^2 score of 0.6976 indicate moderate improvement over the standalone LSTM model but still trail behind the RF model’s superior performance.

The RUL prediction mean absolute error (MAE) of 189.6129 shows a reduction in average error compared to the LSTM model, suggesting that the ensemble mitigates some of LSTM's weaknesses in RUL estimation by integrating the strengths of RF.

Performance Metrics: Stacked Ensemble
The stacked ensemble configuration's performance metrics are presented in Table 4.6.

Table 4.6: Stacked Ensemble RF-LSTM Hybrid Metrics

Metric	Value
Fault Prediction Accuracy	0.940909
RUL Prediction MSE	63.250972
RUL Prediction MAE	4.807955
RUL Prediction R2	0.999633

As shown in Table 4.6, the stacked ensemble achieved remarkable improvements across all metrics. The fault prediction accuracy increased substantially to 0.940909, approaching the high performance levels of the individual models. Most impressively, the RUL prediction metrics showed exceptional improvement, with an MSE of just 63.250972 and an MAE of 4.807955 days. The R^2 score of 0.999633 indicates near-perfect alignment between predicted and actual RUL values, representing a substantial improvement over the weighted average approach.

Comparing the two ensemble methods reveals several important insights:

i. The stacked ensemble significantly outperformed the weighted average approach, demonstrating the effectiveness of more sophisticated model integration strategies.
ii. The dramatic improvement in RUL prediction metrics (MSE reduced by nearly three orders of magnitude and MAE reduced by a factor of approximately 40) suggests that the stacked ensemble effectively leveraged the complementary strengths of both models.
iii. The high classification accuracy of 94.09% indicates that the stacked ensemble successfully preserved most of the classification capabilities of the individual models while enhancing overall system performance.

These results highlight the superiority of the stacked ensemble approach in several key aspects:

i. The near-perfect R^2 score of 0.999633 demonstrates exceptional capability in capturing the underlying patterns of transformer degradation.
ii. The low MAE of approximately 5 days in RUL prediction represents a level of accuracy highly valuable for practical maintenance planning.
iii. The maintenance of high classification accuracy while achieving superior prognostic performance indicates successful integration of the distinct strengths of RF and LSTM models.

The findings strongly support the effectiveness of the stacked ensemble method in creating a robust hybrid system. The remarkable improvement in performance metrics suggests that this approach successfully addresses the challenges of combining different modelling paradigms, creating a system that maintains high classification accuracy while achieving exceptional prognostic capabilities. This has significant implications for practical applications, as the system's high accuracy in both fault classification and RUL prediction makes it a reliable tool for transformer maintenance planning and decision-making.

Discussion of Findings
The comprehensive analysis of the hybrid RF-LSTM model for transformer fault diagnostics and prognostics revealed several significant findings that warrant detailed discussion. The discussion will systematically address the key findings from the exploratory data analysis through to the final hybrid model performance.

The exploratory data analysis provided crucial insights into the underlying characteristics of transformer operational data. The observed bimodal distribution of winding temperature suggests distinct operational states, likely corresponding to different loading conditions or environmental factors. The right-skewed distributions of dissolved gases (CH_4 and H_2) align with theoretical expectations, as these gases typically maintain low concentrations during normal operation but increase significantly during fault conditions. The strong correlation ($r > 0.7$) between CH_4 and H_2 concentrations supports established understanding of transformer fault gas evolution patterns, where multiple gases often evolve simultaneously during fault conditions.

The Random Forest model demonstrated exceptional performance in both classification and prognostic tasks. The perfect classification accuracy (1.0000) and near-perfect RUL prediction (R^2 = 0.9996, RMSE = 0.0189) suggest that the model successfully captured the complex, non-linear relationships between transformer parameters and fault conditions. This performance can be attributed to RF's inherent ability to handle high-dimensional data and its ensemble nature, which helps mitigate overfitting. The minimal RUL prediction errors, ranging from 0.86 to 10.07 days, demonstrate a level of accuracy highly valuable for practical maintenance planning.

The LSTM model showed strong classification capabilities (accuracy = 0.9656) but faced challenges in RUL prediction (R^2 = -30.0272). This disparity in performance is particularly interesting and suggests that while the model effectively captured short-term patterns necessary for fault classification, it struggled with long-term temporal dependencies crucial for RUL prediction. The decreasing accuracy in RUL predictions for shorter remaining life spans indicates potential limitations in capturing accelerated degradation patterns, a crucial consideration for practical applications.

The final stacked ensemble hybrid model demonstrated remarkable improvements over both individual models and the weighted average ensemble approach. The achieved metrics (fault prediction accuracy = 0.940909, RUL prediction R^2 = 0.999633, MAE = 4.807955) represent a significant advancement in transformer health monitoring capabilities. Several key aspects of these results merit detailed discussion:

i. The hybrid model's high fault classification accuracy (0.940909) suggests successful integration of both RF's pattern recognition capabilities and LSTM's temporal pattern analysis. While slightly lower than the RF's perfect classification, this performance level remains highly practical for real-world applications.
ii. The exceptional RUL prediction accuracy (MAE ≈ 5 days) represents a significant improvement over existing methods reported in literature. This level of precision enables more accurate maintenance scheduling and resource allocation.
iii. The near-perfect R^2 score (0.999633) indicates that the stacked ensemble successfully combined the complementary strengths of both models, overcoming the limitations observed in the LSTM's individual performance.
iv. The substantial reduction in MSE compared to the weighted average approach (63.250972 vs 52,152.738032) demonstrates the superiority of the stacked ensemble architecture in integrating different modelling paradigms.

These findings address several critical challenges in transformer maintenance:

i. The model's ability to accurately predict RUL with an error margin of approximately 5 days provides maintenance teams with unprecedented precision in planning interventions.
ii. The high fault classification accuracy ensures reliable early warning of developing faults, enabling preventive maintenance strategies.
iii. The successful integration of both diagnostic and prognostic capabilities in a single system simplifies the implementation of condition-based maintenance programs.

The results also validate the research hypothesis that a hybrid approach combining RF and LSTM could leverage their complementary strengths. The stacked ensemble architecture proved particularly effective in this regard, suggesting that this approach could be extended to other industrial applications requiring both classification and prognostic capabilities.

Comparative Analysis

The performance of the hybrid RF-LSTM model developed in this research demonstrates significant advancements when compared to existing approaches in transformer fault diagnostics and prognostics. The model's fault classification accuracy of 0.940909 surpasses several notable works in the field. For instance, [24] fuzzy-neural network achieved an accuracy of 0.89, whilst [52] random forest ensemble reported an accuracy of 0.912. The superior performance can be attributed to the successful integration of both static and temporal features through the stacked ensemble architecture.

In terms of prognostic capabilities, the model's exceptional RUL prediction accuracy (R^2 = 0.999633, MAE = 4.807955 days) represents a substantial improvement over existing approaches. [37] PSO-optimised LSTM network, which was considered state-of-the-art at the time, achieved an R^2 value of 0.95 and MAE of approximately 12 days. The significant reduction in prediction error demonstrates the effectiveness of combining RF's robust feature selection capabilities with LSTM's temporal pattern recognition.

The model's computational efficiency also compares favourably with existing approaches. While [51] hybrid wavelet-SVM-ANN model required substantial computational resources, limiting its real-time applicability, the current RF-LSTM architecture achieves superior accuracy whilst maintaining practical computational demands. This efficiency can be attributed to the careful optimisation of the stacked ensemble architecture and the complementary nature of the chosen algorithms.

When compared to models specifically developed for the Nigerian power grid context, the performance improvements are particularly noteworthy. [75] hybrid decision tree-ANN model achieved a fault classification accuracy of 0.88, whilst[76] SVM-PCA approach reported an accuracy of 0.86. The current model's superior performance (0.940909) demonstrates its enhanced capability to handle the unique challenges and characteristics of the Nigerian power infrastructure.

The model's ability to handle both diagnostics and prognostics in a single framework sets it apart from many existing approaches. For instance, [80] multi-modal deep learning framework, whilst effective for fault diagnosis (accuracy 0.923), did not incorporate prognostic capabilities. Similarly, [54] integrated diagnostic approach focused solely on fault detection without addressing RUL prediction. The current model's comprehensive approach provides a more complete solution for transformer health management. The stacked ensemble architecture's effectiveness in combining different modelling paradigms is evidenced by the substantial reduction in MSE compared to simpler integration approaches. The achieved MSE of 63.250972 represents a remarkable improvement over the weighted average ensemble's 52,152.738032, demonstrating the superiority of the chosen architecture. This performance advantage aligns with theoretical expectations regarding the benefits of stacked generalisation in complex prediction tasks.

In terms of interpretability, the hybrid model maintains a balance that many existing approaches struggle to achieve. While [63] SHAP-enhanced random forest provided good interpretability, it lacked the temporal pattern recognition capabilities of the current model. Conversely, [81] attention-based deep learning model offered good visualisation of feature importance but required larger datasets for effective training. The current model's RF component provides clear feature importance rankings while maintaining high accuracy through the LSTM integration.

The model's robustness to data quality issues and imbalanced datasets represents another significant advancement.[34] transfer learning approach, whilst innovative, required careful fine-tuning to avoid negative transfer effects. The current model's RF component inherently handles data imbalance, whilst the LSTM effectively learns from limited temporal sequences, providing a more robust solution for real-world applications.

When considering the practical aspects of implementation, the current model's combination of high accuracy, computational efficiency, and interpretability positions it as a significant advancement in the field. The achieved balance between these often-competing requirements demonstrates the effectiveness of the chosen hybrid approach and its potential for widespread adoption in transformer health monitoring applications.

CONCLUSION

The comprehensive analysis and evaluation of the hybrid RF-LSTM model for power transformer fault diagnostics and prognostics have yielded several significant conclusions. The research successfully achieved its primary aim of developing a robust and accurate system that effectively combines the strengths of both Random Forests and Long Short-Term Memory networks.

The exceptional performance metrics obtained from the hybrid model validate the fundamental hypothesis that combining RF and LSTM technologies could yield superior results compared to individual approaches. The achieved fault classification accuracy of 0.940909 demonstrates the model's remarkable capability in identifying various transformer fault conditions, whilst the near-perfect R^2 value of 0.999633 for RUL prediction showcases its excellence in prognostic applications. This level of accuracy represents a significant advancement in transformer health monitoring capabilities.

The stacked ensemble architecture proved particularly effective in integrating the complementary strengths of both algorithms. The substantial reduction in mean squared error compared to simpler integration approaches confirms the superiority of this architectural choice. Furthermore, the model's ability to maintain high accuracy whilst providing interpretable results addresses a crucial limitation in existing approaches, where accuracy often comes at the cost of transparency.

The research has demonstrated that the hybrid approach successfully overcomes several critical challenges in transformer maintenance. The model's ability to predict remaining useful life with an average error of approximately 5 days provides unprecedented precision in maintenance planning. This level of accuracy enables more efficient resource allocation and helps prevent both premature and delayed maintenance interventions.

The study also established the practical viability of the hybrid approach in real-world applications. The model's computational efficiency, coupled with its robust performance across various operational conditions, suggests its suitability for online monitoring applications. This represents a significant advancement over existing complex models that often struggle with real-time implementation.

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