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Mermer Türlerinin Makine Öğrenmesi Teknikleri Kullanılarak Sınıflandırılması

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Öz

Doğal taşlar, insanların barınmadan silaha kadar vazgeçilmez unsurlarından bir tanesidir. Bu taş türleri içerisinde mermerler ve mermer türevli ürünler banyodan mutfağa, bahçe tasarımından küçük dekoratif ev süslerine kadar insanların sürekli tercih ettiği objelerdendir. Mermerler çıkarıldıkları bölgelere göre isimlendirilirken bu alanda uzman olarak nitelendirilen kişiler tarafından gözleme dayalı olarak türleri ve kaliteleri sınıflandırılmaktadır. Uzman kişilerin gözleme dayalı yaptığı bu sınıflandırma ekonomik anlamda risk taşımakta, iş yükünü arttırmakta ve hata oranı yüksek olabilen zorlu bir süreçtir. Bu süreçlerin hızlı, kolay ve doğruluk oranı yüksek bir dijital dönüşüme ihtiyacı bulunmaktadır. Bu çalışmada mermerlerin tür sınıflandırmasında derin öğrenme kullanılarak özellik çıkarımı yapılmıştır. Çıkarılan özellikler makine öğrenme teknikleri kullanılarak sınıflandırma uygulaması gerçekleştirilmiştir. 28 ayrı türe ait 3703 mermer ve mermer türevli doğal taş imgesinden oluşan veri seti ile yapılan uygulamanın test sonucunda DenseNet derin öğrenme modeli ve K-En Yakın Komşu metodu ile %99,7'lik sınıflandırma başarımı elde edilmiştir.

Classification of Marble Types Using Machine Learning Techniques

Keywords
Marble; Deep Learning; Machine Learning; Image Processing

Abstract

Natural stones are one of the indispensable elements of people from shelter to weapons. Among these stone types, marbles and marble-derived products are among the objects that people always prefer, from bathroom to kitchen, from garden design to small decorative home decorations. While the marbles are named according to the regions where they are extracted, their types and qualities are classified based on observation by people who are qualified as experts in this field. This classification, which is made by experts based on observation, carries risks in economic terms, increases the workload and is a difficult process with a high error rate. These processes need a fast, easy and highly accurate digital transformation. In this study, feature extraction was done by using deep learning in the species classification of marbles. The extracted features were classified using machine learning techniques. As a result of the application made with the data set consisting of 3703 marble and marble-derived natural stone images belonging to 28 different species, a classification success of 99.7% was obtained with the DenseNet deep learning model and the K-Nearest Neighbor method.

1. Introduction

Throughout their lives, people use products that they either produce themselves or that they obtain from the resources that nature offers them. While people sometimes use nature-based products to meet their individual needs, they sometimes prefer them in the design of the environments they live in. Due to its aesthetic structure and durability, natural stones are frequently preferred by people in environments where they live, such as the environment, home or work area. This frequency of use also brings about an increase in natural stone production. Technology plays an important role in the manufacturing sector. With Society 5.0, it is expected that artificial intelligence will take place more in our lives. These breakthroughs in technology also bring advantages in the production sector. The reason for this is that Industry 5.0 requires the design of the product according to the needs of the person. As a result, a personalized product will be prepared and this product will be both high quality and optionally produced at low cost (Doyle-Kent and Kopacek 2020).

Apart from technology, people also use the resources offered by nature to beautify their living spaces and the environments they live in. The most valuable parts of this beautification are made of natural stones due to its durability and aesthetics.

Marble and marble types (Granite, Travertine, Onyx, etc.) come first in terms of use of natural stones. Marble is a type of natural stone that is widely used in decoration, monuments and sculptures, ornaments and souvenirs, especially in the construction industry.

Türkiye has approximately 40% of the world's natural stone reserves. According to the researches, there are approximately 650 types of marble in color and texture in our country (IntRes. 1).

Marble production in Türkiye started 4000 years ago on the Marmara Island. Currently, Turkey exports 2 billion dollars worth of marble and natural stone to 179 countries (IntRes. 2).

Most of Türkiye's marble reserves are located in Western Anatolia and Thrace. Afyon, Çanakkale, Muğla, Tokat, Denizli, Bilecik, Eskişehir, Bursa, Balıkesir and Burdur provinces are at the top of the collective reserve provinces in our country. In addition to these provinces, there are marbles unique to our country such as Elâzığ Cherry, Akşehir Black, Milas Lilac and Süpren in the international market.

Marbles are classified according to their types or quality. There are many studies on marble classification in the literature.

In the industrial application of Martinez et al., a data set with 3 classes and 30 samples was classified. K-means clustering algorithm was used in classification, and textural features such as mean variance, contrast, entropy were included in the classification process. 98.9% texture accuracy has been achieved (Martínez-Alajarín et al. 2005).

In the study of Selver et al., classification from the surface images of 1158 marble slabs was studied using Hierarchical Neural Networks. 99% success was achieved in the study, which revealed that the Hierarchical Radial Based Function Network (HRBFN) for industrial applications produced successful results (Selver et al. 2009).

In the adaptive marble slab classification study of Topalova and Tzokev, the classification of marble slabs with similar textures was made. It was stated that the data given turbidity and different lighting produced an accurate result between 87% and 96% with 100 samples with 6 classes as a result of the test (Topalova and Tzokev 2011).

Torun et al (2019) performed a classification using AlexNet and Local Binary Patterns (LBP) methods in their study. At the end of the classification performed by taking 600 marble images belonging to 3 different classes from a company producing marble in Sivas province, a classification success of 99.8% with LBP+DVM and 99.2% with AlexNet was achieved.

In their studies, Pençe and Çeşmeli used Convolutional Neural Networks to classify marble slabs using 80 different marble images and various architectures and algorithms. A 75% success rate was achieved in the study without any data augmentation (Pençe and Çeşmeli 2019).

In the study of Canayaz and Uludağ, who used images of 28 different types of marble, marble classification was realized with deep neural networks. The system tested with VGG16, ResNet and LeNet models showed a 97% success rate with the VGG16 model (Canayaz and Uludağ 2020).

The work done by Karaali and Eminağaoğlu for quality classification was carried out using convolutional neural networks. A data of 2100 samples obtained from a marble company serving in the province of Izmir was used. As a result of various algorithms, the system achieved a success rate of 71.5% in the test data. By augmentation the data, this rate was obtained as 92% (Karaali and Eminağaoğlu 2020).

Elmas (2022) carried out a study on the classification of marble and granite varieties with transfer learning. He prepared a data set consisting of 21120 marble and 3360 granite images in total by taking 240 images from 16 different plates for each type of 88 marble and 14 granite types. With data augmentation, 171360 images were obtained. Data was trained with 7 pre-trained convolutional neural networks. With the ResNet-50 model, it achieved a success rate of 97.4%.

In this study, marble type classification was carried out using deep learning architectures in the MATLAB (2020a version) environment. The data set consists of 3703 marble images belonging to 28 types of marble classes. In the application, feature extraction was done with 8 deep learning models. 24 different methods were tried to classify each model. The cross validation value was chosen as 10. With the study, a 99.7% success rate was obtained with the DenseNet201 model and Weighted KNN classification method.

Table 1. Literature review summary table

Author	Number of Sample	Method	Succes Rate
Martinez-Alarjin et al.	30	K-Means Clustering	98,9%
Selver et al.	1158	Hierarchical Radial Basis Function Network	99%
Topalova and Tzokev	100	MultiLayer Perceptron	Between 87% - 96%
Torun et al.	600	AlexNet and Local Binary Patterns	99.8%
Pençe and Çeşmeli	80	Convolutional Neural Networks	75%
Canayaz and Uludağ	3073	VGG16	97%
Karaali and Eminağaoğlu	2100	Convolutional Neural Networks	92%
Elmas	171360	ResNet-50	97.4%

In the first part of the publication, various studies on marble and marble classification were examined. In the second part of the study, information about the data set used, feature extraction and classification methods are mentioned. In the third part, the results of the application are presented with the support of figures and tables. Finally, in the Conclusion section, an explanation was given about the contribution of the study.

2. Material and Method

The process steps and components of the application method are given in Figure 1.

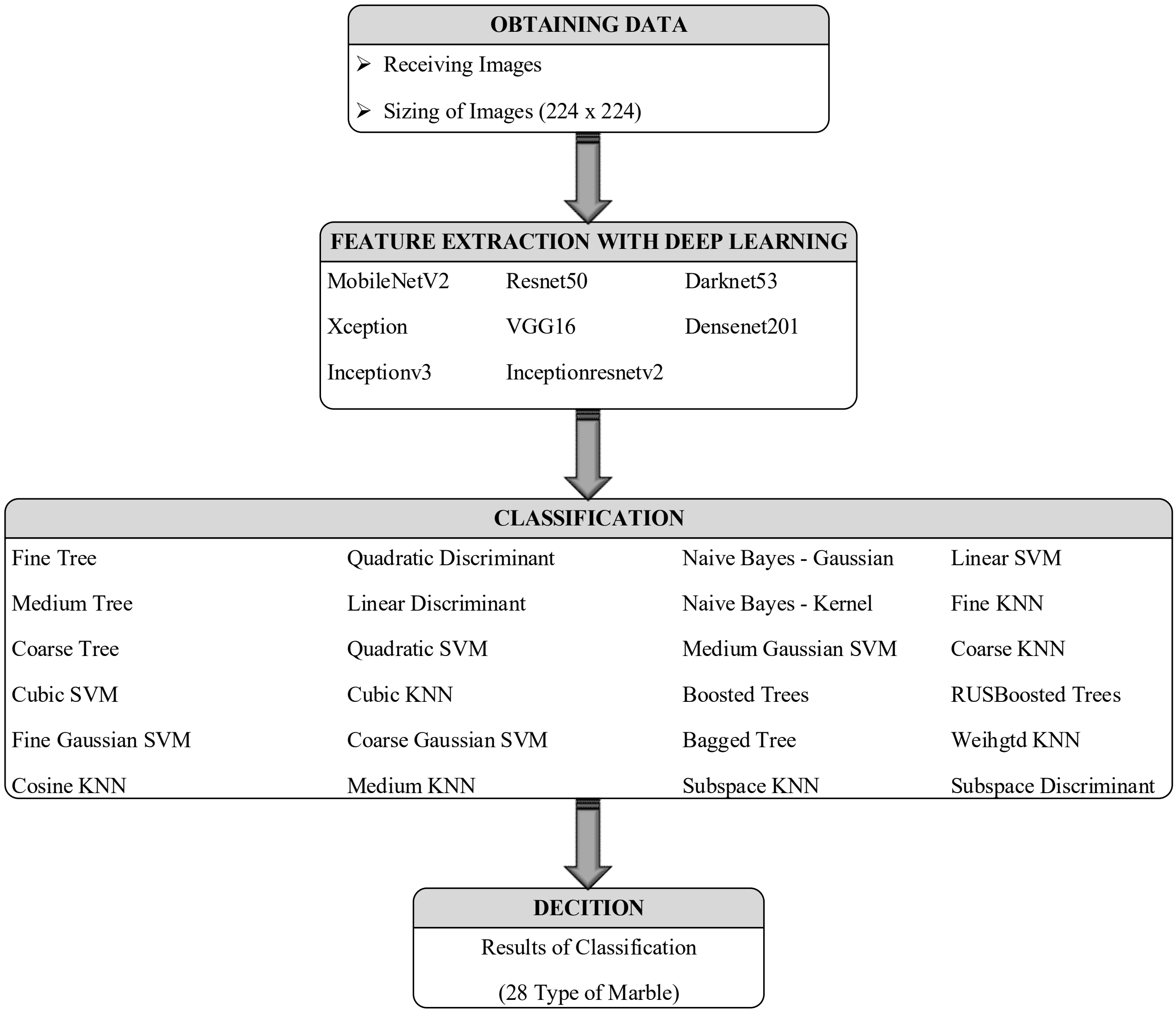

Figure 1. Components of the Application Method

The applied method consists of a 4-stage process. In the first step of the process, marble images are taken and resized to 224x224 pixels. In the second stage, separate features of the images are extracted for 8 Deep Learning models and stored in separate matrix files. The names of the models used are given in Table 2 as column names. In the third stage, the extracted features are classified with the machine learning module of MATLAB. In classification, 24 different Classification Learner tools of MATLAB were used. The names of the vehicles used are given in the Classification Type column in Table 2. The cross-validation value was kept constant at 10 in the classification. In the fourth and final stage, classification is finalized according to 28 marble types.

The CPU of the computer used is Intel Core i7 – 8750H series and has a processor speed of 2.20 GHz. The computer has 16GB of RAM and a 4GB memory display adapter with NVDIA GTX 1050Ti chipset.

2.1. Data Set

A total of 3703 marble images from 28 species using OpenCV-sourced Convolutional Neural Network were used as the dataset of the study (Canayaz and Uludağ 2020). The marble sample images of 28 species that make up the data set and the number of samples used for that species are given in Figure 2.

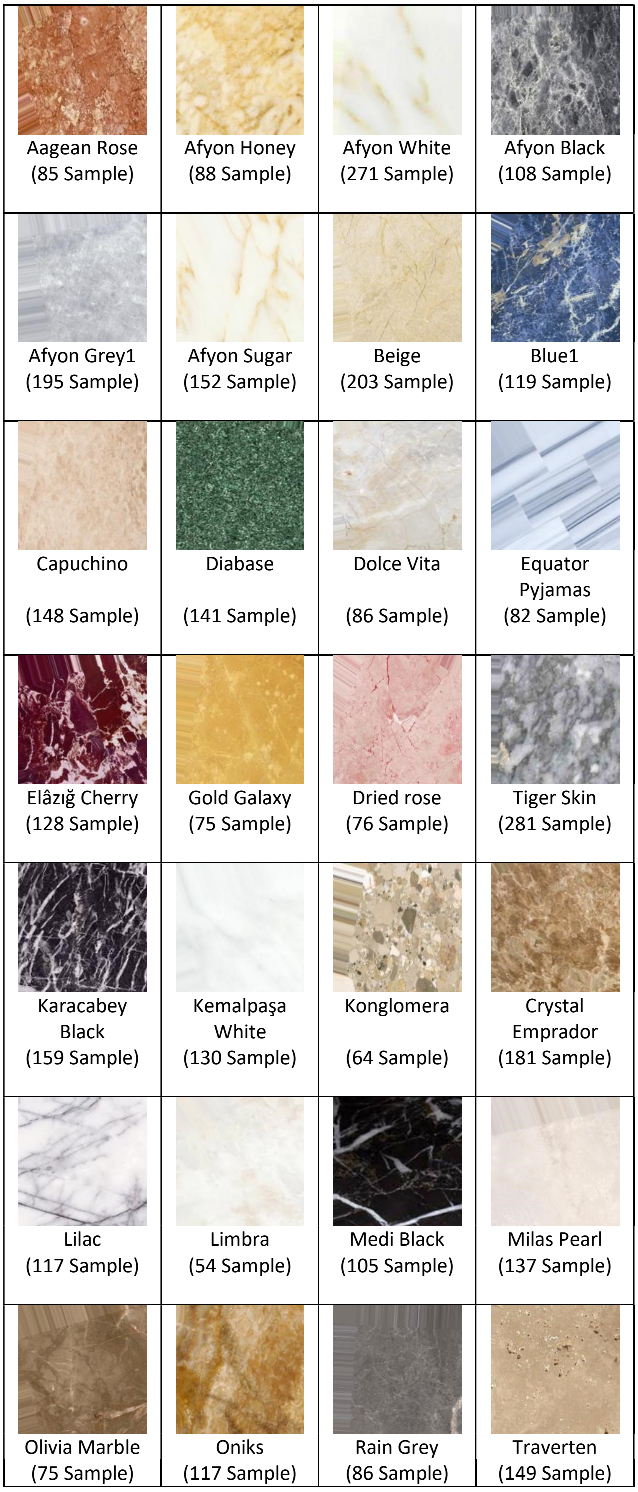

Figure 2. Sample images and sample numbers of each species in the data set used

2.2. Feature extraction methods

Deep learning models are used for feature extraction. Different performance results were obtained for each model and each algorithm. Today, applications that behave like humans or try to think like humans are increasing. Essentially, these applications mean that there is a human phenomenon in engineering applications. This is known as machine learning (Goldberg and Holland 1988)

Machine learning applications have been developed by utilizing the working logic of neurons in the human brain. An artificial neuron model has emerged. This model was developed over time and started to be used frequently in machine learning studies. Machine learning has started to be used in many fields such as medical and security (Hinton and Salakhutdinov 2006).

Deep learning is a type of artificial neural networks. It has also had success in areas such as natural language processing or sound (Masters and Luschi 2018). Since the preprocessing and feature extraction processes are automatic in deep learning, multiple processes are performed and finalized at the same time. In the deep convolutional neural network, feature extraction is determined within the network and the features belonging to the structure to be detected are determined within the layers (Doğan and Türkoğlu 2019).

The MobileNet model has been developed for use in embedded systems and mobile applications, image processing and classification studies. It has higher efficiency because it uses decomposable convolutions. A fast and small network is formed by decomposition. This network can be implemented on mobile devices. With the development of the model, accurate results were obtained in applications such as object recognition, facial features, geolocation (Howard et al. 2017).

The VGG model was developed by the Visual Geometry Group formed by Simonyan and Zisserman from Oxford University in 2014. VGG showed a successful performance with an error rate of 7.3% in the ILSVRC (The Imagenet Large Scale Visual Recognition Challenge) competition held by ImageNet in 2014. There are 6 different architectural models. These models consist of 11, 13, 16 and 19 convolution layers (Simonyan and Zisserman 2015).

ResNet architecture, which achieved an error rate of 3.6% in the ILSVRC competition held by ImageNet in 2015, consists of 152 layers. This architecture, unlike other architectures, is formed by including the blocks that feed the residual values to the next layers into the model (Kızrak and Bolat 2018).

Inception, which is defined as a network within a network; It is an architecture based on performing simultaneous filtering and pooling operations in the convolutional layer. Operations are carried out in modules. In the InceptionV3 model, additional modules are used as batch normalization in the network and as an auxiliary classifier in the fully connected layer (Szegedy et al. 2016).

The Xception network, which is basically an evolving network by building on the InceptionV3 network, has been successful with differences in the convolution layer. This model offers two different approaches in the convolution layer as smart depth convolution and smart point convolution. In the smart depth approach, it processes only one channel, not every channel, and reaches the result. This approach causes loss of features and largely unsuccessful results. Smart dot convolution obtains the result by applying a classical convolution in the form of 1x1xChannel Number to the image obtained as a result of the single channel processing (Chollet 2017).

DenseNet, another pre-trained network, is similar to ResNet. The difference from ResNet is that the value added to a system in 2 layers is added to all subsequent layers in order to train the network more easily. Thus, the dysfunction problem of many layers in high-layer networks is also optimized (Huang et al. 2017).

2.3. Classification Methods

Machine learning algorithms were used for classification in the study. Machine learning algorithms are structures that learn the structure and function of the data and make predictions about the data set. They work as structures that take input data and make a database-based prediction and decide (Kononenko 2001).

In this study, Support Vector Machine, Separation Analysis, K Nearest Neighbor Classification, Decision Trees, Naive Bayes Classifier and Ensemble Learning classifier were used.

Decision trees consist of a node representing the properties and branches representing the value that this node can take (Gültepe 2019). It is a machine learning algorithm that divides the independent variables existing in the data into nodes according to the information gain during the prediction and specifies the average in the interval learned during the training during the prediction (Duda et al 2001).

Classification is discriminant analysis, which aims to divide the independent variables of the data into homogeneous groups. It processes each data by calculating the probability of belonging to that group for each group and assigning it to the highest scoring group (Sayılgan et al. 2021).

Naive Bayes classifier is a simple probabilistic classification method based on Bayes theorem. It uses existing classified data and calculates the probability of the new data falling into which class. Features are evaluated separately from each other. In this classification, the value of one attribute does not have information about the value of another attribute. (Karakoyun and Hacıbeyoğlu 2014).

Support Vector Machines are used to optimally separate data belonging to two or more classes using hyperplanes (Lotte et al. 2018). It performs the classification through a linear or non-linear function. SVM’s are based on estimating the best fit function while separating the data (Özkan 2013).

K Nearest Neighbor (KNN) makes an estimation by utilizing sample data for which class it belongs to beforehand for classification. The distance of the newly added element to the other elements in the data set is calculated. Distance functions such as Euclidean, Manhattan are used in this calculation. After these operations, k neighbors are checked. The element is included in the class of the nearest neighbor (with the lowest distance) (Sayılgan et al. 2021).

Ensemble Learning is formed when more than one weak learning algorithm combines to form a stronger learning algorithm (Freund and Schapire 1999).

3. Results and Discussion

The application is prepared in MATLAB environment. Deep learning models such as MobileNet, ResNet, DarkNet, Xception, VGG16, DenseNet, Inception and InceptionResNet were used for feature extraction. Input images were taken at a resolution of 224 x 224 pixels.

The results obtained in the classification study are given in Table 2.

Table 2. The results of applying the model on 3703 images

S. Num	Sınıflandırma Türü	MobileNetV2	Resnet50	Darknet53	Xception	VGG16	Densenet201	Inceptionv3	Inceptionresnetv2
1	**Fine Tree**	55,9	75	70,3	52,1	60,6	76,4	56,5	59,9
2	**Medium Tree**	35,9	52,8	44,3	38,5	38,7	54,3	36,1	42,4
3	**Coarse Tree**	19,5	25,5	25,2	22	21	28,3	19,4	23,6
4	**Linear Discriminant**	90	93,5	93,7	89,6	89	94,9	90,9	91,6
5	**Quadratic Discriminant**	F	F	F	F	F	F	F	F
6	**Naive Bayes - Gaussian**	F	F	93,1	83,1	F	93,8	89,1	86,4
7	**Naive Bayes - Kernel**	80,8	87,8	93,7	70,3	81,1	95,5	89,3	86,3
8	**Linear SVM**	94,5	97,3	97,8	93,5	94,4	98,3	95,7	94,8
9	**Quadratic SVM**	97,2	98,9	98,9	96	97	99,4	97,6	97
10	**Cubic SVM**	97,4	98,9	98,9	96,6	97,2	99,4	97,7	97,2
11	**Fine Gaussian SVM**	10,2	14,1	12,2	10,1	11,3	14,2	9,9	11,7
12	**Medium Gaussian SVM**	96,3	97,9	98,1	93,9	95,5	99,2	97	96
13	**Coarse Gaussian SVM**	88,8	92,6	93,7	84,7	88,8	95,2	90,6	89,5
14	**Fine KNN**	98,2	99,3	99	97,1	97,6	99,6	99,2	97,5
15	**Medium KNN**	96,3	98,3	98,1	94,3	95,5	99,6	98	95,5
16	**Coarse KNN**	78,2	82,7	84,3	77,5	77,8	86,7	79,5	78,3
17	**Cosine KNN**	96,5	98,5	98,2	94	95	99,4	97,8	95,2
18	**Cubic KNN**	96,1	98,3	97,9	93,3	95,2	99,4	97,8	94,9
19	**Weihgtd KNN**	97,6	99,1	98,5	96,2	96,7	**99,7**	98,4	96,7
20	**Boosted Trees**	55,4	70,5	62,7	49,9	58,3	71,6	50,1	58,1
21	**Bagged Tree**	87,1	95,7	92,9	81,7	87,5	97,6	90,9	88,1
22	**Subspace Discriminant**	88	92	92,5	86,6	88,5	93,7	89,1	89,4
23	**Subspace KNN**	**98,3**	**99,4**	**99,1**	**97,4**	**98**	99,6	**99,3**	**97,6**
24	**RUSBoosted Trees**	51,3	67,3	65	51,5	57,8	67,1	64,7	59,3

F : Classification Error (Fail)

As a result of the application, it has been observed that the achievement performance of DenseNet, one of the deep learning models, is higher than the other models.

In the machine learning phase, the highest performance was obtained with KNN (Weighted KNN).

The Complexity Matrix of the classification result with the highest performance result in Figure 3; In

Figure 4, the distribution of the highest performance result is given.

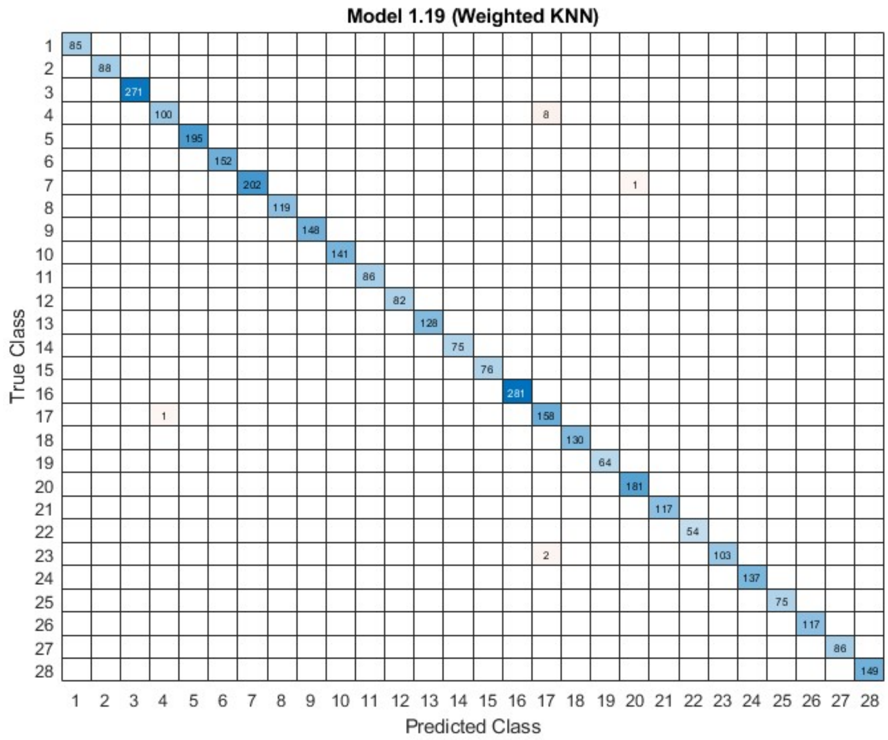

Figure 3. The Complexity Matrix for the Most Successful Classification

The complexity matrix of the classification is given in Figure 3. As can be seen in the figure, 12 images belonging to only 4 species could not be classified. Among the unclassifiable images, there are 8 images in Afyon Black and Karacabey Black species, and 4 images in other species. All remaining images were classified correctly and a classification success of 99.7% was achieved.

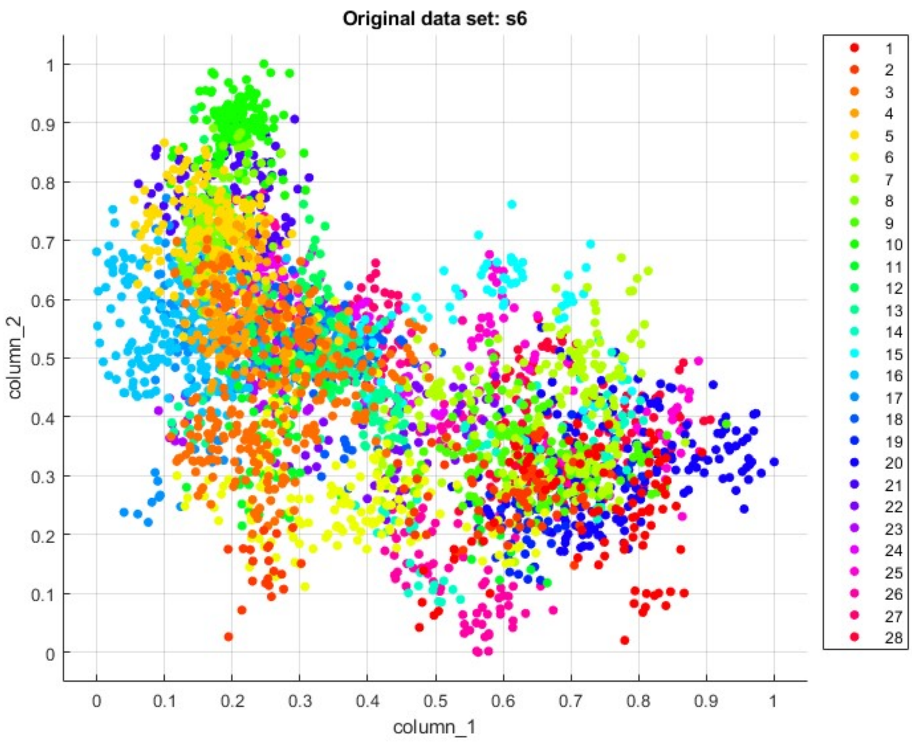

Figure 4. Distribution Result of the Most Successful Classification

4. Conclusions

In this study, the features of a data set consisting of 3703 marble images were extracted using deep learning models, and then it was classified by machine learning. The highest performance was obtained with the KNN classification architecture (Weighted KNN) of the DenseNet deep learning module, with cross-validation at 10 and 99.7%. This rate is approximately 2% higher than the performance of the resource owner from whom we obtained the data set. Unlike other studies, despite the high number of species (28 types of marble), the high performance result is an advantage of the study. The study was tested on two computers with different technical specifications and very close results were obtained.

The study was prepared in MATLAB environment and 8 different deep learning architectures were applied. With deep learning, 1000 features of each image are extracted. While extracting the features, the error rates were calculated and the features with the least errors were kept as a matrix. After feature extraction, machine learning classification models such as DVM, Naive Bayes, and KNN were tested on these matrices at once and sequentially, and classification was performed. In this way, the classification results of each model were seen simultaneously, thus shortening the intermediate processing time. In addition, since the application is made in MATLAB environment, image processing is provided to be more efficient. Since the system processes all deep learning modules at once, it worked for an average of 8-9 hours. Classification processes also took an average of 25 minutes for each deep learning module matrix. This extra time causes an increase in the processing time of the system.

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