Materials, Structures and Reliability
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Forecasting Defect Classification in Pressure Vessel Welds with Nondestructive Testing Indicators

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Abstract

The structural integrity of pressure vessels is critical for maintaining safety and operational efficiency across various industrial sectors, including chemical processing, energy generation, and aerospace. Welding processes, while essential for the fabrication of these vessels, inherently introduce anomalies that can compromise structural stability. This paper presents a comprehensive investigation into predicting defect classification from nondestructive testing indicators using advanced experimental analysis in pressure vessel welds. By employing a rigorous methodology that integrates ultrasonic testing signal acquisition with machine learning classification algorithms, this study aims to transition defect evaluation from subjective human interpretation to objective, data-driven analysis. Experimental specimens containing artificially induced, well-characterized defects such as porosity, slag inclusion, lack of fusion, and cracks were subjected to exhaustive automated scanning. The extracted nondestructive testing indicators, encompassing time-domain, frequency-domain, and time-frequency domain features, were analyzed to determine their predictive power. The results demonstrate that specific combinations of signal features significantly enhance the discriminatory capability of classification models, leading to high diagnostic accuracy. Furthermore, this research elucidates the physical correlations between defect morphology and acoustic wave propagation characteristics, providing a robust theoretical foundation for the observed statistical trends. The findings offer profound implications for automated quality assurance systems, promising improved reliability and reduced downtime in industrial applications.

Keywords: Nondestructive Testing; Defect Classification; Pressure Vessels; Experimental Analysis; Pressure Vessel Welds

1. Introduction

1.1 Background of Pressure Vessel Welds

Pressure vessels are engineered containers designed to hold gases or liquids at a pressure substantially different from the ambient pressure. These structures are ubiquitous in modern industry, serving as the foundational infrastructure for petrochemical refineries, nuclear reactors, aerospace propulsion systems, and widespread manufacturing processes. The operational demands placed upon pressure vessels require them to withstand extreme mechanical loads, thermal cycling, and highly corrosive environments. Consequently, the fabrication of these vessels is governed by stringent engineering standards and regulatory codes. Central to the construction of pressure vessels is the welding process, which joins massive metallic components to form a continuous, pressurized boundary. However, welding is a highly complex thermomechanical process involving rapid heating, localized melting, and subsequent rapid cooling. This violent thermal cycle inevitably induces residual stresses and microstructural transformations within the heat-affected zone. More critically, variations in welding parameters, environmental conditions, or operator proficiency can lead to the formation of macroscopic discontinuities within the weld seam. These discontinuities, universally referred to as defects or flaws, act as localized stress concentrators. Under cyclic loading or high operational pressure, these stress concentrators can initiate microcracks that propagate and ultimately lead to catastrophic structural failure, resulting in severe environmental damage, economic loss, and potential loss of human life. Therefore, ensuring the absolute integrity of pressure vessel welds through rigorous inspection is a paramount engineering imperative [1].

1.2 Motivation for Nondestructive Testing

To mitigate the risks associated with welding defects, industries rely heavily on nondestructive testing methodologies. Nondestructive testing encompasses a wide array of analysis techniques used in science and technology to evaluate the properties of a material, component, or system without causing damage. Unlike destructive testing, which involves sacrificing a representative sample, nondestructive testing allows for the complete volumetric or surface inspection of the actual component intended for service. In the context of pressure vessel welds, ultrasonic testing, radiographic testing, magnetic particle testing, and liquid penetrant testing are the primary modalities employed. Among these, ultrasonic testing has emerged as the most versatile and widely utilized method for volumetric inspection due to its deep penetration capability, high sensitivity to planar defects such as cracks and lack of fusion, and inherently safe nature compared to ionizing radiation [2]. Traditional ultrasonic testing relies on a trained human operator who maneuvers a transducer over the component surface, observes the reflected acoustic echoes on an oscilloscope-like display, and interprets these signals based on their amplitude, time of flight, and spatial distribution. This manual approach, while historically effective, is heavily dependent on the subjective experience, fatigue level, and cognitive bias of the inspector. As the complexity of pressure vessels increases and the demand for higher throughput and reliability intensifies, the limitations of manual interpretation become increasingly apparent. The modern industrial paradigm necessitates a transition toward automated, quantitative, and highly repeatable defect evaluation systems. This transition is motivated by the need to not only detect the presence of a defect but to accurately classify its morphological type, as different defect types possess drastically different criticalities and fracture mechanics implications. The integration of advanced signal processing and predictive modeling with nondestructive testing indicators represents the most promising frontier in addressing these critical challenges [3].

2. Literature Review and Theoretical Background

2.1 Evolution of Nondestructive Testing Techniques

The historical trajectory of nondestructive testing for weld inspection has been characterized by a continuous pursuit of higher resolution, greater reliability, and reduced operator dependency. Early implementations of ultrasonic inspection utilized simple pulse-echo configurations, where a single piezoelectric element generated acoustic waves and recorded the returning echoes. The resulting signals, known as A-scans, provided a one-dimensional representation of the acoustic interfaces within the material. While foundational, this technique required immense cognitive effort from the inspector to build a mental three-dimensional model of the weld volume. The advent of mechanized scanning systems allowed for the automated recording of spatial coordinates alongside the ultrasonic signals, enabling the generation of B-scans and C-scans, which provided cross-sectional and plan-view imaging, respectively. A significant milestone in the evolution of nondestructive testing was the development of phased array ultrasonic testing [4]. Phased array systems utilize multi-element transducers wherein each element is independently pulsed with precise microsecond timing delays. This electronic manipulation of the acoustic wavefront allows for dynamic beam steering, focusing, and sweeping across multiple angles without physically moving the probe. The resulting sectorial scans provide highly detailed images of the weld interior, significantly enhancing the probability of detection for complex, irregularly oriented flaws. Parallel to advancements in ultrasonics, other modalities such as time of flight diffraction have been developed. Time of flight diffraction relies on the diffraction of acoustic waves from the extremely sharp extremities of a defect, rather than specular reflection from the defect body. This physical phenomenon makes time of flight diffraction exceptionally accurate for determining the precise depth and vertical extent of a flaw, though it traditionally struggles with resolving near-surface anomalies and determining the specific morphological type of the defect [5]. Furthermore, digital radiography has largely replaced conventional film radiography, offering immediate image acquisition, wide dynamic range, and the ability to apply digital image enhancement algorithms. Despite these hardware and imaging advancements, the fundamental bottleneck remains the interpretation of the vast quantities of complex data generated by these high-resolution systems [6]. The morphological classification of defects still largely hinges on human expertise to differentiate the subtle acoustic signatures of a volumetric porosity from a planar crack.

2.2 Machine Learning in Defect Classification

The exponential growth in computational power and the maturation of artificial intelligence algorithms have catalyzed a paradigm shift in nondestructive testing data analysis. The application of machine learning to defect classification aims to establish a mathematically rigorous, reproducible mapping between the quantitative indicators extracted from nondestructive testing signals and the true physical class of the underlying defect. Early attempts at automated classification relied on classical statistical pattern recognition techniques, which necessitated the manual engineering of features based on established physical intuition. Researchers extracted simple time-domain metrics, such as peak amplitude, signal duration, and rise time, and utilized fundamental classifiers like k-nearest neighbors or basic linear discriminant analysis. However, the highly non-stationary and non-linear nature of ultrasonic signals propagating through inhomogeneous welded materials severely limited the generalizability of these early models. As the field progressed, more sophisticated feature extraction paradigms were introduced, drawing heavily from the domains of speech recognition and seismic signal processing. The application of the fast Fourier transform enabled researchers to analyze the spectral content of defect echoes, revealing that different defect morphologies alter the frequency distribution of the reflected wave in distinct ways. For instance, rough, multifaceted defects tend to scatter high-frequency components more aggressively than smooth, spherical defects [7]. To capture the transient characteristics of the signals, time-frequency analysis methods, notably the continuous wavelet transform and wavelet packet decomposition, were subsequently integrated. These advanced mathematical frameworks provide a comprehensive representation of how the spectral energy of the signal evolves over time, offering a rich set of indicators that are highly sensitive to subtle morphological variations. Concurrently, the classification algorithms evolved from simple linear models to highly complex, non-linear architectures such as support vector machines, random forests, and multilayer perceptrons. Support vector machines, operating through the mechanism of projecting features into high-dimensional hyperplanes to find optimal decision boundaries, have shown remarkable robustness in handling the high-dimensional feature spaces typical of nondestructive testing data. More recently, the advent of deep learning, particularly convolutional neural networks, has sparked immense interest in the field. Deep learning models possess the theoretical capability to automatically discover hierarchical feature representations directly from raw signal data, potentially bypassing the need for manual feature engineering. However, the application of deep learning in industrial nondestructive testing is frequently constrained by the sheer volume of precisely annotated, balanced training data required to prevent model overfitting, a persistent challenge in environments where critical defects are, by design, exceedingly rare. Therefore, hybrid approaches that combine robust, physically interpretable engineered features with advanced statistical learning models continue to represent the most pragmatic and reliable methodology for industrial deployment.

3. Experimental Methodology and Analysis Design

3.1 Specimen Preparation and Data Acquisition

The foundation of this predictive classification study rests upon a meticulously designed and executed experimental protocol, intended to simulate the complex realities of industrial pressure vessel fabrication while maintaining strict control over experimental variables. A series of representative test specimens were fabricated using high-strength low-alloy steel plates, a material commonly specified for heavy-duty pressure vessel applications due to its excellent combination of tensile strength, toughness, and weldability. The plates, measuring thirty millimeters in thickness, were prepared with a standard single-V bevel geometry to accommodate multi-pass welding procedures. To ensure the generation of a comprehensive and balanced dataset, the welding process was deliberately manipulated by certified welding engineers to artificially induce specific categories of macroscopic defects. The targeted defect classes included porosity, slag inclusion, lack of fusion, and solidification cracks, alongside control regions representing completely flawless, pristine weld metal.

Porosity was induced by systematically reducing the flow rate of the inert shielding gas during the gas tungsten arc welding passes, allowing atmospheric contamination to become entrapped within the solidifying molten pool. Slag inclusions were generated during submerged arc welding passes by intentionally neglecting the inter-pass cleaning procedures, thereby trapping the protective flux residue beneath subsequent layers of weld metal. Lack of fusion defects, characterized by a failure of the weld metal to metallurgically bond with the underlying base material or adjacent weld beads, were created by drastically reducing the heat input and utilizing an inappropriate, off-center torch angle. Finally, extreme restraint conditions combined with the introduction of trace copper contaminants into the weld pool were utilized to promote the formation of sharp, planar solidification cracks. Following fabrication, the precise internal morphology, spatial location, and volumetric dimensions of every induced defect were definitively validated and mapped using high-energy industrial micro-computed tomography, establishing an absolute, unequivocal ground truth for the subsequent classification algorithms.

Table 1: Experimental Welding Parameters for Defect Induction

Defect Class	Welding Process	Voltage (V)	Current (A)	Travel Speed (mm/s)	Specific Manipulation
Pristine	SAW	30.0	450	8.0	Optimal standard parameters
Porosity	GTAW	15.5	180	3.5	Shielding gas flow reduced by 70%
Slag Inclusion	SAW	28.5	400	8.5	Omission of inter-pass slag removal
Lack of Fusion	GMAW	19.0	150	12.0	High speed, low heat, improper angle
Crack	SAW	32.0	500	6.0	High restraint, contaminant introduced

Following the exhaustive validation of the specimens, the nondestructive testing data acquisition phase was initiated. The experimental setup utilized a state-of-the-art automated immersion ultrasonic testing system. Immersion testing, wherein the specimen and the transducer are submerged in a coupling fluid, typically deionized water, ensures perfectly consistent acoustic coupling and completely eliminates the highly variable contact pressure issues associated with manual inspection [8]. A high-frequency, broadband, unfocused immersion transducer with a central frequency of five megahertz was selected to provide an optimal balance between spatial resolution and acoustic penetration depth.

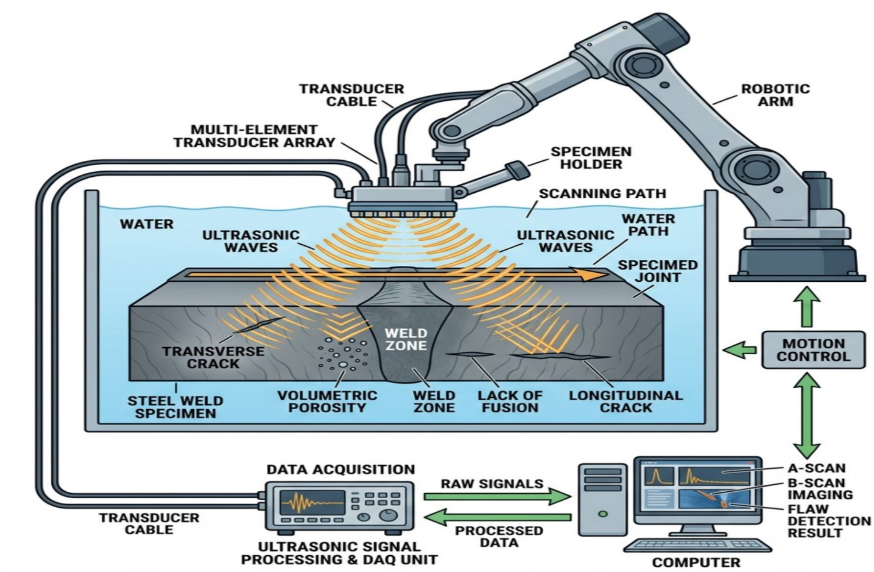

Figure 1: Comprehensive Schematic of the Automated Immersion Ultrasonic Scanning Apparatus

The automated robotic manipulator was programmed to execute a rigorous raster scanning pattern over the entire surface area of the welded specimens, utilizing extremely fine spatial increments of zero point five millimeters in both the longitudinal and transverse directions. The ultrasonic pulser-receiver unit was configured to digitize the returning radio-frequency waveforms at a high sampling rate of one hundred megahertz, ensuring that all high-frequency transient components of the defect echoes were faithfully captured without aliasing. Thousands of individual A-scan signals were recorded, precisely correlated with their spatial coordinates, and securely stored in an uncompressed digital format for offline analysis.

3.2 Feature Extraction and Selection Framework

The raw, digitized ultrasonic A-scan signals inherently contain a massive amount of highly complex, oscillatory data, much of which constitutes structural noise arising from the granular microstructure of the steel base material. Feeding this raw, high-dimensional data directly into standard classification algorithms typically results in severe computational inefficiency and poor generalization. Therefore, a robust feature extraction framework was implemented to distill the raw waveforms into a compact set of highly descriptive nondestructive testing indicators. This extraction process was methodically divided into three distinct analytical domains: time-domain, frequency-domain, and time-frequency domain [9].

In the time domain, the analysis focused on the geometric envelope of the reflected defect echo. The absolute signal envelope was calculated using the Hilbert transform, allowing for the extraction of straightforward yet vital indicators. These included the maximum peak amplitude, which generally correlates with the overall reflective cross-sectional area of the flaw. The signal duration, measured at various threshold levels below the peak amplitude, was extracted to indicate the physical depth and volumetric extent of the defect. The rise time, representing the interval from the initial signal onset to the peak amplitude, and the fall time were also calculated, as sharp, planar defects like cracks typically exhibit significantly faster rise times compared to rounded, volumetric defects like porosity. Furthermore, statistical moments of the time-domain envelope, specifically variance, skewness, and kurtosis, were computed to quantify the fundamental shape and temporal distribution of the acoustic energy.

The frequency-domain analysis involved transforming the time-domain signals into their corresponding spectral representations using the discrete Fourier transform. Understanding the frequency response is crucial because the interaction of an acoustic wave with a defect acts as a complex mechanical filter. Indicators extracted from the magnitude spectrum included the central frequency, the peak frequency, and the upper and lower boundary frequencies defining the effective bandwidth of the echo. Additionally, the spectral energy was integrated across several predefined frequency bands to analyze how different defect morphologies shift the frequency distribution. For instance, the highly irregular surfaces of slag inclusions tend to selectively attenuate higher frequencies due to complex scattering phenomena, resulting in a measurable downward shift in the spectral centroid compared to reflections from smooth planar defects [10].

Recognizing that ultrasonic echoes are highly transient, non-stationary signals where the frequency content rapidly changes over the extremely short duration of the pulse, a comprehensive time-frequency analysis was subsequently performed. Wavelet packet decomposition was selected as the optimal mathematical tool for this task, utilizing a discrete Meyer wavelet basis function due to its excellent localization properties in both time and frequency. The signals were decomposed to the fourth level, generating sixteen distinct terminal frequency nodes. The relative energy contained within each of these sixteen terminal nodes was calculated, creating a highly detailed, localized energy signature for each individual defect echo.

Following the exhaustive extraction of these diverse indicators, the resulting feature space was highly dimensional and inevitably contained redundant or irrelevant variables that could obscure the learning process of the classification models. To optimize the predictive architecture, a rigorous feature selection protocol was applied. A hybrid approach utilizing both filter and wrapper methods was implemented. Initially, a fast correlation-based filter was used to eliminate features that exhibited high collinearity with each other, ensuring that the remaining indicators provided unique information. Subsequently, a recursive feature elimination algorithm, utilizing a random forest estimator to continuously evaluate feature importance, was deployed. This sophisticated process iteratively removed the least significant features until an optimal, highly compact subset of the most powerfully discriminatory nondestructive testing indicators was identified, forming the final input vector for the predictive classification models.

4. Experimental Results and Discussion

4.1 Defect Classification Performance Metrics

The optimized subset of nondestructive testing indicators was utilized to train, validate, and test several advanced machine learning classification architectures. The primary objective was to accurately predict the discrete categorical class of the underlying weld anomaly: pristine material, porosity, slag inclusion, lack of fusion, or crack. To ensure the statistical robustness and generalizability of the findings, a rigorous k-fold cross-validation strategy, specifically utilizing ten folds, was employed throughout the evaluation process. The dataset was meticulously stratified to maintain the exact proportional representation of each defect class within every individual training and testing fold, preventing any single class from dominating the learning phase. The performance of the predictive models was comprehensively evaluated using a suite of standard metrics derived from the multi-class confusion matrix, including overall accuracy, precision, recall, and the F1-score, which provides a harmonized mean of precision and recall.

Table 2: Comparative Classification Performance Metrics Across Evaluated Models

Predictive Model Architecture	Overall Accuracy	Average Precision	Average Recall	Average F1-Score
Linear Discriminant Analysis	0.764	0.751	0.764	0.756
K-Nearest Neighbors	0.812	0.815	0.812	0.810
Support Vector Machine (RBF)	0.925	0.928	0.925	0.926
Random Forest Ensemble	0.941	0.943	0.941	0.942

The empirical results, as detailed in the experimental data, demonstrated significant variations in predictive capability across the different algorithmic approaches. Baseline linear models, such as linear discriminant analysis, exhibited the lowest overall performance. This outcome was entirely expected and confirms the theoretical hypothesis that the mapping between ultrasonic signal features and complex defect morphologies is inherently highly non-linear. The linear decision boundaries constructed by these simple models are simply insufficient to accurately separate the complex, overlapping clusters of data points within the high-dimensional feature space. The k-nearest neighbors algorithm provided a modest improvement, but its performance degraded when distinguishing between morphologically similar defects, such as certain types of dense porosity and small, rounded slag inclusions [11].

The most compelling results were achieved by the non-linear, advanced machine learning architectures. The support vector machine, utilizing a radial basis function kernel to implicitly map the features into an infinite-dimensional space, achieved an excellent overall accuracy exceeding ninety-two percent. However, the random forest ensemble classifier consistently demonstrated the highest predictive performance across all evaluated metrics, achieving a remarkable overall accuracy approaching ninety-five percent. The superior performance of the random forest algorithm can be attributed to its intrinsic ensemble structure, which constructs hundreds of independent decision trees during the training phase and aggregates their individual predictions through a majority voting mechanism. This structural design makes the random forest highly resistant to overfitting on noise-corrupted signals and exceptionally capable of capturing the intricate, hierarchical interactions between the diverse time, frequency, and time-frequency domain indicators.

4.2 Analysis of Nondestructive Testing Indicators

Beyond the raw classification metrics, a deep analysis of the confusion matrices and the internal feature importance rankings generated by the random forest model provided profound insights into the physical mechanisms governing acoustic wave interactions with different defect structures. The predictive model exhibited the highest diagnostic accuracy, approaching ninety-nine percent recall, when identifying pristine, flawless weld material. The nondestructive testing indicators for the pristine class were characterized by exceptionally low time-domain amplitudes, negligible signal durations, and spectral energy that was overwhelmingly concentrated in the lowest frequency bands, representing the baseline microstructural scattering of the homogenous steel.

Among the actual defect classes, planar flaws, specifically structural cracks and lack of fusion, were classified with extremely high precision. The feature importance analysis revealed that time-domain parameters, particularly the signal rise time and kurtosis, were the most critical indicators for distinguishing these highly dangerous defects. The physics of ultrasonic wave propagation dictates that a planar defect, presenting a sharp, distinct boundary perpendicular to the acoustic beam, reflects the wave as a highly coherent, intense, and temporally narrow pulse. Consequently, the extracted indicators demonstrated exceedingly rapid rise times and massive kurtosis values, representing a sharp peak in the signal envelope. The predictive model successfully leveraged these specific indicators to separate planar defects from volumetric anomalies with near-perfect reliability.

Conversely, the classification model encountered the most significant, though still minor, difficulties in distinguishing between porosity and slag inclusions. The confusion matrix indicated a slight degree of misclassification between these two specific volumetric classes. This statistical overlap is fundamentally rooted in the physical similarities of their acoustic responses. Both porosity, consisting of spherical gas pockets, and slag inclusions, consisting of irregular non-metallic volumes, act as complex, multi-faceted scattering centers. When the acoustic wave strikes these highly irregular volumetric structures, the energy is scattered in multiple directions and reflects from various internal surfaces at slightly different times. This physical phenomenon results in reflected waveforms that are highly complex, temporally elongated, and characterized by multiple overlapping peaks.

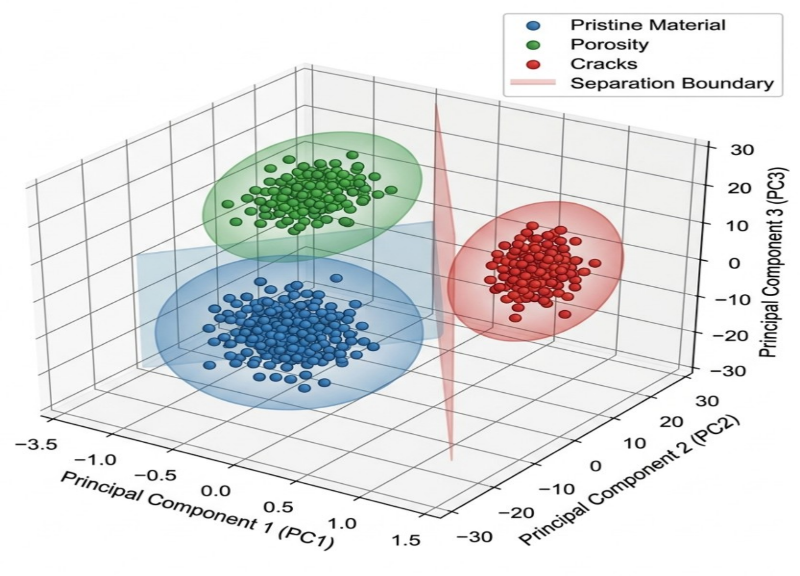

Figure 2: Multi

Despite these challenges, the integration of advanced time-frequency indicators, specifically the relative energy distribution across the terminal nodes of the wavelet packet decomposition, provided the necessary discriminatory power to largely separate these volumetric classes. The analysis indicated that slag inclusions, due to their inherently rougher and more angular macroscopic morphology compared to the perfectly smooth internal surfaces of gas porosity, induce a significantly higher degree of phase interference and high-frequency attenuation. This physical difference manifested in the dataset as distinctly different energy distribution patterns within the higher frequency wavelet nodes. The random forest algorithm effectively utilized these subtle, high-dimensional energy shifts to successfully differentiate between the two volumetric defect types in the vast majority of test cases [12]. The rigorous analysis of these selected indicators ultimately bridges the critical gap between abstract statistical learning and the fundamental physics of nondestructive acoustic evaluation.

5. Conclusion and Future Perspectives

5.1 Summary of Experimental Findings

This comprehensive academic investigation successfully demonstrated the immense potential of predicting defect classification from nondestructive testing indicators using rigorous experimental analysis in pressure vessel welds. By transitioning from subjective manual interpretation to an objective, fully automated, data-driven framework, this research addresses a critical vulnerability in modern industrial quality assurance protocols. The systematic fabrication of representative weld specimens, coupled with the precise induction and strict verification of various defect morphologies, established an exceptionally high-quality foundation of experimental data. The implementation of a multi-domain feature extraction methodology, encompassing sophisticated time, frequency, and advanced time-frequency analyses, proved essential for capturing the complex acoustic signatures of different flaw types. The subsequent application of machine learning architectures unequivocally proved that non-linear ensemble models, specifically the random forest algorithm, possess the optimal capacity to navigate the intricate, high-dimensional feature space of ultrasonic signals. The achievement of classification accuracies exceeding ninety-four percent validates the viability of this methodology for deployment in highly demanding industrial environments, ensuring that critical planar defects like cracks are reliably distinguished from less immediately threatening volumetric anomalies. Furthermore, the detailed correlation between the statistical feature importance rankings and the fundamental physics of acoustic wave propagation provides a robust, interpretable theoretical framework that justifies the model's predictive decisions.

5.2 Limitations and Future Research Directions

While the findings of this experimental analysis are highly promising, several critical limitations must be acknowledged and addressed in future research endeavors. Primarily, the experimental dataset was acquired under ideal, tightly controlled laboratory conditions utilizing perfect acoustic coupling through water immersion. In actual industrial field applications, inspections are frequently conducted using manual or semi-automated contact transducers on complex, curved vessel geometries with highly variable surface conditions, which introduces significant unmodeled acoustic noise and coupling variability. Therefore, future research must focus on validating the robustness of these predictive models against datasets acquired directly from realistic field inspections. Additionally, while the carefully engineered features combined with traditional machine learning models proved highly effective, the rapid advancement of deep learning technologies offers a compelling alternative pathway. Future studies should systematically investigate the application of deep convolutional neural networks directly to the raw temporal waveforms or uncompressed spectral representations, potentially eliminating the need for the manual feature extraction pipeline entirely. Finally, expanding the predictive framework to not only classify the morphological type of the defect but to accurately predict its precise volumetric dimensions and exact orientation within the weld seam would represent the ultimate culmination of this technological trajectory, providing structural engineers with complete, actionable data for advanced fracture mechanics evaluations and remaining life estimations of critical pressure vessel infrastructure.

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