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Industrial White Quartz Stone Classification Using Image Processing and Supervised Learning

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Abstract: A vision-based stone classifying method was developed for industrial mine stone grading applications. The image-based solution is used to extract visual parameters and stones are classified by their color and shape parameters with the help of the machine learning algorithms. In the experiments, four groups, each including ten arbitrarily selected stones; in total forty stone samples with complex colors and shapes were examined. Four different images are captured under four different angles and processed to extract visual parameters of each stone sample. In training stage 67% of the data were used for training and rest were used for testing process. The method correctly classifies mine stones up to 98% from still images using labeled inputs. A confusion matrix derived from the experimental results is employed in order to emphasize the efficiency of the system more clearly and emphasize the results in a certain manner.

Keywords: Computer vision, stone grading, image processing, nearest neighbors.

Görüntü İşleme ve Gözetimli Öğrenme Yardımıyla Endüstriyel Beyaz Kuvars Taş Sınıflandırması

Öz: Endüstriyel maden ve taş sınıflandırma uygulamalarına yönelik, görü tabanlı bir sınıflandırma metodu geliştirilmiştir. Görü tabanlı çözümleme taşlara ait görsel parametrelerin çıkartılması için kullanılmış ve makine öğrenme algoritmalarından yararlanılarak renk ve şekil parametrelerine göre sınıflandırılmıştır. Gerçekleştirilen deneylerde, her biri gelişigüzel seçilmiş 10 adet taş içeren 4 grup, toplamda 40 karışık renk ve şekil özellikleri gösteren numune sınıflandırılmıştır. Her bir numunenin 4 farklı açıdan alınan birer görüntüsü, görsel parametrelerin elde edilmesi amacıyla işlenmiştir. Elde edilen verinin %67'si programın eğitimi amacıyla; kalan veri ise test süreçlerinde kullanılmıştır. Geliştirilen yöntem, durgun görüntüleri çekilerek etiketlenen maden numunelerinin %98'e kadar sınıflandırılmasını sağlamaktadır. Yöntemin verimliliğinin daha açık bir şekilde görülmesi ve sonuçların daha iyi değerlendirilmesi amacıyla deneysel verilerden türetilmiş bir karışıklık matrisi kullanılmıştır.

Anahtar Kelimeler: Bilgisayarlı Görü, Taş Sınıflandırma, Görüntü İşleme, En Yakın Komşu

1. Introduction

Large-scale production needs and tendencies of companies in mining, technology and consumer goods fields shape the state-of-the-art in mass production with the help of continuous manufacturing processes and advanced technologies. Production lines enable manufacturers in a variety of fields to take advantage of the scale economics: more the quantity of goods

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manufactured, lower the costs [1–4]. In production line design and implementation, certain, process-driven features rely on automated solutions. Due to operational ease, efficiency and yield advantages, small- to mid-scale manufacturer companies transform their operations into automated production lines. In automated industrial production, the place and requirement of Machine Vision (MV) technologies are well established in the recent years [6–9]. In general, an automated grading process involves a Computer Vision System (CVS) as CVS's basically provide fast calculations and a relatively high precision given the time consumed in categorizing goods based on their size, shape, color etc. features [10–13]. The overview of a typical CVS system can be seen on Fig. 1.

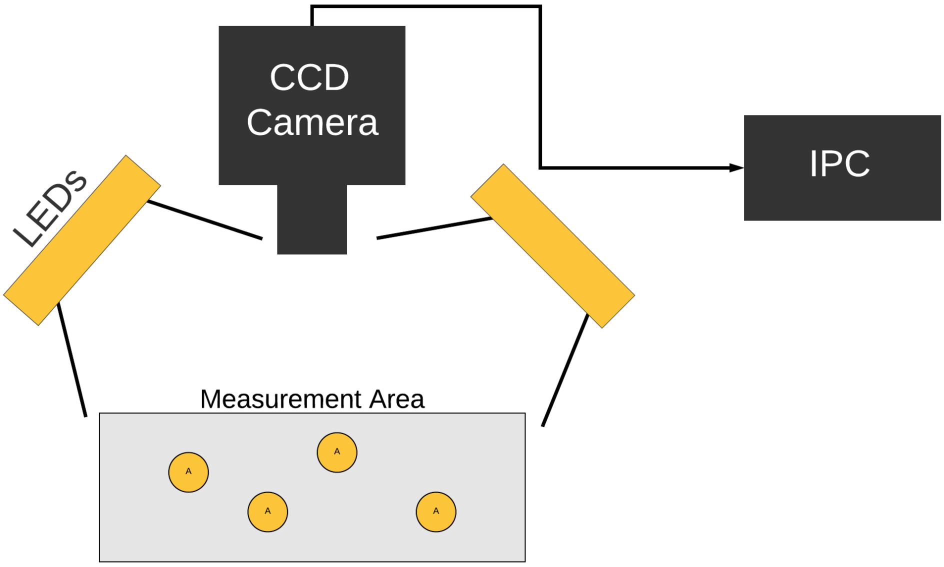


Fig. 1. The typical structure of a CVS.

2. Literature Review

Machine Vision Systems (MVS) are used for performing duties such as sorting, classifying and grading by inspecting, evaluating and identifying objects in an image or video stream. These systems have proved themselves to be a very sought-after technology, especially for automated industrial production flow lines. The available studies so far consist of the detection capability improvements by advanced imaging technologies and image processing methods supported with Neural Networks, Machine Learning Algorithms, Fuzzy Logic etc. Beside automated industrial production flow lines, considering only the accuracy rate of an MVS is not a sufficient parameter to assess the rate of success. There are other dominating factors such as cost and operation rate, especially for mass production applications. Sorting and categorization processes of the product play an important role in modern industry [1] in improving the product value in marketing and retail [2] as well as modern medicine [3]. A successful sorting process provides uniformity in size and shape with high confidence intervals, decreasing the packaging- and transportation-related costs: product uniformity offers the most convenient packaging configurations [4–5] gradually increasing the competitive value of the process. Computer vision combined with machine learning is developed for a variety of applications with significant results. Activity Recognition (AR) is one of these areas where different sports activities such as walking, pedaling, climbing and swimming are recognized by smart wearable devices [20]. Learning algorithms paired to operate together with classification models such as k-Nearest Neighbors (kNN), Multilayer perceptron (MLP), Decision Tree (DT) and Support Vector Machine (SVM) have been proven effective in a variety of applications ranging from dry bean crops to cherry tomatoes and egg volume estimation [21, 23-25]. Most of the studies published in the field of vision-based product classification agree that in object categorization and grading, image resolution, sorting method and color represent the critical parameters of the process [13, 26–27]. The imaging resolution indirectly determines the detail an image holds and acquiring more detail from a production line gives more accurate results. However, the data size and image processing speed are negatively correlated due to the time consumed on the operation of each pixel. An RGB image is a 2D matrix which is consisted of 24-bit color data. The resolution of the image therefore determines the size of this matrix as well. Image processing media in practical applications is basically a set of images or video streams [6]. Encoded image formats JPEG, GIF and PNG store many layers digital numbers in them. A bitmap image file with three channels on the other hand contains 24-bit data for each pixel addressed with 8-bits of RGB color for each channel [7]. Principally, images from vision sensors are the reflected light of a light emitter/source from the exterior of an object. This data is harvested by the imaging sensor and mapped pixel by pixel. Also, as encountered in modern digital single-lens reflex (DSLR) cameras as well as CV applications, the reflectance measurement is implemented by considering the area enveloping the base object and not solely the object to be imaged. On this basis, surface lighting character and quality on the sorting (hence, production) lines become a prominent parameter of image processing in terms of accuracy and rate. In CVS applications, parameters like light source character, ground reflectance, imaging resolution, image and data processing rate of the Central Processing Unit (CPU) and Graphical Processing Unit (GPU) units of the CV systems are considered carefully [8–9] alongside specialized software packages for product classification by size, shape, color and turbidity of products [10]. Among these, the processing speed and resolution towards a cost-effective solution become parameters of priority in such industrial applications.

This study focuses on industrial mine stone classifying using a cost-effective and accurate solution based on supervised machine learning technology. It aims to provide an emphasis on the processing speed of a low-cost and accurate solution for grading of stones using CV based solution. For this purpose, an illumination cabinet was used for isolated imaging environment. All measurements were conducted in the conditioned light box. Stone images were acquired via an industrial color camera. 40 different stones of complex shapes were examined under four different angles to investigate the correlation of imaging resolution, processing speed, accuracy and precision. To minimize the possible errors due to the effect of measuring area, stones' images were obtained for four different angles for each measurement. Stones in the measuring area were rotated concerning four viewing angles before the images were acquired by the imaging system. In experimental stages, an identical image processing technique was applied to every stone sample under the same measurement environment. In this respect, in a conditioned environment, stones with random orientations were investigated. In the learning stage the acquired data from the image processing procedure executed with five machine learning model. The machine learning models, due to the successful reports in the earlier studies as summarized above was evaluated and very high recognition and classification results were obtained. The accuracies of the models and confusion matrices were given in the results.

In the light of the evidence, we suggest in this study, machine learning models with image processing procedures proves to be a promising option for classifying bulk mine stones in large-scale industrial applications.

3. Material and Method

Typically, an automated production line is composed of electronic units, mechanical actuators and a main control unit to perform various sorting, classifying and grading tasks in real-time [11–12]. For this purpose, an MVS based production line mainly uses image processing techniques and the visible range imaging is the method of choice for a variety of operations of sensing a target object. The electrical units and mechanical actuators work according to the outputs of the MVS. For a typical MVS based industrial production flow line, the base components can be summarized as follows: a conveyor band, a light source, programming, an image-processing library, MCU boards, a camera, and a PC for processing the image data. The MVS uses image processing techniques to achieve detecting and classifying the objects. In this study a Red Green Blue (RGB) camera was used to acquire images for a conditioned environment on the conveyor line. Open-Source Computer Vision Library (OpenCV) is a very convenient option for image processing applications [13-14], providing myriad of real-time image processing toolboxes in C++ programming language, a general-purpose programming language [15–16]. OpenCV also many functions for processing images and provides swift calculation with the help of C++ for processes such as contour finding, image thresholding and resizing. This study was conducted with two main stages: data acquisition and data processing.

3.1. Image Processing Procedure for Data Acquisition

The experiment was conducted using a light-proof illumination cabinet. A color camera with 1280x768 pixels was used as the imaging device. Adjustable LED white light sources with 25W rated output were integrated by referencing the cross-lighting technique. An industrial computer (IPC) with Intel i5 Central Processing Unit (CPU) was used to obtain images from the imaging device over the Universal Serial Bus (USB). The image processing procedures were accomplished using C++ language and an open-source OpenCV image processing library. In the experimental stage of the study, four group of stones were used and the actual images are shown in Fig. 2.

Fig. 2. The typical structure of a CVS.

In the image processing stage, a two-staged thresholding operation was applied to each image in the image processing procedure stage (Fig. 3). The method used for image processing initially converts the source image's Red Green Blue (RGB) channels to Hue Saturation Value (HSV) for minimizing the side effects of shadows and saturated regions on the processed image. Thereafter a thresholding process was applied to remove backgrounds. Subsequently, a clone of the image is created and these two images are processed using sequential sub-processing steps but with different thresholds. The contour properties are determined for each image. In the last stage, the result data including area, arc length and coordinate properties were used to predict color intents.

K-Nearest Neighbors (KNN) is an algorithm that determines the possible relations due to measuring similarities and is mostly based on Euclidean Distance or Manhattan Trilateration [17–19]. It is widely recognized in statistical inference and pattern recognition applications [20]. In this study, the contour properties of the images were used for predicting the color intent. To compare the properties of a detected object both image contour centers should be matched. Mass center of the contours for each detected object in images were determined (Fig. 6).

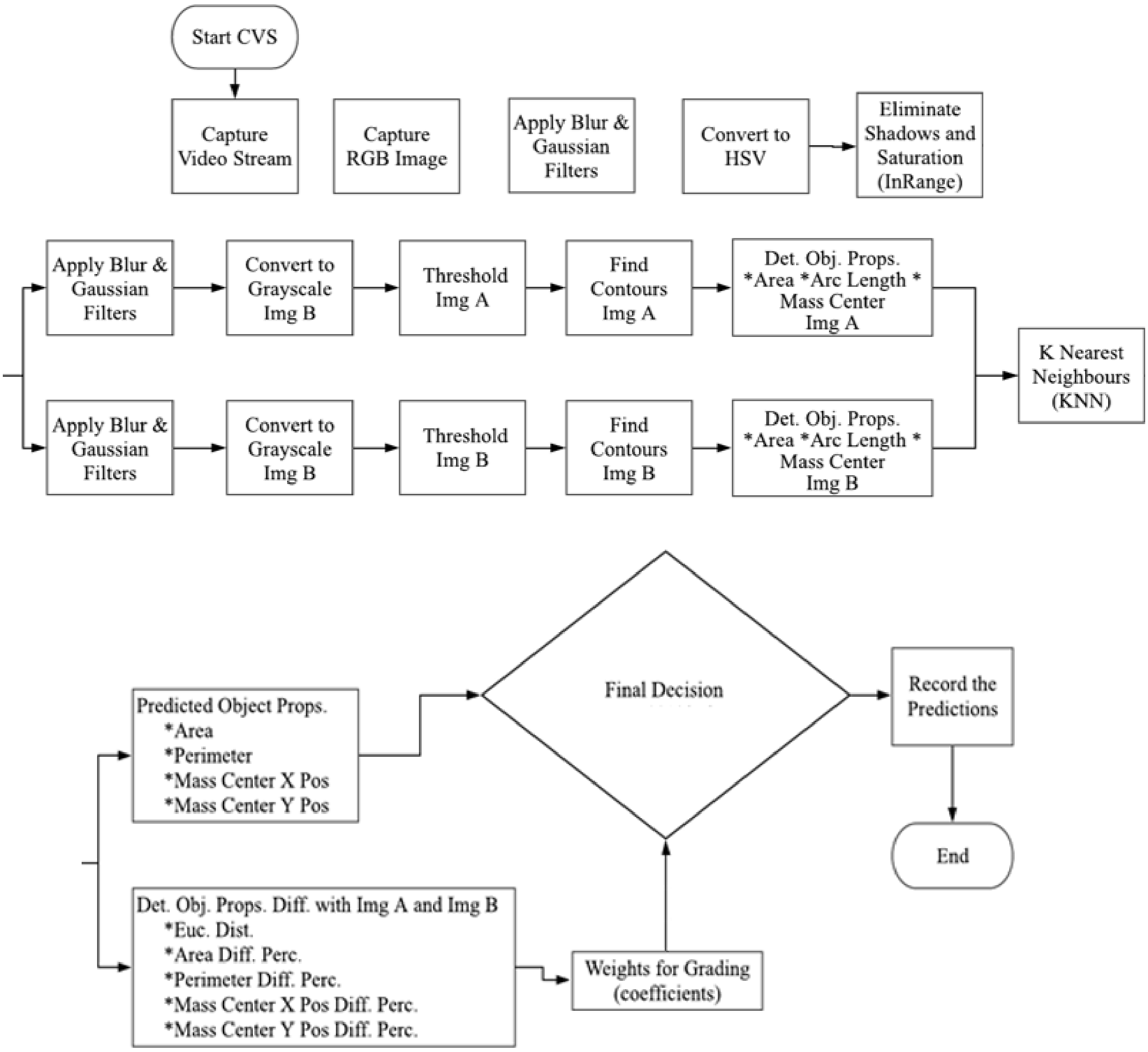


Fig. 3. Image processing procedure flowchart.

A demonstration of the workflow in terms of main steps for image processing procedure using an actual image can be seen in Fig. 4.

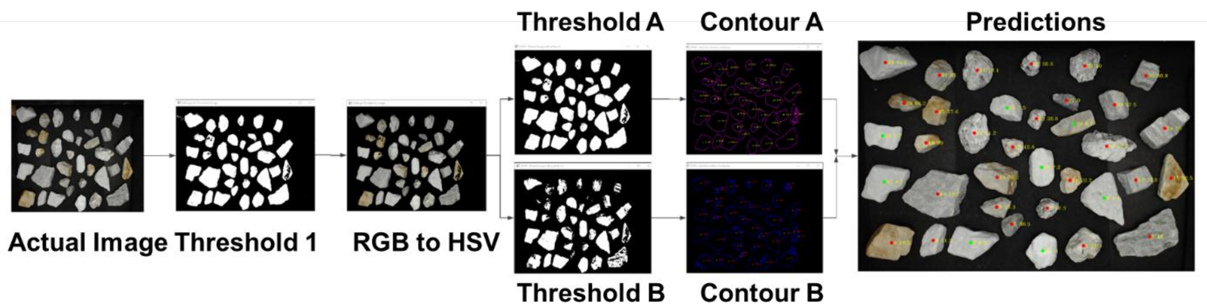


Fig. 4. Image processing procedure main steps.

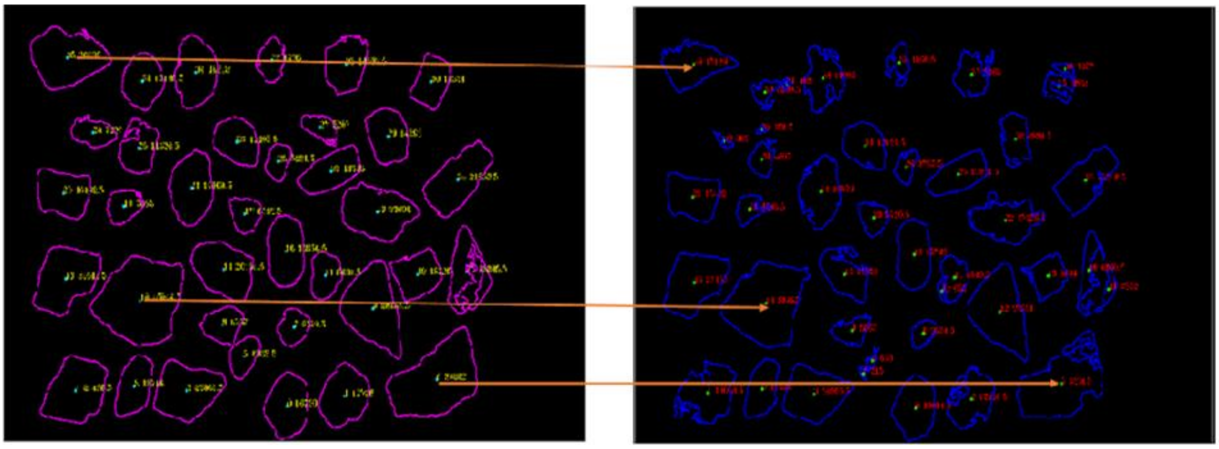
Background removing stage was conducted using in range operation on HSV image and a masking process was applied to obtain the actual image without background (Fig. 5).

(a) **(b)** **(c)**

Fig. 5. Removing background from the image, **(a)** actual, **(b)** mask and **(c)** removed background.

Each contour of the detected object was numbered, and the mass centers of the contours were compared based on Euclidean distance in Eq. (1). The predictions of matched objects depend on the contour area, perimeter and mass center parameters. A prediction gives a ratio concerning these parameters to grade a stone by its color intent.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$



(a) **(b)**

Fig. 6. Matching identical objects using detected **(a)** contours A and **(b)** contours B.

Image obtaining steps were conducted by acquiring images from four angles for all stone samples. The objects were rotated in the measurement cabinet manually for four different angles. The obtained images of the objects including 0°, 90°, 180°, 270° angle images are shown in Fig. 7.

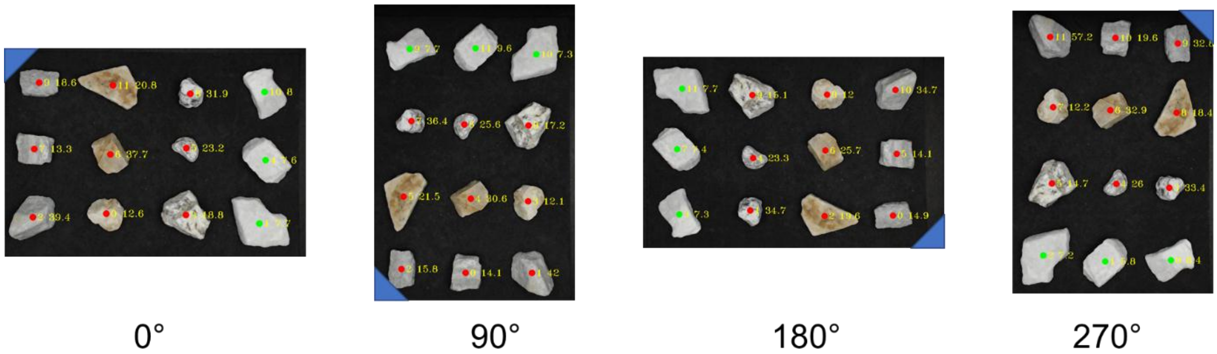


Fig. 7. An obtained image from the experiment with four different angles.

Every object within the field of view were rotated to provide four different alignments then black/white ratios were predicted. Groups and color distribution as well as statistical feature distribution of the stones (Table 2) are extracted and summarized in Tables 1 and 2, respectively.

Table 1. Groups and color distribution of the stones.

#	Group ID	Sampling Count	White Color Intent
1	A	40	High
2	B	38	Medium
3	C	37	Low
4	D	37	Very Low
Total	-	152	-

Table 2. Groups and color distribution of the stones.

No	Features	Min.	Max.	Mean	Std. Deviation
1	Euclidian distance	0.000	46.700	8.657	11.267
2	Area difference	5.300	97.500	34.277	28.395
3	Perimeter difference	0.100	85.100	24.985	24.322
4	Mass center X axis position	0.000	42.700	5.488	8.683
5	Mass center Y axis position	0.000	42.800	5.287	8.280

3.2. Machine Learning Process

The selection of the classification model is very important as the functionality in computer vision systems depend heavily on classification algorithms. Based on that fact, four different classification algorithms, namely Multi-layer Perceptron (MLP), Support Vector Machine (SVM), Decision Tree (DT) and k-Nearest Neighborhood (kNN) were considered in our study due to their widespread applications in the literature.

MLPs generate their own experiences from the information provided for the specific events. These experiences are then utilized to make decisions for similar problems conveniently. The artificial neuron structures formed by MLP algorithms are connected in a way to represent the fundamental characteristics of human brain, therefore the parallel processing with MLPs is possible for many CV applications [21, 22]. As a kernel-based algorithm, SVM offers a high computational power for classification and regression problems mainly due to its well-structured theoretical background [23]. Using an approach called a 'kernel-trick', SVMs can be employed for nonlinear data classification.

They can also operate with a small group of data, generating acceptable classification results [24]. These properties give SVMs the upper hand when dealt with more difficult classification tasks. The SVM configuration with a cubic core function (where d=3) utilized in this study (Eqn.'s 2 and 3).

$$k(x_i, x_j) = (x_i, x_j + 1)^d \tag{2}$$

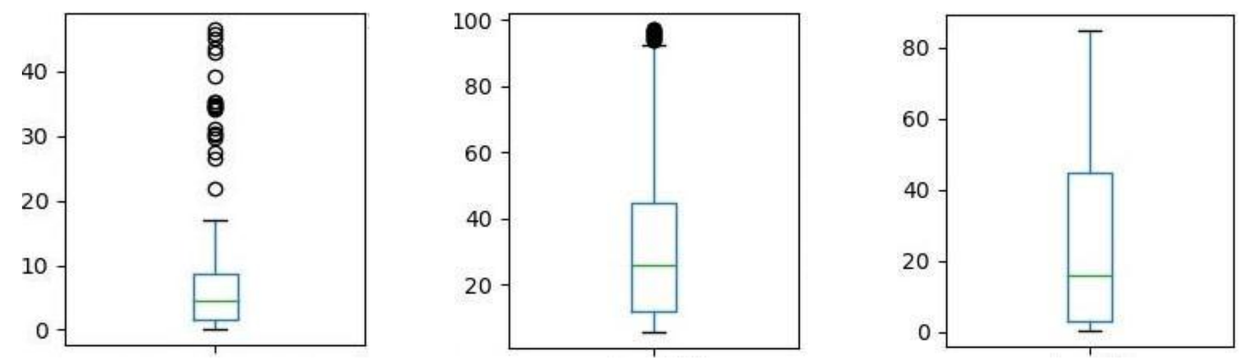
$$Max \sum_{i=1}^{i} \alpha_i - \frac{1}{2} \sum_{j=1}^{i} \alpha_i \alpha_j y_i y_j k(x_i * y_j) \tag{3}$$

DT models are frequently preferred in a variety of CV applications due to their easier implementation, computational economy and integration capabilities with databases [26]. DT, as the name implies, uses a tree-like model structure where the decisions it made can be observed. In the kNN algorithms, the specimens that form the classification problem are compared to a collection of educational samples, performing a pattern-recognition [27]. As an operating principle, the kNN algorithm compares the specimen to be classified to each sample in the training set. In this study, the Euclidean criterion is utilized (Eqn. 4):

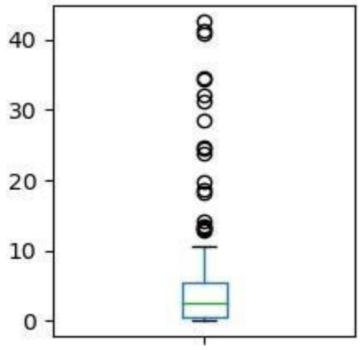
$$D_{L2}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{4}$$

In the machine learning stage, a total of 152 stone objects were used for the training and testing stage and the samples are A (40), B (38), C (37), D (37) grades, and sample counts, respectively.

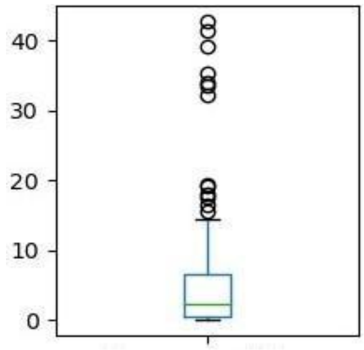
In the machine learning step, five normalized input parameters were evaluated: Euclidian distance, area difference, perimeter difference, mass center position of the contour for X and Y axes. Distributions of the parameters for grading stones are shown in Fig. 8. The plotted data shows that the stone group A is more differentiable compared to other groups. The area and arc differentiations and positions for X and Y axes parameters were observed separately and similar results were obtained. These results can be seen depending on the area and diameter data (Fig. 9) and mass center positions (Fig 10).



(a) (b) (c)



(d)



(e)

Fig. 8. Discriminating parameters, a) Eucledian distance, b) area, c) perimeter, d) mass center X position, e) mass center Y position.

In the machine learning stage 67% of the data was used for training and the testing process were conducted with 33% of the data. The criterion of measurement of different CV parameters are summarized on Table 3.

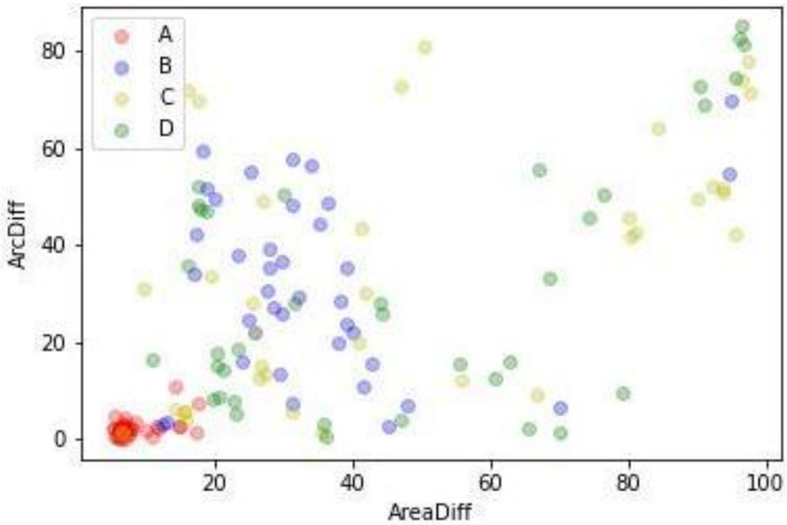


Fig. 9. Distribution of the raw dataset (with regards to area and perimeter).

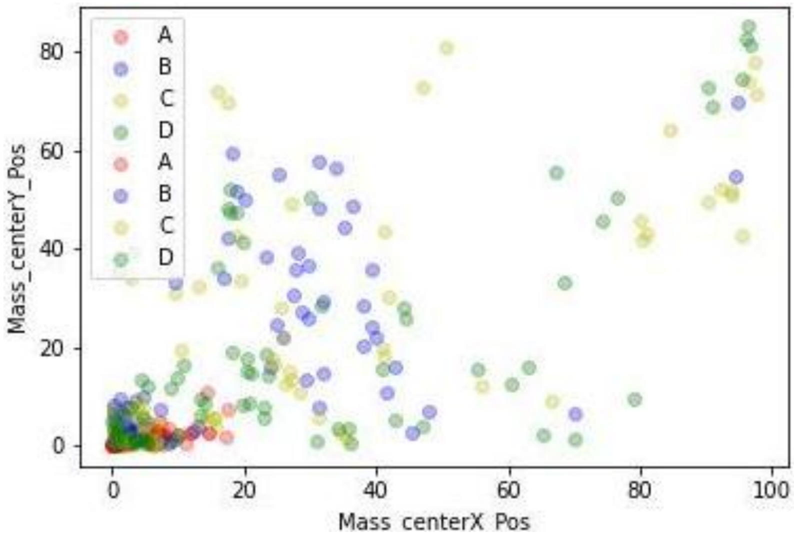


Fig. 10. Distribution of the raw dataset (concerning mass center positions for X and Y axes).

Table 3. The measurand for classification.

Measure	Formula
Accuracy	$\frac{tp+tn}{tp+fp+tn+fn}$
Misclassification Rate (Error Rate)	$\frac{fp+fn}{tp+fp+tn+fn}$
True Negative Rate	$\frac{tp}{actual\ no}$
True Positive Rate	$\frac{tp}{actual\ yes}$
Precision	$\frac{tp}{tp+fp}$
Recall	$\frac{tp}{tp+fn}$
F1 Score	$\frac{\frac{tp}{tp+fn}}{\frac{tp}{tp+fp}}$

4. Results and Discussion

In the experiments, four groups, each including ten arbitrarily selected stones, hence forty stone samples in total were used. The stones in the images were successfully detected by CVS and the accuracy of the image processing method proved by comparing the processed images with a scientific image processing software ImageJ. In Fig. 11 the CVS and ImageJ image processing results were demonstrated. Error bars in Fig. 11 show the standard deviation of four different measurement results from one experiment which includes four groups of stones. In the last stage of the experiment, the machine learning performance shown highly accurate results for classifying white stones in a multi class stone group.

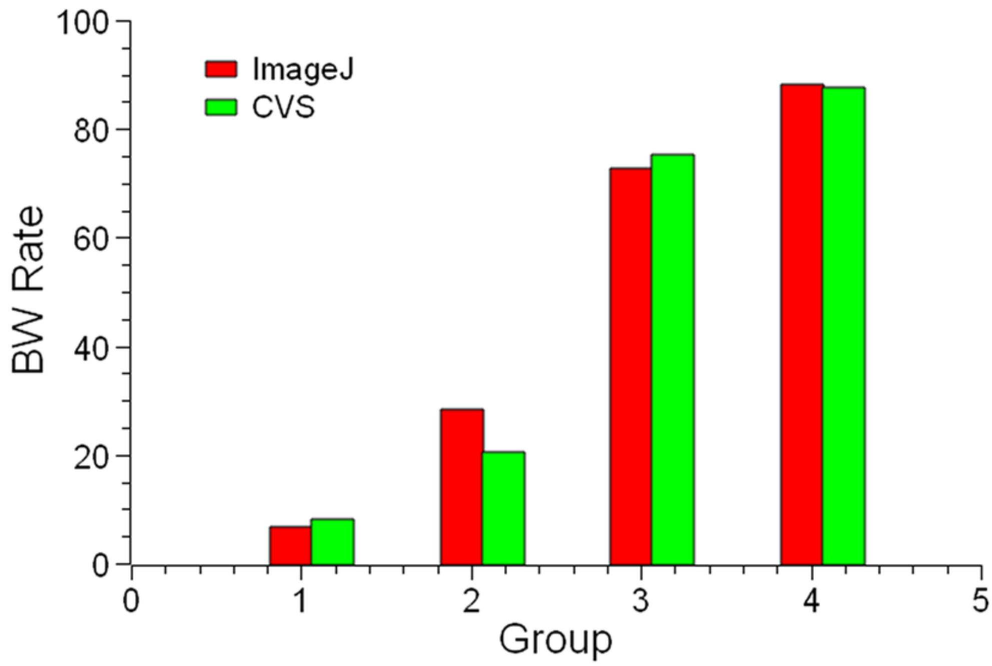


Fig. 11. Comparison of the CVS and ImageJ for image processing method.

The classification performance of the alternative models is shown in Table 4. The conducted experiments on learning process demonstrate that the predictions are highly accurate for kNN, Naïve Bayes and SWM models. The accuracies (F1 scores) of the models based on precision and recall parameters are 0.98, 0.98, 0.98 for kNN, Naïve Bayes and SWM models, respectively.

Table 4. Performance of the models.

Model	Precision	Recall	f1-score
Multi-layer perceptron (MLP)	0.95	0.94	0.94
Support vector machine (SVM)	0.98	0.98	0.98
Logistic Regression	0.95	0.94	0.94
K-nearest neighborhood (kNN)	0.98	0.98	0.98
Naïve Bayes	0.98	0.98	0.98

In the mine stone classifying applications for selecting white quartz stone, it is important to separate white stones from other groups concerning the quality of the end product. The binary based classification method was used to classify white stones from other groups due to the industrial requirements. A confusion matrix is composed to evaluate the prediction results concerning the accuracy, precision and recall parameters together, as seen on Table 5.

Table 5. The confusion matrices.

Model	Predictions			
	TN	FP	FN	TP
Multi-layer perceptron (MLP)	39	0	3	9
Support vector machine (SVM)	39	0	1	11
Logistic Regression	39	0	3	9
K-nearest neighborhood (kNN)	39	0	1	11
Naïve Bayes	39	0	1	11

This study suggests a relatively low-cost solution with an adequate accuracy developed specifically for the purpose of sorting white quartz-mine stones. An application on stone classifying using learning models based on size and color parameters of the stone was demonstrated. The initial parameters were obtained from stone images using a successful image processing procedure. The experimental results assert that the accuracy of the machine learning models depends on the distinguishing parameters. Concerning the conducted experiments, a CVS using the proposed image processing method with the help of the machine learning models is remarkably accurate. It is possible to apply the method with the models for classifying the targeted objects in real-time MVS with a conveyor line.

4. Conclusion and Recommendations

Classification is an indispensable process in industrial mass production applications where competitive marketing and increasing the product value by reducing time and saving costs are in question [28]. Today, with the help of the modern technology, more and more researchers focus on the image processing techniques for grading products mostly by their size and shape [29–30]. As suggested previously, the results obtained from the experimental setup, the image processing method is a dominant factor in object classifying applications. Also, there is a strict relationship between obtained parameters and learning model accuracy. In mass production, the accuracy of an MVS integrated on conveyor lines are very important to provide competitive solutions in the market. In conclusion, the accuracy mainly depends on the image processing procedure and the learning model as it has a positive correlation with the accuracy of the solution.

Authors Contributions

FA: Conceptualization, Methodology, Software and Validation, OE: Investigation, Sources, Validation, Editing, ÖS: Machine Learning Algorithm Implementation. All authors have read and agreed to the published version of the manuscript.

Competing Interests

The authors declare that they have no competing interests.

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