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Logsig Activation Function based Multilayer Perceptron Network for Aggregate Classification

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ABSTRACT

Mechanical filtration and manual sorting have long been the standard methods for evaluating aggregate quality. While producing high-quality aggregates necessitates a variety of mechanical, chemical, and physical assessments, these tests are often conducted manually, leading to inefficiencies, subjectivity, and significant labour-demands. This research aims to develop an innovative image-based classification system to categorize aggregates more effectively. An artificial neural network (ANN) has been employed for the classification of the images captured in this process. In contrast to the Purelin activation function, the Logsig activation function shows improved performance, indicated by a decrease in mean square error (MSE) and better regression outcomes. Notably, the BR training algorithm utilizing a multilayer perceptron (MLP) network, aimed at reducing the MSE, provides the most effective regression results and the lowest MSE. The MSE achieved by the network trained with BR was 1.4235, accompanied by a regression coefficient of 0.9760. These findings suggest that implementing advanced computational techniques can significantly enhance the quality control processes in aggregate production, thereby promising improvements in efficiency and material performance standards.

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

INTRODUCTION

Quarries serve as vital sources for geological materials such as sand, clay, gravel, and crushed stone, which are utilized as raw materials across construction, agriculture, and various industries. The demand for these materials is influenced by the requirements of the end products, with each industry establishing its own standards to align with their output needs. The construction sector, in particular, experiences escalating demand for aggregates essential for concrete production, with granite and limestone being the predominant types used. The characteristics of aggregate particles such as shape, size, and surface texture are critical for producing high-strength concrete. Factors including the nature of rock deposits, the type of crushing equipment employed, and the size reduction ratio significantly influence aggregate particle shape and the quality of both fresh and cured concrete (Ray et al. 2021; Amin et al. 2020).

Reducing the water-to-cement ratio during concrete production is crucial for enhancing particle shape. Utilizing high-quality aggregates can lead to lower concrete production and pouring costs (Sosa et al. 2021). Since aggregates constitute at least 75% of concrete's volume, their quality is paramount. Zhang et al. (2020) highlight important aspects influencing aggregate particle shape and the quality of concrete, including the type of crushing equipment, stratification of rock deposits, and the size reduction ratio. Recent developments in concrete technology have facilitated the creation of high-strength concrete characterized by exceptional bonding properties while retaining workability and strength in its hardened state. Improvements in aggregate morphology have considerably reduced the necessary water-to-cement ratio in concrete mixtures. Employing high-grade aggregates can minimize costs associated with concrete production and placement while also enhancing properties such as strength and overall quality.

According to Khorram et al. (2017)), one significant feature of high-quality aggregates for the concrete and construction industries is their ability to improve the shape of crushed rocks utilized as aggregates. Aggregates that exhibit superior characteristics, such as a cubic and equidimensional shape, enhanced surface texture, and suitable grading, are gaining attention in the concrete domain due to their notable impact on concrete strength and quality. Unlike poorly shaped aggregates, which tend to be irregular, elongated, or flaky, this research has successfully determined the optimal orientation and configuration of high-quality shaped aggregate particles that are cubical and angular in a concrete mix (British Standard BS1881 1983). As a result, aggregates with enhanced particle shape and texture improve the mechanical bonding and interlocking within a concrete mixture, leading to overall stronger concrete. These improved aggregates minimize weak points and structures, thus contributing to greater strength. Due to their reduced surface area relative to unit volume, these aggregates facilitate tighter packing during consolidation, resulting in higher density and strength compared to flattened or elongated particles.

Conversely, flat or elongated aggregates create subpar packing, leading to poorer workability and bulk density, which in turn reduces the compressive strength of concrete and increases the need for additional sand, cement, and water. Therefore, it is crucial to evolve traditional quarrying practices to optimize crusher performance and produce premium aggregates that align with modern advancements in the concrete industry. An enhanced quantitative and consistent classification methodology is also vital to ensuring aggregate quality consistently meets industry standards. Research by Duboscla rd et al. (2015) has demonstrated the application of machine vision systems for aggregate classification. These systems focus on two primary components: classification and image processing. The classification component identifies the type of aggregate, while the image processing component extracts essential features of the aggregate. They proposed a machine vision technique for evaluating overall granularity based on multi-scale image entropy obtained from images (Tripathy & Guru, 2017). Additionally, Tripathy & Guru, (2017) classified ore particles by assessing their visual texture, which varies according to mineral composition. This approach utilized image processing within the RGB colour space to analyse the visual textures of ore particles.

The ANN leveraged second-order statistical measures, including entropy, contrast, energy, and homogeneity, alongside first-order statistical analysis based on grayscale values for classification. Disparities in grayscale values, entropy, contrast, energy, and uniformity facilitated the differentiation of manganese, iron, alumina, and aggregate zones. ANNs are highly efficient for solving complex and nonlinear problems, outperforming other methods like fuzzy logic, evolutionary algorithms, and statistical techniques. Their capacity to generalize beyond the training dataset and learn from various instances has led to widespread adoption. ANNs are particularly effective for data mining and categorization, as they can handle the "curse of dimensionality" while maintaining low computational costs using extensive datasets and multidimensional analysis. These networks have been successfully applied across numerous fields, including pattern recognition, classification, image processing, robotics, meteorological forecasting, financial projections, and medical diagnostics. Radial Basis Function (RBF) and Multilayer Perceptron (MLP) are prominent ANN architectures designed for classification tasks (Norizan et al. 2018; Ahmad Jamil et al. 2020), with MLP being the most recognized and widely used. Due to their computational simplicity, finite parameterization, stability, and smaller size compared to other architectures, MLPs are recommended for specific applications (Sabri et al. 2024). Direct MLP methods can accurately approximate any input-output mapping.

However, neural network models exhibit substantial nonlinearity regarding unknown parameters, necessitating a nonlinear optimization strategy. This often presents challenges such as slow parameter convergence, high computational expense, and undesirable local minima. Thus, these models require significant data and extended training periods to achieve adequate training. Nevertheless, enhancing the learning capacity of training algorithms can address these issues effectively. The Bayesian Regularisation (BR) training algorithm, an advanced adaptation of the Backpropagation (BP) training method, can proficiently handle these challenges, particularly since BP tends to get trapped in local minima (Hang et al. 2023). In this study, the aggregate data showed considerable variability due to manual sampling, which restricted the standard MLP's ability to accurately categorize and classify these intricate data into six distinct shapes. By incorporating a diverse dataset and implementing improved sampling techniques, the efficacy of the MLP could be further enhanced, ensuring that the system develops robust classification capabilities that meet the demands of modern concrete production standards.

Moreover, ongoing research into the integration of artificial intelligence and machine learning algorithms with traditional quarrying processes is expected to revolutionize the industry. By employing advanced predictive analytics, quarry operators can forecast demand, optimize production schedules, and minimize waste. Additionally, the exploration of alternative materials and recycling of existing aggregates can significantly contribute to sustainability efforts within the construction sector. The use of recycled aggregates not only reduces the environmental impact but also plays a crucial role in resource conservation. Enhanced sorting technologies combined with AI-driven analytics can ensure that recycled materials meet stringent quality standards, thus further contributing to the creation of high-performance concrete mixes.

METHODOLOGY

From a dataset of 625 images, 425 displayed desirable shapes (angular and cubic), while 200 showed undesirable shapes (elongated, flaky, a combination of flaky and elongated, and irregular). This segregation of shapes is crucial in assessing the quality of aggregates, as the shape significantly impacts the performance and durability of concrete mixes. Materials from a Malaysian quarry were crushed using the Metso Barmac Rock on Rock Vertical Shaft Impact (RoR VSI) crusher sourced from New Zealand. The selection of this specific crusher is important; the RoR VSI is known for its ability to produce high-quality aggregates with a desirable shape, as it utilizes a unique crushing approach that maximizes the reshaping of particles. Experiments were conducted based on Euler's Polyhedron formula, which indicates that the sum of the vertices (V) and faces (F) equals the sum of the edges (E) plus two, expressed mathematically as $V + F = E + 2$.

This fundamental theorem serves as a guiding principle in analysing the geometrical configuration of the feed materials and the resultant crushed aggregates. The three characteristics faces (f), edges (e), and vertices (c) were counted for all standard-shaped particles in both the feed and the crushed output. This analysis provides a deeper understanding of how the crushing process affects the shapes of particles, allowing for a detailed comparison to the characteristics of a perfect cube, which is defined by six faces (f: 6), twelve edges (e: 12), and eight vertices (c: 8). The aggregates were systematically organized into six shape classifications: cubical, angular, irregular, flaky, elongated, and a combination of flaky and elongated. Among these classifications, aggregates were further categorized into two primary groups: poorly shaped aggregates (including irregular, flaky, elongated, and both flaky and elongated) and well-shaped aggregates (consisting of cubical and angular types) (Wang et al. 2022).

The distinction between these categories is essential, as well-shaped aggregates are known to enhance the mechanical properties of concrete significantly. The classification results of the shapes, which are consistent with Euler's Polyhedron formula, facilitate a precise analysis and categorization of the distribution of each particle type in both the feed and crushed aggregates, particularly under different rotor speeds or during cascade testing. Empirical observations reveal that angular particles commonly exhibit more faces, typically ranging between four and eight, while flaky and elongated particles may possess as few as two faces. Simply put, the more faces a particle has, the better it can bond with other particles in the concrete mix, leading to higher structural integrity. Conversely, flaky and elongated aggregates present a flatter profile with fewer crushed faces compared to their angular and cubic counterparts. This leads to poorer packing in concrete, which can adversely affect the overall strength and durability of the mixture.

Irregular particles also demonstrate a reduced number of faces, edges, and corners compared to the distinctly shaped cubic and angular particles. The lack of standardized shape in irregular particles can lead to uneven packing and weak points in concrete, which are undesirable characteristics in high-performance applications. To address these challenges, various methodologies are implemented to enhance the quality and contrast of images used in the classification process. Preprocessing methods are applied, alongside a feature extraction tool designed to highlight key information essential for the classification process. The images undergo automatic segmentation using repeated thresholding, followed by contraction and expansion techniques to amplify details and improve the differentiation between objects and their backgrounds. This meticulous preprocessing is vital, as the clarity of the images directly influences the accuracy of the shape classification. A significant challenge faced during the feature extraction phase of aggregate shape classification is the utilization of geometric moments. The Hu and Zernike moments serve as effective feature extractors for group identification, due to their invariance to geometric transformations such as scaling, translation, and rotation. These mathematical constructs allow for a consistent and reliable characterization of particle shapes, regardless of their orientation or size in the captured images. Two sets of seven Hu moments were generated, one extracted from the region and the other from the boundary, serving to provide comprehensive data for analysis.

The ANN is then engineered to replicate brain functions, based on principles derived from human neural structures. Its design aims to emulate the structure, learning mechanisms, and operational capabilities of biological neural networks (Hashim et al. 2019). Through training, the ANN can effectively learn patterns and characteristics associated with different aggregate shapes, culminating in improved classification accuracy. Figure 1 depicts the model of nonlinear neurons, illustrating the architecture that facilitates complex computations within the network. The integration of machine learning with aggregate classification is anticipated to further enhance the efficiency and precision of the categorization process. By automating the identification of aggregate shapes, the industry can reduce labour costs and minimize the subjectivity associated with manual classifications.

The application of advanced neural network architectures can also pave the way for real-time monitoring and quality control of aggregate production, ensuring that the materials used in construction meet stringent performance and regulatory standards. In summary, the insights derived from this comprehensive study underline the critical role that aggregate shape plays in the concrete production process. By leveraging advanced imaging and machine learning techniques, the industry can make significant strides toward producing high-quality aggregates that enhance the performance of concrete in various applications.

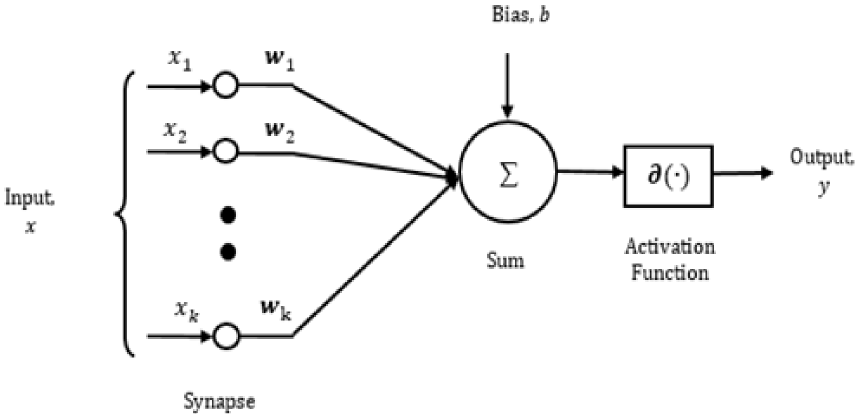

FIGURE 1. Nonlinear neuron model (Elbrächter et al. 2021)

Fig. 1 depicts the structure of a neuron as consisting of a network of synapses or connections, a summation process, and an activation function. Each synaptic connection is assigned a weighted value. Assuming the neuron has k synapses, it consequently has k inputs. The model's activation function is denoted as ∂(·), with the inputs at each synapse represented as(x_1,x_2… x_k), and the weights corresponding to each synapse represented as (w_1,w_2… w_k). The value of the jth synaptic weight [W_j] affects the processing of the synapses to yield the neuron's output. For each input synapse connected to the neuron, the value of the jth synaptic weight [w_j] is multiplied by the input x_j. The activation function then calculates the total by summing all the multiplied input signals along with a bias term (b). The mathematical model for neurons can be articulated through the following two equations, as shown in Fig 1.

$$u = \sum_{j=1} W_j x_j + b \tag{1}$$

and

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

In Eq (1) and (2),W_j represents the weights assigned to the j^{th} synapse in the neuron, ∂(·) refers to the activation function, and y is the resulting output. The variable u denotes the summed output, while x_j signifies the input signal from the jth data or synapse. Common activation functions in ANNs include Log-sigmoid (Logsig), piecewise linear, fixed limiter, and linear functions (Makmor et al. 2024).

These activation functions play a crucial role in determining the network's ability to model complex relationships within the data. The predictive accuracy of ANNs is significantly influenced by both the training methods employed and the architectural design of the network itself. As a result, numerous improved training methodologies have been investigated in recent years to further enhance the performance of these networks. One notable architecture is the MLP network. Distinguished by its nonlinear functional structure, an MLP network can be effectively trained to create specific input-output mappings (Hashim et al. 2021). MLPs typically consist of an input layer, one or more hidden layers, and an output layer. However, it has been observed that when a nonlinear model, such as an MLP network, replaces a simpler linear model, the predictions made by the neural network may exhibit variations and may not always be exact. This variability underscores the importance of fine-tuning the network's parameters to achieve optimal performance.

Fig. 2 illustrates the architecture of the MLP network, which comprises one input layer, one hidden layer, and one output layer. Previous research conducted by Funahashi (1989) and Cybenko (1989) supports the notion that a single hidden layer in an MLP network is often sufficient for producing highly accurate prediction outputs. This finding suggests that for many applications, the complexity introduced by additional hidden layers may not be necessary. Therefore, this study will focus solely on maximizing the efficiency and effectiveness of neural networks with a single hidden layer, exploring their capacity to deliver reliable and accurate predictions across various datasets.

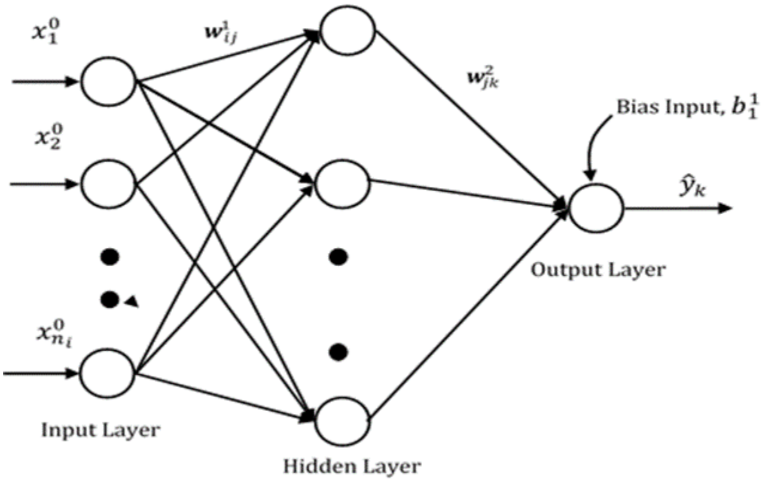

FIGURE 2. MLP architecture with one hidden layer (Makmor et. al., 2024)

The network's output can be 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 $1 \le j \le n_h$ and $1 \le k \le m$

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

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

The actual output of the system is represented as $\hat{y}_k(t)$, while the predicted output is denoted as $\hat{y}_k(t)$. The training phase is critical in neural networks, ensuring that the network adheres to the defined design specifications. There are two main learning methods: supervised learning, which is guided by a teacher, and unsupervised learning, based on experience. Supervised learning allows for the development of a comprehensive model that connects inputs to the desired outputs. However, this method does not require predictions from the evaluated training models. In contrast, the learning process in unsupervised learning is characterized by the absence of an output target. Here, input data is viewed as a collection of random variables, which serves as the foundation for creating a density model and relies on pre-existing knowledge. This form of learning is entirely reliant on past experiences and lacks specific goals (Neagoe & Stoica, 2018). Additionally, unsupervised learning aids in data compression. This study adopted an experimental approach followed by modelling through a neural network method, including the collection of an additional dataset along with the target. Consequently, guided training was preferred. Supervised training methods such as BP, Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), and BR were employed to simulate the predicted outputs (Ahmad et al. 2019; Ling & Mat Isa, 2023).

RESULT AND DISCUSSION

A study cantered on assessing the predictive performance of MLP networks is essential to confirm their reliability in predicting explosive pressure accurately. This analysis was conducted using MATLAB's neural network tools (nntool), which provides a robust framework for developing and testing neural network models. In the study, 70% of the available data was designated for training the model, while the remaining 30% was reserved for testing its predictive capabilities. The network was configured with 10 hidden nodes, chosen to optimize the balance between complexity and performance. This process involved a detailed evaluation of the MSE to identify potential inaccuracies in predictions and employing advanced regression techniques to achieve the best fit for the model (Nadia et al. 2020; Tuan Zizi et al. (2023)).

The effectiveness of the training was measured by targeting the lowest achievable MSE while maximizing regression performance metrics. During the prediction phase, minimizing the relative error becomes crucial, aiming for the lowest possible MSE value. It is noteworthy that the worst regression performance is typically observed when the measurement is close to 0, while optimal outcomes are achieved when the measurement approaches 1, indicating high predictive accuracy. MATLAB's neural network tool proved invaluable, offering critical insights into the MSE and regression results pertaining to the differential training method. Furthermore, Table 1 displays the performance of the MLP network using two distinct training methods, organized in descending order of MSE performance, ranging from highest to lowest. This structured approach underscores the rigor of the analysis and its significance in validating the reliability of MLP networks for explosive pressure predictions.

TABLE 1. MLP Performance on MSE and Regression

Training Algorithm	MSE Performance	Regression Performance	Number of Epoch
BR with Logsig	1.4235	0.9760	316
BP with Logsig	1.9752	0.9368	17
BR with Purelin	2.6956	0.9228	402
BP with Purelin	3.0275	0.8257	21

The MLP network employed Logsig and Purelin activation functions during its activation process, which are essential for determining the output of the neurons based on the input received. According to the simulation findings, the BR training method using the Logsig activation function resulted in the best performance, achieving a MSE of 1.4235. This performance indicates that the network can make predictions with minimal error, highlighting the effectiveness of the BR approach. In comparison, the MLP network trained with the BP algorithm and the Logsig function recorded an MSE of 1.9752, which, while relatively good, indicates that the BR method offers superior performance. When utilizing the Purelin activation function, the MSE values for the BR and BP training algorithms were found to be 2.6956 and 3.0275, respectively, indicating a noticeable decrease in performance compared to when the Logsig function was employed. Table 1 illustrates the regression performance of the MLP network following training with these various methods and activation functions, showcasing how different configurations can significantly impact outcomes. The MLP network trained using the BR algorithm with the Logsig activation function achieved a regression performance score of 0.9570. Meanwhile, the network trained with the BP algorithm and Logsig function reached a slightly lower regression score of 0.9368, placing it second. The regression scores for the MLP networks trained with the BR and BP algorithms alongside the Purelin activation function were 0.9228 and 0.8257, respectively, further emphasizing the effectiveness of the MLP network trained using the BR algorithm and the Logsig activation function. These MSE and regression results underscore the overall effectiveness of the MLP network trained with the BR algorithm and the Logsig activation function, even though it does not outperform the basic MLP architecture utilizing the BP algorithm, which also employed the Logsig activation function over 17 epochs. Notably, the BR training algorithm operates on a stochastic model, while the BP training algorithm follows a deterministic model. This distinction highlights the performance disparities between these training methods, as shown in Table 1. The deterministic model has undergone thorough analysis in pursuit of a standard algorithm, while the stochastic model consists of a series of random variables, leading to varied performance outcomes. As a result, many BP-based training algorithms struggle to achieve optimal performance due to their tendency to get stuck in local minima during training. Although the BR training algorithm may take longer to converge, requiring 316 epochs to reach optimal results, it ultimately delivers superior accuracy compared to the other combinations tested. In contrast, the BP training algorithm can quickly converge within just 17 epochs but does not achieve adequate accuracy. This contrast in convergence speed and accuracy illustrates the trade-offs inherent in selecting a training method for MLP networks, influencing the choice of approaches in practical applications.

CONCLUSION

The MLP network's accuracy and efficiency in predicting aggregate shapes are illustrated by its prediction outcomes. The BR training algorithm demonstrated exceptional accuracy, producing a very low MSE and a regression performance score approaching 1. In contrast, while the BP training method requires fewer epochs and has a quicker processing time, it results in lower regression scores and a higher MSE. Although the BR method surpasses the BP approach, it still does not reach the efficiency levels of the BR training algorithm. Modifying the architecture of the MLP network could further improve both MSE and regression performance. Moreover, exploring a deep learning neural network could prove advantageous, as it has the potential to integrate multiple perspectives as input parameters.

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DECLARATION OF COMPETING INTEREST

None

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