International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Sorting Speckled Granites (Nehbandan) and Measuring Their Surface Veining using Machine Vision

Hossein KardanMoghaddam, Amir Rajaei, MohamadReza Maraki

Abstract*: Quality control and the appearance evaluation of stones are quite challenging in the industry today. The similar appearance of different stones containing the same minerals may result in economic losses, and if the customers fail to identify the type of slates delivered to them correctly, disagreements may arise between the buyers and granite vendors. This study is an attempt toward the automation of surface quality assessment of the Nehbandan(Iran) speckled granite and measurement of the surface patterns under fixed conditions using image processing techniques in order to classify the granite tiles based on their type and amount of impurities and veins. The experimental tests comparing the presented approach with the texture descriptors in the introduced dataset prove the efficiency of the proposed method and its applications under controlled conditions, including the classification of speckled granite tiles with different image resolutions.

***Keywords* : Image Processing, Speckled Granite, Segmentation of Minerals, Classification.**

I. INTRODUCTION

Natural stones were the first construction materials employed by man and have been incorporated into new structures to date. Decorative stones are selected based on their elegance, price, durability, strength, and popularity. The natural stone industry has seen a gradual but significant growth in the past three decades. Granite is a natural stone that has attracted considerable attention for its beautiful appearance and strength. According to the University of Tennessee [1], granite is an intrusive igneous rock that is spread across a wide area of the earth and 31 miles (50 Km) deep into its crust. The texture of granite features medium-to-large grains that can be spotted with the naked eye. The stone is resistant to frost and weathering and, due to its hardness, could not have been extracted in the form of plaques until recently. However, technological development and the introduction of new diamond stone cutters helped increase its production. Granite weighs 2/6 tons/m^3 on average, features a low absorption (below 1%) due to the low porosity and compactness, and has a compressive strength of 100-300 MPa. The strength and hardness of granite allow it to be produced in the form of sheets with a thickness no more than a few millimeters. However, this hardness increases the cutting costs compared with lime stones. Granite has been incorporated in interior and exterior building purposes for millennia. The word "Granite" was derived from "Granum" in Latin, which means "Grain". The grainy texture of granite was formed by the amalgamation of slowly-solidified, molten rock crystals in the deep layers of the Earth's crust. The size of granite crystals depends on the time they took to cool down. Granite is often extracted in the form of dimension stones (natural stones cut into blocks of specific length, width, and thickness). Granite is sufficiently hard, strong, and neutral to, respectively, withstand harsh abrasion, endure a considerable weight, and resist weathering. It can also be polished by grinding. All these features make granite a popular and useful option as a construction stone. Polishing the surface of granite displays the best appearance of this stone, which helps the incorporated crystals shine and reveal the background color vividly. Thanks to its natural abundance, granite is a well-known igneous rock. Many recognize granite for it is the most common stone found on the ground surface and is widely used to fabricate daily objects. The most notable granite reserves in Iran include mountains Sahand, Sabalan, Alvand in the west, Shirkooh in Yazd and South Khorasan, and Taftan. Granite is formed by the slow crystallization of magma deep into the Earth's crust. As an intrusive igneous rock, granite features medium-to-large grains and minerals such as feldspar, quartz, mica, and a few others. The color of the stone varies from pink to dark gray and even black based on the minerals and chemical composition of the stone. Boasting a density of 2.75 gr/cm3, granite is one of the heaviest stones found in nature. Features of granite may vary from one country to another. This shows the necessity of unified denomination criteria that are established by the European Standard EN12440 (2009) [2]. However, when it is required to sort and grade granite products based on their appearance, the standard is of little use.

Manuscript published on 30 September 2019
* Correspondence Author
Hossein KardanMoghaddam*, Department of Computer Engineering, Birjand University of Technology, Birjand, Iran. h.kardanmoghaddam@birjandut.ac.ir
Amir Rajaei, Faculty Member of Computer Engineering, Velayat University,Iranshahr, Iran. a.rajaei@velayat.ac.ir
MohamadReza Maraki, Department of Materials Engineering, Birjand University of Technology, Birjand, Iran

In fact, depending on the natural origins of the stones, the visual appearance of granites with identical mineralogy can be notably different to the extent where stones extracted from the same ore may appear differently. Non-uniformity in the appearance of the same plates forming granites can result in disputes between the buyers and the vendors. Such tensions may exert heavy losses on granite companies due to the shipping costs and delay penalties. Furthermore, globalization has increased the need for a standard denomination system for granites. Given the various colors of granite, its denomination varies by country. Even using the established standards, including that of the European Committee for Standardization (CEN) (2009) [3] and Stone Industry SA Standards Board (2015) [4], the visual appearance of granites with identical minerals may have notable differences in some cases in the industry, forcing the vendors to conduct costly and time-consuming slab-by-slab evaluations. Customers will not be satisfied if the color of the delivered product is different from the first slabs that were purchased. The customer may reject a group of tiles due to their difference with the samples based on which the purchase was made, or due to the major changes in the appearance of the stone compared with the initial sample. Current granite inspection standards draw on the geometrical specifications including the longitudinal dimensions of the blocks, the flatness of the slates, or the straightness of the tile edges. Nonetheless, the visual specifications are not very accurate [5]. Granites are often described by a generic name, as well as a predominant color, for example, Baltic brown, emerald pearl, or imperial pink. It must be noted that the terminology varies from one country to another.

II. Mineralogy of Granites

Silicon and aluminum are the essential elements in the chemical composition of all granites (nearly 85%), with potassium, calcium, iron, magnesium, and titanium scattered in the constituent minerals as different silicates. The essential minerals in granites are quartz, potassium feldspar, plagioclase, and dark minerals, the abundance of each is reported in Table 1. In addition, the accessory minerals include zirconia, apatite, opaque minerals (ilmenite, magnetite, hematite, and pyrite), and in case of metasomatism, metasomatic minerals such as kaolinite, and epidote are also present in the granite structure. The approximate mineral content of the granite is presented in Table 1 [6].

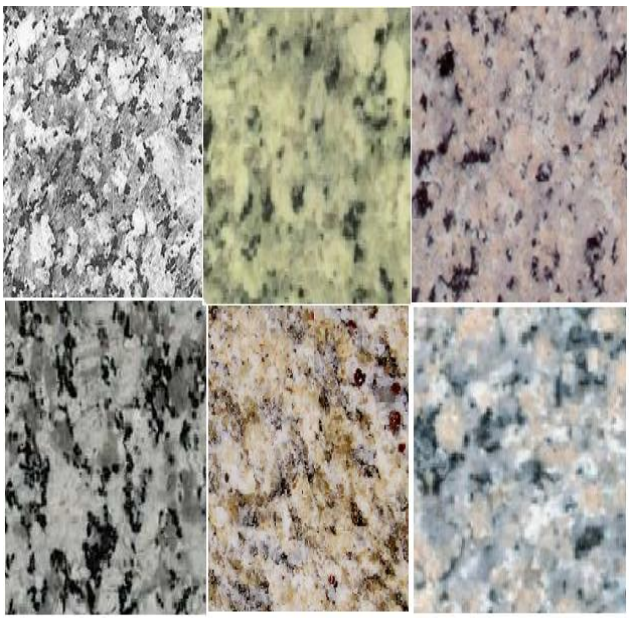
Table 1: The essential minerals in granites [6].

Percentage	*Mineral*
20-60	Quartz
0-35	Sodic Plagioclase (Albite & Oligoclase)
30-60	Potassic Feldspar (often orthoclase, sometimes microcline)
5-35	Mafic Minerals (Hornblende & Mica)

III. Nehbandan Granite

South Khorasan is a province located east of Iran with Birjand as its capital. The province spreads across 151,193 square kilometers, making it the third largest province of Iran. The province boasts many mining opportunities which include decorative stones and granite. South Khorasan enjoys a varied geology which includes all the three principal formations, namely sedimentary, igneous, and metasomatic zones. The southern regions of the province, which are located on top of sedimentary, igneous, and even metasomatic zones, are rich with immense reserves of construction materials, copper, chromite, magnesite, and several other valuable elements, minerals, and stones. As the largest copper mine in Iran, Qaleh Zari mine, located in Birjand, is an example of these resources. Located south of the province, the Nehbandan speckled granite mine is one of the best-known granite mines of Iran. The Nehbandan granite is a type of speckled granite with larger grains compared with white Natanz or Borujerd granites or the Zahedan granite. The Nehbandan granite is found in multiple color schemes that are assigned separate names. Types of Nehbandan granites include the Gray Nehbandan Granite, also known as the Astan Nehbandan Granite, the Cream Nehbandan Granite, the Orange-Cream Nehbandan Granite, the Thalath Nehbandan Granite, and the Shaghayegh Nehbandan Granite. Nehbandan granites feature a low absorption and excellent resistance and are easy to grind. A high-quality grade Nehbandan Granite is uniform and has no voids or black lumps.

Fig. 1. Various types of Nehbandan speckled granite (top a, b, c, and bottom d, e, f).



This study addresses the Gray Nehbandan Speckled Granite. This stone features a light background and darker grains inside the stone and is very popular both in the Iranian and global markets. Unlike travertine or marble, the Gray Nehbandan Speckled Granite is not sorted into many types. As a result, it is a great candidate for large-scale projects. The results of the analysis of the Nehbandan granite are presented in Table 2 [7].

Table- 2: Analysis results for the Nehbandan Granite [7].

	Water Absorption	*Gravity*	*Porosity*	*Compressive Strength*	*Abrasion Resistance*
Nehbandan Granite	0.08	2.7	0.18	2140	3.2

IV. THE NATURAL RADIATION OF GRANITES (NEHBANDAN)

According to the European Commission manual no. 112, Radiological Protection Principles concerning the Natural Radiation of Building Materials, 1999, all construction materials with an effective dose of 0.3 mSv/y are exempt of all limitations concerning natural radiation, while those with an effective dose above 1 mSv/y exceed the standards and are required to be insulated. Given the radioactivity of granite, it is not suitable for usage in environments exposed to X and gamma rays, powerful magnetic fields, or harmful chemicals. According to laboratory examinations, granite emits sinusoidal radioactive rays at periods specific to each of its constituent elements, thus polluting the environment with carcinogens. Radium is the most notable nucleus in the decay chain of Uranium (238U), with respect to which the uranium-related radioactivity is often measured. The radiation dose of any stone specimen can be evaluated using the radioactivity concentrations of, 232Th40K, and 226Ra [8] [9]. The natural radiation of granite specimens employed as construction materials in Iran was studied in [10]. This study addresses the Nehbandan granite and the mineralogy (Table 3) and the natural radiation of this stone (Table 4).

Table 3:. The Mineralogy of the Nehbandan Granite.

Commercial Name	Essential Minerals	Accessory Minerals
Nehbandan Granite	Potassium Feldspar + Plagioclase + Quartz + Biotite	Apatite + Zirconia + Iron Oxides

Comparing the data obtained from measuring the radioactivity and the mineralogy results are indicative of the role of potassium feldspar as the essential mineral and zirconia, sphene, apatite, and allanite as accessory minerals in the high radioactivity of granite. As evident from Table 4, the effective annual dose of natural radiation of the Nehbandan granite is 0.74, which is lower than many similar granites (Takab, Ahar, Mahabad, Hamedan speckled, Khorramdarreh, Borujerd, and Bukan granites) that were studied in [10]. Furthermore, this does not exceed the standard recommended annual dose, which is 1, making it a justifiable choice as construction material.

V. EVALUATING THE STONE QUALITY

In most cases, the quality of stones is evaluated by human experts in a manual process that is prone to errors. This process should be faster and more accurate in international operations of rock industries.To prevent such issues, stone manufacturers have adopted visual appearance inspections that are often carried out manually by skilled operators, giving room to personal preferences and human error. Similar approaches have been widely accepted in recent years. However, the increased stone production and need for a quantitative standardization at a global scale have changed the circumstances, leading to the formation of organizational and ultrastructural changes aiming to maintain high service and production standards in the stone industry. In an attempt to survive, grow, and compete in the global market, granite producers have turned to automated systems to classify and compare the visual appearance of granites to grade and sort them according to similar criteria. Automated systems can be very useful in this respect. Granite producers have expressed their interest in computer vision which, accompanied by machine learning, can detect patterns in granite images. These patterns can be used for classifying and categorizing products based on the rock façade. Thus improving product traceability and facilitating warehouse management. Furthermore, having access to smart tools on-site can help reveal the true nature of a product and resolve the misunderstandings between customers and producers upon delivery. An example of such automated visual inspection systems designed for marble is presented in [11]. The advantages of these systems include: 1. Improved quality control through a standard, objective, repeatable process; 2. Increased profits and reduced economic losses; 3. Better warehouse management and product traceability. These problems have been a matter of interest to researchers and studies have been conducted on the use of well-known colors and texture descriptors. These attempts include the works of [12-16].

Table- 4: The Natural Radiation of Nehbandan Granite.

Effective Dose(mSv/y)	Absorbed dose(nGy/h)	Hin	Hex	Raeq	40K Bq/Kg	232Th Bq/Kg	226 Ra Bq/Kg	Commercial Name
0.74	150.69	1.20	0.86	316.97	1260	65	127	Nehbandan Granite

VI. LITERATURE REVIEW

Thanks to its strength, attractive appearance, and affordable price, granite has become increasingly popular in the building industry. Segmentation of the minerals -in particular, granite- in thin sections of rocks using image processing methods have attracted considerable attention among geologists and others dealing with stones. Detecting the minerals [17], their size and shape [18], and the types and names of stones [19] is highly dependent on the accuracy of segmentation of minerals on the surface of the stone.

The impact of the texture, mineralogy, and fractures of granite stones on the cutting efficiency was addressed in [20]. In [21], the authors introduced a software package for analyzing and employing geological and economic modeling results to plan for production from decorative stone reserves.

Given the improved efficiency of computer models and their application in building stones [22], a smart decorative stone production planning algorithm was developed and presented. In [18], an algorithm based on image processing techniques have been developed, Gaussian smoothing, color variation calculations, threshold value, and image skeletonization methods. In other research [23], an algorithm was developed for detecting the mineral boundaries using the Lazy Grain Boundary (LGB) method. Drawing on the region growing algorithm as the primary tool for detecting the boundaries, an algorithm based on the color specifications of the minerals was developed in [24] to find mineral boundaries in thin sections. Moreover, [25] proposed a method based on color-system transition and color spaces (RGB, CIELab, YIQ, and YUV). In this method, the final segmentation is carried out using the watershed algorithm. In another study [19], a computer program by the name of TSecSoft was developed. Based on the least color interference and by running image processing algorithms, the software separates minerals in different sections and, ultimately, the final mineral segmentation model is prepared through user adjustments and modifications.

In general, the stone classification methods are divided into two groups: those based on image processing and those running on spectrophotometric data. The first group can be further divided into two sub-groups that are based on the texture features alone or a combination of color and texture. A review of previous studies shows that approaches that are solely based on texture features are more common. Topalova et al. (2010) [26] proposed a method for grading surface tiles based on gray-scale histograms, reporting an excellent accuracy for a grading process that included four classes and five brightness variations. Similar texture features were also incorporated in the study by Carrino et al. (2002) [27] on the automated classification of the Rosa Perlato of Coreno. Other texture descriptors have also been successfully used in the past. Kurmyshev et al. (2003) [12] developed a software based on Coordinated Clusters Representation (CCR) to control the quality of polished Rosa Porrino granite tiles. Bianconi et al. (2006) [13] used different Gabor filter banks to classify granites. Classification of marbles was also addressed using the scale-space [28] and wavelets [29]. Employing color and texture features in combination to classify natural stones has received significantly less attention in comparison with the latter approach. These approaches are limited and to the best of our knowledge, they are all based on the same idea of applying gray-scale texture descriptors to each color channel separately. Ershad (2011) [30] introduced a method based on morphological operators and primitive pattern units that employed each color channel separately to distinguish four classes of natural stones. Similarly, drawing on the sum and difference histogram features extracted separately from each color band using neural networks, Martı´nez-Alajarı´n et al. (2005) [31] classified marble slabs into three quality categories. Lepisto, Kunttu, and Visa (2005) [14] proposed separate Gabor filtering on each color band for the classification of four granite-like rock image classes.

In the second group of methods, the data source is represented by spectrophotometric data. The approach proposed by López, Martinez, Matías et al. (2010) [32] belongs to this group. Nevertheless, the manuscript did not address which spectral features were used and how they were obtained, which makes it difficult to replicate their tests. A similar method was discussed by Araújo et al. (2010) [15]. This study focused on identifying the different types of granites. They employed spectrophotometry to capture spectral data from different parts of granite tiles and examined the data from ten randomly-selected points on each granite specimen and graded them using support vector machines. Automated classification of granite textures has been addressed in a number of papers. The former approaches involved granite texture modeling based on color features, including the color histogram [33] or chromaticity moments [34]. Later, better results were obtained by using gray-scale texture classification, including cooccurrence matrices [35] [36], Gabor filter banks [13] [14], and Coordinated Clusters Representation (CCR) [37] [38][39]. This arises from the fact that granite plates are defined by strong crystalline structures while their color information is less pronounced. The classification accuracy was improved by considering color and texture features together [40] [41]. In all these works, granite images were captured under controlled environmental conditions, and a recognition rate of 70 to 100% was achieved. Fernández et al. (2011) [42] investigated how common image descriptors including local binary patterns, improved local binary patterns, and coordinated clusters representation perform in granite image classification after rotation conditions.

Most description approaches in the literature are simply based on texture features. Bianconi, Bello, Fernández, and González (2015) [43] addressed the problem of selecting the adequate color representation in granite grading. They joined the debate on different color spaces for granite classification by experimenting with simple color descriptors: mean, mean + standard deviation, mean + moments from second to fifth, quartiles and quintiles of each color channel. They showed that, depending on the employed classifier, some color spaces, including Lab and Luv spaces, are better than others for linear classification. It is evident that the solutions proposed for granite color classification are solely based on feature engineering. In other words, these approaches are inspired by patterns assumed to occur in all investigated images and require different expertise.

A similar approach to what is adopted in some of the previous studies [44], [45], [46], [47] on converting manuscripts and printed texts into blocks can be assumed to block dark (or light) grains on the surface of speckled granites. In this method, that seems to need more scientific attention, by grouping dark (or light) grains on the surface of the speckled granite, patterns may be obtained that can help identify the type, mineral origins, and the structure of the stone.

Hadoop and its applications can also be employed to accelerate image processing in this regard [48].

VII. Creating an Image Database

Due to the lack of a suitable, specialized database of images from gray Nehbandan speckled granites used in buildings across Iran or the globe, first, such database of common, available, speckled granites was created in this study. To this end, 100 sample 250*300 JPEG images were captured from the surfaces of cut, polished, speckled granites in the RGB color space at the standard 96 dpi resolution. The images were captured from the stones produced in the Nehbandan Granite Mine, South Khorasan, and stored at the Aliabadi storage. All images were captured vertically from a 15 cm distance from the stone surface and under similar lighting conditions using a Sony 14.1 Mega Pixels optical SteadyShot DSC-W380 camera.

VIII. The Proposed Method

In the proposed method, the impurities and veins (grain intersections) on the surface of Nehbandan speckled granites are automatically separated using digital image processing and clustering methods. Figure 2 illustrates a flowchart of the proposed classification method which is described in detail in the following sub-sections.

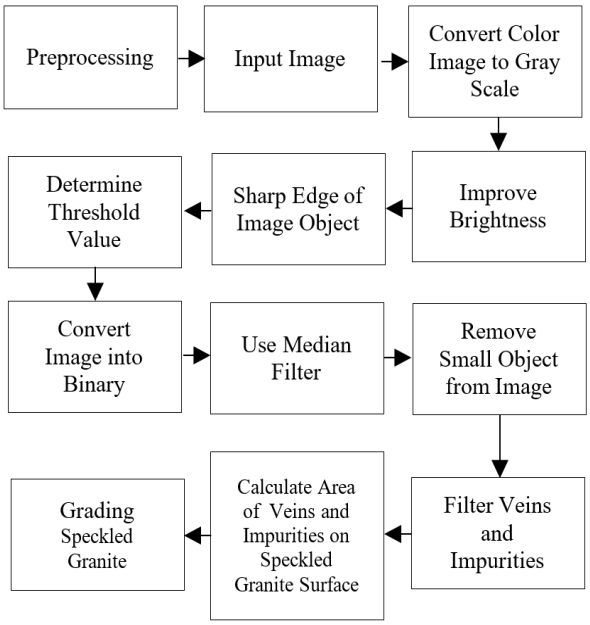


Fig. 2.The Steps of the Employed Method.

Aiming to identify sets of similar patterns and significant structures in a database [49], clustering is an important subject in computer science [50]. Impurities and veins on the surface of speckled granites are separated automatically based on color properties. Veins and non-uniformities on the surface of the speckled granites degrade its appearance, leaving the customers unsatisfied. Customers are interested in using uniform slates with no veins or impurities. Various types of impurities and veins can be spotted on speckled granites, including:

- Accumulation of black dots (Fig. 3).
- Veins (black, white, yellow, etc.) (Fig. 4).
- Black, white, or gray dots (Fig. 5).
- Overly-fine or overly-coarse grains (Fig. 6).

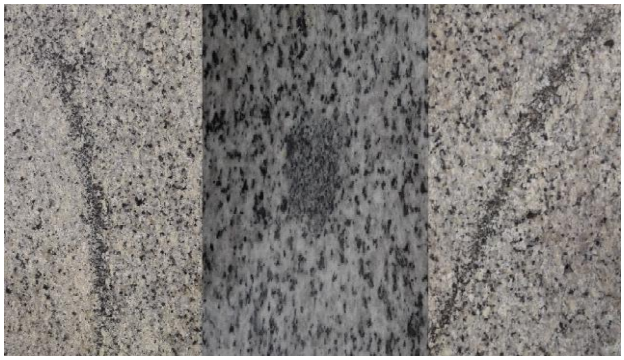


Fig. 3.Accumulation of Dark Dots on a Speckled Granite.

Fig. 4.Veins on a granite.

Fig. 5.Spots on Speckled Granites.

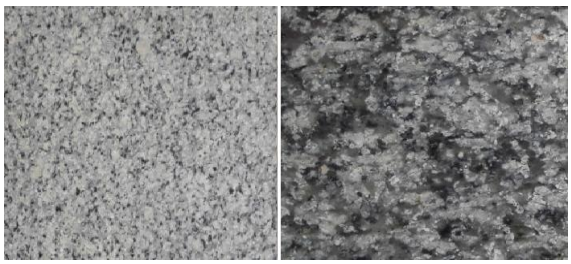


Fig. 6. (a, b) a: Granite with overly-fine grains. b: Granite with overly-coarse grains.

The problem that many users of speckled granites face is the over-sized dark spots (Figure. 7) that damage the overall visual quality of the stone-works incorporating them.

Therefore, the veins and impurities on the speckled granite are classified by size. In this study, the veins on the surface of granite slates were classified into four groups of different market values. Dark veins and impurities larger than α were grouped into the first cluster, while those sized between α and β were put in the second cluster, those sized between β and λ in the third, and the veins smaller than λ were classified into the fourth group. The grouping can be carried out based on different measures and presented in the form of gray images of separated impurities and veins.

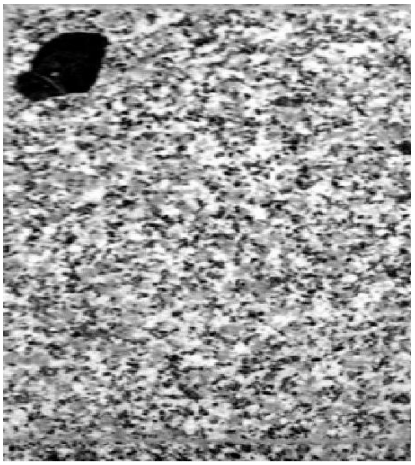


Fig. 7.The Surface of a Speckled Granite with Black Spots.

Before importing the images, they were first preprocessed, which prepared and optimized them for the proposed algorithm. As a step in preparation of the input image, pre-processing helps the algorithm yield better results. After importing the images, the color images had to be converted to gray-scale, which was carried out by the "rgb2gray" MATLAB function. Then, the brightness of the images was improved using the "imadjust" function. The image brightness can be adjusted with the help of the said function. That said, the object edges were sharpened to enhance the contrast between image segments and to facilitate the segmentation process. It must be noted that many speckled granites incorporate black or gray dots of various darkness intensities on their surfaces that the process may fail to consider, thus, practically omitting them if they fall short of a specific darkness level. The granite surface image was then converted into binary. To that end, it was required to define a threshold value for the im2bw function to replace the points with a brightness above that level with white and those below it with black. Therefore, establishing the threshold value significantly affects the conversion results. MATLAB features the "graythresh" function that was used to define a global threshold value for the image using the Otsu's method. As illustrated in Figure 8, the image was then converted into a binary image using this threshold value.

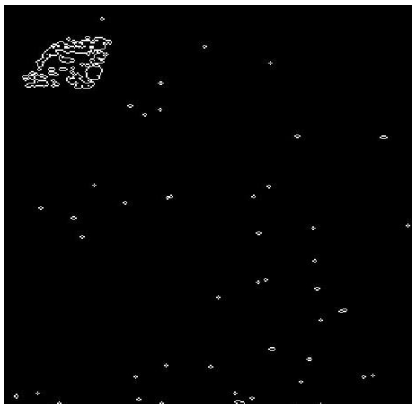


Fig. 8.The Binary Image of the Granite Surface.

Then, a median filter was used, which is a linear local filter with several applications in image processing and analysis. The filter makes the image smoother, facilitating the image processing [51]. The objects in the image were then dilated at 45°, connecting the image segments that are close to each other (Fig 9).

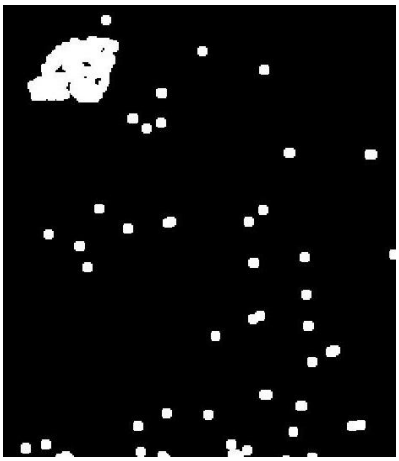


Fig. 9.Dilation of Objects in the Image.

The problem at this point was some small binary objects on the stone surface that could be processed and were required to be removed, leaving only the objects larger than a particular size in the image. After removing the objects, the empty spaces inside veins and impurities and the color-variations inside the veins and impurities were filled using the "bwareaopen" command in MATLAB to even out the parts with veins and impurities. In the last step, the remaining small segments in the image were removed (Fig 10).

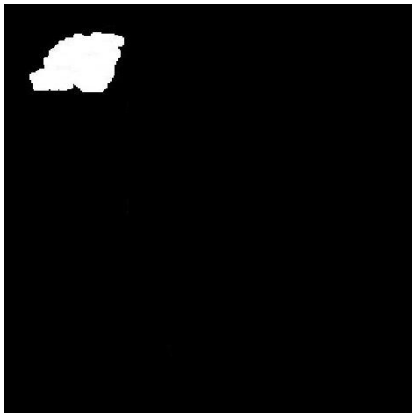


Fig. 10. The Image After Removing Small Objects and Filling the larger Ones.

By calculating the total area of the veins and impurities across the surface of each granite tile and dividing it by the overall tile surface area, one can obtain the portion (%) of impurities and veins on the surface. Obtaining the area is very important as it helps classify the stones into four quality grades with different market values.

IX. Results and Discussions

In [52], an advanced granite tile classification system was presented based on color and texture features. The study focused on a series of visual features and classified a group of twelve granite classes using five different classifiers. The results of the study indicate that an excellent classification accuracy (>90%) can be achieved using a few features and a limited number of training samples. The results can be further improved (to an accuracy of over 94%) using support vector classifiers. Furthermore, the SVM parameters prevent time-consuming procedures. The SVM method yielded better results in this study compared with other methods. The classification results of this study, for a Training Samples to Total Samples ratio of ½, are summarized in Table 5.

Table- 5: Classification Results from [52].

Descriptor	Classifier				
	Nearest Neighborhood	Nearest Mean Classifier	Linear classifier	Naïve Bayes	Support Vector Classifier
Training samples/total samples = 1/2					
cooccurrence matrix + chromatic features	95.2	87.7	88.6	94.6	97.3
cooccurrence matrix + percentiles	93.2	82.9	88.9	87.3	96.3
Gabor + chromatic features	88.1	65.1	90.3	75.3	95.5
Local Binary Patterns(LBP) + percentiles	94.0	83.5	89.8	76.9	97.2
Intra-channel Gabor features	92.3	79.6	88.3	91.4	97.3
Integrative cooccurrence matrix	95.5	85.4	95.2	91.6	98.5

Sensitivity to the number of training samples was significant in this study. The tests were replicated with three different ratios of training samples to the total number of samples (1/2, 1/4, and 1/8). The results are presented for 8, 16, and 32 training samples, respectively (Table 5, Table 6, and Table 7).

Table- 6: Classification Results from [52].

Descriptor	Classifier				
	Nearest Neighborhood	Nearest Mean Classifier	Linear classifier	Naïve Bayes	Support Vector Classifier
Training samples/total samples = 1/4					
cooccurrence matrix + chromatic features	93.4	87.9	87.8	94.2	96.3
cooccurrence matrix + percentiles	91.1	82.8	88.0	86.6	94.9
Gabor + chromatic features	84.6	65.6	80.0	73.4	93.4
Local Binary Patterns(LBP) + percentiles	92.3	83.5	87.3	51.7	96.1
Intra-channel Gabor features	89.7	79.9	84.7	90.6	96.0
Integrative cooccurrence matrix	93.8	85.6	93.6	91.1	97.1

Table- 7: Classification Results from [52].

Descriptor	Classifier				
	Nearest Neighborhood	Nearest Mean Classifier	Linear classifier	Naïve Bayes	Support Vector Classifier
Training samples/total samples = 1/8					
cooccurrence matrix + chromatic features	90.8	87.3	86.8	92.5	94.1
cooccurrence matrix + percentiles	88.4	81.8	86.8	84.5	92.1
Gabor + chromatic features	79.1	65.7	78.2	69.0	89.1
Local Binary Patterns(LBP) + percentiles	89.8	82.5	80.5	31.3	93.6
Intra-channel Gabor features	86.3	79.8	76.2	87.8	93.1
Integrative cooccurrence matrix	90.8	84.9	87.2	89.2	94.6

A computer vision system was addressed in [53] for identifying the constituents of granite in an RGB space using artificial neural networks. The study also addresses the laser cleansing of granite stoneworks. The results are suggestive that artificial neural networks are suitable for identifying mineral grains, including quartz, plagioclase, K-feldspar, and biotite, across different granite tiles in the RGB space. The employed Artificial Neural Network (ANN (3, 10, 4)) was analyzed by running a three-layer perceptron with three neurons in the input layer and four others in the output layer. Moreover, the number of neurons in the hidden layer was optimized to 10. The study results were suggestive of approximately 90% correct identification and covered most constituent minerals of different types of granites, including Marrón Estrela, Rosavel, and Rosa Delta. The estimated ratios (based on area) of the ANN output of all types of granites studied are presented in Table 8.

Table- 8: The Estimated Ratio (% area) Obtained from the ANN Output for each Mineral Constituent of the Studied Granites [53].

Granitic forming mineral	Marrón Estrela (% area)	Rosavel (% area)	Rosa Delta (% area)
Quartz	38.5	24.5	31.9
K-feldspar	17.5	46.8	38.0
Plagioclase	35.5	22.3	18.3
Biotite	8.6	6.5	11.8

Granite tile classification was addressed in [54] drawing on the Convolutional Neural Network method. The results of correct classification obtained from 32*32 granite image blocks are compared with similar works in Table 9.

Table- 9: Classification Results from [54].

Reference	Year	Results	Methodology
[55]	2014	% 33.73	Cri1 Gonzalez et al.(2014)
[56]	2015	% 33.24	CTGF Ferreira et al. (2015)
	2017	% 87.26	CIFAR

The algorithm proposed in this study managed to provide a 97.3% accuracy in analyzing images captured from speckled granite specimens extracted from Nehbandan mine, South Khorasan province. The results are suggestive that the image processing technology can be employed to accurately grade speckled granites based on the dark spots on their surfaces into quality classes by size and color. The algorithm presented in this study was successfully applied to images of samples from the Nehbandan speckled granite mine, South Khorasan Province, Iran. The results are indicative that the image processing technology can be employed to grade speckled granites into different quality classes based on the number of dark spots on their surfaces, their size, and their color at an excellent accuracy. The results of the study indicate that the method can perform at a high correctness level, which offers many economic advantages.

The results achieved using the software were compared visually with the Nehbandan speckled granite. As a problem that needs to be addressed in future studies, it must be noted that the software mistakes cracks, scratches, and also inscriptions as spots.

X. CONCLUSION

The software offers several economic advantages to the producers of Nehbandan speckled granites. The software offers several economic benefits to the producers of Nehbandan speckled granites as many of them sell large ore slabs at low prices. That said, using this software to grade the cut slates can be remarkably profitable.The software was tested on at least 100 images captured from sample slates produced in Nehbandan speckled granite mine in South Khorasan province of Iran, and the results were in agreement with the visual inspection by the operator. The software improves the efficiency of production of stones from mines as the large slabs produced in mines contain different amounts of veins and impurities that affect their market value. Selling the uncut ores is not considerably profitable. However, cutting and grading them into different classes of quality can be more satisfying to the customers, which consequently increases the profits.

REFERENCES

1. University of Tennessee (2008). Granite dimensional stone quarrying and processing. Report . University of Tennessee –Center for Clean Products.
2. EN12440, (2009). EN 12440:2008 Natural stone – denomination criteria. European Committee for Standardization (CEN).
3. European Committee for Standardization (CEN) (2009). EN 12440:2008 natural stone: Denomination criteria. Report . European Committee for Standardization (CEN) .
4. Stone Industry SA Standards Board (2015). Stone standards. Report . Stone Industry SA Standards Board .
5. Shadmon, A.: Stone Absolute (by any other name). Litos 78 (2005).
6. http://en.youstone.com/?page_id=443
7. https://karinostone.com/en/ (https://karinostone.com/stone/455/granite-nehbandan).
8. Tzortzis,M., et al. 2003. Gamma radiation measurements and dose rates in commercially-used natural tiling rocks (granites). Journal of Environmental Radioactivity 70, 223–235.
9. Anjos,R.M., et al. 2004. Radioecology teaching: evaluation of the background radiation levels from areas with high concentrations of radionuclides in soil. European Journal of Physics, 25 (2), 133–144.
10. JAHANGIRI A., ASHRAFI S. "Natural Radioactivity in Iranian Granites Used as Building Materials", Journal of Environmental Studies, Vol. 36, No. 56, March 2011, 55-60.
11. H.KardanMoghaddam, et al. "Marble Slabs Classification System Based on Image Processing (Ark Marble Mine in Birjand)", Civil Engineering Journal, Vol. 4, No. 1, January, 2018, DOI: 10.28991/cej-030972
12. Kurmyshev, E. V. , Sánchez-Yáñez, R. E. , & Fernández, A. (2013). Colour texture classification for quality control of polished granite tiles. In Proceedings of the third IASTED international conference on visualization, imaging and image processing: Vol. 2 (pp. 603–608). ACTA Press .
13. Bianconi, F. , & Fernández, A. (2006). Granite texture classification with Gabor filters. In Proceedings of international congress on graphical engineering (INGEGRAF), Sitges, Spain .
14. Lepisto, L. , Kunttu, I. , & Visa, A. (2005). Rock image classification using color features in Gabor space. Journal of Electronic Imaging, 14 (4), 040503-1–040503-3 .
15. Araújo, M. , Martínez, J. , Ordóñez, C. , & Vilán, J. A. (2010). Identification of granite varieties from colour spectrum data. Sensors, 10 (9), 8572–8584 .
16. Bianconi, F. , González, E. , Fernández, A. , & Saetta, S. A. (2012). Automatic classification of granite tiles through colour and texture features. Expert Systems with Applications, 39 (12), 11212–11218 .
17. Izadi. H, Sadri. J, Mehran. N.A, (2013), "Intelligent Mineral Identification Using Clustering and Artificial Neural Networks Techniques", Published in the Proceedings of The First Iranian Conference on Pattern Recognition and Image Analysis (PRIA 2013), Birjand, Iran.
18. Goodchild. J. Scott and Fueten. F. (1998). "Edge Detection iv Petrographic Image Using The Rotation Polarizer Stage". Computer & Geosciences 24(8). 745-751.
19. Yesiloglu-Gultekin. N, Keceli. A.S, Sezar. E.A, Can. A.B,Gokceoglu.C, Bayhan. H, (2012), " A Computer Program (TSecSoft) to Determine Mineral Percentages Using Photographs Obtained from Thin Sections". Computers & Geosciences 46. 310-316.
20. Sanchez Delgado N., Rodriguez-Rey A., Suarez del Rio L.M., Diez Sarria I., Calleja L., Ruiz de Argandona V.G., "The influence of rock microhardness on the sawbility porrino granite (Spain)", Technical note, International Journal of Rock Mechanics & Mining Sciences.(2005) 42, 161-166.
21. Latham J. P., Meulen J. V., Dupray S., "Prediction of in-situ block size distributions with reference to armourstone for breakwaters", Engineering Geology.(2006) 86,18-36.
22. Sharif J.,Bakhtavar E., "An intelligent algorithm of minimum cutting plane to find the optimal size of extractable-blocks in dimension stone quarres"., Arch. Min. Sci., (2009), No 4.
23. Heilbronner. R. (2000). " Automatic Grain Boundary Detection and Grain Size Analysis Using Polarization Micrographs or Orientation Images". Journal of Structural Geology 22. 969-981.
24. Zhou. Y., Starkey, J., Mansinha, L. (2004A), Identification of Mineral Grains in a Petrographic Thin Section Using Phi-and Max-Images. Mathematical Geology 36(7), 781-801.
25. Obara. B, (2007), "A New Algorithm Using Image Color System Transformation for Rock Grain Segmentation". Mineralogy and Petrology 91,271-285.
26. Topalova, I., & Tzokev, A. (2010). Automated texture classification of marble shades with real-time PLC neural network implementation. In The 2010 international joint conference on Neural networks (IJCNN). (pp. 1–8).
27. Carrino, L., Polini, W., & Turchetta, I. (2002). An automatic visual system for marble tile classification. In Proceedings of the institution of mechanical engineers, part B: Journal of engineering manufacture. (Vol. 216, pp. 1095–1108).
28. Dislaire, G., Pirard, E., & Vanrell, M. (2004). Marble classification using scale spaces. In R. Pr˘ikryl (Ed.), Dimension stone 2004: New perspectives for a traditional building material. Prague (Czech Republic): Taylor & Francis Group.
29. Luis-Delgado, J. D., Martinez-Alajarin, J., & Tomas-Balibrea, L. M. (2003). Classification of marble surfaces using wavelets. Electronics Letters, 39(9), 714–715.
30. Ershad, S. (2011). Color texture classification approach based on combination of primitive pattern units and statistical features. The International Journal of Multimedia and Its Applications, 3(3), 1–13.
31. Martinez-Alajarin, J., Luis-Delgado, J. D., & Tomas-Balibrea, L. M. (2005). Automatic system for quality-based classification of marble textures. IEEE Transactions on Systems, Man and Cybernetics, 35, 488–497.
32. López, M., Martínez, J., Matías, J. M., Taboada, J., & Vilán, J. A. (2010). Functional classification of ornamental stone using machine learning techniques. Journal of Computational and Applied Mathematics, 234(4), 1338–1345.
33. Tan, T.S.C., Kittler, J.: Colour texture analysis using colour histogram. IEE Proc. Vis. Image Signal Process. 141, 403–412 (1994).
34. Paschos, G.: Fast color texture recognition using chromaticity moments. Pattern Recogn. Lett. 21, 837–841 (2000).
35. Paclík, P., Verzakov, S., Duin, R.P.W.: Improving the maximum likelihood co-occurrence classifier: A study on classification of inhomogeneous rock images. Lect. Notes Comput. Sci. 3540, 998–1008 (2005).

36. Partio, M., Cramariuc, B., Gabbouj, M., Visa, A.: Rock texture retrieval using gray level co-occurence matrix. In: Proc. of the 5th Nordic Signal Processing Symposium, 2002 (NORSIG 2002), on board Hurtigruten (Norway), 4–7 October (2008).
37. Guillén-Bonilla, J.T., Kurmyshev, E.V., Fernández, A.: Quantifying a similarity of classes of texture images. Appl. Opt. 46, 5562–5570 (2007).
38. Kurmyshev, E., Poterasu, M., Guillén-Bonilla, J.T.: Image scale determination for optimal texture classification using coordinated cluster representation. Appl. Opt. 46, 1467–1476 (2007).
39. Sánchez-Yáñez, R.E., Kurmyshev, E.V., Fernández, A.: One class texture classifier in the CCR feature space. Pattern Recogn.Lett. 24, 1503–1511 (2003).
40. Bianconi, F., Fernández, A., González, E., Caride, J., Calviño, A.: Rotation-invariant colour texture classification through multilayer CCR. Pattern Recogn. Lett. 30, 765–773 (2009).
41. Larabi,M., Colot, O., Richard, N., Fernandez-Maloigne, C.: Using a CBIR scheme based on experts knowledge for a computer-aided classification of ornamental stones. In: Proc. of the 6th International Conference on Quality Control by Artificial Vision, Gatlinburg (USA), pp. 189–200, May 19–23 (2003).
42. Fernández, A. , Ghita, O. , González, E. , Bianconi, F. , & Whelan, P. F. (2011). Evaluation of robustness against rotation of LBP, CCR and ILBP features in granite texture classification. Machine Vision and Applications, 22 (6), 913–926 .
43. Bianconi, F. , Bello, R. , Fernández, A. , & González, E. (2015a). On comparing colour spaces from a performance perspective: Application to automated classification of polished natural stones. In New trends in image analysis and processing . In Lecture notes in computer science: Vol. 9281 (pp. 71–78). Genoa, Italy: Springer .
44. Alaei, A., Pal, U., Nagabhushan, P.: A new scheme for unconstrained handwritten text-line segmentation. Patten Recognition 44(4), 917–928 (2011).
45. Hossein KardanMoghaddam, "Segmentation of lines in Handwritten Texts based on Fuzzy Intervals", The First Iranian Conference on Pattern Recognition and Image Analysis, March 6-8, 2013, DOI: 10.1109/PRIA.2013.6528439
46. H.K. Moghaddam, "The Horizontal Segmentation of Lines in Chinese Handwritten Texts Based on the Intervals (Distances) in Fuzzy Triangles" Journal of Basic and Applied Scientific Research, 3(4)165-172, 2013.
47. Hossein KardanMoghaddam, "Proposing an Algorithm for Converting Published and Handwritten texts to CAPTCHA by Using Image Processing", The 8th Conference on Information and Knowledge Technology (IKT 2016), Hamedan, Iran, 7-8 sep, (2016). doi: 10.1109/IKT.2016.7777762.
48. S. M. Banaei and H. K. Moghaddam, "Hadoop and Its Role in Modern Image Processing," Open Journal of Marine Science, vol. 4, issue (4), October 2014. http://dx.doi.org/10.4236/ojms.2014.44022
49. Osmar R. Zaïane: "Principles of Knowledge Discovery in Databases - Chapter 8: Data Clustering" http://www.cs.ualberta.ca/~zaiane/courses/cmput690/slides/Chapter8/index.html
50. Prudent. Y and Ennaji. A, (2005), "A New Learning Algorithm for Incremental Self-Organizing Maps", Proc. of European Symposium on Artificial Neural Network (ESANN) 2005, Belgium, April.
51. Gonzalez. R.C, Woods. R.E, and Eddins. S.L, (2003), "Digital Image Processing Using MATLAB", Pearson Prentice Hall.
52. Bianconi, F., et al. Automatic classification of granite tiles through colour and texture features. Expert Systems with Applications (2012), http://dx.doi.org/10.1016/j.eswa.2012.03.052
53. J.S. Pozo-Antonio., et al. A computer vision system for identification of granite-forming minerals based on RGB data and artificial neural networks, Measurement 117 (2018) 90–95, https://doi.org/10.1016/j.measurement.2017.12.006
54. A. Ferreira, G. Giraldi ," Convolutional Neural Network approaches to granite tiles classification", Expert Systems With Applications 84 (2017) 1–11.
55. González, E. , Fernández, A. , & Bianconi, F. (2014). General framework for rotation in- variant texture classification through co-occurrence of patterns. Journal of Mathematical Imaging and Vision, 50 (3), 300–313 .
56. Ferreira, A. , Navarro, L. C. , Pinheiro, G. , dos Santos, J. A. , & Rocha, A. (2015). Laser printer attribution: Exploring new features and beyond. Forensic Science International, 247 , 105–125 .

AUTHORS PROFILE

Hossein KardanMoghaddam received M.Tech(CCT) from the University of Mysore, India (2009-2011), He is currently faculty member in the department of computer engineering, Birjand University of Technology, Birjand, Iran. His research interests are in Image processing, Machine Learning, Information Technology Management, Health Engineering.

Amir Rajaei received MCA and PhD degrees in computer science and technology from the University of Mysore, India, in 2008 and 2013. He worked on UGC sponsored major project. He is currently a faculty in the department of computer engineering, University of Velayat, Iranshahr, Iran. His research interests are in computer network, image processing, object recognition and data mining.

MohamadReza Maraki, He is currently faculty member in the department of Materials engineering, Birjand University of Technology, Birjand, Iran.