



P-ISSN: 2788-9971 E-ISSN: 2788-998X

NTU Journal of Engineering and Technology

Available online at: <https://journals.ntu.edu.iq/index.php/NTU-JET/index>



# Fault Classification and Localization in Power Transmission Lines Using LSTM and Vibration Data Analysis

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## Article Informations

**Received:** 15-03-2025,  
**Accepted:** 28-04-2025,  
**Published online:** 01-03-2026

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**Key Words:**  
Power transmission line,  
LSTM,  
AI,  
RRNs.

## ABSTRACT

The precise classification and localization of faults in power transmission lines are very important to ensure grid stability and to minimize service interruptions. Traditional methods of fault detection frequently have difficulty with complicated fault scenarios, faults of high impedance, and varying conditions of operation. Throughout this paper, an approach of a new machine learning-based for fault classification and localization in power transmission lines adopting Long Short-Term Memory (LSTM) networks and vibration data analysis is proposed. In contrast with conventional impedance-based and methods of traveling wave, the proposed approach takes advantage of temporal dependencies within vibration signals for enhancing predictive precision. Through capturing different faults types, simulation as well as location, a dataset of fault conditions is being generated. For recognizing distinguishing fault patterns and predicting location's fault with high accuracy, LSTM-based model we proposed is trained. The experimental results show how the LSTM model is superior in dealing with sequential data and, subsequently, improves fault localization precision. Moreover, experimental outcomes confirm that the proposed approach is robust, which leads to high classification precision and minimum localization error. The findings show the potentiality of vibration-based machine learning models to revolutionize fault management within power grids, which offers a solution that is more adaptive and data-driven to the challenges of fault classification and localization.

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## 1. Introduction

Power transmission systems being reliable and stable are essential to ensure the constant delivery of electricity to commercial, industrial and residential consumers [1, 2]. In face, faults in transmission lines pose a real threat to grid stability and might cause power outages, infrastructure destruction and eventually economic losses [3]. There are many possible factors leading to the faults, such as bad weather conditions, insulators breakdowns, failure of equipment, and external factors animals intrusion and tree contracting. The results of these faults might be serious. They might lead to wide range blackouts that affect consumers. For example, In india, in 2012 a blackout left behind nearly 400 million people with no power. Another incident occured in 2003 in North American where a blackout losses eastimated to be nearly \$6 billion [4, 5]. Hence, there are many essential factors that could minimize and facilitate fast recovery, including the critical nature of power transmission infrastructure, timely and efficient fault classification and localization [6].

Conventional fault detection ways, including relays of impedance-based distance and techniques of traveling wave, have been commonly used in diagnosing faults in power systems [7, 8]. Nevertheless, these traditional methods shows many limitations, especially they are sensitive to changing fault conditions, being inaccurate in dynamic network environments, and vulnerable to transient disturbances. For example, techniques Impedance-based depend on voltage and current measurements in estimating fault locations. However, they struggle with being inaccurate owing to varying of fault resistance and load conditions [9]. In a similar way, methods of traveling wave-based demand high-frequency signal analysis. In addition, noise and attenuation over long distances affect them [10]. Therefore, due to the above-mentioned challenges, fault detection methodologies that are more robust and adaptive, which could be operated various and complex fault scenarios, are very essential.

In spite of developments in fault detection methods, many challenges prevent their work effectively [11]. The fault conditions variability represents a major challenge, since transmission networks don't operate under similar environmental and loading circumstances, that make it hard to develop a comprehensive fault detection model. In addition, another major challenge represents data acquisition and processing constraints, since many available fault detection systems depends on Phasor Measurement Units (PMUs) and Remote Terminal

Units (RTUs), having limitations in regard with data resolution and real-time processing [12]. Moreover, computational complexity is another challenge, since AI-based models frequently require considerable computational resources, consequently they might hinder real-time implementation [13]. Another critical challenge includes distinguishing similar fault types, as some conditions, such as three-phase-to-ground faults and line-to-line faults, show similar characteristics of waveform, which make differentiation hard even for advanced ML models [14].

Recently, techniques of machine learning (ML) and deep learning (DL) have become a encouraging alternatives for fault classification and localization in power transmission systems [15]. ML-based models use historical fault data to distinguish patterns and anomalies, which enable automated and highly precise fault detection. Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Decision Trees (DTs), and eXtreme Gradient Boosting (XGBoost) have been discovered for the purpose of fault classification tasks [16, 17]. Nevertheless, many of these models have difficulties with processing of sequential data and long-term dependencies, that are crucial for precise fault localization. In this regard, Long Short-Term Memory (LSTM) networks, a special form of recurrent neural networks (RNNs), represent a convincing solution owing to their capability in capturing temporary dependencies in time-series data [18], Figure 1 shows LSTM architecture [19].

The proposed study introduces a novel LSTM-based approach for fault classification and localization in power transmission lines, using vibration data as an extra source of diagnosed information. In contrast with methods of conventional electrical signal-based, vibration data gives a substitute means of faults detecting, especially in situations in which electrical disturbances are minimum or ambiguous. The integrating of vibration data with LSTM networks promote the the fault detection system robustness through capturing mechanical anomalies related with various fault conditions. Moreover, the approach focuses on the limitations of traditional ML models by efficiently modeling progression of sequential fault, consequently leading to the enhancement of fault localization precision and reliability.

The major contributions of the research can be summarized follow:

1. Enhanced LSTM-Based Fault Classification and Localization: The LSTM model we proposed is enhanced so as to process sequential data out of electrical and vibration sources,

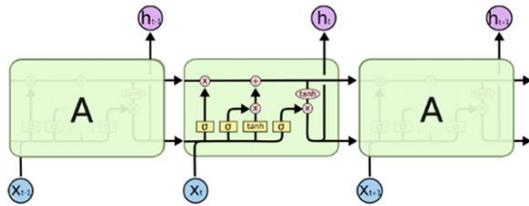


Fig. 1. LSTM architecture.

essentially enhancing fault classification precision and localization accuracy in power transmission systems.

2. Multi-Modal Data Integration for Robust Fault Diagnosis: By combination of electrical with vibration data, the approach develops capabilities of fault detection. That allows for early distinguishing of mechanical disturbances preceding electrical anomalies. It also reduces false positives and improve diagnostic reliability.

3. Comprehensive Dataset Generation and Model Validation: A varied simulation-based dataset is produced by using MATLAB Simulink, that covers various fault scenarios for ensuring model robustness. Extensive validity, which includes cross-validation and comparing with state-of-the-art methods, shows how the proposed approach is superior.

The remain of the paper is divided as follows: Section 2 mentions a review of existing techniques of fault detection with their limitations. Section 3 represents the methodology, including data acquisition, preprocessing, and architecture of the model. Section 4 includes the experimental setup, metrics evaluation, and analysis of performance. Section 5 mentions the results and comparing the approach with traditional methods. Finally, Section 6 makes conclusion of the study we have made and summarized outlines directions for future work.

## 2. Related Works

Many studies have been done related to the detection and localization of faults in power transmission lines. Although conventional methods like techniques of impedance-based and methods traveling wave methods were commonly used, yet they have many limitations such as difficulties with complicated network topologies, faults of high impedance, and variety in operating conditions [20]. Methods of Impedance-based, such as distance relays, where fault locations are estimated by measurement of impedance. However, they are vulnerable to errors owing to fault resistance and CT saturation [21]. On the other hand, in methods of traveling wave, although they are accurate, highly

sophisticated equipment are required. In addition, they computationally intensive [22]. Due to its capabilities in analyzing time and frequency components, Wavelet transform has been adopted for fault detection. It, however, has some limitations, including requiring manual feature extraction and being sensitive to noise [23]. Techniques of ML, including Support Vector Machines (SVM) and Decision Trees (DT), have enhanced fault classification by using historical data, despite the fact that SVM's performance relies on kernel selection. Additionally, DT models are apt to overfitting [24, 25]. On the other hand, models of DL, especially traditional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have become popular due to its ability to extract features automatically out of raw data, with CNNs excelling in spatial feature extracting and LSTMs through capturing temporary dependencies in time-series data [26, 27].

Nevertheless, there are still many challenges, including quality and availability of data, requirements of real-time, system being complex, limitations in sensor deploying, and model interpretability [28, 29]. Hybrid approaches, in fact, like combining wavelet transform with fuzzy logic or integrating CNNs with LSTMs, have become promising in dealing with these challenges through using methods of the strengths of multiple [30, 31]. Lately enhancements in transformer-based models, using self-attention mechanisms in capturing global context, have further advanced fault detection precision [32]. Moreover, vibration data has become a encouraging alternative for fault detection for being sensitive to mechanical anomalies. However, its application in power transmission lines remains at an early stage [33]. In spite of the above-mentioned advancements, integrating vibration data with advanced DL models like LSTMs and transformers offers an encouraging path for real-time fault detection, providing challenges relating to noise, scalability, and interpretability are addressed [34]. Usage of ensemble learning techniques for improving fault detection precision have also been explored recent studies. For instance, combination of multiple ML models, including Random Forests and Gradient Boosting, has shown promising results in enhancing fault classification performance since it reduces the risks of overfitting and improves generalization [35]. In a similar way, ensemble methods integrating CNNs and LSTMs are proposed in capturing spatial and temporal features in fault data, where high precision in fault classification and localization is achieved [36]. Another encouraging approach is the usage of transfer learning, in which pre-trained DL models are fine-tuned for tasks of fault detection. This approach shows ways to decrease the large amounts of labeled data, which is seen as a challenge in applications of fault detection [37].

Beside electrical signals, like voltage and current, the usage of other kinds of data for fault detection, such as vibration, acoustic, and thermal signals, have been explored by researchers. Vibration data, specifically, has become popular since they are sensitive to mechanical anomalies, including loose connections, cracks, and imbalances. For example, vibration data are used in detecting faults in rolling bearings, that achieve high accuracy in fault classification and localization [38]. Nevertheless, the vibration data application in power transmission lines is newly used, with limited research done its efficiency in real-world scenarios. Another space of research is the advancement of real-time fault detection systems that could be operated under noisy conditions and limited sensor deployment. For example, micro-phasor measurement units ( $\mu$ PMUs) are proposed as a way of a cost-effective solution for real-time that monitor of power systems. The above-mentioned devices supply high-resolution data which could be used for fault detection and localization, yet their deployment is sometimes limited because of the cost and space constraints [39]. For addressing this challenge, using of data augmentation techniques have been proposed, including synthetic data generation and noise injection, for improving the robustness of ML and DL models. At last, the interpretability of ML and DL models is a decisive challenge in applications of fault detection. Many models are sometimes considered "black boxes," making interpreting their decisions and understand the underlying mechanisms difficult. For addressing this case, researchers have used explainable AI (XAI) techniques, including as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), so as to supply insights into process of the decision-making of ML and DL models. These techniques have enhanced the trustworthiness and transparency of fault detection systems, making them more appropriate for highly important applications like power system protection.

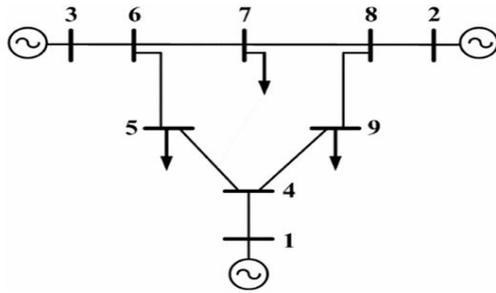
### **3. Proposed Methodology**

In this research methodology, electrical and vibration data with techniques of ML are integrated aiming at improving the precision of fault classification and localization in power transmission lines [7]. The process of data acquisition includes the process of collecting electrical signals, like voltage and current waveforms, based on simulations using the IEEE 9-Bus system in MATLAB Simulink [9]. In addition, vibration data to be captured employing high-sensitivity accelerometers strategically mounting on towers of transmission line. This approach of dual-sensing guarantees that electrical anomalies and mechanical disturbances are both recorded, which provides

more complete understanding of fault features. The datasets that are acquired are subject to strict preprocessing, including noise filtration via wavelet denoising process, normalizing signal consistency, and segmenting into time windows aligning electrical and vibration signals. The structure of this approach guarantees that solely high-quality and synchronized data to be used in subsequently analyses. Among the crucial challenges in fault detection is the difficult distinguishing of similar fault kinds, in particular the noise presence and transient variations. Conventional methods that depend only on electrical signals sometimes couldn't succeed in differentiating faults that show overlapping electrical features [11]. By combining vibration data, this limitation is overcome by our proposed method through capturing mechanical oscillations relating to fault appearances. Furthermore, conventional techniques struggle with computational inefficiencies, making real-time fault detection challenging. To address this, our methodology employs advanced feature extraction and dimensionality reduction techniques, ensuring optimal processing speed and accuracy [15]. Moreover, traditional techniques have difficulty with computational ineffectiveness, which makes real-time fault detection a challenging issue. For addressing this challenge, advanced feature extracting and dimensionality reducing are employed in our methodology, whereby best processing speed and precision are ensured.

Feature extracting plays a crucial role in transformation of raw data into structured inputs enhancing the model performance [17]. Features of Time-domain, including statistical parameters (mean, standard deviation, skewness, and kurtosis), peak detection, and root mean square (RMS) values, to be computed for quantifying variations in the signals that are recorded [20]. The previously mentioned features help in identifying suddenly changes in levels of voltage, current, and vibration which might indicate faults. In addition, for providing insights into transient disturbances nature, zero-crossing rate and crest factor have been extracted[25]. On the other hand, employing features of fast Fourier Transform (FFT) and Wavelet Transform, frequency-domain are also extracted. This enables an in-depth analysis of dominant frequency components and characteristics of transient fault. A global view of frequency distribution is provided by the FFT, whereas the Wavelet Transform captures localized time-frequency variations which are important to distinguish different kinds of faults. For assessing the intensity and complexity and detected signals, spectral entropy and energy distributing are computed. To get computational burden minimized, techniques of dimensionality reduction, such as Principal Component Analysis (PCA) and mutual information-based selection, to be applied. These methods guarantee that solely the features that are

discriminative and most relevant are retained, which enhance model interpretability and effectiveness.



Furthermore,

Fig. 2. IEEE 9 bus system diagram.

techniques of feature ranking, including Relief F and recursive feature elimination (RFE) are used to give the priority to the most affecting features, which reduce redundancy at time of maintaining accuracy [30].

Long Short-Term Memory (LSTM) networks are used to build the model architecture, particularly are designed for processing sequential data effectively [7]. LSTM networks are a specialized pattern of Recurrent Neural Networks (RNNs) addressing the vanished gradient problem by combining memory cells that are able to retain long-term dependencies [31]. There are three key mechanisms by which these memory cells are controlled which are: the input gate, forget gate, and output gate. The input gate works to determine which new information have to be added to the memory cell. The forget gate works to decide which previous information have to be discarded [33]. The output gate works to control the flow of information out of the memory cell up to the coming time step. This gated structure permits LSTMs to efficiently capture temporal relations in time-series data, which make them especially appropriate for fault detecting in power transmission lines. Dealing with large volumes of streaming data represents another crucial challenge in real-time fault detecting. LSTM networks, with their capability in remembering long-term dependencies, supply a sustainable solution by decreasing the need for comprehensive retraining while keeping performance over prolonged operations [32].

The structure of the input layer allows electrical and vibration data to be handled separately, using independent embedding layers for encoding information before it is passed through the LSTM network. Stacked LSTM layers, each one consists of 128 hidden units, are used for capturing long-term dependencies in the signal sequences, efficiently to distinguish between transient disturbances and persistent faults. The rate of dropout is set to 0.3 to avoid overfitting. For stabilizing training, we apply batch normalization. An incorporated attention mechanism further

enhances interpretability by giving much more importance to critical timing steps inside the fault sequences.

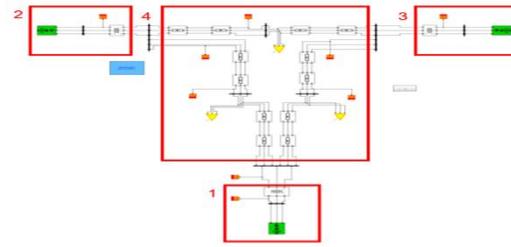


Fig. 3. IEEE 9 bus system diagram.

The output of the LSTM layers is processed by completely connected layers with ReLU activation, which refine the extracted characteristics before the last classification. The function of Softmax in the output layer categorizes faults according to the kind and location.

For optimizing model performance, the Adam optimizer having a learning rate of 0.001, which ensures effective weight updates, is employed by training process. The size of batch is set to 64, which balances speed training and stability. Categorical cross-entropy is the used loss function, that is appropriate for tasks of multi-class classification. The dataset is being split into an 80-20 ratio to train and test, with k-fold cross-validation (k=5) used to enhance model generalization. Employing multiple metrics, performance is estimated, including, precision, accuracy, recall, F1-score, and Mean Absolute Error (MAE) for fault localization accuracy. The training is done for 100 epochs with a mechanism of early stopping to avoid overfitting. Through using an approach of multi-modal data, techniques of advanced deep learning, and an advanced training pipeline, this methodology efficiently handles with major challenges in fault detecting, which provides a scalable and dependable solution for monitoring of real-time power transmission. Moreover, the capability of integrating multiple data sources and optimizing computational effectiveness guarantee that this way can be deployed practically in applications of real-world grid monitoring. It also overcomes the limitations and challenges of existing techniques.

#### 4. Experimental Work with Result

The implementing of models of Long Short-Term Memory (LSTM) for fault classification and localization in the IEEE 9 Bus system as in Figure 2, showed great performance in pinpointing and identifying faults [19]. MATLAB Simulink is used to simulate the proposed system as shown in Figure 3, which consists of nine buses, three generators, three loads, and three transformers, producing overall datasets under normal and fault conditions. Under normal circumstances, the load is

changed at three levels (high, medium, and low) with  $\pm 10\%$   $P_{max}$  as fluctuations, with a dataset of 21,000 instances.

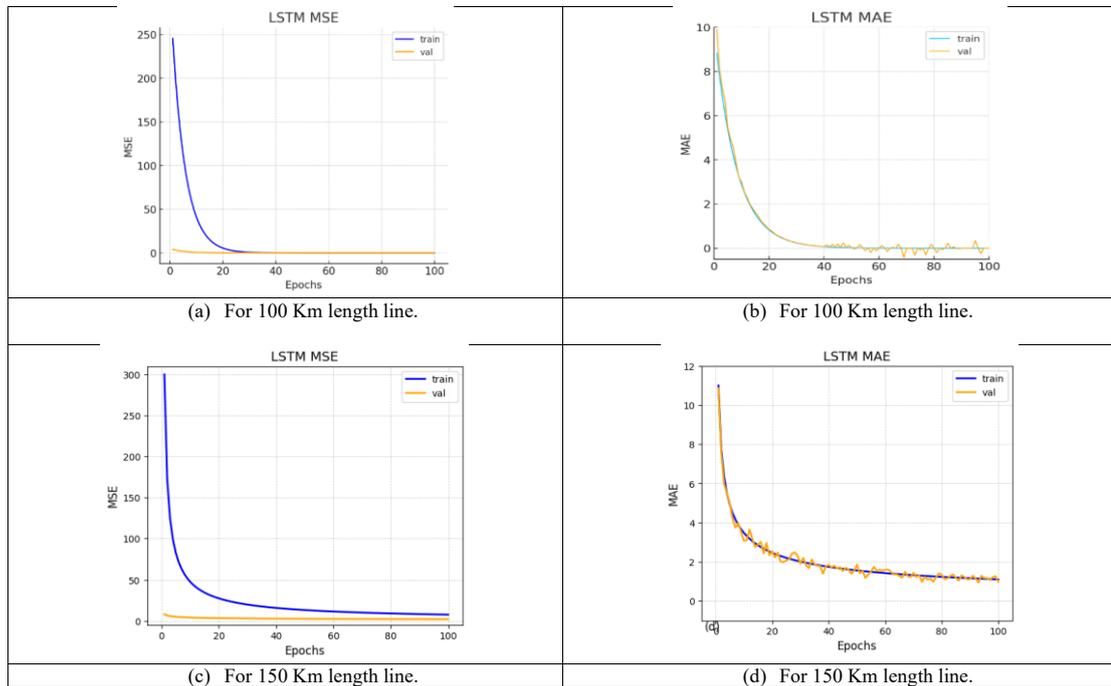


Fig. 4. Comparison between MSE and MAE of LSTM algorithm.

Under fault circumstances, the load is set at specified levels (95%, 65%, and 50%  $P_{max}$ ), and 10 different short-circuit fault kinds are simulated with varying values of fault resistance at 5 various levels, across 12 fault positions in four zones. The dataset resulting consist of 16,200 fault instances, which leads to a total of 37,200 instances. The faults are labeled according to their kind, which includes line-to-ground, line-to-line, line-to-line-to-ground, and three-phase faults, with the data splitting, 80% goes for training and 20% goes for testing. The LSTM model is trained for capturing the temporal dependencies in the voltage and current data out of buses 1, 2, and 3, with 12 output labels for fault classification and localization of the fault position measured in kms. In addition, LSTM is employed for localizing the fault position on transmission line 4–5, that is selected as the line in which faults occur. The length line in the experimental work is 100 and 150 kilometer, and faults are produced at each kilometer alongside the line. With ten kinds of short-circuit faults (AG, BG, CG, AB, BC, AC, ABG, BCG, ACG, and ABC), 3 load levels (95%, 65%, and 50%  $P_{max}$ ), and five values of fault resistance.

For fault localizing, the phase current and voltage at Bus 1, 2, and 3 (generators) are employed as the input data, whereas the distance from the fault location up to Bus 4 is used as the output data. The dataset is split into 70% to training and 30% to testing. In regressing problems, like fault localization, the aim is prediction of a continued

output variable—in this situation, the fault position in kms.

For evaluating the performance of the regressing model, Mean Absolute Error (MAE) and Mean Squared Error (MSE), metrics are employed for measuring the difference of predicting and actual values. MAE is used calculate the absolute difference average between actual and predicting values, the lower values indicate better model performance. MSE is also used to calculate the squared difference average, granting more weight for larger errors, and is widely used as the loss function for regressing models. Figure 4 shows the MSE and MAE of LSTM algorithm in training (blue curve) and testing (orange curve) datasets for the 100 and 150 kilometer respectively.

The horizontal axis indicates the epochs number during the process of training. In our research, MSE is employed as the loss function for all regressing models, resulting in a stable MSE curve at time of training. On the other hand, the MAE curve is fluctuated at the early stages of training process, due to many factors such as randomly initialization of model parameters, batch variability during process of training, and data complexity. As the progressing of training and the model parameters are adjusted, the MAE fluctuations reduced, and the model performance, on the other hand, consistently improved. The model

reaches to a best state after about 100 epochs, with an obvious reduction in error and enhanced predictive precision. These results emphasize the efficiency of LSTM models in tasks of fault classification and localization, especially in the challenging context of systems of power transmission.

### 5. Result Comparison

In this section, we compare our proposed method result of localize the fault position on transmission lines in IEEE 9 Bus system with different classification algorithms as shown in Table (1). The length of this line is 100 km, with multiple faults generated to measure the accuracy of model classification. The results show that LSTM achieve a higher classification accuracy, which can be very useful for understanding the model and select the better features, moreover, the LSTM often delivers high performance in terms of accuracy and other metrics compared to other algorithms.

**Table 1.** Comparison between classification methods.

Metric	SVM	Decision Trees	XGBoost	LSTM (our method)
Accuracy	87.29 %	89.1 %	92.43 %	98.51 %
Training time	20 s	12 s	10 s	9 s

### 6. Conclusion

This research displays a novel approach for classifying and localizing faults in transmission lines based on ML algorithms. Using MATLAB Simulink, the IEEE 9 Bus system is simulated for generating large dataset for model training. Fault datasets were generated with different parameters link fault types, load level, fault resistance, fault position, for mimicking the practical condition. 37,200 samples were created for fault classification, whereas 16,200 datasets were created for fault localizing. The results showed that ML models are capable of classifying and localizing faults with very high precision. In classifying task, the classified faults with the accuracy of 98.51%. In regressing task, the LSTM is capable of localizing faults with MAE <150m in a 100 km transmission line. To classify and localize faults in transmission lines in correct way plays an important role in enhancing stability and reliability of the power system. In future works, the error in fault data shall be taken into consideration for mimicking the transformers error of current and voltage in

practical. Moreover, the models shall be enhanced fir reducing the training time, particularly the regression models.

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