IJAMSET
INTERNATIONAL JOURNAL OF ADVANCED MATERIALS, SMART ENGINEERING AND TECHNOLOGY

IJAMSET | Vol. 1 No. 1 | 2026 ISSN : xxxx-xxxx

Sensitivity Analysis of Process Parameters and Microstructural Features Affecting the Mechanical Properties of AlSi10Mg Fabricated by Laser Powder Bed Fusion

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Received 20 June 2026; Received in revised form 22 June 2026; Accepted 30 June 2026

Abstract

The mechanical properties of AlSi10Mg fabricated by the Laser Powder Bed Fusion (LPBF) process are strongly influenced by processing parameters and the microstructural characteristics developed during fabrication. However, the relationships among process parameters, defect formation, and mechanical responses are highly complex and difficult to explain using conventional statistical approaches. This study aims to investigate the sensitivity of process parameters and microstructural characteristics on the mechanical performance of AlSi10Mg using a combination of Random Forest and SHapley Additive exPlanations (SHAP) approaches. The input variables include laser power, scan speed, hatch spacing, porosity, pore characteristics, and surface roughness, while yield strength and ultimate tensile strength are used as prediction targets. The developed Random Forest models achieved coefficients of determination (R^2) of 0.645 for yield strength and 0.640 for ultimate tensile strength, indicating satisfactory predictive capability. SHAP analysis revealed that porosity-related variables contributed most significantly to variations in mechanical properties. XCT porosity was identified as the most influential parameter affecting yield strength, with a mean absolute SHAP value of 10.87, whereas hatch spacing exhibited the highest contribution to ultimate tensile strength, with a value of 20.80. The findings indicate that the influence of process parameters on mechanical properties is not direct but is mediated through changes in densification quality and defect formation during the fabrication process.

Keywords: *Mechanical properties; AlSi10Mg; Laser Powder Bed Fusion; sensitivity analysis; SHAP*

1. Introduction

Laser Powder Bed Fusion (LPBF) is one of the most rapidly advancing metal additive manufacturing technologies due to its capability to produce components with complex geometries, high dimensional accuracy, and improved material utilization efficiency compared with conventional manufacturing processes. This technology has been widely adopted in the aerospace, automotive, and biomedical industries because it enables the fabrication of lightweight components with superior mechanical performance [1], [2]. Among the various materials employed in LPBF, AlSi10Mg alloy has attracted considerable attention owing to its favorable combination of low density, good mechanical strength, and excellent corrosion resistance [3].

However, the quality of LPBF-fabricated AlSi10Mg components is highly dependent on manufacturing process parameters. Variations in laser power, scan speed, and hatch spacing can significantly influence powder melting behavior, melt pool formation, and cooling rates during fabrication. These process-induced changes directly affect the formation of porosity, pore morphology, surface roughness, and other microstructural characteristics, which ultimately determine the mechanical response of the material. Inappropriate process parameter settings may lead to the formation of defects such as lack-of-fusion and keyhole porosity, resulting in reduced density and accelerated crack initiation within the material [4], [5].

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Previous studies have demonstrated that the relationships between process parameters and the mechanical properties of LPBF-fabricated AlSi10Mg are highly complex and involve significant interactions among variables. Most existing studies have primarily focused on investigating the individual effects of process parameters on material density or tensile properties through conventional experimental approaches [1]. Although these approaches provide valuable insights, they generally require extensive experimental efforts and are unable to comprehensively quantify the relative contributions of individual parameters to variations in mechanical performance. Furthermore, the relationships among process parameters, microstructural characteristics, and mechanical responses are often nonlinear, making them difficult to represent using conventional linear statistical analyses [6], [7].

Recent advances in machine learning have created new opportunities for investigating complex relationships in LPBF processes. Machine learning models are capable of capturing nonlinear interactions among process parameters, microstructural features, and material properties more effectively than conventional empirical approaches [8], [9]. Nevertheless, most machine learning studies in LPBF have primarily focused on improving prediction accuracy, while the physical interpretation of how individual variables contribute to variations in mechanical properties remains limited. As a result, many predictive models function as black-box systems, providing limited insight into the underlying mechanisms governing material behavior.

One promising approach for improving the interpretability of machine learning models is SHapley Additive exPlanations (SHAP) [10], [11]. This method enables the quantitative evaluation of the contribution of each input variable to model predictions, allowing the relationships among process parameters, microstructural characteristics, and mechanical responses to be analyzed more systematically. Through this approach, the dominant factors influencing the yield strength and ultimate tensile strength of AlSi10Mg can be identified not only based on linear relationships but also through nonlinear interactions among variables.

Although several previous studies have applied Random Forest and SHAP in the context of additive manufacturing, most have primarily focused on optimizing process parameters to maximize prediction accuracy rather than providing a comprehensive understanding of the relationships among variables. Moreover, studies that simultaneously incorporate process parameters, microstructural characteristics (including XCT-derived porosity, pore diameter, and sphericity), and surface roughness as input variables in sensitivity analysis for LPBF-fabricated AlSi10Mg remain limited. This study addresses this gap by integrating SHAP-based sensitivity analysis with a Random Forest model to reveal how process parameters indirectly influence mechanical properties through changes in densification quality and defect formation. This approach provides a more comprehensive understanding of the process–structure–property relationships governing LPBF-manufactured AlSi10Mg.

Therefore, this study aims to investigate the sensitivity of process parameters and microstructural characteristics affecting the mechanical response of LPBF-fabricated AlSi10Mg using Random Forest and SHAP approaches. The analysis is conducted to identify the most influential variables governing yield strength and ultimate tensile strength, thereby providing a deeper understanding of the process–structure–property relationships in metal additive manufacturing.

2. Materials and Methods

The research methodology employed in this study is illustrated in Figure 1. This study aims to investigate the influence of process parameters and microstructural characteristics on the mechanical properties of AlSi10Mg fabricated using Laser Powder Bed Fusion (LPBF) technology. To achieve this objective, the research was conducted through several stages, including data preparation, predictive model development, model evaluation, and sensitivity analysis.

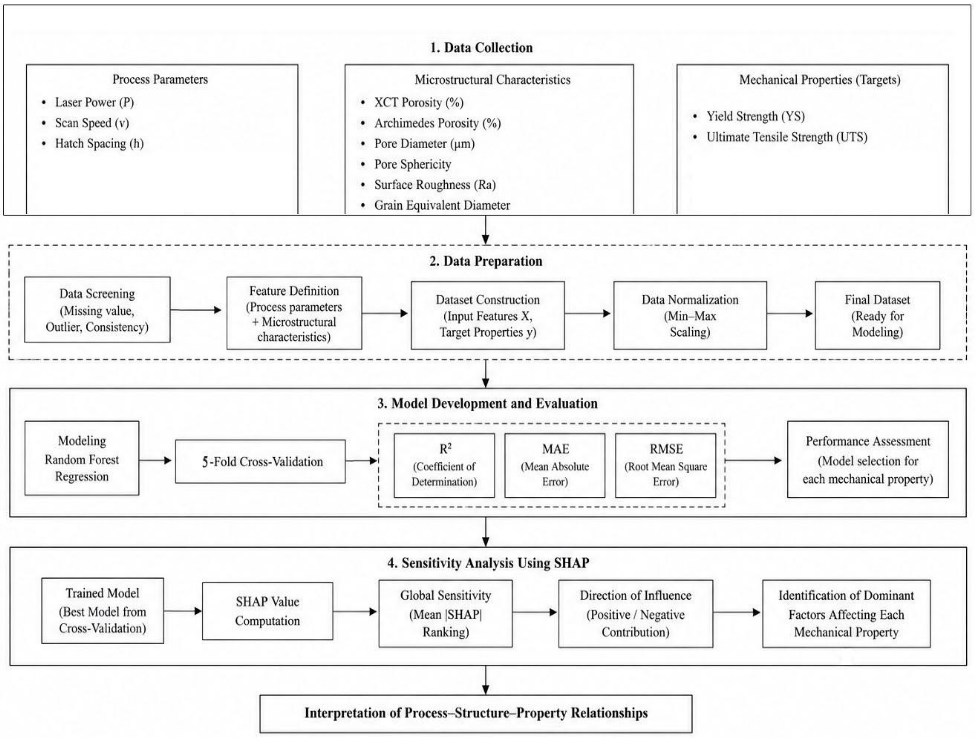

Figure 1. Research framework for the sensitivity analysis of the relationships between process parameters, microstructural characteristics, and the mechanical properties of LPBF-fabricated AlSi10Mg.

2.1 Data Preparation

This study utilized a secondary dataset published by Luo et al. (2024) in the journal Data in Brief [12]. The dataset provides information on the relationships among manufacturing process parameters, microstructural characteristics, and the mechanical properties of AlSi10Mg alloy fabricated through the Laser Powder Bed Fusion (PBF-LB) process. The dataset consists of 60 combinations of process parameters, including variations in laser power, scan speed, and hatch spacing, while the layer thickness was maintained at a constant value of 60 µm throughout the fabrication process. These variations in processing conditions resulted in differences in material characteristics, enabling an investigation of the relationships between manufacturing parameters, the resulting microstructure, and the corresponding mechanical response.

2.2 Predictive Model Development

The relationships between the input variables and mechanical properties were modeled using the Random Forest Regression algorithm. This algorithm was selected because of its capability to capture nonlinear relationships commonly observed in additive manufacturing processes and its effectiveness in identifying the relative contributions of individual variables to prediction outcomes [13],[14].

In this study, the Random Forest model was implemented using the scikit-learn library with its default hyperparameter settings, including 100 decision trees (n_estimators = 100), unlimited tree depth (max_depth = None), and the default number of features considered at each split (max_features) for regression tasks. No further hyperparameter optimization was performed because the primary objective of this study was to investigate variable sensitivity using SHAP rather than to maximize predictive performance. This approach is also appropriate given the relatively small dataset (60 samples), where extensive hyperparameter tuning could increase the risk of overfitting, resulting in a model that is overly tailored to the training data and less capable of generalization while reducing the interpretability of the relationships among variables. Separate predictive models were developed for each mechanical property investigated, resulting in dedicated models for yield strength and ultimate tensile strength. This approach enables the effects of process parameters and microstructural characteristics on individual mechanical property to be evaluated independently.

2.3 Model Evaluation

The reliability of the developed models was assessed using a 5-fold cross-validation approach. In this method, the dataset was divided into five subsets, with each subset being used alternately as testing data while the remaining subsets served as training data. The validation procedure was repeated five times, ensuring that every data sample was used once as testing data and four times as training data.

Model performance was evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) [15], [16]. The coefficient of determination was employed to quantify the model's ability to explain the variability of the observed data and is calculated using Equation (1).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \qquad (1)$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value of the model, and $\bar{y}$ is the mean of the actual values. The average prediction error was calculated using the Mean Absolute Error (MAE) as shown in Equation (2).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad (2)$$

Furthermore, the Root Mean Square Error (RMSE) was used to assess the overall magnitude of prediction errors by placing greater emphasis on larger deviations between the predicted and observed values. The RMSE is determined according to Equation (3).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (3)$$

Models exhibiting high R^2 values together with low MAE and RMSE values were considered capable of adequately representing the relationships between process parameters and mechanical properties and were subsequently employed for the sensitivity analysis.

2.4 Sensitivity Analysis

Sensitivity analysis was performed to evaluate the relative contributions of process parameters and microstructural characteristics to the mechanical properties of AlSi10Mg. The analysis was conducted using the SHapley Additive exPlanations (SHAP) approach, which enables the quantitative assessment of the influence of each input variable on the model predictions. The resulting sensitivity values were used to determine the relative importance of individual variables in influencing the mechanical properties of the material.

Variables exhibiting larger contributions were interpreted as having a more dominant influence on variations in mechanical performance. The outcomes of the sensitivity analysis were subsequently utilized to identify the key factors governing the mechanical performance of LPBF-fabricated AlSi10Mg and to provide insights into the underlying process–structure–property relationships.

3. Results and Discussion

3.1 Data Characteristics

The dataset employed in this study comprises Laser Powder Bed Fusion (LPBF) process parameters, microstructural characteristics, and the mechanical properties of AlSi10Mg alloy. Variations in process parameters resulted in changes in porosity levels, pore characteristics, and surface quality, which subsequently influenced the mechanical response of the material. Therefore, the analysis began with an examination of data distributions and inter-variable relationships to provide a comprehensive overview of the dataset characteristics used for predictive modeling.

The distributions of the investigated variables are presented in Figure 2. The variables include laser power, scan speed, hatch spacing, XCT porosity, Archimedes porosity, pore diameter, pore sphericity, surface roughness (Ra), surface roughness (RMS), yield strength, and ultimate tensile strength. Overall, all variables exhibit sufficiently broad ranges of values, indicating substantial variability within the dataset and enabling the representation of diverse processing conditions and resulting material qualities.

Such variability provides a robust foundation for developing predictive models and facilitates the identification of the key factors influencing the mechanical properties of AlSi10Mg. Furthermore, the diversity of the dataset enhances the capability of machine learning models to capture the complex relationships among process parameters, microstructural characteristics, and mechanical performance.

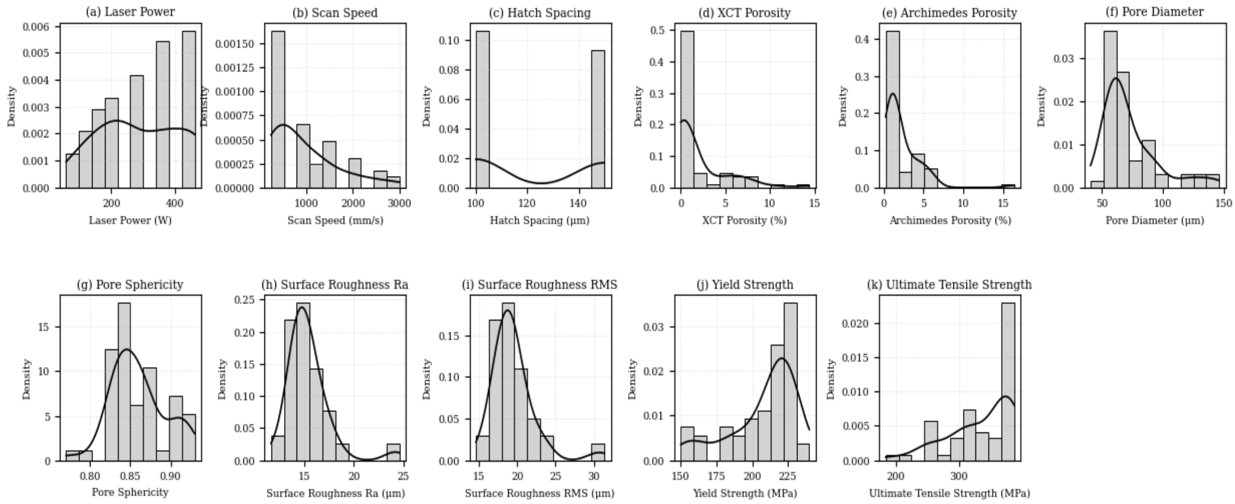

Figure 2. Distribution of manufacturing process parameters, microstructural characteristics, and mechanical properties of the AlSi10Mg alloy.

The relationships between the input variables and the mechanical properties were subsequently evaluated using Pearson correlation analysis, as presented in Figure 3. This analysis was performed to identify the tendencies of linear relationships among process parameters, microstructural characteristics, and the mechanical response of the material.

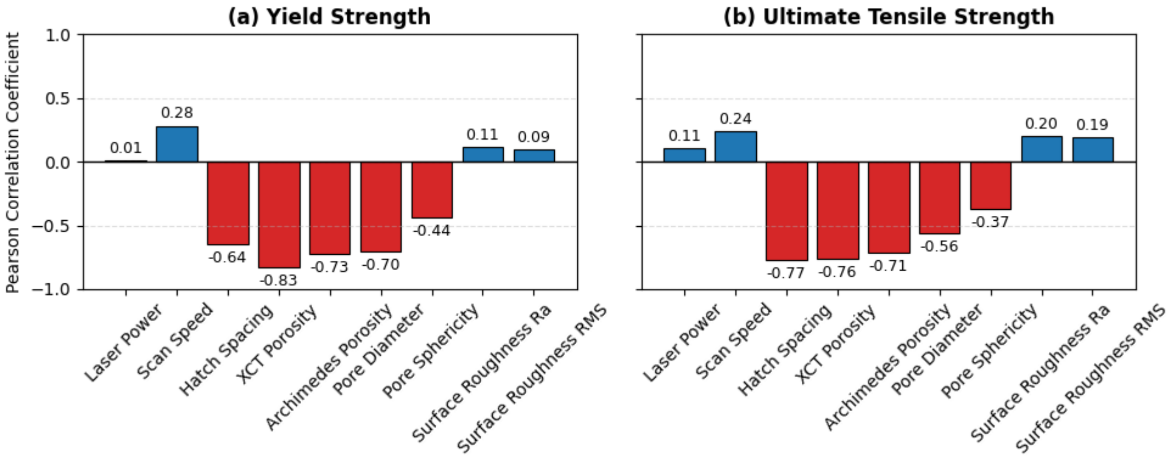

Figure 3. Correlation matrix of process parameters, microstructural characteristics, and mechanical properties.

The correlation analysis indicates that porosity-related variables exhibit the strongest relationships with the mechanical properties of AlSi10Mg. Both XCT Porosity and Archimedes Porosity consistently show strong negative correlations with yield strength and ultimate tensile strength. These findings suggest that increasing porosity is associated with a reduction in the load-bearing capacity of the material. This observation is consistent with the characteristics of PBF-LB-fabricated materials, where pores act as stress concentrators and preferential sites for crack initiation during tensile loading [17].

Among the investigated process parameters, hatch spacing exhibits the strongest correlation with both mechanical properties. An increase in hatch spacing tends to reduce material strength due to decreased overlap between adjacent melt pools and an increased likelihood of lack-of-fusion defect formation. This finding is consistent with previous studies [18], which identified hatch spacing as one of the key process parameters governing the densification of PBF-LB components.

Pore diameter also demonstrates a negative correlation with mechanical properties, particularly with ultimate tensile strength. This result indicates that pore size not only influences the presence of defects but also contributes to accelerated crack initiation and propagation, ultimately leading to material failure. In contrast, surface roughness exhibits weaker correlations than porosity-related variables, suggesting that its influence on mechanical property variability is less pronounced than that of internal defects. Overall, the correlation analysis reveals that variations in the mechanical properties of AlSi10Mg are more closely associated with porosity characteristics than with process parameters directly. Therefore, the influence of process parameters on material strength is likely mediated through changes in the microstructural features developed during the fabrication process. These findings provide a basis for further investigation using Random Forest and SHAP analyses to quantitatively determine the relative contributions of individual variables and to better understand the underlying process–structure–property relationships.

3.2 Random Forest Prediction Model

Random Forest models were developed to predict the yield strength and ultimate tensile strength of AlSi10Mg based on process parameters and microstructural characteristics. This approach was selected because the relationships between LPBF process parameters and mechanical properties are generally nonlinear and involve complex interactions among multiple variables [3]. Model performance was evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) under a 5-fold cross-validation scheme.

The evaluation results indicate that the developed models were capable of adequately capturing the relationships among process parameters, microstructural characteristics, and mechanical responses. For yield strength prediction, the model achieved an R^2 value of 0.64, with an MAE of 10.57 MPa and an RMSE of 13.74 MPa. Meanwhile, the model developed for ultimate tensile strength prediction yielded an R^2 value of 0.63, with an MAE of 20.18 MPa and an RMSE of 30.26 MPa.

These results suggest that the Random Forest algorithm can effectively model the complex process–structure–property relationships of LPBF-fabricated AlSi10Mg. Although the prediction accuracy is not perfect, the obtained R^2 values indicate that a substantial proportion of the variability in mechanical properties can be explained by the selected process parameters and microstructural features. A comparison of the evaluation metrics for both mechanical property models is presented in Table 1.

Table 1. Comparison of evaluation metrics.

Target	R^2	MAE	RMSE
Yield Strength	0.645	10.57	13.74
Ultimate Tensile Strength (UTS)	0.640	20.18	30.26

The difference in prediction errors between the two models indicates that ultimate tensile strength exhibits higher variability than yield strength. This finding suggests that the mechanisms governing UTS are more complex, as they are influenced not only by the onset of plastic deformation but also by crack propagation and the final failure of the material. Nevertheless, the R^2 values obtained for both models indicate that the Random Forest algorithm is capable of capturing most of the relationships among process parameters, microstructural characteristics, and the mechanical response of AlSi10Mg.

The prediction results of the models are presented in Figure 4. The results demonstrate that the models have a satisfactory ability to learn the relationships among variables, although some deviations remain within certain value ranges. These deviations are likely attributable to the complex interactions of process parameters during melt pool formation, as well as variations in microstructural defects that cannot be fully represented by simple linear relationships.

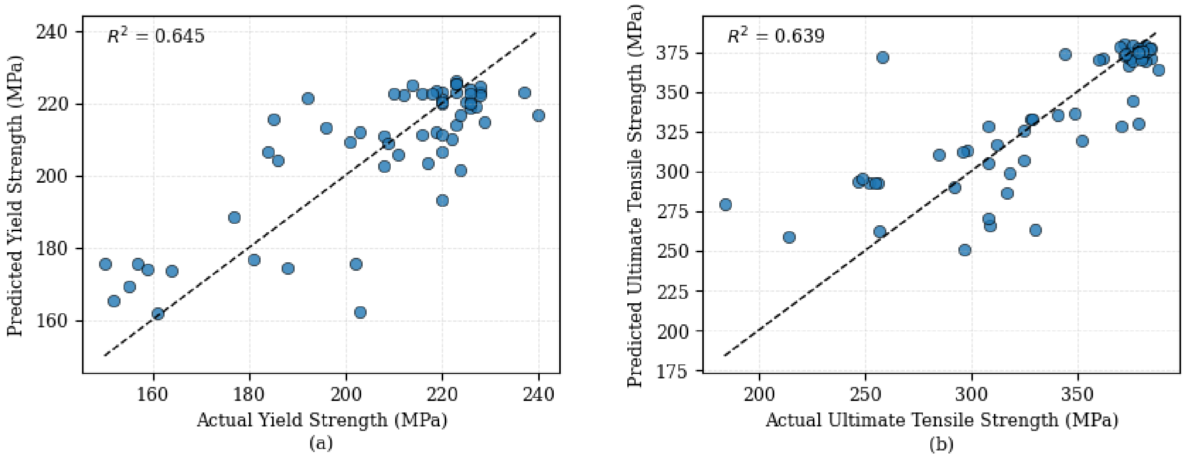

Figure 4. Comparison between actual and predicted values for (a) yield strength and (b) ultimate tensile strength.

The Random Forest models in this study were not developed through complex hyperparameter optimization or aggressive predictive performance enhancement strategies. Instead, a relatively simple model configuration was adopted to maintain a balance between predictive capability and model interpretability. This choice was made because the primary objective of the study was not to achieve maximum prediction accuracy, but rather to analyze the relationships among process parameters, microstructural characteristics, and the mechanical response of AlSi10Mg. The Random Forest model was employed as a tool for evaluating variable sensitivity and identifying the factors that most significantly influence variations in mechanical properties. Therefore, the ability of the model to preserve the underlying relationships among variables was considered more important than achieving highly optimized prediction performance for a specific dataset.

Excessive optimization may lead to models that become overly fitted to the training data, thereby reducing their interpretability and limiting the generalizability of the physical relationships being investigated. Despite the use of a relatively simple model configuration, the evaluation results demonstrate that the models are capable of adequately representing the relationships among process parameters, microstructural characteristics, and mechanical properties. Therefore, the obtained model performance is considered sufficient to support the SHAP-based sensitivity analysis conducted in this study.

3.3 Sensitivity Analysis of Parameters Affecting Mechanical Properties

Sensitivity analysis was performed using the SHAP method to evaluate the contribution of each process parameter and microstructural characteristic to variations in the yield strength and ultimate tensile strength of AlSi10Mg. This approach was employed because it enables the interpretation of the individual influence of each variable on the model output, including nonlinear relationships and parameter interactions that cannot be adequately explained by conventional linear correlation analysis.

The sensitivity analysis results for yield strength are presented in Figure 5. Overall, porosity-related variables exhibit the most dominant contributions to variations in material strength. XCT Porosity was identified as the most influential parameter, followed by Archimedes Porosity and pore diameter. The dominance of these porosity-related variables indicates that material densification quality is the primary factor governing yield strength variations in PBF-LB-fabricated AlSi10Mg. An increase in porosity tends to reduce yield strength because the presence of pores decreases the effective load-bearing cross-sectional area and promotes stress concentration during the early stages of deformation.

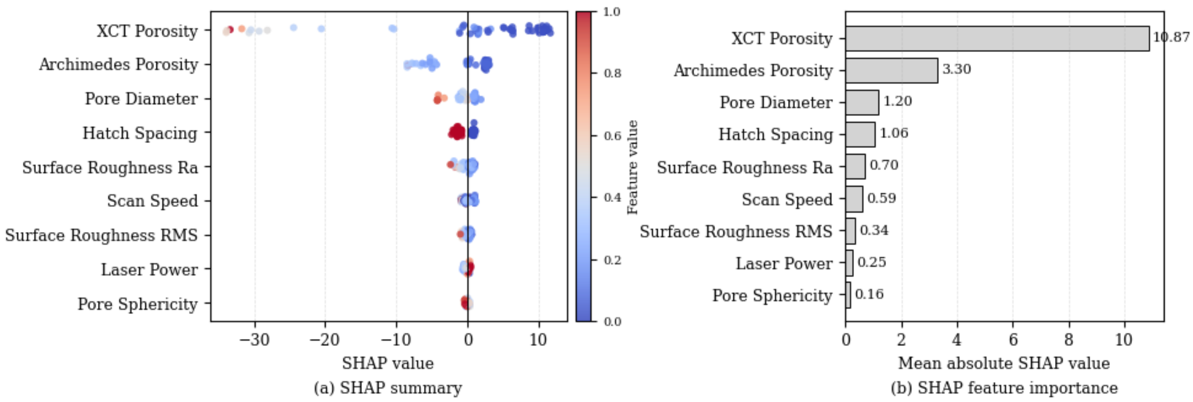

Figure 5. SHAP analysis for yield strength.

Among the process parameters, hatch spacing exhibits a greater influence than laser power and scan speed. This result indicates that variations in the distance between adjacent scan tracks contribute more significantly to the development of microstructural conditions that govern material strength. Increasing hatch spacing may reduce the overlap between neighboring melt pools, thereby increasing the likelihood of lack-of-fusion defects and internal porosity formation. The dominant influence of porosity is consistent with the findings reported in [19], which demonstrated that the formation of lack-of-fusion defects and spherical pores in AlSi10Mg is directly associated with changes in process energy conditions during LPBF, ultimately affecting material density and mechanical performance. The present results further confirm that densification quality remains the primary factor controlling the yield strength of PBF-LB-fabricated AlSi10Mg. From a metallurgical perspective, XCT-derived porosity represents the total three-dimensional pore volume within the material, providing a more comprehensive assessment of densification quality than the conventional Archimedes method. The pores identified by XCT encompass various defect types, including lack-of-fusion (LOF) pores, which typically exhibit irregular morphologies and are particularly detrimental to tensile performance because they act as stress concentrators. This explains why XCT-derived porosity exhibits the highest SHAP value for yield strength, as both the volume fraction and spatial distribution of pores directly influence the effective load-bearing cross-sectional area during the onset of plastic deformation.

The sensitivity analysis results for ultimate tensile strength are presented in Figure 6. Unlike yield strength, hatch spacing emerged as the parameter with the highest sensitivity contribution, followed by XCT Porosity and Archimedes Porosity. This pattern indicates that ultimate tensile strength is more sensitive to process conditions that affect melting continuity and internal defect formation. In addition, pore diameter exhibits a relatively high sensitivity contribution to UTS, suggesting that pore size plays an important role in crack propagation leading to the final failure of the material. These findings are consistent with those reported in [20], which showed that variations in hatch spacing directly influence pore distribution and tensile strength due to their effect on the quality of melting between adjacent scan tracks. This similarity suggests that process parameters do not affect UTS directly but rather through modifications in the microstructural condition and internal defects formed during fabrication.

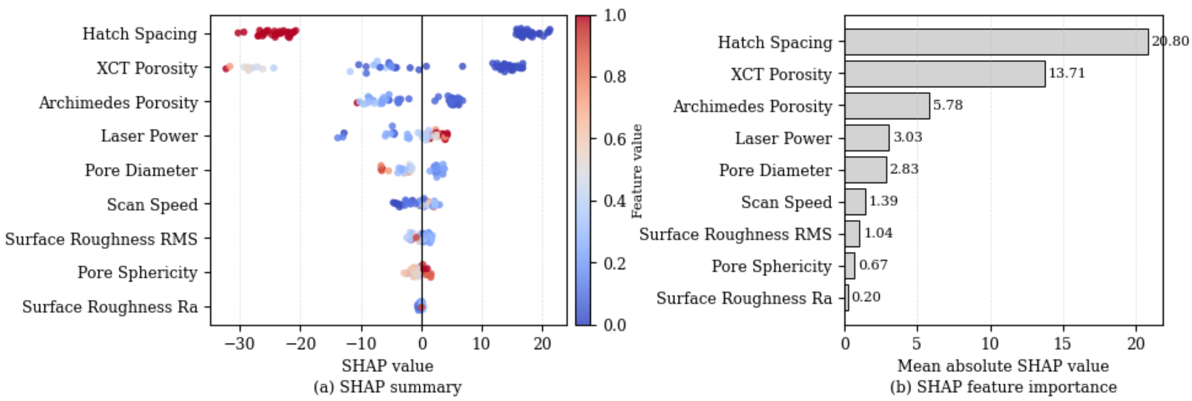

Figure 6. SHAP analysis for ultimate tensile strength.

The dominant influence of hatch spacing on UTS can be explained by the melt pool formation mechanism. Excessively large hatch spacing reduces the overlap between adjacent scan tracks, thereby increasing the likelihood of lack-of-fusion (LOF) defects. These defects have a pronounced effect on UTS because LOF pores serve as preferential crack initiation sites, facilitating crack propagation until final material failure occurs. In contrast to yield strength, which is primarily governed by the overall porosity level, UTS is more sensitive to the spatial distribution and morphology of pores, both of which are directly controlled by hatch spacing during the LPBF fabrication process.

Overall, the SHAP results show a pattern consistent with the Pearson correlation analysis, while providing a more detailed interpretation of the nonlinear relationships among variables. Porosity-related variables consistently contribute the most to variations in mechanical properties, whereas hatch spacing emerges as the most influential process parameter affecting the development of these microstructural conditions. These findings indicate that the mechanical properties of AlSi10Mg fabricated by PBF-LB are not directly controlled by a single process parameter, but rather by how process parameters influence defect formation and material densification during fabrication.

4. Conclusion

This study successfully analyzed the sensitivity of process parameters and microstructural characteristics affecting the mechanical response of AlSi10Mg fabricated by Laser Powder Bed Fusion using Random Forest and SHAP approaches. The Random Forest models demonstrated satisfactory performance, achieving R^2 values of 0.645 for yield strength and 0.640 for ultimate tensile strength. The corresponding MAE and RMSE values were 10.57 MPa and 13.74 MPa for yield strength, and 20.18 MPa and 30.26 MPa for ultimate tensile strength, respectively. The sensitivity analysis revealed that porosity-related variables contributed most significantly to variations in mechanical properties. XCT Porosity exhibited the highest sensitivity to yield strength, with a mean absolute SHAP value of 10.87, whereas hatch spacing was identified as the most influential parameter affecting ultimate tensile strength, with a mean absolute SHAP value of 20.80. Archimedes Porosity and pore diameter also showed relatively high sensitivity contributions to both mechanical properties, confirming that densification quality and internal defect characteristics are the primary factors governing the mechanical performance of LPBF-fabricated AlSi10Mg. The findings indicate that the influence of process parameters on mechanical properties is not direct but is mediated through changes in microstructural conditions and porosity formation during the fabrication process. Therefore, controlling hatch spacing and material densification quality is essential for optimizing the mechanical performance of AlSi10Mg produced by LPBF. Future studies may incorporate larger datasets and additional variables, including thermal parameters, melt pool morphology, and more detailed microstructural characteristics, to enable a more comprehensive analysis of the process–structure–property relationships.

Authors' Contributions

YPK: Conceptualization, Methodology, Writing (Original Draft) DL:Data Curation, Formal Analysis, Visualization. YY: Supervision, Writing (Review and Editing). NQ: Project Administration, Validation.

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