Chaotic Attentive Recurrent Transformer Network for Intelligent Power Grid Fault Diagnosis

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Abstract. The main objective of this study is to enhance the intelligence level of power grid fault diagnosis systems to address increasingly complex fault scenarios and ensure the overall security, stability, and resilience of modern power grids. Traditional diagnostic methods often fall short in handling high-dimensional, nonlinear, and dynamic data generated in smart grid environments. To overcome these limitations, this research proposes a data-driven framework based on Deep Learning (DL), introducing a novel hybrid architecture called the Chaotic Attentive Recurrent Transformer Network (CARTNet). The proposed method begins with comprehensive data acquisition from various sources, including fault logs, real-time system parameters, weather data, and renewable energy outputs. The data undergoes preprocessing steps such as integration, cleaning, and advanced exploratory analysis to improve quality and extract latent features. CARTNet is specifically designed to model nonlinear dynamics and temporal dependencies in time-series data by synergistically combining chaotic system modeling with attention-based recurrent transformer mechanisms, allowing for more accurate and robust fault identification. The most important results are demonstrated through extensive simulations using Python, where CARTNet achieves a fault diagnosis accuracy of 99.88%, significantly outperforming conventional deep learning models. Its ability to learn complex patterns and adapt to diverse data inputs ensures reliable and timely fault detection. The significance of the obtained results is that CARTNet provides a powerful and scalable solution for intelligent fault diagnosis in smart grids, laying a strong technological foundation for the future of automated and resilient power system operations.
***Keywords*:** data acquisition, pre-processing, exploratory analysis.

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Rețea haotică atentă de transformatoare recurente pentru diagnosticarea inteligentă a defecțiunilor rețelei electrice

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Rezumat. Obiectivul principal al acestui studiu este de a îmbunătăți nivelul de inteligență al sistemelor de diagnosticare a defecțiunilor rețelelor electrice pentru a aborda scenarii de defecțiuni din ce în ce mai complexe și pentru a asigura securitatea, stabilitatea și reziliența generală a rețelelor electrice moderne. Metodele tradiționale de diagnosticare sunt adesea insuficiente în gestionarea datelor de înaltă dimensiune, neliniare și dinamice generate în mediile de rețele inteligente. Pentru a depăși aceste limitări, această cercetare propune un cadru bazat pe date, bazat pe Deep Learning (DL), introducând o nouă arhitectură hibridă numită Chaotic Attentive Recurrent Transformer Network (CARTNet). Metoda propusă începe cu achiziția completă de date din diverse surse, inclusiv jurnale de defecțiuni, parametri de sistem în timp real, date meteorologice și ieșiri de energie regenerabilă. Datele trec prin etape de preprocesare, cum ar fi integrarea, curățarea și analiza exploratorie avansată, pentru a îmbunătăți calitatea și a extrage caracteristici latente. CARTNet este special conceput pentru a modela dinamica neliniară și dependențele temporale în datele din seriile de timp, combinând sinergic modelarea sistemului haotic cu mecanismele de transformare recurentă bazate pe atenție, permițând o identificare a defecțiunilor mai precisă și robustă. Cele mai importante rezultate sunt demonstrate prin simulări extinse folosind Python, unde CARTNet atinge o precizie de diagnosticare a defecțiunilor de 99,88%, depășind semnificativ modelele convenționale de deep learning. Capacitatea sa de a învăța modele complexe și de a se adapta la diverse intrări de date asigură o detectare fiabilă și la timp a defecțiunilor. Semnificația rezultatelor obținute constă în faptul că CARTNet oferă o soluție puternică și scalabilă pentru diagnosticarea inteligentă a defecțiunilor în rețelele inteligente, punând o bază tehnologică solidă pentru viitorul funcționării automate și reziliente a sistemelor energetice.

Cuvinte-cheie: achiziție de date, preprocesare, analiză exploratory.

Хаотическая, основанная на внимании, рекуррентная трансформерная сеть для интеллектуальной диагностики неисправностей электросети

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Аннотация. Основная цель данного исследования — повысить уровень интеллекта систем диагностики неисправностей электросетей для решения всё более сложных сценариев неисправностей и обеспечения общей безопасности, стабильности и отказоустойчивости современных электросетей. Традиционные методы диагностики часто не справляются с обработкой многомерных, нелинейных и динамических данных, генерируемых в интеллектуальных сетях. Для преодоления этих ограничений в данном исследовании предлагается управляемая данными инфраструктура, основанная на глубоком обучении (ГО), представляющая собой новую гибридную архитектуру, называемую хаотической внимательной рекуррентной трансформаторной сетью (CARTNet). Предлагаемый метод начинается со сбора комплексных данных из различных источников, включая журналы неисправностей, системные параметры в реальном времени, метеорологические данные и данные о выработке возобновляемой энергии. Данные проходят этапы предварительной обработки, такие как интеграция, очистка и расширенный исследовательский анализ, для повышения качества и выявления скрытых признаков. CARTNet специально разработан для моделирования нелинейной динамики и временных зависимостей во временных рядах данных путём синергетического сочетания моделирования хаотических систем с рекуррентными трансформаторными механизмами, основанными на внимании, что обеспечивает более точную и надёжную идентификацию неисправностей. Наиболее важные результаты продемонстрированы с помощью обширного моделирования на Python, где CARTNet достигает точности диагностики неисправностей 99.88%, значительно превосходя традиционные модели глубокого обучения. Способность CARTNet изучать сложные закономерности и адаптироваться к разнообразным входным данным обеспечивает надежное и своевременное обнаружение неисправностей. Значимость полученных результатов заключается в том, что CARTNet представляет собой мощное и масштабируемое решение для интеллектуальной диагностики неисправностей в интеллектуальных сетях, закладывая прочную технологическую основу для будущего автоматизированной и устойчивой работы энергосистем.

Ключевые слова: сбор данных, предварительная обработка, исследовательский анализ.

I. INTRODUCTION

The harmless and stable operation of the power system is ensured by prompt and precise power grid fault diagnostics, which also helps to system recovery procedures [1, 2]. Model-based and data-driven approaches are commonly used in fault diagnosis techniques [3]. Validated system models that accurately depict the failure effects in both healthy and flawed scenarios are necessary for model-based approaches [4-6]. The power grid dispatching centre receives a large amount of alarm data as soon as a defect occurs due to the growth of the smart grid and the expanding use of intelligent electronic devices in the power grid [7]. It is an extremely challenging for dispatchers to identify malfunctioning devices based on operational knowledge due to the intricate logical linkages among alarm information. Finding the fault elements is the primary goal of power system diagnosis when a malfunction occurs [8, 9]. DL is used in several power system domains, including fault diagnostics, because of its potent learning capabilities [10].

The conventional approaches Regression analysis [16], Support Vector Machine (SVM) [17], CNN [18] and Long Short Term Memory (LSTM) [19] are exploited in fault diagnosis on the grid. However, that approaches are trouble with multi-class classification issues, decreased susceptibility and inferior classification accuracy. The temporal recurrent graph neural networks [20] offer a higher generalization for fault diagnosis. Spatial-temporal properties are extracted from voltage measurement unit data at important busses using temporal recurrent graph neural network topologies.

Their computational complexity is a major disadvantage, particularly when working with high-frequency voltage data and large-scale power networks, which result in longer training times and higher resource usage.

The Bidirectional Gated Recurrent Unit is developed in [21] has high reference values, a strong diagnostic performance and the ability to precisely diagnose transformer defects. However, a single fault diagnostic model is not significantly enhance fault diagnosis performance and high accuracy necessitates a lengthy training period.

More precise problem diagnosis results are attained from improved feature vector processing due to the Data-Driven Feature Extraction (DDFE) Transformer [22]. Nevertheless, its reliance on high-quality, labelled datasets which aren't always available in real-world grid situations where data is noisy, missing or unbalanced. Because of its remarkable effectiveness, the LSTM-Attention [23] is positioned as a very promising solution for expanding bearing fault classification applications. Their computational complexity is a significant disadvantage that make it more difficult to detect faults in large-scale grid systems in real time. To identify defects and their differences, deep fault characterisation is extracted using the global Attention temporal CNN [24].

Table 1

Survey of existing approaches

References	Benefits	Drawbacks
Knowledge graph method [11]	▪ Common faults are easily recognized. ▪ For situations with well-defined rules, it has a high diagnostic efficiency.	▪ Complex fault scenarios are challenging to manage. ▪ Unknown fault types have a limited capacity for reasoning and their reasoning is prone to deviation.
Big data-driven framework [12]	▪ Big-scale data is processed efficiently and monitored in real time. ▪ The system performs better in real time and responds faster.	▪ Complex nonlinear relationships in the grid system are hard to capture by statistically based big data analysis and the detection effect is restricted.
GNN [13]	▪ It is possible to manage the intricate connections among nodes in the grid topology. ▪ The problematic nodes analyse structured data and are precisely positioned.	▪ The electrical grid's dynamic time series features are challenging to manage.
Improved BP neural network [14]	▪ It is possible to process the power grid's time series data effectively. ▪ Outstanding performance in identifying fault features in a time-dependent manner.	▪ Time series analysis has limited relevance to complicated failure scenarios and overlooks the power grid's topology.
Edge computing method [15]	▪ Real-time processing capabilities is enhanced by the increase in computer efficiency. ▪ Future designs is guided by the cooperative processing of cloud and edge computing.	▪ Complex fault analysis activities are beyond the capabilities of a stand-alone edge computing architecture, which requires greater integration with cloud computing.

The global attention technique increases the accuracy of complex defect identification and the mining capacity of deep feature information. Additionally, because the attention layers add delay that can impede quick reaction in dynamic grid systems, GA-TCNNs might have trouble detecting faults in real time. The Vision Transformer (ViT) model [25] is more capable of generalization and diagnosis. Nevertheless, it is discovered that the number of ViT models utilized for integrated learning had an impact on the fault identification process's diagnosis accuracy. Thus, a novel Chaotic Attentive Recurrent Transformer Network (CARTNet) that integrates chaotic dynamics and attention mechanisms is developed. The main objectives are,

- ❖ Integration of preprocessing stage eliminate inconsistencies and missing values, ensuring high quality data appropriate for DL model.
- ❖ Incorporation of exploratory analysis for extracting new features and encoding categorical variables, enabling the model to capture hidden fault patterns.
- ❖ The CARTNet improves temporal and contextual feature learning, crucial for complex fault diagnosis.

II. PROPOSED METHODOLOGY

The block diagram for fault diagnosis system is presented in Fig. 1. It initiates with data acquisition where vital data like power system parameters, fault logs, weather data and renewable energy inputs that are gathered from Smart grid real-time load monitoring Dataset. Then, it is fed into pre-processing, where the collected data undergoes integration, cleaning and exploration to avert inconsistencies, manage missing values and structure the data for efficient analysis. Subsequently, an exploratory analysis extracts new features and encodes categorical variables, thereby improving the model's ability to capture hidden fault patterns.

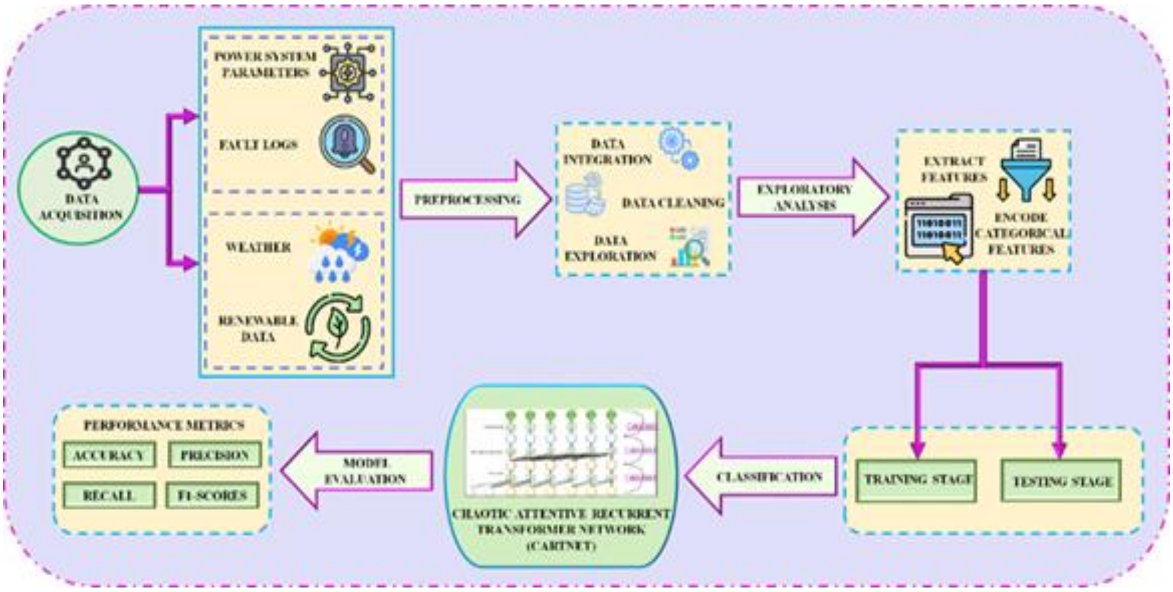

Fig. 1. Block diagram for power grid fault diagnosis.

In data splitting stage, the data is divided into training and testing phase. Consequently, it is given to CARTNet classifier that incorporates chaotic dynamics and attention mechanisms to efficiently learn complex temporal dependencies and contextual relationships in power grid data, allowing precise fault detection. It assures an automated, precise and scalable fault diagnosis system for modern power grids, enhancing reliability and operational efficacy.

A. Data Preprocessing

Data pre-processing is the vital step of converting raw, unstructured or imperfect data from Smart Grid Real-Time Load Monitoring Dataset into a clean, reliable and systematized format appropriate for DL models. It comprises incorporating data from numerous sources, managing missing values and eliminating noise or errors. Efficient pre-processing improves accuracy and performance of fault detection by offering high-quality inputs. The stages of pre-processing are indicated in Fig. 2.

Data Integration

It comprises integrating fault data from several sources into a single dataset. Approaches such as record linkage and data fusion aid in uniting data proficiently, confirming reliability and accuracy of fault prediction.

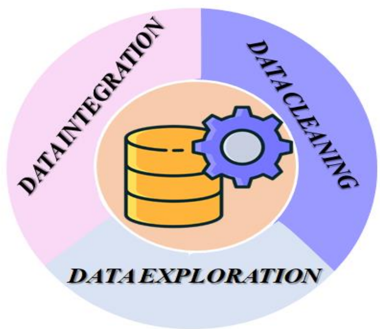

Fig. 2. Steps in pre-processing.

Data Cleaning

It is the process of predicting and correcting errors or discrepancies in the power grid dataset. It comprises managing missing values, eradicating duplicates and correcting improper data to assure the dataset is precise and consistent. Clean data is vital for efficient analysis, as it enhances the quality of outcomes and improves the performance of fault classification models.

Data Exploration

Data exploration is the procedure of analysing and visualizing fault grid datasets to recognize their patterns, structure and key characteristics. It aids detect missing values, trends, outliers and relationships among variables. It highlights correlation among faults and particular grid components. Efficient data exploration assures improved decision-making in predict the fault on grid and model training**.** Then, an exploratory analysis is utilized for extracting the features, as discussed below.

B. Exploratory Analysis Based Feature Extraction

An exploratory analysis is a vital stage to improve the model performance for intelligent fault detection. It comprises analysing the dataset to uncover hidden patterns and variable relationships by Spearman and Pearson correlation. Date time patterns and logical port characteristics are explored to understand fault timing and distribution. Hypothesis testing aids to statistically validate differences among variables like fault origins. Furthermore, categorical data is encoded and new features are extracted, enabling the model to learn significant representations for enhanced fault classification. It comprises the following sub stages,

Correlation among the variables

The relationships among the variables are found in this stage. The Spearman correlation finds the monotonic relationship amongst the variables and Pearson correlation finds the linear relationship. In pairs of variables, the relationships are found and data distribution is plotted with the aid of heat maps.

Date time analysis of fault diagnosis and detailed analysis of logical ports

To find patterns and understand the timing of the fault's tactics, a detailed analysis of the fault's date and time is exploited. Each fault is represented by a point connected to the destination port in a scatterplot that is made for analysis. The behaviour of the source and destination logical ports during the grid fault is analysed.

Summarizing statistics by hypothesis testing

Hypothesis testing is used to identify the important findings from an experiment. It is reasonable to do a statistical test to see if the means of the two groups are different, that is, if the mean of the fault assaults' source ports is different from the mean of their destination ports. Hypothesis testing is one of the most important concepts since it allows one to ascertain whether a phenomenon occurred, whether specific treatments are effective, whether groups are different from one another or whether one variable predicts another.

C. Chaotic Attentive Recurrent Transformer Network Based Classification

The growing complexity of power grids requires fault diagnosis system capable of capturing both local fluctuations and global dependencies. To overcome these requirements, the CARTNet is developed that efficiently incorporates chaotic dynamics, local recurrent structures and attention mechanisms for reliable classification of power grid faults. Fig. 3 depicts the structure of CARTNet classifier. The original long sequence is segmented into overlapping windows of size M, where each window comprises local information ending at a target position,

$$M = x_{t-M+1}, x_{t-M+2,\cdots,\ x_t} \quad (1)$$

Each window is processed via a chaotic RNN and is improved with controlled chaotic signals that simulate nonlinear distributions in grid behaviour. The occurrence of chaos introduces variability and sensitivity into the network, enabling it to detect minor oscillations and transient anomalies. The hidden representation of each local sequence is,

$$h_t = Local\ RNN\left(x_{t-M+1}, x_{t-M+2,\cdots,\ x_t}\right) \quad (2)$$

Here, the chaotic RNN processes each window independently. By sliding the window over the sequence, CARTNet generates the local hidden vector representation for the entire sequence as,

$$\left[h_1, h_2, \cdots, h_N\right] = Local\ RNN\left(x_1, x_2, \cdots, x_N\right) \quad (3)$$

These local vectors form the primary representation layer, capturing spatially localized behaviours like hidden surges or drops in signal magnitude that are vital in detecting faults. Nevertheless, these faults often has complex propagation and impact patterns over time. To capture long term dependencies over grid data, CARTNet incorporates a multi head self-attention mechanism improved with chaotic dynamics to evade over fitting and assure diverse feature extraction. The attention based updated hidden representation is,

$$u_t = MultiHead\ Attention\left(h_1, h_{2,\cdots,} h_t\right) \quad (4)$$

This stage incorporates context over the sequence, enabling each position to attend to relevant signals. The attention mechanism is comprised of multiple independent heads. Those outputs are concatenated and transformed using W^o to generate the final contextual vector,

$$u_t = Concatenation\left(head_1(h_t), head_2(h_t), \cdots, head_k(h_t)\right)W^o \quad (5)$$

This multi-perspective view strengthens the model allowing it to learn diverse features related to the types and locations of faults. Where, the linearization mapping matrix is denoted as W^o and k^{th} attention head's result is $head_k(h_t)$. Each attention head applies a weighted sum based on similarity among queries and keys,

$$[\alpha_1, \alpha_{2,\dots}\alpha_n] = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

The output of each head is the weighted sum of values based on the attention score,

$$head_i(h_t) = \sum_{j=1}^{n} \alpha_j v_j \quad (7)$$

The inclusion of chaos modulated dynamics in attention enhances generalization and diminishes the risk of over fitting on particular patterns. Where, the matrix of query, keys and values are denoted by Q, K and V. The chaotic component impacts these projections to simulate variations in signal behaviour under different fault conditions,

$$q = W^q h_t \quad (8)$$

$$k_j = W^k h_j \quad (9)$$

$$v_j = W^v h_j \quad (10)$$

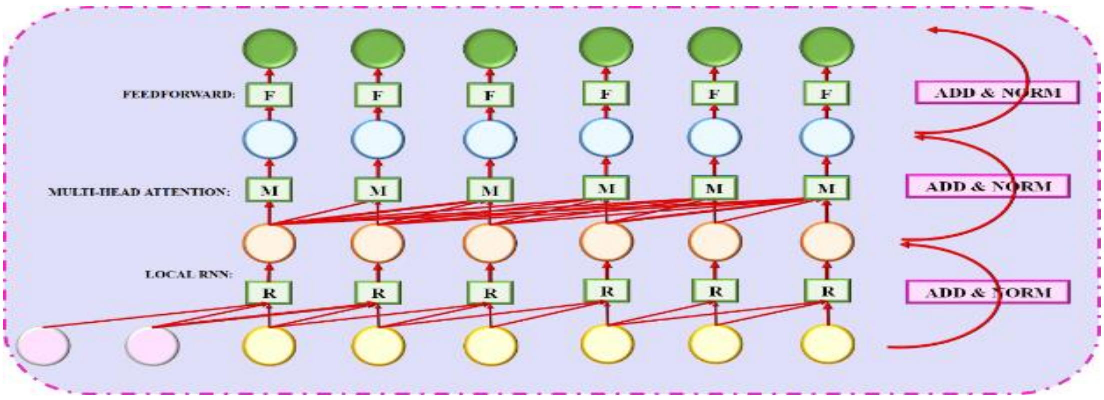

Fig. 3. Structure of CARTNet.

These projections are dynamically adjusted in training, enabling the attention mechanism to evolve and adapt to diverse signal contexts. Each attended output is passed via a feed forward network that introduces extra nonlinearity. It improves the capacity of model to transform features and enhances classification robustness. A feed forward network applies a nonlinear transformation as,

$$FeedForward(m_t) = max(0, u_t W_1 + b_1)W_2 + b_2 \quad (11)$$

The ReLU activated transformation offers nonlinear capabilities vital for capturing complex feature interactions. Layer normalization and residual connections stabilize the network at each stage. The 3-layer CARTNet processes contextual embedding $Rc = [rc_1, rc_2, \cdots, rc_n]$ as follows for each layer i,

$$[\omega_1^i, \omega_2^i, \cdots, \omega_n^i] = LocalRNN\left(rc_1^i, rc_2^i, \cdots, rc_n^i\right) \quad (12)$$

$$[\omega_1^i, \omega_2^i, \cdots, \omega_n^i] = LayerNorm\left(\omega_1^i + rc_1^i, \cdots, \omega_n^i + rc_n^i\right) \quad (13)$$

$$[u_1^i, \cdots, u_n^i] = MultiHeadAttention\left(\omega_1^i, \cdots, \omega_n^i\right) \quad (14)$$

$$[u_1^i, \cdots, u_n^i] = LayerNorm\left(u_1^i + \omega_1^i, \cdots, u_n^i + \omega_n^i\right) \quad (15)$$

$$[v_1^i, \cdots, v_n^i] = FeedForward\left(u_1^i, \cdots, u_n^i\right) \quad (16)$$

$$[r_1^{i+1}, \cdots, r_n^{i+1}] = LayerNorm\left(v_1^i + u_1^i, \cdots, v_n^i + u_n^i\right) \quad (17)$$

After 3 layers, the final hidden state indicating the power grid sequence as,

$$H_r^n = [h_1^r, h_2^r, \cdots, h_n^r] \quad (18)$$

This output is a comprehensive embedding of the input signal, enriched with temporal and spatial fault characteristics. CARTNet utilizes a self-attention mechanism to extract fault relevant features, focusing on specific grid components. For the aspect sequence hidden vectors h_t^i,

$$\gamma\left(h_t^i\right) = tanh\left(W_a h_t^i + b_a\right) \tag{19}$$

$$\alpha_i = \frac{exp\left(\gamma\left(h_t^i\right)\right)}{\sum_{j=1}^{m} exp\left(\gamma\left(h_t^j\right)\right)} \tag{20}$$

The aspect representation is,

$$V_t = \sum_{i=1}^{m} \alpha_i h_t^i \tag{21}$$

The aspect specific context information V_s is extracted by weighting the global hidden vectors,

$$\beta_i = \frac{exp\left(\gamma\left(h_r^i, V_t\right)\right)}{\sum_{j=1}^{n} exp\left(\gamma\left(h_r^j, V_t\right)\right)} \tag{22}$$

$$V_s = \sum_{i=1}^{m} \beta_i h_r^n \tag{23}$$

The average hidden vector of the aspect term offers additional context as,

$$M_{avg} = \frac{1}{m} \sum_{i=1}^{m} h_t^i \tag{24}$$

The fault classification integrates V_s and M_{avg} as,

$$Z = \left[M_{avg}, V_s\right] \tag{25}$$

Non-linear transformation and Softmax activation yield the probability of fault classes,

$$x = tanh\left(W_r Z + b_r\right) \tag{26}$$

$$y = softmax\left(W_s x + b_s\right) \tag{27}$$

The integration of chaotic dynamics enhances exploration, averts convergence to suboptimal patterns and improves sensitivity to grid disturbances, making CARTNet a powerful solution for intelligent fault diagnosis in modern power grid systems.

III. RESULT AND DISCUSSIONS

This section demonstrates the outcomes of CARTNet classifier for intelligent power grid fault diagnosis in Python software and also comparison with state-of-the-art approaches are also included in this section. The power consumption vs grid supply for highlighting fault cases is illustrated in Fig. 5.

The scattered distribution depicts the transformer faults occur over a wide range of power consumption and grid supply levels. The dense clustering of blue points indicates most operations remain no fault and red points denotes fault class. It validates the complexity of data set and significance of robust fault diagnosis mechanism.

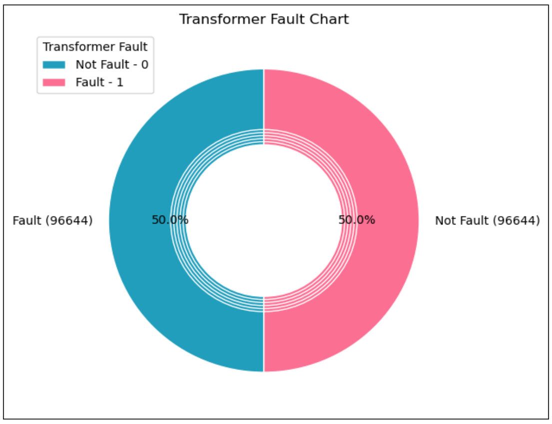

Fig. 4. Data distribution.

Fig. 4 represents the data distribution for fault and not fault classes. Both has an equal rate with 96,644 instances that assures unbiased model training and evaluation. The separation of classes offers optimal conditions for binary classification with the aid of CARTNet. It contributes to improved fault detection accuracy and averts over fitting toward any particular class.

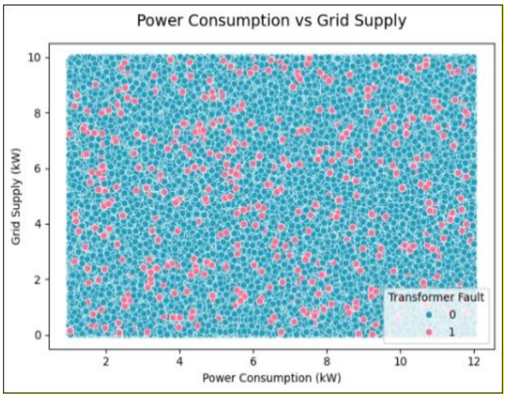

Fig. 5. Power consumption vs grid supply.

Fig. 6 depicts the density distribution of power consumption. It exposes the most power consumption values lie among 2kW and 12kW with peak density regions denoting higher data concentrations. Lower density values denotes minimal extreme operating conditions like comprehensive coverage over the dataset improves the learning ability of CARTNet, allowing accurate fault detection.

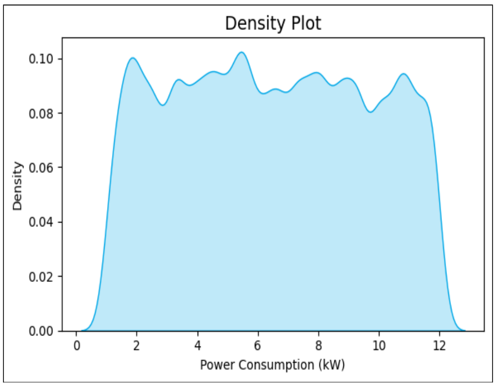

Fig. 6. Density plot.

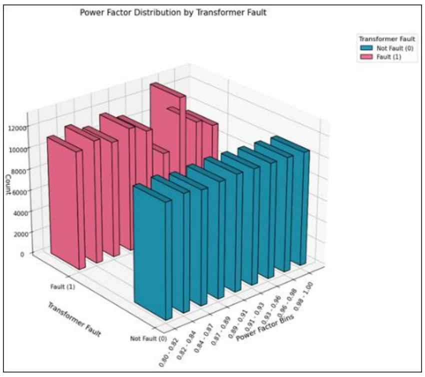

Fig. 7. Power factor distribution.

The power factor distribution is presented in Fig. 7. It reveals the fault occurrences are more frequent in lower power factor bins replicating degraded operating efficacy leading to faults. The higher power factor has fewer faults and more stable operation. It aids the ability of model to diagnose faults impacted by system efficacy variations.

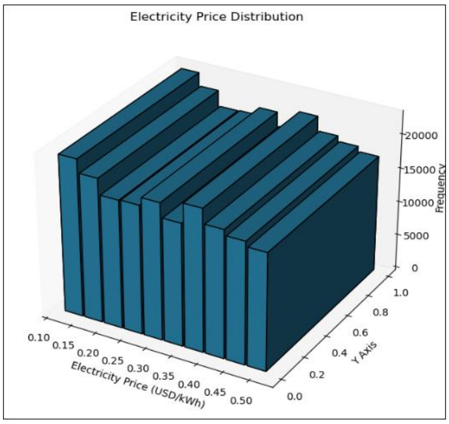

Fig. 8. Electricity price distribution.

Fig. 8 presents an electricity price distribution. This uniform distribution denoting diverse pricing scenarios are represented for model training. This variation reflects real market conditions, where electricity price fluctuations impact operational patterns. It confirms that dataset captures economic diversity vital for intelligent grid fault dia

The training and validation results is displayed in Fig. 10. The training and validation accuracy has the nearest value of 99.9% and training and validation losses are below 0.01 has minimal prediction errors. It confirms the ability of CARTNet model for precise fault detection with minimal over fitting. The confusion matrix is indicated in Fig. 11. Here, the true negative value is 29000 denoting no fault is properly predicted while true positive has the value of 28915, indicating correct fault prediction. False positives are 72 showing incorrect fault alarm and false negative is 0, denoting no missed faults. It highlights the efficacy for real time intelligent grid monitoring and fault management.

Fig. 12 presents the ROC curve that evaluates the performance of the classifier model. The AUC value is 0.99998 for both classes, denoting the robustness in managing imbalanced grid conditions. It precisely identify faults while diminishing incorrect alarms, crucial for smart grid stability and safety.

Fig. 13 depicts the analysis of accuracy for LSTM [26], Stacked Auto Encoder (SAE) [27], Multi-Layer Perceptron (MLP) [28] and CARTNet approach. The LSTM attains the accuracy of 95.31% while the SAE enhances the performance with 97.52% accuracy. Then, the MLP has the 92.91% accuracy and the developed approach has the better value of 99.88%, thereby enhancing the superior capability of CARTNet to capture temporal dependencies for precise prediction of fault.

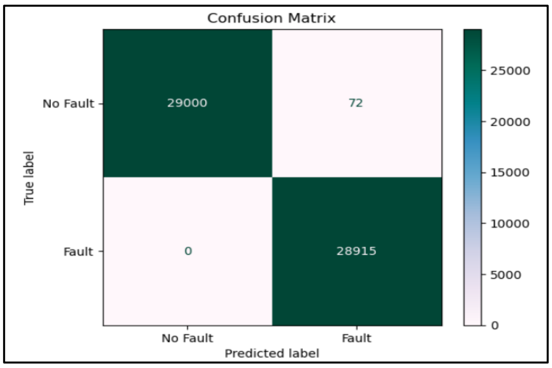

Fig. 11. Confusion matrix.

An analysis of precision and recall for Logistic Regression (LR) [16] and developed approach is revealed in Fig. 14. The LR has the precision and recall of 97.22% and 95.83%, denoting moderate fault detection ability. errors.

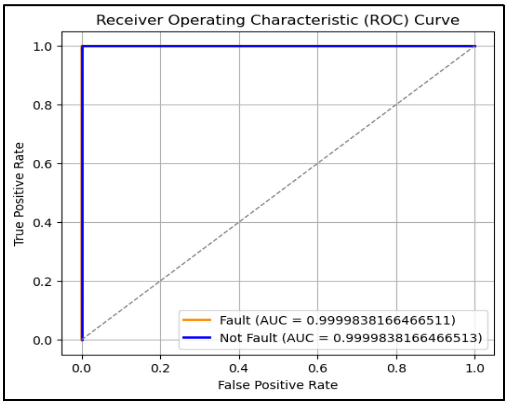

Fig. 12. ROC curve.

On the other hand, the CARTNet has the precision and recall of 99.75% and 99.88%, demonstrates its ability to deliver reliable, real-time fault diagnosis with minimal

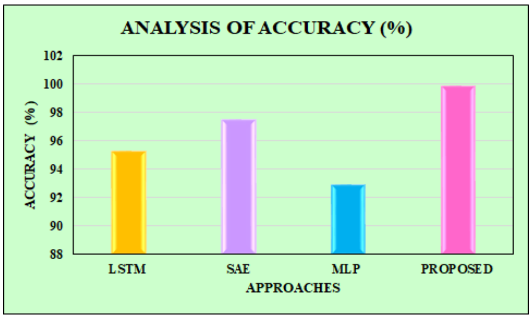

Fig. 13. Analysis of accuracy.

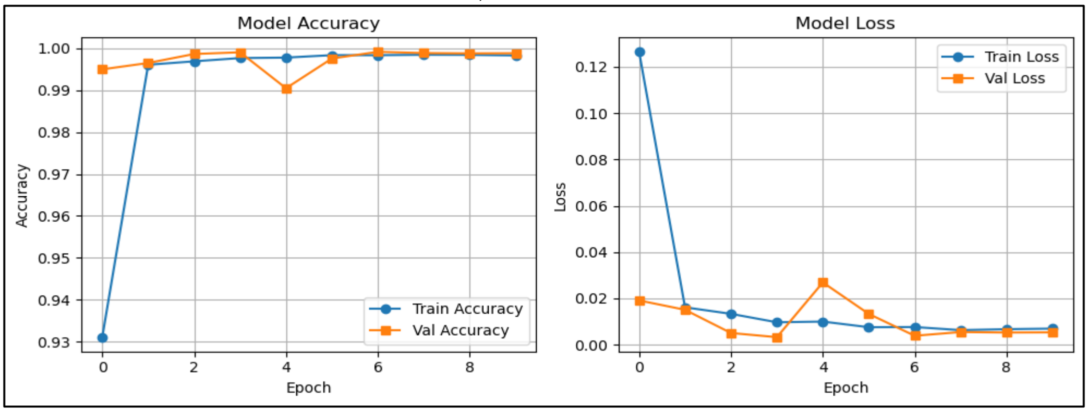

Fig. 10. Training and validation results.

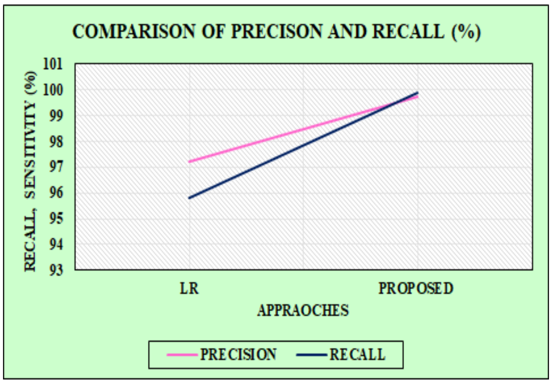

Fig. 14. Analysis of precision and recall.

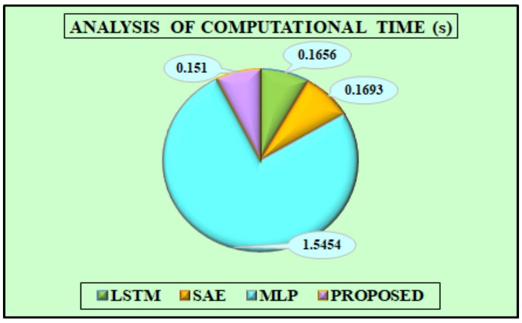

Fig. 15. Analysis of computational time.

The comparison of computational time for LSTM [26], SAE [27], MLP [28] and CARTNet approach. The LSTM, SAE and MLP has the computational time of 0.1656s, 0.1693s and 1.5454 s while the CARTNet has the computational time of 0.151 s, there by balancing both high performance and acceptable computational efficacy for smart grid applications.

Table 2

Analysis of energy consumption and latency

Approaches	**Energy consumption** (kWh)	**Latency** (ms)
GNN-transformer fusion	8.2	150
Proposed	7.9	139

The Table 2 compares the energy consumption and latency among the GNN-transformer fusion [8] and developed approach. The GNN-transformer fusion has the energy consumption of 8.2 kWh and latency of 150 ms. Also, the CARTNet approach has the reduced energy consumption of 7.9 kWh and latency of 139 ms, allowing faster, real-time fault detection critical for grid stability.

IV. CONCLUSION

This research implements an innovation approach for fault diagnosis on the power grid. The pre-processing stage enhances the reliability and quality of data, diminishing the influence of inconsistencies and missing values. By efficiently incorporating chaotic dynamics into the recurrent transformer structure, CARTNet improves the model's capability to capture difficult temporal dependencies and sudden variations of power grid disturbances. The self-attention mechanism further assures that both global and local fault- features are proficiently extracted, allowing exact fault classification even in the occurrence of noisy or incomplete data. This research is applied in Python software, demonstrates that the CARTNet approach attains better diagnostic accuracy of 99.88%, faster response time and better generalization under diverse grid operating conditions. The CARTNet approach not only advances the field of intelligent fault diagnosis but also contributes towards developing smarter and secure power grid infrastructures. Thus, CARTNet serves as a promising solution for improving situational awareness, operational efficacy and security in modern power systems.

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