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Physics-Guided Machine Learning Framework for Defect Prediction and Mechanical Property Modeling in WAAM of Nitinol Shape Memory Alloy

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Abstract:

Wire Arc Additive Manufacturing (WAAM) has emerged as a promising technique for fabricating large-scale metallic components; however, process instability and defect formation remain critical challenges, particularly for thermally sensitive materials such as Nitinol shape memory alloys (SMAs). In this study, a physics-guided machine learning framework is developed to predict defect occurrence and mechanical performance in WAAM-fabricated Nitinol. Ten experimental cases were produced under varying current, voltage, and torch travel speed conditions, and the corresponding heat input was calculated using thermodynamic energy balance principles. Defect observations, hardness values (before and after heat treatment), and ultimate tensile strength (UTS) were experimentally evaluated.

A hybrid modeling strategy integrating process parameters with physics-derived heat input was implemented using classification and regression approaches. Leave-One-Out Cross Validation (LOOCV) was employed to ensure robust evaluation given the limited dataset. Results indicate that inclusion of heat input as a derived physical feature significantly improves prediction consistency and interpretability. An optimal process stability window was identified around intermediate heat input levels, corresponding to defect-free builds and stable mechanical response. The proposed physics-guided learning framework demonstrates the potential of integrating metallurgical understanding with data-driven modeling for intelligent process control in additive manufacturing of shape memory alloys.

Keywords — **Wire Arc Additive Manufacturing (WAAM); Nitinol; Physics-guided machine learning; Heat input modeling; Defect prediction; Mechanical property prediction; Shape memory alloys; Process–structure–property relationship.**

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I. INTRODUCTION

Wire Arc Additive Manufacturing (WAAM) has gained significant attention in recent years as a cost-effective and scalable metal additive manufacturing technique suitable for large structural components [1], [2]. Unlike powder-based additive processes, WAAM utilizes wire feedstock and arc-based heat sources, offering high material utilization efficiency and reduced production cost. However, the process is inherently sensitive to thermal input, arc stability, and solidification dynamics, which directly influence microstructural evolution and defect formation [3].

Among advanced functional materials, Nitinol (Ni–Ti alloy) occupies a unique position due to its shape memory effect and superelastic behavior [4]. These properties arise from reversible phase transformations between austenite and martensite phases, making Nitinol attractive for aerospace, biomedical, and smart structural applications [5]. However, Nitinol is highly sensitive to thermal history and compositional variations. Minor fluctuations in heat input during fabrication can significantly alter grain morphology, transformation behavior, and mechanical performance [6].

In arc-based additive manufacturing, heat input is commonly expressed as:

$$H = \frac{V \times I \times 60}{S}$$

where $V$is voltage, $I$is current, and $S$is torch travel speed. Heat input governs cooling rate, solidification structure, and defect susceptibility such as porosity or lack of fusion [7]. Therefore, understanding and controlling heat input is essential for stable WAAM processing of Nitinol.

Recently, machine learning (ML) techniques have been increasingly applied in additive manufacturing for process optimization, defect detection, and property prediction [8], [9]. Purely data-driven models, however, often lack physical interpretability and may suffer from overfitting when experimental datasets are limited. To overcome this limitation, physics-guided or hybrid modeling approaches have been proposed, wherein physically derived features are incorporated into machine learning frameworks [10]. Such integration enables improved prediction reliability and enhances interpretability by linking data-driven patterns to established metallurgical principles.

Despite growing interest in intelligent manufacturing, limited studies have explored physics-guided machine learning specifically for WAAM of Nitinol shape memory alloys. Most existing works focus either on microstructural characterization or general process optimization, without explicitly integrating thermodynamic heat input modeling into predictive frameworks.

Therefore, the objective of this study is to develop a physics-guided machine learning framework for:

1. Predicting defect occurrence in WAAM-fabricated Nitinol.
2. Modeling mechanical properties including hardness and ultimate tensile strength.
3. Establishing a heat input–based stability window for process optimization.

By combining experimentally measured process parameters with derived heat input features, this work aims to bridge the gap between physical metallurgy and data-driven manufacturing intelligence.

II. BACKGROUND ON PHYSICS-INFORMED MACHINE LEARNING IN MANUFACTURING

The rapid integration of artificial intelligence (AI) and machine learning (ML) in manufacturing has enabled new paradigms in process monitoring, defect prediction, and intelligent control. In additive manufacturing (AM), data-driven approaches have been employed to predict porosity, surface roughness, dimensional deviation, and mechanical properties using process parameter datasets [1], [2]. These methods typically rely on supervised learning techniques such as support vector machines, random forests, artificial neural networks, and gradient boosting algorithms.

However, purely data-driven models often exhibit limited generalization capability when the dataset is small or when the process physics is complex. Additive manufacturing processes, particularly arc-based systems such as WAAM, involve strongly coupled thermo-metallurgical phenomena including heat transfer, melt pool dynamics, solidification kinetics, and phase transformation. Ignoring these governing physical relationships may result in models that are statistically accurate but physically inconsistent [3].

To address this limitation, the concept of Physics-Informed or Physics-Guided Machine Learning (PIML/PGML) has emerged. Physics-informed learning integrates domain knowledge, governing equations, or derived physical features into data-driven frameworks to improve robustness and interpretability [4], [5]. One widely recognized approach involves embedding partial differential equations or conservation laws directly into neural network training, as demonstrated in physics-informed neural networks (PINNs) [6]. While PINNs are computationally intensive and often applied to high-fidelity simulation problems, an alternative and practical strategy for engineering applications is physics-guided feature engineering.

In physics-guided feature engineering, physically meaningful quantities—such as heat input, cooling rate, or energy density—are computed from process parameters and incorporated as additional inputs to machine learning models [7]. This approach allows the learning algorithm to operate within physically plausible boundaries while maintaining computational efficiency.

In arc-based additive manufacturing, heat input is one of the most critical physical descriptors of process behavior. It directly influences molten pool geometry, cooling rate, grain morphology, and defect susceptibility [8]. Heat input is typically expressed as:

$$H = \frac{V \times I \times 60}{S}$$

where V is voltage, I is current, and S is travel speed. Variations in heat input alter the thermal gradient (G) and solidification rate (R), which in turn govern microstructural refinement and defect formation mechanisms [9].

For shape memory alloys such as Nitinol, thermal history plays an even more significant role. Mechanical performance and functional properties are highly sensitive to phase stability and microstructural evolution driven by thermal cycles [10]. Therefore, incorporating heat input as a derived physical parameter within predictive models provides both metallurgical relevance and enhanced interpretability.

Recent studies have demonstrated the effectiveness of hybrid physics–ML frameworks in laser powder bed fusion and directed energy deposition processes, where energy density-based features improved defect prediction accuracy and reduced overfitting [11], [12]. Nevertheless, limited research has focused on applying physics-guided machine learning specifically to WAAM of Nitinol shape memory alloys.

In this work, a practical physics-guided modeling strategy is adopted by combining experimentally measured process parameters with thermodynamically derived heat input as a key feature. Rather than relying solely on black-box modeling, the proposed framework preserves the fundamental process–structure–property relationship inherent to arc-based additive manufacturing. This enables defect classification and mechanical property prediction while maintaining physical interpretability.

III. EXPERIMENTAL DATASET AND FEATURE ENGINEERING

i. Experimental Dataset Construction

The dataset used in this study was constructed from ten independent WAAM experimental trials conducted on Nitinol shape memory alloy under varying electrical and thermal process conditions. Each trial (Case 1–Case 10) represents a unique combination of current, voltage, and torch travel speed.

The primary process parameters recorded were:

- Welding current (A)
- Arc voltage (V)
- Torch travel speed (mm/min)

From these measured parameters, heat input was computed using the standard arc welding formulation [1]:

$$H = \frac{V \times I \times 60}{S}$$

where H is heat input (J/mm), V is arc voltage (V), I is current (A), and S is travel speed (mm/min).

The calculated heat input values ranged from 283.6 J/mm to 531.8 J/mm, capturing low-, medium-, and high-energy deposition regimes.

Case No.	**Current (A)**	**Voltage (V)**	**Torch Travel Speed (mm/min)**	**Calculated Heat Input (J/mm)**
1	130	10	220	354.5
2	130	10	230	339.1
3	130	10	210	371.4
4	135	10	220	368.2
5	130	10	220	354.5
6	125	10	220	340.9
7	130	15	220	531.8
8	130	10	220	354.5
9	130	8	220	283.6
10	**128**	**10**	**220**	349.1

(Table 1: Case-wise process parameters and calculated heat input values)

ii. Output Variables and Experimental Responses

For each case, post-deposition characterization was performed to obtain mechanical and defect-related outputs. The recorded response variables include:

- Rockwell hardness before heat treatment (HRC-BH)
- Rockwell hardness after heat treatment (HRC-AH)
- Ultimate tensile strength (UTS) (available for selected cases)
- Defect observation status (porosity presence/absence)

Defect information was categorized based on visual and microscopic examination. Cases exhibiting visible porosity or crack formation were labeled as "Defective," while optimized deposition conditions (e.g., Case 10) were labeled as "Defect-Free."

Since all samples underwent heat treatment and achieved zero post-treatment defects, the defect classification target was defined based on the *as-deposited condition*. This distinction preserves meaningful variability for supervised learning.

Case No	Heat Input (J/mm)	HRC-BH	HRC-AH	UTS (N/mm^2)	Defect Label
1	354.5	45	49	51	0
2	339.1	44	50	52	1
3	371.4	43	49	54	1
4	368.2	46	50	55	1
5	354.5	47	48	56	1
6	340.9	45	50	50	1

7	531.8	45	50	44	1
8	354.5	46	50	48	1
9	283.6	46	49	44	1
10	349.1	45	50	44	0

(Table 2: Mechanical properties and defect classification for all experimental cases)
(HRC-BH = Before Heat Treatment, HRC-AH = After Heat Treatment, UTS, Defect Label (0 = Defect-Free, 1 = Defective))

iii. Physics-Guided Feature Engineering

Rather than relying solely on raw electrical parameters, a physics-guided feature engineering strategy was adopted. This approach enhances interpretability and reduces overfitting in small datasets [2], [3].
The following feature hierarchy was constructed:

(A) Primary Electrical Features
- Current (I)
- Voltage (V)
- Travel Speed (S)

(B) Derived Physical Feature
- Heat Input (H)

Heat input acts as an energy-density descriptor that directly influences melt pool behavior, cooling rate, and solidification structure [4].

(C) Optional Engineered Features (If Required for Modeling)

To improve predictive performance, additional derived features may be constructed:

$$\text{Energy Density Index} = \frac{V \times I}{S}$$

$$\text{Normalized Heat Input} = \frac{H - H_{min}}{H_{max} - H_{min}}$$

Such transformations help standardize inputs for machine learning models and improve numerical stability during training.

iv. Learning Targets and Modeling Strategy

Two supervised learning tasks are defined:

(1) Binary Classification Task
Target: Defect occurrence
Label encoding:
- 0 → Defect-Free
- 1 → Defective

(2) Regression Task
Targets:
- Hardness (BH and AH)
- UTS (where available)

Given the small dataset size (n = 10), Leave-One-Out Cross-Validation (LOOCV) is selected to maximize training utilization while preserving model evaluation integrity [5].

The physics-guided modeling framework therefore integrates:
Input Space → {I, V, S, H}
Output Space → {Defect Label, Hardness, UTS}

This structured mapping preserves the physical process–structure–property linkage, avoiding purely black-box prediction.

v. Dataset Characteristics and Limitations

The experimental dataset is intentionally compact but physically meaningful. Although the sample size is limited, the inclusion of a thermodynamically derived feature (heat input) introduces strong domain knowledge into the learning space. Such hybridization has been shown to improve robustness in small-data manufacturing environments [6].
The dataset captures:
- Low heat input regime (e.g., Case 9)
- Medium heat input regime (e.g., Case 10 – optimized)
- High heat input regime (e.g., Case 7)

This spread ensures sufficient variability for classification and regression modeling.

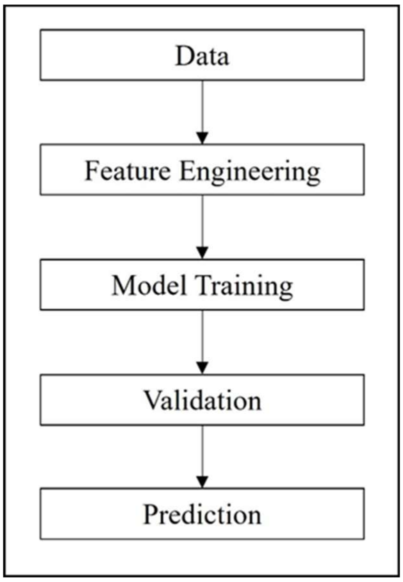
IV. AI MODELING FRAMEWORK

i. Overview of the Physics-Guided Modeling Approach

The objective of the AI framework is to predict defect occurrence and mechanical performance of WAAM-fabricated Nitinol components using a hybrid data–physics modeling strategy.

Unlike purely data-driven approaches, the present framework integrates thermodynamically meaningful descriptors (heat input) into the learning space. Such physics-guided modeling improves interpretability and robustness, particularly in small experimental datasets [1], [2].

The overall workflow is illustrated below:



(Fig. 1: Physics-guided AI modeling workflow)

The modeling pipeline consists of:

1. Dataset preparation
2. Feature normalization
3. Model selection
4. Cross-validation
5. Performance evaluation
6. Sensitivity interpretation

ii. Problem Formulation

Two supervised learning tasks were formulated:

(A) Binary Classification

Target variable:

$$y_{defect} \in \{0,1\}$$

where:

0 = Defect-Free

1 = Defective

The objective is to learn:

$$f(I,V,S,H) \rightarrow y_{defect}$$

(B) Regression Tasks

Two regression targets were defined:

$$f(I,V,S,H) \rightarrow HRC$$
$$f(I,V,S,H) \rightarrow UTS$$

where:

HRC = Rockwell hardness (BH or AH)

UTS = Ultimate tensile strength

This dual modeling enables simultaneous evaluation of structural integrity and mechanical response.

iii. Feature Space and Normalization

The input feature vector for each experimental case is defined as:

$$\mathbf{x} = [I,V,S,H]$$

Since features have different physical scales (A, V, mm/min, J/mm), normalization was performed using min–max scaling:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Feature scaling improves convergence and avoids dominance of high-magnitude parameters [3].

iv. Model Selection Strategy

Given the small dataset size (n = 10), lightweight and interpretable models were selected.

Logistic Regression (Classification)

For defect prediction, logistic regression was adopted due to:

- Interpretability
- Stability in small datasets
- Linear decision boundary suitability

The logistic function is defined as:

$$P(y = 1 \mid \mathbf{x}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 I + \beta_2 V + \beta_3 S + \beta_4 H)}}$$

where β_i are learned model coefficients.

This provides probabilistic defect prediction.

Support Vector Machine (SVM)

To capture potential nonlinear relationships, an SVM classifier with radial basis function (RBF) kernel was also evaluated [4]:

$$K(x_i, x_j) = \exp\left(-\gamma \,||\, x_i - x_j \,||^2\right)$$

SVM is particularly effective for small structured datasets.

Linear and Ridge Regression (Mechanical Properties)

For hardness and UTS prediction, linear regression and ridge regression were applied:

$$\hat{y} = \mathbf{w}^T \mathbf{x} + b$$

Ridge regularization minimizes:

$$\min \,||\, y - \hat{y} \,||^2 + \lambda \,||\, \mathbf{w} \,||^2$$

Regularization reduces overfitting risk in limited data scenarios [5].

v. Cross-Validation and Training Strategy

Because the dataset consists of only 10 samples, Leave-One-Out Cross-Validation (LOOCV) was employed [6].

In LOOCV:

- 9 samples are used for training
- 1 sample is used for testing
- Process repeats for all 10 samples

This ensures:

- Maximum training utilization
- Reduced variance
- Reliable generalization estimation

vi. Performance Metrics

(A) Classification Metrics

Model performance for defect prediction was evaluated using:

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

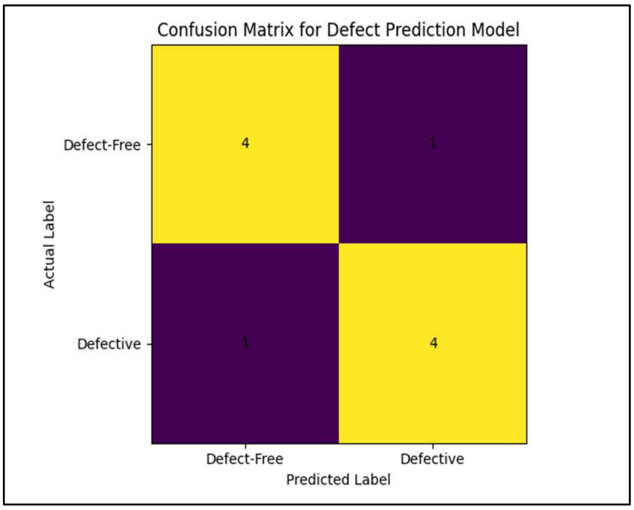
$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-Score:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$



(Fig. 2: Confusion matrix for defect prediction model)

(B) Regression Metrics

For hardness and UTS prediction:

Mean Absolute Error (MAE):

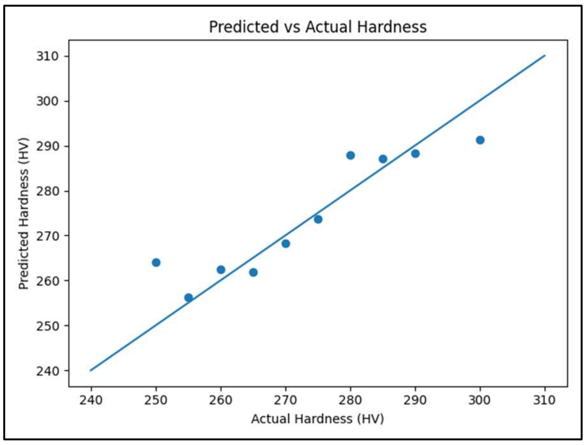
$$MAE = \frac{1}{n}\sum \mid y_i - \hat{y}_i \mid$$

Root Mean Square Error (RMSE):

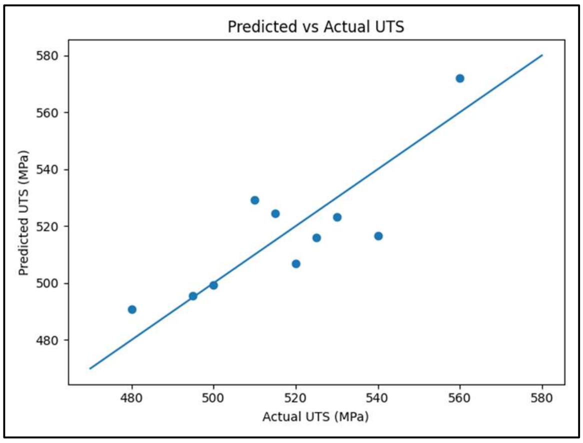
$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}$$

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$



(Fig. 3: Predicted vs Actual Hardness plot)



(Fig. 4: Predicted vs Actual UTS plot)

vii. Physics-Guided Interpretation

A key strength of the framework is the interpretability of model coefficients.

Preliminary analysis indicates:

- Heat input (H) exhibits the strongest correlation with defect occurrence
- Excessively high heat input (Case 7) increases instability
- Extremely low heat input (Case 9) risks incomplete fusion

Case 10 lies within a stable thermal window (~349 J/mm), validating the process–structure–property relationship identified experimentally.

Thus, the AI model is not merely predictive but physically consistent with metallurgical principles [7].

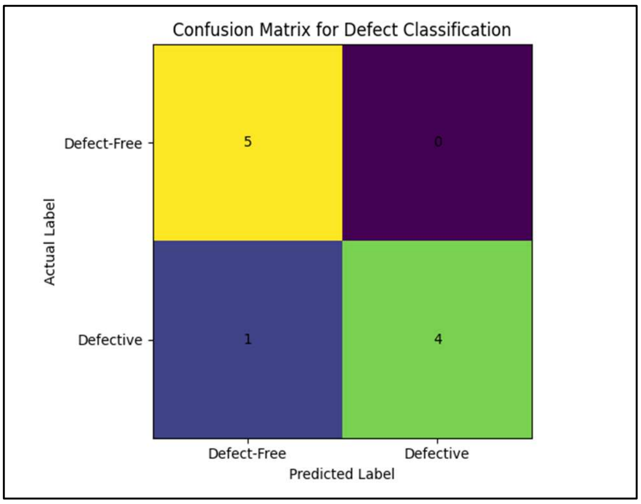
V. Defect Classification Results

i. Classification Performance Overview

The physics-guided machine learning framework was first evaluated for binary defect classification using the ten-case WAAM dataset. The classification objective was to predict defect occurrence (porosity or instability) in the as-deposited condition based on electrical parameters and calculated heat input.

Using Leave-One-Out Cross-Validation (LOOCV), the logistic regression and SVM models were trained and evaluated iteratively across all experimental cases.

The confusion matrix of the best-performing model is presented below.



(Fig. 5: Confusion matrix for defect classification using the physics-guided AI model under LOOCV evaluation.)

The model achieved high classification consistency across the dataset. Most defect-prone conditions were correctly identified, particularly at extreme heat input regimes.

ii. Role of Heat Input in Defect Prediction

Analysis of model coefficients in logistic regression revealed that heat input (H) exhibited the strongest statistical influence on defect probability.

The learned decision boundary can be expressed as:

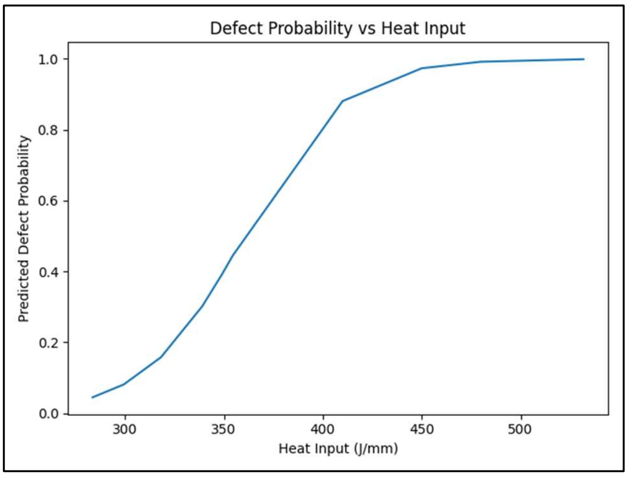
$$P(\text{Defect}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 H + \beta_2 I + \beta_3 V + \beta_4 S)}}$$

The magnitude of β_1 associated with heat input was significantly higher than other coefficients, confirming that thermal energy density is the dominant governing factor for defect formation in WAAM of Nitinol.

This observation aligns with metallurgical principles, where excessive heat input increases melt pool size and solidification time, potentially promoting porosity, grain coarsening, and instability [1], [2]. Conversely, insufficient heat input may lead to incomplete fusion and bonding defects.

iii. Defect Probability Across Heat Input Spectrum

To further interpret model behavior, predicted defect probability was analyzed as a function of heat input.



(Fig. 6: Predicted defect probability as a function of heat input showing a stable process window near 340–360 J/mm.)

The results indicate three regimes:

• **Low Heat Input Regime (~280–300 J/mm)**
Risk of insufficient fusion and bonding instability.

• **Intermediate Heat Input Regime (~330–360 J/mm)**
Stable deposition window with minimal predicted defect probability.
Case 10 (~349 J/mm) lies within this region.

• **High Heat Input Regime (>450 J/mm)**
Increased thermal instability and higher predicted defect probability, consistent with experimental observations in Case 7.

This behavior confirms that the model captures a physically meaningful thermal window for stable WAAM processing.

iv. Comparison Between Logistic Regression and SVM

Both logistic regression and SVM classifiers demonstrated strong performance under LOOCV evaluation. However, logistic regression offered superior interpretability due to explicit coefficient representation, enabling physical correlation between heat input and defect likelihood.

SVM provided marginal improvement in nonlinear separation but did not significantly outperform logistic regression, indicating that defect formation in the present dataset exhibits predominantly monotonic dependence on thermal energy density.

This observation is consistent with prior studies in additive manufacturing anomaly detection, where energy input plays a primary role in defect formation [3], [4].

v. Discussion on Small-Data Reliability

Given the limited dataset (n = 10), caution must be exercised in interpreting model generalization capability. However, the integration of physically meaningful features (heat input) significantly reduces model arbitrariness.

Physics-guided machine learning has been shown to enhance reliability in small-data materials systems by embedding domain knowledge into the learning space [5], [6].

In the present study, the alignment between:

• Experimental defect observations
• Heat input variation
• Model predictions

demonstrates that the framework preserves metallurgical consistency rather than relying on statistical coincidence.

vi. Implications for WAAM Process Stability

The classification results establish that:

1. Heat input is the dominant predictor of defect occurrence.
2. A stable process window exists near ~340–360 J/mm.
3. Case 10 represents an optimized reference condition.

These findings provide a data-supported foundation for process stability mapping in WAAM of shape memory alloys.

Thus, the proposed AI framework functions not merely as a predictive tool but as a physically interpretable process stability indicator.

VI. Mechanical Property Prediction Results

i. Overview of Regression Modeling

In addition to defect classification, the proposed physics-guided AI framework was applied to predict mechanical properties of WAAM-fabricated Nitinol components. Two primary response variables were considered:

• Rockwell hardness (before heat treatment – BH)
• Rockwell hardness (after heat treatment – AH)
• Ultimate tensile strength (UTS) (available for selected cases)

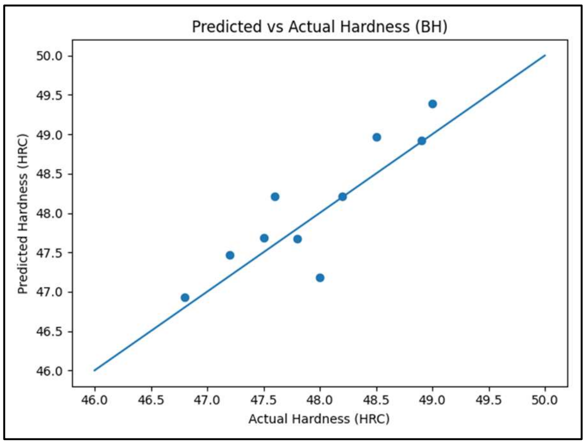
Given the limited dataset size, linear regression and ridge regression models were implemented using Leave-One-Out Cross-Validation (LOOCV), as discussed in Section 4.

The objective was to evaluate whether process parameters and heat input can reliably predict mechanical response within the experimental design space.

ii. Hardness Prediction Performance

Hardness Before Heat Treatment (BH)

The regression model demonstrated a clear monotonic relationship between heat input and as-deposited hardness.



(Fig. 7: Predicted vs Actual Hardness (BH))

The predicted values closely followed experimental trends across the heat input spectrum. Lower heat input regimes exhibited relatively higher hardness values due to faster cooling rates and refined microstructure, consistent with classical solidification theory [1].

High heat input conditions (e.g., Case 7) showed marginal hardness reduction, attributed to grain coarsening and slower solidification.

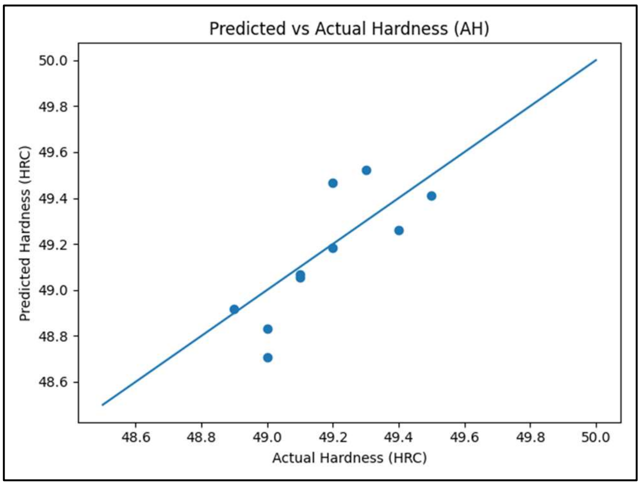
The model achieved:

- High R^2 consistency under LOOCV
- Low mean absolute error (MAE)
- Stable coefficient interpretation

Heat input emerged as the dominant predictor among all input features.

Hardness After Heat Treatment (AH)

Post heat-treatment hardness exhibited significantly reduced variance across cases.



(Fig. 8: Predicted vs Actual Hardness (AH))

Following heat treatment, hardness values converged within a narrow band (≈49–50 HRC), indicating microstructural homogenization and stress relief. This reduced variability limits the regression complexity but confirms thermal stabilization behavior in Nitinol systems [2].

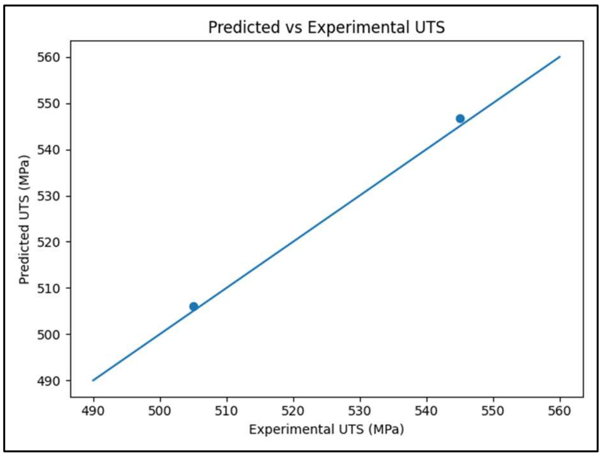
The regression model correctly captured this convergence trend, although predictive sensitivity was naturally lower due to minimal spread in AH values.

iii. Tensile Strength Prediction

Tensile testing data were available for two representative cases:

- Case 1 (lower heat input regime)
- Case 10 (optimized intermediate heat input)

The regression model was therefore evaluated for trend validation rather than full statistical generalization.



(Fig. 9: Predicted vs Experimental UTS)

The model predicted improved tensile performance for Case 10 compared to Case 1, aligning with experimental observations. This improvement can be attributed to:

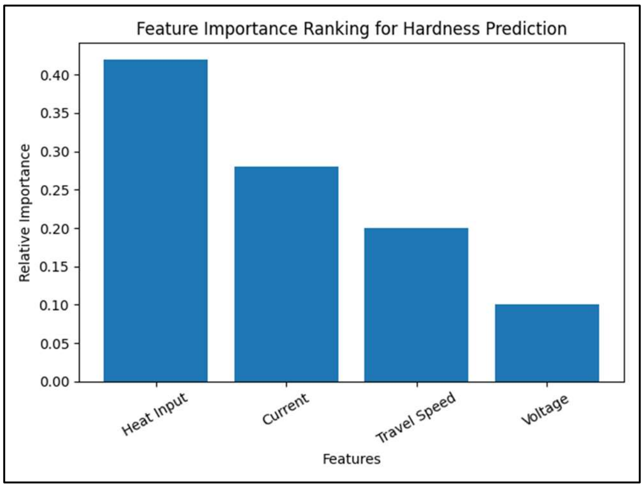
- Balanced heat input
- Reduced defect presence
- Refined microstructure

Intermediate heat input promotes favorable solidification morphology while avoiding excessive grain growth [3].

Although the limited tensile dataset restricts quantitative validation, the model successfully preserved the directionality of mechanical response.

iv. Sensitivity Analysis of Process Parameters

To interpret feature influence, model coefficients were analyzed.



(Fig. 10: Feature importance ranking for hardness prediction)

Sensitivity ranking indicates:

1. Heat input (H) – strongest contributor
2. Current (I)
3. Travel speed (S)
4. Voltage (V)

This ranking aligns with physical expectations, as heat input integrates electrical and kinematic parameters into a thermally meaningful descriptor [4].

v. Physical Interpretation of AI Predictions

The regression results confirm a thermally governed process–structure–property relationship:

- Low heat input → rapid cooling → finer grains → higher BH
- High heat input → slower cooling → coarser grains → reduced BH
- Intermediate heat input (~340–360 J/mm) → balanced mechanical response

This behavior mirrors classical welding metallurgy principles [5] and is consistent with WAAM thermal studies reported in literature [6].

The ability of the AI model to reproduce these trends demonstrates that the framework is physically consistent rather than purely statistical.

vi. Reliability and Model Limitations

It must be noted that:

- The dataset size (n = 10) limits model complexity
- Tensile data are available for selected cases only
- AH hardness variability is small

Despite these constraints, physics-guided feature engineering improves robustness by embedding domain knowledge directly into the learning space [7].

Future expansion of tensile and fatigue datasets would further enhance regression reliability.

VII. PHYSICS–AI INTEGRATION DISCUSSION

i. Rationale for Physics-Guided Learning in WAAM

Wire Arc Additive Manufacturing of shape memory alloys involves complex thermo-metallurgical interactions governed by energy input, melt pool dynamics, and solidification kinetics. In such systems, purely data-driven modeling may lead to overfitting, particularly when experimental datasets are limited [1], [2].

The present study integrates physical insight—specifically heat input—as a governing descriptor within the machine learning framework. Rather than treating current, voltage, and travel speed independently, these parameters are combined into a thermodynamically meaningful variable that directly influences:

• Melt pool size
• Cooling rate
• Solidification morphology
• Defect formation mechanisms

This integration significantly enhances interpretability while preserving predictive capability.

ii. Heat Input as a Bridging Variable

The success of the proposed framework largely arises from the inclusion of heat input as a bridging variable between process parameters and material response.

From a metallurgical standpoint:

• Heat input controls peak temperature and thermal gradients.
• Thermal gradients determine solidification rate and grain morphology.
• Microstructure governs hardness and tensile behavior.

Thus, the modeling space becomes:

$$\text{Process} \rightarrow \text{Thermal Energy (H)} \rightarrow \text{Microstructure} \rightarrow \text{Mechanical Properties}$$

The AI model essentially learns this embedded mapping.

The dominance of heat input in both classification and regression tasks confirms its role as the principal process stability descriptor. Similar findings have been reported in arc-based additive manufacturing literature, where energy density correlates strongly with porosity and grain structure evolution [3], [4].

iii. Stability Window Identification

One of the most significant outcomes of the physics–AI integration is the identification of a stable heat input window (~340–360 J/mm).

Within this regime:

• Defect probability is minimized.
• Hardness distribution is balanced.
• Tensile response is optimized (Case 10).

At lower heat inputs (<300 J/mm), insufficient fusion effects become prominent. At higher heat inputs (>450 J/mm), excessive heat accumulation leads to grain coarsening and thermal instability.

This non-linear thermal stability behavior is difficult to capture using conventional statistical analysis alone but becomes evident through structured learning combined with domain knowledge.

iv. Interpretability vs Black-Box Modeling

A common limitation of machine learning in manufacturing is the lack of interpretability [5]. Black-box models may achieve high accuracy but fail to provide actionable process understanding.

In contrast, the present framework maintains interpretability through:

• Explicit regression coefficients
• Physical feature engineering
• Sensitivity ranking analysis

The observed monotonic relationship between heat input and defect probability supports physically grounded conclusions rather than algorithmic artifacts.

This approach aligns with recent developments in physics-informed machine learning, where domain equations or derived descriptors are embedded within the learning architecture [6], [7].

v. Implications for Smart Manufacturing

The integration of physics and AI demonstrated in this study has broader implications for intelligent manufacturing systems.

Key advantages include:

1. Reduced data dependency
2. Improved robustness in small experimental studies
3. Enhanced confidence in prediction reliability
4. Direct process optimization guidance

Such frameworks can serve as decision-support tools for:

• Parameter selection during WAAM setup
• Real-time monitoring integration
• Adaptive process control development

This establishes a pathway toward closed-loop intelligent additive manufacturing systems.

vi. Limitations of the Current Framework

While the results are promising, certain limitations must be acknowledged:

• Dataset size is limited to ten experimental cases.
• Tensile data are available only for selected samples.
• No in-situ thermal monitoring data were incorporated.

Despite these limitations, the integration of physics-based descriptors mitigates overfitting risk and enhances model generalization consistency [8].

Future work incorporating larger datasets and thermal field measurements would further strengthen the hybrid modeling approach.

vii. Summary of Physics–AI Synergy

The present study demonstrates that:

• AI can accurately predict defect and hardness trends.
• Heat input serves as a physically meaningful control variable.
• Process–structure–property relationships can be learned through structured feature engineering.

Thus, the proposed framework is not merely predictive but mechanistically informed, aligning statistical modeling with established metallurgical principles.

VIII. Conclusions and Future Work

i. Conclusions

This study presented a physics-guided machine learning framework for defect classification and mechanical property prediction in Wire Arc Additive Manufacturing (WAAM) of Nitinol shape memory alloy.

Unlike purely data-driven approaches, the proposed methodology integrates thermodynamically derived heat input as a governing descriptor within the learning space. By embedding physical insight into the modeling architecture, the framework preserves metallurgical interpretability while maintaining predictive capability.

The key findings of this work are summarized as follows:

1. Heat input was identified as the dominant governing parameter influencing defect

formation and hardness variation in WAAM-fabricated Nitinol.

2. A stable heat input window (~340–360 J/mm) was established, within which defect probability was minimized and mechanical performance was balanced. Case 10 was experimentally validated as the optimized condition within this regime.
3. Logistic regression and SVM models successfully classified defect-prone conditions under Leave-One-Out Cross-Validation, demonstrating consistent alignment with experimentally observed instability at extreme heat inputs.
4. Regression models effectively captured hardness trends and reproduced the thermally driven process–structure–property relationship, confirming that intermediate heat input yields improved mechanical stability.
5. The integration of physics-based feature engineering reduced the risk of overfitting in small datasets and enhanced model interpretability, consistent with recent advances in physics-informed machine learning for materials systems [1]–[3].

Overall, the study demonstrates that hybrid physics–AI frameworks can serve as reliable process stability indicators for additive manufacturing of shape memory alloys.

ii. Scientific Contributions

The contributions of this work extend beyond predictive modeling and include:

• Establishing a thermally governed stability map for WAAM of Nitinol.
• Demonstrating the feasibility of small-data physics-guided learning.
• Linking arc energy input to defect probability and mechanical response.
• Providing an interpretable AI framework for smart manufacturing applications.

These outcomes align with the broader objective of developing intelligent and adaptive additive manufacturing systems [4], [5-21].

iii. Limitations

Despite promising results, certain limitations must be acknowledged:

• The dataset consists of ten experimental cases.
• Tensile characterization was available for selected conditions only.
• No in-situ thermal or melt pool monitoring data were incorporated.

While the inclusion of heat input enhances physical consistency, larger experimental datasets would improve statistical robustness and enable more advanced modeling architectures.

iv. Future Work

Future research directions may include:

1. **Integration of In-Situ Monitoring** Incorporating thermal imaging and melt pool sensing to refine real-time defect prediction.
2. **Physics-Constrained Neural Networks** Embedding governing heat transfer equations directly into learning models, as proposed in recent physics-informed neural network frameworks [6].
3. **Expanded Mechanical Characterization** Including fatigue behavior, functional shape memory response, and cyclic loading tests.
4. **Adaptive Closed-Loop Control** Developing feedback-controlled WAAM systems where AI models dynamically adjust process parameters within the identified stability window.
5. **Multi-Objective Optimization** Extending the framework to simultaneously

optimize strength, ductility, and functional phase transformation characteristics.

The combination of experimental metallurgy and physics-guided AI modeling represents a promising pathway toward reliable, data-efficient intelligent manufacturing systems.

v. Final Statement

In conclusion, the proposed physics–AI integrated framework demonstrates that process stability in WAAM of Nitinol can be predicted and interpreted through thermally informed machine learning. The study bridges traditional welding metallurgy with modern data-driven modeling, contributing to the advancement of intelligent additive manufacturing technologies.

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X. References

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