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Recent development in artificial neural network based distributed fiber optic sensors

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***Abstract*—Distributed fiber optic sensors are promising technique for measuring strain, temperature and vibration over tens of kilometres by utilizing the backscattered Rayleigh, Raman and Brillouin signals. Recently, the use of an artificial neural network (ANN) has been adopted into the distributed fiber sensors for advanced data analytics, fast data processing time, high sensing accuracy and event classification. In this paper, the recent developments of ANN-based distributed fiber sensors and their operating principles are reviewed. Moreover, the performance of ANN is compared with the conventional signal processing algorithms. The future perspective view that can be extended further research development has also been discussed.**

***Keywords*—distributed fiber sensor, artificial neural network.**

I. INTRODUCTION

The use of distributed fiber sensors in structural health monitoring applications gained a lot of attention due to their high measurement accuracy, small size, immune to electromagnetic interference, harsh environmental capability and long sensing range up to tens of kilometers. The applications includes, oil/gas pipelines monitoring, civil infrastructures, border security monitoring, aeroplane and railroads [1]. Once an optical signal launched into the optical fiber, the light will experience a scattering mechanism in three different forms of Rayleigh, Brillouin and Raman scattering [2]. Whenever a fiber undergoes a strain, temperature and vibration/acoustic changes, the backscattered signal modulated by these parameters. By analysing the modulated backscattered signal, one can realize a distributed fiber sensor over the fiber distance. Whereas, the measurement location is quantified by the pulse light classical time-of-flight method, which is same as the standard optical time-domain reflectometer (OTDR) system.

The familiar Brillouin based distributed fiber sensors are; the Brillouin optical time-domain reflectometry (BOTDR) based on spontaneous Brillouin scattering, the Brillouin optical time-domain analysis (BOTDA) based on stimulated Brillouin scattering (SBS) and Brillouin optical correlation domain reflectometry (BOCDR) based on laser modulation. The well-known Rayleigh based distributed fiber sensors are; optical frequency domain reflectometry (OFDR) and phase-optical time-domain reflectometry (Φ-OTDR) [3]. All the above distributed fiber sensors require data processing methods to extract the sensing parameters. For instance, the BOTDR/A systems typically use the nonlinear curve fitting models such as (i) Lorentzian (ii) Gaussian, (iii) pseudo-Voigt and (iv) quadratic curve fitting to find the local Brillouin frequency shift (BFS) along the sensing fiber. These curve fitting methods require a high number of data points on measured Brillouin gain spectrum (BGS) with careful initialization for better measurement accuracy. However, the measurement accuracy of these fitting models inadequate in practical condition for high noise BGS. Furthermore, when short pulses use for better spatial resolution with long sensing fiber, the BGS spectral shape could deviate completely from Lorentzian/Gaussian spectral shape [4]. Hence, these curve fitting models are not effective for accurately estimate the peak BFS and degrades the measurement accuracy. Moreover, the computational time of these fitting models poses a hurdle for long-range sensing since the fitting algorithms often require numerous iterations for convergence. Therefore, there is an increasing attention to develop enhanced signal processing algorithms to accelerate the processing of distributed fiber sensing data using advanced machine learning methods such as artificial neural networks (ANN).

In 1940s, mathematicians Warren McCulloch and Walter Pitts introduced a simple ANN algorithm to replicate human brain function [5]. From that time, the development of ANN increasing tremendously for various applications with greater computing power and more sophisticated software platforms. The applications include in the field of healthcare [6], robotics [7], aerospace [8], audio signal processing [9] and fiber optics [10]. In the field of fiber optics, ANN was used for optical communication systems [11], mode-locked lasers [12], nonlinear fiber optics [13] and fiber optic sensors [14]. Until now the implementation of ANN in distributed fiber sensor systems has been a relatively recent development. In this paper, we reviewed recent developments in ANN-based signal processing methods and performances that applied to distributed fiber sensors with their operating principles and experimental procedures.

II. OPERATING PRINCIPLE OF ARTIFICIAL NEURAL NETWORK

An ANN is a computational model inspired by the way of biological nervous system such as brain process information. It is composed by a large number of highly interconnected systems, consisting of basic computational units or neurons arranged in layers. The neuron receives a weighted input and produces an output if the sum of the inputs exceeds the threshold level for that neuron. The multilayer feedforward network describes one of the most extensively used ANN architectures. Its architecture consists

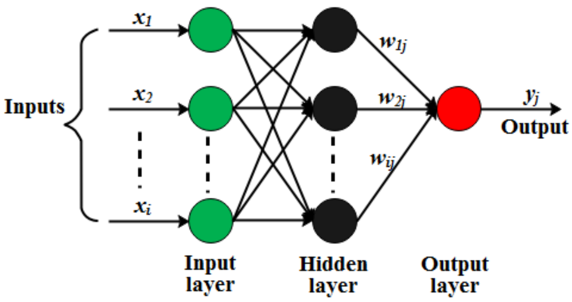


Fig. 1. ANN schematic architecture with one hidden layer

of three sections: an input layer section, one or more hidden layers section, and an output layer section. The basic ANN architecture with one hidden layer is shown in Fig. 1. The input layer receives the input vectors and distributed to the first hidden layer. The hidden layer neuron sums up all input vectors and transforms through a suitable nonlinear transfer function. Each node connected every node to the next layer and every connection (shown in black arrow) has a weight attached which may have either a positive or negative value associated with it. Where the positive weight activates the neuron while the negative weights inhibit it. As shown in Fig. 1, the inputs (x_1, x_2, . . x_i) are connected to neuron j with their associated weights (w_{1j}, w_{2j}, . . w_{ij}) on each connection. The output layer sums all the received signals, where each signal multiplied by its associated weights on the connection. The output of each node can be expressed as [15],

$$y_j = f_i\left(\sum_i w_{ij} - \theta_j\right) \tag{1}$$

where, y_j is the node output, f_i is the nonlinear transfer (activation) function, w_{ij} is the weight between nodes i and j, θ_j is the constant bias of the j^{th} node. In recent years, the ANN has been adopted into the distributed fiber optic sensors to accelerate the sensing performance, such as fast data processing speed, event classification, high sensing accuracy, and/or calibration of the sensor [14].

III. BRILLOUIN BASED DISTRIBUTED FIBER SENSORS USING ARTIFICIAL NEURAL NETWORK

Compared to traditional curve fitting models, the ANN-based approach has unique advantages of (i) real-time strain/temperature extraction (ii) BGS model flexibility, (iii) high measurement accuracy, (iii) short processing time and (iv) a lesser demand for training data. Moreover, it does not require the complete and accurate knowledge of the system model. Therefore, it is usually more flexible when implemented in practice. In recent years, ANN getting progressively more attention and have found many applications in fiber optic sensors. The experimental setup of the BOTDR system using a passive depolarizer is illustrated in Fig. 2 [16]. A DFB laser source at 1550 nm is used as a laser source. The laser output split into two propagation paths using 50/50 coupler, the upper branch signal is used for the pump and the lower branch is used for the local oscillator signal. The upper branch modulated with a dual drive MZM (DD-MZM), which modulates the electrical pulses into optical pulses with a high extinction ratio. A passive depolarizer is employed in local oscillator to suppress the polarization noise. The backscattered beat signal is detected by a photodetector (PD) and then analysed.

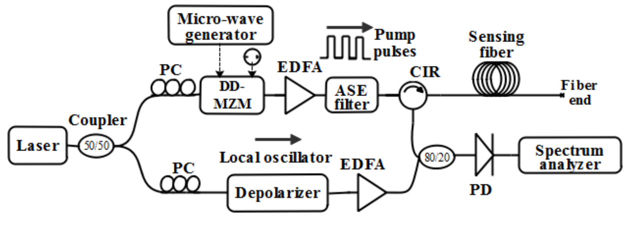


Fig. 2. Experimental setup of BOTDR system [16]

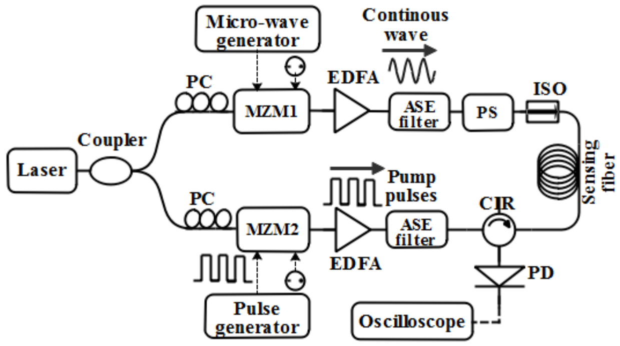


Fig. 3. Experimental setup of BOTDA system [17]

The experimental setup of the BOTDA system is illustrated in Fig. 3 [17]. The theoretical Brillouin gain spectrum has a Lorentzian shape and can be expressed as [18],

$$g(v) = g_B \frac{(\Delta v_B / 2)^2}{(v - v_B)^2 + (\Delta v_B / 2)^2} \tag{2}$$

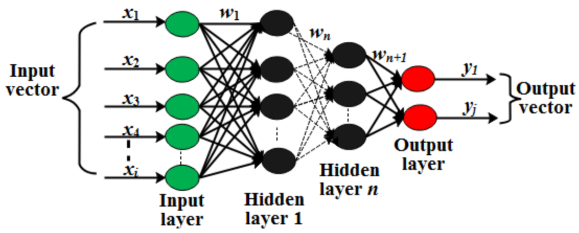
where g_B is the Brillouin gain coefficient, Δv_B is the Brillouin linewidth at FWHM, v_B is the peak BFS. Sweeping the continuous wave probe frequency, the BGS spectrum can be constructed [19]. The measured peak BFS determine the strain and/or temperature information over the sensing fiber. The use of ANN to directly retrieve the strain and temperature information over the sensing fiber distance without the procedure of estimation of BFS. The ANN has benefits of adaptive learning ability, distributed associability, as well as nonlinear mapping ability.

In 2009, A. Klar *et al.* [20] demonstrated a 76 m long underground tunnel monitoring using BOTDR system followed by a neural network that is trained to recognize the tunnel status. The ability of the sensing system to detect tunnel activities with pattern recognition of external disturbances, while insensitive to measurement noise and ground disturbances. In 2013, Y. Zhang *et al.* [21] proposed a novel fitting algorithm for the BOTDR sensing system based on radial basis function neural networks (RBFNN). The novel RBFNN algorithm improves the processing speed with accurate measurement of BFS. This approach does not require knowledge of the signal, resulting in a fast data processing time.

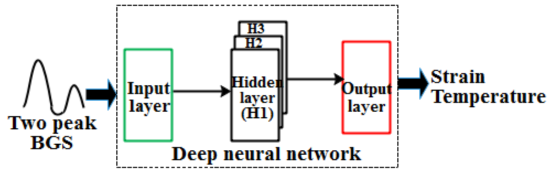
In [22], proposed a neural network-based data processing using commercially available distributed temperature sensor (DTS, AP Sensing, N4385B). The neural network approach model is composed of three steps: characteristics extraction, regression, and reconstruction of the signal. The proposed neural network algorithm is experimentally demonstrated using a 2 km sensing fiber with 1 m spatial resolution and acquisition time of 30 s.

In 2017, H. Wu *et al.* [23] proposed and experimentally demonstrated an ultrafast (15.75 s) temperature extraction using a BOTDA system with ANN-based support vector machine (SVM). The SVM algorithms trained by ideal pseudo-Voigt curves with various BFSs, linewidths and spectral shape parameters. They processed 101,500 BGSs along the 40.6 km sensing fiber with 2 m spatial resolution and the SVM based data processing speed obtained 100 times greater than standard Lorentzian curve fitting method. The temperature errors at end of the sensing fiber are ±3.1 °C with SVM and ±5 °C using standard Lorentzian curve fitting at 5 MHZ frequency scanning step and the signal-to-noise ratio (SNR) of 6.1 dB. Therefore, compared to the conventional curve fitting methods, the ANN-based data processing is a promising technique for real-time temperature extraction with fast speed and low measurement temperature error.

In 2019, B. Wang *et al.* [24] demonstrated a deep neural networks (DNN) based BOTDA system using a 25 km large-effective-area fiber (LEAF) sensing fiber with 2 m spatial resolution. The simulation and experimental data for various temperatures and strains have been measured to prove the reliability of DNN based simultaneous strain and temperature sensing, and demonstrate its advantages over the conventional curve fitting methods. Fig. 4(a) shows the schematic representation of DNN structure comprising input vectors, hidden layers and an output vector. Fig. 4(b) shows the operating principle of DNN using a LEAF fiber, which have two BGS spectrums. Here, the number of input vectors equal to the number BOTDA system scanned frequencies and the output consists of strain and temperature information. The neural network is trained by various clean and noisy BGS spectrums from the two BGS (double peak) LEAF fiber. The strain measurement uncertainty using DNN and standard solving method are 66.2 με, and 529.1 με, respectively. Whereas, the temperature measurement uncertainty using DNN and standard solving method are 2.6 °C, and 19.4 °C, respectively. Moreover, the strain and temperature measured by DNN from 600,000 BGSs along the 24 km LEAF, which requires the computational time of only 1.6 s, which is much shorter than 5656.3 s by the conventional equational curve fitting method.



(a)



(b)

Fig. 4. (a) schematic structure of DNN with 'n' hidden layers, (b) operating principle of DNN based discriminative strain and temperature monitoring using a double BGS LEAF fiber [24].

In [25], A. K. Azad *et al*. demonstrated the use of ANN in BOTDA system for a longer sensing range of 41 km by using different linewidths of BGSs to train the ANN. Hence, the effect of BGS linewidth variation on sensing accuracy can be minimized. They also found that large frequency scanning step of continuous probe wave, the temperature extraction performance with ANN does not degrade significantly. Therefore, the use of ANN can also benefit to reduce the processing time by adopting the large frequency

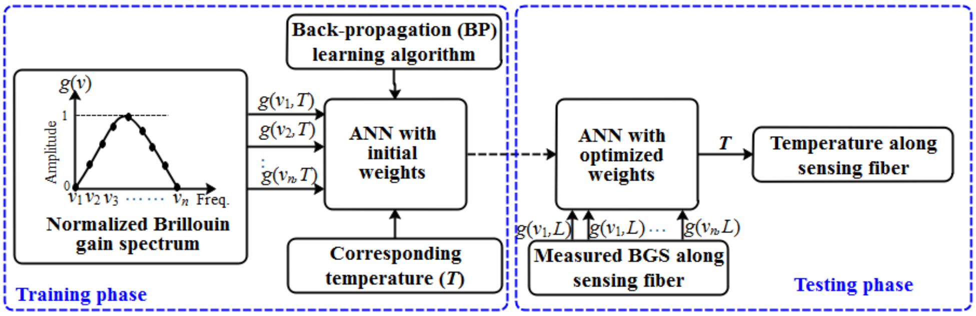


Fig. 5. BGS data processing using ANN with two independent phases [25]

Table 1. Performance comparison of Brillouin based distributed fiber sensors using ANN and conventional curve fitting methods

Ref.	Data analysis method	Temperature error (at end of the fiber)	Strain error (at end of the fiber)	Data processing time	Sensing fiber length	Spatial resolution
[24]	DNN	±2.6°C	±66.2με	1.6 s	25 km	1 m
	Conventional equational curve fitting	±19.4°C	±529.1με	5656.3 s		
[25]	ANN	±1.172 °C	Not stated	32s	41 km	4 m
	Lorentzian curve fitting	±1.705 °C	Not stated	994 s		
[15]	ANN	±0.41°C	Not stated	Not stated	100 m	4 m
	Lorentzian curve fitting	±0.8°C	Not stated	Not stated		
[23]	ANN-Support vector machine (SVM)	±3.1°C	Not stated	15.75 s	40 km	2 m
	Lorentzian curve fitting	±5°C	Not stated	1574 s		

scanning step, thus lesser number of data points and without sacrifice the sensing accuracy. The learning or training phase and testing phase of the ANN for measuring temperature profile from the BGSs is shown in Fig. 5. The neural network architecture is trained using a dataset of BGSs corresponding to a uniformly sampled subset of temperature measurements, as denoted as training phase. The ANN learning essentially consists of modifying the weights of the connections between the neurons, where the initial weights are modified by an algorithm. The weights connecting the neurons of different layers are optimized by back-propagation (BP) algorithm [26]. Without the process of estimation of BFS, the ANN with optimized weights generate the temperature distribution along the sensing fiber. At the end of the sensing fiber, the temperature measurement error using ANN and Lorentz curve fitting methods are ±1.172 °C and ±1.705 °C, respectively. Whereas, the data processing time of 32 s using ANN and 994 s using Lorentzian curve fitting method. The progress summary of ANN and conventional curve-fitting methods performances are compared and shown in Table 1.

IV. Rayleigh Based Distributed Fiber Sensors using Artificial Neural Network

The Rayleigh backscattering based phase-optical time domain reflectometry (Ø-OTDR) (also called distributed acoustic sensor (DAS)) is a promising technique for real-time vibration/acoustic measurement with high sensitivity and large dynamic range. The Φ-OTDR system is widely used for distributed acoustic sensing with an application of, pipeline monitoring, structural health monitoring, perimeter security, and wellbore integrity monitoring. The need for automatic and efficient sensing data processing, detection and classification algorithms are essential to advance the DAS technology. Therefore, the ANN is an ideal candidate, where they learn by themselves to extract the sensing features in the training phase. The experimental setup of the coherent Φ-OTDR system is illustrated in Fig. 6 [3]. A highly coherent laser with a narrow linewidth (1 kHz) split into two different paths, the upper path used for pulse generation and lower path used for the local oscillator. The pump pulses modulated by an acousto-optic modulator (AOM) with a frequency shift of 200 MHz. Thereafter, the signal amplified to an optimised power level using an EDFA and the ASE noise filtered by an optical bandpass filter. The backscattered signal amplifies using an EDFA2 and unwanted components filtered by a tunable fiber Bragg grating (TFBG) filter. The signal is then detected by a balanced photodetector to eliminate the DC component. Thereafter, a low-noise amplifier (LNA) is used for signal conditioning and filtered by a band-pass filter (BPF). The received signal is analysed by an oscilloscope at a sampling rate of 1.25 GSa/s [3].

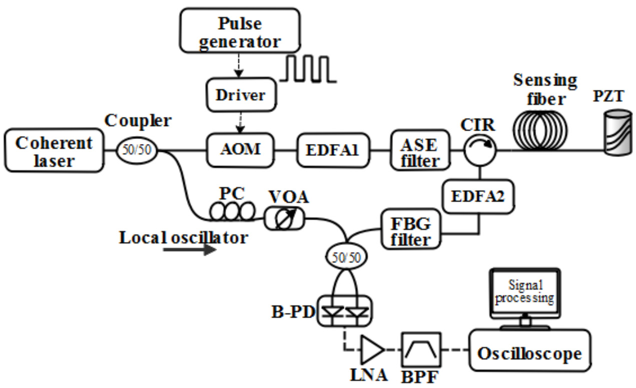


Fig. 6. Experimental setup of the coherent phase-OTDR system [3] (AOM=acousto-optic modulator, EDFA=Erbium-doped fiber amplifier, ASE=amplified spontaneous emission, PC=polarization controller, VOA=variable optical attenuator, FBG=fiber Brag grating, PZT=Piezoelectric transducer, B-PD=balanced photo-detector, LNA=low-noise amplifier, BPF=band-pass filter)

Table 2. Comparison of sweep linearization and strain extraction time using standard LMS correlation method and ANN method [27]

Signal processing method	Sweep linearization time	Strain extraction time
LMS correlation method	33.21 s	94.77 s
ANN method	0.122 s	0.353 s

In Ø-OTDR or DAS sensing technology, the efficient algorithms for detection of events of interest and their classification are the utmost importance. In 2019, S. Liehr *et al.* [27] demonstrated a real-time strain measurement (970 m long sensing fiber) based on a wavelength scanning coherent optical time-domain reflectometry (COTDR) and the raw data was processed using ANN to improve the measurement accuracy, computational speed and laser wavelength sweep linearization. Typically, the laser wavelength sweep using sawtooth laser current modulation results in a frequency drift, thus the laser wavelength sweep is not linear [28]. Using a trained ANN network, the nonlinear sweep correction with high-speed strain extraction is demonstrated and compared with least-mean squared (LMS) correlation algorithm. The sensing performance comparison of sweep linearization and strain extraction time using standard LMS correlation method and ANN method are shown in Table 2. The ANN-based computation of linearization is 272 times and the strain extraction is 268 times higher than the standard LMS correlation-based method.

Compared to standard deterministic algorithms in Φ-OTDR system, the ANN got more attention for an advanced data analysis, pattern recognition and classification of vibration events. Several Φ-OTDR systems based on ANN method has been demonstrated for train position, speed, the number of bogies and classification of events such as pedestrians or construction work next to the rail tracks. In [29], the authors used a commercially available Helios DAS system for real-time monitoring of train position, velocity and number of bogies. From the results, the train velocity is calculated in three different ways using train-view, rail-view, and bogie cluster data analysis. They used ANN model in DAS sensing data and trained large number of data sets. The filtering, processing and train localization using standard peak finding algorithm takes 300 s, while, the ANN model takes only 22 s. the use of ANN also offers flexibility to process different data sets with high processing speed.

In 2019, Q. Che *et al.* [30] demonstrated a partial discharge (PD) detection in cross-linked polyethylene power cables using ANN-based Ø-OTDR system. The sensing fiber is composed of weak Bragg gratings (wFBGs) to enhance the Rayleigh backscattering signal. The proposed ANN algorithm recognises and categorize different types of events, including internal PD, corona PD, surface PD, and noise as well. In their experiments, 1280 training samples and 832 test samples are used to improve precision, sensitivity, and

Table 3. Progress summary of ANN-based distributed acoustic sensing (DAS) systems

Sensing system	Classification task	Accuracy	Computational time	Sensing fiber length	Spatial resolution
Commercial Helios DAS system [29]	Train view analysis for 4 trains (position, speed and number of train bogies)	±0.8 km/h (@160km/h train speed)	22 s	35 km	10 m
DAS assisted by wFBGs [30]	Power cables partial discharge (PD) (internal PD, corona PD, surface PD)	96.3%	Not stated	1.5 km	5 m
DAS [31]	Walking, digging, digging with shovel, digging with harrow.	93%	Not stated	40 km	10 m
DAS [32]	Seismic events (human steps, ambient noises)	94%	0.5 s	5 km	5 m
DAS [33]	Ambient noise, human footsteps, vehicle moment	94% for 5 km fiber 89.3% for 20 km fiber	0.5 s	5 km and 20 km	5.5 m for 5 km fiber, 10.3 m for 20 km fiber
DAS assisted by wFBGs [34]	Human moment (one person walk, one person run, two person walk, two person tun, two person walk and one person run)	90%	1.25 s	7 wFBGs in sensing fiber	n/a
DAS assisted by wFBGs [34]	Pipeline corrosion excited by different hammers (aluminium, plastic, rubber, steel)	94.29%	Not stated	7 wFBGs in sensing fiber	n/a

specificity for each event up to 96.3%, 96.4%, and 98.7%, respectively. Therefore, the event recognition based on ANN is a promising method in DAS or Ø-OTDR system.

In [34], the authors experimentally verified human movement detection and pipeline corrosion monitoring with neural network DAS system. The wFBGs employed in the sensing fiber to enhance the Rayleigh backscattered signal SNR by 29 dB. The use of ANN is cable for human movement classification, whether one/two-person walking or running with 90% accuracy. In addition, they also developed ANN model for pipeline corrosion monitoring and classified the vibration excitation sources, where the pipeline knockout by aluminium, rubber, plastic and steel hammers. The accuracy of pipeline corrosion detection reaches 94.29% using the DAS combined with a neural network approach. The progress summary of the ANN-based DAS system is shown in Table 3. We can see that the role of ANN as a signal processing tool has been a great use in distributed optical fibre sensor systems.

V. Conclusion

We reviewed the recent developments of ANN-based distributed fiber sensor and compared the sensing performance with conventional signal processing methods. In BOTDR and BOTDA systems, the difficulty of accurate monitoring of BFS, small frequency scanning step, low sensing accuracy, low data processing speed are greatly enhanced by ANN-based algorithms. Moreover, the ANN offer greater tolerance to measurement noise and real-time strain and temperature extraction even for long sensing range (>100 km). The DAS sensing system requires efficient data processing, detection and classification algorithms. Once the ANN is trained by widest possible acoustic conditions data, the ANN is more capable to extract real-time acoustic information with high classification accuracy. This trend of development will likely continue in the future with complex fiber sensor signals being interpreted by increasingly sophisticated processing hardware and software. It is envisaged that the power of ANN in interpreting the sensor data and classification of the results may be used to solve complex signal processing issues. Furthermore, it is anticipated that the use of ANN will gradually become smart intelligent sensor systems with the expanded field of applications.

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