Jurnal Kejuruteraan 37(1) 2025: 471-475
https://doi.org/10.17576/jkukm-2025-37(1)-34

Log-sigmoid Activation Function based MLP Network for Aggregate Classi fication

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Received 30 April 2024, Received in revised form 15 October 2024
Accepted 8 November 2024, Available online 30 January 2025

ABSTRACT

Mechanical sifting and manual grading have conventionally been utilised to assess the grade of aggregates. Nonetheless, such evaluations require a range of mechanical, chemical, and physical examinations, typically conducted manually, resulting in a process that is tedious, subjective, and labour-intensive. This research aims to provide an image-based classification system for the categorisation of aggregates. An artificial neural network (ANN) has been used to analyse the acquired images and categorise their shapes. The composite images are obtained and utilised as the input parameter for prediction prior to the thresholding step. The Log-sigmoid (Logsig) activation function, utilised in a Multilayer Perceptron (MLP) network, exhibits a lower mean square error (MSE) and superior regression performance relative to the Pureline activation functions. The Logsig-based network has a MSE of 1.7473 and a regression capability of 0.9521.

Keywords: Aggregate; MLP network; Training algorithm; MSE; Regression

INTRODUCTION

Aggregate is a crucial component in concrete manufacture, with granite and limestone being the two main types of rocks utilised for aggregate generation. The aggregate's shape, dimensions, and surface texture are crucial in the formulation of high-strength concrete. The quality of freshly poured and cured concrete is affected by several aspects, including the characteristics and degree of stratification of the rock deposit, the type of crusher facility utilised, and the size reduction ratio. Enhancing the shape of aggregates is crucial for minimising the water-cement ratio in concrete production, hence reducing the overall costs associated with concrete manufacturing and installation (Ray et al. 2021; Amin et al. 2020).

Aggregates are commonly classified into two categories: good aggregates and poor aggregates. Poor aggregate is categorised into four types: elongated, flaky, flaky & elongated, and irregular, while good aggregate is classified into two types: angular and cubical (Zhang et al. 2020). British Standards BS812, Section 103.1, indicates that mechanical sifting and manual gauging have conventionally been utilised to determine the dimensions and shape of coarse aggregates (BS 1881, 1983). Variations in particle morphologies may result in errors during the screening process, sometimes referred to as "grading analysis." Various techniques have been developed to improve the conventional categorisation method, employing imaging technologies and analytical algorithms to evaluate aggregate dimensions.

Khorram et al. (2017) and Dubosclard et al. (2015) have created instantaneous machine vision systems for the classification of aggregates. These systems comprise two primary stages: classification and image processing. The classification phase determines the type or quality of the aggregate, whereas the image processing phase collects pertinent aspects of the aggregate to evaluate its granularity.

Khorram et al. (2017) introduced a machine vision system that employs multi-scale picture entropy to produce a composite image. Dubosclard et al. (2015) classified mineral particles according to their visual texture, which varies with mineral content. Their technology employs an image processing technique within the RGB colour space to retrieve the visual texture of mineral particles. The Radial Basis Function (RBF) neural network utilises second-order statistical measures, including entropy, contrast, energy, and homogeneity, alongside first-order statistical analysis based on greyscale values for classification purposes. The manganese, iron, alumina, and aggregate zones are differentiated by variations in greyscale, entropy, contrast, energy, and homogeneity values for each region (Tripathy & Guru, 2017).

ANNs are robust analytical instruments that address complex, non-linear problems, outperforming alternative methodologies including fuzzy logic, evolutionary algorithms, and statistical techniques. Their enduring appeal is partly attributable to their capacity to generalise beyond the training data and derive insights from examples. ANNs excel in classification within data mining due to their resilience to the "curse of dimensionality" and their low computing expense while utilising extensive datasets across numerous dimensions. The ANNs have been effectively employed in diverse domains including pattern recognition, signal and image processing, robotic control, meteorological forecasting, financial predictions, and medical diagnostics. In the literature on pattern categorisation, radial basis function (RBF) and multilayer perceptron (MLP) are two prominent ANN network topologies, with MLP being the most utilised (Jamil et al. 2020).

The MLP is preferred due to its computational simplicity, stability, finite parameterisation, and reduced structural size relative to alternative architectures. This technique is straightforward yet efficient in approximating any input-output mapping (Sabri et al. 2024). ANNs exhibit significant non-linearity about unknown parameters, requiring the application of a non-linear optimisation method. This may result in issues such as delayed parameter convergence, high computational demands, and undesirable local minima. Consequently, substantial data and an extended training duration are required to adequately train the neural network model. This issue may be addressed by augmenting the learning capacity of the training algorithm. The backpropagation (BP) training method learns from errors and seeks to minimise the cost function by making predictions and subsequently modifying weights based on those errors. The Levenberg Marquardt (LM) training algorithm, an enhanced version of the BP training method, can address the problem of BP becoming entrapped in local minima.

METHODOLOGY

Of the 1250 aggregate images, 850 demonstrated favourable shapes, whereas 400 revealed unfavourable shapes. Pre-processing techniques are performed to improve quality and contrast, while a feature extraction tool is utilised to discover important information for classification. The image undergoes automatic segmentation using an iterative thresholding method, followed by expansion and contraction procedures to enhance the differentiation between the object and background (Wang et al. 2022). In the feature extraction phase, a significant challenge in aggregate form classification is the application of geometrical moments. Hu and Zernike moments are effective feature extractors for group recognition because of their invariance to geometric changes, including scaling, translation, and rotation. Consequently, two sets of seven Hu moments were acquired, one from the region and the other from the border. Artificial neural networks (ANN), modelled after the brain's functioning, are utilised. Figure 1 illustrates the nonlinear neurone model.

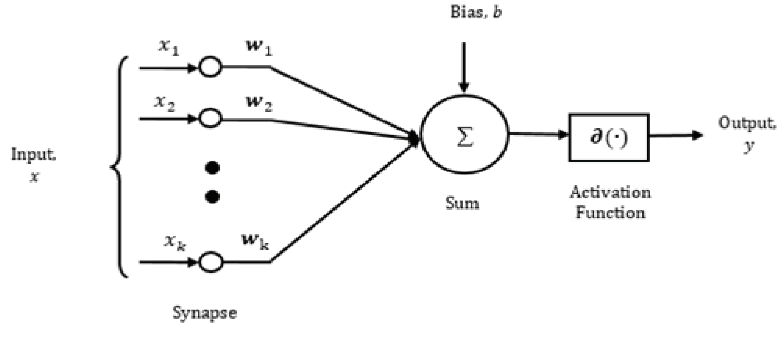

FIGURE 1. Nonlinear neuron model (Elbrächter et al. 2021)

Figure 1 illustrates that the development of a neurone comprises a network of connections or synapses, a summation, and an activation function. Each synapse in a neurone is assigned a weight, and if the neurone includes k synapses, it will have k inputs. The model's activation function is represented by $\partial(\cdot)$, the input at each synapse by $(x_1, x_2 .. x_k)$, and the weight at each synapse by $[w_1, w_2 .. w_k]$. The value of the j^th^ synaptic weights $[w_j]$ influences the weight value for processing the synapses to the neuron's output. At the input synapses attached to the neuron, the value of the j^{th} synaptic weights $[w_j]$ will be multiplied by the input x_j. The activation function gets a sum process' output and adds up all the multiplied input signals and bias (b). The modelling of neurons can be defined using the two equations below based on Figure 1:

$$u = \sum_{j=1} W_j x_j + b \qquad (1)$$

and

$$y = \partial(u) = \frac{1}{1+e^{-u}} \qquad (2)$$

Equation (1) and (2) define the mathematical model of a neuron, where W_j represents the weights assigned to the j^{th} synapse, $\partial(\cdot)$ denotes the activation function, y is the output, and u is the summing output. The input signal for the j^{th} synapse is represented by x_j. Common activation functions are the linear function, piecewise linear function, fixed limiter function, and Logsig activation function (Wang et al. 2022). This research uses the Logsig activation function to activate the network. The precision of predictions generated by ANNs is significantly influenced by the training techniques employed and the architecture of the structure. Researchers have investigated advanced training techniques to improve performance. An MLP neural network, characterised by its nonlinear functional architecture, can be instructed to establish a specific input-output mapping (Hashim et al. 2021). Nonetheless, a prediction cannot be precise when employing a nonlinear network such as MLP to simulate a linear system. Figure 2 illustrates a MLP network with an input layer, one hidden layer, and an output layer. Elbrächter et al. (2021) and Hahm (2023) propose that a single hidden layer is sufficient for achieving precise predictions with a multilayer perceptron network. This study will exclusively concentrate on neural networks using only one hidden layer.

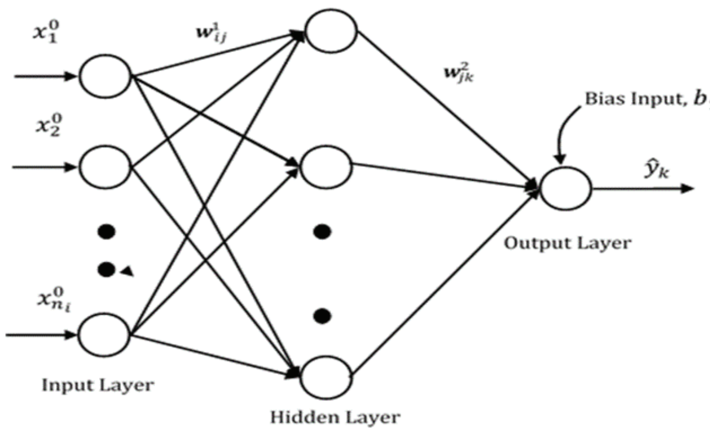

FIGURE 2. MLP architecture with one hidden layer

The output of the network is given by:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \, \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right) \qquad (3)$$

for $1 \le j \le n_h$ and $1 \le k \le m$

where the equation represents the prediction error that needs to be minimized by finding optimum values for the unknown variables w_{ij}^1, w_{ij}^2, w_{ik}^3 and threshold b_j^1. Here, $y_k(t)$ is the actual output of the MLP network, $\hat{y}_k(t)$ is the desired or target output, and N is the total number of training examples used for training the MLP network. The error, $e_k(t)$ is computed as the summation of squared deviations between the actual output and the target output. The process of reducing prediction error is referred to as training the MLP network and can be accomplished by various optimisation strategies. The objective of training the MLP network is to acquire optimal weights and biases that can precisely forecast the output for novel, unexpected inputs. Both MSE and regression studies have been employed to evaluate the network's performance.

$$e_k(t) = y_k(t) - \hat{y}_k(t) \quad (4)$$

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(e_k(t))^2 \quad (5)$$

$$Regression = \beta_0 + \beta_1 X_K \quad (6)$$

with β_0 is the constant or intercept, β_1 is the slope or coefficient and X_K is the independent variable.

Supervised learning is an approach to machine learning in which the algorithm is trained on labelled input, with each data point linked to a corresponding desired output. The objective of supervised learning is to establish a correspondence between input and output data, enabling the algorithm to accurately predict the output for novel, unobserved inputs. The main supervised learning methods comprise linear regression, logistic regression, decision trees, and neural networks. Conversely, unsupervised learning is a category of machine learning when the algorithm is trained with unlabelled data. The objective of unsupervised learning is to discern patterns or structures within the data without relying on direct input or predetermined outcomes. The predominant unsupervised learning algorithms encompass clustering, principal component analysis, and autoencoders. The selection of an activation function may significantly impact the performance of a neural network. The Logsig activation function is a sigmoidal function that transforms the input into a value ranging from 0 to 1. It is frequently employed in the output layer of a neural network for binary classification tasks. The Purelin activation function is a linear function that directly maps input to output and is frequently employed in the output layer of a neural network for regression tasks due to its linear characteristics (Nagappan et al. 2023 & Mat et al. 2023).

RESULTS AND DISCUSSIONS

A study was undertaken to evaluate the predictive efficacy of the MLP neural network in forecasting aggregate shapes, utilising MATLAB neural network tools (nntool). The analysis comprised three phases: 70% for training and 30% for testing, incorporating error assessment using MSE and regression to ascertain the optimal fit. The effectiveness of the training approach was evaluated by the minimum MSE and maximum regression figures, the lowest relative error during the prediction phase. Regression performance was determined to be worst-case when the measurement approached 0 and best-case when it approached 1. The MSE and regression values were computed via MATLAB's neural network tool for each training technique, with the results displayed in Table 1, organised in descending order from highest to lowest MSE performance.

TABLE 1. MSE and Regression Performance of MLP network

Training Algorithm	MSE Performance	Regression Performance	Number of Epoch
LM with Logsig	1.7473	0.9521	31
BP with Logsig	1.9151	0.9266	17
LM with Purelin	2.8752	0.8572	36
BP with Purelin	3.1334	0.7949	25

The MLP network was developed with the LM and BP training algorithm functions, with Table 1 demonstrating the training outcomes employing Logsig and Purelin activation functions. The Logsig activation function utilising the LM training technique yielded the lowest MSE score of 1.7473, while the Logsig activation function with the BP training algorithm resulted in an MSE of 1.9151. The Logsig activation function yielded 2.8752 for the LM training algorithm and 3.1334 for the BP training algorithm. The MLP network utilising the LM training procedure and Logsig activation function achieved the maximum regression performance score of 0.9521, whereas the MLP network employing the BP training algorithm and Logsig activation function obtained a score of 0.9266. The MLP networks utilising Purelin activation functions achieved regression scores of 0.8572 and 0.7949 for the LM and BP training procedures, respectively. The optimum configuration demonstrated by the MLP utilising the BP training technique and Logsig activation function over 17 epochs; however, the MLP trained with LM and activated by Logsig surpasses other network combinations, achieving the lowest MSE and the highest regression score. The Purelin activation function is ineffective in activating nonlinear patterns due to its proximity to linearity. On the other hand, the Logsig activation function may yield superior outcomes due to its ability to accommodate both linear and nonlinear patterns, while reducing the output into a range of 0 to 1.

CONCLUSION

The MLP network's prediction outcomes demonstrate its capability in predicting the shape of aggregates. The Logsig activation function demonstrated superior accuracy, characterised by the lowest MSE, optimum regression performance, and its simple development. The LM training method demonstrates superior performance compared to

BP's in terms of both MSE and regression value. The findings indicate that a wider range of output values at the activation function may enhance performance capability.

ACKNOWLEDGEMENT

This investigation is entirely supported by the UPNM/2022GPJP/TK/2 grant from the GPJP. The authors express their gratitude to the Ministry of Higher Education (MOHE) and the National Defence University of Malaysia (UPNM) for providing the approved funding that made this vital research possible and productive.

DECLARATION OF COMPETING INTEREST

None,

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