Classification of Shape Aggregate by using MLP Network based Training Algorithm

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Abstract. Historically, mechanical sifting and hand grading have been used to assess the quality of aggregates. It must pass a number of tedious, slow, subjective, time-consuming mechanical, chemical, and physical testing in order to produce better aggregates. This study's objective is to develop a classification scheme that can categorise aggregates based on pictures of aggregate morphologies. Using an artificial neural network, the image was reprocessed for shape categorization after it had been taken. The Lavenberg Marquardt (LM) training algorithm technique outperforms Backpropagation (BP) training algorithms in terms of performance, mean square error (MSE), and regression. The LM training approach that uses Multilayer Perceptron (MLP) networks has the lowest mean square error (MSE) and maximum regression. With 1.6923 on MSE and 0.9572 on regression, the LM-trained network can successfully classify.

Introduction

A crucial ingredient in the creation of concrete is aggregate. The two most popular types of rocks used to generate aggregates are still granite and limestone. Form, size, and surface roughness of the aggregate are crucial in the production of high-strength concrete. Features including the kind and degree of stratification of the rock deposit, the type of crushing plant used, and the size reduction ratio all have a significant impact on the form of aggregate particles and the quality of freshly-poured and curing concrete [1-2]. It has been shown that a key factor in enhancing the shape is reducing the water to cement ratio necessary to produce a concrete mixture. They found that the price of producing and pouring concrete can be decreased by using this high-quality aggregate.

Good aggregates and bad aggregates are frequently used as categorizations for aggregates. The two forms of good aggregate are angular and cubical, while the four categories of poor aggregate are elongated, flaky, flaky & elongated, and irregular [3]. According to British Standards BS812, Part 103.1 [4], the traditional methods for determining the size and shape of coarse aggregates include mechanical sifting and manual gauging. The sieving process, also known as "grading analysis," is susceptible to errors because different particle morphologies might occur. The traditional categorization approach has been improved by the development of several techniques involving imaging tools and analytical processes to quantify aggregate dimensions.

Machine vision systems for aggregate categorization are used by Murtagh et al. (2005) and Singh and Rao (2005), respectively [5–6]. These systems are made to operate instantly. In general, the two key phases of the systems are classification and image processing. While the classification stage establishes the kind or calibre of aggregate, the image processing stage extracts significant aggregate features. To evaluate aggregate granularity, Murtagh et al. (2005) proposed a machine vision system based on a multiple-scale image entropy generated from a given image [5]. Based on their visual texture, which differs depending on the mineral content [6], Singh and Rao (2005) categorised ore particles. In the created system, an image processing technique in the RGB colour space is used to retrieve the ore particles' visual texture. For classification, the Radial Basis Function (RBF) neural network uses 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 zones are distinguished from one another based on differences in the values of grayscale, entropy, contrast, energy, and homogeneity for each region.

Analytical tools like Artificial Neural Networks (ANNs) are incredibly effective in solving difficult and non-linear problems, outperforming other competing techniques (fuzzy logic, evolutionary algorithms, and statistical methods). The ability of ANNs to generalise beyond training data and learn from instances is what has made them so popular. Because they are immune to the "curse of dimensionality" and have a low computing cost by utilising a large amount of data and a lot of dimensions, ANNs are competitive in classification in data mining. A few of the fields where ANNs have been successfully used include pattern recognition and classification, signal and image processing, robot control, weather prediction, financial forecasts, and medical diagnostics. Radial Basis Function (RBF) and Multilayered Perceptron (MLP) are two examples of ANN architectures for pattern categorization problems that have been proposed in the literature [7, 8]. The MLP structure is the most well-known and often applied of all of these.

Because to its computational ease, finite parameterization, stability, and smaller structure size for a given problem when compared to other structures, the MLP is well-liked. A straightforward technique that provides a good approximation of any input-output mapping is the MLP [7]. The neural network models are very non-linear with respect to the unknown parameters. The drawback of this characteristic is that it calls for the use of a non-linear optimisation technique, which is frequently associated with problems like slow parameter convergence, demanding computation, and undesirable local minima. As a result, the neural network model needs a large amount of data and a lengthy training period in order to be properly trained. However, enhancing the learning capacity of the training algorithm might be able to resolve the issue mentioned earlier. The Lavenberg Marquardt (LM) training algorithm, an improved variant of the Backpropagation (BP) training method, can solve the issue even though BP is known to be stuck in local minima.

Methodology

There were a total of 625 aggregate photos, of which 425 showed good shapes and 200 showed bad shapes. Quality and contrast are enhanced using pre-processing techniques, and a features extraction tool is employed to find key data for categorization. The image is automatically segmented using an iterative thresholding procedure, followed by expanding and shrinking methods, to produce a clearer and better separation between object and backdrop [9]. One of the most challenging problems in this endeavour is the use of geometrical moments for feature extraction in aggregate form classification during the feature extraction stage. The Hu and Zernike moments' invariance property against geometrical changes like scaling, translation, and rotation makes them a promising candidate feature extractor for group recognition. Two sets of seven Hu were obtained, one from the region and the other from the border, based on this reasoning. An artificial intelligence called artificial neural networks (ANN) is modelled after the way the brain works. The artificial neural network is based on principles found in the human brain and is intended to mimic the way the brain constructs its structures, learns, and operates. The model of nonlinear neurons is shown in Figure 1.

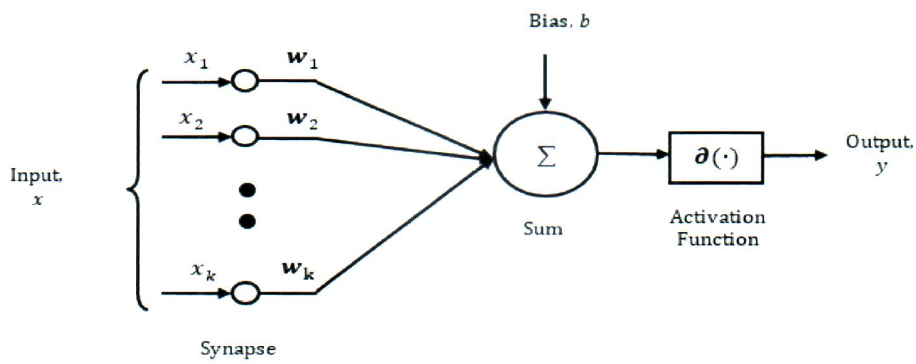

FIGURE 1. Nonlinear neuron model [10]

Figure 1 depicts the genesis of a neuron as consisting of a network of synapses or connections, a sum, and an activation function. A weighted value is assigned to each neuron's synapse. Assuming the neuron has k synapses, it has k inputs. The model's activation function is represented by $\boldsymbol{\partial}(\cdot)$, the input at each synapse by $(x_1, x_2 .. x_k)$, and the weight at each synapse by $[\mathbf{w}_1, \mathbf{w}_2 .. \mathbf{w}_k]$. The value of the j^{th} synaptic weights $[\mathbf{w}_j]$ 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 weights $[\mathbf{w}_j]$ 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 mathematical modelling of neurons can be defined using the two equations below based on Figure 1:

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

and

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

In Equations (1) and (2), $\mathbf{W}_j$ stands for the neuron's weights to the j^{th} synapse, $\partial(\cdot)$ is the activation function, and y is the output product. u is the summing output. x_j represents the j^{th} data or synapse's input signal. Common activation functions include the linear function, piecewise linear function, Logsig function, and fixed limiter function [10]. The ability of ANNs to make accurate predictions is significantly influenced by the training methods used and the architecture of the structure. Hence, improved training techniques were looked into to increase performance even more. A nonlinear functional structure called an MLP neural network can be trained to provide a certain input-output mapping [11]. They added that a forecast cannot be correct when a linear system is modelled using a nonlinear network, such as MLP. Figure 4 is composed of an input layer, a single hidden layer, and an output layer. A single hidden layer in an MLP network is adequate to give accurate prediction results, according to Funashashi (1989) [12] and Cybenko (1989] [13]. The remainder of this study will therefore only cover neural networks with a single hidden layer.

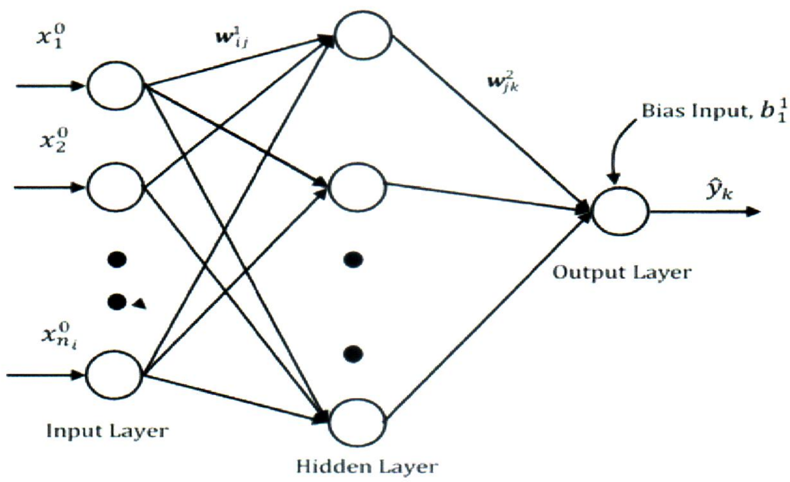

FIGURE 1. MLP architecture with one hidden layer

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 m represents the number of network outputs and n_h stands for hidden nodes. The activation function used in this instance with the Logsig activation function to activate the MLP network is $\partial(\cdot)$. The prediction error is determined by minimising the unknown variables w_{ij}^1, w_{jk}^2, w_{ik}^3 and threshold b_j^1, which must converge to optimal values as follows:

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

The system's actual output is y k (t), but the expected output is y _k (t). The learning phase is a critical stage in a neural network. The process makes sure the neural network can function according to its design requirements. The two most popular learning paradigms are supervised learning and unsupervised learning. Using supervised learning, a global model that links the input and intended result can be developed. On the other hand, supervised learning techniques don't need to estimate utilising tested training models. The learning procedure is distinct from supervised learning because there is no output target. The gathering of a set of input data, which is thought to be a set of random variables, is necessary for unsupervised learning. The datasets will be used to create a density model, and unsupervised learning will be based on prior knowledge. Or, to put it another way, learning is simply dependent on prior experience and is not directed by any specific goals [14]. Unsupervised learning facilitates data compression. For the study, an experimental procedure was followed by a modelling procedure utilising a neural network approach. The additional dataset is collected in addition to the target. Thus, guided training is the better option. Backpropagation (BP), Scaled Conjugate Gradient (SCG), Lavenberg-Marquardt (LM), and Bayesian Regularization (BR) are examples of supervised training algorithms that are used to model the Blast Pressure Prediction system [15–16].

Result And Discussion

Prediction performance study is required to show that the MLP neural network can predict explosive pressure. The three steps of analysis in the MATLAB neural network tools (nntool) consist of 70% training and 30% testing. Examples include checking the MSE for errors and using regression to get the best fit [17]. The performance of the training method is assessed using the lowest MSE and highest regression performance. The relative error during the prediction phase should be as low as possible, according to the lowest MSE. The worst-case scenario for regression performance happens when the measurement is closest to 0, and the best performance happens when the measurement is closest to 1. Using MATLAB's neural network tool, the MSE and regression values for the difference training procedure were determined. In Table 1, the performance of the MLP network using three distinct training algorithms is presented 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	1.6923	0.9572	22
BP with Logsig	1.9752	0.9368	17
LM with Purelin	2.9476	0.8954	23
BP with Purelin	3.0275	0.8257	21

Using the activation functions of Logsig and Purelin, the MLP network is turned on. The simulation suggests that the LM training procedure with the Logsig activation function may offer the lowest MSE performance, with a 1.6923 MSE value, as shown in Table 1. MLP network trained by LM training algorithm with Logsig activation function, MSE of 1.9752. The LM and BP training algorithms with MSE values of 2.9476 and 3.0275, respectively, were activated by Purelin activation function to produce the simulation results. The MLP network's regression performance after being trained using those training techniques and activation functions is also shown in Table 1. Once more, the MLP network trained using BR with Logsig can provide a regression performance score of 0.9572. With a regression score of 0.9368, the MLP network using the BP training technique and Logsig activation function comes in second. Regression results from the

MLP network trained by LM and the BP activated by the Purelin activation function, respectively, reveal values of 0.8954 and 0.8257. However, it is unable to beat MSE and regression performance shown by MLP network trained by LM training algorithm and Logsig activation function. The simplest structure is provided by MLP trained by BP training algorithm activated by Logsig with 17 number of epoch.

Although various changes have been made to release from local minima, Table 1 clearly displays the performance differences between the training algorithm and activation function approach. As seen in both tables, the LM training procedure is based on the BP training algorithm. Nonetheless, the network was able to locate them because to the addition of a second Gauss-Newton algorithm to the BP's gradient descent training method. Sadly, the LM algorithm takes longer to converge when 22 is used, but the accuracy is higher than with other combinations. The BP training algorithm, on the other hand, can converge faster with only 17 epochs, but it cannot deliver acceptable accuracy.

Conclusion

The effectiveness and capacity of the MLP network in forecasting aggregate form are shown by the prediction results. The accuracy shown by the LM training method is the best, with the smallest MSE and maximum regression performances, according to the data. Because of this, even though the BP training strategy just needs a few epochs and has a short processing time, it can only produce worse regression results and a larger MSE. Although the LM performs better than the BP, it cannot match the LM training algorithm's performance.

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