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Cable Fault Detection using Deep Learning Kernel Techniques

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Abstract: While supplying power, transmission and distribution are crucial. Any flaw in these systems may prevent the delivery of energy, which would be quite problematic in today's society. Hence, fault diagnosis has become crucial for providing a consistent supply of electricity. This essay offers an examination of several systems for categorizing transmission line failures. Any disruption in the power system will be discovered by strategically situating the relay medium inside the network. Often, fault detection in the distribution system is the main problem. The fault diagnosis is time-consuming if it occurs during the power swing. In order to guarantee the efficiency of the distributed system, early fault identification is crucial. The complexity and ambiguity of system observations must be managed in order to perform an accurate detection, despite the fact that there are various techniques for fault detection. Fault classification is more crucial for a dependable, high-speed protective relay that is followed by digital distance safety. It is a quick overview of transmission line problems and an evaluation of the applicability of several previous methods to this problem. In this article, we examine research on machine learning algorithms for defect detection. It provides a succinct summary of all prevalent and hybrid methodologies. This study also discusses the necessity for creative fault categorization methods.

Introduction:

Electricity has recently been recognized as a survival necessity. Electricity must be carried from one location to another in order to be given to everyone since it is a kind of energy that is transformed from different other forms of energy. Energy may take many different forms. Electrical energy, which may be created from a variety of sources including coal, solar, nuclear, etc., is the most often used type of energy, according to numerous studies [1–5]. The other two crucial factors are transmission and power distribution since it is feasible to generate clean electrical energy utilising a variety of renewable resources, such as wind turbines, solar panels, hydropower, and others, which are taken into account from the point of view of generation. Alternating current (AC) is preferable over direct current (DC) for transmission because it is simpler and more affordable to step-up or step-down the voltage level with little loss.

While supplying power, transmission and distribution are crucial. Any flaws in these systems might prevent the delivery of energy, which is a major issue in today's society. Hence, fault detection has become crucial for providing a consistent supply of electricity. Faults can be categorised as either man-made or a natural calamity and arise for a variety of causes. When compared to defects caused by natural disasters, man-made problems are more likely to be foreseeable since it is impossible to anticipate when, when, and how they will occur. According to Bulent and Donmez [6] (2010), natural catastrophes not only cause problems with the electrical grid but also produce interruptions that frequently result in blackouts.

Related Work

In order to identify defects in power transmission networks, Musa et al. [7] (2018) devised a method that combined the cumulative approach with the current signal covariance during a power swing. The results of the authors' testing for various fault circumstances indicated a satisfactory time response.

Sheath voltage, transient voltage, and wavelet transform were used by Ashrafi et al. [8] (2015) to suggest a technique for diagnosing DC problems in a transmission system with the use of a VSC (voltage source converter) HVDC system. The authors also came to the conclusion that the suggested approach is a quick, trustworthy, and innovative way for finding DC defects.

Samantaray [9] (2009) described using a decision tree to identify a problem zone in a flexible AC transmission line (DT). The authors have also experimented with fault inspection by using one cycle of post-fault current and voltage samples as an input vector. The goal output is '1' for faults that follow the flexible AC equipment in line and '0' for faults that precede the flexible AC equipment in line. The authors also came to the conclusion that this system's outputs were reliable for classifying faults in a flexible AC transmission line and detecting fault zones. Regardless of their areas, from agriculture to medical, several researchers have shown the value of the Raspberry PI in numerous research efforts and projects. The Raspberry PI has played a significant role in a number of cutting-edge research projects, including IOT-based health care, iris mobility wheelchair control, color-aware robotic arm control in space, an automated blood bank, WSN-based automatic watering, and security systems [10–14].

Thermal cameras have recently demonstrated their strength through a number of innovations that are useful for both business and the greater good of humanity. These innovations include the use of thermal cameras in the medical field for the early detection of diseases like cancer, thyroid disease, Reynaud's phenomenon, and others. The use of thermal cameras for face identification has shown them to be far more secure than conventional facial recognition systems, and they have also been used in neonatal critical care units to detect body temperature since they are accurate and non-contact. When transmission line fault detection becomes a non-contact type, the mechanism will have a number of benefits over fault detection that is a contact type. Less operational time, less material degradation, less labour consumption, and the ability to deploy from any place thanks to cloud connectivity are some of the benefits. By creating a small, transportable, non-contact fault detector that can take thermal pictures of conductors and pinpoint the position of faults, the goal of this effort is to make fault detection more straightforward.

In order to improve the performance and efficiency of the electric grid, recent developments in information processing and sensor technologies have made it possible to implement intelligent automation, authorities in relation, hybrid communication networks, and the Internet of Things (IoT) technologies (Hossein Motlagh et al., 2020).

A possibility that was not imaginable when previous power generation and distribution systems were designed with legacy technologies is now possible thanks to new IoT devices, which allow for the quick collection of large amounts of information from various grid systems, preprocessing, and transmission to the central control systems. Modern artificial intelligence techniques may be applied to the enormous quantity of data made available by the grid network to effectively identify and categorise issues. Convolutional Neural Network (CNN), recurrent neural network (RNN), Feed-forward Neural Network (Convolution neural), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) were some of the deep learning models investigated. In order to identify the most effective model for the applications, the performances of the RNN, GRU, and LSTM were evaluated using the same data set collected from a portion of the secondary distribution network (between the years 2014 and 2020). As a case study and source of training data, TANESCO, a public utility corporation, was chosen as part of the research's challenge-driven teaching strategy. With the engagement of specialists from the business world and personnel from academic institutions, this study followed the Challenge-Driven Education (CDE) strategy from the issue identification stage through the solution formulation stage. The secondary electrical distribution network, from the 11KV/0.4KV transformer to the end customers, is the only area of the network that is the subject of this research. The study also concentrated on problems brought on the voltage and current readings from the secondary distribution network AMR, which mimicked the values to be recorded from the IoT-based sensor node throughout the SDN.

Recent publications have examined defect detection techniques based on machine learning or deep learning. For instance, a support vector machine-based technique for detecting and classifying faults in transmission networks has been published in [5]. This method has an accuracy of more than 93% and can identify and categorise fault types using busbar voltages.

The artificial neural network (ANN) was employed by Nanda and Fu [6] for fault classification in distribution networks, and steady state voltages of all busbars were used to identify faults, categorise them, and pinpoint their locations.

on a network using IEEE 37-bus. Recurrent neural networks (RNNs) were created by Yu et al. [3] to identify and classify faults in microgrids. Gated recurrent units (GRUs) were utilised to diagnose faults using time information with an accuracy of over 97%. Deep learning-based SPS defect detection techniques have recently been researched in the literature [6]–[10].

For instance, Chanda and Fu [6] used a fully connected deep neural network (DNN) to identify the fault type in a cable of voltage levels DC (MVDC) SPS and shown that the accuracy of DC fault detection and position identification is greater than 95% in all cases examined.

A Navy DC-pulsed load was the subject of a system for DC load monitoring and fault identification suggested by Ma et al. [7]. The time-series current signals of the DC-pulsed load were monitored by the authors in order to identify component failures using a long short-term memory (LSTM) technique.

An ANN-based fault detection and classification system was developed in the MVDC SPS by Li et al. [8] with 99% accuracy for detecting fault kinds at each busbar. The majority of earlier research relied on data from a single busbar, component, or steady state voltage to identify faults, which may not have been able to effectively safeguard the whole network.

Time-series voltages of all busbars are used for the first time to track the status of the SPS. Three distinct deep learning architectures, a fully connected DNN, an LSTM, and a GRU architecture, are adopted and evaluated to identify the defect, categorise the fault type, and pinpoint the fault site in SPS in order to assess the efficacy of the holistic framework. The dependence and sensitivity of the model to load fluctuations and noisy inputs are also examined to assess how resilient the suggested technique is. The following is a quick summary of the work's contributions.

- Develop a holistic deep learning-based framework for fault detection, classification, and location identification in SPS, and
- Real-time monitor and detect faults for the entire SPS network.

Wavelet, which uses wavelet transformations, Artificial Neural Networks (ANN), and fuzzy logic are some of the popular techniques. In order to identify and categorise flaws, hybrid approaches are used. They include wavelet and neuro-fuzzy methodology, wavelet and ANN, wavelet and fuzzy logic, and wavelet and fuzzy logic. The third category consists of contemporary techniques, which include lately popular methods like Support Vector Machine (SVM), genetic algorithms, decision trees, deep learning, and pattern recognition, to mention a few.

In his research (Chakraborty et al., 2012), Chakraborty presented a wavelet transform technique for identifying and categorising electrical transmission network line faults. In order to calculate the Root Mean Squire (RMS) value of the wavelets of electrical charge signals at either end of the transmission line while taking into account considerations throughout a variable window length of half cycle, the algorithm employed mathematical approaches. Using db4 wavelet in PSCAD and MATLAB, the resulting current signal was analysed to extract the specifics of the coefficient, which were then compared with the benchmarks values to detect and categorise errors. Nevertheless, this method only addressed the shunt class of electrical failures and concentrated on the transmission portion of the network.

A second research by Jamil et al. (2015) looked at the application of artificial neural networks in transmission lines for the detection and classification of electrical defects. The three-phase currents and voltages of one end served as the proposed scheme's input. The findings showed that the technique is effective in identifying and categorising transmission line defects.

Techniques for Classification

A cable has a 30-year lifespan assuming it is in good condition and is put correctly. Unfortunately, incorrect installation or poor couplings can quickly harm the wires. In essence, third-party civil employees will be responsible for this kind of error. The entire cable needs to be removed from the ground to verify and fix any flaws because it is very difficult to pinpoint the source of the problem. For this reason, the cable must be tested for faults. Generally, there are three frequently occurring faults namely,

• Open Circuit Fault,

• Short Circuit Fault &

• Earth Fault

A break in the wire conductor causes an open circuit fault. Megger may be used to check for this problem. It will display 0 resistance for a conductor that is not broken and 0 resistance for a conductor that is broken. Due to insulation failure, a short circuit fault occurs when two conductors of a multi-core wire come into electrical contact with one another. Due to the cable passing a lot of current across it, it may be detected. The conductor of the cable makes touch with the earth during an earth fault. Megger may also be used to check for this problem. The conductor displays zero resistance when it is grounded. Generally, fault location techniques for underground cable network can be categorized in two groups namely,

• Tracer method

• Terminal method

By traversing the cable circuits, the tracer approach might be a costly way to find a faulty segment. It takes a lot of labour to identify a defective section using electromagnetic or audio signals. An underground cable network's problem location using the terminal approach can be determined without tracing from either one or both ends. [1-6] The drawbacks of the current methods are

• Exact fault location not determined

• Need more man power

• Insulation problems occur at high voltages

• Need entire cable is to be reconstructed

• Requires high initial cost

• Require more time to fault location

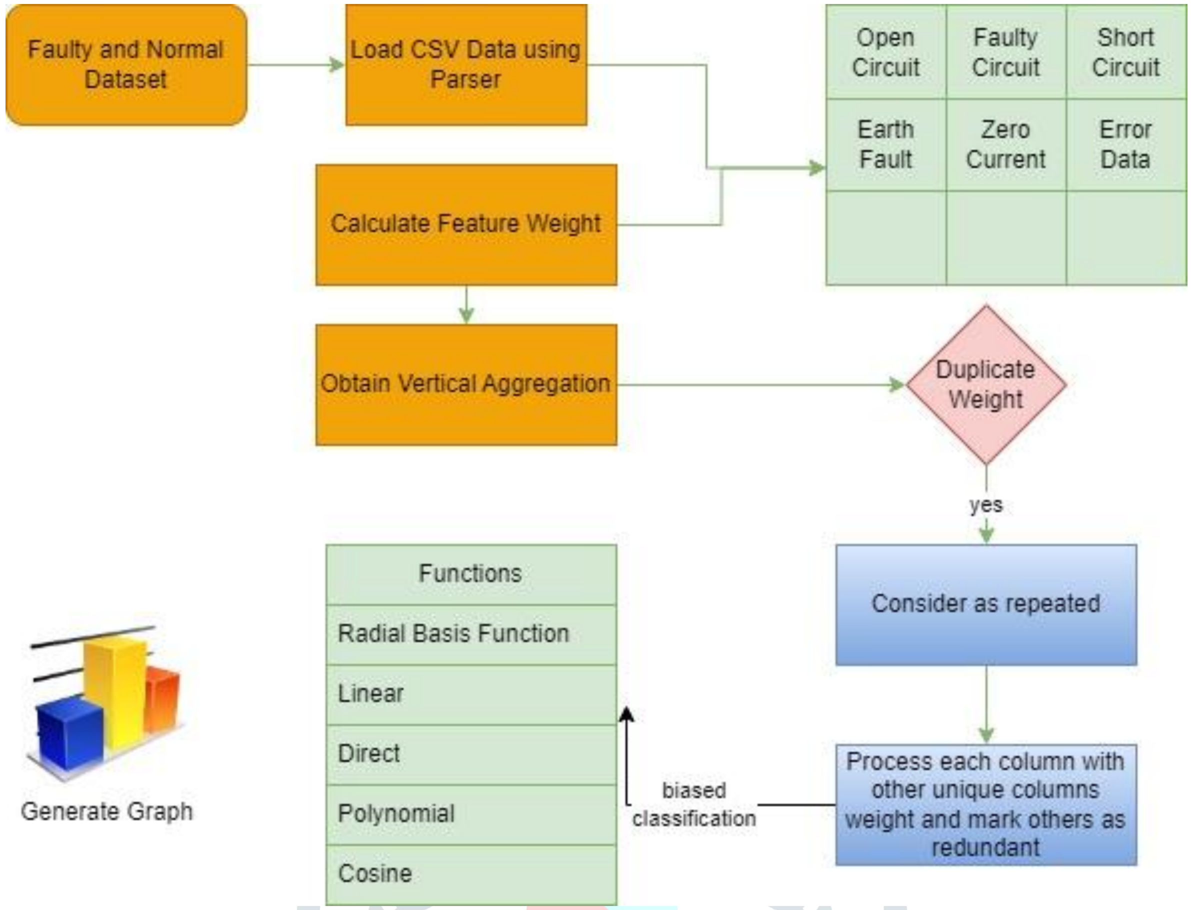

Figure 1.0 Proposed Architecture

A system is trained to learn from data using a technique called machine learning (ML). Artificial intelligence is used in machine learning. You must train your machine using ML software if you design any machine like a robot (with a camera). Humans cannot acquire information without learning, and machines cannot develop artificial intelligence without machine learning. The structures of all items are already stored and learned in our human brain. Your brain informs you that you are seeing what is there if you see the thing. The Wavelet diagram of the defect is created using this straightforward machine learning approach, and the computer then reveals that the error is in your system. So, we need to educate our machine to calculate faults.

So, we acknowledge that the model isn't representative. Developing machine learning [4] models to foresee damaged wires is the aim of our review. The process of machine learning is similar to how computer computations learn via experience rather than through human input, making them substantially more adept than people. Similarly, machine learning is becoming more well-known these days. There is no question that it can manage problems in high-layered space. Strategic relapse [5, 6] demonstrates the linear association between the binary ward variable and independent, transformation-dependent parameters.

Support vector machine (SVM) [7] puts all of the models into highly layered space, divides the samples into two halves with unmistakable holes roughly as wide as predicted, and assigns one category to each half. Choice tree [8,9] is a structure that resembles a tree. Every casual breakfast discusses different outcomes. The non-linear connection may be handled by both SVM and decision trees. Two typical outfit learning [12] methods are random forest [10] and boosting [11].

A technique for averaging several different decision trees and reducing volatility is random forest. By changing the weight of each sample in the training system, boosting is another technique for lowering variation. Neurons and layers make up the neural architecture. The last layer will get the data after the main layer. In this post, we create a defective cables expectation model using the six machine learning models that were stated before.

Deep learning algorithms

Deep Learning originated from a multi-layer Artificial Neural Network (ANN) and is a subset of machine learning. Deep learning refers to a large deep neural network (Zhang et al., 2018). Deep Learning is a computational learning technique whereby raw data is used to hierarchically model high-level abstractions (Cardoso, 2017). There are different structures or architectures of deep learning including Feed Forward Deep Networks (FDN), Convolutional Neural Networks (CNN), Deep Belief Networks (DBN), Long-short Term Memory (LSTM) Networks, Recurrent Neural Networks (RNN), Gated Recurrent Unit (GRU) and Generative Adversarial Networks (GAN) (Alom et al., 2019).

The effectiveness of several deep learning algorithms was examined in this study for the secondary distribution network fault detection and classification tasks. The Feed Forward Neural Network (FFNN), Gated Recurrent Unit (GRU), Recessive Neural Network (RNN), and Convolutional Neural Network are among the designs taken into consideration in this study (CNN).

Proposed System

By traversing the cable circuits, the tracer method is a time-consuming way to find a faulty segment. It takes a lot of labour to identify a defective section using electromagnetic or audio signals. An underground cable network's problem location using the terminal approach can be determined without tracing from either one or both ends. [1-6]. The disadvantages in the existing techniques are

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- Need more man power
- Insulation problems occur at high voltages
- Need entire cable is to be reconstructed
- Requires high initial cost
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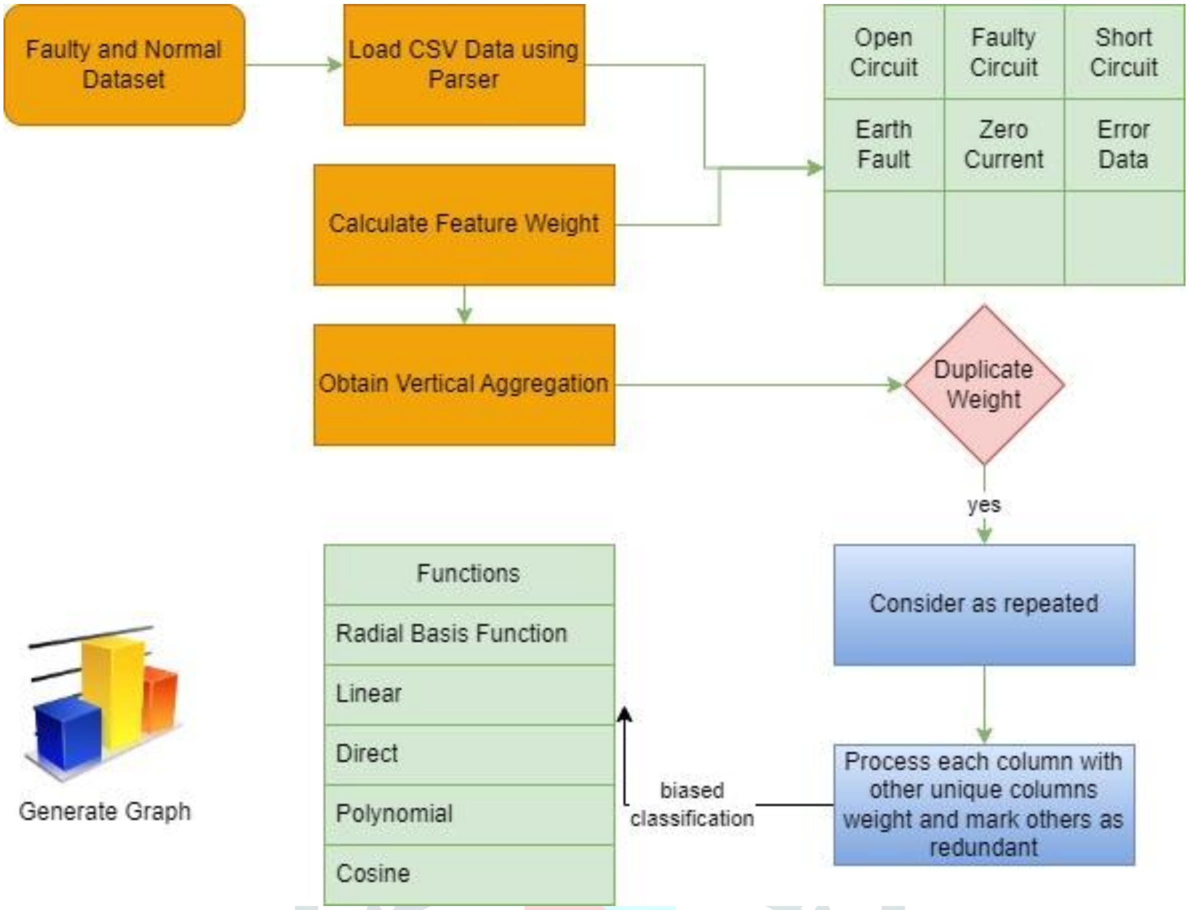

Figure 1 Proposed System Architecture

Data Collection

At this step, all four datasets collected for pre-processing. These datasets are vary in size in the training and testing set. Many quantitative and qualitative aspects may be found in this dataset. The kaggle and uci repositories have collected the dataset.

Data Splitting

The dataset was split into training and testing sections, which were split 80:20. The dataset is pre-processed before data splitting, with undesirable material, duplicate data, and data normalisation removed. Here, the divided data is utilised for machine learning and assessment as a training set and testing set. Due to the fact that the desired datasets contain a variety of data values, this data separation phase becomes crucial. It assists with data management and provides clear, simple facts.

System learning and feature selection metrics

Kernel-based Strategies

Kernel-based techniques or tactics are crucial for system development. In order to calculate the attribute values and update them to the feature selection metrics, we have built direct kernel-based strategies and linear kernel-based strategies.

Obtaining threshold values

The training approach takes into account each attribute separately and uses kernel-based algorithms to derive the weight or score values from the attribute. Using these scores and the settings listed below before the resulting threshold value. Starting at zero, we increase the threshold value incrementally until we find the best threshold, which will then be used to the classification process.

Classification using biased classifier

As part of the categorization process, we divide the recordings into two categories: regular cable and problematic cable. We already have scores for each individual characteristic as well as the highest threshold values. As a fresh record is processed, these scores or values will be useful in determining if the cable is normal or defective. So, throughout the testing process, we take a sample of the data that has been labelled as normal or containing a class designation for a bad cable. As soon as we have their property, we compare it to the cutoff value. Since the system has already been trained using this value, we then compare the results and categorise.

The parameters which are used to machine learning task are explained below.

- **Task Selection**

Learn & Evaluate Classifier:

Train a classifier using examples with labels in a training data file, and then verify the classifier's accuracy using examples with labels in a test data file or using some other method of cross-validation.

Learn & Use Classifier: Use a classifier that has been learned based on labelled samples in a training data file to categorise a batch of unlabeled data.

Training Data: The training data file, which contains the labelled examples used to train a classifier, is necessary. Each named example should have its own row in the file, with items separated by spaces.

The last column chosen to represent the class labels of that record of datasets is the class label for the training and testing dataset. There is also the choice to choose a column as the dataset's class label.

Evaluation Options

Use Test Data: The test data file, which should have one row for each labelled example with entries separated by spaces or commas, must be specified in the cable.

K-Fold Cross Validation: indicates that a cross-validation test should be performed to evaluate the classifier's generalisation. In this test, the training data is divided into K equal-sized subsets, one of which is kept out while the classifier is being taught. The classifier is then used to classify the held-out subset. Since learning this simply takes K different classifiers. If K is not given, the default value is (10).

- **Randomization**

Within Classes: Make sure that each class is represented in each subset or subgroup in the same proportion as in the entire training set when choosing the K subsets for K-fold cross-validation.

Cross Validation: Randomly choose the K subsets for K-fold cross validation, but partition without taking into account class membership. The order of the instances in the training data file should always be taken into consideration when choosing the K subsets for K-fold cross-validation.

Parameter Selection

- **Bias:** The dataset features should be biassed. A column that is totally set to a constant value is the bias term. This constant can be adjusted to any amount; 1.0 is the default value. The classifier may discover a decision boundary without passing through the origin thanks to the bias. If you already have such a feature in your data, you don't need it. Several values for the bias can be entered as a list with spaces or commas. The same thing as choosing "Do not add bias" is having a bias value of zero.
- **Priors**

Laplacian: As a consequence, a MAP estimate of the weights under a l-1 penalty prior that promotes sparsity is produced. The default and suggested option is Laplacian since it promotes the sparsity of the learnt weights.

Gaussian: As a result, the weights are estimated using MAP under a l-2 penalty prior, which favours shrinkage but not sparsity. In essence, gaussian is similar to ridge regression.

No Prior: With no shrinkage or sparsity, this yields a straightforward maximum likelihood (ML) estimate of the weights.

- **Sparsity:**

By scaling the log prior, lambda regulates how much regularisation is performed to the weights. With a Gaussian prior, which monitors the shrinkage, and a Laplacian prior, which regulates the sparsity of the acquired weights. The value of lambda must be positive. A higher lambda indicates more regularisation (more sparsity or shrinkage). Several values of lambda may be specified as a list with spaces or commas.

- **Update Rule**

Component-Wise: An algorithm in which each element of the weight vector is updated one-at-a-time using a simple round-robin strategy. As the objective function is convex and thus has a unique optimum, this algorithm will converge to the same final weight vector as the non-component-wise version, but the computational savings may be significant with this option when the product of the number of classes with the number of features (or the number of examples when using a kernel) is quite large.

Non-Component-Wise: An algorithm in which all the elements of the weight vector are updated at once in every per iteration. As the objective function is convex and thus has a unique optimum, this algorithm will converge to the same final weight vector as the component-wise version while the computational savings may be significant with this option when the number of examples is quite large. The default value is the component-wise algorithm.

- **Convergence Settings**

Kill Threshold: Any weight considered is to be zero if its absolute value becomes smaller than the kill threshold. If chosen sufficiently small, this should not alter the final solution but unambiguously accelerate the process of convergence; if the value selected is much too large, however, it might possibly alter the final solution. This only applies to the non-component-wise update procedure and will be ignored for the component-wise update procedure.

Convergence Tolerance: The weight vector defining a classifier considered to have converged to a final solution if the Euclidean difference between weight vectors in successive iterations becomes smaller than the convergence tolerance. Note that this number may need to be scaled based on the length of the weight vector. Maximum Iterations: The classifier learning process will stop, regardless of the degree of convergence, if the number of iterations exceeds this value.

- **Settings**

Adaptive Over-Relaxation: For only the non-component-wise algorithm, applies an over-relaxation technique whose goal is to accelerate convergence to the optimum weights, but which might overshoot and thus increase the time required for convergence. It is not explicit to the cable when this is a good option when it is not; your mileage may vary.

Cache Exponentials: For only the component-wise algorithm, this option creates a cache of computed exponentials that may reduce the overall aggregate computation time if the cache becomes heavily used; it may also result in a small loss of accuracy because of sooner rounding.

Cache Kernel Functions: This option builds a cache of the results from applying the kernel to all pairs of points in cross-validation, when a kernel is applied to the same two points repeatedly throughout all folds of cross-validation. Hence, data that is excluded from each fold will still be included in the normalisation, which necessitates doing normalisation on the full data set in advance.

Conclusion

The fully connected DNN, LSTM, and GRU were three deep learning models that were investigated in this work for defect detection, classification, and position identification in subterranean cable lines. Real-time line voltages of each SPS busbar were utilised in the created models to identify problems throughout the whole network. More particular, the DNN model, the LSTM model, and the GRU-based fault detection model all outperformed the competition. The approaches were further examined using load generation and noisy input data.

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