Classification of Shape Aggregates using Activation Function Based Multilayer Perceptron (MLP)

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Abstract. Mechanical sifting and hand grading have traditionally been employed to evaluate the quality of aggregates. However, such assessments require various mechanical, chemical, and physical tests, which are usually carried out manually and are slow, subjective, and time-consuming. This study seeks to develop an image-based classification system for categorizing aggregates. An artificial neural network was utilized to process the captured images and classify their shapes. The aggregate images are captured and used as the input parameter for prediction before the threshold process occurs. The Logsig activation function, based on a Multilayer Perceptron (MLP) network, has the lower mean square error (MSE) and the higher regression, compared to the Pureline activation functions. The Logsig-based network has an MSE of 1.7473 and a regression capacity of 0.9521.

INTRODUCTION

Aggregate is a critical component in the production of concrete, with granite and limestone being the two most commonly used types of rocks for generating aggregates. The shape, size, and surface roughness of the aggregate play a crucial role in the creation of high-strength concrete. The quality of freshly-poured and cured concrete is influenced by various factors such as the nature and degree of stratification of the rock deposit, the type of crushing plant employed, and the size reduction ratio. Improving the shape of aggregates is essential in reducing the amount of water cement required to produce concrete, which, in turn, can lower the cost of concrete production and installation.

Good aggregates and poor aggregates are two classifications that are frequently used to categorise aggregates. Poor aggregate can be divided into four types: elongated, flaky, flaky & elongated, and irregular, whereas good aggregate can be divided into two types: angular and cubical [3]. According to British Standards BS812, Section 103.1, mechanical sifting and hand gauging have traditionally been employed to determine the size and shape of coarse aggregates [4]. Due to different particle morphologies, errors may be generated during the sieving process, also known as "grading analysis." Several methods have been developed to enhance the traditional categorization approach, utilising imaging tools and analytical algorithms to assess aggregate dimensions.

Singh and Rao (2005) and Murtagh et al. (2005) have developed machine vision systems for the classification of aggregates that operate instantaneously [5-6]. These systems consist of two main stages: classification and image processing. The classification stage determines the type or quality of the aggregate, while the image processing stage extracts relevant features of the aggregate to evaluate its granularity. Murtagh et al. (2005) proposed a machine vision system that uses multiple-scale image entropy to generate an aggregate image [5]. Based on their visual texture, which changes depending on the mineral composition, Singh and Rao (2005) classified ore particles [6]. In their system, an image processing technique in the RGB color space is used to extract the ore particles' visual texture. For classification, the Radial Basis Function (RBF) neural network employs second-order statistical analysis, such as entropy, contrast, energy, and homogeneity, as well as first-order statistical analysis, such as grayscale values. The manganese, iron, alumina, and aggregate regions are distinguished from one another based on differences in the grayscale, entropy, contrast, energy, and homogeneity values for each region.

Artificial Neural Networks (ANNs) are powerful analytical tools that excel at solving complex, non-linear problems, surpassing other techniques such as fuzzy logic, evolutionary algorithms, and statistical methods. One of the reasons for their popularity is their ability to generalize beyond the training data and learn from examples. ANNs are competitive in classification in data mining because they are immune to the "curse of dimensionality" and have a low computational cost by using a large amount of data and many dimensions. ANNs have been successfully used in various fields such as pattern recognition, signal and image processing, robot control, weather prediction, financial forecasts, and medical diagnostics. Among the ANN structures suggested in the literature for pattern categorization problems, Radial Basis Function (RBF) and Multilayered Perceptron (MLP) [8] are two well-known structures, with MLP being the most frequently applied one.

The MLP is favored for its computational ease, stability, finite parameterization, and smaller structure size compared to other structures. It is a simple yet effective technique that can approximate any input-output mapping [9]. Neural network models are highly non-linear with respect to unknown parameters, which requires the use of a non-linear optimization technique. However, this can lead to problems such as slow parameter convergence, demanding computation, and undesired local minima. As a result, a large amount of data and a lengthy training period are needed to properly train the neural network model. However, this issue can potentially be resolved by enhancing the learning capacity of the training algorithm. The Lavenberg Marquardt (LM) training algorithm, an improved version of the Backpropagation (BP) training method, can address this issue, even though BP is often stuck in local minima.

METHODOLOGY

Out of a total of 1250 aggregate images, 850 displayed good shapes while 400 exhibited poor shapes. To enhance quality and contrast, pre-processing techniques are utilized, and a feature extraction tool is employed to identify key data for categorization. The image is automatically segmented using an iterative thresholding procedure, then expanded and shrunk through expanding and contracting techniques to achieve a clearer distinction between the object and backdrop [9]. During the feature extraction stage, one of the most challenging problems in aggregate form classification is the use of geometrical moments. Hu and Zernike moments are promising candidate feature extractors for group recognition due to their invariance property against geometrical changes such as scaling, translation, and rotation. Based on this reasoning, two sets of seven Hu were obtained, one from the region and the other from the border. Artificial neural networks (ANN), which are modeled after the way the brain operates, are used. The nonlinear neuron model is depicted in Figure 1.

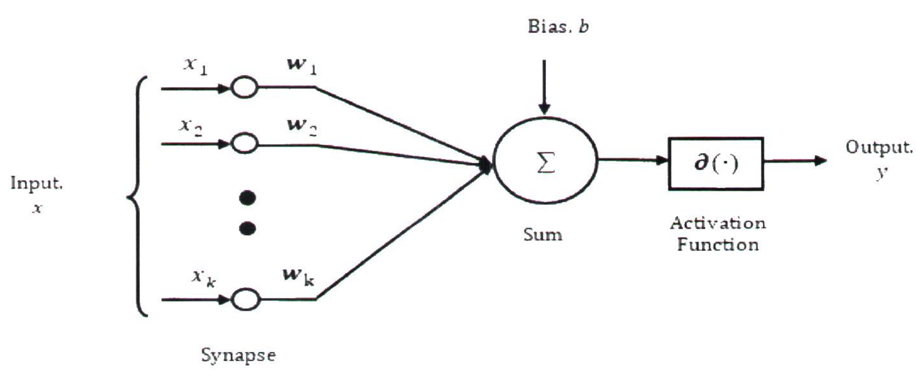

FIGURE 1. Nonlinear neuron model [10]

In Figure 1, the formation of a neuron is shown to consist of a network of connections or synapses, a sum, and an activation function. Each synapse in the neuron is assigned a weighted value, and assuming the neuron has k synapses, it will have k inputs. The activation function of the model is represented by $\partial(\cdot)$, while the input at each synapse is represented by $(x_1, x_2 \ldots x_k)$, and the weight at each synapse by $(\mathbf{W_1}, \mathbf{W_2} \ldots \mathbf{W_k})$. The value of the jth synaptic weight $[\mathbf{w_j}]$ 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 weight $[\mathbf{w_j}]$ is multiplied by the input x_j. The activation function then performs a sum process and adds up all the multiplied input signals and the bias (b). The mathematical modeling of neurons can be defined using the two equations below in light of Figure 1:

$$u = \sum_{j=1} \mathbf{W}_j x_j + b \tag{1}$$

and

$$y = \partial(\mathbf{u}) \tag{2}$$

Equations (1) and (2) define the mathematical model of a neuron, where $\mathbf{W}_j$ 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 include the linear function, piecewise linear function, fixed limiter function, and Logsig function (Haykin, 2011). The accuracy of predictions made by ANNs depends greatly on the training methods used and the structure's architecture. To further improve performance, researchers have explored enhanced training techniques. An MLP neural network, a nonlinear functional structure, can be trained to provide a specific input-output mapping [11]. However, a forecast cannot be accurate when a nonlinear network like MLP is used to model a linear system. Figure 2 shows an MLP network with an input layer, a single hidden layer, and an output layer. Funashashi (1989) [12] and Cybenko (1989) [13] have suggested that a single hidden layer is adequate to achieve accurate predictions with an MLP network. Therefore, this study will only focus on neural networks with a single hidden layer.

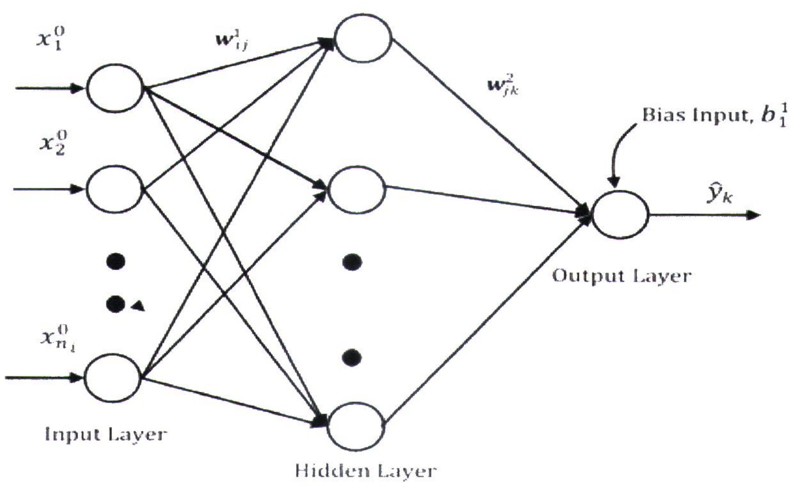

FIGURE 1. MLP architecture with one hidden layer

The output of the network is given by:

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

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

where the equation represents the prediction error that needs to be minimized by finding optimum values for the unknown variablesw^1_{ij}, w^2_{jk}, w^3_{ik} and threshold b^1_j. 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 is calculated as the sum of squared differences between the actual output and the target output. The process of minimizing the prediction error is known as training the MLP network, and can be achieved using various optimization algorithms. The aim of training the MLP network is to obtain optimum weights and biases that can accurately predict the output for new, unseen inputs.

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

Supervised learning is a type of machine learning in which the algorithm is trained on labelled data, where each data point is associated with a target output. The goal of supervised learning is to learn a mapping between the input and output data so that the algorithm can accurately predict the output for new, unseen inputs. The most commonly used supervised learning algorithms include linear regression, logistic regression, decision trees, and neural networks. In contrast, unsupervised learning is a type of machine learning in which the algorithm is trained on unlabeled data. The goal of unsupervised learning is to identify patterns or structure in the data without the use of explicit feedback or target outputs. The most commonly used unsupervised learning algorithms include clustering, principal component analysis, and auto encoders. The choice of activation function can significantly impact the performance of a neural network. The Logsig activation function is a sigmoidal function that maps the input to a value between 0 and 1. It is commonly used in the output layer of a neural network for binary classification tasks. Purelin is a linear function that maps the input to the output directly, and is commonly used in the output layer of a neural network for regression tasks.

RESULT AND DISCUSSION

To demonstrate the MLP neural network's ability to predict aggregate shapes, a prediction performance study was conducted using the MATLAB neural network tools (nntool). The analysis involved three stages, namely 70% training, and 30% testing, with error checking through mean squared error (MSE) and regression to determine the best fit. The training method's performance was evaluated based on the lowest MSE and highest regression values, with the aim of achieving the lowest possible relative error during the prediction phase. Regression performance was considered worst-case when the measurement was closest to 0 and best-case when closest to 1. The MSE and regression values were determined using MATLAB's neural network tool for each training algorithm, and the results are presented in Table 1, arranged in descending order of 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 trained using the LM and BP training algorithm functions, and Table 1 shows the results of the training using Logsig and Purelin activation functions. The Logsig activation function with LM training algorithm produced the lowest MSE score of 1.7473, followed by Logsig activation function with BP training algorithm with an MSE of 1.9151. The Logsig activation function with resulted 2.8752 for LM training algorithm while 3.1334 for BP training algorithm. In terms of regression performance, the MLP network trained with LM training algorithm and Logsig activation function the highest score of 0.9521, followed by the MLP network trained with BP training algorithm and Logsig activation function with score of 0.9266. The MLP networks with Purelin activation functions had regression scores of 0.8572 and 0.7949, for LM and BP training algorithms, respectively. The optimal structure shown by MLP with BP training algorithm and Logsig activation function with 17 epochs but MLP trained with LM and activated by Logsig outperform other combination networks with lowest MSE and highest score of regression. The Purelin activation function is not effective in activating nonlinear patterns since it is very close to linear. On the other hand, the Logsig activation function is capable of producing better results because its characteristics can cover both linear and nonlinear patterns, and it can compress the output into a range of 0 to 1.

CONCLUSION

The prediction results of the MLP network show its proficiency in predicting the shape of aggregates. Based on the findings, the Logsig activation function exhibited the highest accuracy, with the smallest MSE, highest regression performance, and simplest structure. The LM training algorithm shows better performance than BP's for both MSE and regression score. The results also suggest that a wider range of output values at the activation function output could increase the chances of better performance.

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