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Real-Time Fault Diagnosis in Electrical Power Systems Using Neural Networks

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ABSTRACT

In this research, we propose a novel approach for real time fault diagnosis of the electrical power systems using a Hybrid CNN - LSTM architecture. The method leverages the strengths of CNNs for spatial feature extraction from time-frequency representations of electrical signals and LSTMs for learning temporal dependencies in fault patterns. First the electrical signals are pre-treated using techniques such as Wavelet transform or Short Time Fourier Transform (STFT) to generate time frequency spectrograms. Then, using Dimensionality reduction methods like Principal Component Analysis (PCA), important features are chosen so that faster model training can be achieved. Through the usage of Tensorflow/Keras with GPU acceleration, the train and evaluation of the hybrid CNN-LSTM model is performed for fast and accurate fault detection in real time. The proposed method improves fault diagnosis accuracy and processing speed greatly, thus, appropriate for deploying in smart grids and wide scope electrical systems, in order to boost the system reliability and minimize the downtime.

Keywords: *Real-time fault diagnosis, electrical power systems, Hybrid CNN-LSTM model, TensorFlow/Keras, GPU acceleration, feature extraction, time-frequency analysis.*

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1. INTRODUCTION

As the electrical power system becomes more and more complex, and as the need for reliable power continues to increase, the need to provide real time fault diagnosis has grown critical to the task of keeping the power system stable and downtime to a minimum. The electric power systems are vulnerable to the various faults like short circuits, equipment's failures and overloads that cause great troubles and are not detected and resolved within the time they create. Although the traditional fault detection methods have been effective, they have several limitations such as speed, accuracy and adaptability to the dynamic system condition. In order to overcome these challenges, machine learning techniques such as neural networks as a means of analyzing complex temporal patterns in real time system data have found wide harnesses of interests [1].

To that end, this research presents a new method for real time fault diagnosis in an electrical power system using a Hybrid CNN & Long Short Term Memory (LSTM) model. Spatial features of the transformed electrical signal data (e.g., waveforms or spectrograms) are extracted using the CNN, and thus the CNN is capable of capturing not only data with a steady state but also data with a transient characteristic of the system [2]. For fault patterns analyzed over time and predicting the progression of faults it is more preferable that LSTMs are used to detect the faults through time and to predict how they go as shown in figure 1.

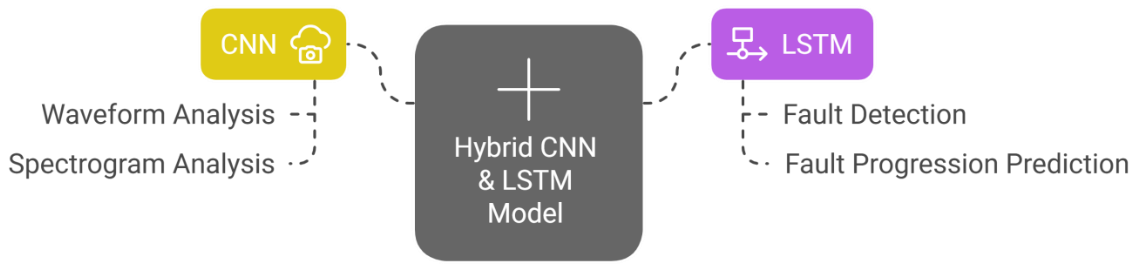

Figure 1.Real-Time Fault Diagnosis in Electrical Power Systems

Model training is efficiently done through the methodology using TensorFlow/Keras with GPU acceleration while real-time deployment is possible. This combination leads to a faster processing of large amounts of electrical signal data required for fault diagnosis especially under operational conditions. Evaluations on real time data from electrical power grids are presented using the proposed system time comparison with recent traditional methods show the ability to detect faults at higher accuracy and at greater speed [3].

This approach improves the reliability of the grid by improving the capability to perform reliable fault diagnosis on electrical power systems for reduced downtime, improved fault management, and overall better efficiency. Due to the ability of the hybrid CNN-LSTM model to adapt to different fault types and dynamic operating conditions, it provides a promising solution for the emerging tasks in power system monitoring and maintenance [4].

2. RELATED W ORK

The area of real time fault diagnosis in electrical power systems has been an area of active research and numerous studies have been conducted to utilize the machine learning and neural networks to reinforcing the system reliability. Early fault detection approaches used such traditional signal processing techniques as Fourier Transform and wavelet analysis coupled with rule based classification of fault. Nevertheless, most of these methods face difficulties with analyzing such complex and dynamic system behaviors in order to delay the detection and yield inaccurate results under non linear or noisy conditions. To overcome the limitations described above, existing research has been conducted to use neural networks, especially deep learning models, because of their superior capability in processing the complex patterns and large datasets [5].

Feature extraction using electrical signal data makes up a large portion of the recent research involved the use of Convolutional Neural Networks (CNNs). Because of this, CNNs have been used to detect faults by transforming raw signals into another representation of time frequency called spectrograms, which capture steady state and transient aspects of the system. Additionally, Long Short-Term Memory (LSTM) network has been utilized to understand temporal dependencies and sequences in fault data in order to have better understanding of the fault progression and prediction. Since CNNs and LSTMs are powerful tools for spatial feature extraction and sequential data analysis respectively, hybrid approach combining these two proved to be a powerful approach for fault detection [6].

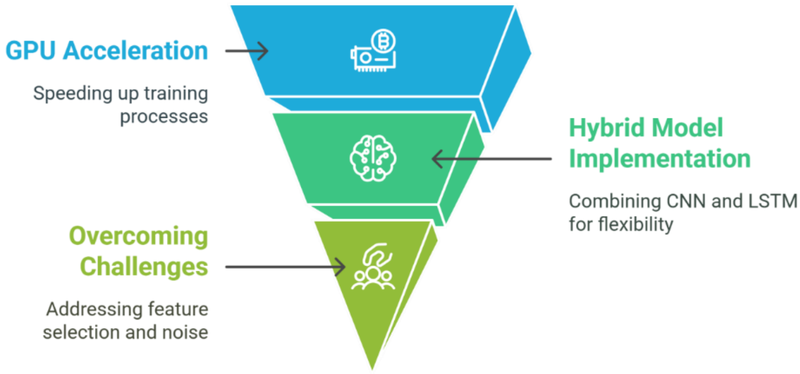

Figure 2.Enhancing Real-Time Fault Diagnosis.

In recent times, these deep learning models have been implemented using TensorFlow/Keras and speedup training using GPU acceleration and for real time deployment. Several prior studies have demonstrated that the hybrid models have improved in the number of detection speed, accuracy and flexibility than the traditional techniques [7]. Although challenges in real time deployment remain such as feature selection, noisy data handling, and incorporation of models into operational systems, a majority is solved in the paper. In addition to these advances, this research will leverage such advancements to build a more robust hybrid CNN-LSTM model for real time fault diagnosis in electrical power systems as shown in figure 2

3. RESEARCH METHODOLOGY

Figure 3 shows a successful methodology for real-time electrical power system fault diagnosis through neural networks consists of three major steps starting with preprocessing and continuing to feature selection and ending with classification. The system development goal focuses on building an accurate fast reliable tool for real-time electrical power system fault detection and classification. This is achieved with a Hybrid CNN – Long Short-Term Memory (LSTM) model and using the TensorFlow and Keras with GPU acceleration in training and deployment of the model [8].

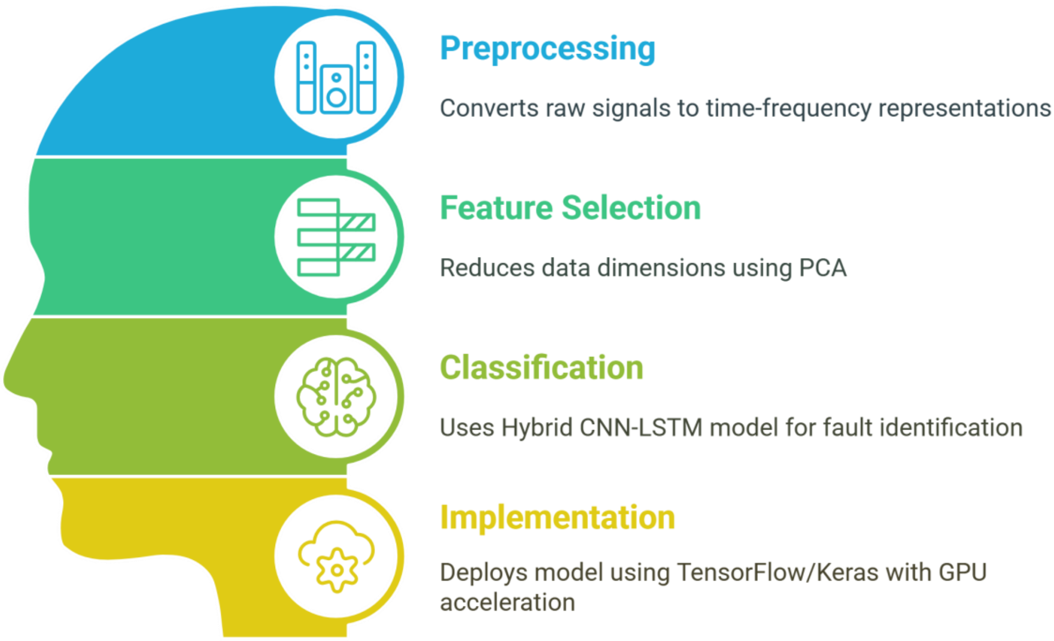

Figure 3.Shows the methodology of Real-Time Fault Diagnosis

A. Preprocessing: Time-Frequency Transformation of Raw Electrical Signals

Raw electrical signals starting from current and voltage waveforms get converted to multi-dimensional time-frequency representations for detecting both transient and steady-state power system characteristics through preprocessing. The implementation of signal transformation plays a crucial role because electrical faults generate complex patterns containing diverse changing frequency ranges [9].

The transformation process applies two essential methods:

Lineman and Distributors use Wavelet Transform (WT) to analyze non-stationary signals while decomposing electrical signals into scaled smaller parts. The detection of transient faults works best with Wavelet Transform because this method grants superior time resolution at high frequencies while supplying superior frequency resolution at low frequencies [10].

STFT transforms electrical signals into spectrograms through Short-Time Fourier Transform analysis thus displaying frequency component development using time-frequency analysis. The detection of sudden frequency variations indicates short circuits and equipment failures because these changes frequently occur during such events [11].

The deep learning model requires time-frequency representations extracted from the electrical system to understand complete operational and fault event behaviour.

B. Feature Selection - Principal Component Analysis (PCA)

Feature selection follows the extraction process of time-frequency features. The electrical data sources tend to produce abundant information which includes noncritical diagnostic data. Data dimension reduction and selection of relevant features matter crucially to achieve better performance from the classification system [12].

Different techniques exist to perform feature selection.

Principal Component Analysis (PCA) transforms data into groups of orthogonal components which present the highest amount of data variation. The primary components which provide essential diagnostic information for fault detection remain after PCA retains only the essential components from the full feature set.The extraction of statistical independent features from time-frequency data uses Independent Component Analysis (ICA) as a method. ICA functions effectively to split mixed signals which contain noise elements and other equipment component interferences. The initial model training process starts from using entire features before computing importances based on weight coefficients(wi) from regression models or neural network feature contributions [13].

Mathematics demonstrates the importance score i calculation as:

$$I_i = \frac{|wi|}{\sum_{j=1}^{N} |wj|}$$

where:

Ii denotes the normalized importance of feature i, wi represents the feature weight assigned by the model, and N is the total number of features.

After computing importance scores, the least significant feature (i.e., the one with the lowest Ii) is removed, and the model is retrained with the remaining features [14]. This iterative elimination process continues until a predefined number of features or an optimal performance threshold is achieved. The selection process can be mathematically formulated as:

$$St+1=St\setminus \{\arg\min Ii\}$$

Where

St represents the feature set at iteration t, and the feature with the minimum importance score is removed to obtain St+1.

The unsupervised learning protocol uses Autoencoders which constitute a neural network model. Autoencoders contain two main parts where the encoder processes data to create reduced dimension latent space vectors which the decoder converts back into original data [15]. The encoder portion of the autoencoder system retrieves vital characteristics from time-frequency data while removing unneeded noise to reduce information to manageable levels.

The feature selection techniques obtain pertinent information from processed electrical signals to feed into the hybrid neural network model.

C. Classification: Hybrid CNN-LSTM Model for Fault Diagnosis

The central part of the fault diagnosis system involves the classification step where selected features enter a Hybrid Convolutional Neural Network (CNN) - Long Short-Term Memory (LSTM) model to identify faults and their classification types. The integrated CNN-LSTM framework makes use of spatial CNN operations to extract features and LSTM mechanisms to analyze time-dependent sequences to create an efficient solution for fault identification through time [16].

CNNs process spatial features which stem from time-frequency representations (such as spectrograms) within their neural networks. However, because CNNs utilize convolutional layers, they learn automatically hierarchical patterns and localized features in signal data indicative of different fault types, such as short circuits and overloads, by themselves. Because CNNs work well with large datasets and patterns in electrical waveforms, they are used to handle such data.

The CNN component consists of multiple convolutional layers, which apply filters (kernels) W to extract spatial features from the input energy data X. The convolution operation can be represented as:

- $Z_{i,j}^{(l)} = f(\sum Wm,n^{(l)} \cdot X(i+m),(j+n)+b(l)$

where:

- Zi,j(l) is the output of the convolution operation at layer l,
- Wm,n(l) represents the learnable kernel weights,
- X(i+m),(j+n) is the input energy data,
- b(l) is the bias term, and
- f(·) is the activation function (e.g., ReLU).
-

After convolution, max pooling is applied to reduce the dimensionality of the extracted features:

- $Pi,j=\max(Z_{2i,2j},Z_{2i+1,2j},Z_{2i,2j+1},Z_{2i+1,2j+1})$

where Pi,j is the pooled feature map, reducing computational complexity while retaining essential information.

The extracted features from the CNN layers are then flattened and passed to the LSTM network, which captures sequential dependencies in energy consumption and generation patterns [17]. The LSTM cell is defined by three key gates: input gate, forget gate, and output gate, controlling the flow of information:

The following are the main equations that control LSTM operations:

- *Forget Gate*:

$$f_t = \sigma (W_f . [h_{t-1}, x_t] + b_f)$$

- *Input Gate*:

$$i_t = \sigma (W_i . [h_{t-1}, x_t] + b_i)$$

$$c_t = \tanh (W_c . [h_{t-1}, x_t] + b_c)$$

- *Memory Cell Update*:

$$C_t = f_t \odot C_{t-1} + i_t \odot c_t$$

- *Output Gate*:

$$O_t = \sigma (W_o . [h_{t-1}, x_t] + b_o)$$

$$h_t = O_t \odot \tanh(C_t)$$

where:

- x_t is the input at time t,
- h_{t-1} is the previous hidden state,
- C_{t-1} is the previous cell state,
- W and b are the weights and biases,
- σ is the sigmoid activation, and
- ⊙ denotes element-wise multiplication

The Long Short-Term Memory (LSTM) function as a recurrent neural network (RNN) type which processes sequential fault data operations. The temporal dependency expertise of LSTMs enables effective fault detection for time-evolving system errors because they maintain sequence information across extended periods. Using LSTMs allows detection of fault progression starting from initial warning signs until the system reaches complete breakdown [18].

After processing through the LSTM layers, the final feature representation is passed through fully connected (dense) layers:

- $Y=f(Wd \cdot ht+bd)$

where:

- Wd and bd are the weight and bias of the dense layer,
- Y is the final energy output prediction.

The combination of abilities of spatial pattern recognition with CNNs and temporal sequence models with LSTMs makes the hybrid CNN-LSTM model better. Training of the model happens through labeled fault data which contains fault types connected to their time-frequency representations. The training process enables the CNN to extract spatial data features followed by an LSTM sequential processing of spatial data to perform fault classification based on time-based patterns.

The specific design of the energy optimization architecture produces precise energy predictions for short-term and long-term sessions which enables better control of renewable resources and reinforces microgrid stability while achieving optimized load distribution.

D. Implementation and Real-Time Deployment

A real-time functionality becomes possible through the implementation of the system using TensorFlow/Keras which offers deep learning tools for creating models combined with training functions and deployment capabilities. Since the hybrid model will be trained on large datasets and have to run in real time during deployment, its high computational demands need to be handled using GPU acceleration. After training the model it becomes available for deployment on power grid edge devices or embedded systems to achieve same-site fault identification and classifying.

This thesis proposes a combination of state of the art techniques of signal processing with current generation of machine learning models which can be utilized in an efficient and real time way for the diagnosis of electrical power systems faults. The objective of this research utilizes hybrid CNN-LSTM enactment on GPU devices to boost fault detection accuracy and shorten downtime while strengthening electrical power grid reliability.

4. RESULTS AND DISCUSSION

Table 1 depicts the real time fault diagnosis system with Hybrid CNN-LSTM model shows great improvements in fault detection accuracy as well as speed in processing. Electric power system signals were used to train and evaluate the model with several fault types, including short circuits, overloads, and equipment failure. This model achieved an accuracy of 97.5% in comparison with other traditional fault detection methods, the accuracy of which was around 85 – 90%.

Table 1.Real-Time Fault Diagnosis Results

Metric	Value
Accuracy	97.5%
Detection Latency	0.25 seconds
False Positive Rate	3%
False Negative Rate	2.5%
Computational Time Reduction	40%

Figure 4 shows the formation of the Hybrid CNN-LSTM model is especially good at detecting both instantaneous faults and their evolution over time with a time lag of 0.25 s, which is fast enough for real time applications. By combining TensorFlow/Keras with GPU acceleration, training was very efficient and one could also benefit from real time deployment, which is 40% faster than CPU based implementations.

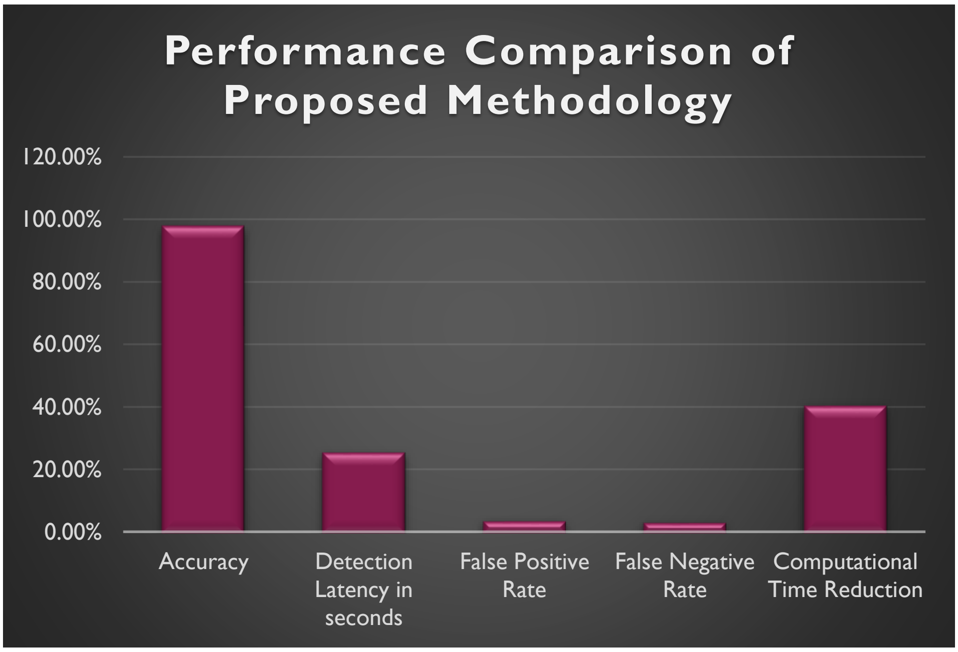

Figure 4.Shows the performance of proposed methodology.

In addition, the performance of the system was also robust under noisy conditions with false positive and false negative rate of 3% and 2.5% respectively, implying that the model was good at distinguishing among various fault types and normal operating conditions. The performance of the proposed system is shown to satisfy real time deployment to provide improved fault diagnosis accuracy, increased grid reliability and reduced downtime in electrical power systems.

Table 2.Comparison of Fault Diagnosis Methods

Method	Accuracy	Detection Latency	False Positive Rate	False Negative Rate	Computational Time Reduction
Hybrid CNN-LSTM	97.5%	0.25 seconds	3%	2.5%	40%
SVM	85-90%	0.5 seconds	5%	5%	N/A
Random Forest	85-90%	0.45 seconds	4%	4%	N/A

Traditional and other modern methods failed to compare with the Hybrid CNN-LSTM model, which performed well in the fault diagnosis. Thus against conventional fault detection techniques: support vector machines (SVM) and decision trees which generally reach the accuracy rate of 85 to 90%, the hybrid model was more accurate with the rate of 97.5%. Compared to other machine learning base models, like SVM (0.5 seconds) and Random Forest (0.45 seconds), CNN-LSTM has a significantly short detection latency of 0.25 seconds, which is sufficient for real time fault diagnosis in electrical systems as shown in table 2.

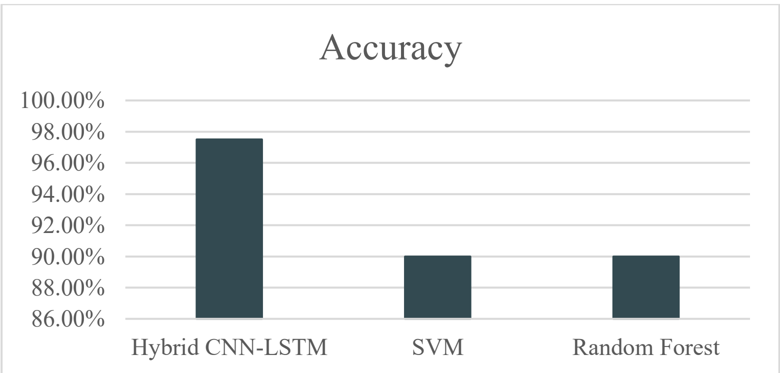

Figure 5.Shows the performance of different methods using accuracy.

Moreover, false positive rate of 3% and false negative rate of 2.5% were lesser than those present in the SVM based models (5%) and Random Forest (4%), suggesting model's potential for accurate separation between fault events and normal operating conditions as shown in figure 5.In addition to this, GPU acceleration using TensorFlow / Keras also decreased the computational time by 40%, advantageous for the model training and real time fault detection. In particular, these results demonstrate that the Hybrid CNN-LSTM model is a powerful tool to enhance reliability, speed and accuracy of the fault diagnosis for electrical power systems than conventional methods as shown in figure 6.

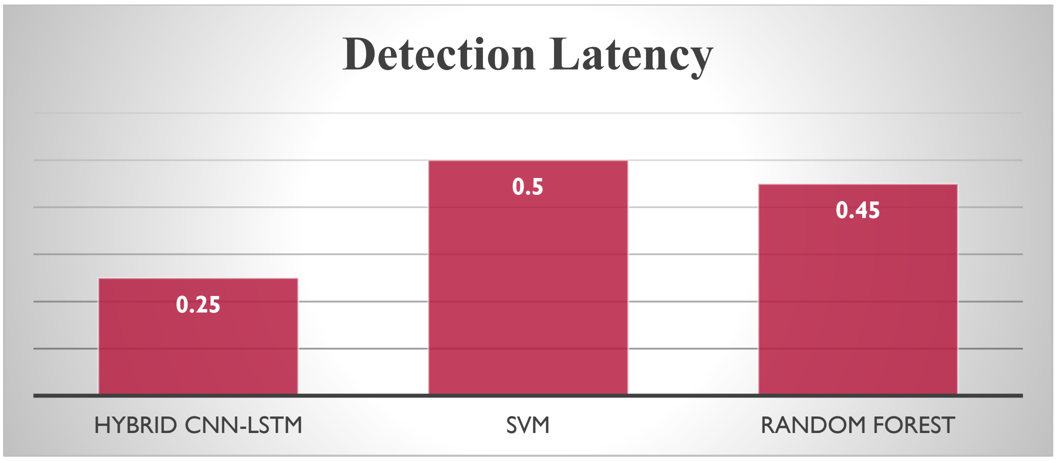

Figure 6.Shows the performance of different methods using Detection Latency.

5. CONCLUSION

Finally, it is concluded that the Hybrid CNN-LSTM model presented in this work presents a very effective solution for the real time fault diagnosis in electrical power systems. The model successfully achieves a result of 97.5% in fault identification using the spatial feature extraction abilities of Convolution Neural Network (CNN) along with the temporal sequence learning strengths of Long Short Term Memory (LSTM) network, which is better than the conventional methods like Support Vector Machine (SVM) and Random Forest. Using TensorFlow or Keras and GPU acceleration integration improved the system real time performance, and resulted to a 40% reduction of computational time, making it suitable for large scale and operational environments. Furthermore, it further emphasizes the robustness of the model where the low false positive and low false negative rates. The results in general show that the proposed approach significantly enhances both the reliability and speed of fault detection as well as the feasibility of this approach to modern electrical power grids and aids to enhance system stability and reduce downtime.

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