

Data-Driven Automation in Welding: Leveraging Advanced Machine Learning for Quality and Efficiency

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Abstract— Automation in manufacturing has played an important role in optimizing the welding process by attaining the utmost level of quality control with high operational efficiency. This paper analyzes 15,000 welding observations that belonged to the Hanthec organization. Through comparative analysis of SVM, MLP, and Decision Tree algorithms, our research establishes an effective machine learning framework for welding parameter optimization. The Decision Tree model obtained an excellent performance with the best accuracy of 80% and perfect recall. High correlations between power and thermal aspects as high as 0.96 have been obtained. The developed framework enables systematic parameter selection and demonstrates the potential for automated decision-making in industrial welding applications, contributing to improved manufacturing quality and reliability.

Keywords— artificial intelligence, machine learning, manufacturing, welding, automation

I. INTRODUCTION

In recent years, the manufacturing industry has seen a significant shift toward automation, driven by the need for enhanced operational efficiency and stringent quality control measures. Automation in welding processes is particularly crucial, as welding is a fundamental step in the production of a wide range of products, from automotive parts to structural components [1]. Traditional welding methods often face challenges in achieving uniformity and precision, which can lead to defects and costly rework. The integration of machine learning techniques into the welding process presents a compelling solution to these challenges, enabling manufacturers to optimize parameters and improve overall product quality [2].

Numerous studies have explored the application of machine learning in manufacturing, focusing on various aspects of process optimization. For example, research has demonstrated the effectiveness of algorithms like Support Vector Machines (SVM) and Neural Networks in predicting welding outcomes based on input parameters such as heat input, travel speed, and filler material composition. Furthermore, Decision Tree algorithms have been used for classification tasks, offering interpretable models that can aid

operators in making informed decisions about welding parameters [4,5].

To achieve high accuracy, our study highlights the strong correlations observed between welding power and thermal parameters, reaching as high as 0.96. Such insights not only enhance the understanding of the welding process but also pave the way for implementing systematic parameter selection in industrial settings. The developed framework represents a significant step toward automating decision-making in welding applications, ultimately contributing to improved manufacturing quality and reliability.

They applied advanced machine learning techniques in welding, CNC & MCT machine data [6,7]. A machine learning-based system for detecting weld porosity in 3.0 mm plates, using arc sound data from pulsed gas tungsten arc welding (P-GTAW) on 1.6 mm plates. By employing Ensemble-Empirical Mode Decomposition and Fast Fourier Transform for feature extraction, the model was validated through k-fold cross-validation and demonstrated strong F-1 scores in identifying porosity [8]. A deep learning approach using convolutional neural networks (CNNs) to automate TIG weld quality assessment, overcoming human limitations like subjectivity and fatigue. Trained on a Kaggle dataset, the model uses five convolutional and pooling layers, followed by three fully connected layers, to classify weld defects with high accuracy across six categories, showing dependable precision, recall, and F1-score metrics [9].

The study collected gas metal arc welding (GMAW) data, using Central Composite Design to capture diverse conditions, aiding in a robust predictive model. By analyzing welding arc and bead geometry images, deep learning detected drop detachment and short circuit modes, calculating related frequencies and molten volume. This data, along with input parameters, was used to build a comprehensive dataset for the GMAW process [10]. The authors addresses the shortage of skilled welders in shipbuilding by developing a machine learning-based evaluation framework to assess the performance of unskilled welders during training. Using data from high-skilled and unskilled welders, it identifies key parameters for effective training, aiming to optimize educational strategies and improve manual welding skills [11]. The study applies Convolutional Neural Networks (CNNs) to

predict the effectiveness of Friction Stir Welded joints by analyzing microstructure images. Using 3,000 training and 300 test images, the research investigates how AI-based methods can enhance mechanical and microstructural properties in welding.

Here are the key contributions from the abstract:

- The research establishes an effective machine learning framework for optimizing welding parameters by analyzing a substantial dataset of 15,000 welding observations.
- The study provides a comparative analysis of different machine learning algorithms, to determine the most effective method for automated grading in welding processes.
- The Decision Tree model achieved notable performance metrics, including accuracy and perfect recall, demonstrating its potential for real-world applications in manufacturing quality control.

II. METHHOD AND METARIALS

This section discusses machine learning models like SVM, MLP, and Decision Tree for classifying welding data. Data preprocessing and model optimization, including cross-validation and pruning, were applied, with the Decision Tree achieving the best performance.

A. Dataset

The experimental dataset provided by Hanthec organization, Korea, consists of 15,000 observations in welding processes with five important parameters: section of welding, 2.5m; specification of welding rod, 1.6mm; welding speed in the range of 200-500 mm/min; electrical current in the range of

200-380 amperes, and voltage ranges from 29 to 48 volts. Given that the data shows clear operational clusters in welding speeds (200-250, 330-350, and 450-500 mm/min), each with corresponding electrical parameters-current and voltage- and there are several measures with similar settings. This extensive data set enable the optimization of welding operations and the development of predictive models for quality control.

B. Data Preprocessing

The preprocessing involved comprehensive cleaning, scaling, and transforming data in the dataset to improve model results. Cleaning entailed standardizing column names and removing extra spaces, among other things. Data checks indicated completeness, while StandardScaler, RobustScaler, and MinMaxScaler were considered for scaling the distribution. The feature adjustments related to normality consideration included Power Transformer and boxcox1p, while selecting key predictive features was done through mutual information classification.

C. Description of Workflow

We implemented typical machine learning techniques, such as SVM, Decision Tree, and MLP, to various manufacturing classification problems. Each algorithm had something different: kernel transformation for complicated patterns in SVM, clear paths showing decisions with certain handling of data types in Decision Trees, and deeper patterns possible with weighted connections in MLP. These approaches were compared regarding their respective heterogeneity handling capabilities, understanding, interpretability, how well they could handle irregularities in the data, and scalability. MLP allowed deep pattern recognition based on weighted connections.

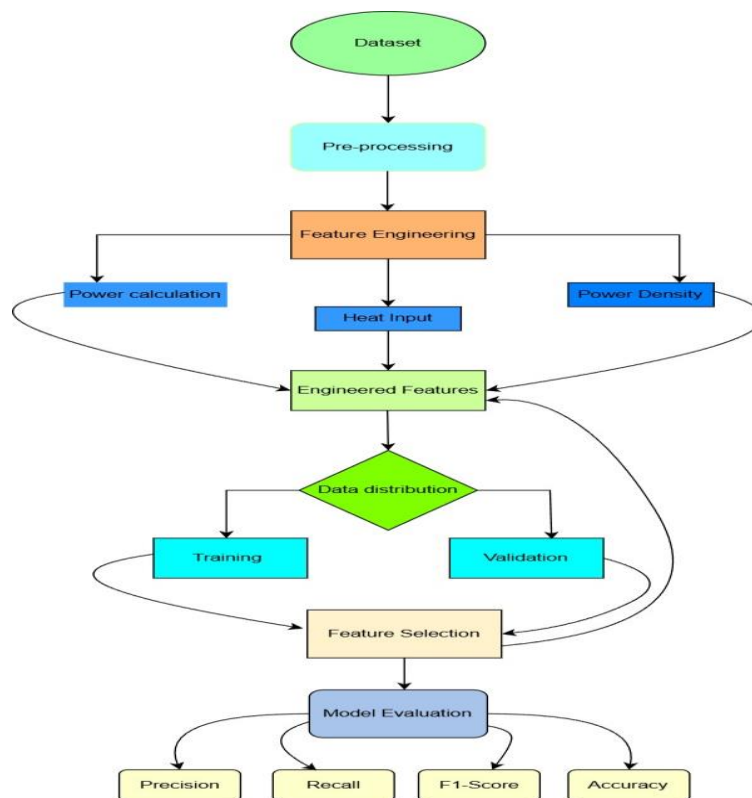


Figure 1. Machine Learning model workflow diagram

In the present study, we have implemented a decision tree model with a random seed of 42 for the consistency of different experiments. Further, it was enhanced with pruning strategies, which produced the best parameters concerning the tree structure and, at the same time, did not lead to overfitting using 5-fold cross-validation. We visualize the structure of the tree using visualization tools. Performance metrics measured-precision, recall, f1-score, and support concerning each category.

III. RESULTS AND DISCUSSION

This section depicted a high correlation between the power and thermal aspects in the welding process analysis. A decision tree system for mapping welding parameters to various material specifications was developed. Among the three machine learning models tested, the Decision Tree classifier performed better in terms of the highest accuracy with perfect recall, making it the best model for welding classification.

A. Correlation Matrix

The correlation matrix shows the great association of the manufactured power with the thermal parameters. Power strongly relates positively to heat input and density, with a

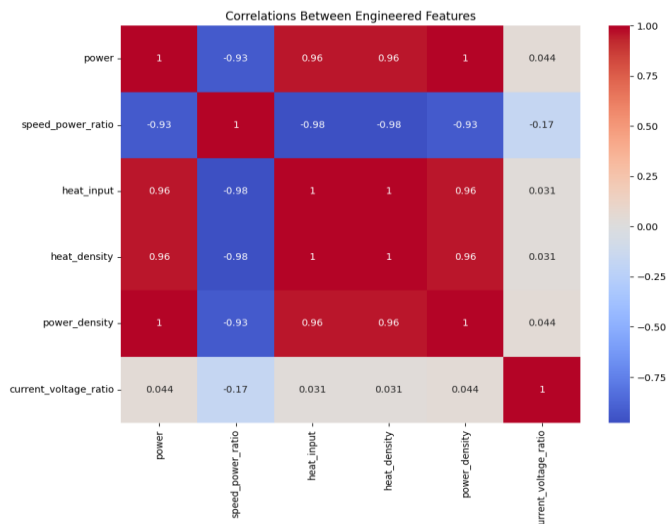


Figure 2. Correlation between after features engineering

correlation of $r = 0.96$ and a full correlation with power density, $r = 1.0$. Most of the parameters strongly negatively correlated with the speed-power ratio in the range of $r = -0.93$ and $r = -0.98$, showing consistent inverse relationships among the parameters under consideration. The heat input and density are perfectly correlated; both correlate with the same pattern to other features, $r = 1.0$. The current-to-voltage ratio is the only one that remains rather independent; its correlations, with all other parameters, were very weak: $|r| \leq 0.17$, indicating this parameter can be considered mostly autonomous in the system.

TABLE I. COMPARISON OF MACHINE LEARNING MODEL PERFORMANCE METRICS

Model	Precision	Recall	F1-score	Accuracy
Support Vector Machine	0.25	0.50	0.33	0.20
Multi-Layer Perceptron	0.60	1.00	0.80	0.60
Decision Tree	0.50	1.00	0.67	0.80

B. Welding Process

The decision tree diagram for the welding process systematically follows how to determine the best setting of welding parameters based on thickness and round type. It branches from categories of different thicknesses into specific settings, which are applied for each round type, namely First Round and Final Round. Each of them provides certain parameters concerning Feed Rate, Ampere, and Voltage settings; hence, it ensures proper welding configurations for all material thicknesses and phases of the welding process, thus resulting in consistent quality and performance in welding operations.

In this paper, we present a comparative analysis of machine learning models for the classification task. We evaluated three techniques in this work, namely Support Vector Machine, Multi-Layer Perceptron, and Decision Tree. Experimental results show quite huge differences in model performance for precision, recall, F1-score, and accuracy, ranging between 0.20 and 0.80. Among them, Decision Tree turned out to be the most effective classifier that attained the highest accuracy of 0.80 with perfect recall of 1.00 and, therefore, is the best suited for this classification task.

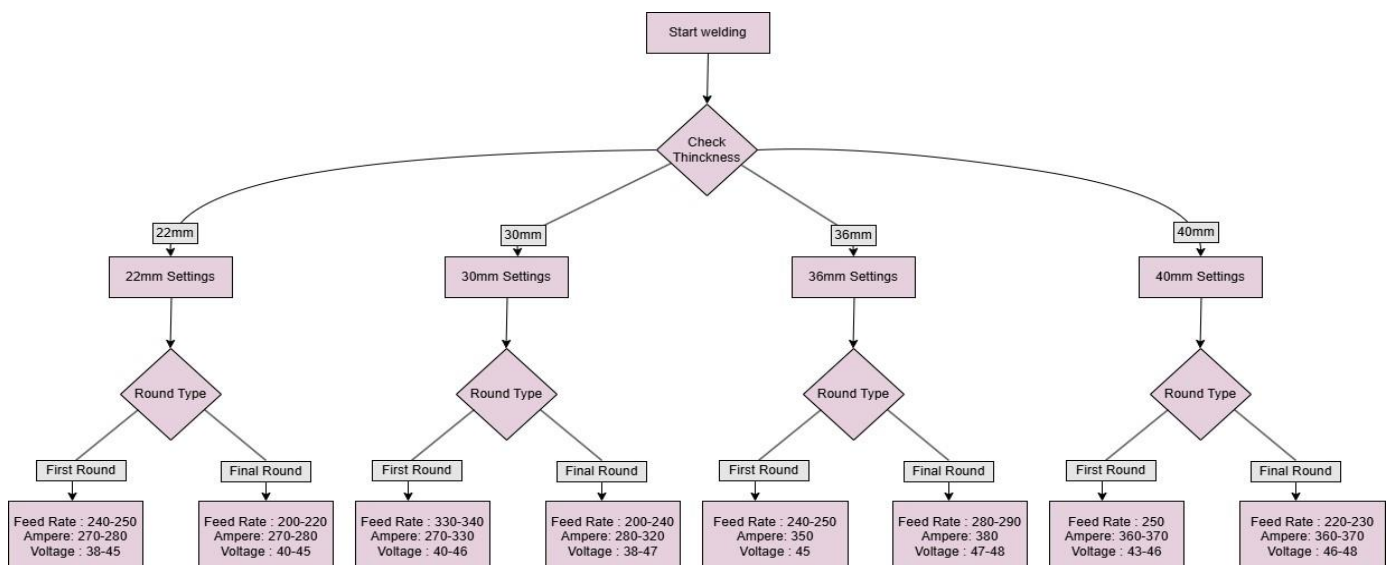


Figure 3. Welding Process Decision Tree

IV. CONCLUSION

In conclusion, this research developed an effective machine-learning framework for optimizing the welding process. The applied Decision Tree model has shown good predictive capability in classifying welding parameters with superior performance compared to conventional techniques. The established strong correlation between power and thermal features also assures a set of insights into parameter selection in industrial welding applications. This systematic way will enhance quality control in welding operations and set a foundation for automated decision-making in manufacturing processes toward improved efficiency and reliability in industrial welding applications.

Acknowledgment

This research was supported by a grant from Korea Health Technology R&D Project through the Korea Health Industry Development Institute validation (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (Grant No: HI21C0977) and the MSIT (Ministry of Science ICT), Korea, under the National Program for Excellence in SW, supervised by the IITP (Institute of Information & Communications Technology Planning & Evaluation) in 2022 (2022-0-01091, 1711175863).

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