https://doi.org/10.46335/IJIES.2026.11.4.4 **e-ISSN: 2456-3463**
Vol. 11, No. 4, 2026, PP. 19-26

International Journal of Innovations in Engineering and Science, www.ijies.net

Machine Learning Model to Predict Optimal Welding Parameters for Dissimilar Welding Between SS316L and SS430

Suhani Kanoje, Krushnakant Gobade, Pragati Meshram, Vishal Ganthade, Prof. Chetan Tembhurkar

Priyadarshini College of Engineering Nagpur, Maharashtra., India, 440019

ssuhanikanoje@gmail.com

***Received on**: 11 March, 2026* ***Revised on**: 18 April, 2026* ***Published on**: 21 April, 2026*

***Abstract –** Dissimilar welding of stainless steels is widely used to combine the advantages of different materials; however, it introduces challenges due to differences in thermal and metallurgical properties. These differences often lead to defects such as poor penetration, reduced mechanical strength, and non-uniform microstructure. The present study aims to improve weld quality by developing a machine learning–based approach for predicting and optimizing Metal Inert Gas (MIG) welding parameters. Experimental work is carried out on SS316L and SS430 stainless steel plates using ER309L filler wire. Key welding parameters, including voltage, current, travel speed, and wire feed rate, are varied systematically. The welded specimens are tested to evaluate tensile strength using a Universal Testing Machine, and penetration depth is measured to assess weld quality. The collected data is used to develop a Random Forest regression model capable of predicting multiple output responses. The results indicate that the model can accurately estimate tensile strength and penetration depth while identifying an optimal heat input range of 0.25–0.35 kJ/mm for improved weld performance. A Streamlit-based interface is also developed to provide real-time predictions and assist in parameter selection. The study demonstrates that the use of machine learning reduces experimental effort, improves consistency, and enhances the overall efficiency of the welding process.*

***Keywords-** MIG Welding (GMAW), Dissimilar Metal Welding, XG Boost, Tensile Strength Prediction, Optimal Heat Input, ER309L Filler Wire, Streamlit GUI, Industry 4.0.*

INTRODUCTION

Welding is a basic and widely used manufacturing process in which two or more materials, mainly metals, are joined together by the application of heat, pressure, or both. It plays a very important role in modern industries such as automotive, aerospace, construction, and shipbuilding. Among different welding techniques, Metal Inert Gas (MIG) welding, also known as Gas Metal Arc Welding (GMAW), is one of the most commonly used processes. It is widely preferred because of its high welding speed, ease of operation, and suitability for automation. In MIG welding, a continuously fed consumable electrode wire is used. An electric arc is produced between the wire and the base metal, which melts both materials and forms a strong joint. A shielding gas such as argon is used Contents lists available at ijies.net MIG Welding Guide homepage: https://ijies.net/submit-sample-manuscript to protect the weld pool from atmospheric gases like oxygen and nitrogen, which can weaken the weld. In recent years, there has been growing interest in dissimilar metal welding, where two different metals are joined together. This is done to combine the useful properties of both materials, such as strength, corrosion resistance, and cost efficiency. In the present investigation, Stainless Steel 316L (SS316L) and Stainless Steel 430 (SS430) have been selected as the base materials for dissimilar welding. SS316L is an austenitic stainless steel characterized by the presence of chromium, nickel, and molybdenum, which imparts excellent corrosion resistance, superior ductility, and high toughness. Owing to its low carbon content, SS316L also exhibits enhanced resistance to sensitization and intergranular corrosion, making it suitable for critical applications in aggressive environments. In contrast, SS430 is a ferritic stainless steel primarily composed of chromium with negligible nickel content. It is known for its good oxidation resistance, moderate corrosion resistance, and relatively lower cost compared to austenitic grades. However, SS430 possesses lower ductility and toughness, and its ferritic microstructure makes it more sensitive to thermal cycles during welding. The dissimilar welding of SS316L and SS430 presents significant metallurgical and mechanical challenges due to the differences in their chemical composition, thermal expansion coefficients, and microstructural characteristics. These disparities lead to non-uniform heat distribution and residual stress development during the welding process. As a result, several welding defects may arise, including cracking, distortion, lack of fusion, and degradation in mechanical properties such as tensile strength and ductility. To overcome these challenges, ER309L filler wire is employed in the welding process. This filler material is specifically designed for dissimilar stainless steel welding applications, as it contains a higher proportion of chromium and nickel. The presence of these alloying elements enhances metallurgical compatibility between the austenitic and ferritic phases, promotes the formation of a stable weld microstructure, and improves the overall strength and corrosion resistance of the welded joint. Conventionally, the selection of welding parameters such as voltage, current, travel speed, and wire feed rate is carried out using a trial-and-error approach. This method involves repeated experimentation and testing, which is not only time-consuming and expensive but also lacks consistency and reliability. Furthermore, improper parameter selection can lead to suboptimal weld quality and increased defect formation. In order to address these limitations, the present research adopts a machine learning–based approach for the prediction and optimization of welding parameters. A Random Forest regression model is developed to capture the complex and nonlinear relationships between input parameters and output responses. The model is capable of predicting key mechanical and geometrical properties of the weld, namely tensile strength and penetration depth, with improved accuracy. Additionally, a Streamlit-based graphical user interface (GUI) is developed to facilitate user interaction with the predictive model. This interface allows users to input welding parameters and obtain real-time predictions and recommendations. The developed system functions as a virtual welding assistant, enabling informed decision-making prior to actual welding operations. Thus, the integration of machine learning techniques with welding process optimization not only enhances prediction accuracy but also contributes to the advancement of smart manufacturing systems and aligns with the principles of Industry 4.0, where automation, data-driven decision-making, and process efficiency are of paramount importance.

Materials and Heat Input

1.Base Materials - Stainless Steel 316L (SS316L): SS316L is an austenitic stainless steel containing molybdenum, which improves its resistance to corrosion, especially in chloride environments. It is widely used in marine, chemical, and food industries due to its good strength, toughness, and weldability. Stainless Steel 430 (SS430): SS430 is a ferritic stainless steel with moderate corrosion resistance and good formability. It is commonly used in automotive parts, kitchen equipment, and household appliances. Compared to SS316L, it has lower ductility and does not contain nickel in significant amounts.

2. Filler Material:

ER309L filler wire is selected for the joining of SS316L and SS430 due to its high chromium and nickel content, which enhances metallurgical compatibility between dissimilar metals. The low carbon content of this filler wire minimizes carbide precipitation and thereby improves corrosion resistance. This filler material ensures good compatibility between dissimilar metals, high weld strength, reduced cracking tendency, and stable weld formation.

3. Shielding Gas:

Argon (Ar) or argon-rich gas mixtures are used as shielding gases in the MIG welding process. The primary function of the shielding gas is to protect the molten weld pool from atmospheric contamination such as oxygen and nitrogen, thereby ensuring improved weld quality and stability.

5. Welding Process:

https://doi.org/10.46335/IJIES.2026.11.4.4 **e-ISSN: 2456-3463**
Vol. 11, No. 4, 2026, PP. 19-26

The welding process employed in this study is Metal Inert Gas (MIG) welding, also known as Gas Metal Arc Welding (GMAW). In this process, a continuously fed consumable electrode wire is melted through the heat

generated by an electric arc, forming the weld joint under the protection of shielding gas.

6. Heat Input in Welding Heat input is a critical welding parameter, as it directly influences the quality of the weld, the depth of penetration, and the mechanical strength of the welded joint. Proper control of heat input is essential to achieve sound weld formation and to ensure desirable metallurgical and mechanical properties in the final joint.

Heat Input: $V\ x\ I\ x\ 60\ S\ x\ 1000$ **Unit:** kJ/mm

7.Effect of Heat Input Heat input plays a crucial role in determining the quality and performance of a welded joint. It significantly influences the thermal cycle, microstructure, and mechanical properties of the weld region.

At high heat input levels, excessive heat is introduced into the material, which leads to grain growth in the heat-affected zone (HAZ). This condition generally results in a reduction in mechanical strength and increases the likelihood of distortion and residual stresses in the welded component.

On the other hand, low heat input results in insufficient melting of the base material, which may cause lack of fusion and poor penetration. Consequently, this leads to the formation of weak weld joints with reduced structural integrity.

8.Optimized Heat Input Range

In the present investigation on the dissimilar welding of SS316L (austenitic stainless steel) and SS430 (ferritic stainless steel) using ER309L filler wire, the control of heat input plays a crucial role in determining the quality and performance of the welded joint. Heat input, which represents the amount of thermal energy supplied per unit length of the weld, directly influences the weld pool characteristics, cooling rate, microstructural transformations, and mechanical properties of the joint.

In this study, the heat input is carefully maintained within an optimized range of 0.25 to 0.35 kJ/mm, which is identified as the most suitable range for achieving defect-free and mechanically sound welds. This range is selected based on its ability to provide a balanced thermal condition that avoids both excessive and insufficient heating during the welding process.

When the heat input is maintained within this optimal range, it ensures adequate melting and proper fusion between the dissimilar base metals, thereby forming a strong metallurgical bond at the weld interface. It also facilitates uniform heat distribution, which minimizes the development of residual stresses and prevents distortion in the welded structure.

From a metallurgical perspective, controlled heat input plays a significant role in governing the microstructural evolution within the weld zone and heat-affected zone (HAZ). In the case of SS430, excessive heat input can lead to undesirable grain growth and coarsening of the ferritic structure, resulting in reduced toughness and increased brittleness. Conversely, insufficient heat input may cause incomplete fusion and formation of weak joints due to inadequate penetration.

The selected heat input range promotes the formation of a stable and balanced microstructure, consisting of appropriate proportions of austenitic and ferritic phases, which enhances the overall mechanical properties of the weld. As a result, improved tensile strength and optimal penetration depth are achieved.

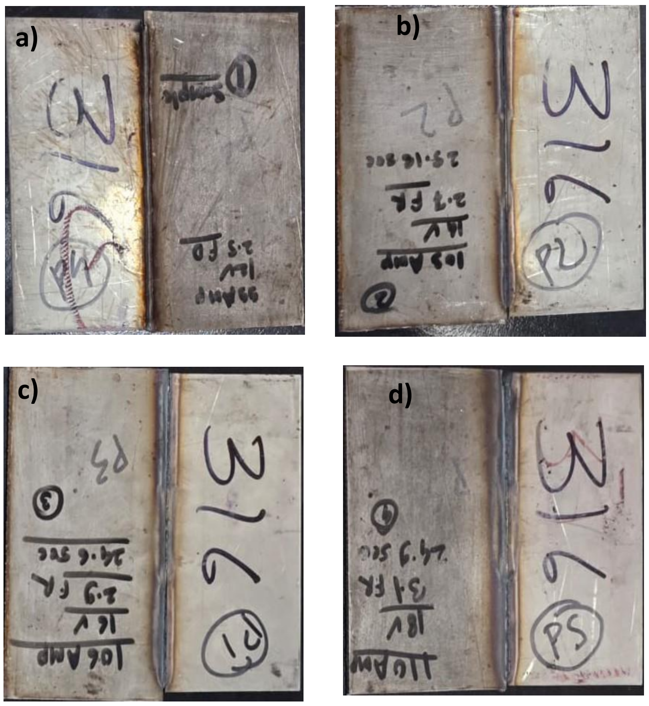

Fig. 1. Comparative analysis of dissimilar SS316L–SS430 weldments: (a) ER316L filler, (b) ER309L filler

https://doi.org/10.46335/IJIES.2026.11.4.4 e-ISSN: 2456-3463
Vol. 11, No. 4, 2026, PP. 19-26

International Journal of Innovations in Engineering and Science, www.ijies.net

Chemical Composition:

Materials	C	Si	Mn	P	S	Cr	Mo	Ni	N	Co	Cu	Fe
SS316L ASS	0.03	0.75	2.00	0.045	0.03	16.5-18.5	2.0-3.0	10-14	0.10	-	-	Balance
SS430 ASS	0.12	1.00	1.00	0.04	0.03	16–18	–	≤0.50	–	–	–	Balance
ER309L Filler	0.03	0.40	1.50–2.50	0.03	0.03	23–25	0.75	12–14	–	–	0.30	Balance

Table 1 Chemical Composition

Mechanical Properties:

Material	Tensile Strength (MPa)	Yield Strength (MPa)	Elongation (%)	Hardness	Density (g/cm³)
SS316L ASS	485–620	~170	~40	~95 HRB	8.0
SS430 ASS	450–600	~275	~22	~89 HRB	7.75
ER309L Filler	~620	~450	~35	–	~7.9

Table 2 Mechanical properties

Chemical Composition:

The chemical composition of materials plays a fundamental role in determining their mechanical, metallurgical, and corrosion behavior. SS316L, being an austenitic stainless steel, contains significant amounts of chromium (16.5–18.5%), nickel (10–14%), and molybdenum (2–3%), which enhance corrosion resistance and toughness. Its low carbon content (≤0.03%) minimizes carbide precipitation and intergranular corrosion. In contrast, SS430 is a ferritic stainless steel with high chromium content (16–18%) but very low nickel, resulting in moderate corrosion resistance and lower ductility. The ER309L filler wire contains higher chromium (23–25%) and nickel (12–14%) content, which improves weld compatibility and promotes a stable microstructure during dissimilar welding. The balanced composition of ER309L helps in reducing dilution effects and enhances mechanical strength and corrosion resistance of the weld joint.

Mechanical Properties:

Mechanical properties are critical for evaluating the performance of welded joints under applied loads. SS316L exhibits tensile strength in the range of 485–620 MPa, with high elongation (~40%), indicating excellent ductility and toughness. SS430 shows comparable tensile strength (450–600 MPa) but lower elongation (~22%), reflecting reduced ductility due to its ferritic structure. The ER309L filler metal demonstrates higher tensile strength (~620 MPa) and good elongation (~35%), contributing to improved weld joint strength. The hardness values of SS316L (~95 HRB) and SS430 (~89 HRB) indicate moderate resistance to deformation. During welding, the combination of these materials and filler metal ensures a balance between strength and ductility, which is essential for reliable structural performance.

Microstructural Properties:

The microstructure of welded joints significantly influences their mechanical behavior and durability. SS316L possesses an austenitic microstructure, which provides high toughness and resistance to cracking. SS430, on the other hand, has a ferritic microstructure, which is relatively less ductile and more sensitive to heat input. During dissimilar welding, the weld zone exhibits a mixed microstructure consisting of austenitic and ferritic phases. The use of ER309L filler promotes the formation of a stable austenitic matrix with controlled ferrite content, which helps in reducing hot cracking and improving weld integrity. Proper heat input control ensures uniform grain structure and prevents excessive grain growth, particularly in the heat-affected zone of SS430.

https://doi.org/10.46335/IJIES.2026.11.4.4 e-ISSN: 2456-3463
Vol. 11, No. 4, 2026, PP. 19-26

Electrical Discharge Machining (EDM) :

Electrical Discharge Machining (EDM) is a non-traditional machining process employed for shaping electrically conductive materials through controlled electrical discharges. Unlike conventional machining processes that rely on mechanical cutting forces, EDM removes material by means of spark erosion, making it highly suitable for machining hard materials and producing intricate geometries with superior precision. The working principle of EDM is based on the generation of repetitive electrical sparks between an electrode (tool) and the workpiece, both of which are immersed in a dielectric medium. When a voltage is applied across a small inter-electrode gap, the dielectric fluid undergoes ionization, leading to the formation of a plasma channel. This results in the generation of highfrequency electrical sparks, producing extremely high localized temperatures (approximately 8000–12,000°C). Consequently, a small portion of the material undergoes melting and vaporization. The eroded material is then flushed away by the dielectric fluid, enabling precise and controlled material removal. In the present study, Wire Cut EDM (WEDM) is utilized for the preparation of tensile test specimens from SS316L and SS430 plates. In this process, a thin conductive wire, typically made of brass, acts as the electrode and travels along a predefined path to cut the material. The machining operation is carried out in the presence of a dielectric medium, generally deionized water, which performs multiple functions such as cooling the machining zone, stabilizing spark generation, and removing debris particles. The tensile test specimens are prepared in a standardized "dog-bone" shape, which is widely adopted in mechanical testing. This geometry consists of enlarged ends for gripping and a reduced cross-sectional area at the center, known as the gauge section. The purpose of this design is to ensure uniform stress distribution during tensile loading and to localize deformation and fracture within the gauge region. This enables accurate measurement of mechanical properties such as tensile strength, yield strength, and elongation. The selection of EDM for specimen preparation is primarily attributed to its ability to achieve high dimensional accuracy, excellent surface finish, and precise reproduction of complex geometries such as the dog-bone profile. Furthermore, since there is no direct mechanical contact between the tool and the workpiece, the process eliminates cutting forces, thereby preventing distortion, residual stresses, and microstructural damage to the material. The performance and efficiency of the EDM process are governed by several process parameters, including discharge current, pulse duration, gap voltage, wire feed rate, and dielectric flushing conditions. Proper optimization and control of these parameters are essential to ensure consistent machining quality, dimensional accuracy, and repeatability. In this investigation, EDM is employed to machine the base materials into standardized tensile specimens with precise geometry and uniform cross-section. This ensures reliable and reproducible tensile testing results. Additionally, the process minimizes surface irregularities and preserves the intrinsic material properties, thereby enhancing the overall accuracy of experimental analysis. Thus, EDM serves as a highly effective and reliable machining technique in this research, playing a crucial role in the preparation of high-quality specimens required for welding and subsequent mechanical characterization.

Tensile Test :

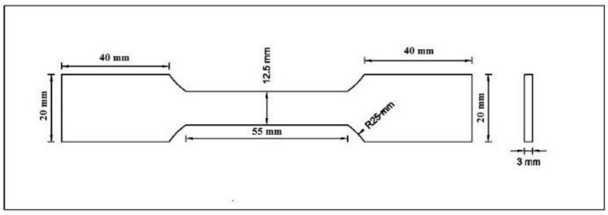

Fig 2: Standard Tensile Test Specimen (DogBone Shape) with Dimensions

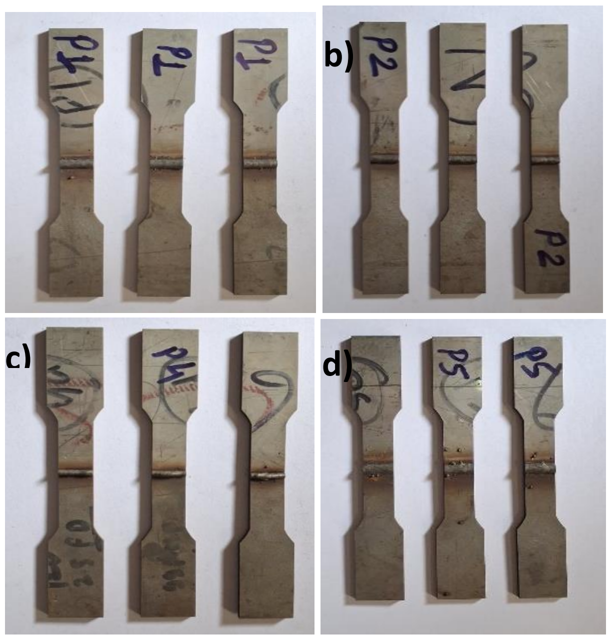

Fig 3: Wire Cut EDM Setup Used for Specimen Preparation

Fig 4: Fractured tensile sample

Methodology:

Phase 1: Data Pipeline and Feature Engineering.

1. Problem Definition: The objective is to develop a machine learning system capable of predicting the tensile strength of dissimilar metal welding (SS316L–SS430) based on input welding parameters. The ultimategoal is to identify optimal conditions that maximize strength while preventing defects caused by improper heat input.

2. Data Collection: Experimental data was gathered by testing various welding parameter combinations.Input Parameters: Voltage (V), Current (A), Travel Speed (mm/min), and Feed Rate.Output Parameter: Tensile Strength (MPa), measured using a Universal Testing Machine.

3. Data Preprocessing: The dataset was structured in CSV format and rigorously cleaned by :Removing redundant variables (e.g., time, where irrelevant).Addressing missing or incorrect values. Standardizing measurement units across all parameters.

4. Feature Engineering: To better capture the thermal effects of welding—which directly influence structural integrity new features were derived: • Heat Input: • Power: 5. Dataset Preparation Heat Input = V ×I ×60S ×1000Power = V ×I • Input Features: Voltage, Current, Travel Speed, Feed Rate, Heat Input, Power. • Target Variable: Tensile Strength (MPa). • Data Split: 80% Training Set, 20% Testing Set.

Phase 2: Model Development and Training

6. Model Selection: An XGBoost Regressor was selected for this task due to its: • Consistently high predictive accuracy. • Capability to interpret complex, non-linear relationships. • Robustness against overfitting on structured tabular data.

7. Model Training: The XGBoost algorithm waFZs trained on the 80% dataset. During this phase, the algorithm mapped the input features to the target variable, learning the underlying patterns between the physical welding parameters and the resulting tensile strength.

8. Model Evaluation: Performance was validated using standard regression metrics: • R2 Score: Assesses the accuracy of the prediction (a high score indicates strong model performance). • Mean Squared Error (MSE): Quantifies the average prediction error margin. Phase 3: Deployment and Application

9. Model Deployment: The trained machine learning model was serialized and saved as a .pkl file using joblib for seamless integration into the final application environment. 10. Graphical User Interface (GUI) A Streamlit-based web interface was developed to make the tool accessible. Core features include: • User input

10. Graphical User Interface (GUI): A Streamlit-based web interface was developed to make the tool accessible. Core features include: • User input fields for manual welding parameter entry. • Automatic background calculation of heat input and power. • Real-time prediction and display of tensile strength.

11. Result Analysis: The system automatically categorizes the generated heat input to assess structural risk:Heat Input Level Range Associated Risk / Outcome Low Optimal High0.35 kJ/mm Risk of grain growth

12. Expert Recommendation System: Dynamic, actionable feedback is provided based on the calculated heat zones: • Low Heat: Suggests increasing the current or voltage. • High Heat: Suggests reducing the overall heat input. • Optimal Heat: Confirms the ideal welding conditions.

13. Visualization & Output Generation: To enhance user interpretability and data export, the application provides: • Interactive visualizations, including a Heat Input vs. Tensile Strength curve and a Pa rameter Importance chart. • Comprehensive final readouts detailing the predicted tensile strength, calculated heat input, optimality indicators, and expert suggestions.

MACHINE LEARNING MODEL

This is an AI-based welding parameter optimization system. The user enters input parameters such as voltage, current, travel speed, and feed rate. The system then calculates the heat input and uses a trained machine learning model to predict the tensile strength of the weld. It also analyzes whether the heat input falls within the optimal 'sweet spot' range (0.25–0.35 kJ/mm). Based on this, the system provides real-time feedback and expert suggestions to improve welding quality. This helps reduce trial-and-error, saves time, and ensures better weld strength and efficiency.

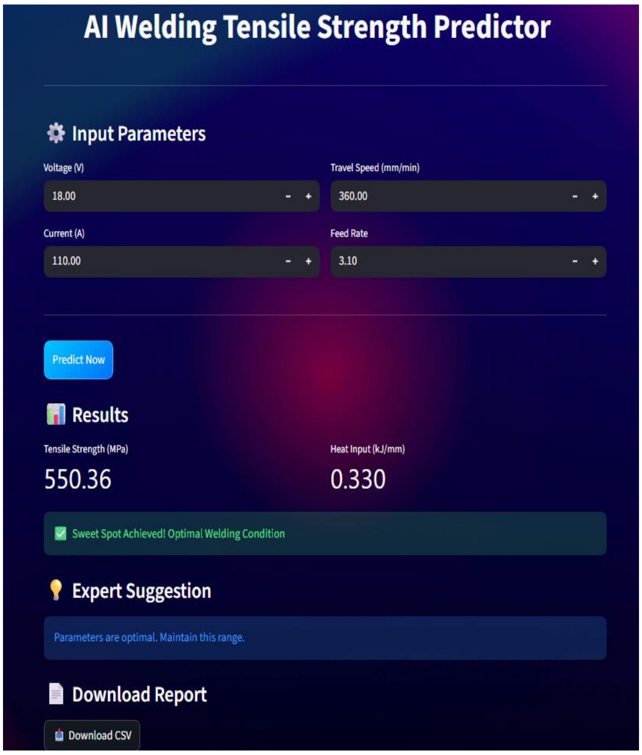

Fig 5. UI of Predict Tensile Strength

CONCLUSION

Conclusion The present study focuses on improving the quality of dissimilar welding between SS316L and SS430 stainless steels using MIG welding. The use of ER309L filler wire helps in achieving better compatibility between the two materials and enhances the mechanical performance of the weld joint. Experimental investigations show that welding parameters significantly influence tensile strength and penetration depth. A machine learning model based on the Random Forest algorithm is successfully developed to predict weld properties with good accuracy. The results confirm that maintaining heat input within an optimized range leads to improved weld quality and reduces defects such as cracking and distortion. The development of a Streamlit-based interface further simplifies the prediction process and supports quick decision-making. Overall, the integration of experimental analysis with machine learning provides an effective approach for welding parameter optimization. This method reduces dependency on trial-and error practices, saves time and cost, and ensures reliable weld performance. The proposed system can be useful in modern manufacturing environments, especially in automated and robotic welding applications.

ACKNOWLEDGMENT

We sincerely express our gratitude to our guide, faculty members, and institution for their valuable guidance and support. We also thank our team members for their cooperation and teamwork in successfully completing this project.

REFERENCES

[1] *Zhang, Y., Liu, H., & Chen, S. (2022). Intelligent design of robotic welding process parameters using learning-based methods. IEEE Access.*

[2] *Kumar, M., Singh, R., & Patel, D. (2025). Machine learning prediction and optimization of welding parameters for stainless steel joints. Journal of Materials Engineering and Performance.*

[3] *Shrivastava, S., Tiwari, P., & Sharma, A. (2020). Optimization of welding parameters in GMAW using multi-criteria decision methods. IOP Conference Series: Materials Science and Engineering.*

[4] *Nagesh, D. S., & Datta, G. L. (2002). Prediction of weld bead geometry and penetration using artificial neural networks. Journal of Materials Processing Technology.*

[5] *Xiong, J., Zhang, G., Hu, J., & Wu, L. (2014). Bead geometry prediction for robotic GMAW-based manufacturing. Journal of Intelligent Manufacturing.*

[6] *Kim, D., Park, J., & Lee, C. (2018). Effect of welding parameters on penetration depth and bead geometry in MIG welding. International Journal of Advanced Manufacturing Technology.*

[7] *Zhao, X., Wang, Y., & Li, Z. (2019). Effect of heat input on microstructure and tensile strength of stainless steel weld joints. Materials Science and Engineering.*

[8] *Singh, P., & Sharma, V. (2021). Dissimilar stainless steel welding using ER309L filler wire: Mechanical and metallurgical study. Materials Today: Proceedings.*

[9] *Gunaraj, V., & Murugan, N. (2000). Prediction and optimization of weld bead geometry and mechanical properties in arc welding. Journal of Materials Processing Technology.*

[10] *Le, V. T., & Paris, H. (2021). Experimental investigation of GMAW welding process parameters and mechanical properties. Journal of Manufacturing Processes.*

[11] *American Welding Society (AWS). (2020). Welding Handbook: Gas Metal Arc Welding (GMAW). AWS Publications.*

https://doi.org/10.46335/IJIES.2026.11.4.4 **e-ISSN: 2456-3463**
Vol. 11, No. 4, 2026, PP. 19-26

[12] *Lancaster, J. F. (1986). The Physics of Welding. Pergamon Press.*

[13] *Kou, S. (2003). Welding Metallurgy (2nd ed.). WileyInterscience.*

[14] *Lippold, J. C., & Kotecki, D. J. (2005). Welding Metallurgy and Weldability of Stainless Steels. Wiley.*

[15] *Davis, J. R. (1994). Stainless Steels. ASM International.*

[16] *ASTM E8/E8M-21. Standard test methods for tension testing of metallic materials. ASTM International*

[17] *ASTM A240/A240M. Standard specification for chromium and chromium-nickel stainless steel plate. ASTM International.*

[18] *AWS A5.9/A5.9M. Specification for bare stainless steel welding electrodes and rods. AWS.*

[19] *Murugan, N., & Parmar, R. S. (1994). Effects of MIG process parameters on weld bead geometry. Journal of Materials Processing Technology.*

[20] *Pal, S., & Pal, S. K. (2011). Prediction of weld bead geometry using artificial neural networks. International Journal of Advanced Manufacturing Technology*

[21] *Kanjilal, P., Pal, T. K., & Majumdar, S. K. (2006). Combined effect of flux and welding parameters on weld quality. Journal of Materials Processing Technology.*

[22] *Sathiya, P., & Abdul Jaleel, M. Y. (2010). Optimization of welding parameters using Taguchi technique. Journal of Materials Processing Technology.*

[23] *Elangovan, S., & Balasubramanian, V. (2008). Influences of welding parameters on tensile strength in friction welding. Materials & Design.*

[24] *Oliveira, J. P., et al. (2018). Dissimilar welding of stainless steels: A review. Metals Journal.*

[25] *DebRoy, T., et al. (2018). Additive manufacturing of metallic components – Process, structure, and properties. Progress in Materials Science.*

.