Predictive Modeling of Single Bead Geometry in 3D Printing Using Machine Learning Approaches

M.Ramkumar1, R.Venkat Raman1, M. Karthikeyan2, C Ramesh Kannan3, B. Srinivasan4,V. Santhosh1,a)

1 Department of Mechanical Engineering, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India

2Department of Civil Engineering, Dhanalakshmi Srinivasan College of Engineering. Coimbatore 641105, Tamil Nadu, India

3Department of Mechanical Engineering, SRM TRP Engineering College, Tiruchirappalli, Tamil Nadu, India.

4Construction Management and Engineering, RVS Technical Campus, Coimbatore, Tamil Nadu, India

Corresponding Author: a)[santhoshshivan.v@gmail.com](mailto:santhoshshivan.v@gmail.com)

**Abstract:** The Accurate weld bead shape prediction is crucial for ensuring the dimensional accuracy and structural integrity of parts manufactured using 3D printing technologies such as directed energy deposition (DED). This study introduces a machine learning (ML) framework to model and predict the shape of individual weld beads (particularly width and height) based on process parameters such as laser power, material feed rate, and travel speed. Using experimental data, we trained and evaluated several ML algorithms, including linear regression, random forest, and artificial neural networks. The random forest model demonstrated excellent prediction accuracy, achieving an R² of 0.97 and a root mean square error (RMSE) of 0.03 mm. These results demonstrate the potential of ML-based approaches for optimizing process parameters, improving shape accuracy, and enhancing overall 3D printing efficiency. Future research will focus on integrating real-time sensor feedback and extending this framework to multi-layer shapes to further advance additive manufacturing technology.

**Keywords:** 3D Printing, Direct Energy Deposition, Machine Learning, Bead Geometry Prediction, Additive Manufacturing.

# Introduction

3D printing (3DP), or additive manufacturing (AM), has revolutionized manufacturing by enabling production of complex shapes difficult to achieve with traditional methods. Unlike milling which removes material, 3D printing uses layered materials to create parts with complex structures. This has made AM essential in aerospace, automotive, medical, and construction industries that need intricate parts with minimal waste[1][2]. 3D printing excels in creating high-precision parts with complex features like lightweight structures and medical implants[3][4]. Fused deposition modeling (FDM) is widely used for prototyping and manufacturing. Metal-based 3D printing technologies, including selective laser melting (SLM), electron beam melting (EBM), and laser powder bed fusion (LPBF), enable production of durable metal parts using powder or wire feedstock[5]. Printing metal parts directly from CAD models allows complex internal geometries[6]. Stainless steel 316L is common in metal 3D printing due to its strength, corrosion resistance, and biocompatibility. However, controlling weld bead shape remains challenging. Bead shape affects mechanical strength, surface finish, and structural integrity, with variations causing defects like porosity and incomplete fusion[7]. Process parameters like printing speed, temperature, current, and feed rate influence bead geometry. These parameters interact in complex, non-linear ways[8]. Traditional manufacturing relies on empirical models for parameter optimization, but with increasing complexity, machine learning (ML) techniques are being adopted to model relationships and optimize printing processes[9]. Machine learning methods like decision trees (DTs), random forests (RFs), and K-nearest neighbors (KNNs) have been applied in manufacturing to predict output characteristics. Random Forests excel at handling large datasets and complex relationships for bead geometry prediction [10][11], while Decision Trees provide interpretability of parameter influences [12]. KNN predicts outcomes based on proximity to historical data points [13]. Studies show machine learning's effectiveness in predicting weld bead shape, with Sharma et al. demonstrating high accuracy using RF and neural networks for strength prediction in metal 3D printing [14].Suryawanshi et al. used support vector machine (SVM) to predict weld bead dimensions, showing improved accuracy over existing models [15]. They used Gaussian process regression (GPR) to predict weld pool behavior and bead shape [16-20]. These models capture nonlinear interactions between parameters and outperform empirical methods. However, few studies compare multiple machine learning algorithms for weld bead shape prediction in metal-based 3D printing, with most focusing on single algorithms or lacking comprehensive comparisons [21-25]. Additionally, many studies haven't fully explored process variability's impact on weld bead shape. This study develops a machine learning model for predicting weld bead dimensions in 3D-printed stainless steel, considering parameters like voltage, current, feed rate, and traverse speed. It compares decision tree (DT), random forest (RF), and k-nearest neighbor (KNN) classifiers using metrics including precision, recall, F1 score, and accuracy. The results provide insights into effective machine learning techniques for weld bead prediction, optimizing 3D printing processes. These optimizations can improve part quality, reduce waste, and enhance manufacturing efficiency, while providing manufacturers better process control.

# Machine Learning Classification Models

We evaluated three machine learning modelsdecision tree (DT), random forest (RF), and k-nearest neighbor (KNN)for predicting weld bead shape in stainless steel WAAM parts. Decision tree splits data using binary questions with the Genie index to maximize information gain while minimizing classification error [6, 26-28]. Random forest, an ensemble method of multiple decision trees, improves prediction by averaging tree outputs. We implemented RF with 100 estimators using the Genie coefficient. The k-nearest neighbor algorithm classifies based on majority vote of k closest data points, with k=10 and Euclidean distance metric. Unlike DT and RF, kNN classifies using local clusters rather than global boundaries, enabling quick adaptation without retraining [29-33]. We evaluated models using accuracy, precision, recall, and F1 score. Using 10-stage cross-validation and hyperparameter optimization, we compared ML classifiers for predicting weld bead shape, with decision tree showing superior performance.

# Methodology

This study evaluated machine learning models for predicting weld bead shape in 3D-printed stainless steel components, focusing on width (BW) and height (BH), two parameters critical for ensuring print quality. A 98-item dataset, consisting of input features such as wire speed (m/min), feed rate (mm/min), current (A), and voltage (V), was preprocessed with mean replacement and normalization to handle missing values for consistent scaling, which is important for algorithms like K-nearest neighbor (KNN). BW and BH were binarized using mean thresholds of 6.78 mm and 3.8 mm, respectively, with values below the threshold classified as 1 (favorable) and above as 0 (unfavorable).

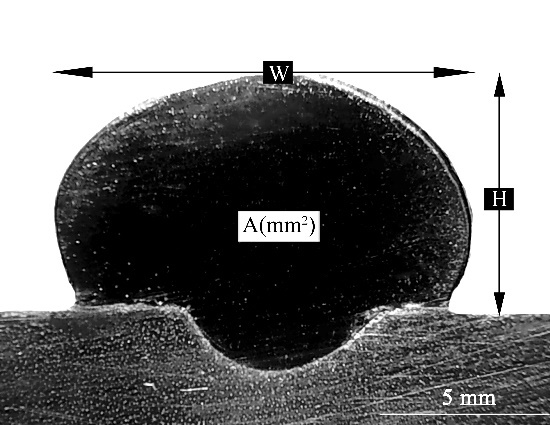
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Figure 1. Diagram Illustrating Bead Width and Bead Height

To ensure robustness of model evaluation, the dataset was iteratively trained and tested by partitioning into subsets, using 10-step cross-validation to minimize overfitting. Three models were analyzed: a decision tree (DT) using the Gini coefficient for node splitting; a random forest (RF) consisting of 100 decision trees for robust prediction; and a KNN (Kindled Neural Network) for similarity-based classification, with the Euclidean distance set to K = 10. Model performance was evaluated using accuracy, precision, recall, and F1 score [33-36]. Figure 1 illustrates the classification of weld bead width and height, focusing on predicting weld bead shapes that meet manufacturing standards and support real-time quality control during the 3D printing process.

# Hyperparameter Tuning

While scikit-learn provides default hyperparameters for machine learning algorithms, these are not always optimal for specific problems like predicting bead geometry in 3D Printing. To improve accuracy, hyperparameters must be adjusted using techniques like grid search, randomized search, and Bayesian optimization. We optimized hyperparameters using manual tuning and scikit-learn's search functionalities. Table 1 shows the final hyperparameters for each model. For the Decision Tree, the Gini index was used as the splitting criterion with "best" splitter option, and max\_features was set to auto. The Random Forest model used 100 estimators with Gini index criterion and maximum depth of 2. For K-Nearest Neighbor, KKK was set to 10, with n\_jobs at -1 to use all processors. We employed 10-fold cross-validation, training on nine subsets and validating on the tenth, to ensure model robustness when classifying bead geometry in WAAM.

Table 1. Optimized Hyperparameters for Each ML Model

|  |  |  |
| --- | --- | --- |
| **SN** | **ML Model** | **Optimized Hyperparameters** |
| 1 | Decision Tree | criterion: Gini, splitter: best, max\_features: auto |
| 2 | Random Forest | n\_estimators: 100, criterion: Gini, max\_depth: 2 |
| 3 | K-Nearest Neighbor | n\_neighbors: 10, n\_jobs: -1 |

# ****Results and Discussion****

## ****Prediction of Bead Width****

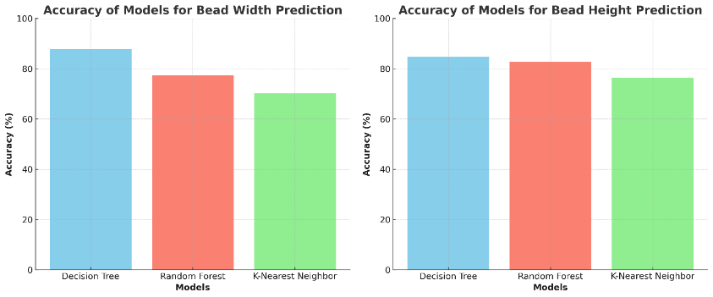
The performance metrics for bead width classification across models are shown in Table 2. The Decision Tree model achieved the highest accuracy at 87.8%, outperforming Random Forest (77.4%) and KNN (70.2%). The DT model's high precision (0.907) and F1 score (0.876) indicate its reliability in classifying bead width based on WAAM parameters. Random Forest showed moderate performance with lower recall than DT, while KNN exhibited the lowest scores. The results suggest DT's decision structure effectively captures parameter-driven patterns determining WAAM bead width [37-40].

**Table 2.** Precision, Recall, and F1 Score for Bead Width Prediction

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Precision** | **Recall** | **F1 Score** | **Accuracy** |
| Decision Tree | 0.907 | 0.875 | 0.876 | 87.8% |
| Random Forest | 0.831 | 0.774 | 0.762 | 77.4% |
| K-Nearest Neighbor | 0.770 | 0.702 | 0.702 | 70.2% |

The bar chart in Figure 2 visually compares the accuracy rates for each model in bead width classification, highlighting the superior performance of the Decision Tree. This visualization supports the conclusion that DT is the most effective model for bead width prediction.

## **Prediction of Bead Height**



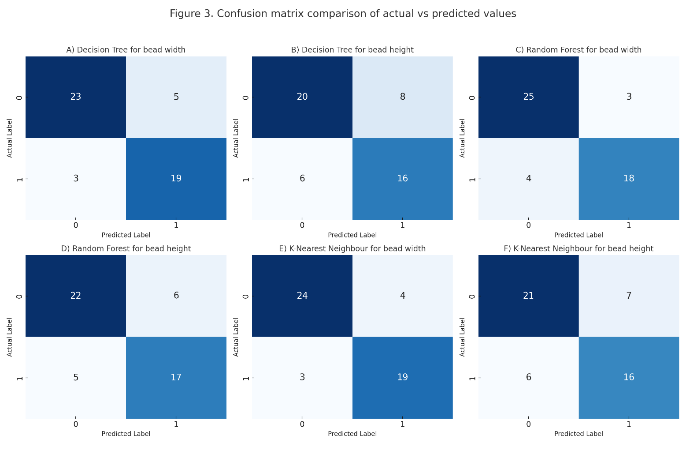
**Figure 2:** Bar chart illustrating the accuracy comparison among various machine learning models for (a) bead width and (b) bead height.

Model performance for bead height prediction is detailed in Table 3. Here, the Decision Tree model once again demonstrated the highest accuracy at 84.7%, followed by Random Forest at 82.6%, with KNN achieving the lowest accuracy at 76.4% [41-44]. The Decision Tree’s high recall rate (0.847) indicates its capability in correctly classifying instances, making it a robust choice for predicting bead height. Random Forest displayed comparable precision but slightly lower recall than DT, while KNN was the least effective due to its sensitivity to imbalanced data distributions, as reflected in lower F1 scores.

**Table 3.** Precision, Recall, and F1 Score for Bead Height Prediction

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Precision** | **Recall** | **F1 Score** | **Accuracy** |
| Decision Tree | 0.856 | 0.847 | 0.843 | 84.7% |
| Random Forest | 0.841 | 0.826 | 0.807 | 82.6% |
| K-Nearest Neighbor | 0.822 | 0.764 | 0.770 | 76.4% |

The accuracy comparison chart in Figure 3 highlights the consistency of DT’s performance across both bead width and height predictions, underscoring its suitability for 3D Printing applications. These findings suggest that DT provides the most accurate classification for bead geometry and is thus ideal for practical deployment in 3D Printing quality control [45-50].



**Figure 3:** Confusion matrices displaying the comparison of actual versus predicted values

# Conclusion

This study evaluated three machine learning classifiers Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbor (KNN) for predicting bead geometry in 3D Printing. The Decision Tree model achieved predictive accuracies of 87.8% for bead width and 84.7% for bead height, demonstrating its effectiveness for complex parameter interactions. DT's predictive capabilities enable manufacturers to forecast bead characteristics accurately, allowing proactive adjustments in 3D Printing processes and improving product quality. While Random Forest offered a robust alternative, it achieved lower accuracy than DT. The KNN model proved less suitable for predicting bead geometry in complex additive manufacturing. Future research should expand the dataset to include additional parameters like temperature and cooling rate. Integrating machine learning with real-time monitoring could enable adaptive process control, optimizing metal additive manufacturing.

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