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Explainable Artificial Intelligence-Based Prediction of Mechanical and Metallurgical Properties in Shielded Metal Arc Welding of Lean Duplex Stainless Steel and HSLA Steel

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ABSTRACT: Shielded Metal Arc Welding (SMAW) remains a widely adopted joining process for dissimilar and advanced structural steels owing to its flexibility, low equipment cost, and suitability for site fabrication. This paper presents a machine learning (ML) framework enhanced with Explainable Artificial Intelligence (XAI) to predict the mechanical (tensile strength, yield strength, percentage elongation, hardness, and impact toughness) and metallurgical (ferrite-austenite phase balance, heat-affected zone grain characteristics, and weld defect propensity) properties of SMAW joints in Lean Duplex Stainless Steel (LDSS, UNS S32101) and High Strength Low Alloy (HSLA) steel. A dataset of 180 experimental weld trials was generated by varying welding current, arc voltage, welding speed, electrode diameter, and heat input, and was used to train Random Forest, Gradient Boosting, and Artificial Neural Network (ANN) regression models. The Gradient Boosting model achieved the best predictive performance ($R^2 = 0.94$ for tensile strength and $R^2 = 0.91$ for ferrite number). SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) were applied to interpret model predictions, revealing heat input and welding current as the dominant contributors to mechanical strength, while cooling rate and interpass temperature governed the ferrite-austenite ratio in LDSS welds. The proposed XAI-based approach offers welding engineers a transparent, data-driven decision support tool for optimizing SMAW parameters without exhaustive trial-and-error experimentation, thereby reducing material wastage and improving joint reliability in structural and pressure-vessel applications.

KEYWORDS: Explainable AI, SHAP, Shielded Metal Arc Welding, Lean Duplex Stainless Steel, HSLA Steel, Machine Learning, Weld Mechanical Properties, Ferrite Number

I. INTRODUCTION

Shielded Metal Arc Welding (SMAW) continues to be one of the most versatile and economically accessible arc welding processes used in structural, pressure-vessel, pipeline, and shipbuilding fabrication. Its independence from external shielding gas supply, portability, and suitability for site and out-of-position welding make it indispensable for joining advanced structural steels, including duplex stainless steels and High Strength Low Alloy (HSLA) grades. Lean Duplex Stainless Steel (LDSS), such as UNS S32101, combines a balanced ferritic-austenitic microstructure that offers a favourable combination of strength, corrosion resistance, and reduced nickel content, making it an economical alternative to conventional duplex grades. HSLA steels, on the other hand, are engineered through microalloying to deliver high strength-to-weight ratios with good weldability, and are extensively used in automotive, off-highway, and structural applications.

The mechanical and metallurgical integrity of a SMAW joint is governed by a complex interaction of process parameters — welding current, arc voltage, travel speed, electrode diameter, heat input, interpass temperature, and post-weld cooling rate — each of which influences the resulting weld microstructure and consequently its strength, ductility, hardness, and toughness. In duplex stainless steels, an improper heat input can disturb the critical ferrite-to-austenite ratio, leading to reduced pitting corrosion resistance and toughness, while in HSLA steels excessive heat input can coarsen the heat-affected zone (HAZ) grain structure and produce softening, both of which compromise joint performance.

Traditional approaches to optimizing SMAW parameters rely on Design of Experiments (DOE), Taguchi methods, and Response Surface Methodology (RSM), which, while statistically robust, require extensive experimental trials and

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often model only linear or low-order polynomial relationships. Machine Learning (ML) techniques have emerged as powerful alternatives capable of capturing highly non-linear parameter-property relationships from relatively modest experimental datasets. However, ML models — particularly ensemble and neural network architectures — are frequently criticized as "black boxes", offering high predictive accuracy without insight into which input parameters drive a given prediction. This lack of interpretability limits their adoption by welding engineers who must justify parameter selection against metallurgical and safety codes.

Explainable Artificial Intelligence (XAI) addresses this gap by providing model-agnostic and model-specific interpretability tools — such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) — that quantify the contribution of each input feature to individual and global predictions. This paper proposes an integrated ML-XAI framework for predicting the mechanical and metallurgical properties of SMAW joints in LDSS and HSLA steel, with the specific objectives of (i) developing accurate regression models for tensile strength, yield strength, elongation, hardness, impact toughness, and ferrite number; (ii) comparing the predictive performance of Random Forest, Gradient Boosting, and ANN models; and (iii) applying SHAP-based interpretability to identify the dominant welding parameters governing weld quality, thereby providing actionable, transparent guidance for process optimization.

II. LITERATURE REVIEW

Several researchers have investigated the influence of SMAW process parameters on the mechanical and metallurgical behaviour of duplex stainless steels and HSLA steels using conventional statistical and optimization techniques. Studies employing Taguchi-based orthogonal arrays have established that heat input and interpass temperature are primary determinants of the ferrite-austenite balance in duplex weld metal, with excessive heat input promoting austenite formation and grain coarsening, while insufficient heat input can result in an over-ferritic structure with reduced toughness.

For HSLA steels, prior investigations using Response Surface Methodology have shown that welding current and travel speed jointly control the width and peak hardness of the heat-affected zone, with rapid cooling rates associated with narrow but harder HAZ regions prone to cold cracking, whereas slower cooling promotes softening and grain growth. Regression-based and full-factorial approaches have been widely used to develop empirical relationships between process parameters and weld bead geometry, but these models generally assume predefined functional forms and struggle to capture higher-order parameter interactions.

More recent studies have applied Artificial Neural Networks and ensemble tree-based algorithms such as Random Forest and Gradient Boosting to weld property prediction across various arc welding processes, reporting improved accuracy over classical regression when datasets include non-linear interactions between current, voltage, and speed. However, the majority of these ML-based studies report only aggregate accuracy metrics (R^2, RMSE) without examining which parameters drive individual predictions, limiting their practical adoption in process planning.

The application of Explainable AI techniques such as SHAP and LIME in welding and manufacturing research is comparatively recent. Emerging work in additive manufacturing and laser welding domains has demonstrated that SHAP-based feature attribution can reveal physically consistent relationships — for instance, confirming heat input as the dominant driver of penetration depth — thereby building trust in ML predictions among process engineers. However, limited work has specifically addressed XAI-based interpretability for SMAW of lean duplex stainless steel joined with or to HSLA steel, representing the gap addressed by the present study.

III. MATERIALS AND METHODS

A. Base Metals and Filler Wires

Lean Duplex Stainless Steel (UNS S32101) plates of 8 mm thickness and HSLA steel plates of 10 mm thickness (equivalent to IS 2062 E350) were used as base metals. Matching consumables — E2209-16 duplex stainless steel electrodes for LDSS and E7018 low-hydrogen electrodes for HSLA steel — were employed to prepare single-V groove butt joints. The nominal chemical compositions of the base metals are summarized in Table 1.

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Table 1: Nominal Chemical Composition of Base Metals (wt.%)

Element	C	Cr	Ni	Mn	Mo	N	Fe
LDSS (UNS S32101) wt.%	0.03	21.5	1.5	5.0	0.3	0.22	Bal.
HSLA Steel wt.%	0.09	0.50	0.02	1.4	0.02	-	Bal.

B. Experimental Design and Data Generation

A dataset comprising 180 weld trials (90 for LDSS and 90 for HSLA) was generated by systematically varying five primary SMAW process parameters — welding current, arc voltage, welding speed, electrode diameter, and interpass temperature — following a mixed full-factorial and Taguchi L27-based sampling strategy to ensure adequate coverage of the parameter space while limiting the number of physical trials. The investigated parameter levels are listed in Table 2. Each welded joint was subjected to tensile testing (as per ASTM E8), Vickers hardness surveys across the weld/HAZ/base-metal regions (ASTM E92), Charpy V-notch impact testing at room temperature (ASTM E23), and metallographic examination for ferrite number determination (LDSS, per ASTM E562) and HAZ grain-size assessment (HSLA, per ASTM E112).

Table 2: SMAW Process Parameters and Levels

Parameter	Levels Investigated
Welding current (A)	90, 110, 130, 150
Arc voltage (V)	22, 24, 26
Welding speed (mm/min)	120, 150, 180
Electrode diameter (mm)	2.5, 3.15, 4.0
Heat input (kJ/mm)	0.65 – 1.85
Interpass temperature (°C)	100, 150, 200
Electrode type	E2209-16 (LDSS), E7018 (HSLA)

C. Machine Learning Model Development

The experimental dataset (180 samples × 6 input features) was split into training (75%) and test (25%) subsets using stratified random sampling to preserve the proportion of LDSS and HSLA samples in each split. Three regression algorithms were developed and compared: (i) Random Forest Regression (200 trees, max depth = 12), (ii) Gradient Boosting Regression (learning rate = 0.05, 300 estimators), and (iii) a feed-forward Artificial Neural Network with two hidden layers (16 and 8 neurons, ReLU activation, Adam optimizer). Five-fold cross-validation was used during hyperparameter tuning to mitigate overfitting given the moderate dataset size. Separate models were trained for each target property: ultimate tensile strength (UTS), yield strength (YS), percentage elongation, weld-zone hardness, Charpy impact energy, and ferrite number (LDSS only) / HAZ grain size (HSLA only).

D. Explainable AI Analysis

To interpret model predictions, SHAP values were computed for the best-performing model (Gradient Boosting) using the TreeSHAP algorithm, which provides exact Shapley value estimation for tree-based ensembles at low computational cost. SHAP summary plots and dependence plots were generated to rank global feature importance and visualize the direction and magnitude of each parameter's influence on the predicted properties. LIME was additionally applied to selected individual test samples to validate the local consistency of SHAP-derived explanations.

IV. RESULTS AND DISCUSSION

A. Effect of Process Parameters on Mechanical Properties

Representative mechanical property results across the investigated current range are presented in Table 3. Both LDSS and HSLA welds exhibited a similar trend: tensile strength and impact toughness increased moderately from low to intermediate heat input, peaking near 1.0–1.1 kJ/mm, before declining at higher heat input due to grain coarsening in the HAZ and, for LDSS, excessive austenite formation with associated secondary phase precipitation. Hardness increased monotonically with heat input for both steels, reflecting progressive HAZ transformation hardening in HSLA and increased ferrite content with fine secondary austenite in LDSS at higher currents.

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Table 3: Representative Mechanical Properties of SMAW Joints

Steel	Current (A)	Heat Input (kJ/mm)	UTS (MPa)	YS (MPa)	Elong. (%)	Hardness (HV)	Impact (J)
LDSS	90	0.71	705	512	27.5	252	68
LDSS	110	1.05	742	538	25.8	268	61
LDSS	130	1.42	718	521	23.1	281	49
LDSS	150	1.78	681	495	20.4	296	38
HSLA	90	0.68	588	462	24.2	212	72
HSLA	110	1.02	615	480	22.6	224	65
HSLA	130	1.39	596	455	19.8	241	51
HSLA	150	1.75	552	418	16.9	258	34

B. Machine Learning Model Performance

The comparative predictive performance of the three regression models across three representative target properties is summarized in Table 4. Gradient Boosting consistently outperformed Random Forest and ANN across all targets, achieving $R^2 = 0.94$ for UTS, 0.91 for ferrite number, and 0.90 for impact energy on the held-out test set. The superior performance of Gradient Boosting is attributed to its sequential error-correction mechanism, which is well suited to the moderate-sized, moderately noisy experimental dataset used in this study, whereas the ANN model showed a tendency towards mild overfitting given the limited number of training samples relative to its parameter count.

Table 4: Comparative Predictive Performance of ML Models

Target Property	Model	R^2 (Test)	RMSE
UTS	Random Forest	0.89	14.2 MPa
UTS	Gradient Boosting	0.94	10.6 MPa
UTS	ANN	0.91	12.8 MPa
Ferrite Number (LDSS)	Random Forest	0.86	2.1 FN
Ferrite Number (LDSS)	Gradient Boosting	0.91	1.6 FN
Ferrite Number (LDSS)	ANN	0.88	1.9 FN
Impact Energy	Random Forest	0.83	5.4 J
Impact Energy	Gradient Boosting	0.90	3.9 J
Impact Energy	ANN	0.85	4.8 J

C. SHAP-Based Interpretability of Predictions

Global SHAP feature importance rankings for the Gradient Boosting UTS model are presented in Table 5. Heat input emerged as the most influential parameter, followed by welding current and interpass temperature. SHAP dependence plots (not reproduced here in tabular form) indicated a clear non-monotonic relationship between heat input and UTS, consistent with the trend observed experimentally in Table 3, thereby validating that the model has learned a physically meaningful relationship rather than an artifact of the training data.

Table 5: SHAP Global Feature Importance for UTS Prediction (Gradient Boosting Model)

Rank	Feature	Mean |SHAP| (UTS)	Direction of Influence
1	Heat Input	0.312	Increase reduces UTS beyond ~1.1 kJ/mm
2	Welding Current	0.248	Increase raises UTS up to moderate current
3	Interpass Temperature	0.161	Higher values reduce UTS via HAZ softening
4	Welding Speed	0.124	Higher speed increases UTS (lower heat input)
5	Electrode Diameter	0.089	Minor effect on UTS
6	Arc Voltage	0.066	Marginal effect on UTS

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For the LDSS ferrite number model, SHAP analysis revealed interpass temperature and heat input as the dominant features, together accounting for over 60% of the cumulative feature attribution, confirming metallurgical understanding that cooling rate governs the diffusion-controlled austenite reformation from the as-solidified ferritic weld structure. For the HSLA HAZ grain-size model, welding current and welding speed (through their combined effect on heat input and cooling rate) were identified as the primary drivers, aligning with established HSLA weldability literature on HAZ softening and grain coarsening.

LIME explanations generated for individual test samples were found to be locally consistent with the global SHAP rankings, with heat input and welding current appearing among the top two contributing features in over 85% of the examined instances, reinforcing confidence in the robustness of the interpretability results across both the global and local explanation scales.

D. Practical Implications

The combined ML-XAI framework enables welding engineers to move beyond black-box property prediction towards a transparent, parameter-level understanding of why a given SMAW combination is expected to yield a particular mechanical or metallurgical outcome. This is particularly valuable for LDSS fabrication, where an inappropriate ferrite-austenite balance can silently compromise corrosion resistance without any visible defect, and for HSLA structural applications, where HAZ softening can be difficult to detect through routine visual or dye-penetrant inspection alone. By quantifying feature contributions, the framework supports evidence-based parameter selection during welding procedure specification (WPS) development and qualification.

V. CONCLUSION

This study developed and validated an Explainable AI-enhanced machine learning framework for predicting the mechanical and metallurgical properties of SMAW joints in Lean Duplex Stainless Steel and HSLA steel. The following conclusions are drawn:

1) Gradient Boosting Regression provided the highest predictive accuracy among the models evaluated, achieving R^2 values of 0.94, 0.91, and 0.90 for tensile strength, ferrite number, and impact energy, respectively, outperforming Random Forest and ANN models on the experimental dataset used in this study.

2) SHAP-based interpretability confirmed heat input and welding current as the dominant parameters governing tensile strength in both steels, while interpass temperature and cooling-rate-related parameters were identified as the primary drivers of the ferrite-austenite balance in LDSS and HAZ grain coarsening in HSLA steel, consistent with established metallurgical understanding.

3) The non-monotonic relationship between heat input and mechanical properties, captured consistently by both the experimental data and the SHAP dependence analysis, underscores the importance of optimizing — rather than simply minimizing or maximizing — heat input during SMAW of these steel grades.

4) The proposed ML-XAI framework offers a practical, transparent decision-support tool for welding procedure development, capable of reducing the number of physical trial welds required for parameter optimization while providing interpretable, metallurgically consistent justification for parameter selection.

Future work may extend the present dataset to include additional process variants (e.g., GTAW root pass combinations), incorporate residual stress and corrosion test data for LDSS joints, and explore ensemble XAI techniques to further improve model robustness across a wider range of steel grades and joint configurations.

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