WHITE PAPER

Smart Monitoring Solutions
Using Deep Neural Networks (DNN)

Machine learning and artificial intelligence (AI) are playing an increasingly important role in a number of different applications throughout our society.

This white paper provides an brief overview as to how machine learning and AI are being applied to improve distributed acoustic sensing (DAS) and the benefits of more advanced solutions that are coming the market.

Traditional Event Classification with Distributed Acoustic Sensing (DAS) Technology

Traditional Distributed Acoustic (DAS) systems are used to classify certain events that would be considered to be a security threat to a particular facility or asset, such as an intruder climbing a fence or digging underneath.

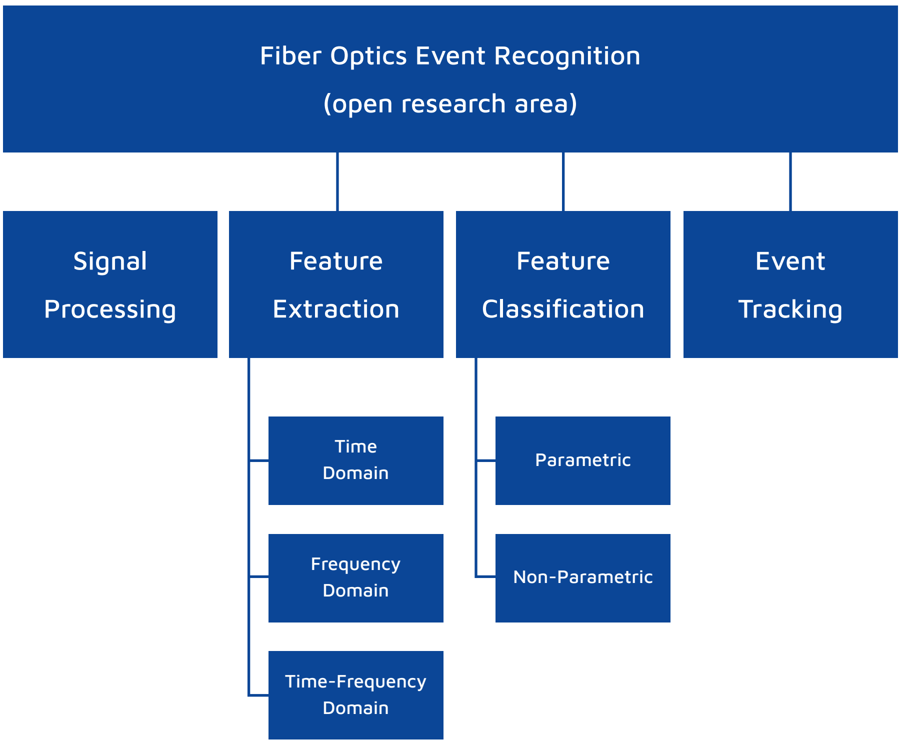
In order to classify and identify an event, there are a number of steps that must take place, including signal processing, feature extraction, feature classification and event tracking. Each stage utilises a unique skillset and approach, requiring a vast amount of domain expertise overall.

The diagram (right) shows a number of different approaches to completing these different stages.

Once the system classifications have been defined and tested, a set of algorithms is created to enable the system to identify these events should they occur in the future. These algorithms are stored in a static library.

Once operational, the Perimeter Intrusion Detection System (PIDS) or Third Party Inteference (TPI) system can constantly compare real-time monitoring data against the library of algorithms.

If a real time event matches a specific algorithm for a pre-defined event, an alarm will be triggered and the appropriate action will be take as defined by the operational protocols.



Monitored | Secured | Safe

Challenges of Traditional DAS Classification

Two of the greatest challenges of conventional event classification with DAS fiber optic systems are the time and resource required. Firstly, in order to classify each algorithm there is a substantial amount of research and development is needed, not only at the mathematical level, but each algorithm must also be rigorously tested against field data.

Secondly, there is a need to classify each type of threat. As well as interference from other noises it is also possible that noise signals change over and will deviate from the algorithms that are initially stored in the libraries.

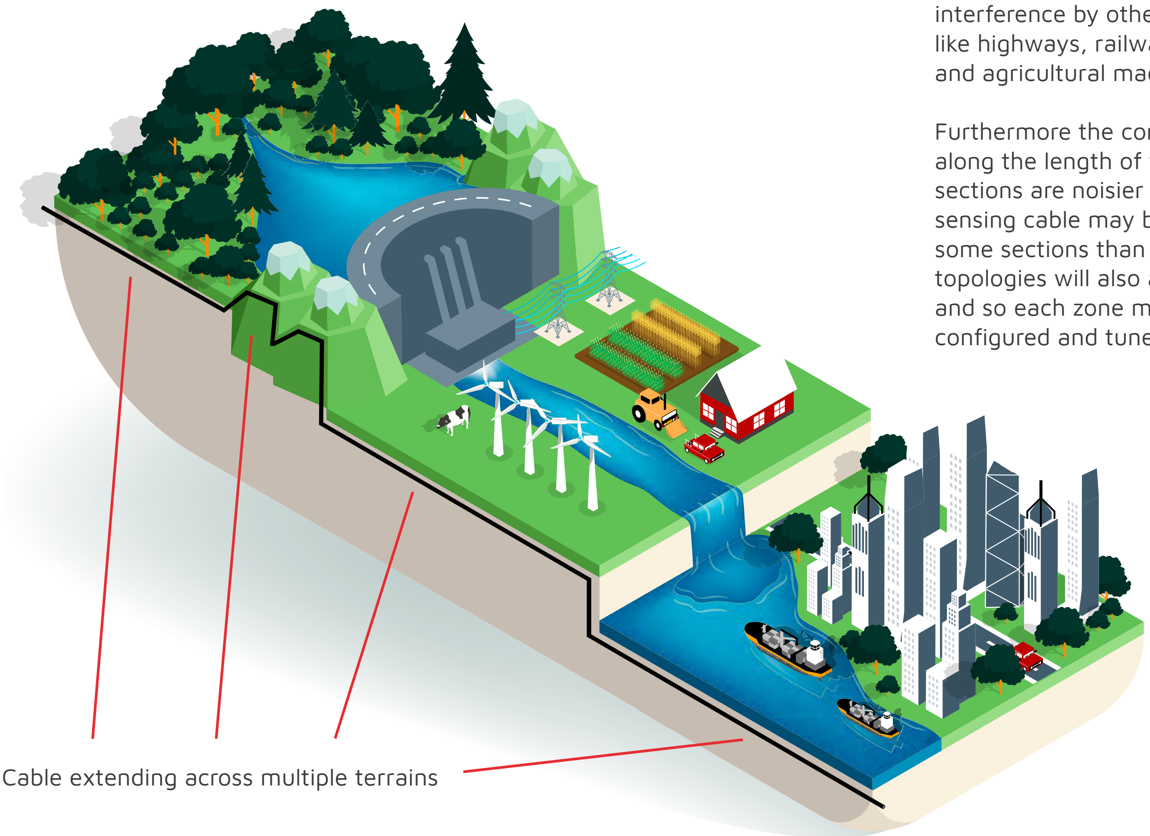
Installation and Commissioning

Conventional DAS classification takes a substantial amount of time to commission, with regards to both installing and configuring the equipment and fine tuning the algorithms. For some projects, up to 6 monnths may be allocated for this stage. This time is potentially expensive and disruptive to overall project timetables.

Environment

It can be particularly difficult to find efficient algorithms for event detection based on DAS measurements. This is due to the huge variety of scenarios that these systems cover, from various kinds of excavators and soil types, different temperature and weather conditions, to possible interference by other signal sources like highways, railways, wind turbines and agricultural machines.

Furthermore the conditions can vary along the length of the cable. Certain sections are noisier than others or sensing cable may be buried deeper in some sections than others. Different topologies will also affect the signal, and so each zone must be individually configured and tuned accordingly.

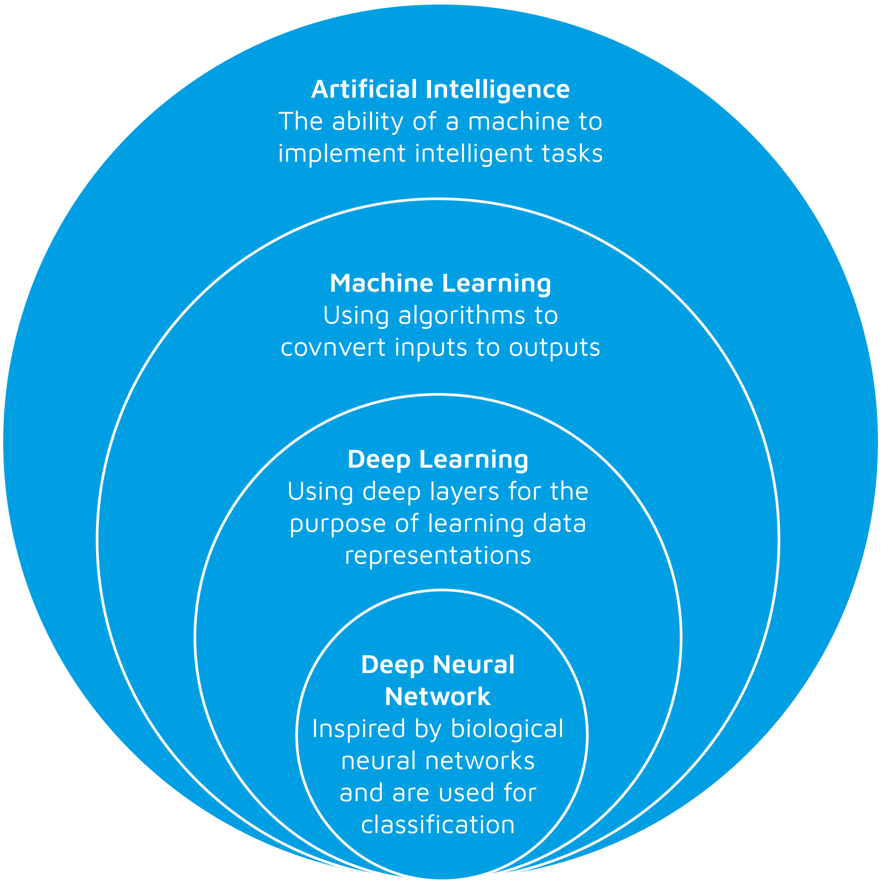


Cable extending across multiple terrains

Managing the Variables

Even once a PIDS/TPI system is installed in the field, additional configuration is required. For any PIDS or TPI installation, there may be a number of discreet section required which will be defined as different zones. The parameters for these zones will depend on a number of factors including environmental noise, topography, cable depth among others. Defining these zones reduces the number of variables that the pre-designed algorithms will need to differentiate in order to successfully classify the events.

Nevertheless, an algorithm must be configured for each zone and then tuned according to the environment and patterns of activity in that particular zone. This can be labour intensive, particularly as it may be necessary to account for seasonal activity throughout the year (e.g. farmers harvesting in a field above a pipeline). In some cases it can even take a year before the full lifecycle is seen.



Overcoming These Challenges with Deep Neural Networks

Fiber Optic PIDS and TPI systems use large amounts of data, so can especially benefit from the application of artificial intelligence and machine learning.

That is why Bandweaver uses deep learning techniques known as Deep Neural Networks (DNN) for its DAS systems.

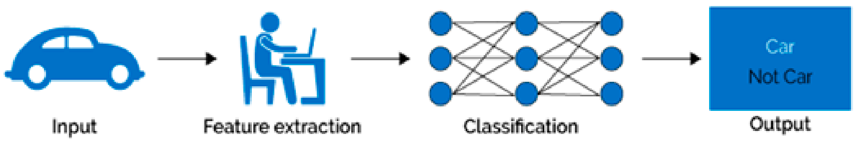
There is a lot of ambiguity in this area regarding the difference between AI, machine learning, deep learning and neural networks. The diagram (left) attempts to show the relationsip between these terms.

How Does it Work?

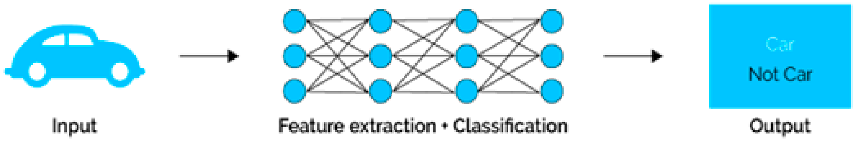
With conventional event classification techniques there is a large amount of work involved in feature extraction and classification, as well as a vast amount of domain expertise.

One of the major differences between machine learning and deep learning model is related to the feature extraction area. Feature extraction is done by human in machine learning whereas deep learning model manages this by itself.

Machine Learning

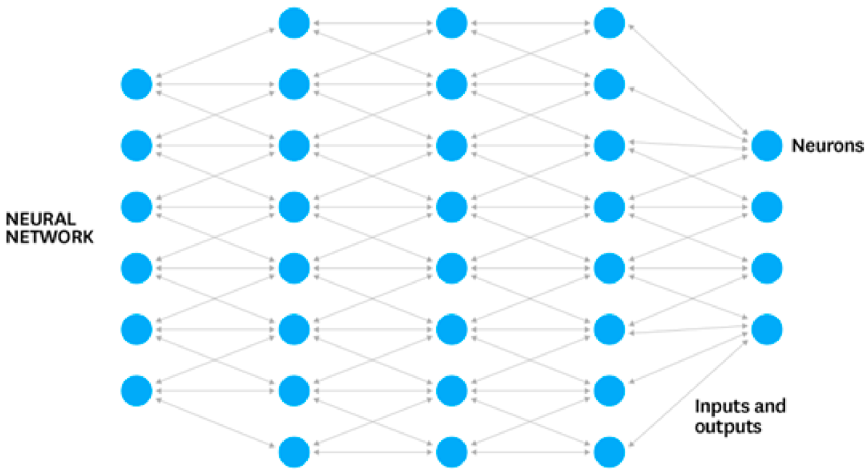


Deep Learning



Layered Learning

For Artificial Intelligence based Deep Neural Network systems there are classifier methods that don't need special assumptions on the underlying models. Similar to the human brain, they are organised in a neural network as shown below, whereby each layer has an input and an output that is passed to the next layer These layers are often referred to as the 'hidden layers' and the end user is only exposed to the input and outputs of the system.



Cat v. Dog

Perhaps the easiest way to understand this is to describe how this method is applied for image recognition. In fact, much of the foundational research into DNN originated from image recognition studies.

Below we take the example of identifying a cat's face. At each of the progressive layers, the task is broken down to a smaller subset and so the complex task of analysing the whole face is broken down into a series of simpler and more manageable tasks.

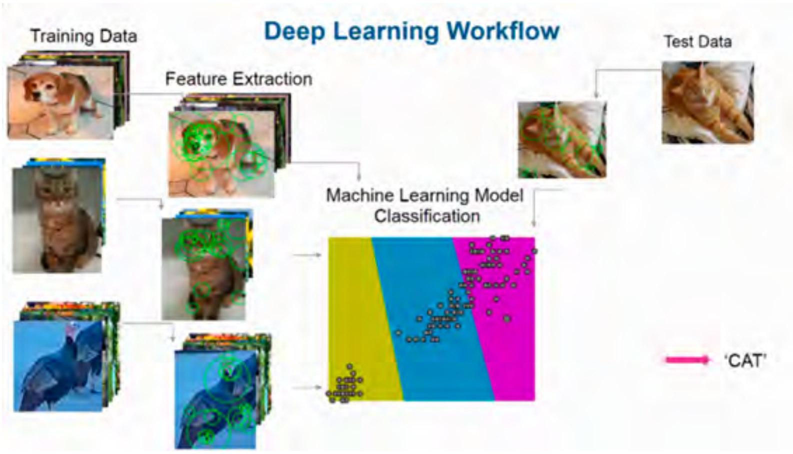
With the deep learning method, each of the nodes is determined using mathematical functions that are used to narrate that how the nodes operate in the presence of an input signal. The signals at the input layer are applied from a digitized representation of something like an image, a sound, an audio clip etc. The response of each node is combined, resulting in an output such as recognition of the original object.

Machine Learning Model Classification

Once the specific layers are defined, then the system will review training data in order to test and improve the algorithm. The diagram below illustrates how the system may organise the data and based on the patter, assign to each piece of test data the probability that it is a cat (this is the pink area in the diagram below).

Thus the system learns by developing a learning set of data. In general, there is a set of inputs whose desirable outputs are known. The mathematical functions of the nodes will then improve through 'experience' and the system performs more accurately.

Deep learning models tend continue to improve the more data they process, whereas older machine learning models stop improving after a saturation point.



Machine Learning for PIDS Applications

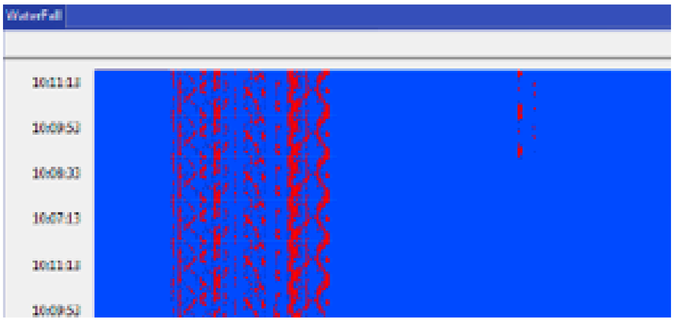
Fiber optics based PIDS systems by their nature, generate a large quantity of data and so lend themselves well to deep learning techniques. Below is a sample from Bandweaver's software that is used at the training stage and an example of how initially the user will assign or reject specific samples to 'teach' the system.

With fiber optic based PIDs and TPI systems the sheer volume of data means that the training phase does not necessarily need to take that long. Sometimes,even a small number of positive events is sufficient. This time can be as short as 2-8 hours of data acquisition in some cases in order to start the training process.

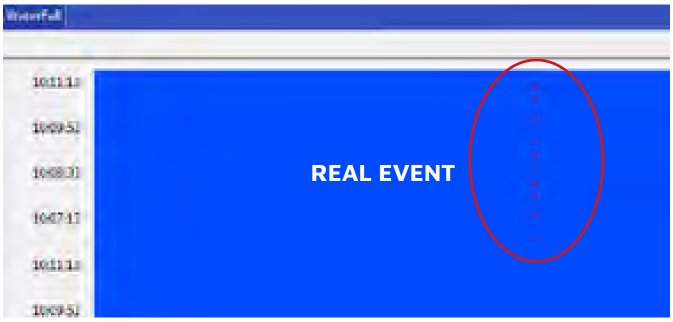
Why use Deep Neural Networks?

The art of science of machine learning consists of selecting of appropriate features and classification algorithms for the task at hand. Feature selection is paticularly demanding task for classical machine learning that often requires high effort and very good domain knowledge. The big advantage of deep neural networks is their ability to extract the relevant features from the raw data in a hierarchical manner without the need for much domain knowledge. This saves both time and expensive resources.

As per the example below, when DNN are applied to Bandweaver's Horizon DAS system, there is a significant improvement in the filtering of alarm events.



Without DNN



Without DNN

In the left picture each of the red dots signifies an alarm event. There are two active areas within the length where there is a lot of activity (the lighter blue colour). The area on the left shows the interference from a noisy environment, which is not relevant to the alarm activity whereas the data on the right corresponds to mechanical digging. In the right hand graph where the DNN algorithm is applied you can see a very significant improvement with no false alarm signals.

Real-World Benefits

There are a number of significant benefits of utilising machine learning and artificial intelligence within DAS solutions and these include (but are not limited to):

Faster and more efficient system calibration

The associated reduction in installation and commissioning time speeds up system deployment whilst reducing labour demands accelerating the return on investment with lowered whole life costs.

Improved classification of algorithms

DNN offers end users and operators more information in relation to alarm events, thus mitigating risk by enabling a fast and appropriate response.

Lower nuisance alarms

With a reduction in false alarms, operators can be more confident in the overall solution, ensuring that genuine alarm events have a prioritised response.

Capacity for self-learning and continual improvement

These solutions maximise whole life investment by deploying the latest constantly evolving algorithms and seamlessly responding to changing environments - ensuring long lasting, reliable operation.

If you would like to learn more, please contact a Bandweaver representative:
info@bandweaver.com | www.bandweaver.com