

Shape Aggregates Classification using Activation Function Based MLP Network

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Abstract. Traditionally, the quality of aggregates has been assessed through mechanical sifting and hand grading methods, which involve manual and time-consuming mechanical, chemical, and physical tests. However, this study aims to develop a more efficient image-based classification system for categorizing aggregates. To achieve this, an artificial neural network was employed to process the captured images and classify their shapes. The aggregate images serve as the input parameter for prediction before undergoing the threshold process. The study found that the Tansig activation function, which is based on a Multilayer Perceptron (MLP) network, performed better than the Purelin activation functions, exhibiting a lower mean square error (MSE) of 1.5237 and a higher regression capacity of 0.9728.

Introduction

Aggregate is a fundamental constituent in the manufacture of concrete, and the two primary rock types used for producing aggregates are granite and limestone. The shape, size, and surface texture of the aggregate significantly impact the strength of the resulting concrete. The quality of freshly-poured and cured concrete is subject to various factors, including the nature and stratification of the rock deposit, the crushing plant employed, and the size reduction ratio. Improving the shape of aggregates is crucial in reducing the amount of water cement needed for concrete production, ultimately leading to cost savings in concrete manufacturing and installation.

Aggregates are commonly classified as either good or poor. Poor aggregates can be further divided into four categories: elongated, flaky, flaky and elongated, and irregular. In contrast, good aggregates fall into two categories: angular and cubical, as outlined in British Standards BS812, Section 103.1. Traditional methods such as mechanical sifting and hand gauging have been used to determine the size and shape of coarse aggregates, but these methods can result in errors due to the different particle morphologies, commonly referred to as "grading analysis." To overcome this limitation, various methods have been developed that utilize imaging tools and analytical algorithms to assess aggregate dimensions and improve the categorization process.

Singh and Rao (2005) and Murtagh et al. (2005) have developed machine vision systems that can classify aggregates instantaneously [5-6]. These systems consist of two primary stages: classification and image processing. The classification stage determines the aggregate's type or quality, while the image processing stage extracts relevant features of the aggregate to assess 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 the visual texture of the aggregate, which varies depending on the mineral composition, Singh and Rao (2005) classified ore particles using an image processing technique in the RGB color space [6]. For classification, the Radial Basis Function (RBF) neural network uses second-order statistical analysis, including entropy, contrast, energy, and homogeneity, as well as first-order statistical analysis, such as grayscale values. The grayscale, entropy, contrast, energy, and homogeneity values of each region distinguish the manganese, iron, alumina, and aggregate regions from one another.

Artificial Neural Networks (ANNs) are robust analytical tools that outperform other techniques such as fuzzy logic, evolutionary algorithms, and statistical methods when it comes to solving complex, non-linear problems. ANNs' popularity stems from their ability to generalize beyond the training data and learn from examples. They are well-suited for classification in data mining because they are immune to the "curse of dimensionality" and have a low computational cost due to their ability to handle large amounts of data and many dimensions. ANNs have been successfully applied in diverse fields such as pattern recognition, signal and image processing, robot control, weather prediction, financial forecasts, and medical diagnostics. Radial Basis Function (RBF) and Multilayered Perceptron (MLP) [8] are two well-known ANN structures suggested in the literature for pattern categorization problems, with MLP being the most commonly applied structure.

MLP is a popular neural network structure because of its simplicity, stability, finite parameterization, and smaller size compared to other structures. It can accurately map any input to output. However, the optimization of the unknown parameters requires a nonlinear optimization technique, which may lead to slow parameter convergence, demanding computation, and undesired local minima. To properly train the neural network model, a significant amount of data and lengthy training period are often required. This issue can be addressed 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 overcome the issue of BP being stuck in local minima.

Methodology

In order to categorize 1250 aggregate images as having either good or poor shapes, pre-processing techniques are used to enhance the images' quality and contrast. Then, a feature extraction tool is utilized to extract important data for classification. One of the most challenging aspects of aggregate shape classification is selecting appropriate geometrical moments for feature extraction, as these moments must be invariant to changes in scale, translation, and rotation. Hu and Zernike moments are promising options for this purpose. Two sets of seven Hu moments are extracted, one from the region and one from the border. Artificial neural networks (ANNs) are employed to perform the classification task, as they are modeled after the human brain and can handle non-linear problems effectively. The nonlinear neuron model used in this task is depicted in Figure 1.

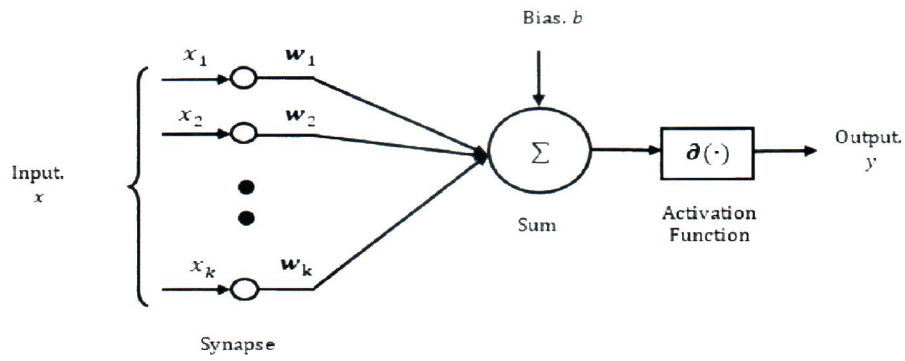


FIGURE 1. Nonlinear neuron model [10]

Figure 1 illustrates the structure of a neuron, which consists of synapses, a sum, and an activation function. Each synapse is assigned a weighted value, and the neuron has k inputs corresponding to k synapses. The activation function is represented by $\mathcal{d}(\cdot)$, and the input at each synapse is represented by $(x_1, x_2 \dots x_k)$, while the weight at each synapse is represented by $(\mathbf{w}_1, \mathbf{w}_2 \dots \mathbf{w}_k)$. The value of the j^{th} synaptic weight $[\mathbf{w}_j]$ affects the weight value for processing the synapses to the neuron's output. At the input synapses connected 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 representation of neurons is described by the two equations given below in the context of Figure 1:

$$\begin{aligned}
 u &= \sum_{j=1}^k \mathbf{w}_j x_j \\
 &+ b
 \end{aligned} \tag{1}$$

and

$$y = \mathcal{d}(u) \tag{2}$$

Equations (1) and (2) describe the mathematical model of a neuron, where \mathbf{w}_j represents the weight assigned to the j^{th} synapse, $\mathcal{d}(\cdot)$ represents the activation function, y is the output, and u is the summing output. The input signal for the j^{th} synapse is x_j . Various activation functions can be used, such as the linear function, piecewise linear function, fixed limiter function, and Logsig function. The accuracy of ANNs predictions depends on the training methods and the structure's architecture. Researchers have explored improved training techniques to enhance performance. The MLP neural network is a nonlinear functional structure trained to provide a specific input-output mapping. However, using a nonlinear network like MLP to model a linear system may result in inaccurate forecasts. Figure 2 shows an MLP network with an input layer, a single hidden layer, and an output layer. Funashashi (1989) and Cybenko (1989) suggest that a single hidden layer is sufficient for accurate predictions with an MLP network. Therefore, this study focuses only on neural networks with a single hidden layer.

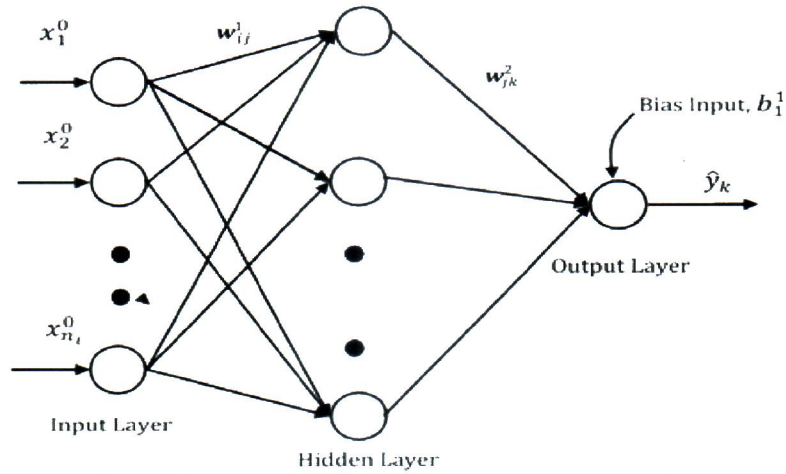


FIGURE 1. MLP architecture with one hidden layer

The output of the network is given by:

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

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

The equation given represents the error in prediction that needs to be minimized by finding the best values for the unknown variables such as w_{ij}^1 , w_{jk}^2 , w_{ik}^3 and threshold b_j^1 . The actual output of the MLP network is represented by $y_k(t)$, and the desired or target output is represented by $\hat{y}_k(t)$. The total number of training examples used for training the MLP network is represented by N . The error is calculated by summing the squared differences between the actual and target outputs. This process of minimizing the prediction error is known as training the MLP network and can be accomplished using various optimization algorithms. The ultimate objective of training the MLP network is to determine the best weights and biases that can accurately predict the output for new, unseen inputs.

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

Supervised learning is a machine learning technique that involves using labeled data to train an algorithm to accurately predict the output for new inputs. Popular supervised learning algorithms include linear regression, logistic regression, decision trees, and neural networks. On the other hand, unsupervised learning is a type of machine learning that does not rely on labeled data, but instead, seeks to uncover patterns or structures in unlabeled data. Common unsupervised learning techniques include clustering, principal component analysis, and autoencoders. The choice of activation function in a neural network can significantly impact its performance. The Tansig activation function is commonly used in the output layer of a neural network for binary classification tasks, as it maps the input to a value between -1 and

+1. Meanwhile, the Purelin activation function is a linear function that maps the input to the output directly and is often used in the output layer of a neural network for regression tasks.

Result And Discussion

A study was conducted to evaluate the MLP neural network's ability to predict aggregate shapes using the MATLAB neural network tools (nntool). The study 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 aim of the study was to achieve the lowest possible relative error during the prediction phase. The performance of the training method was evaluated based on the lowest MSE and highest regression values. MATLAB's neural network tool was used to determine the MSE and regression values for each training algorithm. Table 1 presents the results 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 Tansig	1.5237	0.9728	29
BP with Tansig	1.8915	0.9472	18
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 Tansig and Purelin activation functions. The Tansig activation function with LM training algorithm produced the lowest MSE score of **1.5237**, followed by Tansig activation function with BP training algorithm with an MSE of 1.8915. The Tansig 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 Tansig activation function the highest score of 0.9728, followed by the MLP network trained with BP training algorithm and Tansig activation function with score of 0.9472. 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 Tansig activation function with 17 epochs but MLP trained with LM and activated by Tansig 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 Tansig 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

That's a good summary of the findings. It is important to note that the choice of activation function and training algorithm depends on the specific problem and dataset being used. In some cases, a different combination of activation function and training algorithm might yield better results. Therefore, it is recommended to perform a thorough evaluation of different combinations before selecting the optimal one for a particular problem. Additionally, it is also important to keep in mind the potential for overfitting the model to the training data, and to use techniques such as regularization and cross-validation to avoid this issue.

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