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An Image Analysis for Designing an Optimal Stirrer in Metal Matrix Composites Manufacturing

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ABSTRACT

The global market for aluminum-based composites, widely used in manufacturing and construction, is expected to grow significantly. However, enhancing the cost-to-performance ratio is essential to improving their commercial viability. Efficient mixing plays a critical role in many industrial and chemical applications. Stir casting is the leading method for producing aluminum alloy matrix composites, but achieving a uniform particle distribution remains a significant challenge. In this study, the optimal stirrer design was identified using image processing techniques to analyze the distribution of ceramic grains. The stirrer that achieved the most uniform grain distribution was selected, eliminating the need for destructive testing. The mechanical properties of the final products validated the accuracy of the image analysis results.

Index Terms: Aluminum Alloy Matrix Composites, Cost-to-performance ratio, Mixing Performance, Stir Casting, Ceramic Reinforcement Particles, Stirrer Design, Image Processing, Mechanical Properties

1. INTRODUCTION

As energy shortages and environmental pollution risks increase, the demand for stronger, lighter, and more environmentally friendly materials continues to grow. Aluminum alloy ceramic matrix composites are extensively used across various industries and are expected to expand further as efforts to protect the environment and reduce fossil fuel usage intensify. Stir casting, also known as the vortex process, is widely recognized as an economical method for producing metal matrix composites. However, achieving mixing homogeneity remains a significant challenge, heavily influenced by stirrer design. In this study, the authors isolated the effect of stirrer design by keeping other key variables – stirring time, stirring speed, and stirrer position – constant, thereby eliminating potential interference or interaction effects from these factors. These parameters were fixed as follows: Stirring time at 60 s, stirring speed at 240 rpm, and stirrer position at two-thirds of the crucible height. This approach allowed the exclusive evaluation of the stirrer design's function. Fig. 1 provides a flowchart summarizing the research methodology used to achieve the study's objectives.

Using image processing to assess the uniform distribution of solid particles in liquids at elevated temperatures, before solidification. Accurately measuring particle distribution in high-temperature fluids presents considerable difficulties due to several key challenges. These include the requirement for sensors that can withstand high temperatures, real-time, non-destructive measurement techniques capable of providing sufficient penetration depth, and the ability to monitor dynamic changes in particle distribution amidst stirring and thermal fluctuations. Traditional methods such as microscopy are inadequate due to their destructive nature.

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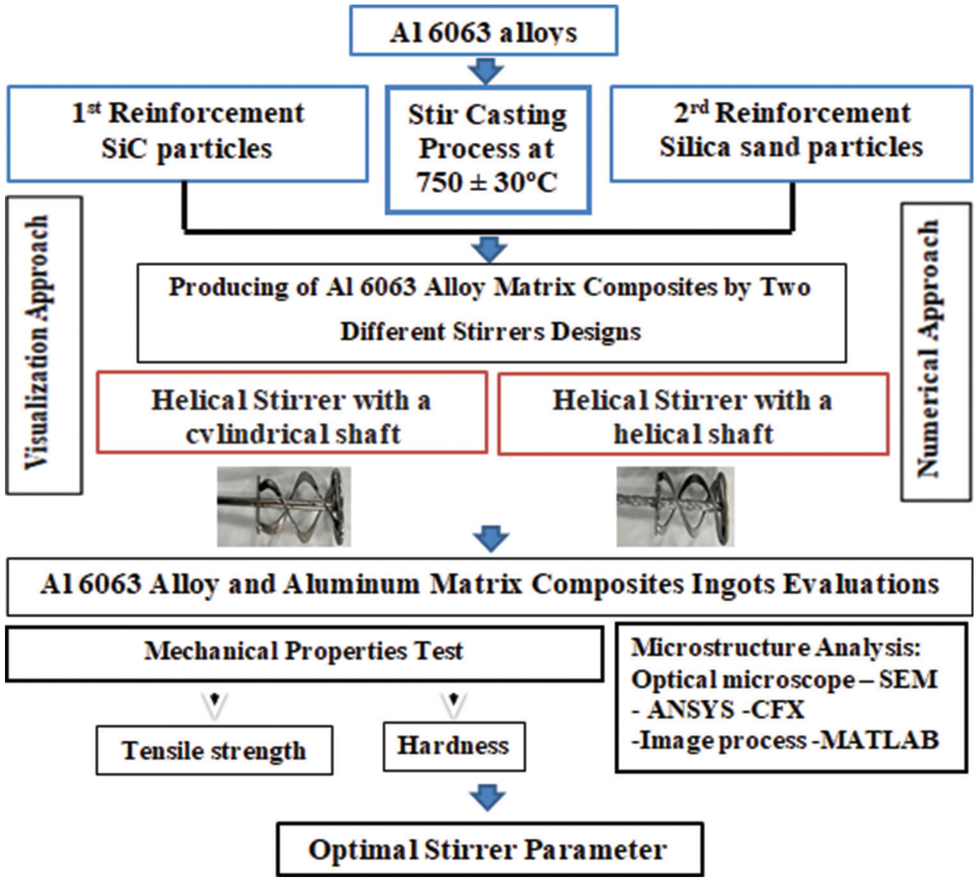


Fig. 1. Diagram of the research work.

Potential alternatives, including high-temperature ultrasound, electromagnetic methods, and specialized optical techniques, each possess their limitations and drawbacks. As such, image processing emerges as a promising alternative deserving further exploration and evaluation.

2. RELATED WORK

Digital image processing (DIP) technology has significant potential in particle mixture analysis. Nowadays, surface analysis has many applications across various fields, and one important area is material surface analysis [1]. Proposed a model where a color histogram was implemented to analyze particle mixtures in fluidized beds. The proposed method serves as a proof of concept, demonstrating that mixing particles changes the color distribution of the image and can be used to evaluate the quality of the mixing process. The results show that particle mixing alters the histograms of images taken at different times, providing an interesting avenue for exploring automatic particle mixing techniques based on image processing. On the other hand [2], [3], proposed an approach in which texture-based image processing plays a more prominent role than standard image enhancement. This method facilitates the detection of small obstacles during surface preparation by making individual features and surface details more visible. Various algorithms and mathematical models were applied to compare different image surfaces. In addition, statistical measures were used to evaluate the performance of this approach, further validating its effectiveness in surface analysis [4] studied the effects of adding micro, nano, and hybrid particles in a 1:1 ratio of $Al2O3$ and $TiO2$ to epoxy resin on thermal conductivity. The study analyzed samples before and after immersion in 0.3 N HCl acid for 14 days, considering weight fractions of 0.02, 0.04, 0.06, and 0.08, with a thickness of 6 mm. Image analysis techniques were employed to evaluate the homogeneity of the mixtures, highlighting the practical application of DIP in material science.

An analysis and comparison of the image analysis approach with other existing methods are necessary to evaluate the homogeneity of mixing in a moving casting. The selection of an appropriate method depends on several factors. These include particle properties such as size, shape, density, and concentration; fluid properties such as viscosity, density, and surface tension; type of mixing equipment, including mixer type, design, and operating conditions; required level of accuracy and sensitivity; and available resources and expertise. This research focuses on finding non-destructive tests. Even if we assume that destructive tests are acceptable, microscopic analysis, as one of the destructive tests, has limitations. It is time-consuming and provides data only from limited sample areas. It is time-consuming and provides data only from limited sample regions [5].

3. METAL MATRIX COMPOSITES

In 2022, the market for metal matrix composites (MMCs) was valued at USD 211.3 billion. It is projected to grow significantly, reaching USD 369.3 billion by 2032, with an annual growth rate of 6.40% during the forecast period from 2023 to 2032. The increasing demand for lightweight materials in the automotive and aerospace sectors is expected to be a key driver of this market growth. Fig. 2 illustrates the projected trend for MMCs in the coming years.

Aluminum matrix composites (AMCs) use pure aluminum or an alloy as the matrix and are becoming more popular in industrial applications due to their outstanding mechanical and tribological properties. The properties of Al alloys might be greatly tailored by adding ceramic reinforcing particles by stir casting. AA 6063 ingot was chosen as a matrix alloy which was analyzed carefully by using an X-MET8000 Handheld XRF analyzer and the compositions of the used material are shown in Tables 1-4.

In previous work [11], the visualization procedure was performed using two stirrer designs: A helical stirrer with a cylindrical shaft (D4) and a helical stirrer with a helical shaft (D5), as shown in Fig. 3. A glass jar, similar in dimensions to a graphite crucible, was filled with fluids of varying viscosities – water (low viscosity) and engine oil (high viscosity) – to simulate the stirring process of molten aluminum and SiC or silica particles. The jar had a height of 150 mm and a diameter of 100 mm. A 1% volume fraction of real micro-sized SiC and silica particles was added to the fluid, and stirring was conducted using an SEI-WA MG-915 radial drill connected to different stirrer designs. The stirring speed was set at 240 rpm, with the stirrer positioned at 30% of the crucible's height from the base. Images were captured immediately after removing the stirrer following a constant holding time of 60 s of stirring. The images, taken from the open top of the jar, minimized glare issues caused by the glass. This visualization experiment was repeated under consistent conditions for all five stirrer designs: Single-blade, double-blade, multi-stage stirrer, helical stirrer, and helical stirrer with a helical shaft, as shown in Figs. 4 and 5. Both stirrers (D4 and D5) were used to mix a 0.05% volume fraction of SiC particles and silica sand particles (50–80 microns in size) under two conditions: Once with one liter of water and then with one liter of engine oil. The mixing was conducted for 60 s at a stirring speed of 250 rpm, with the stirrer operating within the top two-thirds of the glass jar's height. Images were captured from the open top portion, as shown in Fig. 6, to ensure clarity

Existing Methods	Description	Limitations	References
Visual Inspection	Observing the distribution of particles with the naked eye or using optical devices.	Subjective and lacks quantitative accuracy.	[6]
Conductivity Measurements	Measuring the electrical conductivity of the mixture, which can change with particle concentration.	Limited Sensitivity to Certain Components: They are primarily effective for detecting ionic species and may not provide accurate results for non-ionic or poorly conductive components in the mixture.	[7]
Computational Fluid Dynamics (CFD)	Using CFD models to predict the flow behavior and particle distribution within the mixing vessel.	High costs in chaotic flows, impairing accurate evaluation of mixing and homogeneity.	[8]
Optical Techniques, Laser Diffraction	Measuring the particle size distribution and identifying any significant variations within the mixture.	Laser diffraction assumes spherical particles, leading to inaccurate size measurements and hindering homogeneity assessment in mixtures with irregularly shaped particles.	[9]
Ultrasonic Testing	Using ultrasound waves to measure the acoustic properties of the mixture, which can be affected by particle distribution.	Anisotropic materials have varying ultrasonic wave velocities due to structural variations, complicating accurate characterization.	[10]

TABLE 1: Composition of the AA 6063 ingot

Element	Al	Si	Fe	Zr	Mn	Mg	Zn	Ni	Pb	Sn	Ti
Average content	98.76	0.19	0.16	0.02	0.02	0.74	<0.00	<0.00	0.04	0.07	<0.01

TABLE 2: Chemical Composition of Silicon Carbide (SiC)

Component	SiC	C	Si	SiO_2	Fe_2O_3
Wt.%	97.2	0.28	0.23	1.73	0.56

TABLE 3: Properties of Silicon Carbide (SiC)

Properties	Measure
Melting point	2200 to 2700
Density	3.1(g/cm^3)
Coefficient of Thermal Expansion	4.1(µm/m/°C)
Fracture toughness	4.6(MPa-m1/2)
Poisson's ratio	0.14
Color	Black

TABLE 4: Properties of (Sio_2)*

Constituent	Percentage
Sio_2	89
Al_2O_3	3.75
Fe_2O_3	1.94
MgO	1.02
Cao	0.99
Loss on ignition	2.63

*Silica sand samples from the Mass company (Iraq) (50–80-micron size) were used. The chemical composition is given in Table 4.

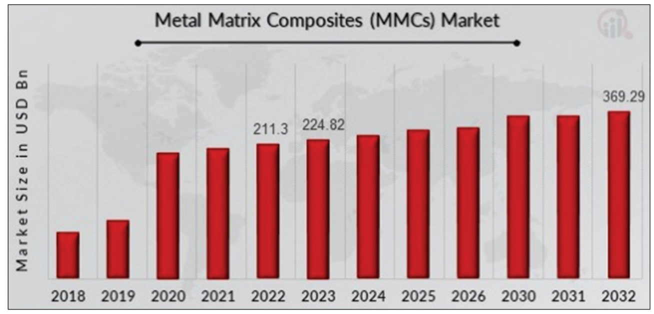


Fig. 2. MMC trend.

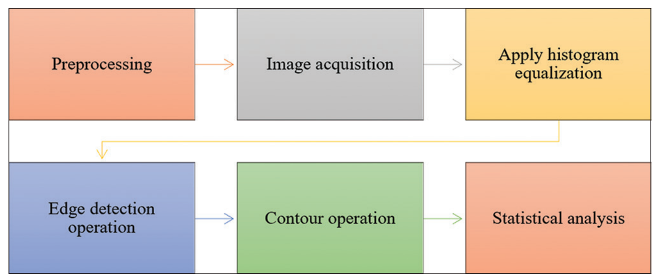


Fig. 3. Implemented approach.

and avoid glare issues. These images were then analyzed using MATLAB to evaluate the mixing process.

5. IMAGE PROCESSING ANALYSIS

Traditional image processing has been widely utilized to enhance the aluminum alloy casting process by automating quality control and optimizing casting methods. Various image processing techniques have been employed for aluminum alloy analysis, including X-ray CT for internal defect detection, surface inspection for identifying surface flaws, real-time monitoring for process optimization, microstructure analysis for understanding material properties, dimensional measurement for precision, and robotic vision for automated handling [12], [13]. Mixing is a critical process that directly influences the quality of final products in several industries. Ensuring homogeneous mixtures requires a thorough examination of the mixing process [14]. This study highlights an alternative, non-invasive method for analyzing particle mixing and segregation using image processing, which has shown great potential. A proposal to utilize low-cost cameras combined with image processing has been introduced as an effective, affordable solution [15]. High-tech methods for analyzing mixing processes are often costly and demand strict safety protocols, making image processing a promising alternative.

In recent years, image analysis has gained significance due to the increasing volume of images transmitted through various media in daily life. Image processing involves applying specific operations to enhance images or extract meaningful information from them. An image is mathematically represented as a two-dimensional function (x,), where x and y are spatial coordinates, and the amplitude at any coordinate pair corresponds to the image intensity. When, the amplitude values of f are finite and discrete, the image is termed a digital image [15]. Digital images are composed of pixels, each with a specific location and value. This paper uses statistical methods to identify optimal mixtures by analyzing images captured under varying incident light conditions and with different stirrer designs. Image content analysis is an essential step for producing accurate and unbiased evaluations.

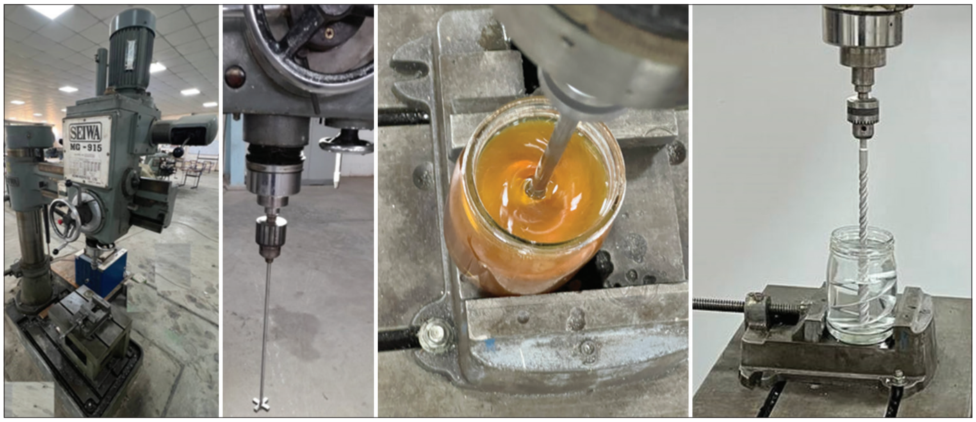


Fig. 4. SEIWA MG-915 Radial Drill setting.

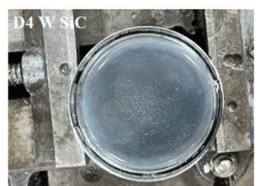
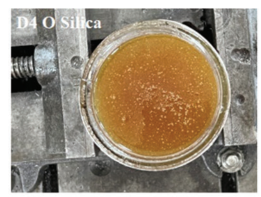
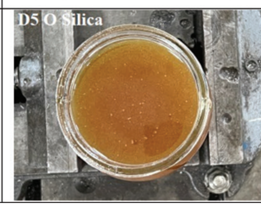
Stirrer types		After 60 seconds stirring at (240 rpm)	
		Water + SiC particles	Oil + Silica particles
Helical stirrer with a cylindrical shaft (D4)			
Helical stirrer with a helical shaft (D5)			

Fig. 5. Images were captured from the exposed upper section.

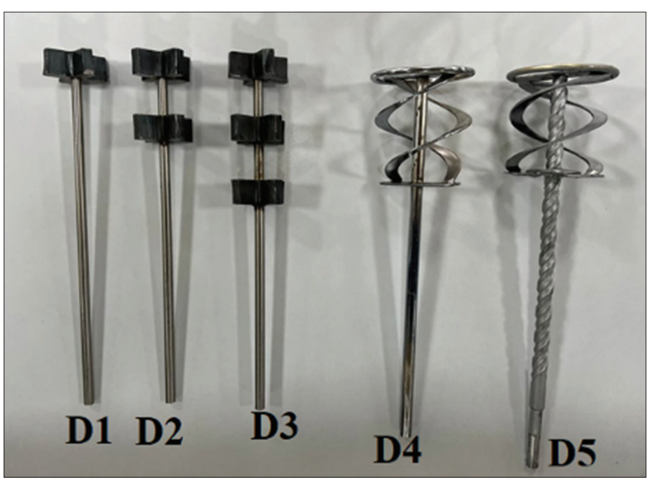


Fig. 6. Five different designs of stirrers, a four blades single stirrer (D1), double stages stirrer (D2), a multi-stages stirrer (D3), a helical stirrer (D4), and a helical stirrer with helical shaft (D5)

Fig. 7. Helical Stirrer helical stirrer with a cylindrical shaft (D4) and a helical stirrer with a helical shaft (D5).

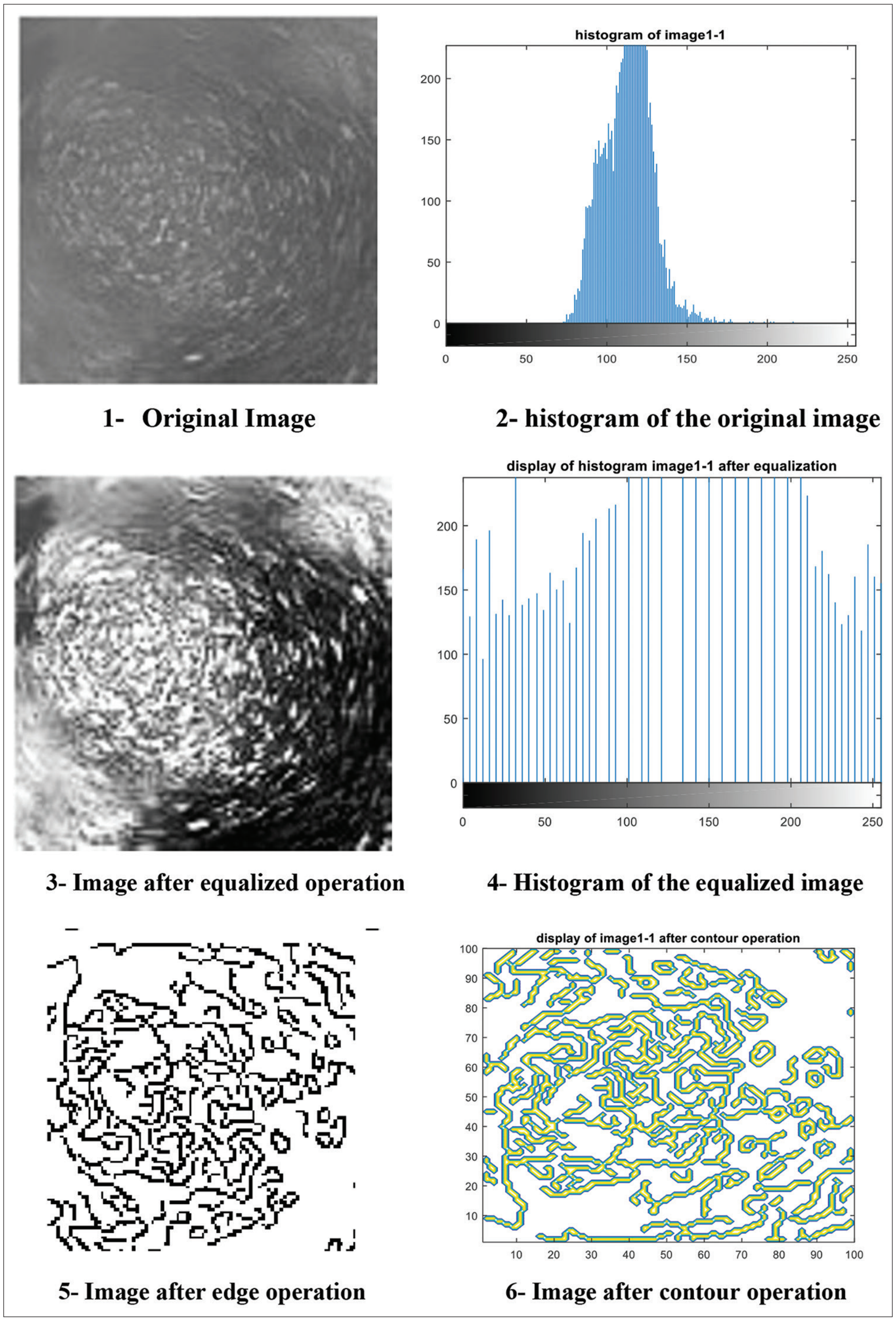


Fig. 8. Image process steps from original to after-edge operations.

Algorithms and techniques for processing color information in three-dimensional scenes and converting them into two-dimensional images in trichromatic color models and digital color spaces demonstrate similarities between color and grayscale image processing [16], [17]. Image processing is integral to modern manufacturing, enabling the manipulation and analysis of digital images to enhance product quality, extract critical information, and optimize processes. Techniques such as object recognition, segmentation, and optimization improve efficiency, automate quality control,

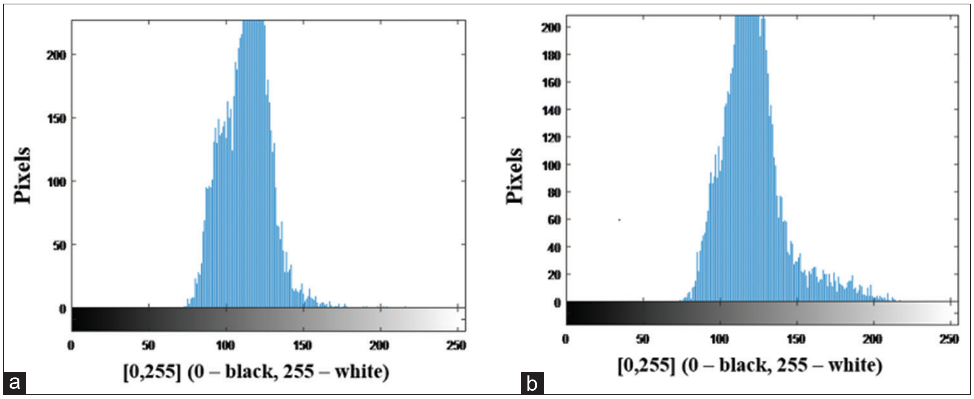


Fig. 9. (a and b) D4 stirrer mixing performance.

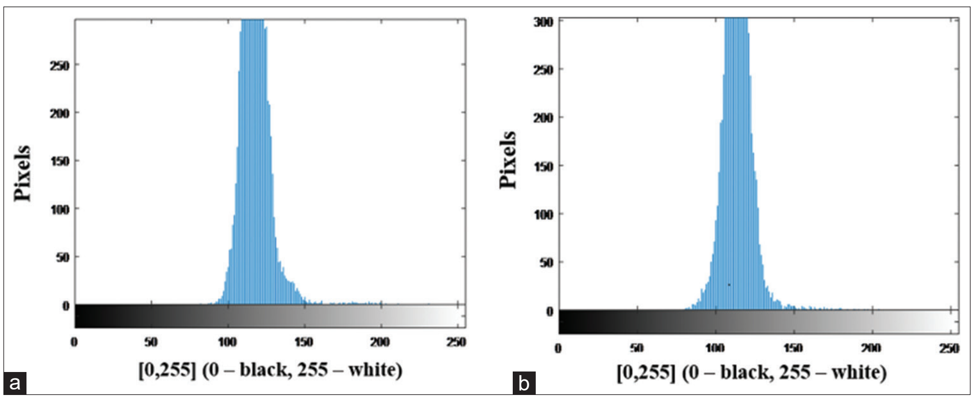


Fig. 10. (a and b) D5 stirrer mixing performance.

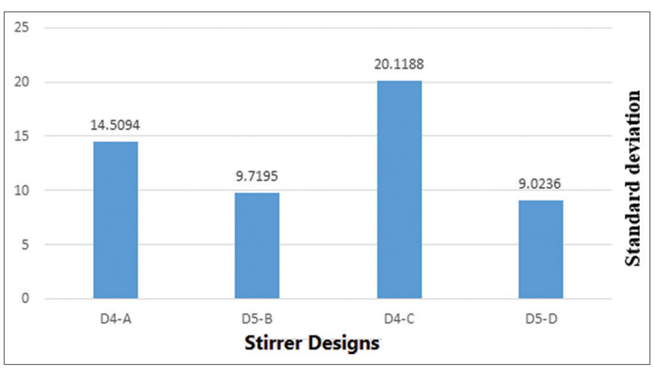


Fig. 11. The standard deviation for D4 and D5 stirrers.

detect defects, and streamline diagnostics, contributing to reliable and cost-effective production systems [18].

Image analysis involves extracting valuable information from images, typically using two main approaches: Spatial domain and frequency domain methods [19].

The statistical approach belongs to the spatial domain category, assessing various functions based on system objectives. Statistical measures such as mean and standard deviation play a significant role in image analysis by providing insights into the properties of incident light and mixing quality [20]. In this study, after completing the sample mixing process, images of the mixture were captured and analyzed using digital image processing techniques. The process involves several steps: Pre-processing, image acquisition, histogram equalization, edge detection, and contour detection. These steps are illustrated in Fig. 10.

Image processing provides an affordable alternative. It is a type of signal processing that generates digital images as its output or a set of properties or parameters connected to the image [15]. This is accomplished by the analysis of the pictures obtained during the mixing process by the camera. As a result of the mixing procedure, it has been discovered that the colors in the image do change. Image analysis was divided into two sections:

5.1. Data Required

In the practical part of this study, four cases were developed as follows:

Case 1 (image1_1): Stirring Silicon carbide microparticles in one liter of water using a helical stirrer with a cylindrical shaft for 60 s at 240 rpm under laboratory conditions.

Case 2 (image1_2): Stirring Silicon carbide microparticles in one liter of water using a helical stirrer with a helical shaft for 60 s at 240 rpm under laboratory conditions.

Case 3 (image2_1): Stirring Silicon carbide microparticles in one liter of engine oil (high viscosity) using a helical stirrer with a cylindrical shaft for 60 s at 240 rpm under laboratory conditions.

Case 4 (image2_2): Stirring Silicon carbide microparticles in one liter of engine oil (high viscosity) using a helical stirrer with a helical shaft for 60 s at 240 rpm under laboratory conditions.

5.2. Implemented Approach

After completing the sample mixing, an image of the mixture is captured and analyzed based on the principles of digital image processing. The processing stage involves several steps, which are illustrated in Fig. 7:

1. Pre-processing: The mixture is prepared, and an image is captured. A portion of the image, sized 100 × 100 pixels, is selected for further processing.
2. Image Acquisition: The captured image is formatted and prepared for the subsequent processing stages.
3. Histogram Equalization: Histogram equalization is applied to enhance image clarity and improve visibility for the next steps.
4. Edge Detection: This step involves identifying the edges within the image using the canny operator, which provides superior edge detection compared to other methods.
5. Contour Detection: The contours of shapes in the image are identified to outline the structures present.
6. Statistical Analysis: Various statistical measures are applied to analyze the image properties, including:
   a. Standard Deviation: Measures the dispersion of data points and their deviation from the arithmetic mean, indicating the spread of pixel values.
   b. Arithmetic Mean: Represents a measure of central tendency, summarizing the data set with a single value that denotes its average distribution.
   c. Entropy: Quantifies the randomness or texture of the input image, providing insights into its complexity and information content.

After processing images as shown its the steps in Fig. 8, the performances of the stirrers were calculated according to their pixel distribution.

The findings from Figs. 9 and 10 suggest that D5 consistently outperforms D4 across various conditions. This includes low and high viscosity (water or engine oil) and low and high ceramic density (Silica sand or SiC). The mixing performance of D4 is characterized by a pixel distribution ranging from 75 to 165 grayscale values, while D5 shows a more refined pixel distribution between 90 and 150 grayscale values. This difference indicates that D5 achieves a higher level of homogeneity in the mixing process, as it maintains a more consistent pixel range, suggesting better uniformity in the particle distribution.

Fig. 11 illustrates the distribution of standard deviation values for the processed images. Standard deviation is a measure of the variation or spread within a set of values. A low standard deviation indicates that the pixel intensities are close to the average, while a high standard deviation suggests a greater deviation from the average. In all conditions, the standard deviation values for D4 are higher than those for D5. This suggests that D4 exhibits greater variation in pixel intensities, indicating a less homogeneous mixing process compared to D5, which shows more consistent pixel values and a higher degree of homogeneity.

6. CONCLUSION

1. This study investigates the use of image processing analysis techniques to optimize stirrer design for the production of aluminum alloy composites. The study involved testing five different stirrer designs and two types of ceramic particle reinforcement using the stir-casting method.
2. The image processing steps included pre-processing, image acquisition, histogram equalization, edge detection, contour operation, and statistical analysis.
3. Image analysis techniques played a crucial role in determining the most effective stirrer design by analyzing the homogeneity of the mixture.
4. The accuracy of the image analysis findings was validated by evaluating the mechanical properties of the produced composites.
5. The analysis of pixel distribution revealed that D5 consistently outperformed D4 under various conditions.
6. Standard deviation values for D4 were higher than those for D5, indicating greater variation in pixel intensity and

suggesting less homogeneous mixing in D4.

7. The helical stirrer with a helical shaft (D5) demonstrated superior particle mixing and improved homogeneity compared to the cylindrical shaft stirrer (D4).

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8. DECLARATION OF CONFLICTING INTERESTS

The authors stated that there are no potential conflicts of interest related to the research, writing, or publication of this article.

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10. DATA AVAILABILITY

No new data were generated or analyzed in support of this research.

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