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Design a suitable Machine Learning Framework for Power System Fault Detection

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Abstract - The country's energy system relies on the electricity transmission network. Overhead transmission lines in an electrical power system are more likely to have problems due to the longer duration of the conductor exposed to the environment. We use MATLAB and TensorFlow to examine we use a number of pattern recognition techniques on the ENET-VSB dataset's voltage signals. In comparison to previous proposed pattern recognition approaches, such as ResNet and Seasonal Trend Decomposition using Loess (STL) with a Support Vector Machine (SVM) classifier...., Long Short-Term Memory (LSTM) outperforms them all in order to identify and categorise PD activity on IOCs, it has been determined that the suggested CNN + LSTM architecture is an appropriate hybrid Machine Learning framework.

Keywords: Machine Learning, Power System, Fault Detection and techniques

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INTRODUCTION

Power System Operators (PSOs) have the difficult challenge of ensuring the uninterrupted supply of electric power to end-users. Accurately detecting, classifying, and locating the fault site is crucially necessary, even when entry of fault is beyond human control. Methods for identifying, classifying, and pinpointing power transmission system faults have been studied extensively. There have been efforts to develop a smart protection system that can consistently detect, categories, and pinpoint errors. Researchers have been able to take a more thorough and focused approach to studies linked to traditional fault prevention measures because to advancements in signal processing techniques, AI, and ML.

Every single industrial sector has recently been seeing a wave of exciting breakthroughs and automations. All or almost all of these sectors use at least one process loop, which contains a plethora of devices and equipment for carrying out different jobs, in relation to the rise of precise control methods in industrial automation. Linear and non-linear types of process equipment are also possible. Lees (2012) states that non-linear equipment, such as sensors, transmitters, and actuators embedded in process control loops, is responsible for over 40% of industrial fatal incidents. For these mission-critical process systems to prevent abnormal events from progressing and productivity from dropping, they must adhere to safety requirements. As a result, the two functions that industries demand to be operational are safety and transparency.

The industry is able to achieve the highest Safety Integrity Level (SIL) via a methodical approach that adheres to industry standards. Dependability in operations will increase as the Safety Integrity Level rises. Though most sensors and equipment in the field are built to conform to Safety Instrumented System (SIS) requirements, their functionality could be compromised when the clock strikes zero due to the circumstances in which they are used. As a result, process loops must include problem diagnostics and fault prediction of significant equipment. The significance of fault monitoring and failure prevention in process industries is emphasized by international standards such as ISO 13849, which was imposed in 1999, 2000, and 2003 and pertains to the safety of machinery in relation to the parts of control system validation. Other standards, such as ISO 14121-1999 and IEC 61511, outline the principles of risk assessment and functional safety for process sectors, respectively. The process industries cannot function without the ability to diagnose and forecast problems.

LITERATURE REVIEW

Hanyu Yang et al. (2021). Power system protection must improve its fault detection methods to avoid damage cascades in the case of failures. This is particularly important as the power system becomes more flexible and complicated. In recent years, several machine-learning based issue identification algorithms have been proposed to tackle the challenges posed by massive amounts of data. This article examines the present situation of machine learning as well as its established and future applications in the field of defect detection.

Vaish, Ms. Rachna et.al. (2021). New dangers posed by contemporary producing sources and loads are testing the limits of conventional power system protection measures. Modern monitoring methods and intelligent defect identification, such ML, provide the basis of an intelligent and adaptive protection system that has proven helpful in addressing these concerns. There is a wealth of literature on the topic of fault diagnostics in power systems using ML. Rapid advancements in ML techniques have prevented a thorough and current literature evaluation on ML-based power system failure diagnoses. This study aims to provide a comprehensive analysis of issue diagnostics in power systems using ML in light of this necessity and the rising popularity of ML. At first, ML methods were well-known for fixing issues with conventional defect identification. Additionally, we provide a basic framework and process for applying ML for fault diagnosis. Subsequently, other researchers have investigated both supervised and unsupervised learning techniques for fault detection. The methodology, simulation tools, and application systems used for defect detection, classification, and localization are supported throughout the presentation by tabular data. We have also included a summary of the pros and cons of each fault detection technique for the readers' benefit, to help with the decision-making process. We also provide a brief introduction to the use of reinforcement learning and transfer learning, as these methods are developing in the field of power system research and show promise for use in fault detection. Finally, we have reviewed the research trends, highlighted some important challenges, and proposed some directions for future research.

Kumari et al. (2012), Another device for sag relief is the DC voltage restorer that operates across lines (IDVR). A number of DVRs, or dynamic voltage restorers, linked together form it. series with a dispersion feeder and featuring a standard dc interface. Voltage drops caused by lengthy spans might be reduced if dynamic power could be transferred between feeders during sag. On the other hand, IDVR compensation cap is highly dependent on load power factor, and we spoke about how greater load control factors lead to worse IDVR performance. In order to overcome this limitation, this research presented an alternative approach that allows for reducing the load power factor during sag conditions, thereby increasing the pay limit. To eliminate the necessity for low-recurrence detachment transformers on one side, the suggested IDVR uses two fell H-bridge multilevel converters to mix air conditioning voltage with bring down aggregate symphonies twisting. Replicas in the MATLAB environment verified the validity of the suggested design. There was progress towards the proposed IDVR's compensation limit when it was linked to the 11kv and 66kv transmission lines.

Smith et al., (2017), In order to address voltage sag/swell problems, the distribution system consistently used an Interline Dynamic Voltage Restorer (IDVR). A simple distributed voltage restoration (IDVR) system consists of many DVRs that share a standard direct current (dc) interface to connect feeds to analytic loads for power anchoring. The usual dc-interface voltage is restored by alternative DVRs when a single DVR adjusts its feeder to counteract the power loss experienced by its neighbor. Getting rid of necessity for low-recurrence isolation transformers on one side and infuse AC electricity with the least amount of total harmonic distortion (THD), the suggested IDVR makes use of two fell H-bridge multilevel converters. A wide range of operating circumstances were investigated for the intended MLI fed induction motor's execution using MATLAB simulation.

Wang et al. (2017), Overseeing the adjustment of voltage sag and swell, the DVR is handled using a model predictive control (MPC) approach. In this research, the framework controller and the MPC method for DVR are detailed. To validate the performance of the DC micro grid integrated DVR system and the comparative control technique, several simulation studies are conducted, some of which include voltage dips and spikes. The results of the simulations demonstrate that the suggested system is functional and successfully compensates for the matrix voltage sag and swell.

RESEARCH METHODOLOGY

The waveform data is processed in MATLAB and TensorFlow to create a pattern recognition algorithm that can identify PD activities on IOCs from stray electrical field voltage measurements. A suite of statistical methods, including PCA, ICA, STL, and HMM, are employed as feature extraction techniques to break down each raw voltage signal. Using a smaller set of "summing up index" that can be more easily displayed and examined, principal component analysis (PCA) allows you to assess the information contained in massive data tables. One statistical and mathematical approach to uncovering the underlying characteristics that drive collections of random variables, measurements, or signals is independent component analysis (ICA). Many see ICA as a natural progression from PCA. STL is a robust and versatile method for breaking down time series. STL stands for "Seasonal and Trend decomposition using Loess," and Loess is just a method for estimating non-linear relationships. This technique is a double stochastic model, and it's HMM.

RESULTS

In light of the criteria used to assess PCA with SVM classifier performance Overall, the model performs at 53%, 54%, and 58% based on F1-Score at the different instances of 5, 10, and 15, respectively, although Precision and Recall values are inconsistent.

Table 1 Evaluation Metrics for Predictions using PCA and SVM

Evaluation Category	Precision			Recall			F1-Score		
	Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15
PD Signals	0.59	0.59	0.63	0.48	0.50	0.54	0.53	0.54	0.58
Non-PD Signals	0.50	0.51	0.56	0.60	0.60	0.65	0.55	0.55	0.60

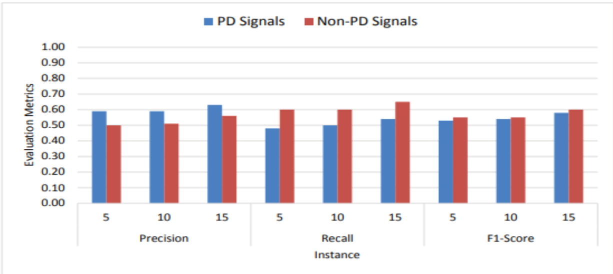

Figure 1 Evaluation Measures for Predictions using PCA and SVM in a Plot

On the basis of the measures used to evaluate the effectiveness of ICA with the SVM classifier The model's overall performance, as measured by F1-Score, is 65%, 68%, and 65% at the different instances of 5, 10, and 15, respectively, but the Precision and Recall values are unstable.

Table 2 Metrics for Evaluating Predictions using ICA and SVM

Evaluation Category	Precision			Recall			F1-Score		
	Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15
PD Signals	0.70	0.69	0.72	0.60	0.61	0.64	0.65	0.65	0.68
Non-PD Signals	0.64	0.66	0.65	0.73	0.74	0.73	0.69	0.69	0.69

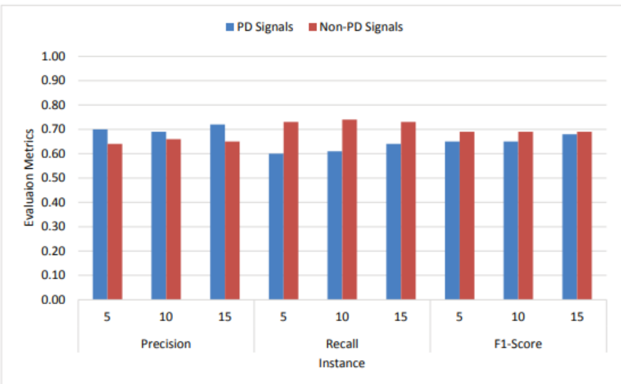

Figure 2 Evaluation Measures Plot for ICA and SVM Predictions

The results are based on the PCA + ICA performance assessment metrics using the SVM classifier. Overall model performance as measured by F1-Score is 67% at examples 5, 10, and 15, whereas Precision and Recall values are unstable at these instances (67%, 67%, and 65%, respectively).

Table 3 Evaluation Metrics for Predictions using PCA, ICA, and SVM

Evaluation Category	Precision			Recall			F1-Score		
	Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15
PD Signals	0.68	0.69	0.69	0.67	0.66	0.61	0.67	0.67	0.65
Non-PD Signals	0.72	0.74	0.65	0.73	0.76	0.73	0.73	0.75	0.69

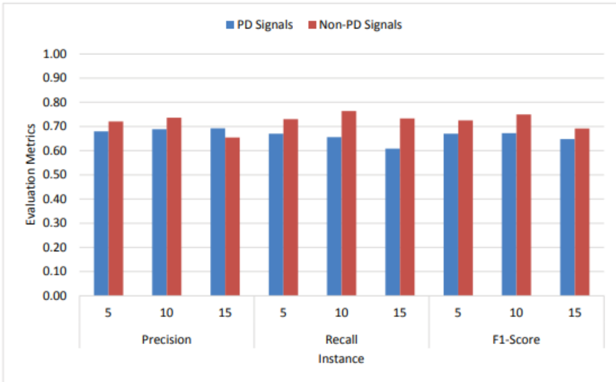

Figure 3 Evaluation Metrics for PCA, ICA, and SVM Predictions

Useful for assessing STL's performance with SVM. For cases 5, 10, and 15, the Precision and Recall values reveal that, out of 82%, 83%, and 76% of detected PD signals that are actual PD signals, respectively. The F1-Score for these instances is 77%, 79%, and 81%.

Table 4 The STL and SVM Evaluation Metrics for Predictions

Evaluation Category	Precision			Recall			F1-Score		
	Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15
PD Signals	0.73	0.75	0.76	0.82	0.83	0.87	0.77	0.79	0.81
Non-PD Signals	0.67	0.69	0.74	0.55	0.57	0.58	0.61	0.62	0.65

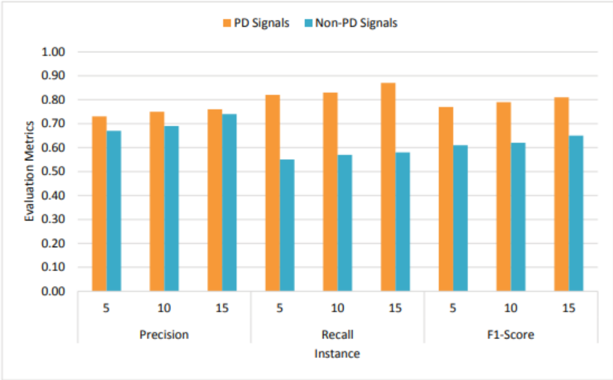

Figure 4 Analysis of STL and SVM Prediction Metrics

The results are based on the HMM and SVM performance assessment measures. The Precision and Recall values for 5, 10, and 15 examples reveal that 67%, 69%, and 71% of identified PD signals are real PD signals, respectively. Out of 77%, 78%, and 80% of successfully detected PD signals, the F1-Score at these instances is 71%, 73%, and 75%.

Table 5 Quantitative Measures for HMM and SVM-Based Predictions

Evaluation Category	Precision			Recall			F1-Score		
	Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15
PD Signals	0.67	0.69	0.71	0.77	0.78	0.80	0.71	0.73	0.75
Non-PD Signals	0.65	0.64	0.65	0.52	0.52	0.54	0.58	0.57	0.59

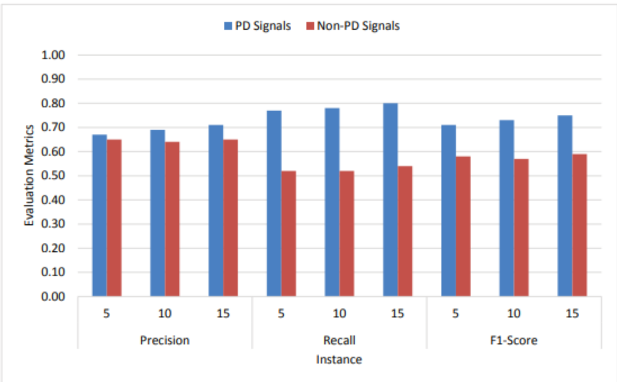

Figure 5 Evaluation Metrics for HMM and SVM Predictions Visualization

Table 6 Comparison of SVM Classifier with F1-Scores from Various Statistical Methods

	PCA & SVM			ICA & SVM			PCA+ICA & SVM			HMM & SVM			STL & SVM		
F1-Score	Instance			Instance			Instance			Instance			Instance		
	5	10	15	5	10	15	5	10	15	5	10	15	5	10	15
PD Signals	0.53	0.54	0.58	0.65	0.65	0.68	0.67	0.67	0.65	0.71	0.73	0.75	0.77	0.79	0.81
Non-PD Signals	0.55	0.55	0.60	0.69	0.69	0.69	0.73	0.75	0.69	0.58	0.57	0.59	0.61	0.62	0.65

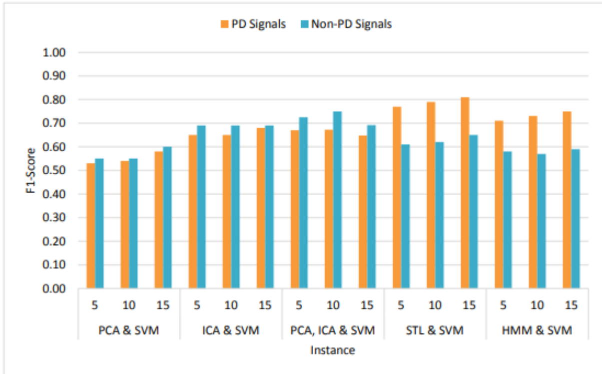

Figure 6 Various Statistical Methods and SVM Classifier F1-Score Plot

Out of the 82%, 83%, and 87% of successfully identified PD signals, respectively, 73%, 75%, and 76% of detected PD signals at instances 5, 10, and 15 are actual PD signals. At each of these points in time, the F1-Score is 77%, 79%, and 81%. The prediction and classification results produced by STL with SVM classifier outperform those of PCA, ICA, PCA + ICA, and other statistical approaches according to the Prediction Evaluation Metrics study.

CONCLUSION

In order to identify power system faults, this study developed a machine learning framework using a CNN and LSTM architecture. The voltage signals in the ENET-VSB dataset are analyzed using MATLAB and TensorFlow, and a variety of pattern recognition approaches are explored and implemented, including PCA, ICA, STL, HMM utilizing SVM Classifier, AlexNet, VGG-16, ResNet, RNN, and LSTM. Other suggested pattern recognition methods, including STL with SVM classifier and ResNet, do worse than LSTM. All the pattern recognition methods that have been suggested have unpredictable Precision and Recall values across different cases. The voltage signals in the dataset are processed using the CNN & LSTM framework that is integrated. Prediction Evaluation Metrics research shows that the best prediction and classification outcomes are achieved by combining CNN with LSTM architecture. When the CNN and LSTM architectures are combined, 84% of the F1-Score is attained at the 5, 10, and 15 instances.

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