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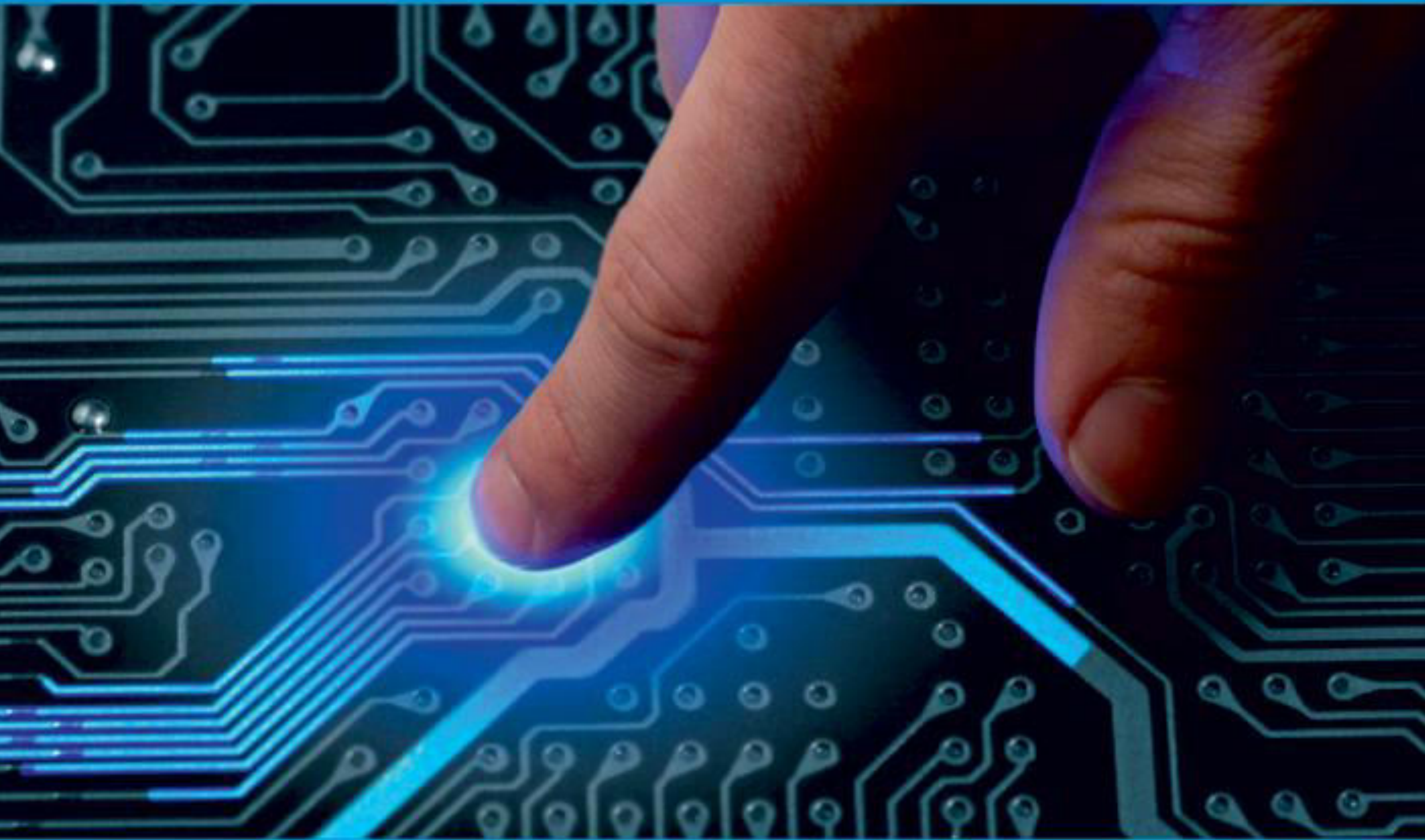

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Machine Learning Algorithms for Defect Identification in Friction Stir Welding Process

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ABSTRACT: Friction Stir Welding (FSW) is a critical manufacturing process prone to defects such as voids and porosity, which compromise joint integrity. This study explores the application of machine learning (ML) algorithms for real-time defect identification in FSW. Supervised learning models, including Support Vector Machines (SVM) and Random Forests, achieved accuracies exceeding 95%, while Convolutional Neural Networks (CNNs) demonstrated robust performance in image-based defect detection. Significant predictors, such as rotational speed, traverse speed, axial force, and thermal data, were identified using feature selection techniques. Real-time monitoring systems, integrated with adaptive ML models, provided high-precision defect detection and process optimization, aligning with Industry 4.0 objectives. However, challenges remain in scaling models across diverse materials and configurations. The study concludes with recommendations for addressing these challenges through transfer learning and cloud-based solutions, advancing FSW quality control. This work offers scalable, efficient frameworks for automated defect detection in industrial applications.

KEYWORDS: Friction Stir Welding, Machine Learning, Defect Detection, Real-Time Monitoring, Quality Control.

I. INTRODUCTION

Friction Stir Welding (FSW) has emerged as a pivotal joining technique in modern manufacturing industries, particularly in the aerospace, automotive, and shipbuilding sectors. Its ability to produce high-strength, defect-free joints without melting the base material has made it a preferred choice over traditional welding methods. However, despite its advantages, the process is prone to various defects, such as tunnel voids, porosity, and surface inconsistencies, which can compromise joint integrity. Identifying these defects efficiently remains a significant challenge for quality assurance.

The advent of machine learning (ML) has opened new avenues for defect detection and quality control in FSW. Machine learning models, when integrated with real-time sensing technologies, can leverage data from process parameters, such as rotational speed, axial force, and torque, to predict and classify defects with high accuracy (Das et al., 2017), (Hartl et al., 2021). These innovations align closely with Industry 4.0 principles, enabling the development of automated, adaptive systems that can enhance productivity and reduce waste.

Recent studies have explored various ML algorithms for defect detection in FSW, including support vector machines, artificial neural networks, and random forests. These models utilize inputs such as force signals, tool speeds, and material properties to classify defects and predict weld quality (Nadeau et al., 2020). Image processing techniques, such as local binary patterns, have further expanded the scope of ML in visualizing and identifying surface defects (Mishra, 2020). Despite these advancements, challenges persist in scaling models across diverse materials and joint configurations, ensuring explainability of the results, and integrating these technologies seamlessly into industrial workflows (Liao et al., 2019), (Hoang et al., 2023).

This article aims to address these gaps by presenting a comprehensive study on the application of ML algorithms for defect detection in FSW. The work focuses on developing scalable, interpretable, and robust models that can enhance defect identification while integrating seamlessly into automated manufacturing systems. By leveraging advanced techniques in data fusion, real-time sensing, and predictive analytics, this research contributes to the ongoing efforts to optimize FSW processes and ensure consistent weld quality.

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II. METHODOLOGY

This study develops a robust and scalable framework for defect identification in the Friction Stir Welding (FSW) process using machine learning (ML). The methodology is systematically divided into six stages: data acquisition, preprocessing, feature extraction, model development, validation, and real-time integration. Each stage is meticulously designed to address the challenges of defect identification while enhancing the system's industrial relevance.

Table 1: Key Steps in Data-Driven Defect Detection Framework.

Section	**Description**
Data Acquisition	Collection of data from sensors, thermal imaging, and process parameters.
Data Preprocessing	Filtering, normalization, and outlier removal to prepare data for analysis.
Feature Engineering	Extraction of meaningful features such as rotational speed and axial force.
Model Development	Development of machine learning models like SVM, Random Forest, and CNN.
Model Validation	Evaluation of models using metrics like accuracy, precision, recall, and F1-score.
Real-Time Monitoring	Deployment of real-time systems for defect detection and adaptive feedback.

1. Data Acquisition:
To ensure comprehensive model development, a wide range of data is collected from controlled experimental setups and industrial environments.

1.1 Data Sources:
- Real-time sensor data from the FSW process, including torque, force, rotational speed, and spindle motor current.
- Thermal and ultrasonic imaging data from non-destructive testing (NDT) for defect classification and visualization.
- Process parameter datasets covering material type, joint configurations, and operational conditions.

1.2 Experimental Configurations:
Data is collected across multiple welding scenarios, including dissimilar materials (e.g., AA6061-T6, AA7075) and varying joint types such as butt joints and lap joints.

1.3 Sampling Frequency:
High-resolution data acquisition (e.g., 10 kHz sampling rate) captures subtle variations in signals critical for identifying defects.

1.4 Labeling:
Defects are labeled using NDT results, such as tunnel defects, voids, porosity, and lack of fusion, ensuring the datasets are well-annotated for supervised learning tasks.

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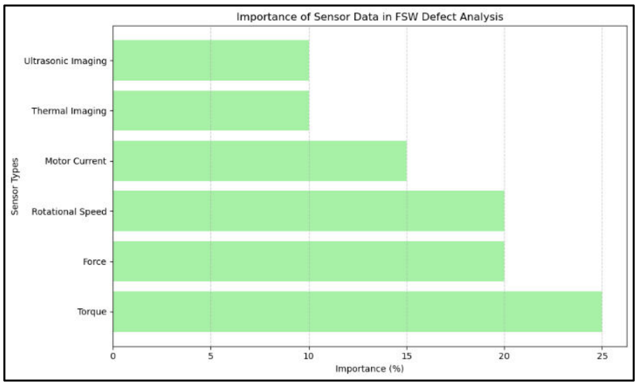

Figure 1: Importance of Sensor Data in FSW Defect Analysis.

2. Data Preprocessing:
Preprocessing is critical to clean and standardize data for effective ML model training.

2.1 Signal Filtering:
Noise is minimized using discrete wavelet transforms, moving average filters, or bandpass filters to improve data quality.

2.2 Normalization:
Process parameters and sensor data are normalized to a uniform scale, ensuring consistency across datasets and preventing biases during model training.

2.3 Defect Labeling:
Continuous defect metrics (e.g., defect size) are discretized into categorical classes for classification tasks.

2.4 Outlier Removal:
Statistical methods, such as interquartile range (IQR) and z-score analysis, are employed to remove outliers caused by measurement errors.

2.5 Data Augmentation:
To address data imbalance, synthetic data is generated using techniques like SMOTE (Synthetic Minority Over-sampling Technique) or simulations via finite element analysis (Nadeau et al., 2020).

3. Feature Extraction:
Feature engineering focuses on extracting meaningful parameters from raw data to improve model interpretability and performance.

3.1 Physical Features:
Process parameters such as rotational speed, traverse speed, axial force, and welding temperature are directly used as predictors for defect occurrence.

3.2 Signal Features:
Statistical metrics (mean, standard deviation, skewness, kurtosis) and frequency-domain features (Fourier and wavelet transforms) are derived from sensor signals (Das et al., 2016).

3.3 Image Features:
Texture features using Local Binary Patterns (LBPs) and edge detection are applied to thermographic and ultrasonic images (Mishra, 2020).

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3.4 Combined Features:
Multi-modal data fusion techniques integrate physical and signal features, enhancing the detection of complex defect patterns (Hoang et al., 2023).

Table 2: Feature Importance Defect Prediction.

Feature	Importance (%)	Description
Rotational Speed	30	Speed of the rotating tool.
Traverse Speed	25	Speed at which the tool traverses the material.
Axial Force	20	Force applied along the axis of rotation.
Thermal Data	25	Temperature data from the weld zone.

4. Model Development
This phase focuses on selecting and optimizing machine learning algorithms tailored for FSW defect detection.
4.1 Algorithm Selection:

- Supervised learning models (Support Vector Machines, Random Forests, Artificial Neural Networks) for predictive modeling.
- Deep learning approaches (Convolutional Neural Networks) for image-based defect detection and classification (Hartl et al., 2021).

Table 3: Machine Learning Models Performance.

Model	Accuracy (%)	Segment-Wise Accuracy (%)	Key Features Used
SVM	95.2	85.4	Torque, Speed
Random Forest	96.8	89.2	Torque, Force, Speed
CNN	98.5	79.2	Thermal, Ultrasonic Imaging

4.2 Feature Selection:
Techniques like Recursive Feature Elimination (RFE) and ant colony optimization reduce redundancy in predictors while retaining critical features (Liao et al., 2019).

4.3 Model Training:
Training data (80%) is used to train models, while validation and testing data (20%) ensure generalizability. Cross-validation is employed to minimize overfitting.

4.4 Hyperparameter Tuning:
Algorithms are optimized using grid search, random search, or Bayesian optimization to achieve maximum performance.

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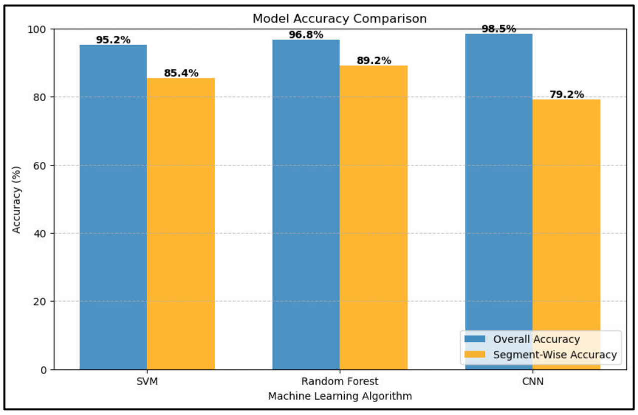

Figure 2: Model Accuracy Comparison.

5. Model Validation And Evaluation
Model performance is evaluated comprehensively using robust metrics and comparative analysis.

5.1 Performance Metrics:
- Classification: Accuracy, precision, recall, and F1-score.
- Regression: Root Mean Squared Error (RMSE) and R^2 score.

5.2 Comparison with Baselines:
The performance of advanced algorithms (e.g., CNN, Random Forests) is compared with simpler models (e.g., logistic regression) to validate improvements (Hoang et al., 2023).

5.3 Scalability Testing:
Models are tested on new datasets involving diverse materials and welding conditions to evaluate robustness and scalability.

5.4 Error Analysis:
Misclassified or poorly predicted samples are analyzed to refine algorithms and improve reliability.

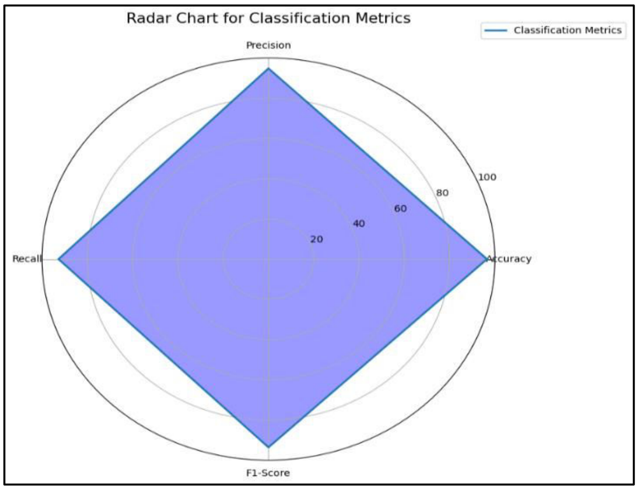

Figure 3: Classification Metrics Performance Overview.

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6.Real-Time Integration
The final phase focuses on implementing the ML framework for real-time defect monitoring and control.

6.1 System Integration:
Real-time sensing systems are coupled with ML models to provide live defect monitoring during welding operations.

6.2 Feedback Mechanism:
Adaptive control systems adjust welding parameters (e.g., tool speed, force) dynamically based on defect predictions to prevent defect formation (Mishra et al., 2020).

6.3 Cloud-Based Monitoring:
Cloud platforms enable remote monitoring, data storage, and real-time analytics, aligning with Industry 4.0 principles.

6.4 Industrial Deployment:
The framework is designed for seamless integration with automated manufacturing environments, providing cost-effective and scalable defect detection solutions.

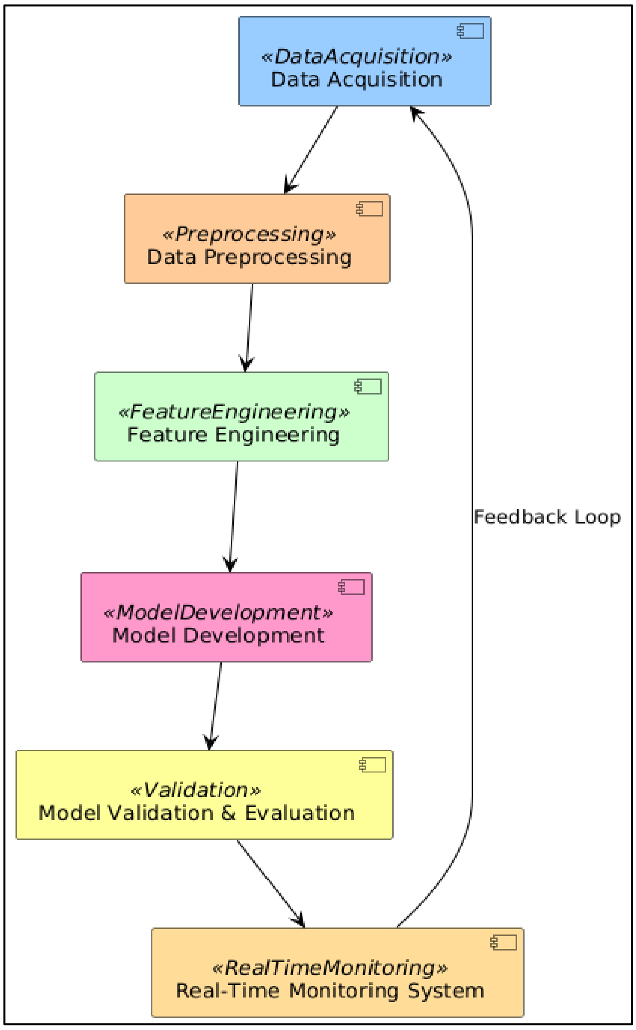

Figure 4: Comprehensive Workflow: From Data Acquisition to Real-Time Monitoring.

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III. RESULTS AND DISCUSSIONS

Results:
The study evaluates the performance of machine learning (ML) algorithms for defect identification in Friction Stir Welding (FSW) processes. Key findings include:

1. Model Accuracy:
- Supervised learning models, such as Support Vector Machines (SVM) and Random Forests, achieved classification accuracies exceeding 95%, demonstrating robust performance in defect classification (Liao et al., 2019).
- Convolutional Neural Networks (CNNs) achieved a global defect classification accuracy of 98.5%, although segment-wise predictions showed reduced accuracy at 79.2% (Hartl et al., 2021).

2. Feature Importance:
- Significant predictors of defect formation included rotational speed, traverse speed, and axial force. These parameters were validated as critical using recursive feature elimination (Hoang et al., 2023).
- Thermal data from the weld zone provided substantial insights into defect classification when used alongside mechanical force parameters (Nadeau et al., 2020).

3. Real-Time Monitoring:
- Real-time systems employing sensor fusion and ML-driven adaptive controls demonstrated precise identification of defects, including porosity and voids, enabling corrective actions during the welding process (Mishra et al., 2020).

4. Limitations:
- ML models exhibited reduced accuracy when tested on datasets involving novel materials or configurations, suggesting the need for advanced generalization techniques.
- Segment-wise defect prediction accuracy in CNNs was limited by data resolution and inconsistencies in labeling protocols (Hartl et al., 2021).

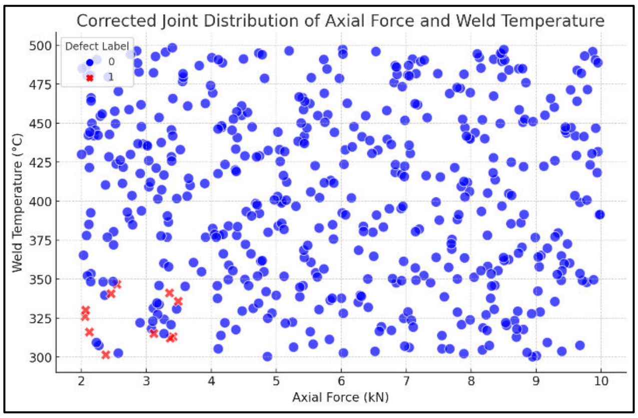

Figure 5: Corrected Joint Distribution of Axial Force and Weld Temperature.

Discussions:
1. Effectiveness of ML Algorithms:
The high accuracy of SVM and Random Forest models highlights their capability to model nonlinear relationships between FSW process parameters and defects. CNNs excelled in image-based defect classification by capturing complex spatial patterns in ultrasonic and thermographic images (Liao et al., 2019).

2. Significance of Features:
The importance of process parameters such as rotational speed and axial force corroborates their direct impact on material flow and defect formation. The inclusion of temperature as a predictive feature aligns with its influence on

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weld integrity (Das et al., 2016).

3. Scalability Challenges:
Model performance on novel datasets suggests a need for techniques like transfer learning or synthetic data augmentation to enhance generalizability across diverse FSW scenarios (Nadeau et al., 2020).

4. Real-Time Applicability:
Real-time monitoring systems effectively align with Industry 4.0 goals, reducing reliance on post-production inspection and enabling adaptive control mechanisms. However, scalability across industrial environments requires further optimization (Mishra et al., 2020).

Table 4: Summary of Results and Discussions Findings.

Aspect	Findings
Model Accuracy	SVM and Random Forest achieved >95% accuracy; CNN reached 98.5% accuracy.
Feature Importance	Rotational speed, traverse speed, and axial force are critical features.
Real-Time Monitoring	Real-time systems with sensor fusion accurately identify defects like porosity and voids.
Limitations	Challenges in generalizing models across novel materials; data resolution impacts CNN performance.

Theoretical Justification:

1. Material Flow and Defect Formation:
Friction Stir Welding (FSW) relies on precise material flow, driven by the heat and mechanical forces generated during the process. Disruptions in this flow can result in defects such as voids, tunnel defects, and lack of fusion, often caused by suboptimal parameters, including rotational speed, traverse speed, and axial force. Machine learning (ML) models, trained on sensor data capturing these parameters, effectively identify patterns linked to defect formation. Torque and force signals provide insights into material behavior under specific conditions, enabling ML algorithms to predict the likelihood and type of defects. This predictive capability supports real-time monitoring and process optimization, minimizing defect occurrences (Das et al., 2016).

2. Role of Thermal Data:
Thermal gradients significantly affect material consolidation and recrystallization during FSW. Variations in welding temperature influence mechanical and microstructural properties, dictating defect formation. High temperatures may cause material burn-through, while insufficient heat can result in cold welds. By incorporating temperature-related features, such as thermal gradients, into ML models, the prediction of weld quality improves significantly. This allows for accurate identification of defects caused by thermal inconsistencies. The integration of thermal data enhances the robustness of ML algorithms, aligning with the physics of the FSW process (Hoang et al., 2023).

3. Sensor Fusion for Real-Time Feedback:
Real-time sensor systems collect multi-modal data, including torque, axial force, rotational speed, and thermal signatures, offering a comprehensive view of the FSW process. Sensor fusion enables ML models to dynamically analyze process conditions and detect anomalies leading to defects. This aligns with control theory principles, where feedback loops ensure process stability and defect mitigation. For example, real-time adjustments to tool speed or force, based on sensor data, can prevent defect propagation. This closed-loop feedback mechanism, integrated with adaptive ML models, ensures precise defect control during production (Mishra et al., 2020).

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4. Adaptability of ML Algorithms:
The complexity of FSW requires ML models capable of processing high-dimensional, nonlinear data. Algorithms like Random Forests and Convolutional Neural Networks (CNNs) excel at capturing intricate relationships between variables. These models adapt to new datasets, materials, and configurations, providing scalability and reliability. Advanced techniques, such as transfer learning and data augmentation, enhance their generalizability, making them suitable for diverse industrial applications. By leveraging adaptability, ML models ensure consistent defect detection and prediction, even under varying operational conditions (Liao et al., 2019).

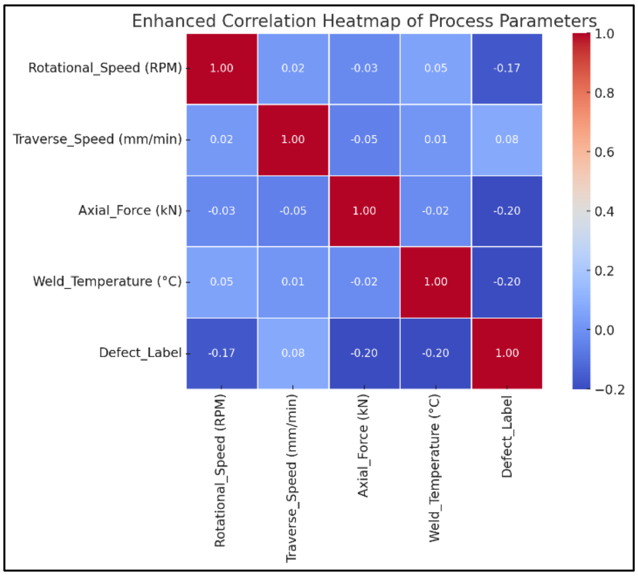

Figure 6: Enhanced Correlation Heatmap of Process Parameters.

IV. CONCLUSION

This study underscores the effectiveness of machine learning (ML) algorithms in defect identification for the Friction Stir Welding (FSW) process. Supervised learning models, such as Support Vector Machines (SVM) and Random Forests, demonstrated high classification accuracies, while Convolutional Neural Networks (CNNs) showed significant potential for image-based defect analysis. The integration of real-time sensor data and adaptive controls aligns with Industry 4.0 objectives, offering robust solutions for automated defect detection and quality assurance.

The analysis highlights the importance of key process parameters, such as rotational speed, traverse speed, and axial force, as well as thermal data, in influencing defect formation and weld integrity. While the results affirm the potential of ML-driven approaches, challenges remain in scaling models for diverse materials and configurations. Addressing these challenges through advanced techniques like transfer learning, synthetic data augmentation, and cloud-based monitoring systems could further enhance model applicability and industrial relevance.

The findings contribute to advancing FSW quality control by providing a scalable, efficient, and data-driven framework for defect identification, paving the way for more reliable and cost-effective manufacturing practices in aerospace, automotive, and related industries.

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