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RESEARCH PAPER

A Machine Learning Based on the Enhancement of Electrical Fault Detection and Classification

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***Abstract*—The electricity transport system relies on transmission lines, which remain vulnerable to faults that can cut off operations and cost the system massive monetary losses. Transmission lines are very crucial over long distances in delivering electricity, but they also have reliability problems. Images of defects that might disrupt the power supply and put people in risk accompany reliability. Therefore, this study uses machine learning on the Electrical Fault Detection and Classification dataset from Kaggle, which comprises voltage and current observations from an 11 kV transmission system. Two models, K-Nearest Neighbors (KNN) and Long Short-Term Memory (LSTM), were constructed following data preparation, which included label encoding and Minmax normalization. The models' performance was then evaluated using metrics such as confusion matrices, accuracy (Acc), precision (Prec), recall (Rec), and F1-score. KNN offered the highest Acc of 99.72, high Prec of 99.99, high Rec of 99.55, and a high F1-score of 99.77, and hence it beats LSTM and the earlier Random Forest and Decision Tree tricks. In addition, the LSTM model demonstrated a high performance also since the training and validation loss were both stable and convergent, which indicates that learning was effective. The above findings indicate that machine learning, including multi-feature fusion, is significant to enhance the accuracy of electrical fault detection; thus, a very precise and reliable solution can be offered to minimize the loss of time and improve the safety of power transmission networks.**

Keywords—Electrical Fault Detection, Fault Classification, Power System Reliability, Transmission Lines, Power Plant.

I. INTRODUCTION

As the primary source of electromechanical energy conversion used in manufacturing, transportation, and renewable energy production, electric machines serve as the foundation of contemporary industrial infrastructure [1][2]. Their efficient operation is essential to economic stability and industrial productivity throughout the many industries of oil and gas, automotive, aerospace, and power generation. These machines alone, along with the systems they power, consume more than 40% of the world's electricity[3].

A vital resource that is probably becoming more and more limited globally is electrical energy [4]. Its rarity might be addressed in the following bi-fold manner. The latter is improved load management and energy demand forecasting, while the former is increased capacity generation [5]. An emerging trend in electrical energy forecasting and management is data-driven electrical energy efficiency management [6][7]. Electricity energy management, data science, and AI have come together to provide the most accurate and reliable system for managing energy use.

Electrical power systems are complicated and interconnected, and therefore prone to disturbances and malfunctions [8][9]. Due to the reliance on massive power plants and linked networks, this is a vulnerability, and any failures would spread swiftly. In order to guarantee timely remedial actions and prevent interruptions, fault detection and categorization are crucial [10][11][12]. The most important issues are to determine the circumstances leading to disturbances, to identify the vulnerable elements and to be aware of how network structures contribute to the propagation of faults [13][14][15]. The scope of fault detection can be related to simple visual inspection and complex AI-based diagnostics. Manual checks, which are considered traditional methods, contribute to the detection of issues such as broken cables.

Machine learning algorithms used as a fault prediction application may enhance the strength of the power transmission system [16]. As a result of the need for solutions for predictive maintenance and the reduction in complexity of industrial systems, the incorporation of AI into fault diagnosis systems has significantly expedited [17][18]. Expert systems, fuzzy logic, and neural networks are the AI methods that have shown more effectiveness in detecting weak defect patterns and changed operating circumstances [19]. Over the past years, machine learning (ML) has been gaining popularity in building systems using automated fault detection and diagnostics (AFDD) [20]. More complicated defect patterns are being found using ML, and particularly DL with CNN and RNN types, which are more adaptable and less reliant on expert knowledge. Concurrently, tools that integrate model- and data-based diagnostics are showing promise for enhancing the accuracy and resilience of fault categorization [21].

A. Motivation and Contributions of the Study

The key purpose of this is to come up with a method that will enhance the reliability and safety of the power transmission system in such a way that even minor and inconspicuous failures would not result in blackouts, damage to equipment, or operational hazards. Traditional detection methods are often not very fast or precise, leading to the exploration of machine learning as a more intelligent, data-driven approach. This, in turn, will result in faster, more reliable responses, less downtime, and greater stability of transmission networks.

- The dataset for Electrical Fault Detection and Classification was used, containing real current and voltage measurements, thus providing a realistic and reliable base for model building.

- Two machine learning models, KNN and LSTM, are developed and deployed to increase the precision of fault detection using multi-feature electrical signals.
- To completely evaluate the diagnostic power of every model, a detailed performance evaluation using various factors that included acc, prec, rec, F1score, and confusion matrices was conducted.
- The practical significance of ML-driven fault has been disclosed, providing a reliable and quick approach that can contribute to the safety of the operations, reduce the stoppages, and contribute to the smarter monitoring of the transmission system.

B. *Justification and Novelty*

The justification for this study is the increasing need for more precise and intelligent methods to detect faults in rapidly evolving power transmission systems. In such systems, the use of traditional methods is increasingly failing to provide timely and reliable diagnoses. This research, therefore, by the use of real electrical measurements and the application of advanced ML techniques, resolves the issues that are left by the conventional methods. The study's originality is the complete integration of multi-feature fusion, thorough preprocessing, and comparative evaluation of both KNN and LSTM models on a realistic fault dataset. Moreover, the finding that KNN outperforms deep learning and classical models with almost perfect accuracy opens up a new, very efficient way of fault detection, which is simpler but more effective for the implementation of the power networks in the real world.

C. *Organization of the Paper*

The paper is formatted as follows: Section II summarizes relevant studies on electrical problem detection. Section III describes the model's design and approach. Section IV presents the experimental results. Section V summarizes the study's findings and outlines future research targets.

II. Literature Review

The recent progress achieved through the use of ML and DL techniques for the betterment of electrical fault detection in inverters, HVDC networks, and circuits, etc., is the main subject of this section. Different researchers have been engaged in the activities of analyzing signals, extracting features, and improving the overall detection accuracy for the purpose of locating faults sooner and more reliably. Table I also summarizes these studies and includes the description of the methods, results, advantages, and limitations of each study and shows how AI continues to enhance the detection of faults.

Pushpavathi et al. (2025) concentrated on defect detection and the determination of faulty inverter switches through simulating different working conditions. Motor current signature analysis (MCSA) data is used to support a deep learning-based fault classification approach that combines signal processing, feature extraction, and feature model training. Experimental validation using data from a bench setup confirmed the efficacy of the proposed approach. The study emphasizes the Self Att-SGRU DL classifier's exceptional performance, showing its potential for reliable defect identification with an accuracy of 97.15% [22].

Dai and Shao (2025) combined the power system topology and fault detection results, and an intelligent algorithm was designed to realize rapid fault location and automatic isolation. Experimental results show that AI model is superior to traditional methods and support vector machine (SVM) in fault detection accuracy, location speed and isolation efficiency, with an accuracy of 98.5%, an average isolation time of 0.2 seconds and a success rate of 98% [23].

Zhao and Peng (2024) decomposed by variational mode decomposition, and the parameters of VMD are optimized by the sparrow search algorithm, so that the number of decomposition layers can be determined adaptively. Finally, the fault feature vector is identified by the least squares support vector machine recognition model for fault diagnosis. The results show that the fault recognition rate is more than 97%, and the parallel arc fault of the inverter load is well identified [24].

Liu and Pan (2024) detected that model only perform fault analysis through current signal characteristics, ignoring voltage and other signal characteristics. Based on the traditional single-layer LSTM model, a series arc-fault detection model combining LSTM and Transformer is proposed, using voltage and current signals to identify faults. Experimental findings demonstrate that the model achieves a fault arc identification rate of about 97% across all operational scenarios. It provides a feasible scheme for arc fault detection in the electric vehicle electrical system [25].

He and Wang (2023) simulated circuit failures using a back-propagating neural network, identified real-world faults using the network, and input fault characteristics using the network's output. It begins with an examination of the concept of circuit fault diagnosis, then goes on to the extraction of defect features from simulations of circuits, training of back-propagating neural networks, and finally, verification of simulation results. Using a neural network as its basis, the experiment demonstrated that the circuit defect detection system could achieve an accuracy rate of up to 94.4% [26].

Subramaniam et al. (2023) examined a range of potential HVDC system failure scenarios and presented the findings of each analysis. The multiple machine learning classifiers in MATLAB were used to train and evaluate the retrieved data for the different types of defects. Approximately eighty thousand samples were used for training. According to the findings, the COARSE classifier had an accuracy of 89.6% and the MEDIUM classifier had an accuracy of 92.6%. However, the FINE SVM classifier had the best accuracy of 96.9% [27].

TABLE I. Overview of Recent Detection of Defects in the Electrical Systems and Machines by Machine Learning

Reference	Methods	Results	Advantages	Limitations	Recommendations
Pushpavathi et al. (2025)	MCSA-based deep learning (Self Att-SGRU).	97.15% accuracy.	Robust detection; strong feature extraction.	Only current signals are used.	Add multi-signal inputs.
Dai and Shao (2025)	AI algorithm for fault detection, location, and isolation.	98.5% accuracy; 0.2 s isolation.	Fast and highly accurate.	Limited to specific systems.	Test on wider topologies.
Zhao and Peng (2024)	VMD + SSA optimization; LS-SVM.	97% recognition.	Adaptive decomposition; good arc fault ID.	High computational load.	Simplify for real-time use.
Liu and Pan (2024)	LSTM–Transformer using voltage + current.	97% accuracy.	Multi-signal, strong performance.	Complex model design.	Optimize for embedded EV systems.

He and Wang (2023)	BPNN for circuit fault diagnosis.	94.4% accuracy.	Simple and feasible.	Lower accuracy vs deep learning.	Upgrade to modern DL models.
Subramaniam et al. (2023)	ML classification for HVDC faults.	Fine SVM: 96,9 %.	Large dataset; good comparison.	Simulation-only; no real-time.	Integrate real system data.

III. Methodology

The proposed methodology for creating the Electrical Fault Detection dataset involves transforming labels into numbers and scaling voltage and current features to a common range. The next step was to split the data so that part was utilized for model training and the rest for model performance testing. Further, two models were applied: KNN and LSTM. As shown in Figure. 1, criteria including acc, prec, rec, and F1score were ultimately used to assess the two models' fault-detection ability.

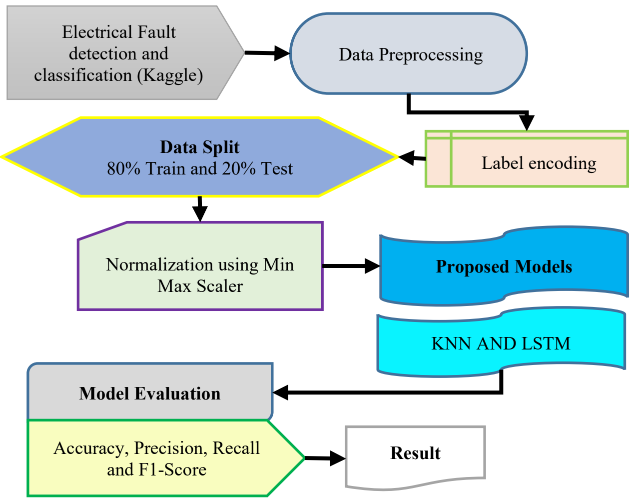

Fig. 1. Flowchart of the Proposed ML-Based Electrical Fault Detection System

A. Data Collection and Analysis

The Kaggle [1] The Electrical Issue Detection and Classification dataset is essential for improving power transmission network issue detection. The transmission line system, which consists of four 11 kV generators and transformers, incorporates line currents and voltages that occurred under different failure situations. This data set allows one to develop algorithms that correctly detect and classify faults, enhance the reliability of the network and reduce downtime. The Binary classification data of 12001 rows and 9 columns is used to identify the presence of a fault.

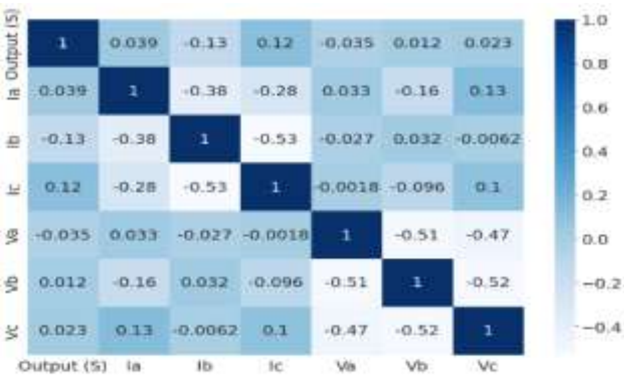

Fig. 2. Correlation Matrix of Current and Voltage Features

Figure. 2 shows the correlation coefficient between the current and voltage characteristics, where the self-correlation of all characteristics is 1. Some of the variables are moderately correlated, such as Ib and Ic with the correlation of -0.38 and Vb and Vc with -0.52. These numbers show that the features interact significantly but not in a redundant way; thus, each feature still contains unique information, which is valuable for fault detection precision.

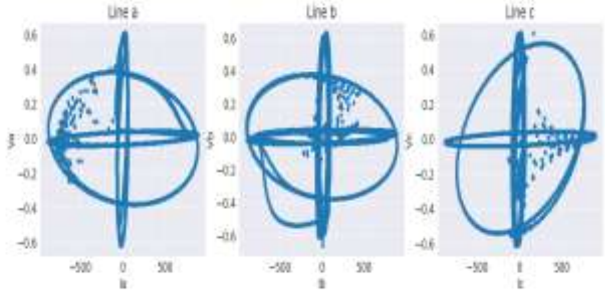

Fig. 3. Scatter Plots of the V-I Relations for Three-Phase Lines

Figure. 3 demonstrates the scatter plots depicting the relationship of current and voltage for phases a, b, and c. The plot of the current (Ia, Ib, Ic) and of the voltage (Va, Vb, Vc) showed a typical elliptical pattern of the three-phase power system. The same stable and balanced operation is indicated by the uniform elliptical shapes in all phases, while the minuscule fluctuations in point density signify the natural signal variations.

B. Data Preprocessing

The process of data preprocessing was mainly aimed at cleaning and organizing the dataset to make it easier to work with and more dependable for the analysis. Indispensable columns were deleted, sorted in a like manner, and the dataset was modified so that all categories got an equal representation. In a nutshell, the data preprocessing acted like a filter that turned muddy raw data into a clear and well-balanced form that was ready for accurate modelling.

C. Label Encoding

Label encoding is one of the most adopted encoding schemes owing to the simplicity of the conversion mechanism. The data values are converted to numbers from the list of enumerations of the different values represented by the feature. Although label encoding is easy to implement, it produces implicit ordinality among the converted values even though none exists.

D. Data Splitting

The dataset was split into 80% for training and 20% for testing, based on its characteristics. This division was done so that every scenario was adequately represented in both sets.

E. Normalization using Min Max Scaler

To normalize the feature dataset (Ia, Ib, Ic, Va, Vb, Vc) of six features, Min Max Scaler from scikit-learn was used. The features are scaled to a common range with this operation. It helps to keep the feature-value relationships intact while

[1] https://www.kaggle.com/datasets/esathyaprakash/electrical-fault-detection-and-classification/data

avoiding training that is hindered by too large variations. If normalization is not done, the loss function can oscillate very much, thus slowing down or destabilizing model convergence. Here min-max normalization was employed and its mathematical expression is provided in Equation (1).

$$\text{Normalized Data} = \frac{X - MIN(X)}{MAX(X) - MIN(X)} \quad (1)$$

F. Proposed Model for Electrical Fault

Machine learning designs predictive systems to uncover meaningful patterns in data. In this research, a comparison was made between KNN and LSTM models. KNN is a classifier that uses auto-similarity, whereas LSTM recognizes traits in a series of time. The performance of the two paradigms was significantly different, as per the results.

1) K-Nearest Neighbors (KNN)

A non-parametric technique for classification, the k-NN algorithm is used to address a variety of classification issues [28]. This method of instance-based learning just uses local area approximations of the function and postpones all calculations until classification time. The majority vote of an object's neighbors determines its categorization; therefore, it is placed in the class that is most common among its kNN. A fuzzy variant of the k-NN technique is frequently employed

2) Long Short-Term Memory (LSTM)

LSTM networks build an RNN during training [29]. In binary classification, the output of the last time step is subjected to a sigmoid activation function σ to get the final prediction yLSTM(x). In particular, this prediction is computed using the output layer's Bias Term b_0, the Weight Matrix Wo, and the Hidden State h_t (Equation 2a). The prediction weight matrix yGRU(x) for each label k in the case of multi-label classification is similarly computed by applying the σ function to the output of the last time step for that label, utilizing the Hidden State h_t Weight Matrix W_o^k and Bias Term b_o^k (Equation 2b).

$$yGRU(x) = \sigma(W_o h_t + b_o) \quad (2a)$$

$$yGRU(x)^k = \sigma(W_o^k h_t + b_o^k) \quad (2b)$$

G. Model Evaluation

The confusion matrix, recall, accuracy, precision, and F1 score were among the measures used to assess the performance of a classification model. Tables showing the counts of TP, TN, FP, and FN make up the confusion matrix, which gives a thorough picture of the model's performance. The accuracy is determined by dividing the total number of occurrences by the ratio of properly predicted cases (TP and TN), as indicated in Equation (3).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Accuracy indicates the model's overall accuracy but might be deceptive in settings with imbalanced datasets, when certain error kinds occur more frequently than others. Precision measures the accuracy of positive predictions, as shown in Equation (4), and is important when false positives are substantial, such as when a problem is mistakenly identified that does not exist. Recall, also known as sensitivity, is determined by Equation (5), which evaluates the model's capacity to accurately detect real flaws. This is crucial when there might be detrimental effects on the functioning of the power system from failing to detect a defect (false negatives). As mentioned in Equation (6), the F1score strikes a compromise between precision and recall, offering a single measure that is helpful for handling uneven classes of defects.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (5)$$

$$\text{F1} - \text{Score} = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \quad (6)$$

IV. Result Analysis and Discussion

The main focus of the use of ML and DL techniques involves multi-feature fusion to enhance electrical fault detection. Experiments were carried out on a computer running Windows 11, an Intel(R) Core (TM) i7-10750H CPU, 16 GB RAM, and an NVIDIA GTX 1650 GPU. As shown in Table II, KNN, which is the best model among those tested, including LSTM, has achieved very impressive results by 99.72% acc, 99.99% prec, 99.55% rec, and 99.77% F1score. The values for performance metrics are very close to 1, thus, it indicates that the proposed approach has strong diagnostic capability and is overall highly effective.

TABLE II. Classification Metrics for Fault Detection Systems

Matrix	KNN	LSTM
Accuracy	99.72	99.25
Precision	99.99	99.63
Recall	99.55	99.72
F1 Score	99.77	99.17

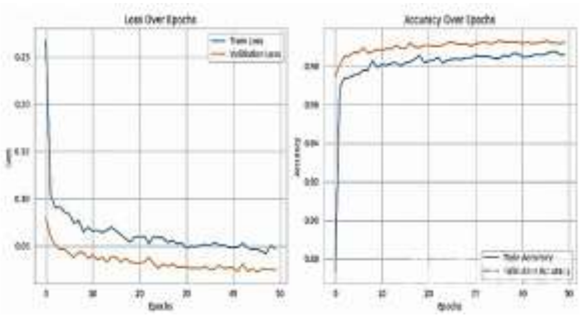

Fig. 4. LSTM Training and Validation Loss and Accuracy Over Epochs

Figure. 4 displays the decrease of both training and validation losses to a great extent, and hence they stabilize at values of approximately 0.02 and 0.03, respectively, which is a clear indication of the model learning effectively and also being able to generalize well. Moreover, the losses for train and validation being very close together imply that no overfitting or underfitting has occurred, which means that the model has a stable and consistent performance on train and validation data.

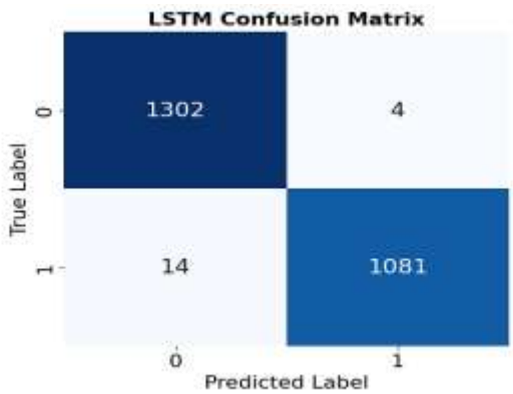

Fig. 5. Confusion Matrices of the LSTM Model

The Confusion Matrix given in Figure. 5 shows the LSTM classifier. The LSTM classifies 1302 examples of class 0 and 1081 of class 1 correctly with very rare misclassifications. The matrix, in general, shows that LSTM achieves an extremely high accuracy rate and a quality similar to that of reliability in fault detection.

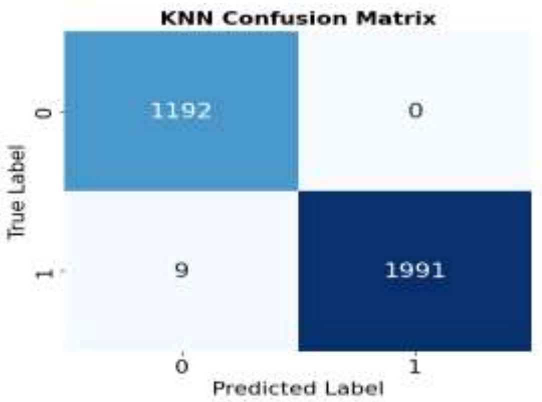

Fig. 6. Confusion Matrices of KNN Model

The K-nearest neighbor confusion matrix presented in Figure. 6 shows superior model performance. The KNN model correctly classifies all 1192 samples of class 0 and 1991 samples of class 1, with only 9 misclassified instances from class 1 to class 0. The performance is more or less perfect, showing that the KNN model for fault detection in accuracy and reliability serves its purpose.

A. Comparison and Discussion

Table III details the results of the different machine-learning models, KNN, LSTM, RF, and DT, used for electrical fault detection. Among these, KNN is the most effective across all performance metrics, achieving 99.72% accuracy, 99.99% prec, 99.55% recall, and 99.77% F1score. LSTM is also a very strong performer, with all its metrics above 99%, while RF and DT are at considerably lower levels, with accuracies of 89.45% and 85.76%, respectively. Therefore, summarizes the comparison and shows that KNN and LSTM outperform the traditional models; thus, the proposed multi-feature fusion approach is more effective.

TABLE III. PERFORMANCE COMPARISON OF ML MODELS FOR ELECTRICAL FAULT DETECTION

Matrix	Accuracy	Precision	Recall	F1 Score
KNN	99.72	99.99	99.55	99.77
LSTM	99.25	99.63	99.72	99.17
RF [30]	89.45	87.5	87.5	87.5
DT [31]	85.76	85.79	85.76	85.76

The electrical fault detection is improved with the help of the proposed multi-feature fusion method, which merges several current and voltage features to models like KNN and LSTM that can then find complex patterns in a more efficient way. Consequently, the accuracy is raised, the system reliability is improved, and the number of misclassifications is reduced in comparison to conventional methods; thus, it is very appropriate for a powerful and smart power system monitoring.

V. CONCLUSION AND FUTURE SCOPE

The electricity generation, transmission, and distribution processes were very important and paramount for the human race's development. Hence, these three processes must operate with high adequacy and very few faults. All systems are prone to faults to some extent, and, thus, ahead of time, fault detection systems that are both accurate and efficient have to be put in place to keep the system stable and safe. The study confirms that, among others, machine learning, in particular the KNN model, is a powerful ally in electrical fault detection, as it provides the highest outcomes with 99.72% acc, 99.99% prec, 99.55% recall, and a 99.77% F1score, which is significantly higher than both LSTM and conventional classifiers. Moreover, the results of the study confirm that KNN denoted a very effective, interpretable, and computationally efficient solution for a real-time monitoring application. On the other hand, the other side of the coin is that the study was limited to one dataset only, which may not be representative of all real-world situations and also by possible models' sensitivity to noise or measurement variations. But again, the results underscore the method's high diagnostic capability and practicality. The study will, in the future, address the use of diverse and real-time datasets, testing the model strength in relation to noisy grid conditions as well as combining different models such as CNN-LSTM hybrids, Gradient Boosting Machines (GBM) and Transformer-based architecture to achieve the accuracy, scalability and adaptability of power system fault detection to a new level.

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