Journal of Soft Computing and Artificial Intelligence

Journal homepage: https://dergipark.org.tr/en/pub/jscai

International Open Access

Volume 04
Issue 01

June, 2023

Review Article

A Review on Measurement of Particle Sizes by Image Processing Techniques

Vahit Tongur [1], Ahmet Burçin Batıbay[2], Murat Karakoyun[3*]

[1]Software Engineering, Engineering and Natural Science Faculty, Konya Technical University, 42000, Konya, Turkey
[2]Metallurgical and Materials Engineering, Engineering Faculty, Necmettin Erbakan University, 42000, Konya, Turkey
[3]Computer Engineering, Engineering Faculty, Necmettin Erbakan University, 42000, Konya, Turkey*

ARTICLE INFO

Article history:
Received December 13, 2022
Revised February 7, 2023
Accepted February 17, 2023

Keywords:
Image processing
Measurement
Particle size
Segmentation

ABSTRACT

This review is based on how to measure particle sizes with different image processing techniques. In addition, particle size significantly affects the material's mechanical properties. In material science, the material's structure is analyzed to understand that a material can provide specific standards, such as toughness and durability. Therefore, it is essential to make this measurement carefully and accurately. The segmentation approach, frequently used in image processing, aims to isolate objects in an image from the background. In this sense, separating particles from the background is a problem of image processing. In image processing applications, there are different approaches used in segmentation, such as histogram-based, clustering-based, region amplification, separation, and merging. In this review, a comparative analysis was examined by recent studies on particle size measurement.

1. Introduction

Developments in computer technology, data collection hardware, laser technology and automated imaging platforms have changed the field of biomedical research. Hardware systems that once needed manual intervention can now be programmed to run continuously for days or even weeks. In addition, high-content screening systems allow multiple experimental hypotheses to be automatically tested simultaneously [1].

Artificial Intelligence is abbreviated as AI technology. AI is a new branch of science that emerged in the 1950s. It not only studies technology, but also applies relevant technology to products and develops intelligent products. It is a technical discipline that resembles or partially resembles humans, used to help humans complete related activities and extend some human intelligence [2]. Breakthroughs in computer-aided diagnosis and AI will shortly transform how we diagnose diseases. The most encouraging development in AI is machine learning, the branch of science that allows computers to analyze and learn from data without human guidance. These technologies are often found in areas such as spell inspection and the development of self-driving cars, and are all performed by neural network algorithms [3]. Recently, modeling methods with artificial intelligence have gained significance. Parameters determined with many data and experiments can be estimated more practically and correctly with artificial intelligence methods. In addition to calculations, artificial intelligence methods are used to determine the cooling system parameters of nuclear reactors, fuel measurement, or any thermophysical properties [4].

Artificial intelligence technology is an interdisciplinary topic: with its development encompassing a wide range of content and intersecting with the fields of philosophy,

* Corresponding author
e-mail: mkarakoyun@erbakan.edu.tr
DOI: 10.55195/jscai.1218662

mathematics, statistics and so on, various more innovative theories and technologies have emerged. For now, the research and application directions of AI technology includes perception intelligence, thinking intelligence, learning intelligence and behavioral intelligence, etc. The AI algorithm mimics some laws; the algorithm is summarized by humans and then transformed into some algorithms to solve some problems. Under the background of the constant development of computer technology, the application of artificial intelligence algorithms obtains a better image processing effect to a certain extent, such as the application of several optimization algorithms in image processing [2].

As a medium containing a wealth of information, imagery is an essential resource for human beings to acquire and exchange information. In general, images are photographs, graphics, movies, videos, computed tomography (CT), magnetic resonance imaging (MRI), remote sensing and even two-dimensional or three-dimensional data. However, the image itself sometimes has some disadvantages. To extract reliable information from the image, it is necessary to process it.

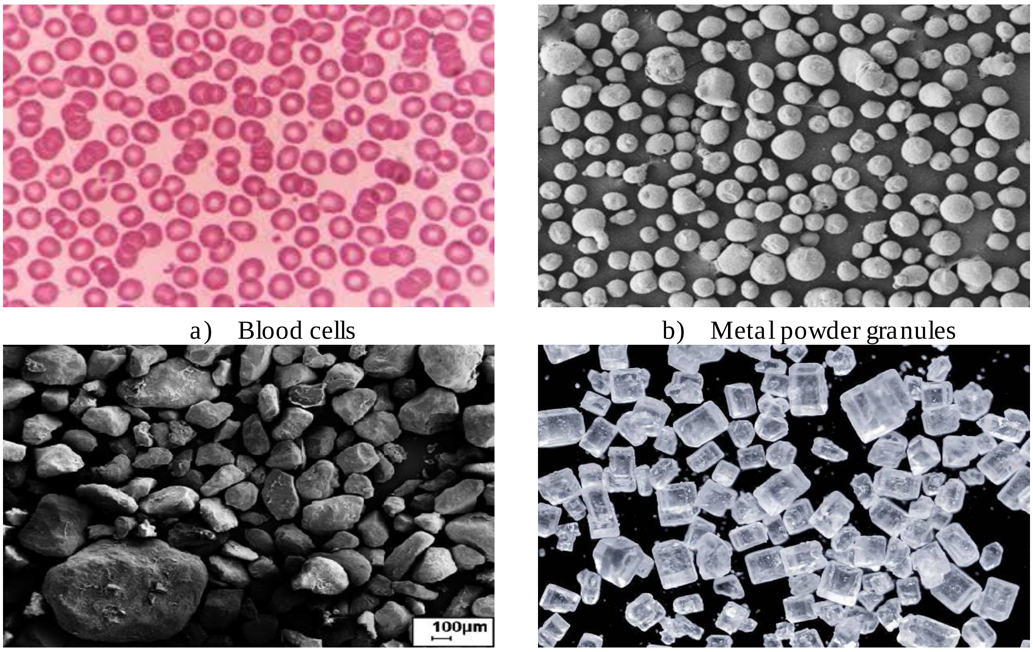
The main application areas of image processing include aerospace, terrain mapping, urban planning, medical research, combating product counterfeiting, engineering surface damage identification, real-time tracking, iris recognition and military, cultural, artistic and communicative aspects of human life, and business [2].

An image is equivalent to two dimensions for a machine and a computer. For the image to be processed by the computer, the image needs to be understood as a two-dimensional function, sampled, digitized and then processed. Therefore, image digitization is a necessary step for the computer to recognize images. After three steps of starting, developing, and popularizing, various disciplines have studied image processing, which has been widely used in various fields. Nowadays, with the fast development of science and technology, the science of image processing is making more and more progress both in theory and practice [2].

Particle size distribution of coarse-grain or fine-grain materials is figured out for experimental studies. Particle size distribution is a standard test used widely in different areas such as materials science, nanotechnology, biotechnology and metallurgy engineering to investigate the quality of materials. In recent decades, specific properties of particles are affected their manufacturing and application [5]. Size distribution is a crucial factor in increasing process performances. One of the earliest and most famous processes of size analysis was sieving or separating. Sieving is the cheapest method for measuring particle size. Particles are allocated according to their size and shape by particle size is defined as the diameter. Nonetheless, the action can be tedious and requires extra working time to process the fine and big particles. Accordingly, on-line particle size analysis was needed for the powder industry to be a critical impulse for particle sizing systems by imaging [6, 7]. Figure 1 presents sample images showing the particle distribution of materials in different areas.

There are several types of systems used for measuring particle sizes such as Dynamic Light Scattering (DLS) Analysis, X-Ray Diffraction (XRD), Scanning Electron Microscope (SEM) and light microscope. These systems are quite expensive and also are not accessible everywhere. The way to overcome this problem is to use an automatic image processing method. This method is fast and cheap for measuring particle size only needs a camera and a computer. And also, image processing methods can be used in biomedical and electronic industries. Besides using this approach, images are evaluated with little people interference and the images are more detailed and more specific than those achieved using a global one [5, 8].

Additionally, particle size distribution by using image processing has been investigated with shape and size characteristics in the past. This method precisely measures interparticle distance and aerodynamic size distribution from medical accessories. This method is more predictable than earlier theoretical models [5, 7].



a) Blood cells b) Metal powder granules

c) Sand particles d) Sugar crystals

Figure 1 Particle distribution of the different materials

One of the significant problems in practicing image processing and analysis methods for powder characterization is the specific selection of objects to allow accurate determination of their particular characteristics. Frequently, it cannot avoid touching or lapping over the particles in the images. This issue is demanding with fine without conducting powders due to electrostatic interaction [7, 9]. Particle images of different materials are presented in Fig. 1. Looking at the distribution of the particles in this example, it is seen that the particles in Fig. 1b are more discrete and separable, the particles in Fig. 1a, Fig. 1c and Fig. 1d are in contact or overlap. In this case, it can be said that the particle analysis of the image in Fig. 1b will be more accessible, on the contrary, the research in Fig. 1a, Fig. 1c and Fig. 1d will be more difficult. In summary, the state of the particle distribution in the images obtained from the materials can also affect the success of the application that analyzes and characterizes the material.

In general, there are five steps to analyze and characterize powder by using image processing. These steps include image acquisition, pre-processing, segmentation, extraction and representation of characteristic parameters. Image acquisition refers to digitalization as a crucial step for image processing techniques to convert images into numerical value for computers. The pre-processing step consists of fixing the image faults. This step includes different types of operations such as filters and edge detection. Segmentation is connected with extraction or discrimination. This step is to acquire a straight selection of the objects and also to uses specific algorithms such as Watershed [10]. Data extraction subjects to the applicable information to obtain specific parameters and shapes of individual particles for powder samples. Finally, representation is the last step to be processed the data by using the traditional statistic method and also shown by different types of graphs, diagrams and histograms [9, 11, 12]. Figure 2 shows the basic steps of an image processing application that performs particle size analysis.

This review's main aim is to research particle size measurement with different image processing techniques. With this review, which methods are used in the segmentation phase in image processing applications are examined in terms of shedding light on future studies.

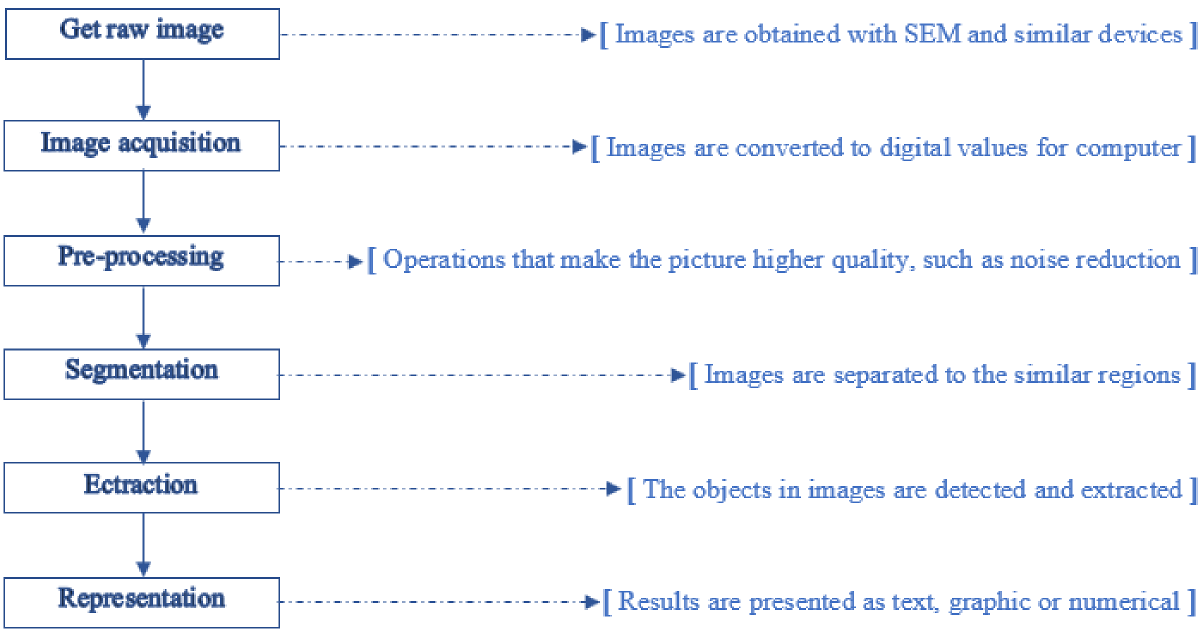


Figure 2 The main steps of an image processing application for particle analyzing

2. Different Approaches

Particle size measurement has long been used in different fields and has attracted the attention of many researchers. Li et al. [13] proposed an algorithm to automate the intercept method for measuring the average particle size of metallic materials. The algorithm can extract continuous and closed particle regions using topological skeletons and measure average particle size by recognizing and classifying the intersections between selected test models and particle boundaries. They used image smoothing and thresholding methods as pre-process steps. They applied their algorithm on 200 microscope images includes different material microstructures. The stated that the proposed automatic algorithm achieved an overall accuracy that is more than %98.

Ro et al. [14] have developed a new microscopic image analysis to increase the accuracy of particle size estimation of very small fragmented minerals. In their work, they have used individual particle segmentation, shape factor, watershed and deep learning methods. For the accuracy of the results obtained, they have sieved three samples as ferruginous quartzite, coal and magnetite and compared them with the results found. Since the samples used were very small, they applied the image stitching method before the image processing. After, they have used both watershed segmentation and deep neural network methods to separate overlap.

Akkoyun and Ercetin [15] used some methods of the image processing includes thresholding, filtering and contouring to calculate the number and size of the particles in Mg alloys. The experiment images taken from SEM. They compared the results of the proposed method with the manual measurement results. They stated that the success of their automatic system is 94% with a 6% standard deviation between automatic and manual results.

Guo et al. [16] have used an improved watershed segmentation method to segment rock fragments. Rock images have been captured using tilt photogrammetry to reduce measurement errors of overlapping rock blocks. Then, image preprocessing techniques have been used to determine the target rock area. Then, morphological operations have been applied to the obtained binary image and the watershed segmentation method has been applied after the distance transformation has been calculated. The performance of the proposed method has been compared with the results of manual screening and the methods in the literature.

Hu et al. [17] stated that traditional watershed and threshold segmentation algorithms are insufficient and the total number of processed particles in the image processing process affects the result. In their work, a deep learning algorithm (DLA) is presented to segment roughly stacked batch images. Aggregate images with different sizes and mixtures have been segmented and the results analyzed. Test results have been compared with the traditional watershed algorithm. Experimental results showed that the deep learning algorithm overcomes the problem of over-partitioning and under-partitioning of the watershed algorithm. In addition, desired results have been obtained in the partitioning of aggregates with different particle sizes and aggregate materials.

An image segmentation method for coal particle size distribution analysis was investigated by Bai et al. [18]. To avoid over-segmentation, the technique used a gradient watershed for pre-segmentation and applied the k-nearest neighbor (KNN) algorithm for region merging. As a result, many images were automatically segmented using the proposed method and the manual method. The proposed method effectively estimated the particle size of coal particles with low dust and moisture content, as the difference in particle size distribution between the two ways was very small. Therefore, the particle size and the number of particle size ranges were used to estimate the size distribution of coal particles. In addition, because it is more automatic, it can reduce the labor of workers and provide real-time data to other equipment. Thus, it can improve the automation level of the whole coal preparation plant.

Yang et al. [19] suggested applying an image processing technique to measure coal pieces produced by uniaxial compression tests. The image processing method based on the MATLAB image processing toolbar was proposed in this paper. The watershed method was applied for fragment segmentation. The contrast between the images demonstrates the suitability of the image processing method proposed for coal seam measurement before and after image processing. The image's fragment was considered an ellipsoid characterized by major, minor, and minor axes. The image-processed cumulative distribution of coal samples was determined based on the image analysis results, the ellipsoid volume equation, and the center-lateral axis value relationship. Comparisons between image processing, manual sieving, and fractal-modeled cumulative distribution curves indicated that digital image processing is an effective and accurate tool for measuring the size distribution of coal fragments. In future applications, only a single photograph will need to be taken and processed, saving more time in the image acquisition process. Image analysis is based on MATLAB coding, and data will be stored automatically. However, code retrieval and data analysis are completed with human interaction. It is possible to make all these processes smarter with programming, artificial intelligence, and deep learning applications.

A variety of ore images and an annotated dataset were studied by Li et al. [20]. In order to solve the problem of over- and under-segmentation in the task of ore image segmentation, the neural network-based U-Net model and a marked watershed were used. The purpose of ore image segmentation in an outdoor environment was achieved by this method. The experimental results have shown that the proposed method has high speed, strong robustness, and high accuracy characteristics. It has great practical value for the actual task of statistical analysis of ore grains.

Wu et al. [21] worked to find a solution to the problem experienced in the measurement of overlapping particles in the particle measurement of iron green pellets. For this purpose, they developed an approach based on morphological operations in the first stage and circle scanning in the second stage. They applied their method at a local steel company, which was a real test environment. They stated that they compared their methods with the success of manual measurement and other methods and they achieved a success rate of 94.3%.

Watano and Miyanami developed a monitoring system for granule growth in the pharmaceutical industry [22]. They have prepared a special mechanism for the system they have developed. This mechanism used a charge-coupled device (CCD) camera with particle-adjusted illumination. Some preprocessing, such as filtering and noise removal, was done on the images obtained with this camera. After these processes, some granules overlapping were observed, and changes were applied on the CCD camera to separate them. After these changes, they tried to separate the particles using circle pattern matching and the eight-neighbor erosion methods on the images they obtained. However, it was observed that most of the particles did not separate. Therefore, these methods were applied twice. Thus, the separation success rate was increased. After this step, the Feter diameter of each object was calculated. The accuracy of the results obtained was compared with the values measured from the fluidized bed granulation system, and the comparison results were similar.

Mora and Kwan used digital image processing to measure coarse concrete's shape factor, sphericity, and convexity. The method used in this study is suitable for estimating both the volume and thickness of the particles [23]. They worked on forty-six rock samples with three different types taken from five sources. Once the sample image was obtained, the particles and the background were distinguished from each other by increasing the contrast between the particles and the background and drawing the particle edges. Then, geometric analysis was performed for size and shape measurement according to the determined particle boundaries.

Lin et al. presented a three-dimensional watershed algorithm for the Automatic Segmentation of Nuclei in Confocal Image Stacks. They performed their experiments on a small microscopic piece of the rat hippocampus. In the segmented region, it was observed connected many objects. For the segmentation to be calculated correctly, connected objects must be separated. The Watershed algorithm needs to provide information about objects' shapes and sizes. This algorithm is generally used to separate connected objects. However, two different image transformations are commonly used to determine the boundaries surrounding the basins. The first is the distance transform. This transformation is usually related to the shapes of objects. However, this method produces better results for regular geometric shapes. Gradient transformation usually causes over-segmentation. Therefore, the authors proposed a hybrid method called "gradient-weighted distance transform", which includes both methods. When preprocessing is done using this method, it is observed that the watershed algorithm also parses singular objects that are not connected. To overcome this, merge methods are implemented to separate singular objects. The results obtained were verified with a human observer and a success rate of 97% was achieved. In addition, a significant improvement was achieved compared to previous studies [24].

Tek et al., in their work, proposed an approach based on the watershed algorithm and Radon transformation (Radon, 1986) for segmenting blood cell images. The images used in this study are microscopic peripheral blood which may include red cells, parasites, and white cells. The proposed approach is a stepwise algorithm with several different steps. An initial rough segmentation has been done with the minimum watershed area (a modified version by authors) as first step. And then, Radon transformation has applied to the rough segmented image to extract markers. Finally, the watershed algorithm has been re-applied to the images generated after the Radon transformation to achieve the final segmented image. To evaluate the performance and accuracy of the proposed approach, the authors used a set of data having 20 microscopic blood cell images, including 2177 different cells (red blood cells, white blood cells, and infected cells with parasites) by using counting and locating criteria. In the experimental results, they stated that they were quite successful, with a high segmentation success of 95.4% [25].

Zelelew et al. proposed a stepwise image processing system named Volumetric-based Global Minimum to segment the asphalt concrete images. Their algorithm includes some pre-processing methods of image processing and thresholding phase and is applied to X-ray computed tomography images of asphalt concrete. The volumetric attributes of asphalt concrete were used to determine the border thresholds of the air-mastic and mastic-mass. So, the proposed algorithm was applied to characterize the microstructure of the asphalt concrete. They stated that the images obtained by their system had satisfied improvement compared to the raw images and that images were ready for the following processes. Thus, they specified that their algorithms are more successful and advanced than many methods used manually in this field [26].

Liao and Tarng developed an automatic optical inspection system based on image processing to measure the size distribution of rough particles. The proposed system works online and consists of four sub-modules: a particle partition module, an image-acquiring module, an image processing/analyzing module, and an electronic inspection module. The system was applied to particles that are non-uniform to measure some metrics of the particles, like the number of particles, particle size distribution, and accumulated weight percentages. They conducted a regression analysis between the results obtained by their system and the traditional net sieving system to measure the quality and accuracy of their work.

According to the results, they stated that the proposed system achieved satisfied precision and accuracy on rough particles and additionally added that their system can be a good alternative to measure the different coarse particles like dolomite, sinter, serpentine, limestone etc. [27].

Sharif et al. proposed a stepwise image processing system to segment the blood cell images. Their work involves some pre-processing steps consists of filtering, image enhancement, color conversion, and segmentation. Typically, the counting of the blood cell is done manually via a hematocytometer using a counting chamber. A complete blood count process includes white blood cells, hematocrit, hemoglobin, platelet, and red blood cell analyses. Each of these elements is very important for the body system and gives information about the body's capacity. The work aims to provide an automatic segmentation system that achieves complete cell count by using some pre-process steps and watershed algorithm [28].

Schorsch et al. proposed a study measuring the size distribution of particles during crystallization [29]. They prepared a special experimental mechanism for measurement and obtain images from it. Before particle size measurement, they performed some tests to minimize the overlap of particles and observed that the overlap was minimal under brighter light.

Then, they carried out image analysis on servers that could perform real-time and parallel analysis. As a result of these analyses, the particles were divided into three classes: sphere, needle, and cube. In their experimental studies, the capabilities of the proposed methods for the size and shape distributions of particles were tested. For this, the experimental results were compared with the Coulter multisizer [30], which is known as a standard for particle size measurement. The results obtained from both methods were observed very close. The authors stated that the device and the image analysis algorithm showed high performance in characterizing the particles' size and shape for different samples. They noted that these results would provide a better understanding of how crystal size and shape depend on the operating conditions of the process and how they can be controlled. They also noted that it led to the developing of a powerful technique for monitoring crystallization.

Bahrami and Honarvar, in their work, stated that raw cane sugar is a very significant raw stuff of white sugar in the sugar industry, and the morphological/physical features of the raw material can directly affect the quality of the final white sugar. So, they aimed to measure the morphological characteristics (perimeter, area size, squareness and crystal numbers) of the raw cane sugar using image processing tool Matlab on the crystal that generated by the flatbed scanner. A data set consisting of two groups of raw sugar cane, imported and domestic, was created to be used in the study. Based on the results they obtained from their studies, they stated that the digital image processing technique they used was useful in determining both the morphological and physical properties of different raw sugar crystals and could be used as an alternative [31].

Pavithra and Bagyamani [32] used watershed and Circular Hough Transform (CHT) [33] image processing techniques for white blood cell count in their study. The number of blood cells is an essential factor in treating of many diseases. A microscopic image obtained for the blood cell count contains around 100 red blood cells, while the white blood cell is only 1 or 3. Therefore, manual blood cell counting is unreliable and can give incorrect results. For all these reasons, they proposed a fully automated method for white blood cell counting in their study. First, preprocessing was applied to the image taken from the microscope. Since white blood cells are darker than red blood cells, the image is converted to a gray level according to a certain threshold value. Pixels below the threshold are black, while pixels above it are white. Thus, the noise and other blood cells in the image are cleared. After the image preprocessing, the median filtering image enhancement method was used to make the objects on the image more apparent. Then, the gradient magnitude technique was used for image segmentation. The Sobel edge detection algorithm was used to make the border of white blood cells more specific. In addition, the watershed algorithm was applied to prevent over-segmentation. Then morphological operations were used. Morphological operations help to determine the shape of the object. Next, erosion and morphological dilation methods were applied to smooth the image and remove unwanted small pixels. Then, opening and closing operations were applied. After all these procedures, the CHT method was used for white blood cell count.

This method calculates the number of white blood cells by calculating the center point and radius of circular shapes on the image. In experimental studies on 20 images obtained from European Leukemia Net, the success rate was observed between 74% and 100%.

In their work, Cai and Su performed a step-by-step image processing study to segment particle images with missing illumination, blurred, and cohesive/adjacent structure. Various improvements have been made in the basic levels of image processing to segment particles consisting of uneven illumination, focus blur, and contact each other automatically and accurately and bypass the deficiencies of existing methods in the literature. As the first step, the grade of focus blur is reduced by analyzing and determining the optimal viewing plane of the particles. Then, the effect of uneven lighting is also eliminated using an adaptive thresholding method. Finally, with the help of the image reconstruction method, changing the result of the Euclidean distance transform of the binary image and coupled with the watershed transform, the touching particles are segmented efficiently. They stated that: experimental results and error analyses show that the proposed method can more accurately segment the contacting particles and also effectively avoid the over-partitioning problem [34].

Jagadev and Virani proposed a study that identified leukemia patients using image processing and machine learning algorithms. They used three different methods in their studies. These are k-means, Marker controlled watershed and Hue-Saturation-Value (HSV) color-based segmentation algorithms. Two hundred images obtained from the Goa Medical College online database were studied. These images include images of patients with leukemia and healthy individuals. First, the data in Cyan-Magenta-Yellow-Key (CMYK) was converted to Red-Green-Blue (RGB). The k-means clustering algorithm was used for the first image segmentation. Here k is taken as 3. These are nuclei (high saturation), background (high brightness and low saturation), and other cells. The distance between the two classes was used as the Euclidean distance. Then each pixel in the cluster is labeled as a cluster index. Second, the Marked controlled watershed algorithm was used. After the foreground objects and background positions were marked separately, the watershed algorithm was applied. Thus, over-segmentation is prevented. Finally, HSV color-based segmentation method was used [35]. Finally the support vector machine (SVM) [36] method was applied to determine whether the samples had leukemia or not.

Meng et al. proposed an algorithm for automated particle size distribution measurement [37]. The proposed algorithm used local adaptive canny edge detection and modified circular Hough transform methods. The images in their studies were obtained from SEM and transmission electron microscopy (TEM) imaging devices. Median filtering [38] method was used to remove noise in the image before the image processing steps. Edges of objects are an important feature in image processing. Various edge detection algorithms have been developed such as Roberts [39], Prewitt [40], Kirsch [41], Sobel [42], Robinson [43] and Canny [44]. Canny edge detection includes a multi-step algorithm with two thresholds, Th and Tl, for detecting and connecting edges. It is not easy to manually select these two threshold values. Therefore, the authors proposed a local adaptive Canny edge detection method. Tl was set as 0.4, while Th was obtained by the Otsu [45] algorithm. The Hough transform (HT) is used to detect geometric shapes. The basic Hough transform was designed for line detection but has been later extended to other shapes. Circular HT (CHT) is a special HT that has proven itself to detect circular objects. The basic principle of CHT is to convert geometric coordinates such as (x, y) into Hough parameter space. The authors proposed a modified CHT method. This method separates the basic CHT into two stages. These are to find the circle center and to determine the circle radius. Experimental studies were shown that modified CHT could detect more circles on overlapping images. The size distributions of the circles obtained by this method were determined and compared with the manual measurement values. Experimental studies were shown that the results obtained from both methods are very close. This proved the success of the proposed method.

Yang et al. used image processing to measure the size of the produced sand grains because they knew that the concrete quality was significantly affected by the grain structure of the sand it contained [46]. The authors developed a sand casting (dispersion) system based on the characteristics of the sand particle contours and an extraction mechanism to overcome the lack of the traditional vibratory screening method. Their work includes both hardware and software parts. Their work includes both hardware and software parts. A sand dispersal vehicle has been designed and developed as a hardware part that can completely disperse the falling sand. On the other hand, a segmentation method was used for the system's software. The Otsu's maximum variance between clusters approach was used as a segmentation method. The segmentation process separated the filtered sand particles from the background. In the study, some settings about particle size are done according to the JTG E42-2005 [47] standard. As a result of the study, they stated: Their system performs non-contact measurements of the produced sand without damaging the particles. It is faster and cheaper than classical methods. This system can also be applied to different material particles, not limited to the sand produced.

Laucka et al. used image processing techniques to measure the size of powder granules used in the chemical industry. In their study, they established an experimental setup to capture the image of the granules. Images of granule particles in the samples were obtained with a line scan camera. They used two different examples in their study. These are monocalcium phosphate and ammonium nitrate. The results needed a correction due to the different compositions of the particle measurement. Therefore, an artificial neural network model was used to increase the efficiency of the particle correction algorithm. In addition, SVM was used for image classification. The main disadvantage of the proposed method is that it gives much better results when the particles are in a certain ratio of circular shapes. The experimental setup was also set up in a fertilizer production factory, and measurements were made every 5 to 7 minutes during actual production [48].

Patmonoaji et al. tested the watershed method for pore-throat identification in unconsolidated porous media with various particle sizes and shapes. One of the most important steps in the watershed method is to find the parameter value that may cause over-segmentation and under-segmentation. If this parameter is below the optimum value, over-segmentation occurs, and if it is above, under-segmentation occurs. Therefore, a value close to the local peak was chosen. Three types of regular spherical particles were modeled to validate the results from the watershed model [49].

Biswal et al. estimated the grain boundaries of the images obtained from the optical microscope using image processing methods. A Median filter was applied to remove noise from images. Histogram Equalization was used for this. Edge detection methods such as Sobel, Robert, Prewitt, and Canny were used to detect granules. The results obtained from these methods were compared, and the canny edge detection method was chosen. Using the canny edge detection method, a watershed transform was applied with the marker-controlled approach on an image. The marker was used to control over-segmentation. After the watershed transformation, the average particle size was found for all the samples used in the experimental studies [50].

Cohn et al. used instance segmentation, a useful and advanced tool in computer vision [51]. The Mask region-based convolutional neural network (R-CNN) [52] which Facebook presented in 2017, was used for the instance segmentation process. The authors aimed to show the utility of instance segmentation in material science using the Mask R-CNN. The images of the metal powder particles generated by the SEM were used for the segmentation. They trained two independent models for segmenting the powder particles and satellites in each image. Training steps improved the models with five particle and ten satellite image instances, respectively. Precision and recall measurement metrics were used to analyze the results of the segmentation of the powder particle images. They stated that false positives occurred because of the separation of large pieces formed by the fusion of particles. On the other hand, according to the authors, the cause of the false negatives is incomplete small, or extremely clogged particles that do not contain a strong visual signal. That Mask R-CNN was also used on the spheroid particles taken from the Ultra High Carbon Steel database.

3. Discussion

This study collects papers related to particle measurement (blood cells, metal powder, sand, sugar, etc.) in the literature. The objects and methods used in these papers and the result of the study are summarized in Table 1. According to Table 1, the Watershed and Thresholding methods are used more frequently for particle measurement. In addition, Edge Detection and Hough Transform methods are also widely used. The examined materials are usually microscopic objects. For this reason, it has been seen that image processing techniques are used for the size of the materials. First, images of the materials to be measured are taken by devices such as SEM. Afterward, the material particles' size is calculated using image processing techniques. In Table 1, it is seen that particle measurements are made in many areas, from blood cells to metal powders, from cane sugar to granules, and from asphalt concrete to sand particles. Although there are different types of materials, it can be seen that measurement techniques are similar. Table 1 shows that the success of the Canny and Hough Transform methods are close to each other, but the edge detection methods are more successful in larger objects. Although the results obtained from the studies on soil particles in the Watershed method could be more satisfactory, it is observed that 97% success is achieved in the studies performed on rat cells. This indicates that a suitable method should be selected for the study material. In addition, it is understood from the studies that the watershed method is an appropriate method for segmentation (especially for contacted particles). It can be seen in the studies that hybrid methods are also used instead of a single image processing method. Hybrid methods have increased the success of the results obtained.

Article	Data	Techniques	Results
[5]	Blood cells	Edge detection and morphological operator	This method is more accurate for larger objects and high-resolution images.
[6]	Limestone, coal, rounded stone, pyrite and iron ore	Watershed	Results showed some enhancements when applying the proposed approach to non-overlapped particles.
[7]	Quartz sands	Split desktop tool	Without wasting time and practical to other method.
[8]	Nanosilver powder	Thresholding	Results show that the suggested image-processing technique from SEM micrographs could measure nanoparticles that cannot be detected by DLS analysis.
[9]	Zirconia powder and adipic acid particles	Watershed and morphological operator	Segmentation process results are shown to be convenient to enable accurate edge detection for heterogeneous particles.
[11]	Soil particles	Watershed	Obtained results of soil samples by image analysis are not satisfied according to the expected results.
[12]	Nanomaterial powder	Thresholding, filtering and morphological operator	The proposed approach is convenient for analyzing the powder particle size.
[13]	Iron and stainless steel	Thresholding and morphological operator	The algorithm can extract continuous and closed particle regions and measure average particle sizes.
[14]	Ferruginous quartzite, coal and magnetite	Watershed and deep learning	Watershed segmentation and deep neural network were successfully applied to separate the overlaps.
[15]	Mg alloys	Thresholding, filtering, contouring	A success rate of 94% was observed between automatic and manual measurement.
[16]	Rocks	Morphological operators and Watershed	The proposed method has been successful in segmenting rock images.
[17]	Aggregate materials	Deep learning	Desired results have been obtained in the partitioning of aggregates with different particle sizes and aggregate materials.
[18]	Coal particles	Watershed and KNN	The proposed method effectively estimated the particle size of coal particles with low dust and moisture content.

[19]	Coal pieces	Watershed	The results showed indicated that digital image processing is an effective and accurate tool for measuring the size distribution of coal fragments.
[20]	Ore grains	NN-based U-Net and Watershed	The proposed method has high speed, strong robustness, and high accuracy characteristics.
[21]	Iron green pellets	Morphological operator and circle-scan	The proposed approach achieved 94.3% success in measuring overlapping particles.
[22]	Granules	Thresholding and morphological operator	Image processing results could detect both granule growth in the low and rapid granule growth in the high moisture with high accuracy.
[24]	Rat hippocampus	Watershed	The results obtained were verified with a human observer, and a success rate of 97% was achieved.
[25]	Blood cells	Watershed and Radon transformation	Results are quite successful, with a high segmentation accuracy of 95.4%.
[26]	Asphalt concrete	Enhancement thresholding	The proposed thresholding algorithm greatly enhances the traditional techniques used in the literature.
[27]	Rough particles	Thresholding	The proposed system achieved satisfied precision and accuracy on rough particles and can be applied to different rough particles such as dolomite, sinter, serpentine, limestone etc.
[28]	Blood cells	Watershed	This work illustrates an automatic segmentation system that reaches a complete cell count using pre-processing steps and a watershed algorithm.
[31]	Cane sugar	Matlab tool	Results show that the digital image processing technique can be useful in determining the morphological and physical properties of different raw sugar crystals as an alternative.
[32]	Blood cells	Watershed and Hough transform	The results' success rate is between 74% and 100%.
[34]	Noisy particles	Thresholding and watershed	Results illustrate that the proposed method can be more accurate by segmenting contacted particles.
[35]	Blood Cells	K-means, watershed and HSV	Many features are extracted to make the detection process more exact and detailed.
[35]	Carbon nanospheres	Canny and Hough transform	Results illustrate that both methods are very close. This proves the success of the proposed method.
[46]	Sand particles	Thresholding	The proposed system applies non-contact measurement of the sand without damaging the particles and is faster and cheaper than classical methods.
[48]	Powder granules	ANN and SVM	The most detailed results of measurements with sieves are reached for correction by using an ANN.
[50]	Aluminum based hybrid composite	Watershed and Canny	Results show that it can be a new image processing technique for grain boundary analysis.
[51]	Metal powders	Mask R-CNN	Results show that Mask R-CNN can be useful for automating image segmentation in material science.

4. Conclusion

Different studies in the literature are examined in Table 1. In these reviews, a summary of various image processing techniques used in many different fields is given. It has been seen that image processing techniques are used to count the blood cell in the health area, investigate different particles (metal powder, sand, cement, etc.) in materials science, and measurement of sugar particles in the food industry. Among these techniques, edge detection and heuristic algorithms, morphological operators, transformation approaches, thresholding, and tools that can be ready have been used in some studies. As it can be understood from the studies in the literature, it has been stated that different methods are recommended for different data. The same method has been observed to give different results on different data. The research concluded that any method was not successful in every data and that the method suitable for the data should be meticulously determined. Considering the past to the present, it is seen that the subject is up-to-date, existing methods and new techniques have continued to be researched, and many recent studies have been carried out in different fields.

Acknowledgments

The authors acknowledge the financial support from Necmettin Erbakan University Scientific Research Project under grant number 211219011.

References

[1] G. González and C. L. Evans, "Biomedical Image Processing with Containers and Deep Learning: An Automated Analysis Pipeline: Data architecture, artificial intelligence, automated processing, containerization, and clusters orchestration ease the transition from data acquisition to insights in medium-to-large datasets," *BioEssays*, vol. 41, no. 6, p. 1900004, 2019.

[2] X. Zhang and W. Dahu, "Application of artificial intelligence algorithms in image processing," *Journal of Visual Communication and Image Representation*, vol. 61, pp. 42-49, 2019.

[3] S. Robertson, H. Azizpour, K. Smith, and J. Hartman, "Digital image analysis in breast pathology—from image processing techniques to artificial intelligence," *Translational Research*, vol. 194, pp. 19-35, 2018.

[4] O. E. Akay and M. Das, "Modeling the total heat transfer coefficient of a nuclear research reactor cooling system by different methods," *Case Studies in Thermal Engineering*, vol. 25, p. 100914, 2021.

[5] S. V. Seyedin, S. H. Seyedin, and A. S. Seyedin, "Designing and programming an efficient software for sizing and counting various particles using image processing technique," *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, vol. 10, no. 2, pp. 103-118, 2019.

[6] S. Al-Thyabat and N. Miles, "An improved estimation of size distribution from particle profile measurements," *Powder Technology*, vol. 166, no. 3, pp. 152-160, 2006.

[7] I. Kursun, "Particle size and shape characteristics of kemerburgaz quartz sands obtained by sieving, laser diffraction, and digital image processing methods," *Mineral Processing & Extractive Metallurgy Review*, vol. 30, no. 4, pp. 346-360, 2009.

[8] E. Emil Kaya, O. Kaya, G. Alkan, S. Gürmen, S. Stopic, and B. J. M. Friedrich, "New proposal for size and size-distribution evaluation of nanoparticles synthesized via ultrasonic spray pyrolysis using search algorithm based on image-processing technique," vol. 13, no. 1, p. 38, 2020.

[9] A. Nazar, F. Silva, and J. Ammann, "Image processing for particle characterization," *Materials characterization*, vol. 36, no. 4-5, pp. 165-173, 1996.

[10] S. Beucher, "Use of watersheds in contour detection," in *Proceedings of the International Workshop on Image Processing*, 1979: CCETT.

[11] K. S. Naphade, "Soil characterization using digital image processing," Lehigh University, 1999.

[12] L. C. Wu and C. Yu, "Powder particle size measurement with digital image processing using Matlab," in *Advanced Materials Research*, 2012, vol. 443, pp. 589-593: Trans Tech Publ.

[13] X. Li *et al.*, "Automation of intercept method for grain size measurement: A topological skeleton approach," *Materials & Design*, vol. 224, p. 111358, 2022.

[14] S. Ro, J. Jon, and K. Ryu, "A method for improving the estimation accuracy of the particle size distribution of the minerals using image analysis," *Computational Particle Mechanics*, pp. 1-13, 2022.

[15] F. Akkoyun and A. Ercetin, "Automated Grain Counting for the Microstructure of Mg Alloys Using an Image Processing Method," *Journal of Materials Engineering and Performance*, vol. 31, no. 4, pp. 2870-2877, 2022.

[16] Q. Guo, Y. Wang, S. Yang, and Z. Xiang, "A method of blasted rock image segmentation based on improved watershed algorithm," *Scientific Reports*, vol. 12, no. 1, p. 7143, 2022.

[17] X. Hu, H. Fang, J. Yang, L. Fan, W. Lin, and J. Li, "Online measurement and segmentation algorithm of coarse aggregate based on deep learning and experimental comparison," *Construction and Building Materials*, vol. 327, p. 127033, 2022.

[18] F. Bai, M. Fan, H. Yang, and L. Dong, "Image segmentation method for coal particle size distribution analysis," *Particuology*, vol. 56, pp. 163-170, 2021.

[19] X. Yang, T. Ren, and L. Tan, "Size distribution measurement of coal fragments using digital imaging

processing," *Measurement*, vol. 160, p. 107867, 2020.

[20] H. Li, C. Pan, Z. Chen, A. Wulamu, and A. Yang, "Ore Method Based on U-Net and Watershed," *Computer, Materials & Continua*, vol. 65, no. 1, pp. 563-578, 2020.

[21] X. Wu, X.-Y. Liu, W. Sun, C.-G. Mao, and C. Yu, "An image-based method for online measurement of the size distribution of iron green pellets using dual morphological reconstruction and circle-scan," *Powder Technology*, vol. 347, pp. 186-198, 2019.

[22] S. Watano and K. Miyanami, "Image processing for on-line monitoring of granule size distribution and shape in fluidized bed granulation," *Powder technology*, vol. 83, no. 1, pp. 55-60, 1995.

[23] C. Mora and A. Kwan, "Sphericity, shape factor, and convexity measurement of coarse aggregate for concrete using digital image processing," *Cement and concrete research*, vol. 30, no. 3, pp. 351-358, 2000.

[24] G. Lin, U. Adiga, K. Olson, J. F. Guzowski, C. A. Barnes, and B. Roysam, "A hybrid 3D watershed algorithm incorporating gradient cues and object models for automatic segmentation of nuclei in confocal image stacks," *Cytometry Part A: the journal of the International Society for Analytical Cytology*, vol. 56, no. 1, pp. 23-36, 2003.

[25] F. B. Tek, A. G. Dempster, and I. Kale, "Blood cell segmentation using minimum area watershed and circle radon transformations," in *Mathematical morphology: 40 years on*: Springer, 2005, pp. 441-454.

[26] H. Zelelew, A. Papagiannakis, and E. Masad, "Application of digital image processing techniques for asphalt concrete mixture images," in *The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG)*, 2008, pp. 119-124: Citeseer.

[27] C. Liao and Y. Tarng, "On-line automatic optical inspection system for coarse particle size distribution," *Powder Technology*, vol. 189, no. 3, pp. 508-513, 2009.

[28] J. M. Sharif, M. Miswan, M. Ngadi, M. S. H. Salam, and M. M. bin Abdul Jamil, "Red blood cell segmentation using masking and watershed algorithm: A preliminary study," in *2012 international conference on biomedical engineering (ICoBE)*, 2012, pp. 258-262: IEEE.

[29] S. Schorsch, T. Vetter, and M. Mazzotti, "Measuring multidimensional particle size distributions during crystallization," *Chemical Engineering Science*, vol. 77, pp. 130-142, 2012.

[30] W. R. Hogg and W. H. Coulter, "Apparatus and method for measuring a dividing particle size of a particulate system," ed: Google Patents, 1971.

[31] M. Bahrami and M. Honarvar, "Measurement of morphological characteristics of raw cane sugar crystals using digital image analysis," 2015.

[32] S. Pavithra and J. Bagyamani, "White blood cell analysis using watershed and circular hough transform technique," *Int. J. Comput. Intell. Inform*, vol. 5, no. 2, pp. 114-123, 2015.

[33] H. Rhody, "Lecture 10: Hough circle transform," *Chester F. Carlson Center for Imaging Science, Rochester Institute of Technology*, 2005.

[34] Y. Cai and M. Su, "An improved image processing method for particle measurement," in *2017 IEEE International Conference on Imaging Systems and Techniques (IST)*, 2017, pp. 1-6: IEEE.

[35] P. Jagadev and H. Virani, "Detection of leukemia and its types using image processing and machine learning," in *2017 International Conference on Trends in Electronics and Informatics (ICEI)*, 2017, pp. 522-526: IEEE.

[36] R. Dietrich, M. Opper, and H. Sompolinsky, "Statistical mechanics of support vector networks," *Physical review letters*, vol. 82, no. 14, p. 2975, 1999.

[37] Y. Meng, Z. Zhang, H. Yin, and T. Ma, "Automatic detection of particle size distribution by image analysis based on local adaptive canny edge detection and modified circular Hough transform," *Micron*, vol. 106, pp. 34-41, 2018.

[38] T. Huang, G. Yang, and G. Tang, "A fast two-dimensional median filtering algorithm," *IEEE transactions on acoustics, speech, and signal processing*, vol. 27, no. 1, pp. 13-18, 1979.

[39] L. G. Roberts, "Machine perception of three-dimensional solids," Massachusetts Institute of Technology, 1963.

[40] J. M. Prewitt, "Object enhancement and extraction," *Picture processing and Psychopictorics*, vol. 10, no. 1, pp. 15-19, 1970.

[41] R. A. Kirsch, "Computer determination of the constituent structure of biological images," *Computers and biomedical research*, vol. 4, no. 3, pp. 315-328, 1971.

[42] I. Sobel and G. Feldman, "A 3x3 isotropic gradient operator for image processing," *a talk at the Stanford Artificial Project in*, pp. 271-272, 1968.

[43] G. S. Robinson, "Edge detection by compass gradient masks," *Computer graphics and image processing*, vol. 6, no. 5, pp. 492-501, 1977.

[44] J. Canny, "A computational approach to edge detection," *IEEE Transactions on pattern analysis and machine intelligence*, no. 6, pp. 679-698, 1986.

[45] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE transactions on systems, man, and cybernetics*, vol. 9, no. 1, pp. 62-66, 1979.

[46] J. Yang, W. Yu, H.-y. Fang, X.-y. Huang, and S.-j. Chen, "Detection of size of manufactured sand particles based on digital image processing," *PloS one*, vol. 13, no. 12, p. e0206135, 2018.

[47] P. China, "Ministry of Communications. JTGE 42-2005 test methods of aggregate for highway engineering [S]," ed: Beijing: China Communications Press, 2005.

[48] A. Laucka, V. Adaskeviciute, and D. Andriukaitis, "Research of the equipment self-calibration methods for different shape fertilizers particles distribution by size using image processing measurement method," *Symmetry*, vol. 11, no. 7, p. 838, 2019.

[49] A. Patmonoaji, K. Tsuji, and T. Suekane, "Pore-throat characterization of unconsolidated porous media using watershed-segmentation algorithm," *Powder Technology*, vol. 362, pp. 635-644, 2020.

[50] S. R. Biswal, T. Sahoo, and S. Sahoo, "Prediction of grain boundary of a composite microstructure using digital image processing: a comparative study," *Materials Today: Proceedings*, vol. 41, pp. 357-362, 2021.

[51] R. Cohn, I. Anderson, T. Prost, J. Tiarks, E. White, and E. Holm, "Instance segmentation for direct measurements of satellites in metal powders and automated microstructural characterization from image data," *JOM*, vol. 73, no. 7, pp. 2159-2172, 2021.

[52] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask r-cnn," in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 2961-2969.