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Neural Protective Relay for a Circuit Breaker

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ABSTRACT

This paper presents a neural network approach to design a protective relay for a circuit breaker. A circuit breaker is an automatically operated electrical switch, which is designed to protect an electrical circuit in case of any fault or overload. It is the advanced version of a "fuse". A fuse just melts when it senses high currents but that is not the case with the circuit breaker. It needs a sensor to trip it. This work is done by the relay. Hence, a relay acts as the brain of the circuit breaker by sensing the fault and giving a trip signal to the circuit breaker. A threshold value for current is set for the relay, which trips the breaker when the current in the transmission line exceeds the threshold value. Hence, a feed forward neural network is designed such that its output is '1' if the current in the transmission line exceeds the threshold value and in the process, tripping the circuit breaker.

Keywords:ANN, ANN Based Relay, Faults, Components of Relay, Protection Relaying System, Neural Network Unit

1. INTRODUCTION

Power systems are built to allow continuous generation, transmission and consumption of energy. Most of the power system operation is based on three-phase system that operates in a balanced mode, often described with a set of symmetrical phasors of currents and voltages being equal in magnitude and have the phase shift between the phases equal to 120 degrees.

The most basic power system components are generators, transformers, transmission lines, buses and load components. They allow for power to be generated (generators), transformed (transformers) from one energy level to another, transmitted (transmission lines) from one location to another, distributed among a number of transmission lines and power transformers (buses) and finally used by the consumers (loads). In the course of doing this, the power system components are being switched or connected in a variety of configurations using circuit breakers. The circuit breakers are capable of interrupting the flow of power at a high energy level and hence may be used to disconnect the system components in case the components experience a fault. The graphical representation of all the power system components is called a one-line diagram and is shown in the figure 1 below.

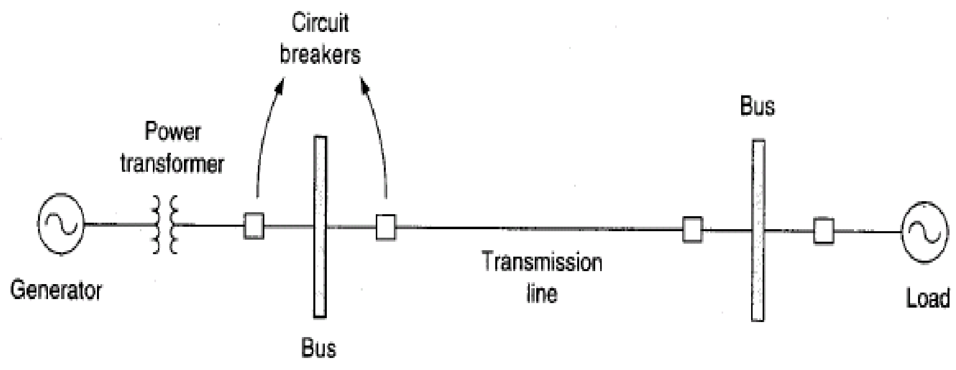


Figure 1.**One-line representation of Power System Components.**

The study of faulted systems requires more detailed three-phase representation, but the one-line diagram is sufficient to discuss the basic relaying concepts. It is also essential to know the various types of faults that can be seen on transmission lines. Then the relay connections and the components of a relaying system, its principles and operation criteria are discussed. Figure 2 and Figure 3 shown below are the different types of faults that may occur on transmission lines.

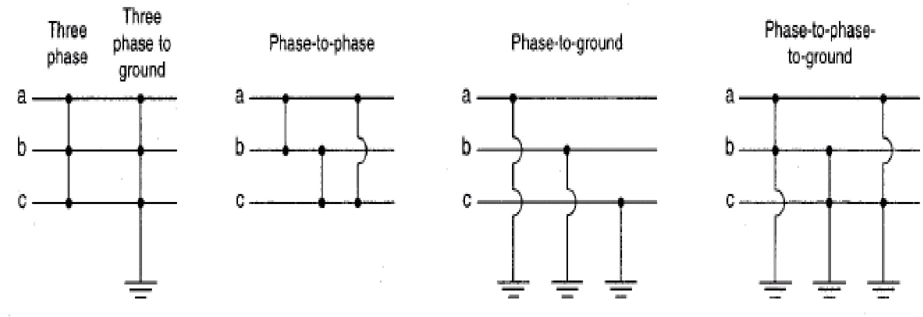


Figure 2.Common transmission line faults

A. Faults can be basically classified into 3 types:

Short circuits - three-phase faults
- phase-phase faults
- phase-phase-ground faults
- phase-ground fault (most common)

Series faults - one phase open
- two phases open
- phase inversion

Other faults - Simultaneous faults
- Mechanical system faults

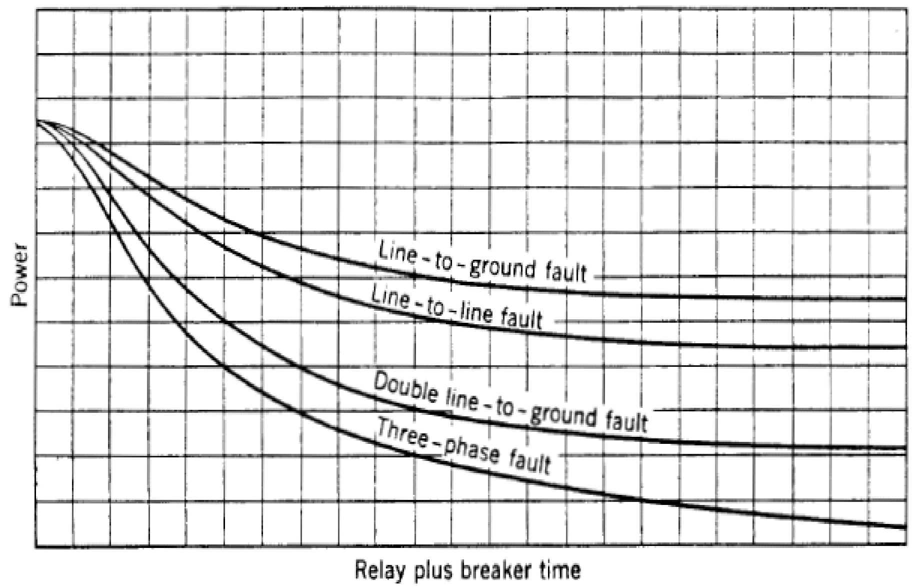


Figure 3.Curves illustrating the relationship between the maximum powers

Transmitted and the relay plus breaker time.

2. RELAY CONNECTIONS AND COMPONENTS OF RELAY

Protective relays are devices that are connected to instrument transformers to receive input signals and to circuit breakers to issue control commands for opening or closing.Often relays are connected to some auxiliary monitoring and control equipment to allow for coordination with other similar equipment and supervision by the operators.C simple protective relaying system.

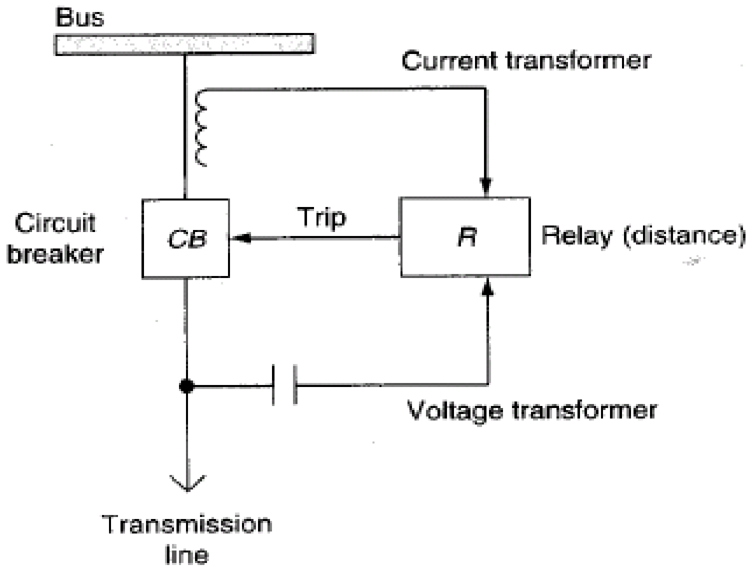


Figure 4.A simple protective relaying system

Any basic relaying system consists of a current transformer, relay and a circuit breaker. A typical connection for protection of high-voltage transmission lines is shown above.Protective relay is a low voltage device and cannot be directly connected to high voltage bus. Voltage transformers are of two types: potential transformer (PT) and capacitor coupling voltage transformers (CVT). Since the voltage levels in the power system range well beyond kilovolt values, the transformers are used to bring the voltages down to acceptable level used by protective relays. They come in standard solutions regarding the secondary voltage, typically 69.3 V or 120 V, depending if either line-ground or line-line quantity is measured respectively. Also a current transformer is placed to step down the high currents to 5 A or 1 A range whichever is suitable for the relay.

B. Types of over-current relays:- Electro-mechanical relays
- Analog electronic relays
- Microprocessor based relays
- Digital relays

C. Proposed Relay based on Artificial Neural Networks:

Major functional blocks of the proposed relay are shown in Figure below. Voltage and current signals at the transmission line end (relay location) will be acquired by the relay through CTs and VTs. Figure 5 shown major blocks constituting the relay.

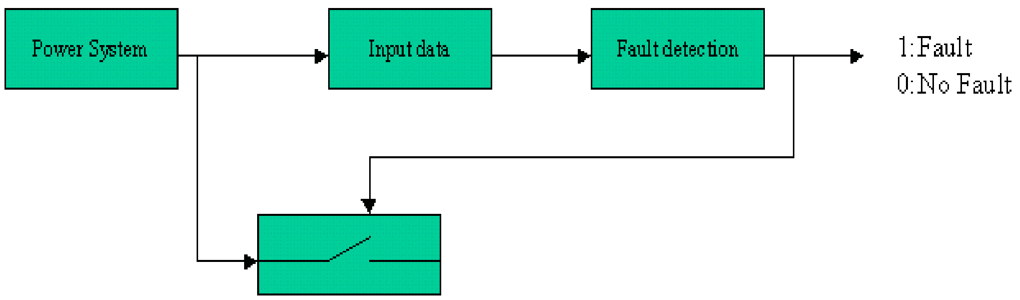


Figure 5.Major blocks constituting the relay.

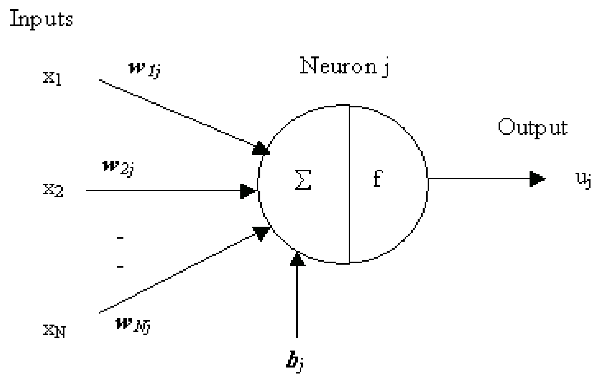
After pre-processing, they will be fed to the fault detector to detect a fault. The proposed fault detector is designed to indicate the presence or absence of a fault. The occurrence of the fault is determined by identifying the power system state directly from instantaneous current (I) and voltage (V) data. The Fault Detector uses only one terminal line data extracted at the relay location.

D. Artificial Neural Networks and Training Algorithm:

A multi-layered feed-forward neural network has been used and was trained with a supervised learning algorithm called the error-back propagation. The feed-forward neural network consists of an input layer representing the input data to the network, some hidden layers and an output layer representing the response of the network. Each layer consists of a certain number of neurons; each neuron is connected to other neurons of the previous layer through adaptable synaptic weights *w* and biases *b*, as shown in Figure below.

E. Information processing in a neural network unit.

If the inputs of neuron *j* are the variables $x_1, x_2, \ldots, x_i, \ldots, x_N$, the output u_j of neuron *j* is obtained as follows:



$$u_j = f\left[\sum_{i=1}^{N}\left(w_{ij}\cdot x_i + b_j\right)\right] \quad (1)$$

An FFNN of three layers (one hidden layer) is considered with N, M and Q neurons for the input, hidden and output layers, respectively. The input patterns of the ANN represented by a vector of variables $x = (x_1, x_2, \ldots, x_i, \ldots, x_N)$ submitted to the ANN by the input layer are transferred to the hidden layer. Using the weight of the connection between the input and the hidden layer, and the bias of the hidden layer, the output vector
$u = (u_1, u_2, \ldots, u_j, \ldots, u_M)$ of the hidden layer is then determined. The output uj of neuron j is obtained as follows:

$$u_j = f_{hid}\left[\sum_{i=1}^{N}\left(w_{ij}^{hid}\cdot x_i + b_j^{hid}\right)\right] \quad (2)$$

Where w^{hid}_{ij} represents the weight of connection between neuron *j* in the hidden layer and the i^{th} neuron of the input layer, b^{hid}_j represents the bias of neuron *j* and f_{hid} is the activation function of the hidden layer. The values of the vector *u* of the hidden layer are transferred to the output layer. Using the weight of the connection between the hidden and output layers and the bias of the output layer, the output vector $y = (y_1, y_2, \ldots, y_k, \ldots, y_Q)$ of the output layer is determined. The output yk of neuron k (of the output layer) is obtained as follows:

$$y_k = f_{out}\left[\sum_{j=1}^{M}\left(w_{jk}^{out}\cdot u_j + b_j^{out}\right)\right] \quad (3)$$

Where w_{jk}^{out} represents the weight of the connection between neuron k in the output layer and the j^{th} neuron of the hidden layer, b_k^{out} represents the bias of neuron *k* and 'out is the activation function of the output layer. The output y_k (corresponding to the given input vector *x*) is compared with the desired output (target value) y^d_k. The error in the output layer between y_k and y^d_k ($y^d_k - yk$) is minimized using the mean square error at the output layer (which is composed of Q output neurons), defined by

$$E = \frac{1}{2}\cdot\sum_{k=1}^{Q}\left(y_k^{d} - y_k\right)^2 \quad (4)$$

Training is the process of adjusting connection weights *w* and biases *b*. In the first step, the network outputs and the difference between the actual (obtained) output and the desired (target) output (i.e., the error) is calculated for the initialized weights and biases (arbitrary values). During the second stage, the initialized weights in all links and biases in all neurons are adjusted to minimize the error by propagating the error backwards (back-propagation algorithm). The network outputs and the error are calculated again with the adapted weights and biases, and the process (the training of the ANN) is repeated at each epoch until a satisfied output y_k (corresponding to the values of the input variables *x*) is obtained and the error is acceptably small. The adjustment by the back-propagation algorithm, which is required in the weights and biases to minimize the total mean square error, is computed as

$$\Delta w = w^{new} - w^{old} = -\eta \cdot \left(\frac{d}{dw} E \right)$$

$$\Delta b = b^{new} - b^{old} = -\eta \cdot \left(\frac{d}{db} E \right) \qquad \textbf{(5\&6)}$$

1) *For the output layer, we have*

$$\Delta w_{ij}^{new} = \alpha \cdot \Delta w_{ij}^{old} + \eta \cdot \delta_j \cdot y_j$$

$$\Delta b_k^{new} = \alpha \cdot \Delta b_k^{old} + \eta \cdot \delta_k \quad \textbf{(7\&8)}$$

where, α is the momentum factor (a constant between 0 and 1) and $\delta_k = y_k^{d} - y_k$

For the hidden layer, we get

$$\Delta w_{jk}^{new} = \alpha \cdot \Delta w_{jk}^{old} + \eta \cdot \delta_k \cdot y_k$$

$$\Delta b_j^{new} = \alpha \cdot \Delta b_j^{old} + \eta \cdot \delta_j \quad \textbf{(9\&10)}$$

where, $\delta_j = \sum_{k=1}^{Q} \left(\delta_k \cdot w_{jk} \right)$

and $\delta_k = y_k^{d} - y_k$

Once the network is trained with the algorithm and appropriate weights and biases are selected, they can be used in the test to identify the output pattern given an appropriate input pattern. The training is performed offline to reduce online computation.

3. ANN BASED RELAY

F. Inputs and Outputs:

In order to build up an ANN, the inputs and outputs of the neural network have to be defined for pattern recognition. The inputs to the network should provide a true representation of the situation under consideration. The process of generating input patterns to the ANN fault detector is depicted in Figure 6 below.

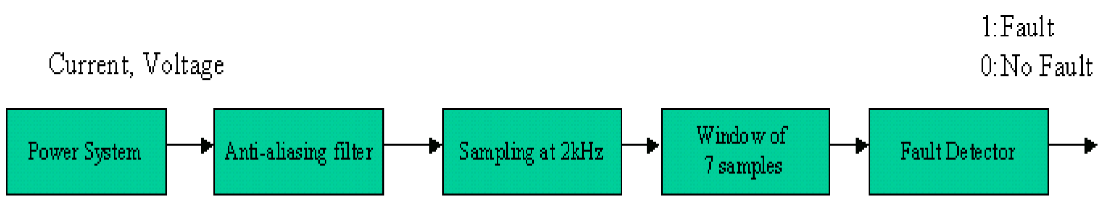


Figure 6.Process of generating input patterns to the ANN based Relay

The current (I) and voltage (V) signals are calculated as a string of samples corresponding to a 100 kHz sampling frequency. These signals are processed so as to simulate a 2 kHz sampling process (40 samples per 50 Hz cycle) using an anti-aliasing filter to remove the unwanted frequencies from a sampled waveform. This sampling rate is compatible with sampling rates presently used in digital relays. The phase current (Ia, Ib, Ic) and voltage (Va, Vb, Vc) signals, and the zero sequence current (I0) and voltage (V0) signals sampled at 2 kHz are used as the inputs to the ANN. Also, the input current and voltage samples have to be normalized in order to reach the ANN input level (±1). The ANN output is indexed with either a value of 1 (the presence of a fault) or 0 (the non-faulty situation).

G. Structure and Training of the Neural Protective Relay:

The fault detection task can be composed as a pattern classification problem. The fully connected three-layer feed-forward neural network (FFNN) was used to classify faulty/non-faulty data sets and the error-backpropagation algorithm was used for training. The numbers of neurons in the input and hidden layers were selected empirically through extensive simulations. Various network configurations were trained and tested in order to establish an appropriate network with satisfactory performances, which were the fault tolerance, time response and generalization capabilities. With supervised learning, the ANN is trained with various input patterns corresponding to different types of fault (a–g, b–g, c–g, a–b–g, a–c–g, b–c–g, a–b, a–c, b–c, a–b–c and a–b–c–g, where a, b, and c are related to the phases and g refers to the ground) at various locations for different fault conditions (fault inception angles, fault resistances) and different power system data.

The ANN fault detector consists of 56 input neurons (seven samples of each signal: Ia, Ib, Ic, Va, Vb, Vc, I0, V0), 18 neurons in the hidden layer (chosen after a series of trials) and one output neuron to indicate the transmission line state. Then the ANN structure of the fault detector is (56–18–1). The sigmoid transfer function was used for the hidden and output layers. The artificial neural network structure of the fault detector is shown in figure 6 below.

$$f(S) = \frac{1}{1 + e^{-S}} \tag{11}$$

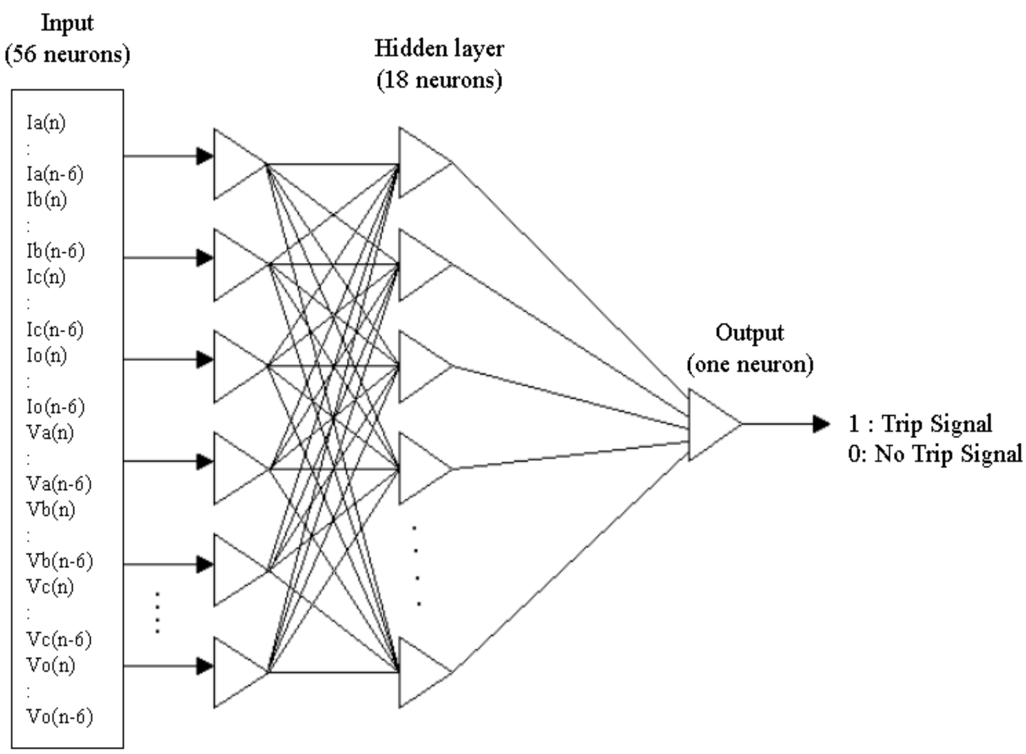
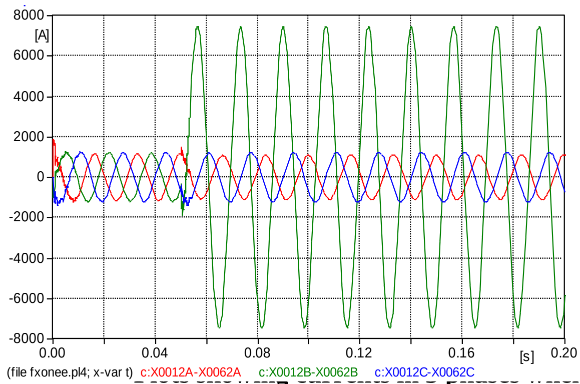


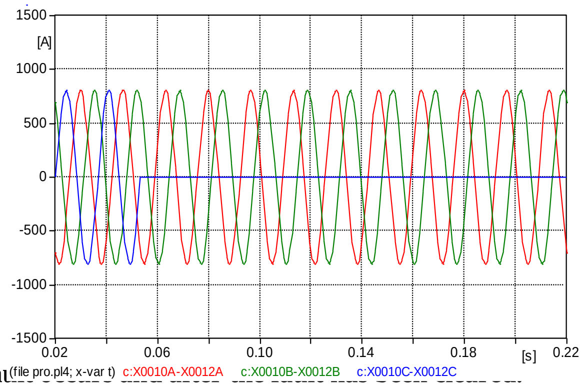
Figure 6. **Artificial Neural Network based relay structure**

The input layer simply transfers the input vector x (which are seven samples of each signal: Ia (n), . . ., Ia(n − 6), Ib(n), . . . , Ib(n − 6), Ic(n), . . . , Ic(n − 6), I0(n), . . . , I0(n − 6), Va(n), . . . , Va(n − 6), Vb(n), . . . , Vb(n − 6), Vc(n), . . . , Vc(n − 6), V0(n), . . . , V0(n − 6)) to the hidden neurons. The outputs uj of the hidden layer with the sigmoid activation function are calculated in accordance with (2) and transferred to the output layer, which is composed of only one neuron. The output value of the neuron in the output layer with the sigmoid activation function calculated in accordance with (3) gives the state of the transmission line: 1 (the presence of a fault) or 0 (the non-faulty situation). It should be mentioned that the final weights and biases are adjusted by using equations (9 & 10) in the training phase by using arbitrary training parameters (source capacitance, source voltages, time constants).

H. Tests and Results:

The plots for the currents in the 3 phases when a fault occurs in one phase and after the relay trips the breaker are shown below. First graph shows a case where fault occurs in phase C at 50 milli-seconds. High currents can be seen in the phase C and our artificial neural network senses the over-current and gives the output 1 (fault) and sends a trip signal to the circuit breaker. The breaker trips and current goes to ‘0’ in phase C. This can be seen in the second graph.





These plots have been obtained by simulating a simple relay network using ATPdraw.

CONCLUSION

Many successful applications of artificial neural networks (ANNs) to power systems have been demonstrated, including security assessment, load forecasting, control, etc. Recent applications in protection have covered fault diagnosis for electric power systems, transformer protection and generator protection. However, almost all of these applications in protection merely use the ANN ability of classification, that is, ANNs only output 1 or 0.

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