Predicting the Engineering Properties of Rocks from Textural Characteristics Using Some Soft Computing Approaches

Davood Fereidooni 1 and Luís Sousa 2,*

1 School of Earth Sciences, Damghan University, Damghan 36716-41167, Iran
2 Department of Geology and Pole of CGeo—Geoscience Center, University of Trás-os-Montes e Alto Douro, 5000-801 Vila Real, Portugal

* Correspondence: lsousa@utad.pt

Abstract: Rock is used as a foundation and building material in many engineering projects and it is important to determine/predict its engineering properties before project construction. Petrographic and textural characteristics are useful parameters for predicting engineering properties of rocks in such applications. In this research, fifteen rock samples were taken and their engineering characteristics, namely dry and saturated unit weights, porosity, water absorption, slake durability index (SDI), Schmidt rebound hardness (SRH), ultrasonic P-wave velocity (UPV), and uniaxial compressive strength (UCS), were measured in the laboratory. Petrographic and textural characteristics of the rocks, determined from thin section and X-ray diffraction investigations, led to the evaluation of the texture coefficient (TC). Based on simple regression analysis (SRA), the TC values have direct relationships with density, SDI, SRH, UPV, and UCS, and inverse relationships with porosity and water absorption. Experimental models were developed using multiple regression analysis (MRA) and artificial neural network (ANN) to predict Id2, SRH, UPV, and UCS of the tested rocks from the values of TC. Some statistical parameters including Pearson regression coefficient (R), coefficient values account for (VAF), root mean square error (RMSE), mean absolute percentage error (MAPE), and performance index (PI) were calculated to assess the performances of the MRA and ANN models. The correlations between experimental and calculated values of Id2, SRH, UPV, and UCS indicated that predicted values of the ANN models are more valid than the MRA. Additionally, the residual error of the ANN models varies less than the MRA. Finally, it has been concluded that the SRA, MRA, and ANN methods can successfully predict the rock engineering properties from the TC.

Keywords: rock; engineering properties; texture coefficient; statistical method; artificial neural network

1. Introduction

Natural stones are used worldwide at an increasing rate because of their availability, excellent physical-mechanical properties, and diversity of textural characteristics [1,2]. Several factors are considered during an exploration campaign of building stones, such as the fracturing in the quarry, which defines if a rock mass can be exploited, or the durability, which delimits the possible applications [3–8]. The evaluation of the geotechnical properties of building stones, such as color and brightness, is a key factor to define their utilization [9–14]. Furthermore, engineering characteristics of different rocks are essential parameters for design and construction of various engineering projects such as dams, tunnels, caverns, and foundations either on or inside rocks. These characteristics could be determined practically through direct methods as described in ISRM [15]. Applying direct tests to assess these properties is usually expensive, time consuming, and requires regularly shaped samples. Therefore, in such cases, experimental approaches and empirical equations can be used to predict the engineering properties of rocks from simple and index test results.

Several researchers have attempted to develop various soft computing models for predicting different parameters from others in material sciences [16–25] and engineering
properties of different rock types from their petrographic characteristics in engineering geology and rock mechanics [26–35]. In the recent years, some research works have been performed to assess correlations between mineralogical and textural characteristics and mechanical properties of different rocks by using statistical analyses and different soft computing approaches such as genetic programing (GP), artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM) [36–52]. The main advantages of these approaches are that (i) they have made it possible to solve nonlinear problems, in which mathematical models are not available, and (ii) they have introduced human knowledge such as cognition, recognition, understanding, learning, and others in the fields of computing [53]. In this regard, Brace [54] recognized that fine-grained rocks have higher strength than coarse-grained ones. Ulusay et al. [55] tested sandstones in a laboratory and found that textural properties are important parameters for predicting engineering properties of these rocks. Tugrul and Zarif [56] stated that textural characteristics are more important than mineral content for estimating the engineering properties of rocks. Eberli et al. [57] observed that the size and shape of grains, grain size distribution, and the ratio of grain to matrix have an influence on the acoustic wave velocity through the unconsolidated carbonate sediments. Meng and Pan [58] and Khanlari et al. [59] indicated that physical properties (i.e., density, porosity, permeability) and mechanical characteristics (such as strength, deformability, durability, and hardness) of rocks are affected by mineral composition, grain size, grain contact, and rock cement. Jensen et al. [38] found that porosity, grain size, weakness planes, and microfractures presented in limestones’ texture have important effects on the strength of the rocks.

The texture coefficient (TC) was developed by Howarth and Rowlands [60] to understand the effect of textural characteristics on the physical and mechanical properties of rocks. They investigated the relations between the mechanical properties and TC for igneous rocks, marbles, and sandstones and found close relationships between mechanical rock properties and the TC. In many research studies, the TC has been applied to predict the engineering properties of rocks [61–64]. Singh et al. [36] used artificial neural networks to estimate the strength of schistose rocks from their petrographic characteristics. In their research, the network was trained to predict axial point load, uniaxial compression, and tensile strengths from mineralogical content, grain size, aspect ratio, surface weight, form factor, and foliation orientation. Alber and Kahraman [65] used regression analysis to predict the elasticity modulus and uniaxial compressive strength of a fault breccia from the TC. The results of their research remarked that the uniaxial compressive strength of the tested breccia could be estimated from the texture coefficient. Manouchehrian et al. [42] applied artificial neural networks and multivariate regression for assessing the uniaxial compressive strength based on textural characteristics of rocks. Ersoy and Acar [66] studied the petrographic and textural properties’ influences on the strength of granites and found that the size of mineral has a higher effect than mineral type on rock strength. Aligholi et al. [67] evaluated relationships between drillability indices on one hand and index properties and petrographic data on the other hand of hard igneous rocks. They revealed that the multiple regression models prepared by using petrographic features provide a better prediction of drillability in comparison to those prepared by using index properties. Akram et al. [68], by assessing petrographic and mechanical characteristics of Sakesar limestone, attempted to establish the relationships between the parameters and the strength parameters such as uniaxial compressive strength, point load index, and Schmidt rebound hardness values. In their research, regression analyses were used to establish correlations between limestone constituents and the parameters of strength. Kolay and Baser [69] focused on the relationships between internal structure and engineering parameters of basalt rocks by digitizing the textural properties. In this research, simple regression analysis was performed using the laboratory results incorporating texture coefficient and engineering parameters including dry unit weight, P-wave velocity, Schmidt rebound hardness, point load strength index, and uniaxial compressive strength of the rocks. Their results showed that the strength of the basalts has direct relation by their texture coefficient.
All the above studies show that the petrographic characteristics and rock texture affect the engineering properties of different rocks. These properties can be easily assessed by routine thin section studies in a laboratory. As sedimentary rocks have a very diverse nature and suitable texture in the presence of grains with different sizes and shapes in microscopic studies, the effect of petrographic and textural characteristics on engineering properties of sedimentary rocks is sensible. Therefore, this research focuses on the assessment of engineering properties and the textural coefficient of the rocks to predict the engineering properties from petrographic and textural characteristics using statistical methods and artificial neural networks. So, the main objective of the research is to establish relationships between the textural characteristics of rocks as a primary and essential parameter from one side and engineering properties as advanced and perfect parameters from the other by using careful approaches such as soft computing methods. Additionally, another benefit of this research is that the use of soft computing methods for predicting rock engineering characteristics is a cheap and quick method, especially for soft rocks such as sedimentary rocks, for which laboratory tests are difficult. On the other hand, this research can be considered as a model for future research and its results can be used by other researchers. These issues motivated this research. Therefore, fifteen sedimentary rock samples including limestones and sandstones have been studied to predict their engineering properties from petrographic and textural characteristics using statistical analysis and soft computing methods.

2. Geological Setting and Methodology

The study area and sampling locations are placed in the north and northwest of the Damghan region in the north of Iran. This region has a continental climate and an irregular topography related to its geological history. The area is situated in the Alborz-Azarbayejan structural zone and contains Paleozoic to Neogene outcropped rocks. Suitable sampling locations were found from the 1:100,000 geological map presented by the Geological Society of Iran [70]. Fifteen rock samples including limestones and sandstones were collected for performing the study. Sampling was carried out from quarries, trenches, and road cuttings during field investigations. The limestone samples include Sibzar (SBZ), Elika (ELK), Dalichai (DLC), and Lar (LAR) and the sandstone samples contain Padeha (PDH), Barut (BRT), and Shemshak (SMK). SBZ samples from the Middle Devonian age were collected from the Bahram and Sibzar formations from the northern part of a ballast mine in the region. ELK samples from the Lower Triassic age were collected from the Elika formation from a new trench near the Astaneh village. DLC and LAR samples, which depend on the Dalichai and Lar formations of the Upper Jurassic age were collected from road cuttings. The samples of PDH were obtained from a ballast mine 10 km from the Chesmeh-Ali road. The age of the Padeha formation is Devonian. The samples of BRT were obtained from the Barut formation with a Lower Cambrian age. The samples of SMK were collected from the Shemshak formation outcropped near a travertine quarry. These samples are from the Middle Jurassic age. Figure 1 illustrates the geological properties and the sampling locations.

After the field investigations, a regular laboratory test program was carried out to assess engineering properties of the collected rocks. XRD analyses and microscopic investigations were performed based on ASTM [71] and ISRM [15] to determine the rocks’ constituent minerals, petrography properties, textural characteristics, and finally texture coefficient (TC). X-ray diffraction (XRD) analysis was carried out by X’Pert HighScore plus (v.3.0.5) software. Composition materials of the studied rocks were identified in the 2θ ranges from 4° to 70°. The dry unit weight, saturated unit weight, effective porosity, water absorption, P-wave velocity, Schmidt hardness, slake durability index, and uniaxial compressive strength of the rocks were measured. The test plan for the present study is summarized in Figure 2. These tests were conducted on standard NX core specimens (prepared based on ISRM [15]) presented in Figure 3. Additionally, the used apparatuses and testing procedures in this study are shown in Figure 4. Physical properties including
dry and saturated unit weights ($\gamma_{\text{dry}}$, $\gamma_{\text{sat}}$), effective porosity ($n$), and water absorption ($W_a$) were determined in accordance with ISRM [15]. The slake durability index (SDI) test was carried out in accordance with ISRM [15] and ASTM [72] up to 3 cycles. This test was performed on 150 irregular or lump prepared specimens. The Schmidt rebound hardness (SRH) test was carried out according to ISRM [73] and ASTM [74] on blocks of the rock samples. The ultrasonic P-wave velocity (UPV) test was conducted based on ASTM [75] in the laboratory. The uniaxial compressive strength test was conducted in accordance with ISRM [15] and ASTM [76]. Five experiments for each rock sample were performed on cylindrical specimens with a length to diameter ratio of 2:2.5 to determine the average values of UCS. Finally, the estimation of engineering properties of the rocks was performed from petrographic and textural characteristics using statistical methods and artificial neural networks.

Figure 1. Sampling locations and geological map of the study area [70].

Figure 2. Test plan in this study for determining different properties of the rocks.
with ISRM [15] and ASTM [76]. Five experiments for each rock sample were performed on cylindrical specimens with a length to diameter ratio of 2:2.5 to determine the average values of UCS. Finally, the estimation of engineering properties of the rocks was performed from petrographic and textural characteristics using statistical methods and artificial neural networks.

Figure 2. Test plan in this study for determining different properties of the rocks.

Figure 3. Block samples in the field and core specimens of the rocks.

Figure 4. Testing procedure and the used apparatuses for the study. (a) P-wave velocity test, (b) uniaxial compressive test, and (c) slake durability test.

Results of the Laboratory Investigations

3.1. Mineralogical and Petrographic Studies

Based on the obtained results, the studied limestones are generally composed of calcite, and the studied sandstones are quartz-rich (see Table 1 and Figure 5). The SBZ samples are sparry limestone (type I) or dolomitic limestone. These samples mainly contain calcite, dolomite, and quartz. The original calcite matrix has been replaced by dolomite, but the micritic allochems are partly replaced. Where replacement is incomplete, euhedral rhombohedral crystals are visible. ELK samples are mainly composed of ooids, peloids, and many fossils such as alga and echinoderms. The allochems are a mixture of ooids and bioclasts. Therefore, these samples are oosparite (type I) according to the Folk or ooid grainstone according to the Dunham classifications. Since the allochems are rounded, it would be a rounded oosparite using the Folk textural spectrum. DLC samples are sparry allochemical limestone (type I) or sandy grainstone. LAR samples are microcrystalline limestone (type III) without allochems. These samples are mainly composed of ooids, peloids, alga, and echinoderms. According to the Folk classification, PDH samples are typical greywacke that are dominantly composed of calcite, quartz, and dolomite. Poor sorting, abundant quartz monocrystalline, sedimentary origin, and the existence of rhombohedra dolomite are the main textural characteristics of these samples. Additionally, the
3. Results of the Laboratory Investigations

3.1. Mineralogical and Petrographic Studies

Based on the obtained results, the studied limestones are generally composed of calcite, and the studied sandstones are quartz-rich (see Table 1 and Figure 5). The SBZ samples are sparry limestone (type I) or dolomitic limestone. These samples mainly contain calcite, dolomite, and quartz. The original calcite matrix has been replaced by dolomite, but the micritic allochems are partly replaced. Where replacement is incomplete, euhedral rhombohedral crystals are visible. ELK samples are mainly composed of ooids, peloids, and many fossils such as alga and echinoderms. The allochems are a mixture of ooids and bioclasts. Therefore, these samples are oosparite (type I) according to the Folk or ooid grainstone according to the Dunham classifications. Since the allochems are rounded, it would be a rounded oosparite using the Folk textural spectrum. DLC samples are sparry allochemical limestone (type I) or sandy grainstone. LAR samples are microcrystalline limestone (type III) without allochems. These samples are mainly composed of ooids, peloids, alga, and echinoderms. According to the Folk classification, PDH samples are typical greywacke that are dominantly composed of calcite, quartz, and dolomite. Poor sorting, abundant quartz monocrystalline, sedimentary origin, and the existence of rhombohedra dolomite are the main textural characteristics of these samples. Additionally, the rock matrix is composed of a hematite and dolomite fill between the fine-grain quartzes in these samples. BRT samples are litharenite and are composed of quartz, calcite, orthoclase, muscovite and others rock fragments such as chert. Quartz is the main mineral in these samples and calcite and feldspar are accessory minerals. SMK samples are classified as sub-litharenite and are composed of quartz (more than 70%) as the main mineral, and calcite and feldspar as accessory minerals. In these samples, the matrix fill is calcite and hematite between quartzes.

The mineralogical and petrographic properties of the studied rocks are summarized in Table 1.

### Table 1. Mineralogical and Petrographic properties of the studied rock samples.

| Sample | Lithology                  | Qtz. | Cal. | Dol. | Fld. | Fos. | Other Minerals |
|--------|----------------------------|------|------|------|------|------|----------------|
| SBZ1   | Dolomitic limestone        | 10   | 60   | 25   | -    | -    | 5              |
| SBZ2   | Dolomitic limestone        | 20   | 40   | 35   | -    | -    | 5              |
| ELK1   | Ooid grainstone (limestone)| 5    | 10   | -    | -    | 80   | 5              |
| ELK2   | Ooid grainstone (limestone)| 5    | 20   | -    | -    | 70   | 5              |
| DLC1   | Sandy grainstone (limestone)| 20  | 65   | 5    | -    | -    | 10             |
| DLC2   | Sandy grainstone (limestone)| 25  | 60   | 5    | -    | -    | 10             |
| LAR1   | Microcrystalline limestone| 15   | 70   | -    | -    | 12   | 3              |
| LAR2   | Microcrystalline limestone| 20   | 63   | -    | -    | 15   | 2              |
| PDH1   | Greywacke (sandstone)      | 70   | 15   | 10   | -    | -    | 5              |
| PDH2   | Greywacke (sandstone)      | 55   | 30   | 10   | -    | -    | 5              |
| PDH3   | Greywacke (sandstone)      | 55   | 30   | 10   | -    | -    | 5              |
| BRT1   | Litharenite (sandstone)    | 70   | 10   | -    | 15   | -    | 5              |
| BRT2   | Litharenite (sandstone)    | 60   | 15   | -    | 20   | -    | 5              |
| SMK1   | Sub litharenite (sandstone)| 70   | 7    | -    | 10   | -    | 13             |
| SMK2   | Sub litharenite (sandstone)| 80   | 7    | -    | 5    | -    | 8              |

Note: Qtz.: Quartz (SiO2); Cal.: Calcite (CaCO3); Dol.: Dolomite (Ca.Mg(CO3)2); Fld.: Feldspar; Fos.: Fossil.

3.2. XRD Analysis

X-ray diffraction (XRD) analysis was performed and the provided diffractograms are shown in Figure 6. The results indicated that calcite and quartz are the two main minerals in all studied rocks. Other minerals such as hematite are present as secondary minerals in the rock samples. Similar to the thin section results, the limestones and sandstones are commonly composed of calcite and quartz, respectively. So, the results of both thin section studies and XRD analysis are completely coordinated with each other.
of PDH samples. Similar to the thin section results, the limestones and sandstones are dry.

**Figure 5.** Microscopic images of the studied rock samples. (Qtz.: Quartz (SiO$_2$); Cal.: Calcite (CaCO$_3$); Dol.: Dolomite (Ca.Mg(CO$_3$)$_2$); Fld.: Feldspar; Fos.: Fossil).

**Figure 6.** XRD graphs of the studied rock samples.
3.3. Engineering Properties Evaluation

The values of all physical properties of the studied rock samples including dry and saturated unit weights (γ_dry, γ_sat), effective porosity (n), and water absorption (W_a) are presented in Table 2. The values of γ_dry are between 2.35 and 2.60 for the samples of PDH3 and SMK2, respectively. Additionally, the values of porosity are between 2 and 10.32 for the samples of SMK2 and PDH3, respectively. Based on the IAEG [77] rock classification, most of the samples were placed in the rock groups with moderate to high unit weight and low to medium porosity. The samples of PDH3 and SMK2 have the lowest and highest values of the slake durability index equal to 95.54% and 99.21% at the third cycle (Id3), respectively. According to the Gamble [78] classification, the tested samples were placed in durable and very durable rock groups. The lowest and highest values of the Schmidt rebound hardness (SRH) are between 24 and 49, which belong to the samples of PDH3 and SMK2, respectively. The value of ultrasonic P-wave velocity (UPV) ranges from 3.09 to 5.75 km/s. The samples PDH3 and LAR2 have the highest and lowest values of wave velocities, respectively. The minimum and maximum values of the uniaxial compressive strength (UCS) are between 16.09 and 127.43 MPa, which belong to the samples of PDH3 and SMK2, respectively. According to Broch and Franklin [79], the tested samples were placed in weak to extremely strong rock groups. The values of engineering properties for the studied rock samples are presented in Table 2.

### Table 2. Values of engineering properties of the tested rock samples.

| Sample | γ_dry (g/cm³) | γ_sat (g/cm³) | n (%) | W_a (%) | Id1 (%) | Id2 (%) | Id3 (%) | SRH | UPV (Km/s) | UCS (MPa) |
|--------|---------------|---------------|-------|---------|---------|---------|---------|-----|-----------|-----------|
| SBZ1   | 2.45          | 2.53          | 3.74  | 1.12    | 99.02   | 98.69   | 98.46   | 43  | 4.89      | 81.99     |
| SBZ2   | 2.45          | 2.53          | 4.98  | 1.78    | 99.25   | 98.87   | 98.52   | 39  | 4.80      | 67.40     |
| ELK1   | 2.48          | 2.55          | 8.15  | 3.49    | 98.91   | 98.43   | 97.75   | 31  | 4.59      | 45.54     |
| ELK2   | 2.45          | 2.52          | 7.01  | 2.87    | 99.10   | 98.15   | 97.89   | 35  | 4.61      | 56.58     |
| DLC1   | 2.50          | 2.61          | 6.50  | 2.40    | 99.41   | 98.66   | 98.21   | 43  | 4.91      | 85.59     |
| DLC2   | 2.50          | 2.62          | 7.21  | 2.98    | 99.15   | 98.57   | 98.02   | 40  | 4.37      | 73.67     |
| LAR1   | 2.51          | 2.73          | 3.96  | 1.24    | 99.37   | 98.99   | 98.94   | 45  | 5.44      | 95.45     |
| LAR2   | 2.57          | 2.70          | 2.85  | 0.64    | 99.56   | 99.34   | 99.18   | 47  | 5.75      | 108.55    |
| PDH1   | 2.44          | 2.53          | 7.58  | 3.69    | 98.10   | 97.25   | 96.56   | 30  | 3.85      | 46.29     |
| PDH2   | 2.45          | 2.52          | 8.41  | 3.42    | 98.19   | 97.26   | 96.42   | 26  | 3.52      | 32.46     |
| PDH3   | 2.35          | 2.46          | 10.32 | 4.82    | 98.04   | 97.04   | 95.54   | 24  | 3.09      | 16.09     |
| BRT1   | 2.59          | 2.67          | 2.15  | 0.26    | 99.52   | 99.05   | 98.76   | 48  | 5.53      | 119.82    |
| BRT2   | 2.56          | 2.62          | 3.33  | 0.90    | 99.03   | 98.71   | 97.87   | 43  | 5.10      | 90.12     |
| SMK1   | 2.56          | 2.67          | 3.10  | 0.77    | 99.61   | 99.29   | 99.15   | 46  | 4.91      | 105.02    |
| SMK2   | 2.60          | 2.68          | 2.00  | 0.18    | 99.65   | 99.38   | 99.21   | 49  | 5.16      | 127.43    |

Some comprehensive linear correlations were obtained between the physical and mechanical properties, which are presented in Table 3. Regression coefficients (R) as Pearson correlations were found between 0.77 and 0.98. Significant level values (Sig.) were between 0.000 and 0.001, and the high values of R show that the determined engineering parameters are significantly related to each other. Based on the results, Gs, γ_dry, γ_sat, SDI, SRH, UPV, and UCS have direct linear relations, whereas n and W_a have inverse linear relations to the other parameters. These results are comparable to the results presented by other authors [34,67,69,80].

3.4. Texture Coefficient (TC) Calculation

The texture of rocks was defined as “the degree of crystallinity, grain size or granularity, and the fabric or geometrical relationships between the constituents of a rock” [81]. The texture coefficient (TC) proposed by Howard and Rowlands [60] is a very good factor to quantify rock texture. The values of TC, which is the so-called rock fabric coefficient by Prikryl [82], were evaluated by performing four processes, namely (1) measuring grain circularity, (2) measuring grain elongation, (3) measuring and quantifying grain orientation,
and (4) weighting of results based on the degree of grain packing [61]. After passing the processes, the TC is calculated from the following equation [61]:

\[
TC = AW \left[ \left( \frac{N_0}{N_0 + N_1} \times \frac{1}{FF_0} \right) + \left( \frac{N_1}{N_0 + N_1} \times AR_1 \times AF_1 \right) \right]
\] (1)

Table 3. Descriptive results of linear regression analysis for correlating the engineering properties of the rocks.

| Correlations | \( \gamma_{\text{dry}} \) | \( \gamma_{\text{sat}} \) | n | \( W_a \) | \( I_{d1} \) | \( I_{d2} \) | \( I_{d3} \) | SRH | UPV | UCS |
|--------------|----------------|----------------|---|--------|---------|---------|---------|------|-----|------|
| \( G_s \)    | R              |                |   |        |         |         |         |      |     |      |
| \( \gamma_{\text{dry}} \) | R              | 0.875          | 1 |        |         |         |         |      |     |      |
|                | Sig.           | 0.000          |   |        |         |         |         |      |     |      |
| \( \gamma_{\text{sat}} \) | R              | -0.845         | -0.768 | 1   |         |         |         |      |     |      |
|                | Sig.           | 0.000          | 0.001 |     |         |         |         |      |     |      |
| n             | R              | -0.855         | -0.774 | 0.994 | 1       |         |         |      |     |      |
|                | Sig.           | 0.000          | 0.001 | 0.000 |         |         |         |      |     |      |
| \( W_a \)     | R              | -0.855         | -0.774 | 0.994 | 1       |         |         |      |     |      |
|                | Sig.           | 0.000          | 0.001 | 0.000 | 0.000   |         |         |      |     |      |
| \( I_{d1} \)  | R              | 0.796          | 0.784 | -0.803 | -0.833 | 1       |         |      |     |      |
|                | Sig.           | 0.000          | 0.001 | 0.000 | 0.000   | 0.000   |         |      |     |      |
| \( I_{d2} \)  | R              | 0.820          | 0.801 | -0.869 | -0.889 | 0.971   | 1       |      |     |      |
|                | Sig.           | 0.000          | 0.000 | 0.000 | 0.000   | 0.000   | 0.000   |      |     |      |
| \( I_{d3} \)  | R              | 0.792          | 0.794 | -0.868 | -0.884 | 0.964  | 0.978   | 1     |     |      |
|                | Sig.           | 0.000          | 0.000 | 0.000 | 0.000   | 0.000   | 0.000   | 0.000 |     |      |
| \( \text{SRH} \) | R              | 0.849          | 0.843 | -0.930 | -0.937 | 0.923  | 0.940   | 0.932 | 1   |      |
|                | Sig.           | 0.000          | 0.000 | 0.000 | 0.000   | 0.000   | 0.000   | 0.000 | 0.000 |      |
| \( \text{UPV} \) | R              | 0.813          | 0.810 | -0.878 | -0.887 | 0.900  | 0.924   | 0.929 | 0.917 | 1    |
|                | Sig.           | 0.000          | 0.000 | 0.000 | 0.000   | 0.000   | 0.000   | 0.000 | 0.000 | 0.000 |
| \( \text{UCS} \) | R              | 0.914          | 0.873 | -0.945 | -0.948 | 0.891  | 0.909   | 0.902 | 0.980 | 0.891 | 1    |
|                | Sig.           | 0.000          | 0.000 | 0.000 | 0.000   | 0.000   | 0.000   | 0.000 | 0.000 | 0.000 | 0.000 |

Note: R: Pearson correlation coefficient and Sig.: significant level, Sig. (two-tailed).

Here, TC is the texture coefficient, AW is the grain packing weighting, \( N_0 \) is the number of grains whose aspect ratio is below a pre-set discrimination level, \( N_1 \) is the number of grains whose aspect ratio is above a pre-set discrimination level, \( FF_0 \) is the arithmetic mean of discriminated form factors, \( AR_1 \) is the arithmetic mean of discriminated aspect ratios, and \( AF_1 \) is the angle factor, quantifying grain orientation.

The AW, AR, and FF are calculated by the following equations [61]:

\[
AW = \sum \left( \frac{\text{grain areas within the reference area boundary}}{\text{area boundary by the reference area boundary}} \right)
\] (2)

\[
AR = \frac{L}{W}
\] (3)

\[
FF = \frac{4\pi A}{P^2}
\] (4)

In these equations, L is length, W is width, P is the perimeter, and A is the area. The angle factor (AF) is calculated by the equations below [61]:

\[
AF = \sum_{i=1}^{9} \left( \frac{X_i}{N(N-1)} \right) \times i
\] (5)

\[
AF_1 = \frac{AF}{5}
\] (6)
where \( x_i \) is the number of angular differences in each class, \( N \) is the total number of elongated grains, and \( i \) is the weighting factor and class number.

Calculation of TC is possible from TIFF format of microscopic images of rocks using the JMicroVision (v1.27) program. This is a valuable software program for determining the size, shape, orientation, and texture properties of different rocks. The JMicroVision (v1.27) environment for calculating TC is presented in Figure 7. The values of TC calculated from Equation (1) for the studied rock samples are presented in Table 4. Additionally, required parameters such as AW, AR, FF, and AF were determined and are summarized in this table. Based on the results, TC values were obtained from “0.42 to 1.06”. The samples of PDH\(_3\) and LAR\(_2\) have the lowest and highest values of TC, respectively. A comparative diagram of the values of TC for the studied rocks is shown in Figure 8a. Based on the histogram, the TC has an average value of 0.79, which is presented in Figure 8b. The standard deviation (Std. Dev.) values are very low, which shows a close dispersion of the TC values (Figure 8b). The parameters of AW, AR\(_1\), and TC have direct relations. Therefore, the value of TC will increase by increasing AW and AR\(_1\). The results are confirmed by the results presented by Howarth and Rowlands [60], Howarth and Rowlands [61], Ersoy and Waller [62], Gupta and Sharma [63], Tandon and Gupta [64], and Kolay and Baser [69].

![Figure 7. JMicroVision (v1.27) software environment for measuring TC of the rocks.](image1)

![Figure 8. (a) Diagram of the texture coefficient (TC) values and (b) histogram of the TC for the studied rock samples.](image2)
Table 4. Texture coefficient derivations for the rocks.

| Sample | AW | $N_0 / (N_0 + N_1)$ | 1 / $FF_0$ | $N_0 / (N_0 + N_1)$ | AR | AF | TC |
|--------|----|---------------------|-------------|---------------------|----|----|----|
| SBZ₁   | 0.66 | 0.81 | 1.29 | 0.19 | 1.73 | 0.5 | 0.8 |
| SBZ₂   | 0.66 | 0.82 | 1.13 | 0.18 | 1.65 | 0.5 | 0.7 |
| ELK₁   | 0.47 | 0.92 | 1.19 | 0.08 | 1.56 | 0.5 | 0.55 |
| ELK₂   | 0.6 | 0.84 | 1.21 | 0.16 | 1.74 | 0.5 | 0.7 |
| DLC₁   | 0.8 | 0.92 | 1.06 | 0.08 | 1.55 | 0.5 | 0.83 |
| DLC₂   | 0.71 | 0.9 | 1.1 | 0.1 | 1.53 | 0.5 | 0.75 |
| LAR₁   | 0.86 | 0.81 | 1.18 | 0.19 | 1.75 | 0.5 | 0.97 |
| LAR₂   | 0.98 | 0.83 | 1.14 | 0.17 | 1.69 | 0.5 | 1.06 |
| PDH₁   | 0.57 | 0.91 | 1.03 | 0.09 | 1.46 | 0.5 | 0.57 |
| PDH₂   | 0.58 | 0.97 | 1.04 | 0.03 | 1.47 | 0.5 | 0.8 |
| PDH₃   | 0.38 | 0.96 | 1.1 | 0.04 | 1.52 | 0.5 | 0.42 |
| BRT₁   | 0.87 | 0.83 | 1.25 | 0.17 | 1.8 | 0.5 | 1.04 |
| BRT₂   | 0.77 | 0.83 | 1.16 | 0.17 | 1.85 | 0.5 | 0.86 |
| SMK₁   | 0.85 | 0.85 | 1.15 | 0.15 | 1.68 | 0.5 | 0.94 |
| SMK₂   | 0.9 | 0.82 | 1.17 | 0.18 | 1.79 | 0.5 | 1.01 |

Note: The meaning of the acronyms and letters in the table were previously presented.

4. Data Analysis
4.1. Simple Regression Analysis (SRA)

The statistical and regression analyses were conducted by using the IBM SPSS Statistics v. 24 [83] computer program. The index, physical, and mechanical properties including dry and saturated unit weight, effective porosity, water absorption, slake durability index, Schmidt hardness, P-wave velocity, and uniaxial compressive strength were considered as independent variables and the TC was used as the dependent variable. Graphs of these correlations are presented in Figure 9. Additionally, the obtained predictive models and coefficient of determination ($R^2$) are presented in Table 5. The $R^2$ shows how the values will fit the data. It is calculated by the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y - y')^2}{\sum_{i=1}^{N} (y - \bar{y})^2}$$

Table 5. Simple regression models for texture coefficient (TC) of the studied rocks.
A three-dimensional view of the correlations among texture coefficient (TC), water absorption (Wa), porosity (n), slake durability index (Id), Schmidt rebound hardness (SRH), and uniaxial compressive strength (UCS) is shown in Figure 10. This figure can simultaneously show the relationship between the TC and two other parameters and expose the simultaneous relationship of these parameters with each other. Figure 9. Relations between texture coefficient (TC) and (a) dry and saturated unit weights (γd, γs), (b) effective porosity (n) and water absorption (Wa), (c) slake durability index (SDI), (d) Schmidt rebound hardness (SRH), (e) P-wave velocity (UPV), (f) uniaxial compressive strength (UCS) for the rocks.

The results of this evaluation show that R² is between 0.77 and 0.94 (similar to Gupta and Sharma [63] and Khanlari et al. [59]). Figure 8a shows direct exponential relationships between dry and saturated unit weights (γd, γs) and TC. High coefficients of determination (R²) of 0.80 and 0.83 were obtained from these evaluations. This means that the density of the studied rock samples is greatly affected by the values of TC. Relationships between porosity and water absorption and TC are inverse linear relations (Figure 9b) with high coefficients of determination (R²) of 0.86 and 0.88, respectively. Figure 9c shows relations between slake durability indexes and TC. For this purpose, Id₁, Id₂, and Id₃ were separately correlated to TC. There were direct power relations with good coefficients of determination (R²) of 0.77, 0.78, and 0.82, respectively. As can be seen, when the cycles of the slake durability test increase, the coefficient of determination increases. Therefore, correlations between SDI and TC present better results in upper cycles of the test. As can be seen in Figure 9d, a good direct logarithmic relationship is recognizable between SRH and TC with a high coefficient of determination (R²) of 0.82. A direct power relation was found between TC and UPV with a coefficient of determination (R²) of 0.85, which is shown in Figure 9e. Figure 9 shows a direct linear relation between UCS and TC with a very good
coefficient of determination ($R^2$) of 0.94. Direct relationships of SDI, SRH, UPV, and UCS with TC indicated that the engineering properties of the rocks are well correlated to texture coefficients (TC). A three-dimensional view of the correlations among texture coefficient (TC), water absorption ($W_a$), porosity (n), slake durability index (I$_d$), Schmidt rebound hardness (SRH), and uniaxial compressive strength (UCS) is shown in Figure 10. This figure can simultaneously show the relationship between the TC and two other parameters and expose the simultaneous relationship of these parameters with each other.

Figure 10. Three-dimensional view of the correlations among (a) texture coefficient (TC), slake durability index (I$_d$) and water absorption ($W_a$); (b) texture coefficient (TC), Schmidt rebound hardness (SRH) and porosity; (c) texture coefficient (TC), uniaxial compressive strength (UCS), and Schmidt rebound hardness (SRH).
To assess the performances of the models, the statistical parameters such as the regression coefficient (R), the root mean square error (RMSE), the coefficient values accounted for (VAF), the mean absolute percentage error (MAPE), and the performance index (PI) were evaluated by the following equations [84]:

\[ R = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}} \]  

(8)

\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y - y')^2} \]  

(9)

\[ \text{VAF} = \left[ 1 - \frac{\text{v} \text{a} \text{r} - y'}{\text{v} \text{a} \text{r}} \right] \times 100 \]  

(10)

\[ \text{MAPE} = \left[ \frac{1}{N} \sum_{i=1}^{N} \frac{|y - y'|}{y} \right] \times 100 \]  

(11)

\[ \text{PI} = \left[ R^2 + \left( \frac{\text{VAF}}{100} \right) - \text{RMSE} \right] \]  

(12)

In these equations, \( y \) and \( y' \) are the experimental and calculated values, respectively, and \( N \) is the total number of points. The models are excellent (the predicted values from the regression equation are equal to the experimental values) if \( R = 1 \), \( \text{RMSE} = 0 \), \( \text{VAF} = 100 \), \( \text{MAPE} = 0 \), and \( \text{PI} = 100 \). Ten predictive models were developed by simple regression analysis (Table 5). The values of parameters related to the model and significance level (Sig.) are presented in Table 6. R values obtained between 0.88 and 0.97 show the high validity of the experimental equations. RMSE values are very low in models 1 and 2, equal to 0.03, that correlate \( \gamma_d \) and \( \gamma_s \) to the TC. High VAF values were obtained from the models of SRH and UCS. However, mean absolute percentage error values are very low in the SDI models, especially in the Id\(_2\) model. Performance assessment by PI indicates model 8 has best performance among all models. This model correlates SRH to TC. The significance level for all developed models was calculated equal to 0.000. This indicates that the obtained predictive models by SRA with a 99% confidence limit predict the values of the independent variable when the TC is considered as an input. The results the simple regression analysis revealed that texture coefficients are good parameters for evaluating and predicting the physical, index, and mechanical properties of the studied rock samples.

**Table 6.** Statistical parameters for performance of SRA models.

| Model | R   | RMSE | VAF (%) | MAPE (%) | PI     | Sig. (Two-Tailed) |
|-------|-----|------|---------|----------|--------|------------------|
| 1     | 0.89| 0.03 | 79.73   | 2.06     | 79.77  | 0.000            |
| 2     | 0.91| 0.03 | 82.47   | 2.76     | 83.79  | 0.000            |
| 3     | 0.93| 0.95 | 85.92   | 40.52    | 85.91  | 0.000            |
| 4     | 0.94| 0.48 | 87.98   | 74.08    | 88.40  | 0.000            |
| 5     | 0.88| 0.25 | 75.85   | 0.13     | 77.51  | 0.000            |
| 6     | 0.88| 0.35 | 78.27   | 0.06     | 78.44  | 0.000            |
| 7     | 0.91| 0.45 | 81.70   | 0.26     | 83.36  | 0.000            |
| 8     | 0.96| 2.17 | 92.42   | 5.37     | 90.75  | 0.000            |
| 9     | 0.91| 0.30 | 82.20   | 2.30     | 83.52  | 0.000            |
| 10    | 0.97| 7.56 | 94.26   | 3.71     | 87.38  | 0.000            |

4.2. Multiple Regression Analysis (MRA)

The multiple regression analysis was performed by IBM SPSS Statistics v. 24 [83]. The multiple regression analysis creates a correlation between more than two parameters, and it results in a more accurate correlation with higher values of correlation coefficients (R) and coefficients of determination (R\(^2\)) than simple regression analysis. In the multiple
regression analysis, physical properties, namely, dry unit weight and porosity that are determined by a simple and cheap test, and also texture coefficient values were developed in this research and were considered as inputs or independent variables. Other engineering properties including $I_{2}$, SRH, UPV, and UCS were considered as dependent variables or outputs. Therefore, by three inputs of $\gamma_d$, $n$, and TC in four models, the values of $I_{2}$, SRH, UPV, and UCS were predicted.

The summary of coefficients related to multiple regression models, namely, Beta coefficient, standard error of Beta, significance level, lower and upper confidence interval, tolerance, and VIF, is presented in Table 7. The variance inflation factor (VIF) and tolerance are the statistical parameters that show multi-collinearity of models. Based on the results, tolerance values are obtained between 0 and 1. Therefore, the issue of collinearity does not exist in MR models.

Table 7. Multiple regression coefficients for the developed models.

| Model | Unstandardized Coefficients | Standardized Coefficients | t | Sig. | 95.0% Confidence Interval for B | Collinearity Statistics |
|-------|-----------------------------|---------------------------|---|------|--------------------------------|------------------------|
|       | B                           | Std. Error                | Beta |      | Lower Bound | Upper Bound | Tolerance | VIF |
| 1     | $I_{2}$                     | 93.635                    | 7.982 | 11.731 | 0.000       | 76.068     | 111.203   |     |
|       | $\gamma_d$                 | 1.743                     | 3.392 | 0.157 | 0.514       | 0.618      | 9.209     | 4.991 |
|       | $n$                         | -0.115                    | 0.107 | -0.391 | -1.068      | 0.308      | -0.351    | 0.139 |
|       | SRH                        | 1.457                     | 1.694 | 0.373 | 0.860       | 0.408      | -2.272    | 5.185 |
| 2     | $\gamma_d$                 | -5.283                    | 21.559 | -0.045 | -0.245      | 0.811      | -52.735   | 42.169 |
|       | $n$                         | -1.013                    | 0.682 | -0.325 | -1.485      | 0.166      | -2.515    | 0.488 |
|       | TC                          | 28.785                    | 10.767 | 0.694 | 2.673       | 0.022      | 5.087     | 52.483 |
|       | UPV                        | 2.969                     | 7.110 | 0.418 | 6.848       | -12.681    | 18.619    |     |
| 3     | $\gamma_d$                 | 0.131                     | 3.022 | 0.012 | 0.043       | 0.966      | -6.520    | 6.782 |
|       | $n$                         | -0.082                    | 0.096 | -0.288 | -0.853      | 0.412      | -0.292    | 0.129 |
|       | UC S                       | 2.349                     | 1.509 | 0.624 | 1.556       | 0.148      | -0.973    | 5.670 |
| 4     | $\gamma_d$                 | 98.474                    | 58.948 | 0.208 | 1.671       | 0.123      | -31.269   | 228.217 |
|       | $n$                         | -3.680                    | 1.865 | -0.295 | -1.973      | 0.074      | -7.786    | 0.425 |
|       | TC                          | 84.860                    | 29.440 | 0.511 | 2.883       | 0.015      | 20.064    | 149.656 |

Note: $\gamma_d$, $n$, and TC are independent variables (predictors); $I_{2}$, SRH, UPV, and UCS are dependent variables.

Table 8 shows the Rs values such as R, R square, adjusted R, standard error, R Square Change, and Dubrin–Watson for the models. The results in this table show that model 4 has greater R, which estimates UCS with $\gamma_d$, $n$, and TC. The Dubrin–Watson (DW) statistic is a number that tests for autocorrelation in the residual form of a statistic regression analysis. The DW statistic is always between 0 and 4. When the value is 0, it indicates negative autocorrelation.

Table 8. Various Rs values for the selected models.

| Model | R  | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change | Durbin–Watson |
|-------|----|----------|------------------|---------------------------|----------------|---------|-----|-----|------------|--------------|
| 1     | 0.892 b | 0.795   | 0.739            | 0.39213                   | 0.795          | 14.220  | 3   | 11  | 0.000       | 0.919        |
| 2     | 0.963 c  | 0.927   | 0.907            | 2.49232                   | 0.927          | 46.397  | 3   | 11  | 0.000       | 1.206        |
| 3     | 0.908 d  | 0.825   | 0.778            | 0.34932                   | 0.825          | 17.315  | 3   | 11  | 0.000       | 0.814        |
| 4     | 0.983 e  | 0.966   | 0.956            | 6.81453                   | 0.966          | 103.421 | 3   | 11  | 0.000       | 1.931        |

Note: a. Predictors (constants): TC, $\gamma_d$, n; b. Dependent variable: $I_{2}$; c. Dependent variable: SRH; d. Dependent variable: UPV; e. Dependent variable: UCS.
Predictive models that were obtained from the multiple regression analysis and statistical parameters for model performance are presented in Table 9. The predictive model for $\text{Id}_2$ has lower values of RMSE and MAPE. Model 4, which predicted UCS, has better values of VAF and PI, whereas this model has higher values of RMSE and MAPE. Significance level values indicated that all models predicted output values with a 99% confidence limit. $\gamma_{\text{dry}}, n$, and TC are good parameters to predict the engineering characteristics of the studied rocks based on the regression coefficients of multiple regression analysis. This result is similar to the results of Singh et al. [85], Alber and Kahraman [65], Manouchehrian et al. [42], Ersoy and Acar [66], and Akram et al. [68].

Table 9. Predictive models from multiple regression analysis and statistical parameters for performance of the models.

| Model | Predictive Model | RMSE | VAF (%) | MAPE (%) | PI     | Sig. (Two-Tailed) |
|-------|------------------|------|---------|----------|--------|------------------|
| 1     | $\text{Id}_2 = 93.64 + 1.74\gamma_{\text{yd}} - 0.12n + 1.46\text{TC}$ | 0.34 | 79.47   | 0.07     | 80.46  | 0.000            |
| 2     | $\text{SRH} = 35.31 - 5.28\gamma_{\text{yd}} - 1.01n + 28.79\text{TC}$ | 2.13 | 92.68   | 3.19     | 91.79  | 0.000            |
| 3     | $\text{UPV} = 2.97 + 0.13\gamma_{\text{yd}} - 0.08n + 2.35\text{TC}$ | 0.30 | 82.52   | 0.34     | 83.53  | 0.000            |
| 4     | $\text{UCS} = -215.93 + 98.47\gamma_{\text{yd}} - 3.68n + 84.86\text{TC}$ | 5.84 | 96.58   | 3.10     | 92.13  | 0.000            |

4.3. Artificial Neural Network (ANN)

The artificial neural network is a mathematical and computational approach that is taken from the structural and functional aspects of biological neural networks [86]. It has been widely adopted by scientists due to its ability to develop complex nonlinear models and is applied for solving a wide variety of applications [87]. In the present research, the feed-forward neural network was used to estimate the engineering characteristics of the studied rocks. Similar to the multiple regression models, $\gamma_{\text{dry}}, n$, and TC are constant input parameters in all models. $\text{Id}_2$, SRH, UPV, and UCS were considered as outputs that were predicted by models 1 to 4, respectively. All data were divided into three data sets for training, validation, and testing. Architectures of ANNs that were used in this research are presented in Figure 11. An ANN toolbox of MATLAB Version 9.1 (R2016b) [88] was used for neural network analyses.

![Figure 11. Schematic representation of the constructed neural network.](image)

Figure 11 shows the training state for the ANN models for predicting the outputs containing $\text{Id}_2$, SRH, UPV, and UCS established in the MATLAB environment. As can be seen from this figure, in models 1 to 4 after the epoch numbers of 4, 2, 3, and 2, the errors occur three times, and the test is stopped at different epoch numbers. Since the errors happen three times before stopping the test, the validation checks would be equal to three. Figure 13 shows the validation curves in ANN models for predicting the outputs containing $\text{Id}_2$, SRH, UPV, and UCS, which are established in the MATLAB (v. 9.1) environment. Based
on Figure 13a, which shows the predicted $I_{d_2}$, the best validation performance is happening at epoch 4, and the test is stopped at epoch 7 after three error repetitions. In models 2 and 4, for predicting SRH and UCS (Figure 13b,d), the test is stopped at epoch 2 after three error repetitions. Figure 13c shows the best validation performance is happening at epoch 3 (in model 3), and the test is stopped at epoch 6 after three error repetitions. The values of mean squared error (MSE), which is found on the $y$-axis in Figure 13, are approximately similar in four models, and in model 1 is less than other models. The plots of regression for training, testing, and validation of the proposed ANN model were established in the MATLAB (v. 9.1) environment. Very accurate correlation coefficients were obtained, as illustrated in Figure 14. In all models, R higher than 0.99 shows the high-performance validity of established models by ANN.

![Gradient vs Epoch](image1.png)

Figure 12. Training state in ANN models for prediction of (a) $I_{d_2}$, (b) SRH, (c) UPV, and (d) UCS.

To assess the performance of the results of the ANN models, the statistical parameter was calculated and is presented in Table 10. As can be seen, R values in all models are equal to 0.99. RMSE values, except in model 4 which predicted UCS, are very low, and in the predictive model of UPV is equal to 0.06. The performance index of the UPV model is equal to 99.94, which is high. Despite high values of RMSE and MAPE in model 4, the VAF value is higher than other models. The significance level in all models is equal to 0.000, indicating that predictive models by ANN estimated the output parameters with a 99% confidence limit.

Table 10. Statistical parameters for performance of ANN models.

| Model | R   | RMSE | VAF (%) | MAPE (%) | PI   | Sig. (Two-Tailed) |
|-------|-----|------|---------|----------|------|-------------------|
| 1     | 0.99| 0.09 | 98.60   | 0.36     | 99.89| 0.000             |
| 2     | 0.99| 0.48 | 99.63   | 0.42     | 99.22| 0.000             |
| 3     | 0.99| 0.06 | 99.39   | 0.85     | 99.94| 0.000             |
| 4     | 0.99| 2.05 | 99.67   | 2.47     | 99.67| 0.000             |
Figure 13. Validation curves in ANN models for prediction of (a) $\text{Id}_2$, (b) SRH, (c) UPV, and (d) UCS.

Figure 14. Regression plots of ANN models for predicting (a) $\text{Id}_2$, (b) SRH, (c) UPV, and (d) UCS.
5. Discussion

Statistical parameters, namely R, RMSE, VAF, MAPE, and PI, were evaluated for the developed models by SRA, MRA, and ANN to assess their accuracy. High values of the determination coefficient obtained from the SRA method indicate TC is an able coefficient for engineering properties estimation of the studied rocks. In MRA and ANN models, $\gamma_{dry}$, $n$, and TC were considered as inputs and four models were created for estimating $I_d$, SRH, UPV, and UCS of the studied samples. Then, the statistical parameter assesses the results of the MR and ANN models. A comparative diagram of R, RMSE, VAF, MAPE, and PI for the results of MRA and ANN models is presented in Figure 15. It is clear that the ANN models have better performance than the MR models. Except in model 4, for predicting UCS that shows approximately similar results for MRA and ANN models, the other models have valuable differences in statistical parameters. A higher R value for the ANN models means that there is a better relationship between experimental and calculated values in comparison to the MRA model. This result is confirmed by the research of Alber and Kahraman [65], Manouchehrian et al. [42], and Ersoy and Acar [66].

![Comparative diagrams of statistical coefficients for results of MRA and ANN models](image)

Figure 15. Comparative diagrams of statistical coefficients for results of MRA and ANN models (a) $R$, (b) RMSE, (c) VAF, (d) MAPE, and (e) PI.

Table 11 presents the experimental and calculated values of $I_d$, SRH, UPV, and UCS provided by the laboratory tests and models of MR and ANN together with the obtained standard deviation (S.D.) for all models. The results show that the values of the mean and standard deviation in ANN models are approximately equal to experimental values, which indicates less variety than MR models.
Table 11. Experimental and calculated values of \( \text{Id}_2 \), SRH, UPV, and UCS obtained from the MRA and ANN models.

| Sample | Model 1 (\( \text{Id}_2 \)) | Model 2 (SRH) | Model 3 (UPV) | Model 4 (UCS) |
|--------|-----------------------------|---------------|---------------|---------------|
|        | Ex. | MRA | ANN | Ex. | MRA | ANN | Ex. | MRA | ANN | Ex. | MRA | ANN |
| SBZ1   | 98.69 | 98.62 | 99.04 | 43 | 41.63 | 43.18 | 4.89 | 4.87 | 4.93 | 81.99 | 79.45 | 84.02 |
| SBZ2   | 98.87 | 98.33 | 98.87 | 39 | 37.50 | 39.14 | 4.80 | 4.54 | 4.80 | 76.40 | 66.4 | 76.88 |
| ELK1   | 98.43 | 97.78 | 98.43 | 31 | 29.82 | 30.74 | 4.59 | 3.93 | 4.57 | 45.54 | 44.96 | 46.14 |
| ELK2   | 98.15 | 98.08 | 98.15 | 35 | 35.45 | 34.89 | 4.61 | 4.37 | 4.62 | 56.58 | 58.93 | 56.67 |
| DLC1   | 98.66 | 98.42 | 98.66 | 40 | 36.42 | 39.95 | 4.37 | 4.48 | 4.37 | 73.67 | 67.36 | 74.01 |
| DLC2   | 98.57 | 98.22 | 98.56 | 40 | 36.42 | 39.95 | 4.37 | 4.48 | 4.37 | 73.67 | 67.36 | 74.01 |
| LAR1   | 98.99 | 98.95 | 98.98 | 45 | 45.98 | 45.15 | 5.44 | 5.26 | 5.48 | 95.45 | 98.97 | 99.09 |
| LAR2   | 99.34 | 99.32 | 99.37 | 47 | 49.38 | 47.90 | 5.75 | 5.57 | 5.83 | 108.55 | 116.6 | 111.65 |
| PDH1   | 97.25 | 97.81 | 97.25 | 30 | 31.18 | 29.88 | 3.85 | 4.02 | 3.84 | 46.29 | 44.91 | 41.78 |
| PDH2   | 97.26 | 97.77 | 97.26 | 30 | 31.18 | 29.88 | 3.85 | 4.02 | 3.84 | 46.29 | 44.91 | 41.78 |
| PDH3   | 97.04 | 97.10 | 97.04 | 24 | 24.57 | 23.25 | 3.09 | 3.44 | 3.07 | 16.09 | 13.14 | 18.22 |
| BRT1   | 99.05 | 99.41 | 99.06 | 48 | 49.40 | 48.30 | 5.53 | 5.58 | 5.35 | 119.82 | 119.45 | 120.68 |
| BRT2   | 98.71 | 98.95 | 98.74 | 43 | 43.19 | 43.84 | 5.10 | 5.06 | 5.13 | 90.12 | 96.88 | 91.46 |
| SMK1   | 99.29 | 99.09 | 99.32 | 46 | 45.72 | 45.03 | 4.91 | 5.26 | 4.96 | 105.09 | 104.51 | 107.73 |
| SMK2   | 99.38 | 99.40 | 99.38 | 49 | 48.64 | 48.67 | 5.16 | 5.52 | 5.17 | 127.43 | 118.44 | 127.97 |
| Mean   | 98.51 | 98.48 | 98.54 | 39.27 | 39.30 | 39.24 | 4.70 | 4.71 | 4.70 | 76.80 | 76.80 | 77.77 |
| S.D.   | 0.77 | 0.70 | 0.77 | 8.16 | 7.85 | 8.36 | 0.74 | 0.67 | 0.74 | 32.64 | 32.08 | 33.30 |

The experimental and calculated values of \( \text{Id}_2 \), SRH, UPV, and UCS have been plotted in diagrams of Figure 15 to compare the results of MRA and ANN for predicting the engineering characteristics of the studied rocks. The adaption rate of trend lines of MRA and ANN with the line \( y = x \) show the validity of the models. The correlations between experimental and calculated values of \( \text{Id}_2 \) that were obtained from \( \gamma_{\text{dry}}, n, \) and TC are shown in Figure 16a. Based on these graphs, the trend line of ANN completely fits the line \( y = x \), whereas the MRA trend line approximately intercepts the line \( y = x \). This shows the moderate validity of the equations of the MRA for estimating \( \text{Id}_2 \). The correlations between experimental and calculated values of SRH are shown in Figure 16b. As can be seen, the MRA and ANN trend lines approximately overlap together and show that both methods in this model obtained the same results for predicting Schmidt rebound hardness. Figure 16c shows the relationships between experimental results and calculated values of UPV. It is obvious that ANN estimated values of UPV are closer to the corresponding calculated values than MRA models. The trend line of the MRA model does not completely fit the 45° line and the results of the ANN are better than those. The correlations between experimental and calculated values of UCS are shown in Figure 16d. It shows that MRA and ANN trend lines of these diagrams entirely overlap together. So, both methods in this model have the same results for estimating the uniaxial compressive strength. Therefore, based on the results of different models, the predicted values from ANN models highly fit 45° lines and show the high validity of this method.

For the final assessment, residual error values were calculated for the results of MR and ANN models (Table 12). These values were calculated by subtraction of experimental and calculated values based on MRA and ANN created models. To compare the obtained values of residual error, their graphs were depicted for \( \text{Id}_2 \), SRH, UPV, and UCS models, respectively (Figure 17). Very low values of S.D. of ANN models show the validity of this method for predicting engineering characteristics of the studied rocks. Additionally, it was found that the average values of residual error in ANN models had a tendency to be 0.00, for instance, in model 3. Based on Figure 17, the ANN model has a lower residual error than the MR model. It can be seen that the error trend lines of ANN are more fit to the horizontal line (x-axis).
Figure 16. Plots of experimental and calculated values of (a) $\text{Id}_2$, (b) SRH, (c) UPV, and (d) UCS from the MRA and ANN.

Figure 17. Residual error plots of MRA and ANN models to predict (a) $\text{Id}_2$, (b) SRH, (c) UPV, and (d) UCS.
Table 12. Residual error values of MR and ANN models.

| Sample  | Model 1 (Id<sub>2</sub>) | Model 2 (SRH) | Model 3 (UPV) | Model 4 (UCS) |
|---------|-------------------------|---------------|---------------|---------------|
|         | MRA         | ANN         | MRA         | ANN         | MRA         | ANN         | MRA         | ANN         |
| SBZ<sub>1</sub> | 0.068 | −0.353 | 1.371 | −0.183 | 0.017 | −0.042 | 2.544 | −2.027 |
| SBZ<sub>2</sub> | 0.543 | 0.003 | 1.503 | −0.141 | 0.261 | −0.005 | 1.003 | −0.479 |
| ELK<sub>1</sub> | 0.650 | 0.000 | 1.181 | 0.264 | 0.659 | 0.021 | 0.583 | −0.599 |
| ELK<sub>2</sub> | 0.066 | 0.000 | −0.447 | 0.107 | 0.240 | −0.005 | −2.347 | −0.087 |
| DLC<sub>1</sub> | 0.238 | −0.001 | 3.559 | 0.089 | 0.188 | −0.021 | 8.831 | −0.269 |
| DLC<sub>2</sub> | 0.350 | 0.014 | 3.580 | 0.049 | −0.115 | −0.001 | 6.313 | −0.339 |
| LAR<sub>1</sub> | 0.042 | 0.007 | −0.984 | −0.155 | 0.182 | −0.042 | −3.521 | −3.639 |
| LAR<sub>2</sub> | 0.023 | −0.029 | −2.379 | −0.900 | 0.186 | −0.080 | −8.051 | −3.104 |
| PDH<sub>1</sub> | −0.558 | 0.000 | −1.181 | 0.123 | −0.166 | 0.012 | 1.477 | 4.508 |
| PDH<sub>2</sub> | −0.510 | 0.000 | −5.154 | 0.176 | −0.509 | 0.010 | −12.829 | −0.919 |
| PDH<sub>3</sub> | −0.064 | 0.000 | −0.571 | 0.752 | −0.344 | 0.027 | 2.952 | −2.133 |
| BRT<sub>1</sub> | −0.357 | −0.011 | −1.405 | −0.295 | −0.049 | 0.177 | 0.370 | −0.857 |
| BRT<sub>2</sub> | −0.240 | −0.030 | −0.189 | −0.840 | 0.045 | −0.032 | −6.758 | −1.339 |
| SMK<sub>1</sub> | 0.195 | −0.029 | 0.275 | 0.970 | −0.358 | −0.054 | 0.576 | −2.645 |
| SMK<sub>2</sub> | −0.019 | 0.002 | 0.360 | 0.335 | −0.361 | −0.008 | 8.989 | −0.536 |
| Mean    | 0.03 | −0.03 | −0.03 | 0.02 | −0.01 | 0.00 | 0.01 | −0.96 |
| S.D.    | 0.34 | 0.09 | 2.13 | 0.48 | 0.30 | 0.06 | 5.84 | 1.81 |

6. Conclusions

In this research, various limestone and sandstone rock samples were investigated to develop predictive models between their engineering properties including dry unit weight (γ<sub>dry</sub>), saturated unit weight (γ<sub>sat</sub>), water absorption (W<sub>a</sub>), porosity (n), Schmidt rebound hardness (SRH), ultrasonic P-wave velocity (UPV), and uniaxial compressive strength (UCS). The texture investigations carried out by using JMicroVision (v1.27) software led to texture coefficients (TC). Predictive models were developed by statistical and soft computing methods including simple regression analysis (SRA), multiple regression analysis (MRA), and artificial neural network (ANN). Ten experimental equations were developed by the SRA for predicting γ<sub>dry</sub>, γ<sub>sat</sub>, W<sub>a</sub>, SDI, SRH, UPV, and UCS from the TC values with very high values of Pearson regression coefficient (R). It was found that the TC has direct relations with γ<sub>d</sub>, γ<sub>s</sub>, SDI, SRH, UPV, and UCS, and inverse relations with n and W<sub>a</sub>. Additionally, four predictive models were developed by the MRA and ANN methods where γ<sub>d</sub>, n, and TC were considered as inputs and Id<sub>2</sub>, SRH, UPV, and UCS were considered as outputs. The values of the obtained correlation coefficients were very high from the MRA. In the ANN, the feed-forward neural network was used to establish predictive models, and the R value was obtained equal to 0.99 in all models. Statistical parameters including the RMSE, VAF, MAPE, and PI were evaluated and compared to each other for assessing the performance of the MRA and ANN models. The calculated statistical parameters indicated that the ANN models have better performance than the MRA models. The experimental and calculated values of Id<sub>2</sub>, SRH, UPV, and UCS obtained from the laboratory tests and predicted by the MRA and ANN models were approximately equal to each other. Additionally, the results of residual error analysis show lower standard deviations for predicted data by the ANN models than the MRA ones. The results of this research indicated texture coefficient analysis is a reliable method (as mentioned in Ersoy and Waller [62], Singh et al. [36], Alber and Kahraman [65], Gupta and Sharma [63], Manouchehrian et al. [42], Tandon and Gupta [64], Akram et al. [68], Kolya and Baser [69]) to predict engineering properties of the studied rocks. Therefore, by using the obtained results from the research and statistical methods as well as artificial neural networks, it is successfully possible to establish credible models for predicting engineering properties of other rocks. This can be an advantage of the present research. On the other hand, indirect estimation of engineering properties of rocks is not always as accurate as direct laboratory methods and this can be a limitation for this research and similar research.
Author Contributions: Investigation, D.F.; supervision, L.S.; writing—original draft, D.F.; writing—review & editing, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Fundação para a Ciência e a Tecnologia in the frame of the UIDB/00073/2020 and UIDP/00073/2020 projects of the I&D unit Geosciences Center (CGEO).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledge the official support of the Engineering Geology and Rock Mechanics Laboratory of Damghan University for performing all laboratory tests of the research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Carvalho, J.M.F.; Lisboa, J.V.; Moura, A.C.; Carvalho, C.; Sousa, L.M.O.; Leite, M.M. Evaluation of the Portuguese ornamental stone resources. Key Eng. Mater. 2013, 548, 3–9. [CrossRef]

2. Siegesmund, S.; Sousa, L.; López-Doncel, R.A. Editorial to the topical collection in Environmental Earth Sciences “Stone in the architectural heritage: From quarry to monuments-environment, exploitation, properties and durability”. Environ. Earth Sci. 2018, 77, 730. [CrossRef]

3. Siegesmund, S.; Dürrast, H. Physical and mechanical properties of the rocks. In Stone in Architecture. Properties, Durability, 5th ed.; Siegesmund, S., Snethlage, R., Eds.; Springer: Berlin/Heidelberg, Germany, 2014; pp. 97–224.

4. Mustafa, S.; Khan, M.A.; Kha, M.R.; Sousa, L.M.O.; Hameed, F.; Mughal, M.S.; Niaz, A. Building stone evaluation—A case study of the sub-Himalayas, Muzafarabad region, Azad Kashmir, Pakistan. Eng. Geol. 2016, 209, 56–69. [CrossRef]

5. Santos, I.; Sousa, L.; Lourenço, J. Granite resources evaluation-example of an extraction area in North of Portugal. Environ. Earth Sci. 2018, 77, 608. [CrossRef]

6. Yarahmadi, R.; Bagherpour, R.; Taherian, S.-G.; Sousa, L.M.O. A new quality factor for the building stone industry: A case study of stone blocks, slabs, and tiles. Bull. Eng. Geol. Environ. 2019, 78, 533–542. [CrossRef]

7. Ahmed, I.; Basharat, M.; Sousa, L.; Mughal, M.S. Evaluation of building and dimension stone using physico-mechanical and petrographic properties: A case study from the Kohistan and Ladakh batholith, Northern Pakistan. Environ. Earth Sci. 2021, 80, 759. [CrossRef]

8. Bogdanowitsch, M.; Sousa, L.; Siegesmund, S. Building stone quarries: Resource evaluation by block modelling and unmanned aerial photogrammetric surveys. Environ. Earth Sci. 2022, 81, 16. [CrossRef]

9. Sousa, L.M.O.; Gonçalves, B.M.M. Differences in the quality of polishing between sound and weathered granites. Environ. Earth Sci. 2013, 69, 1347–1359. [CrossRef]

10. Sousa, L.; Siegesmund, S.; Wedekind, W. Salt weathering in granitoids: An overview on the controlling factors. Environ. Earth Sci. 2018, 77, 502. [CrossRef]

11. Menningen, J.; Siegesmund, S.; Lopes, L.; Martins, R.; Sousa, L. The Estremoz marbles: An updated summary on the geological, mineralogical and rock physical characteristics. Environ. Earth Sci. 2018, 77, 191. [CrossRef]

12. Vázquez, P.; Sánchez-Delgado, N.; Carrizo, L.; Thomachot-Schneider, C.; Alonso, F.J. Statistical approach of the influence of petrography in mechanical properties and durability of granitic stone. Environ. Earth Sci. 2018, 77, 287. [CrossRef]

13. Sousa, L. Behaviour of hard stones submitted to different foot traffic. Environ. Earth Sci. 2019, 78, 680. [CrossRef]

14. Freire-Lista, D.M.; Sousa, L.; Carter, R.; Al-Na‘ím¯ı, F. Petrography and petrophysical characterisation of the heritage stones of Fuwairit Archaeological Site (NW Qatar) and their historical quarries: Implications for heritage conservation. Episodes 2021, 44, 43–58. [CrossRef]

15. ISRM. The Blue Book: The Complete ISRM Suggested Methods for Rock Characterization, Testing and Monitoring, 1974–2006; Compilation Arranged by the ISRM Turkish National Group, Ankara, Turkey; Ulusay, R., Hudson, J.A., Eds.; Kazan Offset Press: Ankara, Turkey, 2007.

16. AbuShanab, W.S.; Abd Elaziz, M.; Ghandourah, E.I.; Mostafa, E.B.; Elsheikh, A.H. A new fine-tuned random vector functional link model using Hunger games search optimizer for prediction of residual stresses during turning of Inconel 718. J. Mater. Res. Technol. 2021, 15, 3622–3634. [CrossRef]

17. Elsheikh, A.H.; Panchal, H.; Ahmadein, M.; Mosleh, A.O.; Sadasivuni, K.K.; Alsaleh, N.A. Productivity forecasting of solar distiller integrated with evacuated tubes and external condenser using artificial intelligence model and moth-flame optimizer. Case Stud. Therm. Eng. 2021, 28, 101671. [CrossRef]
20. Khoshaim, A.B.; Moustafa, E.B.; Bafakeeh, O.T.; Elsheikh, A.H. An optimized multilayer perceptrons model using grey wolf optimizer to predict mechanical and microstructural properties of friction stir processed aluminum alloy reinforced by nanoparticles. *Coatings* **2021**, *11*, 1476. [CrossRef]

21. Thangaraj, M.; Ahmadein, M.; Alsaleh, N.A.; Elsheikh, A.H. Optimization of abrasive water jet machining of SiC reinforced aluminum alloy based metal matrix composites using Taguchi–DEAR technique. *Materials* **2021**, *14*, 6250. [CrossRef]

22. Elsheikh, A.H.; Abd Elaziz, M.; Ramesh, B.; Egiza, M.; Al-qaness, M.A. Modeling of drilling process of GFRP composite using a hybrid random vector functional link network/parasitism-predation algorithm. *J. Mater. Res. Technol.* **2021**, *14*, 298–311. [CrossRef]

23. Elsheikh, A.H.; Abd Elaziz, M.; Das, S.R.; Muthuramalingam, T.; Lu, S. A new optimized predictive model based on political optimizer for eco-friendly MQL-turning of AISI 4340 alloy with nano-lubricants. *J. Manuf. Process.* **2021**, *67*, 562–578. [CrossRef]

24. Moustafa, E.B.; Hammad, A.H.; Elsheikh, A.H. A new optimized artificial neural network model to predict thermal efficiency and water yield of tubular solar still. *Case Stud. Therm. Eng.* **2022**, *30*, 101750. [CrossRef]

25. Abdolrasol, M.G.; Hussain, S.S.; Ustun, T.S.; Sarker, M.R.; Hannan, M.A.; Mohamed, R.; Ali, J.A.; Mekhilef, S.; Milad, A. Artificial neural networks based optimization techniques: A review. *Electronics* **2021**, *10*, 2689. [CrossRef]

26. Deere, D.U.; Miller, R.P. *Engineering Classification and Index Properties for Intact Rock*; Air Force Weapons Lab Tech Report AFWL-TR 65–116, Kirtland Base; US Air Force Weapons Laboratory, Kirtland AFB: Albuquerque, NM, USA, 1966.

27. Bell, F.G. Physical and mechanical properties of the Fell sandstones, Northumberland, England. *Eng. Geol.* **1978**, *12*, 1–29. [CrossRef]

28. Coggan, J.S.; Stead, D.; Howe, J.H.; Faulks, C.I. Mineralogical controls on the engineering behavior of hydrothermally altered granites under uniaxial compression. *Eng. Geol.* **2013**, *160*, 89–102. [CrossRef]

29. Alikarami, R.; Torabi, A.; Kolyukhin, D.; Skurtveit, E. Geostatistical relationships between mechanical and petrophysical properties of deformed sandstone. *Int. J. Rock Mech. Min. Sci.* **2013**, *63*, 27–38. [CrossRef]

30. Cantisani, E.; Garzonio, C.A.; Ricci, M.; Vettori, S. Relationships between the petrographical, physical and mechanical properties of some Italian sandstones. *Int. J. Rock Mech. Min. Sci.* **2013**, *60*, 321–332. [CrossRef]

31. Abdimutalib, A.; Abdullah, A.; Korkin, G.; Abduralheem, A. The relationship between lithological and geomechanical properties of tight carbonate rocks from Upper Jubaila and Arab-D Member outcrop analog, Central Saudi Arabia. *Arab. J. Geosci.* **2015**, *8*, 11031–11048. [CrossRef]

32. Koralegedara., N.H.; Maynard, J.B. Chemical, mineralogical and textural properties of the Kope Formation mudstones: How they affect its durability. *Eng. Geol.* **2017**, *228*, 312–322. [CrossRef]

33. Cowie, S.; Walton, G. The effect of mineralogical parameters on the mechanical properties of granitic rocks. *Eng. Geol.* **2018**, *240*, 204–225. [CrossRef]

34. Fereidooni, D.; Khajevand, R. Determining the geotechnical characteristics of some sedimentary rocks from Iran with an emphasis on the correlations between physical index and mechanical properties. *Geotech. Test. J.* **2018**, *41*, 555–573. [CrossRef]

35. Lawal, A.I.; Oniyide, G.O.; Kwon, S.; Onifade, M.; Köken, E.; Ogunsola, N.O. Prediction of Mechanical Properties of Coal from Non-destructive Properties: A Comparative Application of MARS, ANN, and GA. *Nat. Resour. Res.* **2021**, *30*, 4547–4563. [CrossRef]

36. Singh, V.K.; Singh, D.; Singh, T.N. Prediction of strength properties of some schistose rocks from petrographic properties using artificial neural networks. *Int. J. Rock Mech. Min. Sci.* **2001**, *38*, 269–284. [CrossRef]

37. Kilić, A.; Teymen, A. Determination of mechanical properties of rocks using simple methods. *Bull. Eng. Geol. Environ.* **2008**, *67*, 237–244. [CrossRef]

38. Jensen, L.R.; Friis, H.; Fundal, E.; Møller, P.; Jespersen, M. Analysis of limestone micromechanical properties by optical microscopy. *Eng. Geol.* **2010**, *110*, 43–50. [CrossRef]

39. Asadi, M.; Eftekhar, M.; Bagheripour, M.H. Evaluating the strength of intact rocks through genetic programming. *Appl. Soft Comput.* **2011**, *11*, 1932–1937. [CrossRef]

40. Cevik., A.; Sezer, E.A.; Cabalar, A.F.; Gokceoglu, C. Modeling of the uniaxial compressive strength of some clay-bearing rocks using neural network. *Appl. Soft Comput.* **2011**, *11*, 2587–2594. [CrossRef]

41. Singh, T.N.; Verma, A.K. Comparative analysis of intelligent algorithms to correlate strength and petrographic properties of some schistose rocks. *Eng. Comput.* **2012**, *28*, 1–12. [CrossRef]

42. Manouchehrian, A.; Shariﬁzadeh, M.; Moghadam, R.H. Application of artificial neural networks and multivariate statistics to estimate UCS using textural characteristics. *Int. J. Min. Sci. Technol.* **2012**, *22*, 229–236. [CrossRef]

43. Ozcelik, Y.; Bayram, F.; Yastith, N.E. Prediction of engineering properties of rocks from microscopic data. *Arab. J. Geosci.* **2013**, *6*, 3651–3668. [CrossRef]

44. Esamaldeen, A.; Guang, W. Selection of influential microfabric properties of anisotropic amphibolite rocks on its uniaxial compressive strength (UCS): A comprehensive statistical study. *J. Appl. Math. Phys.* **2014**, *2*, 1130–1138.

45. Liu, Z.; Shao, J.; Xu, W.; Zhang, Y.; Chen, H. Prediction of elastic compressibility of rock material with soft computing techniques. *Appl. Soft Comput.* **2014**, *22*, 118–125. [CrossRef]

46. Chen, W.; Konietzky, H.; Abbas, S.M. Numerical simulation of time-independent and -dependent fracturing in sandstone. *Eng. Geol.* **2015**, *193*, 118–131. [CrossRef]
47. Ajalloeian, R.; Mansouri, H.; Baradaran, E. Some carbonate rock texture effects on mechanical behavior, based on Koohrang tunnel data. Iran. Bull. Eng. Geol. Environ. 2016, 76, 295–307. [CrossRef]
48. Fereidooni, D. Determination of the geotechnical characteristics of hornfelsic rocks with a particular emphasis on the correlation between physical and mechanical properties. Rock Mech. Rock Eng. 2016, 49, 2595–2608. [CrossRef]
49. Ahmad, M.; Ansari, M.K.; Singh, R.; Sharma, L.K.; Singh, T.N. Assessment of durability and weathering state of some igneous and metamorphic rocks using micropetrographic index and rock durability indicators: A case study. Geotech. Geol. Eng. 2017, 35, 827–842. [CrossRef]
50. Germinario, L.; Siegsmund, S.; Maritan, L.; Mazzoli, C. Petrophysical and mechanical properties of Euganean trachyte and implications for dimension stone decay and durability performance. Environ. Earth Sci. 2017, 76, 739. [CrossRef]
51. Yalcinalp, B.; Aydin, Z.O.; Ersoy, H.; Seren, A. Investigation of geological, geotechnical and geophysical properties of Kiratli (Bayburt, NE Turkey) travertine. Carbonates Evaporites 2018, 33, 421–429. [CrossRef]
52. Matin, S.S.; Farahzadi, L.; Makarem, S.; Chelgani, S.C.; Sattari, G.H. Variable selection and prediction of uniaxial compressive strength and modulus of elasticity by random forest. Appl. Soft Comput. 2018, 70, 980–987. [CrossRef]
53. Brace, W.F. Dependence of fracture strength of rocks on grain size. In 4th US Symposium on Rock Mechanics (USRMS); OnePetro: University Park, PA, USA, 1961; pp. 99–103.
54. Das, D.K.; Kumar, A.; Das, B.; Burnwal, A.P. On soft computing techniques in various areas. Comput. Sci. Inf. Technol. 2013, 3, 166.
55. Ulusay, R.; Tureli, K.; Ider, M.H. Prediction of engineering properties of selected litharenite sandstone from its petrographic characteristics using correlation and multivariate statistical techniques. Eng. Geol. 1994, 37, 135–157. [CrossRef]
56. Tugrul, A.; Zarin, I.H. Correlation of mineralogical and textural characteristics with engineering properties of selected granitic rocks from Turkey. Eng. Geol. 1999, 51, 303–317. [CrossRef]
57. Eberli, G.P.; Baechle, G.T.; Anselmetti, F.S.; Incze, M.L. Factors controlling elastic properties in carbonate sediments and rocks. Lead. Edge 2003, 22, 654–660. [CrossRef]
58. Meng, J.; Pan, J. Correlation between petrographic characteristics and failure duration in elastic rocks. Eng. Geol. 2007, 89, 258–265. [CrossRef]
59. Khanlari, G.R.; Heidari, M.; Noori, M.; Momeni, A. The effect of petrographic characteristics on engineering properties of clastic rocks from Hamedan province. Iran. J. Geol. 2016, 49, 2609–2621. [CrossRef]
60. Howarth, D.F.; Rowlands, J.C. Development of an index to quantify rock texture for qualitative assessment of intact rock properties. Geotech. Test. J. 1986, 9, 169–179. [CrossRef]
61. Howarth, D.F.; Rowlands, J.C. Quantitative assessment of rock texture and correlation with drillability and strength properties. Rock Mech. Rock Eng. 1987, 20, 57–85. [CrossRef]
62. Ersoy, A.; Waller, M.D. Textural characterization of rocks. Eng. Geol. 1995, 39, 123–136. [CrossRef]
63. Gupta, V.; Sharma, R. Relationship between textural, petrophysical and mechanical properties of quartzites: A case study from northwestern Himalaya. Eng. Geol. 2012, 135, 1–9. [CrossRef]
64. Tandon, R.S.; Gupta, V. The control of mineral constituents and textural characteristics on the petrophysical and mechanical (PM) properties of different rocks of the Himalaya. Eng. Geol. 2013, 153, 125–143. [CrossRef]
65. Alber, M.; Kahraman, S. Predicting the uniaxial compressive strength and elastic modulus of a fault breccia from texture coefficient. Rock Mech. Rock Eng. 2002, 35, 117–127. [CrossRef]
66. Ersoy, H.; Acer, S. Influences of petrographic and textural properties on the strength of very strong granitic rocks. Environ. Earth Sci. 2016, 75, 1461–1476. [CrossRef]
67. Aligholi, S.; Laskaripour, G.R.; Ghafoori, M.; Azali, S.T. Evaluating the relationships between NTNU/SINTEF drillability indices with index properties and petrographic data of hard igneous rocks. Rock Mech. Rock Eng. 2017, 50, 2929–2953. [CrossRef]
68. Akram, M.S.; Farooq, S.; Naeem, M.; Ghazi, G. Prediction of mechanical behaviour from mineralogical composition of Sakesar limestone, Central Salt Range, Pakistan. Bull. Eng. Geol. Environ. 2017, 76, 601–615. [CrossRef]
69. Kolay, E.; Baser, T. The effect of the textural characteristics on the engineering properties of the basalts from Yozgat region, Turkey. J. Geol. Soc. India 2017, 90, 102–110. [CrossRef]
70. Geological Society of Iran (GSI). Geological Quadrangle Map of Iran. No. D6, Scale 1:100,000; Offset Press: Tehran, Iran, 1977.
71. ASTM. Standard Guide for Petrographic Examination of Dimension Stone (C1721); Book Standards vol 04.07; ASTM International: West Conshohocken, PA, USA, 2009. [CrossRef]
72. ASTM. Standard test method for slate-durability of shales and similar weak rocks (D-4644). In Annual Book of ASTM Standards; ASTM International: West Conshohocken, PA, USA, 1996; Volume 4.08, pp. 863–865.
73. ISRM. Suggested Methods for Determining Hardness and Abrasiveness of Rocks; Commission on Standardization of Laboratory and Field Test; International Society for Rock Mechanics: Salzburg, Austria, 1978; Volume 15, pp. 89–97.
74. ASTM. Standard Test Method for Determination of Rock Hardness by Rebound Hammer Method; ASTM standards on disc 04.09; ASTM International: West Conshohocken, PA, USA, 2001; pp. D5873–D5880.
75. ASTM. Standard Test Method for Laboratory Determination of Pulse Velocities and Ultrasonic Elastic Constants of Rock; ASTM International: West Conshohocken, PA, USA, 1996; pp. D2845–D2895.
76. ASTM. Standard Test Method for Unconfined Compressive Strength of Intact Rock Core Specimens; ASTM standards on disc 04.08; ASTM International: West Conshohocken, PA, USA, 1995; p. D2938.
77. IAEG. Classification of rocks and soils for engineering geological mapping, Part 1: Rock and soil materials. Bull. Int. Assoc. Eng. Geol. 1979, 19, 364–371. [CrossRef]

78. Gamble, J.C. Durability-Plasticity Classification of Shales and Other Argillaceous Rocks. Ph.D. Thesis, University of Illinois, Urbana-Champaign, IL, USA, 1971; p. 161.

79. Broch, E.; Franklin, J.A. The point load strength test. Int. J. Rock Mech. Min. Sci. 1972, 9, 669–697. [CrossRef]

80. Sousa, L.; Menningen, J.; López-Doncel, R.; Siegesmund, S. Petrophysical properties of limestones: Influence on behaviour under different environmental conditions and applications. Environ. Earth Sci. 2021, 80, 814. [CrossRef]

81. Williams, H.; Turner, F.J.; Gilber, C.M. Petrography: An Introduction to the Study of Rocks in Thin Section; W.H. Freeman Company: San Francisco, CA, USA, 1954; p. 406.

82. Prikiry, R. Assessment of rock geomechanical quality by quantitative rock fabric coefficients: Limitations and possible source of misinterpretations. Eng. Geol. 2006, 87, 149–162. [CrossRef]

83. IBM Corp. Released. IBP SPSS Statistics for Windows; Version 24.0; IBM Corp: Armonk, NY, USA, 2016.

84. Fereidooni, D. Importance of the mineralogical and textural characteristics in the mechanical properties of rocks. Arab. J. Geosci. 2022, 15, 637. [CrossRef]

85. Singh, R.; Kainthola, A.; Singh, T.N. Estimation of elastic constant of rocks using an ANFIS approach. Appl. Soft Comput. 2012, 12, 40–45. [CrossRef]

86. Sirdesai, N.N.; Singh, A.; Sharma, L.K.; Singh, R.; Singh, T.N. Development of novel methods to predict the strength properties of thermally treated sandstone using statistical and soft-computing approach. Neural Comput. Appl. 2017, 31, 2841–2867. [CrossRef]

87. Suparta, W.; Alhasa, K.M. Modeling of Tropospheric Delays Using ANFIS. Springer Briefs in Meteorology; Springer: Cham, Switzerland, 2016.

88. MATLAB and Statistical Toolbox; The Mathworks, Inc.: Natick, MA, USA, 2016.