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Artificial Intelligence

BCS-7A

ANN Activation functions

Research Paper # 1:

Questions:

1. **How it is used?**

   Firstly the vibrations for the faulty bearing is calculated and then it is compared to the healthy bearings using FFT analyzer, The vibration data recorded for the bearings have been used to categorize the condition of the bearing as healthy or faulty by applying machine learning techniques. The dataset of healthy and faulty bearings is collected using a four-channel Fast Fourier Transform Analyzer (FFT) analyzer. However, the statistical feature extraction technique has been used to evaluate the accuracy and performance of artificial neural network, support vector machine, logistic regression, and decision tree algorithms based on their classification accuracy and total costs.

2. **Why it is used?**
   In this work, different machine learning techniques such as decision tree, logistic regression, support vector machine (SVM), and artificial neural network (ANN) are used and compared to find healthy and faulty conditions of the bearing. This experiment was carried out to compare ANN Activation functions and SVM with logistic regression.

3. **What is output of this activation function?**

   The result of the work reveals that the performance of the activation function based artificial neural network (ANN-AF) and SVM algorithm is better than logistic regression and decision tree models.

4. **Any drawbacks of this function?**

   It is observed that the use of appropriate activation functions within the ANN-AF technique improves the accuracy of the machine learning model so if the activation function will not be appropriate so it will give least accuracy resulting in faulty results.

[1] Reference :

Bekar ET, Nyqvist P, Skoogh A (2020) An intelligent approach for data pre-processing and analysis in predictive maintenance with an industrial case study. *Advances in Mechanical Engineering* 12(5): 1–14.

[1] IEEE style reference:

Rayjade G., Bhagure A., Kushare P. B., Bhandare R., Matsagar V. and Chaudhari A., "Performance evaluation of machine learning algorithms and impact of activation functions in artificial neural network classifier for bearing fault diagnosis," *Journal of Vibration and Control*, vol. 31, no. 9–10, pp. 1859–1873, 2025, doi: 10.1177/10775463241235778.

Research Paper # 2:

Questions:

1. **How it is used?**

The activation function inside the hidden layers of MLP-ANN transforms the input features like substrate type, pH, temperature, and inoculum type into meaningful signals for the next layer. MLP is designed to capture complex nonlinear relationships in biological hydrogen production, and activation functions are essentially a necessity to produce nonlinear relationships.

2. **Why it is used?**

It is used because the production of biohydrogen depends on many nonlinear biological factors, and activation functions allow ANN to learn and represent such complex patterns with much accuracy. Biological processes are nonlinear and that MLPs are specifically chosen for their ability to model nonlinear behaviour, which is afforded by the presence of activation functions.

3. **What is output of this activation function?**

It generates a numerical output from the activation function to be used as input by the next layer and ultimately contributes to the final prediction of hydrogen yield. Activation function's role is to help shape the internal values that lead to this final prediction.

4. **Any drawbacks of this function?**

Using any unsuitable activation function can reduce the the accuracy of the model in which it is used.

[2] Reference :

E. Abdelsalam *et al.*
Sustainable production of green hydrogen, electricity, and desalinated water via a Hybrid Solar Chimney Power Plant (HSCPP) water-splitting process
Int. J. Hydrogen. Energy
(2024)

[2] IEEE style reference:

I. Shomope, M. Tawalbeh, A. Al-Othman, and F. Almomani, "Predicting biohydrogen production from dark fermentation of organic waste biomass using multilayer perceptron artificial neural network (MLP–ANN)," *International Journal of Hydrogen Energy*, vol. 49, no. XX, pp. XXX–XXX, 2024

Research Paper # 3:

Questions:

1. **How it is used?**

In this work, optical devices such as Mach-Zehnder Interferometers (MZIs) and Micro-Ring Resonators (MRRs) will be used to implement activation functions in ONNs. Activation functions introduce non-linearity in the network to allow for complex computations; for example, image recognition using MNIST. The study demonstrates that the ANN model can optimize these devices to approximate nonlinear functions like Clipped ReLU, Sine, and Exponential, which then transform input signals into outputs for the next layer in the optical network.

2. **Why it is used?**

Activation functions are very important because ONNs require nonlinearities in order to process and map complex input-output relationships. Without them, optical neural networks would only perform linear operations, limiting their ability to handle such tasks as image recognition. The current work demonstrates that using optimized optical activation functions allows the network to achieve extremely high accuracies, 99.9% training and 99.3% validation, in simulations**.**

3. **What is output of this activation function?**

It provides as output an optical signal transformed according to the nonlinear activation applied. These outputs are numerical in nature for the MNIST task, representing features of images after processing that make a certain prediction for the class of each handwritten digit.

4. **Any drawbacks of this function?**

The paper further mentions practical limitations:

Performance may degrade due to fabrication errors, waveguide roughness, or variations in temperature.

The nature of ONN architecture and optical hardware contributes to making its implementation a difficult task in the real world.

[3] Reference :

- R. Xu
  A survey of approaches for implementing optical neural networks
  Opt Laser. Technol.
  (2021)
- H. Zhang

All-optical neural network nonlinear activation function based on the optical bistability within a micro-ring resonator
Opt Commun.
(2024)

[3] IEEE style reference:

T. Jia, R. Jiang, Z. Fu, Z. Xie, X. Ding, and Z. Wang, "Optimization and inverse design of optical activation functions based on neural networks," *Optics Communications*, vol. 687, 131370, 2024, doi: 10.1016/j.optcom.2024.131370.

Research Paper # 4:

Questions:

1. **How it is used?**

The PWL activation function is used in Hopfield Neural Networks to generate nonlinear dynamics including chaos. The input to each neuron, $x_j$is passed through the PWL function to get its output $y_j = f(x_j)$. It can be implemented in circuit based and also software based. First input voltage is processed through the linear segments then the output voltage gives us neuron activation. Finally, the output is fed back to other neurons to update the network state iteratively.

2. **Why it is used?**

Traditional tanh functions are hardware intensive that require resistors, transistors etc, so the PWL activation functions are easy to implement in hardware and they maintain similar behaviour as tanh. It also allows adjustable behaviour of slope and saturation and also allows control over the network dynamics.

3. **What is output of this activation function?**

The output of this is a bounded, piecewise-linear value representing the neuron's activation.

4. **Any drawbacks of this function?**

It only approximates smooth functions like tanh tanh, some fine dynamics may be lost. Non-smooth transitions: Sharp corners at breakpoints might introduce unwanted artifacts in some sensitive simulations

[4] Reference :

Sarić, R., Jokić, D., Beganović, N., Pokvić, L.G., Badnjević, A.: FPGA-based real-time epileptic seizure classification using artificial neural network. Biomed. Signal Process. Control **62**, 102106 (2020)

[4] IEEE style reference:

L. C. Lujano-Hernandez, J. M. Munoz-Pacheco, and V.-T. Pham, "A fully piecewise linear Hopfield neural network with simplified mixed-mode activation function: dynamic analysis and analog implementation," *Nonlinear Dynamics*, vol. 113, pp. 18583–18604, 2025, doi: 10.1007/s11071-025-11099-y.

Research Paper # 5:

Questions:

1. **How it is used?**

In this look at, the neural network is used to expect the fatigue lifestyles of corroded metal cord via taking inputs like stress range, suggest strain, and corrosion charge. Each input is processed by means of neurons, which use an activation function to decide how a good deal have an impact on the enter need to have at the final prediction. The network combines most of these processed alerts to output a anticipated value for the metallic wire's fatigue existence, helping engineers recognize how corrosion and pressure have an effect on durability.

2. **Why it is used?**

The activation feature is critical because it permits the neural network to seize complicated and nonlinear relationships among the factors affecting fatigue lifestyles, like corrosion and stress. Without it, the network might best handle simple immediately-line relationships and fail to are expecting actual-global steel twine behavior as it should be. By introducing this feature, the model can research styles in information that aren't obvious, enhancing prediction accuracy.

3. **What is output of this activation function?**

The output of the activation function is a converted model of the input signal, which determines how strongly a neuron contributes to the final prediction. In this example, it allows the neural community produce a significant estimate of the logarithmic fatigue existence of the corroded steel cord, combining facts from pressure, corrosion, and other enter features.

4. **Any drawbacks of this function?**

Although activation functions are important for studying complicated styles, they are able to every so often introduce issues. For instance, certain features may additionally reason the network to train slowly or suffer from problems like vanishing gradients, particularly in deeper networks. Choosing the incorrect activation function should reduce the accuracy of predictions or make the gaining knowledge of process inefficient.

[5] Reference :

- P. Roffey
  The fracture mechanisms of main cable wires from the forth road suspension
  Eng Fail Anal

(2013)

[5] IEEE style reference:

F. Yi, H. Lei, Q. Lv, and Y. Zhang, "Coupling physics in artificial neural network to predict the fatigue behavior of corroded steel wire," *Int. J. Fatigue*, vol. 203, p. 108669, 2024, doi: 10.1016/j.ijfatigue.2024.108669.

Research Paper # 6:

Questions:

1. **How it is used?**
   In this research, artificial neural network (ANN) is used to predict the nominal lateral resistance of a drilled shaft in soil with cohesive properties. Engineers provide the model with data from load tests, including soil properties, axle dimensions and other relevant variables. The network processes these inputs through layers of neurons and activation functions, learns the complex relationships between soil behavior and shaft resistance, and finally provides an estimate of the lateral resistance of the shaft.
2. **Why it is used?**

   ANNs are used because traditional design methods often do not fully account for uncertainties such as soil variability, geometry differences and construction effects. These uncertainties introduce non-linear behavior that is difficult to capture with traditional formulas. By using ANNs, the model can handle these non-linearities and provide more accurate predictions, helping engineers design safer and more cost-effective foundations.

3. **What is output of this activation function?**

   The activation function in an ANN transforms the input of each neuron to capture non-linear conditions. The output of the activation function contributes to the overall network prediction, which in this case is the nominal lateral resistance of the drilled shaft. This allows ANNs to make realistic predictions even with complex soil behavior.

4. **Any drawbacks of this function?**
   Despite its usefulness, the activation function can sometimes lead to challenges such as slow training, overfitting, or vanishing gradients, especially in networks with many layers. Choosing an inappropriate activation function can reduce the model's prediction accuracy or make learning ineffective, although these problems can often be mitigated with careful model design.

[6] Reference :

1. Brown D. A., Turner J. P., Castelli R. J., Loehr E. J. *Drilled shafts: Construction Procedures and LRFD Design Methods*. No. FHWA-NHI-18-024. United States Federal Highway Administration, Washington, D.C., 2018

[6] IEEE style reference:

A. K. H. Agbemenou, R. Motamed, and A. Talaei-Khoei, "Prediction of the Nominal Side Resistance of Drilled Shafts in Dominantly Cohesive Soils using ANN," *J. Transp. Eng., Part B: Pavements*, vol. 2679, no. 2, 2024, doi: 10.1177/03611981241273310.

Research Paper # 7:

Questions:

1. **How it is used?**
   In this study, the SM_EFD_LS model is used to predict the potential soil failure depth for rainfall-induced shallow landslides by training an artificial neural network (ANN_GA-SA_MTF) with simulated rainfall events and slope stability data. The model takes rainfall-related factors such as maximum rainfall intensity, rainfall depth and cumulative rainfall in the 3 hours ahead as input and produces estimated landslide depths with associated confidence intervals, enabling early warning and hazard assessment.
2. **Why it is used?**

This model is used to improve the prediction of landslide failure characteristics, especially soil depth, under uncertainty associated with rainfall events. Traditional deterministic or AI-based models often do not determine the stochastic properties of the fault depth, while the SM_EFD_LS model integrates ANNs with genetic algorithm calibration and multiple transfer functions to provide probabilistic estimates, which are important for risk assessment, early warning systems and design of mitigation strategies.

3. **What is output of this activation function?**

Activation functions in the ANN_GA-SA_MTF model transform weighted inputs into outputs representing estimated soil fault depths at specific locations. Through several transfer functions, the model outputs not only the expected depth values, but also their statistical magnitudes, enabling the quantification of confidence intervals and stochastic variations in shallow landslide depths under different rainfall conditions.

4. **Any drawbacks of this function?**
   While the model accurately predicts fault depth with low relative errors and high reliability, its shortcomings include sensitivity to misclassification, reliance on simulated data rather than comprehensive real-world measurements.

   [7] Reference :
   Huang, J.; Ju, N.P.; Liao, Y.J.; Liu, D.D. Determination of rainfall thresholds for shallow landslides by a probabilistic and empirical method. *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 2715–2723. [Google Scholar] [CrossRef]

[7] IEEE style reference:

S.-J. Wu, S.-R. Chen, and C.-D. Wang, "Modeling ANN-Based Estimations of Probabilistic-Based Failure Soil Depths for Rainfall-Induced Shallow Landslides Due to Uncertainties in Rainfall Factors," *Geosciences*, vol. 15, no. 3, p. 88, Mar. 2025, doi: 10.3390/geosciences15030088.

Research Paper # 8:

Questions:

1. **How it is used?**

In antenna design studies, activation functions are used inside the hidden layers of an ANN so that the network takes input performance parameters (resonant frequency, gain, reflection coefficient) and transforms the weighted input into a nonlinear signal; These transformed signals are passed through the network to predict the antenna's physical dimensions and feed point location.

2. **Why it is used?**

Activation functions are necessary because the relationship between antenna performance characteristics and physical design parameters (size, feedpoint) is very complex and non-linear; Without activation functions, the network will reduce to a simple linear regression and will not capture the correct mapping between input performance and antenna geometry.

3. **What is output of this activation function?**

Depending on which activation function is used in a given layer – for example 'Tansig' (hyperbolic-tangent type), 'LogSig' (logistics) or 'Purelin' (linear for the output layer) – the neuron outputs a transformed value (bounded between -1 and 1 for Tansig, 0 to 1 for Logsig, or unbounded until the final calculation leading to the final calculation). antenna dimensions. and feeding point.

4. **Any drawbacks of this function?**

There are specific limitations when using these activation functions: bounded nonlinear (tensig, logsig) can suffer from vanishing problems (especially if many layers), which can reduce training or reduce accuracy; And using purely linear output activations (pure lines) means that the layer itself cannot model nonlinearities—so the network relies heavily on the nonlinear activations of the hidden layers, which can limit flexibility or robustness if the chosen architecture or training data is suboptimal.

[8] Reference :

F. Mir, L. Kouhalvandi, and L. Matekovits, “Deep neural learning based optimization for automated high performance antenna designs,” *Sci. Rep.*, vol. 12, no. 1, p. 16801, Oct. 2022.

[8] IEEE style reference:

J. P. Dhar, M. Hasan, E. Nishiyama, and I. Toyoda, “Microstrip Patch Antenna Design Using a Four-Layer Feed Forward Artificial Neural Network Trained by Levenberg-Marquardt Algorithm,” *IEEE Access*, vol. 13, pp. 55244–55257, 2025, doi: 10.1109/ACCESS.2025.3553913.

Research Paper # 9:

Questions:

1. **How it is used?**

In this study, the GA-ANN model is used to predict the lap shear strength (LSS) of CF/PEEK resistance weld joints over a wide range of operating temperatures. The network receives input parameters such as welding current, pressure, time and temperature, and through its trained layers outputs the predicted joint strength. The genetic algorithm optimizes network weights and biases, ensuring accurate predictions by efficiently navigating complex nonlinear relationships between multiple process parameters.

2.**Why it is used?**

GA-ANNs are used because traditional regression and analytical models cannot fully capture the highly nonlinear, temperature-sensitive behavior of polymer composite weld interfaces. By combining the ability of ANNs to model complex patterns with GA-based optimization, the approach enables accurate prediction of LSS under extreme conditions, taking into account microscale interfacial phenomena such as polymer chain diffusion and entanglement that strongly affect joint performance.

3.What is output of this activation function?

Activation functions in GA-ANN transform the summed weighted inputs of each neuron into nonlinear outputs, which are collectively propagated through the network to make the final prediction of the weld joint strength. Depending on the actuation type selected, these outputs can be finite or infinite values representing the estimated LSS, capturing the complex interdependencies between welding parameters.

2. **Any drawbacks of this function?**
Typical shortcomings of activation functions in GA-ANNs include potential vanishing or exploding gradient problems when dealing with deep or complex networks, which can slow down training or reduce prediction stability. In addition, network performance largely depends on quality

[9] Reference :

- A.R. Offringa
  Thermoplastic composites—rapid processing applications
  Compos Appl Sci Manuf
  (1996)
- J.R. Duflou *et al.*
  Environmental impact analysis of composite use in car manufacturing
  CIRP Annals
  (2009)

[9] IEEE style reference:

L. Shen, Y. Zhang, H. Zhang, M. Sun, X. Jian, and J. Xu, "Strength evaluation of CF/PEEK resistance welding based on improved artificial neural network: Interface failure mechanism study under extreme service temperatures," *Composites Part B: Engineering*, vol. 312, p. 112290, 2025, doi: 10.1016/j.compositesb.2025.112290.

Research Paper # 10:

Questions:

1. **How it is used?**
   In this study, a four-layer feed-forward ANN is used to predict the dimensions and feed point location of microstrip patch antennas with square, triangular, and trapezoidal geometries. The network takes the resonant frequency, the gain and the reflection coefficient as inputs and outputs the optimal antenna amplitude and feed point distance. ANNs are trained using datasets generated from electromagnetic simulations in ADS, enabling the network to learn complex nonlinear relationships between antenna performance and physical parameters, and then generalize these predictions to new designs.

2. **Why it is used?**

ANNs are used because traditional full-wave electromagnetic simulations are computationally expensive and time-consuming, especially when optimizing multiple antenna geometries simultaneously. By using machine learning-based ANNs with the Levenberg-Marquardt training algorithm, the design process becomes faster, more efficient, and less dependent on repeated simulations, while maintaining high accuracy in predicting antenna dimensions and feed points, which is critical to achieving desired resonance, gain, and impedance matching

3. **What is output of this activation function?**

   Activation functions in an ANN transform the weighted inputs of each neuron into nonlinear outputs that propagate through the network layers. The 'tensig' function in the first hidden layer produces an output between -1 and 1, the 'logsig' function in subsequent hidden layers produces a squashed output between 0 and 1, and the 'pureline' function in the output layer produces continuous linear values. Together, these outputs provide predicted antenna dimensions and feedpoint locations consistent with input performance parameters.

4. **Any drawbacks of this function?**

[10] Reference :

Z. Guan, P. Zhao, X. Wang, and G. Wang, “Modeling radio-frequency devices based on deep learning technique,” *Electronics*, vol. 10, no. 14, p. 1710, Jul. 2021.

[10] IEEE style reference:

J. P. Dhar, M. Hasan, E. Nishiyama, and I. Toyoda, “Microstrip Patch Antenna Design Using a Four-Layer Feed Forward Artificial Neural Network Trained by Levenberg-Marquardt Algorithm,” *IEEE Access*, vol. 13, pp. 55244–55257, Mar. 2025, doi: 10.1109/ACCESS.2025.3553913.