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Review

Review of Image Processing Methods for Surface and Tool Condition Assessments in Machining

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Abstract: This paper systematically explores the applications of image processing techniques in machined surface analysis, a critical area in industries like manufacturing, aerospace, automotive, and healthcare. It examines the integration of image processing in traditional Computer Numerical Control (CNC) machining and micromachining, focusing on its role in tool wear analysis, workpiece detection, automatic CNC programming, and defect inspection. With AI and machine learning advancements, these technologies enhance defect detection, surface texture analysis, predictive maintenance, and quality optimization. The paper also discusses future advancements in high resolutions, 3D imaging, augmented reality, and Industry 4.0, highlighting their impact on productivity, precision, and challenges such as data privacy. In conclusion, image processing remains vital to improving manufacturing efficiency and quality control.

Keywords: machining; image processing; cutting tool; surface evaluation; burr analysis

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1. Introduction

Understanding and evaluating machined surfaces is essential in various industries, and image processing techniques offer significant insights and advanced analysis methodologies. These techniques have been instrumental in refining the mechanisms used for measuring surface roughness and have revealed the intricate details, minimizing the complexities of machined surfaces and offering new perspectives in engineering studies.

1.1. Background of Machined Surfaces

The measurement and analysis of machined surfaces have evolved significantly over the decades, driven by the need for greater precision and understanding of surface characteristics. Initially, touch-based methods were the go-to, where probes delicately interacted with the surface to measure roughness [1,2]. These methods were limited in their precision and ability to capture detailed surface features, necessitating a transition to more advanced techniques.

As the demand for higher accuracy grew, more advanced techniques were developed. Hydraulic and pneumatic methods emerged, offering better control and more precise measurements [3,4]. These advancements marked a noteworthy improvement but still faced limitations in capturing the full complexity of machined surfaces [5,6].

The development of optical reflection techniques represented a major leap forward. These methods allowed for non-contact measurements, significantly reducing errors and providing higher-resolution data [7,8]. Instruments such as tracker-tip devices enhanced the ability to measure surface roughness with great precision by magnifying surface vibrations [9–11]. These instruments demonstrated the integration of mechanical, pneumatic, electronic, and optical technologies, emphasizing the multidisciplinary nature of advancements in surface measurement.

The machining field has evolved to include image processing techniques that provide detailed, real-time analysis of surface characteristics. This evolution highlights the ongoing development toward precision and a deeper understanding of the study of machined surfaces.

1.2. The Need for Surface Evaluation

Surface evaluation has emerged as an essential aspect of machining processes, primarily due to machined components' quality, structural integrity, and functional proficiency. Careful assessment of machined surfaces is essential, as it directly impacts components' performance, reliability, and durability in different applications. The importance of evaluating surfaces becomes clear when considering the negative effects, such as defects or inconsistencies on machined surfaces [12,13]. Even the slightest imperfection can propagate into severe complications, possibly leading to catastrophic failure of components and machine systems. This crucial interrelation between surface quality and component functionality renders surface evaluation a paramount concern in manufacturing disciplines [14].

Surface evaluation, with its wide range of applications, is not confined to laboratory investigations, particularly in the realm of metals and plastics [15,16]. It extends to broader commercial applications where more devices and techniques are employed for determining surface roughness and quality [17,18]. The diversity in application domains illustrates surface evaluation's universal importance and applicability across various materials and scales. The interplay of surface texture images and probe laser beams emphasizes the intricate refinements and critical complexities inherent to surface evaluation processes. The aforementioned complex interactions focusing on multidimensional aspects provide profound insights into the microscopic world of machined surfaces, leading to significant contributions to materials science and the engineering domain [19].

The inherent challenges and complexities of machined surfaces, such as maintaining the optical system's focus and meticulously accounting for variations in returned probe light, emphasize the imperative for precision, accuracy, and careful evaluation methodologies. These challenges are not merely technical hurdles but complex aspects that need significant attention and resolution to ensure the comprehensive and accurate assessment of surface characteristics and qualities. Each intricacy and challenge in surface evaluation explains the complex interplay between precision and understanding, emphasizing the need for continuous refinement and advancement in evaluation methodologies. This constant drive for precision and experience ensures the ongoing advancement of surface evaluation, expanding our knowledge of machined surfaces and leading to innovations that improve the reliability and performance of machined components [20].

1.3. Role of Image Processing in Surface Evaluation

With the ever-evolving advancements in digital technologies, image processing has become a key and transformative solution for navigating and addressing the intricate and multifaceted needs of surface evaluation. Image processing techniques enable the detailed analysis of critical indicators such as surface roughness, surface hardness, and wear patterns, which are crucial for assessing the quality of machined surfaces and tool life.

Surface roughness is a critical functional parameter that influences machined components' performance, reliability, and durability. Advanced image processing techniques enable the high-resolution, non-contact measurement of surface roughness, facilitating the precise control and optimization of machining processes [21–23]. Additionally, analyzing wear patterns through image processing helps predict tool life and scheduling maintenance, thereby reducing downtime and improving overall manufacturing efficiency [24]. Incorporating image processing technologies within the manufacturing sector has significantly enhanced operational productivity, accuracy, and management efficiencies [25]. By enabling real-time, detailed analysis of machined surfaces post various machining processes such as turning, milling, and drilling, these technologies address the limitations of traditional methods and ensure optimal surface quality [17,25,26].

In conclusion, the profound impact and transformative role of image processing in evaluating machined surfaces emphasize the significance of technological advancements in manufacturing sciences. The precise analysis of key indicators facilitated by image processing strengthens the quality assessment of machined surfaces and extends tool life, ensuring reliability and performance in manufacturing processes [27,28].

In the following sections, this paper provides a detailed analysis of the evolution of surface evaluation techniques, emphasizing the transition from traditional contact methods to modern image processing technologies. Section 2 explores the fundamental principles and techniques of surface evaluation, focusing on contact and non-contact methods. Section 3 discusses the role of image processing in surface analysis, highlighting its applications in surface roughness measurement, tool wear detection, and quality control. Section 4 explores the integration of image processing with artificial intelligence and machine learning, focusing on its transformative impact on predictive maintenance and defect detection. Finally, Section 5 presents the future directions of image processing in manufacturing, emphasizing advancements in 3D imaging and Industry 4.0. The paper concludes with key findings and recommendations for future research in machined surface analysis.

2. Image Processing: An Overview

Image processing is integral to many industrial fields, such as medicine, automotive, security systems, and entertainment. It is crucial for information extraction, object recognition, face recognition, image compression, medical imaging, and autonomous vehicle perception [29–31]. This study aims to provide a simple and understandable introduction to image processing methods directly relevant to our focus. This section will briefly outline the fundamental concepts and techniques of image processing pertinent to surface image analysis in milling, turning, and similar operations. This introduction will guide researchers, providing a strong foundation for more in-depth studies and projects in this area.

2.1. Basics of Image Processing

Images contain different levels of information and detail depending on the bit depth. Bit depth refers to the number of color or intensity levels a pixel can represent. The literature uses bit values such as 1, 2, 4, 8, and 16 [32,33]. In applications where speed is important, images are expressed with a low number of bits, while a high number of bits is used in applications that require a wide range of colors. In gray and color images, 8-bit images are commonly used [32,33].

In computer systems, images are expressed in 2D or 3D matrices with values ranging from 0–255. This basic image unit contains color and intensity information. While grayscale images are represented with 2D matrices, 3D matrices combine red, green, and blue (RGB) color triads. Figure 1 shows the representation of a colored image in a 3D matrix format by a computer system. The value of n × m represents the resolution of the image section.

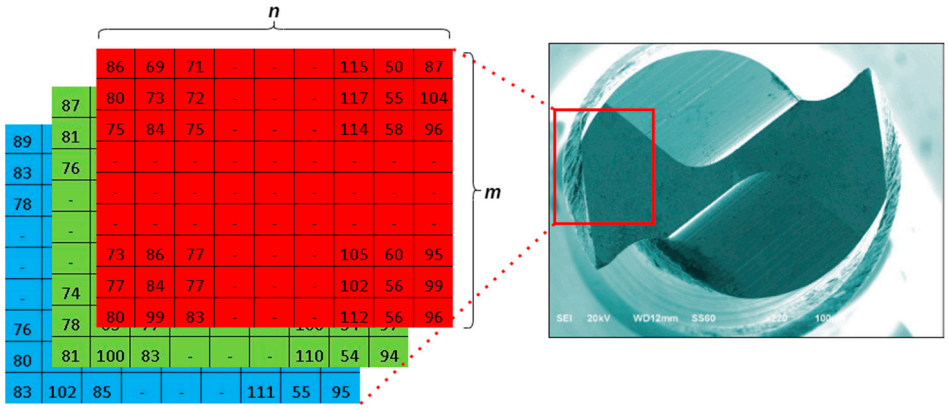
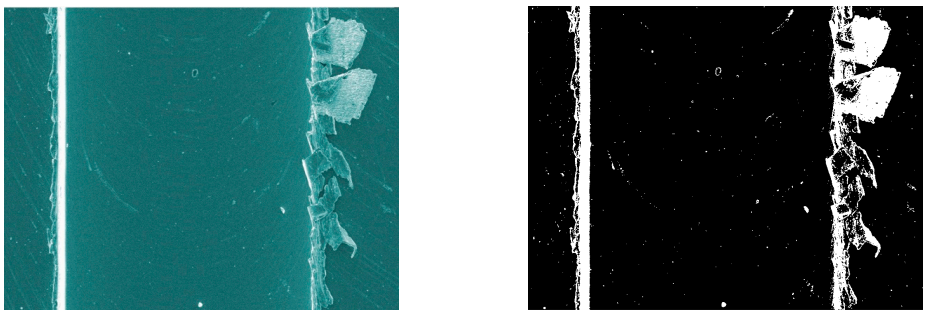


Figure 1. The representation of colorful images in 3D matrix format (produced from [12]).

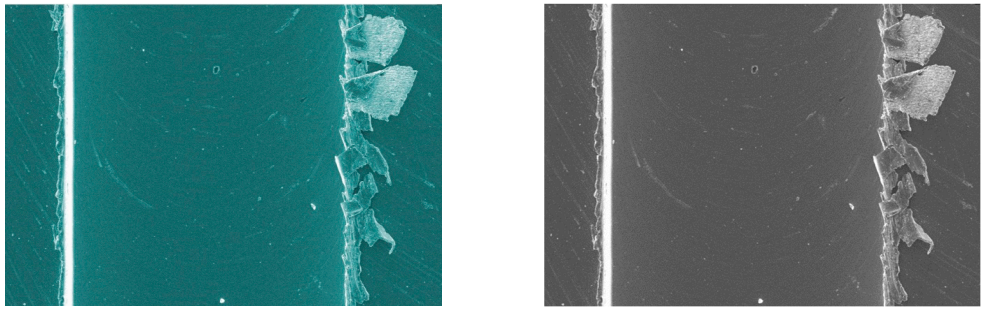
Computer vision systems use several types of images depending on the function. Binary images are commonly used in applications where data are represented and processed in a simpler manner [34]. In binary images, pixels are represented only by values of 0 (representing black) and 1 (representing white). Having two colors simplifies the processing procedures and can be ideal for emphasizing certain characteristics of objects. As shown in Figure 2, binary imaging is generally used for segmentation processes.



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

Figure 2. The result of the segmentation process expressed with RGB images and binary imaging: (**a**) RGB image and (**b**) its binary version (produced from [35]).

Grayscale images are expressed in black and white tones, and each pixel is represented by an intensity range of 0 to 255. This range indicates the brightness level of the pixel from black to white. Grayscale images are preferred over color images in real-time image processing applications because they contain fewer data. Figure 3 shows a colored image in RGB format and its grayscale version.



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

Figure 3. (**a**) RGB image and (**b**) its grayscale version (produced from [35]).

Color images are represented by three channels: red, green, and blue (RGB). These channels are superimposed as three equal-sized matrices, each with values ranging from 0 to 255. In an RGB image, a pixel will appear black when its pixel value is (0, 0, 0), and white when it is (255, 255, 255). All colors are combinations of these three values. Figure 4 shows an RGB image and an example of its channel components separated.

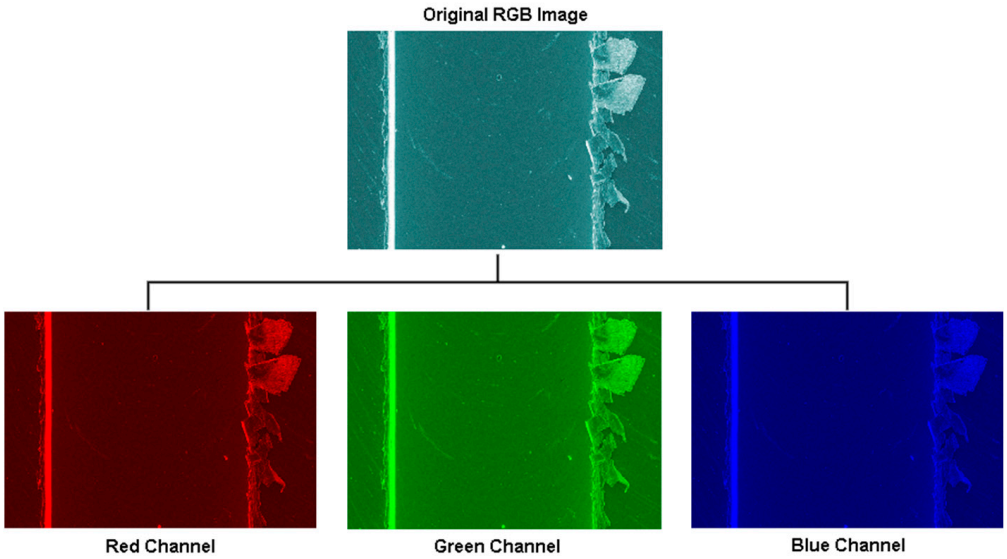


Figure 4. Channel-decomposed RGB image (produced from [35]).

Equation (1) shows how to convert an RGB image to gray. In the equation, the abbreviations R, G, and B represent the values constituting the colored pixel. $\alpha_r, \alpha_g, \alpha_b$ are the coefficients for the gray conversion and their sum is set to be 1.

$$I = \alpha_r R + \alpha_g G + \alpha_b B \alpha_r + \alpha_g + \alpha_b = 1 \quad (1)$$

One of the most important topics in basic image processing is the histogram, which shows an image's frequency of intensity values. The frequency distribution is calculated as shown in Equation (2). Histogram processing is frequently used in basic image processing tasks such as separating an object from the background in segmentation processes, image sharpening, contrast adjustment, etc. [36]. Histogram processing is a fundamental image processing method that plays an important role in surface and tool condition assessments. This technique effectively enhances surface detail, facilitates defect detection, and provides analyzable images.

The histogram of grayscale images is expressed as a two-dimensional bar graph. In the graph, pixel intensity is represented horizontally, while their frequencies are shown on the vertical axis. In an 8-bit grayscale image, there are 256 intensity values ranging from 0 to 255. A value of 0 represents the minimum intensity and is depicted in black, while a value of 255 represents the maximum intensity and is depicted in white. The frequency distribution is calculated as shown in Equation (2).

$$n = \sum_{i=1}^{k} m_i \quad (2)$$

Here, m_i represents the intensity value of each pixel in the image, while n represents the total number of each pixel's intensity value. Figure 5 shows the histogram graph of the image.

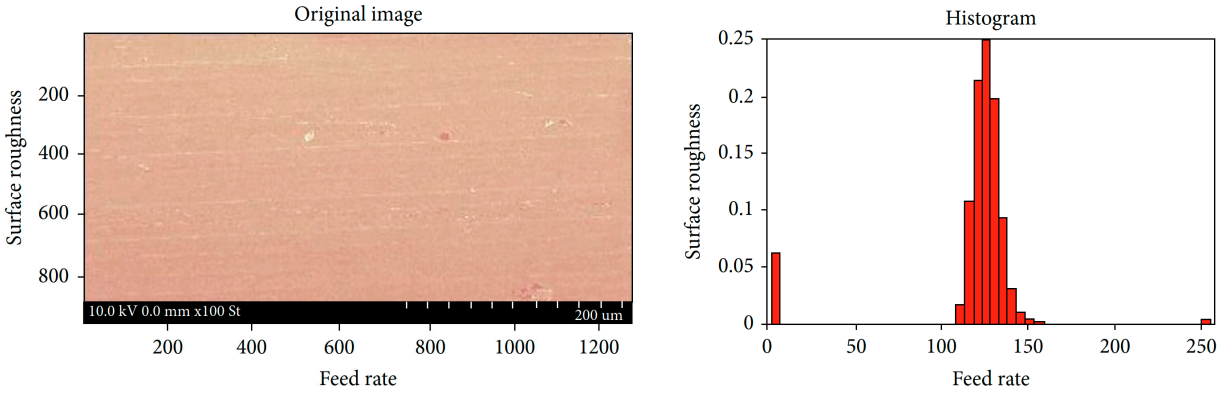
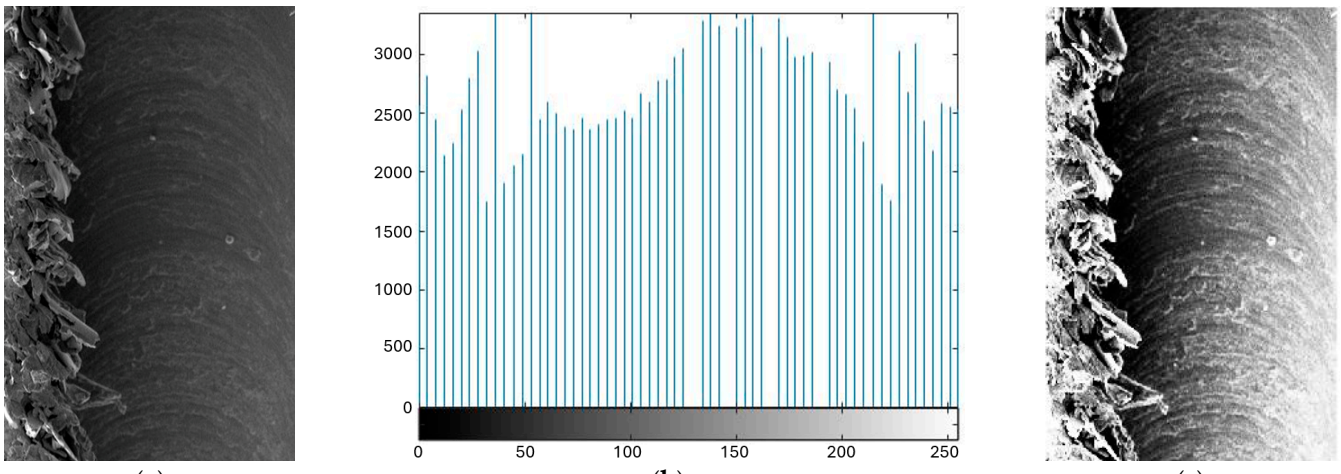


Figure 5. Sample image and histogram graph [37].

When examining the histogram graph of the image, it is observed that dark colors are prevalent while light colors are almost non-existent. Due to the image's color values being clustered in a certain area, details in the image are lost. Therefore, histogram equalization processes are needed in images. Histogram equalization increases the contrast in the image, allowing fine details on the surface to appear more clearly. This technique helps to make small imperfections on the surface, such as abrasions, scratches, cracks, etc., more visible, especially in low-contrast, extremely bright, or very dark images. In Equation (3), the histogram of an image is represented by $h(i)$. Here, n represents the total number of pixels and L represents the total number of gray levels in the image. The histogram equalization process expressed in Equation (4) is performed to reduce the impact of clustering in the histogram. As seen in Figure 5, to prevent situations where there is no intensity in the histogram graph, the value of α in the histogram equalization process should be greater than 1. β is a parameter of the power function. Here, $h(i)$ represents the original histogram and $\hat{h}(i)$ represents the equalized histogram. Figure 6 shows the original image, the graph formed after histogram equalization, and the resulting image.

$$n = \sum_{i=0}^{L-1} h(i) \tag{3}$$

$$\hat{h}(i) = pow(\log(h(i) + \alpha), \beta), 0 \leq i \leq L-1, \ \alpha > 1 \tag{4}$$



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

Figure 6. (**a**) Grayscale image [38], (**b**) graph formed after histogram equalization, and (**c**) histogram equalized image (Figure 6b,c are produced from Figure 6a).

Figure 6 shows the histogram equalization technique applied to the machined metal surface's Scanning Electron Microscopy (SEM) image. The first image on the left shows the original surface in grayscale format (Figure 6a). It can be seen that the color tones in the image are close to each other. This makes it difficult to recognize fine details on the surface, and it can be difficult to detect defects or abrasions on the surface due to the image's low contrast. A significant contrast increase is observed in Figure 6c in the image obtained after histogram equalization. In Figure 6b, the formed graph is seen after histogram equalization. The details on the surface, especially the structural changes on the edges, are more clearly revealed. This allows for easier detection of erosion and other defects on the surface. This technique can be very useful for monitoring the surface's structural integrity and determining the defects' level by highlighting surface imperfections.

Thresholding is a technique that offers precision and control in distinguishing objects or features on an image. This process is based on the pixel's brightness or color values [39]. Thresholding techniques are widely used in many areas, such as medical imaging, industrial control, object recognition, and automatic visual inspection. The primary goal of these techniques is to convert the input images into binary images. In basic thresholding, images are represented in black and white based on a predetermined threshold value. Figure 7 shows the image after the thresholding process is applied.

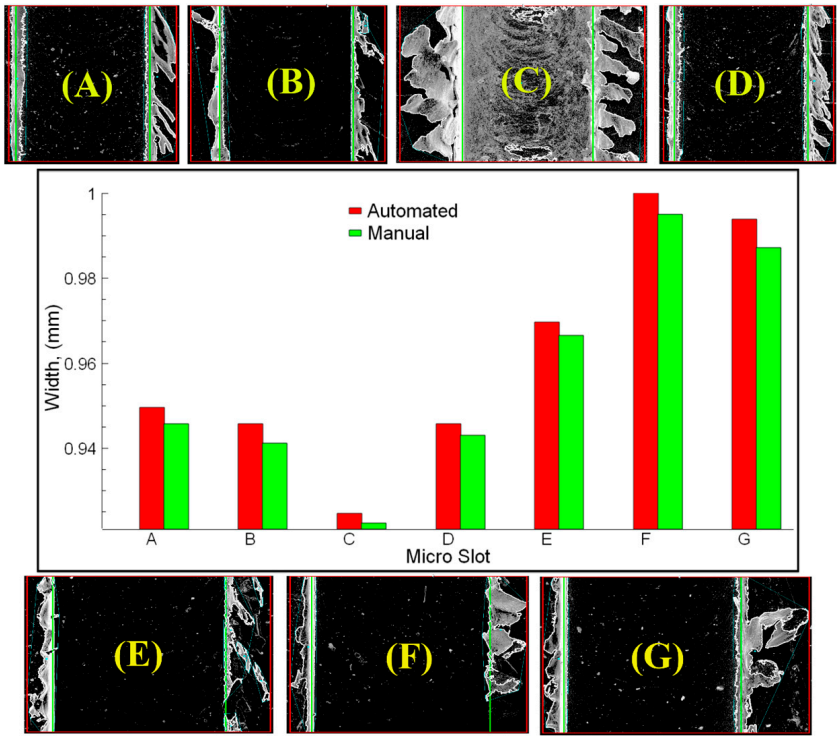


Figure 7. The colored image and the binary image obtained after the thresholding process (micro slot widths measured by manual and automated with image process figs; (**A**) slot-A, (**B**) slot-B, (**C**) slot-C, (**D**) slot-D, (**E**) slot-E, (**F**) slot-F, and (**G**) slot-G [35]).

In basic thresholding, the threshold value needs to be manually selected. The chosen threshold value will produce different results when applied to multiple images. By analyzing the image, methods like Otsu, Kapur, and Adaptive thresholding determine the optimum threshold value [40]. Of many methods, the Otsu method produces better results based on the assumption that the image consists of two color classes: background and foreground. The optimal threshold value is determined by calculating the within-class variance value for all threshold values for these two color classes [41]. Figure 8 shows an image where thresholding has been performed according to the Otsu method.

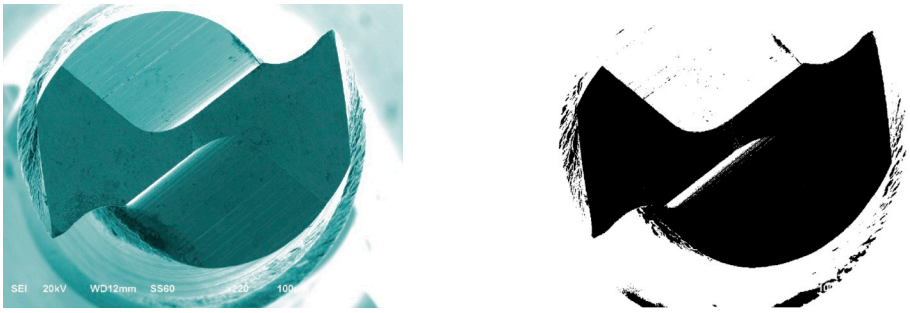


Figure 8. Colored image and the image applied with the Otsu method (produced from [12]).

Edge detection, a key application of image processing, enables the identification of object boundaries and facilitates object detection. This process determines the boundaries of objects by analyzing the intensity differences in pixel values in the image. The edge detection process involves identifying and defining the sharp discontinuities in the image. By determining the boundaries between different regions in the image, segmentation and image-matching processes can be performed. Most edge-detection operators are based on the use of first-order derivatives [42]. These operators calculate the distribution of neighboring pixel intensity values of the processed pixel. This helps in deciding whether the pixel should be classified as an edge. Operators such as Sobel, Canny, Prewitt, Roberts, and Laplacian are frequently used in edge detection [43,44]. While the Roberts operator uses a 2×2 convolution mask, other operators use 3×3 to detect edges at the maximum level.

These masks are designed to respond maximally to edges along the vertical and horizontal axes of the image. For this purpose, Gx and Gy masks are applied separately to the input image. The absolute sum of the results obtained from both masks constitutes the pixel value of the edge image. For the Sobel operator, the gradient magnitude calculation is given in Equation (5).

$$|G| = \sqrt{Gx^2 + Gy^2} \approx |Gx| + |Gy| \quad (5)$$

As shown in Figure 9a, the Sobel operator consists of 3×3 convolution masks. This pair of masks scans the image in horizontal and vertical directions to create new pixel values. Figure 9b shows the calculations of the convolution mask on the image, Figure 9c presents the original image, and Figure 9d shows the image with edges detected using the Sobel operator.

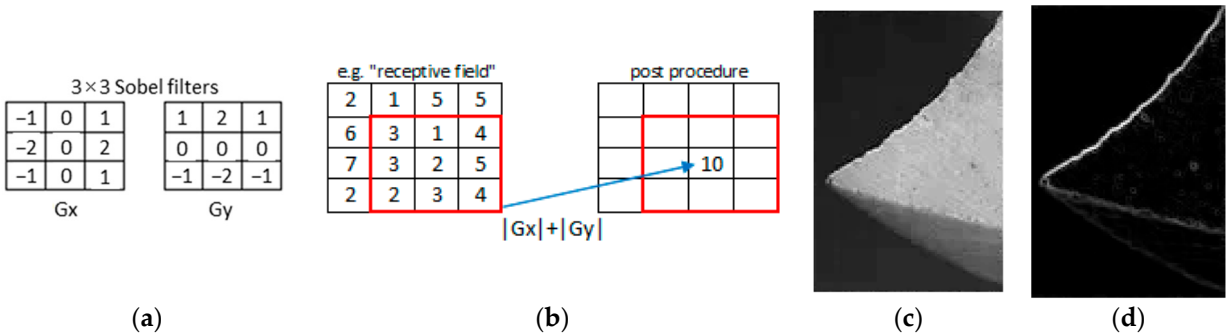


Figure 9. Example of the Sobel filter and the image with detected edges: (**a**) 3×3 convolution masks of Sobel operator (produced from Figure 9c), (**b**) the calculations of the convolution mask (produced from Figure 9c), (**c**) original image [12]), (**d**) the image with edges detected using the Sobel operator (produced from Figure 9c).

Morphological operations are frequently used in image processing to emphasize object shapes in images, reduce noise, or make the image more analyzable. Morphological operations, used to highlight the structural features of objects, include a series of mathematical expressions such as opening, closing, erosion, and dilation [45]. The dilation

process enlarges and merges objects in an image, making them more distinct and reducing noise. The erosion process is used to reduce the size of objects in an image or to smooth out their irregularities. This process increases the space between objects and clarifies their boundaries. The sequential application of dilation and erosion to emphasize objects in an image is called as morphological closing. The morphological opening process, applied to reduce noise in the image or to thin objects, involves the sequential application of erosion followed by dilation.

Morphological operations are used to perform tasks such as object edge detection, image analysis, noise reduction, contrast enhancement, and clarifying object outlines. These processes are generally applied to grayscale or binarized images. These processes are carried out using a kernel or mask, a structural element. This matrix-shaped structural element, with a specific shape or pattern, produces results based on the neighborhood of pixels. Figure 10 shows the results of morphological operations on example images.

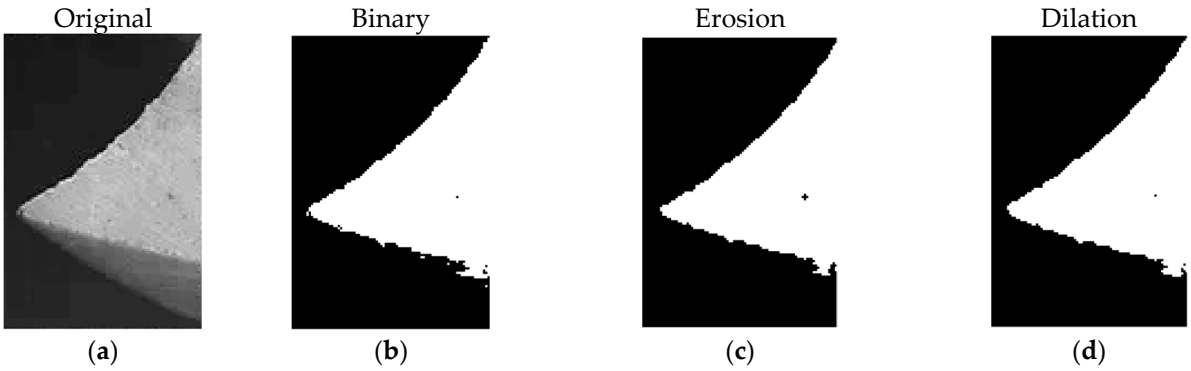


Figure 10. Morphological operation results: (**a**) original image [12], (**b**) binary, (**c**) erosion, and (**d**) dilation images (Figure 10b–d are produced from Figure 10a).

2.2. Noise Reduction Techniques in Machining Surface Images

In machining processes, noise may occur in the images used to evaluate the surface and tool condition for various reasons. These noises adversely affect the image quality, make it difficult to detect defects on the surface, and may cause false detections. Therefore, it is important to eliminate noise types such as Speckle Noise, Salt-and-Pepper Noise, and Gaussian Noise in machining images.

Speckle Noise is a type of noise frequently encountered, especially in laser and ultrasound-based coherent imaging systems. This noise appears as randomly distributed small particles in the image and can make it difficult to recognize fine details during surface analysis. Speckle Noise-based noise can be removed with techniques such as Wiener Filter and Bilateral Filter [46]. Salt and Pepper noise, caused by sensor and data transmission errors or pixel distortions in the image, occurs because pixels take random values. Random whites or blacks can occur independently of the image in pixels where this type of noise occurs. Salt and Pepper noise can be removed with mean and median filters [47]. Another common type of noise is Gaussian Noise. This type of noise is usually caused by low light conditions, thermal noise in sensors, or environmental factors, and the distribution of noisy pixels in the image resembles a Gaussian distribution. These noises can be removed using Gaussian and Wiener filters [48].

Noise reduction techniques to be applied to images obtained in machining processes are critical to increase the accuracy of surface and tool condition analyses. For this reason, choosing the right filtering techniques according to the noise that may occur will ensure that the noise is minimized by preserving the details on the analyzed surfaces. The correct use of noise reduction techniques will contribute to producing more accurate results in artificial intelligence-based surface and tool condition analyses. In this context, selecting and effectively using appropriate filters will help improve machining processes and increase surface quality.

2.3. Tools and Software in Image Processing

Image processing tools and software are used to analyze and interpret the characteristics and structure of digital images. These tools and software are utilized in various applications, including image recognition, medical imaging, and industrial inspection [49]. Image processing, an important subfield of engineering sciences, also plays a significant role in AL and ML applications [49,50]. While image processing is used to improve image quality, extract information from images, or transform images by performing various operations on digital images, ML enables inferences from new data using the information in the dataset. When used together, image processing and ML algorithms assist computer systems in understanding and interpreting the content of real-world images. These interpreted data play an active role in classifying images, detecting objects, and identifying abnormalities. Basic image processing techniques involve pixel-level operations such as reducing noise in the image, sharpening the image, filtering, or segmenting the image [51]. Image processing techniques supported by machine learning include image recognition, classification, and synthesis [52].

Various toolboxes and software are used in engineering to perform image processing techniques. Some tools and software used with machine learning are specifically designed for image processing, while general-purpose programming languages or libraries support others. A short list of commonly used open-source and commercial products in image processing within the engineering field is provided below.

2.3.1. OpenCV

One of the most popular open-source libraries, OpenCV (open-source Computer Vision Library), is frequently used for image processing, ML, and deep learning. It can be used in C++, Python, Matlab, and Java on many platforms. OpenCV supports a wide range of functions, including basic image processing functions, image recognition, classification, segmentation, and semantic analysis of images. One of its biggest advantages is its usability in real-time image processing applications. OpenCV is optimized for real-time operations to identify specific objects in images or videos [53].

2.3.2. TensorFlow

TensorFlow, widely used in large-scale artificial intelligence and deep learning operations, has gradually expanded its applications across various industries. Developed by Google and open source, this library is used in applications such as image, language, and sound processing. With its modular structure, TensorFlow hosts high-level APIs like Keras for rapid prototyping. Image processing is frequently used in stages such as data acquisition and preprocessing, followed by model creation and training, and then evaluation and deployment of the model. TensorFlow operates independently of platforms and can function on various desktop computers, servers, mobile devices, and IoT devices with low processing capacity [53].

2.3.3. PyTorch

PyTorch is an open-source machine learning library designed for researchers and engineers often favored for image processing applications due to its comprehensive toolkit and flexible architecture. PyTorch, written in Python, offers a variety of toolboxes and libraries specifically for image processing [54]. PyTorch enhances computing performance significantly with its robust GPU support, which accelerates vector and matrix calculations essential for image processing applications. Its integration with Python's Numpy library allows for directly converting Numpy arrays to PyTorch tensors and vice versa. This feature makes PyTorch a favored choice for scientific calculations. PyTorch is utilized in mechanical engineering for various applications, including predictive maintenance, quality control, automation, simulation, and modeling. These applications include predicting equipment failures, detecting faulty parts, controlling robots, and simulating physical systems. For industrial control, the PyControl library offers various models and algorithms [55,56].

2.3.4. Matlab

Matlab is a high-level programming language platform widely used in engineering fields for numerical computation, data analysis, and visualization [57]. In addition to mathematical calculations and matrix operations, it provides an extensive graphical toolset for data visualization. Matlab, a commercial product, has a variety of toolboxes and function sets for image processing in various engineering applications. Capable of addressing a wide range of engineering problems, Matlab can also be used in different areas such as signal processing, artificial intelligence, system modeling, thermal analysis, and fluid dynamics.

2.4. Stages of Image Processing

Image processing encompasses all the application steps involving extracting and analyzing information from digitally obtained images. Within this scope, outputs can be in the form of a new image, marking a specific area of interest, or categorizing images. In the diagram, with the details given in Figure 11, the basic image processing steps are grouped under the heading of preprocessing. This basic image preprocessing step can only be completed with ML techniques. In this context, ML methods for classification, segmentation, and detection, which will be discussed in this paper, form an integral part of modern image processing techniques. By applying ML techniques to image processing problems in the relevant sections, a preliminary presentation of the combined use of these two areas is achieved.

The first stage of image processing begins with the acquisition of digital images. Digital images are obtained using imaging devices such as cameras, scanners, microscopes, etc. The types of images obtained can be RGB, thermal, multispectral, etc. [58,59]. In image processing, the types of images obtained from different sources are often converted to grayscale to enable more efficient and faster processing.

The images obtained often contain errors due to noise, ambient light, and issues related to the angle of the image. Pre-processing steps such as image correction, noise reduction, contrast enhancement, and image compression can be performed to eliminate such errors. Unwanted random pixel values in images are called noise, which can be reduced or completely removed using cleaning methods. The overall light level of pixels is expressed as image brightness, and more distinct images can be obtained by adjusting the brightness. Different techniques, such as edge detection, size scaling, and color transformations, can also be applied during pre-processing.

Features refer to the information representing the shape, color, pattern, or other characteristics of objects in an image. The feature extraction stage aims to uncover significant information within the image. Consequently, the image will be represented with lower-dimensional data. Common techniques used in this stage include Histogram extraction, Wavelets Transform [60], Local Binary Pattern (LBP) [61], Histogram of Oriented Gradients (HOG) [62], Speeded-Up Robust Features (SURF) [63], and Edge detection [64]. Figure 11 illustrates the classification of images with different surface textures, marking a specific area on the surface and the recognition of the surface.

In the previous stage with feature selection, the aim was to reduce the number of attributes in the large-scale feature dataset obtained. As a result, the performance of ML models can be enhanced with the lower-dimensional attributes obtained while eliminating unnecessary information. Some attributes can carry more information compared to others. Common techniques used at this stage include Principal Component Analysis (PCA) [65], Linear Discriminant Analysis (LDA) [66], Particle Swarm Optimization (PSO) [67], Artificial Bee Colony (ABC) [68], and Genetic algorithms [69]. The success of feature selection varies across different datasets, making it challenging to predict which method will be effective.

At the recognition and presentation stages, tasks such as classification, segmentation, and object identification are performed in the image, tailored to the problem at hand [51,61,70].

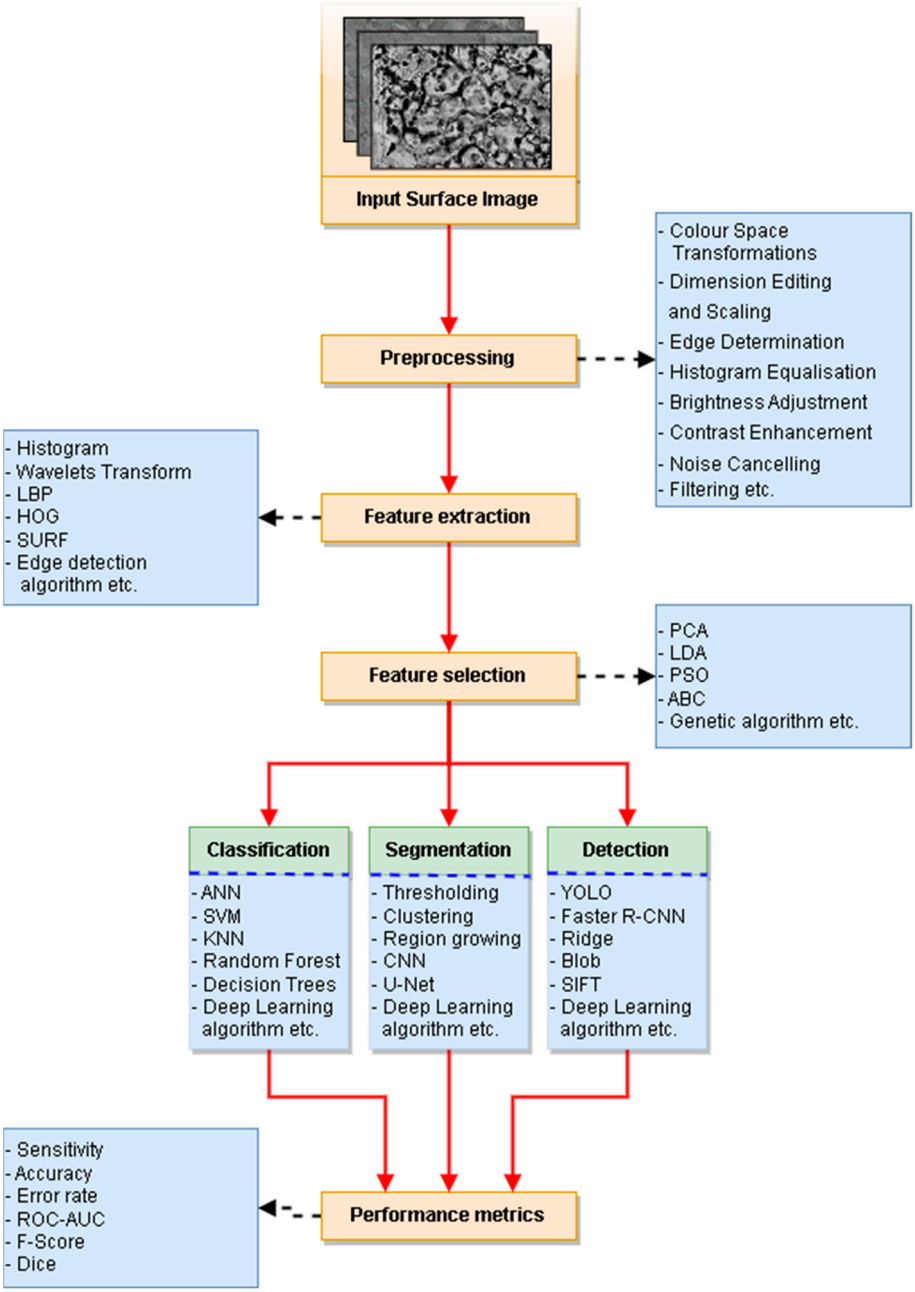


Figure 11. The fundamental stages of image processing.

By analyzing the information in the images, classification is performed to determine which category the image belongs to. The distinction between rough and smooth surfaces determines material properties, manufacturing processes, and functionality. For example, these surface types' rapid and accurate automatic differentiation is critically important in quality control applications. In classification processes, techniques such as Artificial Neural Networks (ANNs) [71], Support Vector Machines (SVMs) [72], k Nearest Neighbors (KNNs) [73], Random Forest [74], Decision Trees [75], and Deep Learning algorithms are frequently used [76].

Segmentation is used to divide the image into meaningful regions. At this stage, images are segmented into objects and areas of the same kind. For example, in a typical segmentation study, rust spots on metal surface images can be automatically distinguished from other surfaces [77]. In segmentation processes, techniques such as Thresholding,

Clustering, Region Growing, Convolutional Neural Networks (CNNs), U-Net Architecture, and Deep Learning algorithms are frequently used [76,78].

We can also detect instances of semantic objects of a certain class (e.g., machines, machine parts, and people) in digital images and videos. In this process, the coordinates of detected objects are identified on the image, and the object is framed and labeled. In detection processes, algorithms such as You Only Look Once (YOLO) [79], Faster R-CNN [80], Scale-Invariant Feature Transform (SIFT) [81], Ridge detection [82], Blob detection [83], and Deep Learning are frequently used.

Performance metrics are used to test and compare the performance of classification, segmentation, and detection processes used in image processing. These metrics evaluate the results' accuracy, reliability, and closeness to the true values. Accuracy, Precision, Recall, F1 Score, Dice, and ROC-AUC are among the most frequently used metrics [84].

2.5. Advantages and Challenges of Using Image Processing for Surface Evaluation

Measuring the properties of an object or structure's surface is referred to as surface evaluation. Surface properties include shape, size, roughness, texture, color, and crack detection. Image processing techniques are necessary for these properties to become meaningful for computers. In surface evaluation applications, image processing techniques are used to measure the surface's shape, size, and roughness [85,86]. These measurements can also improve production, manufacturing, and quality control processes.

The use of image processing in surface evaluation has many advantages. Image processing can automate the process and make faster inferences by producing high-resolution and precise results in surface evaluation. Surface details too small to be discerned by the human eye can easily be detected with image processing techniques. Image processing algorithms offer significant time and cost savings compared to traditional methods and can quickly analyze large datasets. This brings significant advantages in process and quality control applications in production lines. Another advantage is the ability to evaluate the surface non-invasively and precisely without touching or damaging the surface structure using image processing techniques. In conclusion, surface evaluation with image processing techniques can be performed consistently, reliably, cost-effectively, and non-invasively.

However, there are also challenges in using image processing techniques for surface evaluation. Factors like surface light reflections, ambient lighting, camera angle, and the sensor quality of the image capture device are the main elements affecting data quality [87]. This situation can affect the accuracy of analysis results, as the data obtained may be noisy, low resolution, or blurry. The choice of image processing algorithm varies according to the problem at hand. Different algorithms may be needed to extract various types of surface properties. Another challenge is that image processing techniques generally require high-performance hardware and can be a limitation for real-time applications.

3. Techniques in Image Processing for Machined Surfaces Analysis

The advancement of image processing techniques has revolutionized the way of analyzing machined surfaces. Accurate and detailed surface analysis is vital in manufacturing and quality control industries, where even minor deviations from desired specifications can have significant consequences. In manufacturing and industrial process applications, achieving precision and maintaining quality are top priorities. Whether it is the automotive sector manufacturing engine components with exceptional accuracy or the aerospace industry ensuring the reliability of vital parts, assessing machined surfaces is a critical task. These surfaces hold the key to performance, durability, and safety. Advanced information technology today facilitates image processing in manufacturing for machined surface analysis, ensuring precision and efficiency through non-contact, vision-based evaluation [88,89].

For defect detection, image processing techniques can detect defects such as cracks, scratches, or irregularities on machined surfaces. It can measure Surface Roughness parameters using texture analysis and filtering methods. The image processing process can assist in measuring the dimensions of machined features with high accuracy for Dimensional

Inspection. Image processing algorithms like edge detection, thresholding, and contour analysis help highlight anomalies. These algorithms can assess factors like the presence of burrs, tool marks, and surface waviness, providing valuable insights for Surface Finish Evaluation in quality control applications. Especially in some industries, like aerospace, the pores or inclusions in machined components can be critical. Image processing algorithms can identify and quantify Porosity and Inclusion Detection. Feature recognition, which identifies specific features like holes, threads, or patterns on machined surfaces, can be automated using image processing techniques to aid inspection. Today, ML-based deep learning techniques, such as CNNs, can be trained to classify and identify defects or features on machined surfaces, achieving high accuracy and automation. For more complex surfaces, 3D Surface Reconstruction (3DR) using multiple images or point cloud data can provide a comprehensive view of the machined component's geometry and surface characteristics. Additionally, the integration of image processing with real-time systems allows for continuous inspection, reducing production downtime and enhancing efficiency using *Real-time Inspection* via image processing algorithms. For this purpose, image processing can be integrated with CNC machines to make real-time adjustments based on the analysis of machined surfaces, ensuring high precision. Data visualization and reporting tools can present the analysis results user-friendly, making it easier for quality control personnel to interpret and act upon the data [90–92].

Figure 12 illustrates the fundamental stages of image processing in quality control applications, particularly for analyzing machined surfaces. These procedures include acquiring images from a specimen using hardware, including a camera, illumination units, and a PC with image acquisition software. The captured image is processed according to the surface parameters such as illumination, reflectance, and background. Finally, an actual image of the specimen and its processed counterpart can be combined to display the outcomes of image processing numerically for analytical purposes.

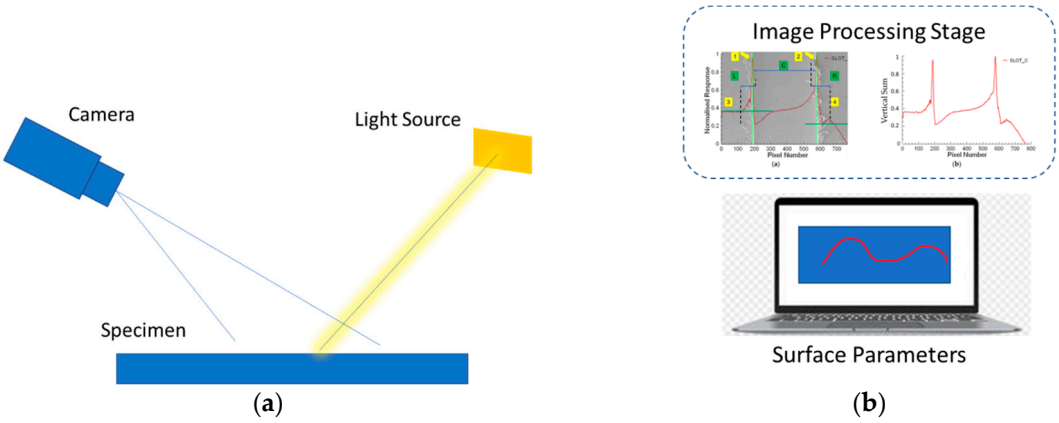


Figure 12. Machined surface analysis stages: (**a**) image acquisition and (**b**) image processing (produced from [38]).

The methodology for a machined surface evaluation using image processing includes sequential steps:

- Specimen preparation stage via machining processes.
- Computer vision system installation, a camera, a PC, and illumination units.
- Image processing stage to extract characteristics from surface images.
- Analysis and evaluation of results.

In Figure 13, a block diagram shows the steps that represent the typical structure of machined surface analysis and common image processing procedures. The process of evaluating machined surfaces begins with specimen preparation and continues with image acquisition and processing steps. The output of image processing is a processed image, commonly masked with an actual image that can be used for surface evaluation duty.

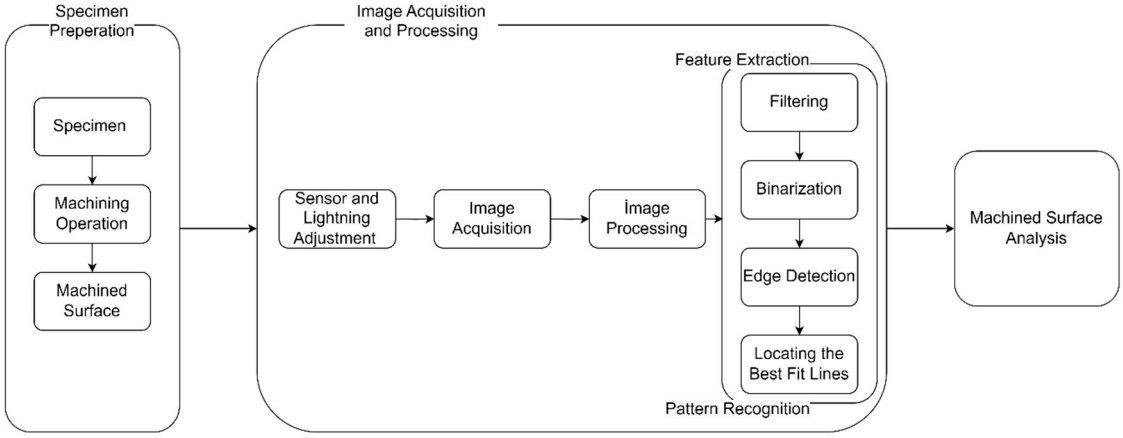


Figure 13. Typical structure machined surface evaluation process using image processing.

In surface evaluation, various techniques, including texture analysis and image processing, are employed to extract critical statistical features from images, enabling the assessment of properties like surface roughness. ML has recently emerged as a rapid and automated approach, with models trained on image datasets capable of directly predicting roughness values from images, further enhancing the efficiency of the evaluation process. Texture analysis involves extracting statistical features from the image, such as contrast, entropy, and homogeneity, through Gray Level Co-occurrence Matrix (GLCM) analysis. This matrix can reveal certain properties about the spatial distribution of the grayscale levels in the texture image. Estimating the surface roughness of a machined component using image processing procedures is possible by comparing the features with known roughness standards.

Image filtering techniques can be applied to image data to enhance and isolate features related to surface roughness. Spatial filtering, the traditional image filtering method, includes linear filters like the Gaussian filter, Laplacian filter, and Neighborhood Average (Mean) filter. Non-linear filters, such as the median filter, replace each pixel's value with the median value of its neighboring pixels. These filters are directly applied to the image pixels. Frequency domain filters remove high and low frequencies and smooth the image. The resulting filtered images can then be analyzed to derive roughness measurements. Wavelet analysis has emerged as a growing area of interest in the global scientific and technological communities recently. It has found wide-ranging applications in signal processing, image manipulation, phoneme examination, and recognizing patterns. The integration of wavelet analysis with surface assessment offers an effective research endeavor. This approach enables the identification and subsequent assessment of surface structure characteristics [93]. In addition to these, ML approaches have gained prominence in recent years. ML models can be trained on a dataset of surface images and corresponding roughness values. Once trained, these models can predict roughness values directly from images. This capability presents a rapid and automated approach to surface evaluation.

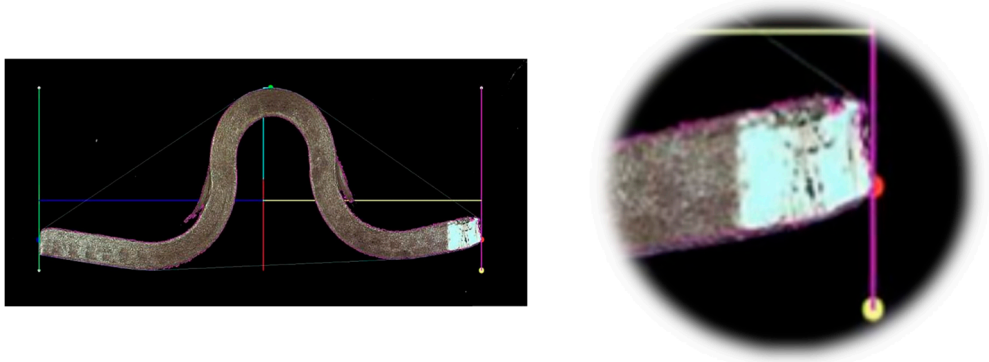
3.1. Surface Roughness Evaluation

Surface roughness plays a pivotal role in evaluating the quality of machined components. It represents a fundamental attribute of machined surfaces that directly affects factors such as friction, wear, and aesthetics. Numerous instruments and techniques are available for measuring surface roughness, including surface profilometers, laser interferometers, optical methods, scanning electron microscopes, and atomic-force microscopes. Accurate quantification and visual representation of surface roughness are critical for process optimization and quality assurance [94,95].

Surface roughness evaluation relies on various image processing techniques to extract meaningful information from surface images. One common method involves using filters to enhance specific features related to surface texture. Spatial filtering, for instance, employs filters like the Gaussian filter to smooth the image and reveal fine details, while the

Laplacian filter highlights abrupt changes in texture. Additionally, frequency domain filters can be applied to eliminate high and low frequencies, offering a different perspective on surface features.

Moreover, wavelet analysis is increasingly employed in surface roughness evaluation. Wavelet transforms allow for a multi-scale surface texture analysis, providing insights into roughness at different levels of detail. This approach can help in capturing and quantifying intricate surface structures. These image processing techniques, combined with advanced algorithms, offer a robust framework for assessing surface roughness accurately, aiding in product quality control and optimization. In Figure 14, the output of a wavelet analysis is presented, showcasing both the input and the results of this analysis. This visualization serves as a valuable representation of the role of wavelet analysis in surface roughness evaluation, highlighting its ability to provide insights into surface characteristics and texture at various scales [96,97].



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

Figure 14. Captured images of a machined surface for quality control process: (**a**) machined part, (**b**) detected defect.

3.2. Defect Detection

Image processing techniques for defect detection encompass various methods, each tailored to specific applications and industries. These methods often include edge detection, which identifies the boundaries and contours of defects, and thresholding to segment defective areas from the background. Morphological operations are employed to analyze and refine defect shapes and structures, while texture analysis helps detect variations in surface patterns that may indicate defects [98].

Integrated with image processing, machine vision systems are equipped with cameras and sensors to capture images of products as they move along production lines. Real-time image processing assesses each image for defects or deviations from quality standards. The systems can trigger alerts or automated actions when defects are detected, such as rejecting or sorting out faulty products [99].

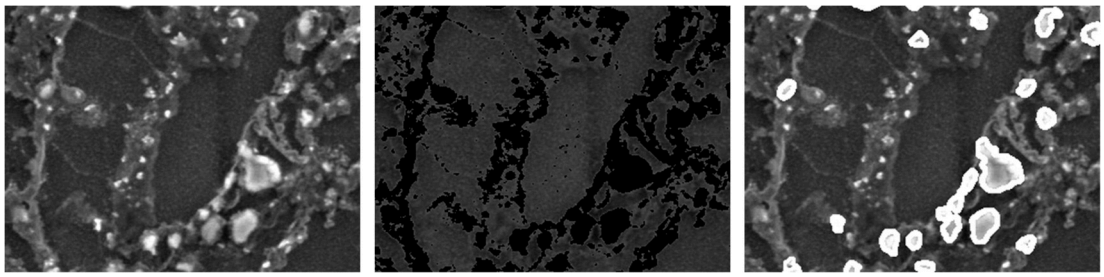
Image processing is crucial in non-destructive testing techniques like X-ray, ultrasound, or thermal imaging, which inspect materials' or components' internal structures and properties. These technologies generate images that require advanced processing to identify defects or irregularities hidden beneath the surface.

In recent years, integrating deep learning and CNNs has led to significant advancements in defect detection. These AI-driven systems can learn from vast datasets of images, recognize complex defect patterns, and adapt to variations in product manufacturing.

In industries where safety and reliability are paramount, detecting defects or anomalies on machined surfaces is crucial. Image processing serves as a valuable tool in identifying and categorizing these imperfections. Two common techniques used in defect detection are thresholding and segmentation. By establishing appropriate thresholds and segmenting the image, areas of interest, such as cracks, pits, or irregularities, can be isolated for further analysis. Another aspect of defect detection is feature extraction, which focuses on

extracting specific characteristics or patterns that indicate defects. This may involve edge detection to locate cracks or shape analysis to identify irregularities. Pattern recognition techniques are often employed to classify defects into different categories. Based on image data, ML algorithms can be trained to recognize various defect types.

In Figure 15, an example is provided of anomalies detected through binarization, filtering, and thresholding, illustrating the crucial role of image processing in defect detection. This technology is important in enhancing quality control and guaranteeing the reliability and safety of products across diverse industries [100].



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

Figure 15. Identified anomalies that correspond to defects in the images: (**a**) actual image, (**b**) main structure, and (**c**) detected anomalies.

3.3. Surface Texture Characterization

In this section, we briefly addressed the features of both Alicona and Leica, emphasizing how Alicona's precision in measuring surface texture aligns with our review focus. This clarification helps readers understand the relevance of these optical measurement systems in the context of our discussion. Comprehending surface textures on machined components holds pivotal significance across diverse applications, encompassing materials science and product design disciplines. Image processing techniques are invaluable tools for delivering quantitative and qualitative insights into these surface characteristics. The Fourier Transform is a widely employed instrument for the analysis of surface textures. This technique effectively dissects an image into its constituent frequency components, thereby facilitating the comprehensive characterization of periodic patterns and surface irregularities inherent to machined components. Fractal Analysis introduces a distinctive and valuable perspective by quantifying the intricacy and self-similarity embedded within surface textures. This analytical approach is relevant, especially when investigating natural or irregular surfaces. Conversely, Wavelet Analysis is vital in examining textures at various scales, proving especially advantageous when addressing surfaces characterized by intricate, multi-scale features. These advanced analytical methodologies collectively contribute significantly to the comprehensive understanding and practical evaluation of surface textures on machined components within formal academic and professional contexts [101–103].

3.4. 3D Surface Reconstruction

For a comprehensive analysis of machined surfaces, it is often necessary to move beyond 2D images and construct detailed 3D models. In computer vision and computer graphics, 3D reconstruction (3DR) is the process of recreating the appearance or shape of a real object. 3DR techniques include creating and processing a point cloud with domain-specific algorithms and methods. Mathematical approaches have been successfully applied in many studies to classify and cluster 2D images [104]. The goal of classifying and clustering 3D point clouds is to label each 3D point in the point cloud, similar to how 2D images are processed. There is a need for the reconstruction of objects as 3D computer models in various fields. Creating three-dimensional models of machined surfaces from 2D image data can provide detailed insights into their geometry and topography. The reconstruction of images in the computer environment allows for better analysis and tracking of the structural features of observed geometry [105].

The 3DR method encompasses creating 3D structures using 2D data. Creating a computer model with the 3DR method can be achieved actively or passively. Depth is lost when objects are captured from a three-dimensional scene to a two-dimensional plane (obtained using a traditional area scanning sensor) [106].

It is impossible to determine which point in the third dimension corresponds to a single point in the image from a single image. The position of a 3D point can be determined using triangulation with two images located at the intersection of two projection rays [107]. Loading an existing 3D object into a computer environment using only a few 2D images is possible. Point clouds, networks, and geometric models are output types used in 3D reconstruction [108]. Despite various methods for 3D reconstruction, the most common approach is called Structure from Motion (SfM). SfM allows determining the 3D structure of an object or scene from multiple images taken from different perspectives. The process involves identifying corresponding points in the images, determining camera parameters for each image, and then triangulating the points to create a 3D model [109]. Other methods for 3DR include stereo reconstruction, which works with pairs of images taken from different perspectives, and LiDAR (Laser Imaging Detection and Ranging), using laser sensors to measure distances [110]. Data acquired from real objects using these non-contact measurement methods are used in the 3D reconstruction of objects. Point clouds representing the surface of an object are used in 3DR methods [111]. Point clouds are created using LiDAR or photogrammetry techniques. In LiDAR-based point clouds, a laser sensor sends a laser beam to the surfaces of objects and calculates the distance from the time it takes for the beam to return to the sensor [107].

The spatial position between each point and the sensor is determined. In photogrammetry-based point clouds, 3D modeling information is obtained by capturing multiple photos of an object from different angles. By processing these image data using various algorithms, 3D information about the position and orientation of each point is extracted, and each point in the point cloud corresponds to a pixel in the photos. Once a point cloud is created, it can be used as input for other algorithms such as surface reconstruction, mesh generation, or texture mapping. Point clouds are transformed into 3D models or saved in different formats for various applications [106]. While some methods used in 3D reconstruction processes are presented with their formulas, many different methods and algorithms are used in 3D reconstruction depending on specific techniques and applications [107].

The physical characteristics of the machined surface (to analyze the geometry, texture, defects, and wear) are represented in digital form with a 3D imaging technique. The 3D scanning or photogrammetry techniques were employed to perform the above-mentioned task. Evaluating the machined surface texture is important because the beneficial impact enables the investigator to select the appropriate machining method and parameters responsible for better machine quality [112]. The amplitude parameters of the machined surface texture image help predict the cutting tool condition and enable online monitoring for improved surface quality and enhanced tool life [113]. The novel 3D imaging technique is developed based on the data gathered from the laser profile sensor to quantify the tool wear profiles in micro-milling [11,114]. The results benefit tool-wear diagnostics and help in automation, leading to higher productivity and quality. The surface integrity of machined samples (AZ31 Magnesium alloy) was evaluated with the help of a 3D imaging technique [115]. The surface roughness with varying heights taken from the images of machined parts analyzes the frictional behavior [116]. The friction behavior analysis based on the surface texture helps investigators to store lubricating oil and improve hydrodynamic effects [112]. The 3D imaging technique was used to detect the defects (pits and voids) in the ultrasonic vibration-assisted milling–grinding-machined surface of ceramic composites reinforced with SiCf/SiC [117]. Augmented reality (AR) is another promising human–computer interaction technology that significantly enhances the precision and safety of CNC machining by enabling real-time, in situ verification of NC codes. In addition, AR helps investigators to visually overlay the machining process to detect and correct issues without the need for costly physical prototypes [118]. AR proved its efficacy in recommending appropriate

workpiece fixturing in turning operations [119]. Augmented reality technology is adopted to monitor the status of the machining process [120]. Augmented reality technology effectively visualizes fixture designs of drilling–milling–boring equipment and develops efficient configurations [121]. Employing augmented reality can successfully design parts like levers, connecting rods, and flat components [121]. Augmented reality also helps the investigator with machine surface evaluation by projecting digital overlays onto a physical machine part that could display data directly on the machined part. AR technology might highlight machining issues by simulating the wear and tear over time.

In machined surface analysis, the use of 3D reconstruction techniques emerges as vital as it empowers a deeper and more comprehensive understanding of surface geometry, enabling thorough examination and evaluation [107].

3.5. Section Conclusions

Precision manufacturing and maintaining high-quality production are fundamental requirements of machining operations in automotive, aerospace, and manufacturing industries. Traditional approaches to machined surface analysis involve manual measurements and subjective evaluations, which can be both time-consuming and expensive. While advanced technology provides the potential for more efficient and cost-effective solutions in the dynamic landscape of modern manufacturing, there is also promise in leveraging advancements in image processing techniques to enhance the accuracy and efficiency of assessing machined surfaces. Image processing is a cost-effective, fast, and reliable option for machined surface inspection and analysis applications [100,122].

Recent advancements in image processing techniques have revolutionized the analysis of machined surfaces, offering unprecedented levels of precision and efficiency in quality control. Traditional methods, often conducted by manual measurements and subjective evaluations, are increasingly being supplanted by automated systems that leverage sophisticated algorithms. These algorithms, including edge detection, contour analysis, and machine learning-based pattern recognition, enable the extraction of critical geometric features from high-resolution images with remarkable accuracy. Moreover, integrating real-time monitoring systems with image processing technologies facilitates the continuous evaluation of machining operations, allowing for immediate adjustments to maintain optimal performance. However, challenges still need to be addressed, particularly in analyzing high-performance alloys, where traditional vision-based techniques may struggle due to complex machining interactions. Ongoing research is focused on refining these methods to overcome such limitations, highlighting the potential of hybrid approaches that combine image processing with sensor data for comprehensive surface analysis. Overall, the state of the art in image processing for machined surfaces reflects a significant shift towards more objective, reliable, and cost-effective inspection methods, ultimately enhancing productivity and product quality in manufacturing.

The field of image processing has seen significant advancements, enabling the extraction of essential geometric features from digital images. By utilizing image processing algorithms such as edge detection, pattern recognition, and contour analysis, it becomes possible to capture the complex structure of machined surfaces in a non-destructive and precise manner. This allows for a more objective and quantitative analysis of the surface's characteristics, potentially leading to an enhanced understanding and optimization of machined surface analysis [123]. The application of image processing techniques in the evaluation of machined surface geometry eliminates the limitations of manual measurements, which are often time-consuming and subject to human error. Moreover, automated image processing methods provide more accurate and consistent results, enabling a deeper exploration of the relationship between machined surface geometry and precision manufacturing performance [35].

Enhancing the abilities of image processing makes it possible to acquire more valuable data on specific geometric features for optimizing machine tool design and selection and improving surface machining parameters. Additionally, integrating image processing with real-time monitoring systems enables the continuous evaluation and control of machining

operations, ensuring prompt adjustments to maintain desired performance levels [100]. In Section 3, we present the state of the art regarding vision-based techniques in machining. However, it is important to acknowledge that such techniques may have limitations when applied to certain high-performance alloys, such as Haynes 282. For these materials, vision systems might struggle to accurately capture machining phenomena like cutting forces and tool wear due to the complex interactions between the tool and workpiece, including high thermal loads and rapid tool degradation, as discussed by Suarez et al. [124,125]. Overall, integrating image processing techniques in surface analysis offers great potential for enhancing productivity, quality, and efficiency in various industrial sectors [126].

4. Applications of Image Processing

The application of image processing is vast [127]; almost all fields use image processing. Figure 16 shows the sectors where image processing is currently used.

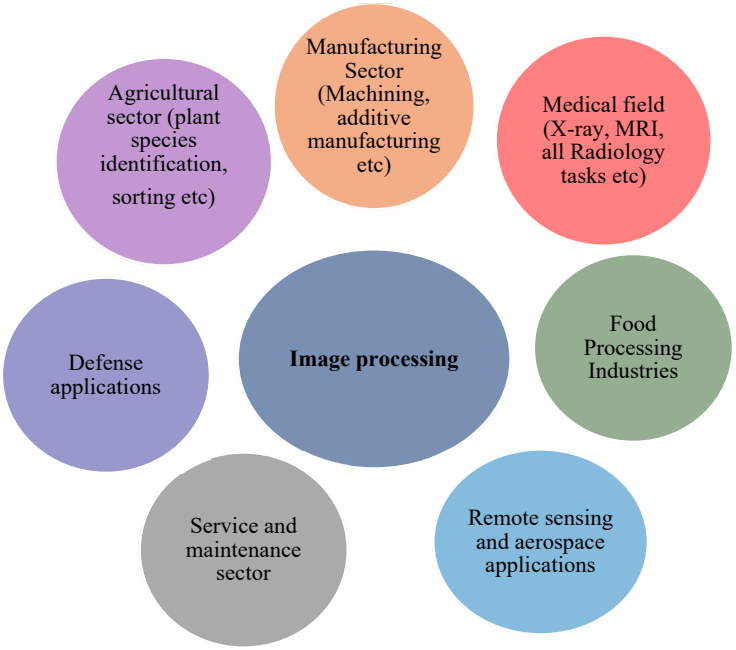


Figure 16. Application of image processing in various fields.

This section discusses image processing applications in the manufacturing sector, such as subtractive manufacturing (CNC machining and micromachining).

4.1. Application of Image Processing in CNC Machining

CNC machines have many advantages over conventional machining processes concerning productivity and quality [128]. Integrating a machine vision system into CNC will improve performance and productivity [129]. Some areas where image processing can be used in CNC machining are presented below.

4.1.1. Tool Wear Analysis

Digital image processing coupled with CNN methods helps the investigator to detect tool wear and monitor tool state condition automatically with an accuracy of 96.5% [130]. The images captured on the micro-milling tool (Figure 17) help to automatically detect the wear (flank, crater, and tool radius reduction) when processed with k-means clustering, and the Otsu multilevel algorithm resulted in less than 5% deviation between the prediction and the actual worn surface [131]. The tool condition-monitoring task was performed with the help of current signal analysis, and machined surface image processing helped investigators improve the tool condition by monitoring wear patterns [132]. ML and image processing methods were applied to monitor the tool wear in turning operation. The image processing

method outperforms the multilayer perceptron and logistic regression models in predicting the wear compared with actual wear values with a deviation of 3.5%, 5%, and 7%, respectively [133]. The limitations of image acquisition in conventional machine vision systems have been overcome by using reconstructed high-resolution images for online monitoring of tool wear [134]. Recent literature reviews on tool wear monitoring have concluded that image processing is an effective technique for tool condition monitoring [135,136].

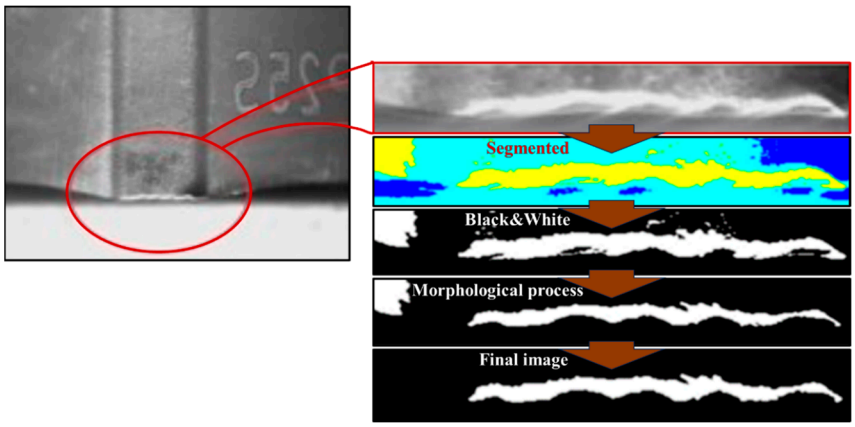


Figure 17. The image processing to analyze the wear on the cutting tool [redrawn from [137]].

4.1.2. Workpiece Origin Detection and Part Referencing

Stereo vision and image processing have driven cloud-based automatic systems that help to automatically detect the origin of the workpiece and part, referencing the activity present in machining processes [138,139]. The results confirmed their effectiveness in real-world machining applications.

4.1.3. Automatic Generation of CNC Program Using Image Processing

The captured images for the product to be manufactured are analyzed with CNC vision software to extract the product geometry details and generate appropriate part programming codes [140]. The captured image quality ensures better accuracy corresponding to the developed system (Figure 18). 2D Image data processed with ML algorithms ensure the automatic generation of process plans and NC part programming [141,142]. The algorithms developed showed their efficacy in generating toolpaths based on 2D profiles [142]. The hybrid CNN with the robot-assisted imaging technique can identify different materials and generate a toolpath program for CNC machining process automation [143]. The successful application led researchers to adapt imaging techniques to create programs leading to automation.

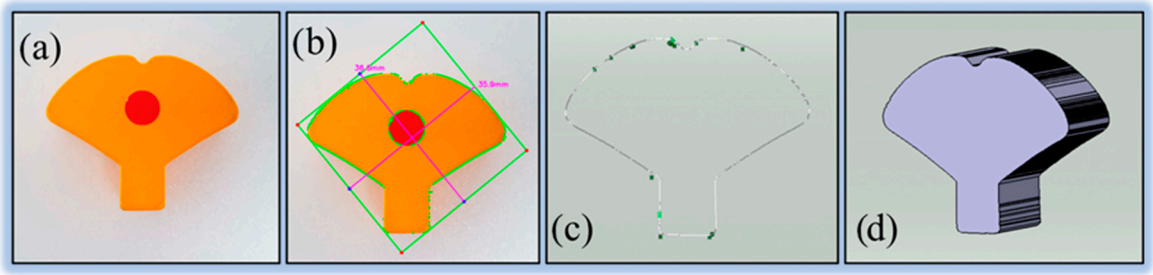


Figure 18. Images of an object processed to generate the CAD model using image processing: (**a**) actual image, (**b**) processed image, (**c**) determined contours, and (**d**) CAD model [144].

4.1.4. Tool Setting in CNC Machine

Implementing computer vision and image processing takes 128 milliseconds and reduces tool setting time. Additionally, a height positioning accuracy of 1 micron enhances

automatic tool setting and workpiece detection systems. Integrating digital image processing into CNC tool setting not only streamlines operations (the designed system captures the images of the workpiece and processes them digitally to extract the coordinates of tool setting position and perform computation for necessary tool position adjustments) but also enhances the overall functionality and automation of the machining process [145,146].

4.1.5. Tool Condition Monitoring

In our literature review of image processing-based tool condition monitoring of machining operations, we observed the use of a direct sensor system (camera-equipped optical system deployed on the tool) and an indirect method of machined surface condition analysis [147]. The images captured could benefit investigators in monitoring tools and workpiece conditions based on cutting forces [147,148]. Furthermore, the image processing technique helps to predict the chip geometry and workpiece surface quality and track the wear and tear of cutting tools, tolerance, chatters, vibrations, and worn-out cutting edges of tools of turning [136], milling [131], drilling [149], and grinding [150]. Modern techniques such as artificial intelligence [147], digital twins [148,151], smart manufacturing [152], Industry 4.0 or the Internet of things [153], and big data [154] have been adopted in conjunction with image processing to monitor tool conditions (Figure 19).

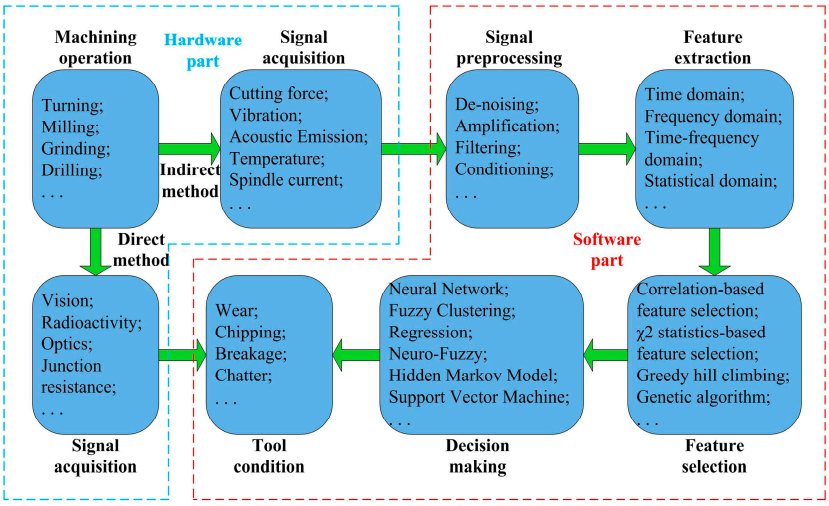


Figure 19. Workflow of the wear detection [155].

4.1.6. Effective Communication in CAD CAM Environment and Collision Avoidance

Minor operator errors and the complexity of CAD/CAM processes can lead to collisions in virtual production simulations. The current CAM software and multi-axis machines can detect collisions but cannot intelligently provide safe avoidance paths. Integrating image processing and CAD/CAM techniques to detect collision based on the images of trajectory and object positions helps to offer intelligent solutions for collision avoidance [156]. The integration of machine vision-based image or video processing and machine intelligence techniques helps to automate the multi-axis production process of safe and efficient collision-free tool trajectory generation [157]. The complexity of five-axis machining in detecting collisions is solved using image processing techniques [158]. Effective communication with image processing techniques in a CAD/CAM environment leads to collision avoidance in the machining process.

4.1.7. Prediction of Surface Roughness

Surface roughness values of machined workpieces, determined through image processing, were fed into a neuro-fuzzy technique [159]. This helped to accurately predict and monitor surface roughness online, ensuring desired outcomes. Artificial Neural Networks and machine vision techniques were used to predict the surface roughness of end-milled

parts with 97.53% accuracy [159]. The machine vision system outperforms the traditional stylus method in predicting the surface roughness in terms of speed, economy, and noise. The non-contact method (i.e., image processing) helps the investigator to capture real-time images that could help to predict and modify the machining parameters with ML algorithms, resulting in the desired surface texture on machined parts [160]. In recent years, surface roughness prediction in turning [133,161], milling [162], and grinding [163] processes have been conducted using ML algorithms that process captured images of machined workpieces. Integrating ML algorithms to predict and modify the process parameters based on the captured images of the machined workpieces could help industry personnel obtain the desired surface quality.

4.1.8. Defect Inspection (Online Inspection)

Image processing systems can easily detect flaws/defects during the machining process [164]. The advantage of such a system is that it avoids the further machining of defective components. Preventive measures can also be taken for the next set of machining if any deviation in the process is causing this defect [165]. With this system, near-zero defects can be easily achieved. Also, it avoids societal losses (losses due to scrap like wastage in energy, labor productivity, coolant, etc.) and hence helps to attain sustainable manufacturing. Manish et al. successfully detected defects in mild steel during grinding using the canny edge detection-based image processing method [90]. Image processing of the machined surface of the grinding process helps to monitor the defects and surface finish by varying grinding parametric conditions. An image processing-based measurement system for in situ machining defect detection proposed based on a stereo-DIC helps investigators move toward better reactivity for corrective actions, contributing to process optimization [164]. Image processing algorithm-integrated fuzzy logic techniques enable the investigator to extract the main features of machined objects (such as defects, borders, and noise), followed by processing and classifying the defective and non-defective parts with an accuracy of 80% [166]. Integrating ML algorithms and image processing techniques helps the investigator monitor online, which could yield near-zero defects in any manufacturing system [98].

4.1.9. Chatter Vibration Identification

Vibration data during the milling operation were collected with a non-invasive data acquisition system, processed to obtain images corresponding to a set of cutting parameters, and fed to a deep CNN for training and testing [167]. The collected data helped the investigator modify cutting parameters and determine chatter vibrations with an accuracy of 99.88%. Intelligent real-time chatter detection and monitoring models were established to obtain images (based on vibration signal features) for the milling process using hybrid variational mode decomposition-based Bayesian optimization, wavelet–synchro–squeeze transform, and CNNs [168]. The developed models resulted in chatter detection and classification with an accuracy of 98.21%, possessing a recognition time of $\pm$4.2 s. The cutting force signals were transformed to images using a multi-layer recurrence plot followed by training and testing the images viz. The CNN model helps investigators to accurately determine the machining quality in micro-milling operations [169]. The integration of data-driven models (neural networks) with cost-effective data acquisition devices [170] and image processing [171] helps investigators monitor the surface quality affected by chatter vibration and tool wear [172]. Detecting and monitoring the chatter vibrations that ensure better-machined surface quality and tool conditions during machining processes, with the integration of image processing with emerging technologies (like computer vision and neural networks), helps investigators move toward improved productivity at a reduced cost.

4.1.10. Post Machining Inspection

Post-machining inspections ensure that machined parts meet the specified quality (dimensions, tolerances, and surface finishes), reduce rejection (early detection of defective parts prior to assembly reduces customer rejections), and require specific space for inspection [173],

with regular inspection helping investigators with immediate feedback for corrective adjustments to machining parameters for the desired outputs [174,175]. Image fusion techniques were applied to classify the defects based on the machined surface finish or texture irrespective of defect orientation [176]. Image processing and ML algorithms were integrated for quality inspection and to measure the pores (edge and normal surface) on the machined parts [177]. Compared to online inspection and monitoring, the post-machining operation possesses significant disadvantages such as being time-consuming, increased cost, inspection quality dependent on the operator's skill, and process and production delays. Integrating emerging techniques for online machining quality ensures technological and economic benefits.

4.2. Evaluating Surfaces in Micromachining

The removal of material in small amounts to manufacture small (micro range) and complex geometries is termed micromachining [178,179]. Image processing finds good applications in such a process, which are listed below.

4.2.1. Surface Texturing

The surface texture, which impacts the quality, aesthetics, and functionality in micro-milling parts of medical and biological applications, is often found to be difficult to design using computer-aided design, and this was solved by the rapid process of capturing texture by image processing techniques [180]. Image processing algorithms applied to classify surface micro-defects help investigators generate data automatically and perform parametric changes in the developed closed-loop system for better quality [181]. The surface integrity of the machined workpiece [182] and tool wear [183,184] were monitored using three sensor technologies (cutting force, acoustic emission, and vibration).

4.2.2. Monitor Tool Wear

Digital image processing using algorithms (k-means clustering and Otsu Multilevel algorithm) on the captured images of the micro milling tool resulted in a 5% deviation between the predicted and actual worn areas of the tool. Monitoring tool wear can be accomplished using the features acquired based on image textures or sensors [185,186]. Image analysis on the worn surface of micro tools was performed to detect the worn surface area of the tool after eliminating the side effects of the image background and noise for tool wear monitoring [187]. Flank wear directly influences a machined work surface, and tool life was monitored online with image processing based on a machine vision system [188]. Applying a machine vision system predicts carbide inserts' tool wear parameters (width, area, and perimeter) with an error of 3.4% [189]. Neural networks predict the tool life by monitoring the values of spindle power in milling operations [190].

4.2.3. Quality Monitoring During Micromachining

Hole-quality prediction of micro-drilled parts was monitored based on tool conditions using multiple sensors integrated into artificial intelligence tools [191]. Image processing methods were applied to the generated burrs and slot width of micro-milled Inconel 718 alloy parts, resulting in an accuracy of 91% for up-milling, 98% for down-milling, and 99% for slot measurements [35].

4.2.4. Inspection of Machined Components

An image processing feedback system was developed to inspect defective machined surfaces automatically. The system compares computer-aided design images with captured machined surface images to determine the differences and classify the defective ones [192]. Image processing techniques were also applied for automatic damage detection in a ceramic material surface finish during grinding operations [193]. The actual images were processed for noise removal, contrast, and segmentation adjustments and classified based on the machined surface's texture.

4.2.5. Analyzing the Effect of Factors on the Quality and Predictive Modeling

An Artificial Neural Network (ANN)-based predictive model for burr formation was established with an influencing parametric set of cutting speed, feed, and drill diameter of the micro-drilling process [194]. The machining quality and tool condition of micro-milled glass were monitored by predicting (based on the image-based deep transfer learning method) the cutting force signals influenced by machining parameters [169]. The quality of micro-holes was predicted by influencing the micro-electric discharge machining process parameters (capacitance, voltage, flushing force, and tool adhesion) based on image processing and experimental design methods [195]. Hybrid deep neural network-particle swarm optimization helps the investigator to accurately predict the machined surface quality with a set of influencing parameters (pulse-on time, pulse-off time, peak current, and working time) of the micro-drilling-based electric discharge machining process [196]. ML algorithms predicted the productive parameters affecting the ultra-precision machining of germanium quality, reducing machining time and cost [197]. ML algorithms predict the micro-turning conditions for better quality in machined surface and tool wear with less than 7% error [198]. The cutting parameters of plasma micromachining with acoustic emission data accurately predicted machining quality using CNNs [199]. The above literature review confirms that determining and optimizing the parameters of any process results in better machinability characteristics.

4.2.6. Measuring and Sorting Machined Components

Image processing has been successfully used to measure the dimensions of machined gemstones (jewelry applications) and assist in sorting [200].

4.2.7. Summary of Image Processing Methods and Their Applications with Advantages in CNC Machining/Micromachining

Image processing is gaining popularity due to its effectiveness in image enhancement, extracting information, and analysis using cost-effective software-based algorithms useful for industrial applications (unlike machine vision systems that require high-resolution cameras, industrial sensors, or advanced lighting setups). Researchers can use many image processing algorithms to manipulate images for their specific outcomes, namely image enhancement, segmentation, feature extraction, classification, compression, restoration, object detection and recognition, texture analysis, and image fusion. The image processing algorithms used for specific purposes are highlighted in Table 1 with their advantages and applications in machining processes. Although individual algorithms perform particular tasks, hybridizing different algorithms helps investigators improve performances in real-world applications yet to be performed.

Table 1. Summary of image processing algorithms and their advantages with specific applications in machining.

Purpose	Algorithms	Imaging Application	Ref.
Image enhancement	Histogram Equalization	Improve the contrast of an image during tool wear analysis	[201]
	Contrast Stretching	↑ (increase) the contrast of different regions of the image during tool wear analysis	[202]
	Smoothing Filters	↓ (decrease) noise and to generate the geometrically corner-free tool path	[203]
	Sharpening Filters	Improve edges and characteristics of feature variables of cutting tool correspond to different drilling conditions	[204]
	Sobel, Prewitt, Roberts Operators	Detects edges of tool wear	[201]
	Canny Edge Detection	A multi-stage edge detection is used to extract the features of the wear area	[202]

Table 1. *Cont.*

Purpose	Algorithms	Imaging Application	Ref.
Image Transformation	Fourier Transform	Transform the spatial domain surface roughness image into the frequency domain of the machined surface	[205]
	Discrete Shearlet Transform	Break down the surface roughness image into sinusoids of the machined surface images	
	Wavelet Transform	Support multi-resolution analysis of surface roughness on the machined surface	
Morphological Image Processing	Dilation and Erosion	Expand or shrink the structural element corresponding to the shape of the cutting tool, ensuring automatic tool selection in CNC machines.	[206]
	Opening and Closing	To check the Codes are available to open and close the NC programming in CNC Machines	[207]
Image Segmentation	Global Thresholding (Otsu's Method)	Automatically detect the tool wear in micro-milling operations	[131]
	Adaptive Thresholding	Calculates different thresholds for different regions that could improve chatter detection and characterization at various conditions, ensuring a low risk of workpiece damage	[208]
	Region Growing	Segmenting an image by growing a region helps to detect automatically the unique machining patches.	[209]
	Watershed Algorithm	Treats the image as a topographic surface and finds ridges helpful for automatic tool path generation, ensuring freeform surface machining.	[210]
	Edge-Based Segmentation	Define object boundaries that determine 24 machining features that correspond to the input 3D model.	[211]
	Clustering (K-Means, Mean Shift)	Segments of images based on pixels identical in color or intensity correspond to tool wear in the micro-milling process.	[185]
Feature Extraction and Representation	Scale-Invariant Feature Transform	Detects and describes local features, wherein the 3D cloud points are reconstructed to get a solid model useful for ease of processing with CNC machines	[212]
	Histogram of Oriented Gradients	Object (tool) detection by analyzing the gradient orientations of the tool for tool condition monitoring and optimizing the milling process.	[213]
	Principal Component Analysis	↓ the dimensionality of the image by reducing the imaging features data processing and increasing the robustness of monitoring tool wear.	[214]
Image Classification	K-Nearest Neighbors	Classifies images based on the tool state, ensuring tool condition monitoring in CNC machines.	[215]
	Support Vector Machines	Classify images by determining the optimal hyperplane that maintains precise force control during milling operations.	[216]
	Convolutional Neural Networks	Performs classification and feature extraction of tool wear, generates toolpath programs for CNC machines, detects chatter vibrations, and predicts machining quality.	[217–219]

Table 1. *Cont.*

Purpose	Algorithms	Imaging Application	Ref.
Compression	Lossless Compression	↓ file size without losing any data allows to transfer machine control instructions to the CNC system with increased function reusability and shortened lead time.	[220]
	Lossy Compression	↓ file size by discarding some data	[221]
	Run-Length Encoding	Compressing images by encoding consecutive identical pixels makes simpler and more effective compression methods available for transforming machine control instructions into a CNC system.	[220]
Image Restoration	Wiener Filter	↓ blurring and noise and ensuring chatter detection in CNC milling operations.	[222]
	Inverse Filtering	Reverse the effects of image degradation and ensure cutting force compensation in the milling of thin-walled parts.	[223]
	Total Variation Minimization	↓ noise while preserving edges by ↓ the total variation	[224]
Object Detection and Recognition	Viola-Jones Algorithm	Detects objects like faces by scanning different parts	[225]
	YOLO	A real-time object detection that ensures determining the process abnormalities (inappropriate coolant flow, chip clogging, and tool failure) during CNC milling.	[226]
	Region-based Convolutional Neural Networks	Identifies regions of interest in an image and classifies the objects that ensure detection and tracking of objects in manufacturing plants.	[227]
Color-Based Processing	Color Space Conversion (RGB, HSV, YCbCr)	Transform the image from one color space to another, and their image processing helps to limit the tool vibration caused during lathe operation.	[228]
	Color Histogram	Represents the distribution of colors helpful for object detection without the need to train the algorithm.	[229]
Image Registration	Mutual Information	Aligning two images based on their mutual information helps the investigator monitor the workpiece quality based on the acceleration and force signals.	[230]
	Feature-Based Registration	Aligning two images by matching corresponding feature points helps the investigator determine the machining time of NC machines, which is useful for scheduling and planning the manufacturing systems.	[231]
	Optical Flow	Estimates the motion between two consecutive image frames useful for tracking failure in NC machines.	[232]
Image De-noising Techniques	Non-Local Means	↓ noise by averaging similar patches corresponding to tool wear detection and their area for drilling process monitoring.	[233]
	Anisotropic Diffusion	↓ the noise while preserving edges	[234]
	Bilateral Filter	Smooth the image while preserving edges useful for estimating tool wear during machining.	[201]
	Wavelet-Based Denoising	Removing noise while retaining important details helps investigators obtain accurate cutting force signals and improve the precision of load static stress in CNC machining.	[235]

Table 1. *Cont.*

Purpose	Algorithms	Imaging Application	Ref.
Super-Resolution	Bicubic Interpolation	↑ the image resolution that improves the path planning (cutter contact point) in the CNC milling system.	[236]
	Super-Resolution Convolutional Neural Network	Reconstructs high-resolution images from low-resolution help investigators for online tool wear monitoring in micro-milling process.	[237]
Image Inpainting	Patch-Based Inpainting	Fills missing parts of an image by copying patches	[238]
	Exemplar-Based Inpainting	Restores lost or corrupted parts	[211]
	Deep Learning-Based Inpainting	Generate missing image regions useful to detect rough surfaces during machining operation.	[239]
Texture Analysis	Gray Level Co-occurrence Matrix (GLCM)	Analyses the spatial relationship between pixels to extract texture features, wherein the images of surface roughness of the deep hole machined workpiece are improved, ensuring better prediction	[240]
	Local Binary Patterns (LBP)	Describes texture by comparing each pixel to its surrounding neighbors, aiming to classify time-series data from a CNC machine, ensuring tool wear monitoring, and improving product quality.	[241]
	Gabor Filters	Extract texture information by filtering with sinusoidal patterns at various scales and orientations. This ensures multiresolution properties, which demonstrate better tool wear predictions.	[242]
Image Fusion	Pyramid-Based Image Fusion	Combines multiple images by merging their multi-resolution representations, resulting in better visual inspections in assembly lines.	[243]
	Wavelet-Based Image Fusion	Combines images by merging high and low-frequency, which enhances the tool condition monitoring of milling operations	[244]

5. Comparative Analysis

Machined products are widely used in numerous applications (defense, aerospace, automotive, medical, and so on) [245,246]. This necessitates the assessment of surface roughness, waviness, and dimensional accuracy on the machined surfaces [247]. The surface textures affect the reliability and service life of machined parts [248–250]. The fatigue life, fit, vibration and noise, wear rate, and stiffness are closely associated with the surface roughness of machined parts [251]. Distinguished researchers worldwide have made attempts to monitor machining surfaces by assessing various factors such as workpiece condition [252,253], waviness [254,255], tool condition [147], machine tool stability [256,257], coolants [258,259], and so on. The machining process is initiated with the tool–workpiece interface, causing the material removal phenomenon in the form of chips and generating the machined surface [260,261]. The machined surface involves complex interrelationships and dynamic interactions between the input variables [262]. The complex machining process requires monitoring of the desired surface roughness [263]. Precise machining process monitoring requires an appropriate evaluation of the machined surface, viz. measurement methods [162,251]. To date, both contact- and noncontact-type measurement methods have been used for machined surface assessments [251]. Comparative analysis of the two methods is essential for accurate and precise measurement of machined surfaces for properly functioning parts in industrial applications.

5.1. Image Processing vs. Traditional Surface Evaluation Methods

Traditional and noncontact-type measurements of machined surfaces are practiced to date across the globe. Table 2 presents the monitoring of machining responses that influence surface generation by applying traditional and noncontact measurement methods. The methods (fast Fourier Transform, autoregressive model, wavelet transform, discrete wavelet transform, wavelet packet transform, short-term Fourier Transform, and the ratio of power) determine the cutting force, vibration, and chatter, which indirectly affect the machined surface during the process. The data derived for intelligent monitoring of the machining process presented in Table 2 use the following: sensors, signal processing, feature selection, and decision-making methods. Figure 20 shows some experimental results for real-time monitoring during the machining operation. The direct assessment of the surface quality of the machining process is performed by applying contact and noncontact types. Surface profilometer and atomic force microscopy are the most commonly used contact methods for surface measurements [264].

The functions of a tool presetter, tool microscope, and visual tool inspector can now be handled by a single system: the VT 122 measuring camera with smart VTC software from HEIDENHAIN. Taken from within the machine envelope, the images on the control screen provide an accurate look at the tool's cutting edge and reliable facts for a holistic evaluation of the tools. The vision system can automatically measure a tool's length, diameter, and wear width, transmitting these data to the TNC control. Detailed tool inspection is available without going to a metrology laboratory [265].

This section provides a comparative context for understanding the advancements in surface evaluation methods. Table 2 presents the traditional and noncontact measurement methods widely used in machining. This background sets the stage for appreciating the transformative impact of image processing techniques, which we discuss in detail in subsequent sections.

Table 2. Summary of machining surface monitoring by applying traditional and noncontact-type measurement methods.

Objective	Method Applied	Parameter Analyzed	Major Remark	Ref.
Realtime monitoring of tool failure during the milling process	Fast Fourier Transform, autoregressive model	Cutting force	The autoregressive model is an efficient tool for the prevention of tool failure	[266]
Tool life monitoring by analyzing the cutting force during CNC Milling process	Fast Fourier Transform	Cutting force	Experimental results are in good agreement with the published literature	[267]
To determine the optimal parametric values of signal current	Wavelet transform	Cutting force and signals	WT derives cutting force information by analyzing signals in CNC machines as a sensor-less approach.	[268]
To optimize the orientation of the cutter path for a better surface finish	Fast Fourier Transform	Vibration and cutting force	Optimization of control variables is essential to obtain a better surface finish	[269]
To establish a systematic approach in modeling and optimization that could compensate for geometrical errors in the machined surface	Fast Fourier Transform	Vibration	The proposed method is beneficial in compensating the geometrical errors	[270]
To minimize the chatter during end-milling operation	Discrete wavelet transform	Chatter	The results of the proposed methodology will be useful for other machining operation	[271]

Table 2. *Cont.*

Objective	Method Applied	Parameter Analyzed	Major Remark	Ref.
Monitoring minimum quantity lubrication for a better-machined surface	Wavelet packet transform	Vibration	Optimizing the flowrate is essential for better quality in machined surface	[272]
Monitor the chatter response with different operating variables of grinding process	Short-term-Fourier transform, ratio of power	Vibration	The proposed methodology is limited to handling frequencies below 20 kHZ.	[273]
Design and analysis for minimizing vibration and chatter	Filtered—X least mean square	Chatter and vibration	Success of the obtained results is beneficial in real-time process monitoring	[274]
Monitoring the chatter produced during multi-scale entropy and gradient tree boosting	Angular synchronous averaging	Chatter	The method could benefit an early detection of chatter during the machining process	[275]
Monitoring acceleration signals in three directions during milling operations	Fast Fourier Transform	Vibration	The presented results would benefit online monitoring through the Internet of Things	[276]

Evolution from Traditional to Image Processing Techniques

Traditional methods such as the Fast Fourier Transform and wavelet transforms have long been used to monitor machining parameters indirectly affecting surface quality. These methods laid the groundwork for the development of more advanced techniques. Integrating image processing with these traditional methods has enabled direct and more precise surface quality assessments, significantly improving productivity and quality control.

The surface profilometer employs a stylus to access the machined surface quality assessments [277]. The stylus produces direct contact on the machined surface with relative movement at a constant speed amplified by the transducer (a linear variable differential transducer or sensor) for the digital conversion of imaging and conducting subsequent analysis utilizing software employed in the instrument [278]. The vertical movement of the stylus generates the line profile. The stylus tip comprises a diamond tip to trace the surface precisely. The force applied through the stylus had to be monitored accurately to reduce surface damage at higher force and ensure precise surface tracing with greater accuracy [279]. A diamond stylus tip is preferred to access the hard machine surface assessments. In contrast, sapphire ruby or silicon nitride tips are also being used to assess the surface of soft materials [280,281]. Although different stylus geometries and tips have been developed, the cone-shaped geometry possessing an angle and radius equal to 60° and 2 μm radius has been adopted by researchers [278,282]. Atomic force microscopy employs the stylus tip at the cantilever end, wherein the cantilever deflection is recorded optically by monitoring the position of the reflected laser beam [283]. Conversely, in the tapping mode, the cantilever resonates such that the tip intermittently makes contact or taps the surface [284]. The tip is raster scanned over a small area to produce a topographical image over the surface assessment [285]. Unlike the profilometer, atomic force microscopy ensures normal and lateral friction force measurements [286]. The Taylor Hobson stylus profilometer, used for the evaluation of different machining surfaces reported in 2023, is summarized as follows: thread-cutting operation [287], grinding [288,289], milling [290], electro-discharge machining [291], electrochemical [292], abrasive aqua jet hole making process [293], laser machining [294], drilling [295], and so on.

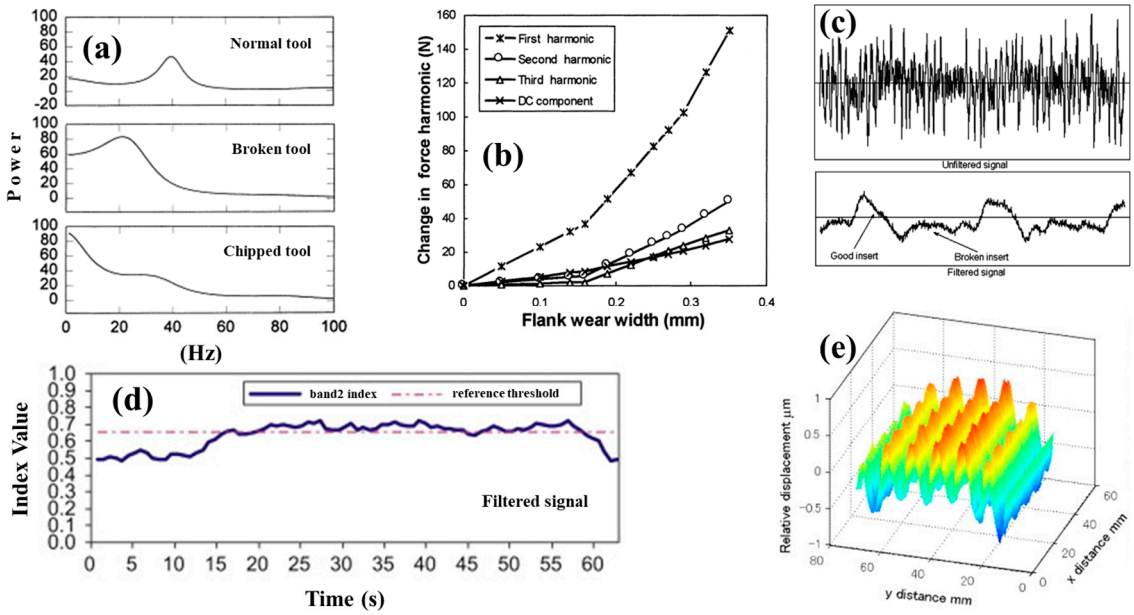


Figure 20. (**a**) AR spectrum of normal, broken, and chipped tools [266]; (**b**) the relationship between change in force harmonics and tool flank wear [267]; (**c**) driver current signal with good and broken inserts [268]; (**d**) chatter detection using the vibration signal [271]; (**e**) max (red color) and min (blue color) points of relative displacement of the tool [270].

The successful application of the stylus-type profilometer measurement technique is due to the following advantages: direct physical contact with actual measurement surfaces [296], compatibility with previously accumulated measured data [296], the measurement of transparent specimens [297], an irregular geometrical surface possessing large depth variations [298], the extremely rough surface [296], non-reflective surfaces [299,300], and the fact that large components can be effectively measured with a contact-type surface profilometer, which is usually difficult with noncontact optical profilometers [296]. However, the mechanical stylus profilometer possesses certain disadvantages, such as distortion of the surface to a certain extent [301], the possibility of liftoff of the tip as the stylus traverses over the measured surface [302], the high load applied through the stylus, which causes permanent damage (scratch or plastic deformation) on the machined surface [303], its unsuitability for all applications due to its destructive and contact-type measurement [251], being limited only to post-processing inspection [304], the systematic error (i.e., the error between the contact point and point measured by stylus tip radius) [296], and the challenge of online monitoring.

Noncontact methods replace the stylus with sound or light for surface characterization. Noncontact-type surface assessment methods overcome the shortcomings of the contact type and, therefore, have been widely accepted in recent years. Noncontact-type (optical and nonoptical) measurements have been deployed for surface measurements [305]. Methods such as white light interferometry, phase shift interferometry, confocal microscopy, the digital holography technique, computed tomography, the machine vision system, and scanning tunneling microscopy are widely used by distinguished researchers across the globe [306]. They are quite expensive, only effective in certain environments, and have a limited measurement range, meaning they are limited to distinguished applications in manufacturing industries [307,308]. Optical sensors and microscopes perform noncontact measurements by replacing contact-type detectors, namely physical probes [309,310]. Noncontact surface characterization offers significant advantages over traditional mechanical stylus profilometry. These advantages include being non-destructive, providing high resolution, repeatability, and accuracy, and its speed of operation. Additionally, it is flexible in examining various materials and supports automation and process monitoring [311–314]. Noncontact-based machine vision systems have shown potential benefits over other noncon-

tact measurement techniques, such as higher measurement accuracy, flexibility efficiency, and information collection [251]. The compute vision (CV) technique comprises a digital camera with a light source connected to a personnel computer to extract the machined surface images [315]. The images are further processed to obtain the arithmetic mean values of grey levels with different adaptive network fuzzy interface systems (ANFISs) to compute the surface roughness and conduct prediction [316]. CV with image processing techniques has been successfully applied for automation, enabling improved production flexibility to ensure safety, reliability, accuracy, and online monitoring during machining [317]. Image processing techniques have quantified the plastic deformation of machined surfaces [318] and tool wear [319]. The measurement process evaluation of machined surface features at the microscale is proposed with three phases in Figure 21.

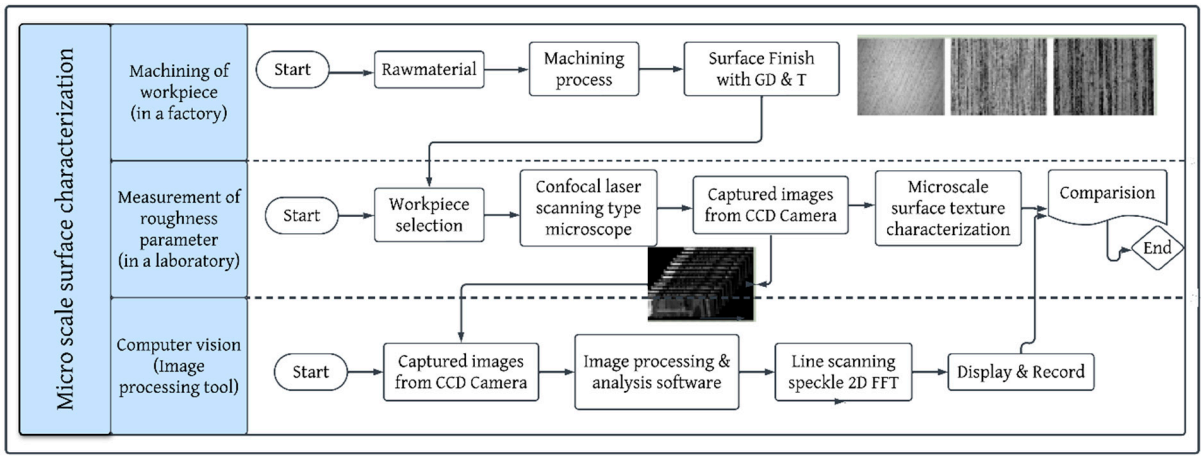


Figure 21. The measurement process evaluation flow for surface roughness characterization [redrawn from [320]].

The three phases are defined with the aim of processing measurements to obtain the roughness values of the machined surface by analyzing the image features. The intelligent process management model employs a systematic approach in real-time process monitoring [320]. The proposed methodology can be used for any machining process with other image-capturing methods (scanning electron microscope) to estimate the surface roughness or other surface characterizations.

ML and image processing techniques can successfully classify the textures of machined surfaces [321]. An image processing-integrated CV technique previously enabled in-process machining monitoring of tool and machined surface quality [322]. The images were processed with ML algorithms to forecast the machining responses. CV technology integrated with ML algorithms (logistic regression, multilayered perceptrons, k-nearest neighbor, random forest, decision tree, and so on) was deployed for micro and macro surface characterizations [323–325].

ML algorithms were integrated into CV technology to limit hardware requirements, maintain the measurement stability cost, and increase efficiency [326]. Distinguished researchers have employed ML application-based CNNs across the globe for intelligent monitoring (based on the images extracted during the actual process) of the machining process, such as tool monitoring [217], chatter detection [327], surface roughness prediction [328], wear prediction [329], and so on. The classification or recognition of the surface feature process from the images using a CNN is proposed in Figure 22. The CNN is trained with the images of machined surfaces. The machined surface features (either tool wear, surface roughness, chatter, or vibration) are directly fed into the CNN for training and testing after normalization and feature extraction processes using image processing software. The images are trained enough to determine the surface feature status of machined surfaces automatically. The CNN network parameters were optimized for the preset goal or iteration. The optimized network is tested for accuracy and validation purposes.

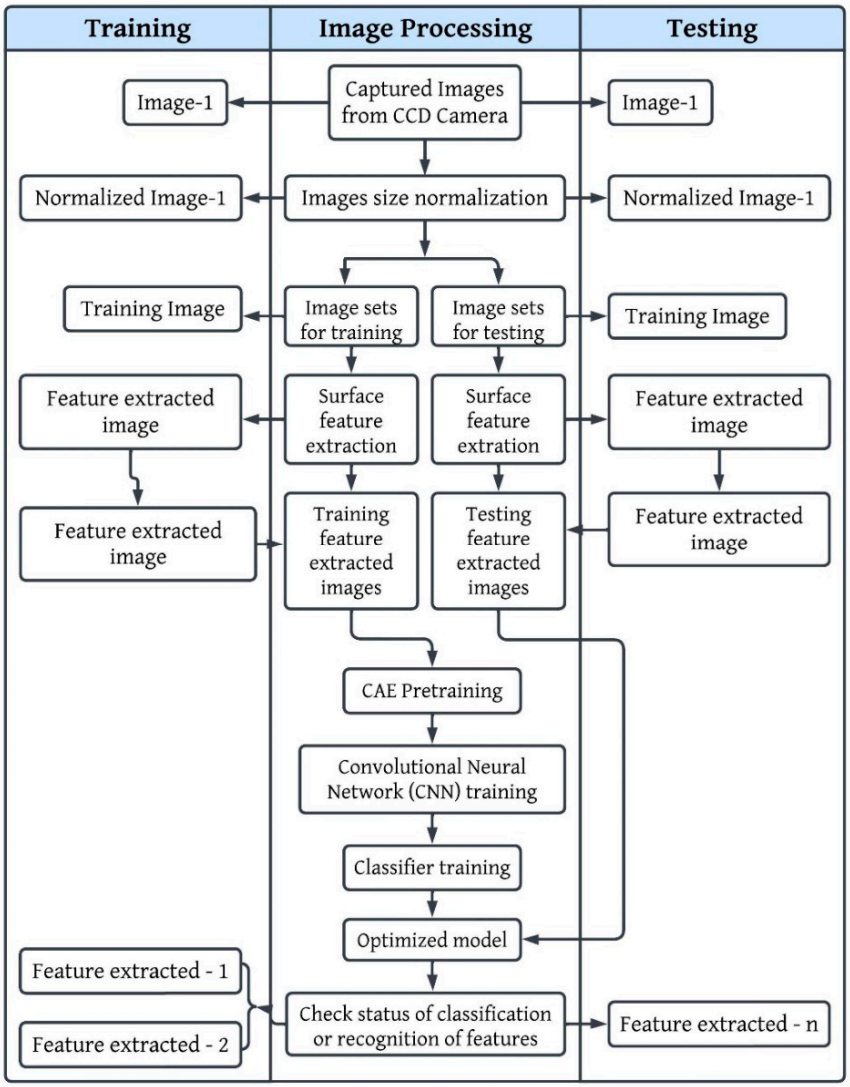


Figure 22. CNN applications for classification or recognition of surface features.

5.2. Limitations of Image Processing in Machined Surface Analysis

Image processing (IP) techniques for process monitoring possess significant advantages and limitations. The advantages of the IP technique are discussed below:

1. Unlike the contact type, the IP technique does not require mechanical force and protects the machined surface from permanent damage, scratch, or plastic deformation [319].
2. Flexible, inexpensive, and in situ process monitoring approach [330].
3. Measurement, control, and monitoring can be performed online at remote locations, making them best suited for unmanned production [319].
4. Indirect sensors (acoustic emission, force, and vibration) provide better real-time monitoring due to their continuous and immediate data-capturing capabilities. However, progressively monitoring tool wear with these sensors is complex due to the intricate data interpretation required over time, a challenge effectively addressed by the IP technique, which offers clear and detailed progressive wear analysis despite its real-time limitations. [331,332].
5. Integrating costly sensors (acoustic emission, force, vibration, and dynamometer) is essential for process monitoring and control. The IP is cost-effective and does not require the fusion of more sensors [331,332].

6. The IP method captures the surface characteristics of tool geometry, roughness, and waviness of machined surface images [129,332].
7. Machining parameter information can be captured from machined work surfaces viz. IP [333].
8. Unlike other sensors, CCD cameras are beneficial as they are less sensitive to noise caused by industrial environments [334].
9. IP allows manipulation (adding, multiplying, subtracting, and storage) or image processing using different optical devices [127,335].
10. Three-dimensional surface textures captured by surface profilers are not quick or economical for real-time processes and tool monitoring [299]. IP overcomes these shortcomings.

The challenges when dealing with the IP technique for machined surface characterizations are discussed below:

- The IP technique poses significant challenges concerning selecting an appropriate illumination system, a robust algorithm, and the adverse effects of machining noises (chips, dust, debris, dirt, etc.) and the environment [333].
- IP of drilling parts quality monitoring is impractical due to inaccessibility [336].
- IP of deep hole parts is difficult and only possible in the development stage [337].

6. Future Prospects and Developments

Image processing for machined surfaces is integral to various industries, including manufacturing, quality control, and automation. As technology continues to advance, there are several anticipated advancements in the field such as high-resolution imaging, 3D imaging, AI and ML, augmented reality (AR), integration with Industry 4.0, improved lighting techniques, rapid processing speed, and remote and cloud-based image processing. Several implications can be observed, such as increased productivity, improved quality control, reduced labor costs, enhanced precision, data-driven decision making, wider adoption of smart manufacturing, and challenges in data privacy and security.

The future of image processing for machined surfaces is promising, with the potential for quality improvement, cost reduction, and process enhancement across various industries. However, the challenges in data security and the requirement for qualified experts to manage and optimize these cutting-edge technologies are also prevalent.

6.1. Advancements in Image Processing Algorithms

Advancements in image processing algorithms have significantly impacted image-based surface analysis, offering more accurate and efficient ways to extract valuable information from images. Here, we have provided a glimpse into some evolving algorithms that are shaping the future of image-based surface analysis.

Deep learning techniques, particularly CNNs, have revolutionized image analysis. They excel in feature extraction and pattern recognition. Applications include surface defect detection and texture analysis [218]. Generative Adversarial Networks are used for generating and enhancing images. They can be employed to inpaint missing parts of surfaces or generate high-quality images from noisy data [338]. Transfer learning allows the creation of models trained on large datasets for specific surface analysis tasks with limited labeled data, making it a practical solution for many industries [339].

Sparse coding techniques are used in surface analysis for feature extraction and reconstruction. Dictionary learning helps capture distinctive features in surface textures [340]. Super-resolution techniques enhance the resolution of images, which is valuable for detailed surface analysis. Deep learning-based methods have shown remarkable results [341]. Super-resolution imaging methods are continuously enhancing imaging techniques in micromachining. In the literature, sub-micrometer features are reported to be fabricated on MEMS-related materials using a laser-induced photonic nanojet through microspheres. It has been demonstrated that a laser beam with an initial beam width of 5 μm can be used to fabricate 250 nm diameter cavities on silica

substrates [342]. Moreover, with the help of a Gaussian laser beam profile, researchers have achieved image spatial sharpening for calibrated 260 nm metal strips, the resolution of plasmonic nanoassemblies, and the visualization of 10 nm gold nanoparticles in graphene and hemoglobin nanoclusters in live erythrocytes with resolutions down to 50 nm [343]. Graph-based algorithms are used to analyze surfaces with complex structures, such as in materials science and geology. They model relationships between pixels as a graph to extract meaningful information [344].

Evolving algorithms continue to drive advancements in image-based surface analysis, enabling industries such as healthcare, materials science, and manufacturing to improve product quality.

6.2. Integration of AI and Machine Learning

By integrating AI and ML with image processing, evaluations of machined surfaces have become more precise and capable, leading to more efficient and accurate quality control and analysis.

AI and ML algorithms with high accuracy can be trained to detect and classify defects on machined surfaces, including cracks, scratches, and imperfections [345]. ML models can identify anomalies or deviations from the expected surface characteristics, enabling the early detection of potential issues [346]. Surface texture analysis is an AI-based algorithm that can assess surface texture and roughness, providing valuable information for manufacturing and product quality control [347].

In predictive maintenance, ML models can predict equipment maintenance needs based on image data, reducing downtime and optimizing maintenance schedules [348]. AI, in conjunction with image processing, can be applied to enhance the quality of manufactured components. This approach analyzes surface defects and suggests process adjustments to improve outcomes [349].

The convergence of image processing with AI and ML has revolutionized machined surface evaluations, provided real-time insights, and enabled automation. Its effectiveness in enhancing efficiency and quality has impacted different industries, ranging from aerospace to manufacturing.

6.3. Potential Industrial Applications

Innovations in image processing for surface analysis have a broad range of applications across various industries.

In manufacturing and quality control, image processing is vital for defect detection, metrology, and quality control, ensuring high-precision and consistent production [98]. Healthcare and medical imaging are emerging areas that must be focused on. Image processing is used for medical image analysis, such as MRI and CT scans, to diagnose diseases, detect abnormalities, and guide surgical procedures [350]. The aerospace industry employs image processing for the inspection of aircraft components, surface quality assessment, and non-destructive testing [219].

Automotive manufacturing is a critical area where image processing is essential for ensuring the quality of automotive parts, from paint finish inspection to weld seam analysis [351]. Agriculture and precision farming will be the focus of the next decade. In agriculture, image processing aids in crop health assessment, soil analysis, and precision farming by monitoring plant health and nutrient levels [352]. In geology and earth sciences, geologists use image processing to analyze rock formations and geological structures, assisting in resource exploration and environmental studies [353].

The next wave of innovations in image processing for surface analysis is poised to transform these and many other industries, enhancing quality, efficiency, and decision-making processes.

7. Conclusions

This paper comprehensively explores the dynamic and evolving field of image processing in the analysis of machined surfaces, highlighting its pivotal role across various industries. Integrating deep learning techniques, AI, and ML into image processing algorithms has significantly enhanced surface analysis capabilities. These technologies have improved accuracy and efficiency and extended image processing applications into diverse sectors such as healthcare, manufacturing, aerospace, automotive, and agriculture.

In traditional and CNC machining, image processing has emerged as a critical tool for tool wear analysis, workpiece origin detection, automatic generation of CNC programs, and tool setting. The ability to conduct real-time inspections and predict surface roughness during the machining process has significantly reduced downtime and improved product quality. In micromachining, applications such as surface texturing and quality monitoring have been revolutionized by integrating image processing techniques, enabling more intricate and precise work.

The field of additive manufacturing has also seen substantial benefits from image processing. It has been instrumental in in-process defect detection, real-time monitoring, and quality improvement during pre- and post-processing operations. This integration has enhanced the overall efficiency and quality of additive manufacturing processes.

This paper also discusses the prospects and potential developments in image processing. With the advent of high-resolution and 3D imaging, and advancements in AI and ML, the scope of image processing is expanding. These technologies are set to significantly improve quality control, predictive maintenance, and overall productivity across various industries. The challenges of data privacy and the need for skilled professionals to manage these technologies are also acknowledged.

In conclusion, this review emphasizes the transformative impact of image processing technologies in machined surface analysis. Its integration into various machining processes has streamlined quality control, improved efficiency, and opened up new avenues for innovation and research. As technology advances, the potential applications of image processing in industrial and scientific domains are bound to expand, heralding a new era of precision, efficiency, and data-driven decision making.

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