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Quality monitoring of hybrid welding processes: A comprehensive review

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Hybrid welding processes have gained significant attention due to their high efficiency and exceptional welding properties. However, there are still significant technological challenges in achieving consistent quality and suppressing welding defects. To overcome this challenge, researchers have focused on the integration of visual analysis techniques, numerical simulation techniques, and advanced technologies such as artificial intelligence/machine learning (AI/ML) and digital twins. This comprehensive review synthesizes current knowledge on quality monitoring in hybrid welding, encompassing an overview of hybrid welding processes, quality assurance, monitoring techniques, key performance indicators, and advancements in monitoring techniques. Furthermore, the review highlights the integration of sensor data with AI/ML algorithms and digital twin technologies, enhancing the capabilities of quality monitoring systems. Notably, the review emphasizes the incorporation of artificial intelligence (AI) and digital twin technologies into quality monitoring frameworks. Artificial intelligence/Machine learning enables real-time analysis of welding parameters and defect detection, while digital twins offer virtual representations of physical welding processes, facilitating predictive maintenance and optimization. The findings underscore the crucial role of sensor technology, AI/ML, and digital twin integration in enhancing defect detection accuracy, improving welded joint quality, and control in hybrid welding. In addition to improving the quality of welded joints, this integration paves the way for further developments in welding technology.

Key words: hybrid welding, defect detection, quality monitoring, artificial intelligence, digital twins.

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1. Introduction

Hybrid welding processes has gained significant popularity in various sectors of the manufacturing industry due to the increasing need for high efficiency, environmental protection, and automation in industrial development [1–4]. Furthermore, hybrid welding processes combine different welding techniques and energy sources to achieve specific welding results [5]. These processes leverage the unique advantages of each method to improve efficiency, quality, and control in welding operations [5, 6]. The list of basic welding techniques includes:

- Gas Metal Arc welding (GMA),
- Tungsten Inert Gas welding (TIG),
- Electron Beam Welding (EBW),
- Resistance Spot Welding (RSW),
- Laser Welding,
- Plasma Welding.

By merging technologies like laser and gas metal arc welding(GMA), these processes achieve deeper penetration, faster welding speeds, and superior joint properties compared to traditional methods. However, ensuring consistent and high-quality welds in these intricate processes presents a significant challenge.

Hybrid welding, despite its advantages, presents significant challenges in achieving consistent, high quality welds [7–10]. The complex interaction between laser and arc parameters, the inherently dynamic nature of the welding process itself, and limitations of the monitoring techniques all contribute to this difficulty [7, 11]. Further complicating the issue is the lack of standardized procedures for quality control between different manufacturers [7]. Overcoming these hurdles requires advancements in sensor technology, data analysis with integration of artificial intelligence (AI), digital twin technology [12], and the standardization of quality monitoring practices in hybrid welding.

Among various welding technologies, this review focuses on hybrid welding processes such as hybrid laser-GMA and plasma-GMA welding, which provide high energy concentration, enable deep penetration and fast welding speeds, and also allow for improved welded joint pool stability [1, 13]. This combination is often used to achieve high-quality welds, especially in applications where precise control over the welding process is crucial [14, 15]. However, hybrid welding involves intricate physical processes, such as the keyhole effect, molten pool flow, and droplet transfer behavior, which give rise to complex heat transport phenomena. In particular in the automotive, new energy, power batteries, and other industrial industries, welding defects cause accidents and large financial losses [14, 16].

Steen was the first to propose hybrid laser-arc welding technology [1]. The advantages of metal active gas (MAG) welding and highly focused laser intensity with deep penetration have led to the widespread use of laser-arc hybrid welding technology in industrial manufacturing, including shipbuilding [1, 17], pipeline girth welding [14], and the automotive industry. Nevertheless, the actual process of the laser-MAG hybrid welding (LMHW) is unpredictable and involves more than just superimposing the two heat sources. In hybrid welding, it might be difficult to get welding status information and to quickly and accurately assess the quality of the weld. These dynamic factors significantly impact the quality of the welded joint [6, 17]. Thus, to guarantee the proper welded joint formation, it is critical to assess the stability of the hybrid welding process. In industrial manufacturing systems, process diagnosis and detection have recently been extensively researched through the use of AI / ML, digital twin, signal processing techniques [5, 15, 18], particularly in the area of welding process monitoring. Quality monitoring in hybrid welding involves the continuous assessment and evaluation of the welding process to detect any potential defects or deviations from the desired result [18–20]. It enables real-time feedback and adjustment of welding parameters to optimize weld quality. Parameters such as welding speed, vibration, acoustic emission (AE), voltage, current, and gas flow rate are crucial for optimization. Welding speed affects heat input and cooling, influencing defects and integrity. Voltage and current control heat, impacting fusion and bead formation, while gas flow rate ensures proper shielding. Vibration can destabilize the weld pool, and AE signals provide early defect detection [18, 19].

Researchers explored various mechanisms to monitor the quality of hybrid welding processes. Gao, Xiangdong, *et al*. [8, 10] studied LMHW and introduced a novel method to evaluate the stability of the process and the formation of welded joints by combining instantaneous status analysis and continuous stability analysis using a double high-speed visual system as shown in Figure 1. Physical phenomena of the top and bottom surfaces, such as the intensity of arc light, metallic vapor, spatter formation, and texture features of the bottom molten pool, were extracted to assess the instantaneous welding state. The cameras show the visual process of the top and bottom views simultaneously during the welding process and illustrate the formation and transition of molten droplets, the generation of spatters, and the ejection of metallic vapor from the bottom surface during the droplet transition. Gray level Co-occurrence Matrices(GLCM) and Gabor wavelets were used to measure the spatial and frequency characteristics of the bottom molten pool. By analyzing these features, the study provided a comprehensive approach to monitoring the stability of the process and the evaluation of welded joint formation in LMHW [21, 22], offering information on the real-time assessment of the welding process and techniques for the diagnosis and detection of critical flaws in welded joint quality assurance.

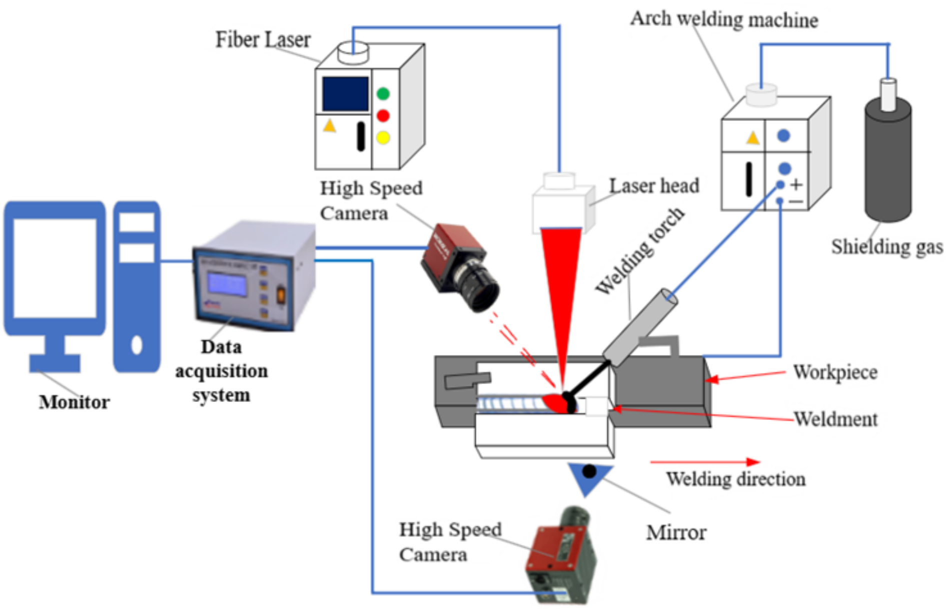

Figure 1: Hybrid welding process monitoring system

Feature extraction is crucial for LMHW process monitoring. High-speed cameras capture visual features like droplet transition and keyhole bottom. The Otsu thresholding algorithm isolates image noise, while morphological operations extract arc light or metallic vapor. Fast Fourier Transform transforms images to remove high-frequency noise, enabling process status quantification. During the hybrid welding process, in order to track and detect welded joint faults researchers proposed different approach. Lü, Xueqin, *et al*. [23] studied the least square method based on the slope analysis method is used to detect the features of the image to obtain the information about the features of the groove of the welded joint groove. The results validate the accuracy of the feature extraction method and the significant improvement in operation time. In He, Yinshui, *et al*. [24] a visual attention model for detecting welded joint seam profiles is proposed. The paper presents a scheme for extracting feature points of the welded joint seam profile to implement automatic multipass route planning and guidance of the initial welding position in each layer during MAG arc welding. Xiao, Runquan, *et al*. [25, 26] proposed adaptive and improved snake model feature extraction algorithm based on a laser vision sensor. The algorithm demonstrates good adaptability for multiple typical welding seams and maintains a satisfactory robustness and precision even under complex working conditions [27,28]. Collectively, these studies underscore the importance of real-time monitoring and analysis to ensure the quality and stability of the LMHW process.

A series of studies have explored the use of optical coherence tomography (OCT) for welded joint classification and quality assessment in copper laser welding. Will, Thomas, *et al.* [29]demonstrated the feasibility of using the FRESH algorithm for feature extraction from OCT data, enabling categorization of the results of the welded joints. This was further explored by the same authors [30], who investigated the influence of different pure copper materials and process gas on welded joint seam surface features, finding negligible effects on surface topographical characteristics. Brežan, Tine, *et al.* [31]the integrated photo-diode and OCT to diagnose in laser weldments, achieving a high classification accuracy. Since Will [29] has developed and tested seven different algorithms for measuring the depth of the welded joint in copper laser welding, identifying the intensity accumulation approach as the most accurate. In general this studies highlight the potential of OCT and advanced algorithms for welded joint classification and quality assessment in laser welding of copper.

Despite these studies, challenges remain in ensuring the stability and quality of hybrid welded joints. Factors such as the complex physical phenomena involved in the welding process, including the keyhole effect and molten pool flow, can lead to defects that compromise the integrity of welded joints. The key factors affecting the quality of LMHW and plasma arc welding processes as shown in Figure 2 include the arrangement of heat sources, such as the lead mode and the distance between the laser spot and the welding wire tip [11, 32, 33]. The coupling effect between heat sources and welding characteristics, such as the morphology of the welded joint, the stability of the process and the transfer of droplets, are significantly influenced by these factors [34]. The lead mode has a more significant impact on welded joint formation than the distance between the laser spot and the welding wire tip [35]. In terms of welding process stability, the arc-lead mode is better than the laser-lead mode. Additionally, the laser power and defocusing amount, as well as the welding speed and current, also affect the coupled arc profile and welding process stability. The quality of the welded joint seam can be influenced by factors such as edge quality, gaps, and misalignment of edges.

The use of Monitoring techniques have a significant impact on the efficiency and effectiveness of laser arc MAG and plasma hybrid welding processes. These techniques allow for real-time monitoring of various parameters during the welding process, such as voltage, current, welding speed, welded joint pool geometry, defects, microstructure, residual stresses, and temperatures. By using suitable

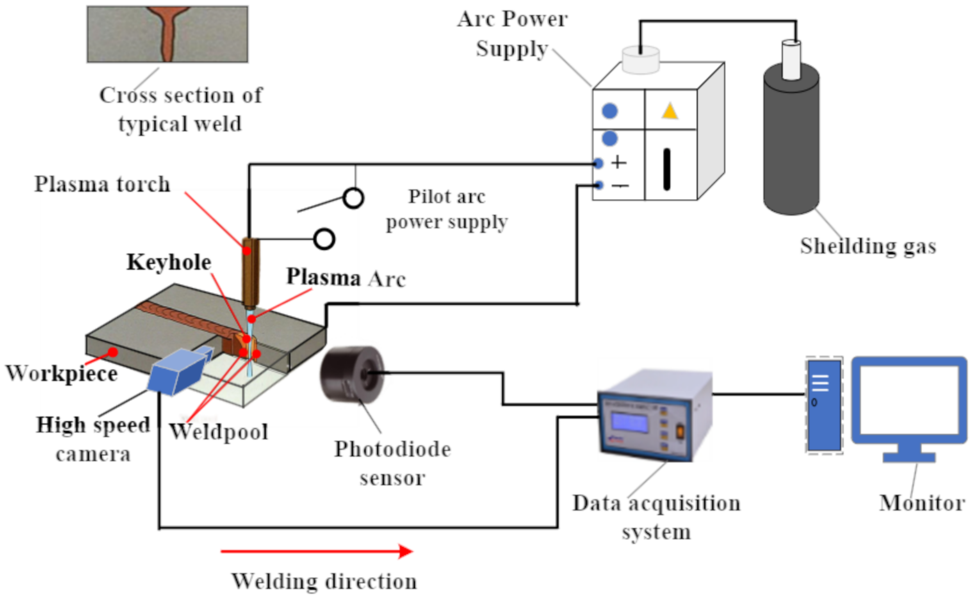

Figure 2: Schematic diagram of plasma arc welding

sensors and data acquisition systems, variations in voltage and current can be recorded and analyzed, providing valuable information about the quality of the final welded joint product [9, 31, 36, 37]. Multi-sensor data fusion networks and convolutional neural networks (CNNs) enable highly accurate, real-time detection of in-process defects [38]. Additionally, the Extended Kalman Filter (EKF) and particle filters improve state estimation in nonlinear systems by linearizing models around current estimates, facilitating precise sensor data integration [31, 38]. Furthermore, numerical simulation technology plays a crucial role in predicting welded joint forming and quality, as well as clarifying the underlying mechanisms of laser welding processes [39]. Overall, monitoring techniques enhance the control and optimization of laser arc MAG and plasma welding processes, leading to improved efficiency and effectiveness in achieving high-quality welds [13, 40]. One study developed a real-time laser welding data acquisition system to collect plasma density, laser intensity, and molten pool temperature data during the welding process. They also established a neural network based on a combination of Long-Short Term Memory (LSTM) and CNN models to detect welding defects with an average accuracy rate of 96% [41]. Another study proposed a hybrid model combining CNN and LSTM to deeply mine acoustic features for penetration monitoring in laser welding. Their approach achieved a remarkable classification performance with a test accuracy of 99.8% [42]. Additionally, a specific methodology using Computer-Aided Inspection (CAI) and cloud manufacturing was reviewed as a candidate technology for a digital twin in laser-welded blanks [43]. These advancements in sensor technology and artificial intelligence have significantly improved the monitoring of hybrid welding processes.

2. Sensing Technology in Weld Quality Monitoring

This section provides a comprehensive overview of both conventional sensors and advanced monitoring techniques employed in welded joint quality monitoring. Additionally, it delves into the prevalent approach of multiple sensor signal fusion technology, offering insights into the collection process of adequate signals for enhanced comprehension.

Sensing technology plays a crucial role in welded joint quality monitoring, ensuring reliable and defect-free joints [44]. Lv, Na, *et al*. [45] introduced an automated control system for pulse gas tungsten arc welding, using audio sensing technology and back propagation ANN for penetration state identification. This system enables precise adjustment of welding current, based on variations in the arc sound signal, ensuring effective online monitoring and control of automated robotic gas tungsten arc welding processes. Wu, Di, *et al*. [46] proposed combined visual and acoustic signals for variable polarity plasma arc welding(VPPAW)penetration monitoring, using t-stochastic neighbor embedding and a deep belief network for effective identification. The paper focuses on monitoring weld penetration status using visual and acoustic signals.

Recent advancements in sensor technologies for detecting defects in welded joints have introduced innovative approaches to non-destructive testing (NDT), aiming for higher sensitivity, accuracy, and efficiency. Sensor signal fusion, microvision sensing, and molten pool sensing are some of the approaches employed in the serious task of welded joint quality monitoring. Quality prediction and defect detection are combined using machine learning (ML) methods. The iRVision system, which uses ANNs for automated quality control and visual inspection [47–49],welding creates an incredibly bright light due to the arc and molten metal. Standard cameras would struggle to capture clear images without being overwhelmed by the light, making it difficult to see the weld pool and surrounding area in practical application [50, 51], detects imperfection using acoustic emission sensors [52], multiple sensors to record physical characteristic changes during laser welding, and other advances in sensing technologies. Subsequent advancements in this area could include refining the model to look for defects of a smaller size and enhancing artificial intelligence within advanced signal processing capacity to detect defects in a variety of welding activities and materials. Table 1 presents an overview of the sensors and their application to welding process monitoring, with references to related publications.

Table 1: Summary of Sensor Technology

Sensor type and [Papers]	Welding signal captured	Analysis techniques	Limitations	Typical applications
Voltage and Current Sensors [53–55]	Welding arc voltage, welding current	Waveform analysis, statistical modeling	Susceptible to electromagnetic interference, transient variations	Arc stability control, penetration depth adjustment, seam tracking
Acoustic Sensors [56–59]	Sound waves generated by the welding arc, electrode-work-piece interaction	Signal processing algorithms, pattern recognition	Background noise interference, limited accuracy in noisy environments	Detection of spatter formation, welded joint seam tracking
Vision Systems [60, 61]	Visual information of welded joint pool, welded joint bead, surrounding area	Image processing, pattern recognition	Limited field of view, susceptibility to optical distortions	Weld defect detection, seam tracking, welded joint bead geometry analysis
Vibration Sensors [5, 62]	Weld stability, Quality assessment	Signal processing (FFT, Wavelet analysis), Machine learning (SVMs, Decision trees)	Sensitive to environmental factors, frequency range	Misalignment, abnormal vibration
Ultrasonic Sensors [63, 64]	Weld defect detection, Material thickness measurement, Weld seam tracking	Time-of-flight analysis, Wavelet analysis, Machine learning (ANNs)	Limited effectiveness in highly reflective materials, Limited penetration depth in thick materials	Non-destructive testing, Structural welding
Photo-diode Sensors [17, 65]	Welding arc intensity, Welding current	Signal processing (amplitude analysis, frequency analysis), Statistical modeling	Limited to arc-based processes, Sensitivity to ambient light	Arc welding processes, Automotive manufacturing

3. Weld Quality Monitoring via Artificial Intelligence or Machine Learning

Artificial Intelligence/Machine Learning (AI/ML) is the field of study focused on enabling machines to learn real-time problems autonomously, using input data (data-driven approach). By leveraging ML, machines can achieve high accuracy, even in high-frequency repetitive tasks, where human involvement may introduce computational errors. ML has become a prevalent trend in various sectors, including manufacturing, welding, and research disciplines [66–70]. AI and ML are transforming welded joint quality control.

The process workflow of AI/ML-supported welded joint quality monitoring is depicted in Figure 3. By analyzing data from sensors, and electrical signal processing during welding, ML models can identify defects in real-time, predict potential problems, and even trigger alerts for corrective actions [71–73]. This non-destructive approach leads to more consistent welded joint quality, with reduced costs through fewer defects, and improved overall production efficiency [4, 44, 74].

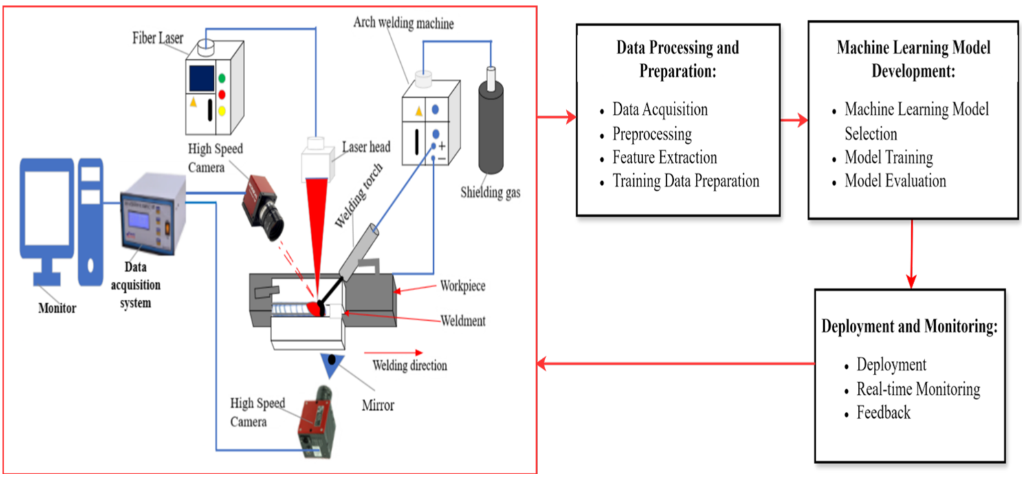

Figure 3: Block Diagram: Welded Joint Quality Monitoring with AI/ML

During the welding process, various parameters, including voltage, current, welded joint pool geometry, welding speed, vibration, acoustic emissions, and temperature are captured by sensors. This raw sensor data undergoes preprocessing to eliminate noise, anomalies, and superfluous information through techniques like filtering, normalization, and feature extraction, which extract pertinent features such as spatter generation, welded joint pool characteristics and arc stability. Subsequently, the preprocessed data, along with corresponding labels indicating good welded joint quality or defects, are utilized to train machine learning models employing various algorithms like, Support Vector Machines (SVM), Decision Trees, CNNs, Recurrent Neural Networks (RNNs), and deep learning. Following model training, evaluation is conducted using separate validation datasets to assess performance metrics like accuracy, recall, F1-score, and precision [4, 44, 75–77]. Once the model is successfully trained and evaluated, it is deployed for real-time welding process monitoring. During welding operations, sensor data is continuously fed into the deployed model, enabling real-time prediction of welded joint quality or defect detection. Immediate corrective actions can be initiated based on feedback generated by the model in case of deviations from desired welded joint quality or defect identification.

A survey of AI in welding by [74, 78] highlights its potential to revolutionize the industry, with applications in process control, robot control, and welded joint quality assurance. Another researcher utilized wavelet packet transform and a back-propagation neural network to intelligently identify resistance spot welding defects [79]. Chaki, Sudipto *et al.* [76] introduced a proposal for neural network models aimed at predicting and optimizing process parameters in hybrid laser beam welding. The study utilized backpropagation neural networks (BPNN) combined with Bayesian regularization as a means to forecast welding strength and penetration depth. Nomura, Kazufumi, *et al.* [77, 80] developed a CNN model to predict welding quality in MAG welding by analyzing molten pool images obtained during the process as shown in Figure 4. They addressed the challenge of predicting excessive penetration and burn-through by treating it as a regression problem rather than a classification problem. The penetration depth estimation

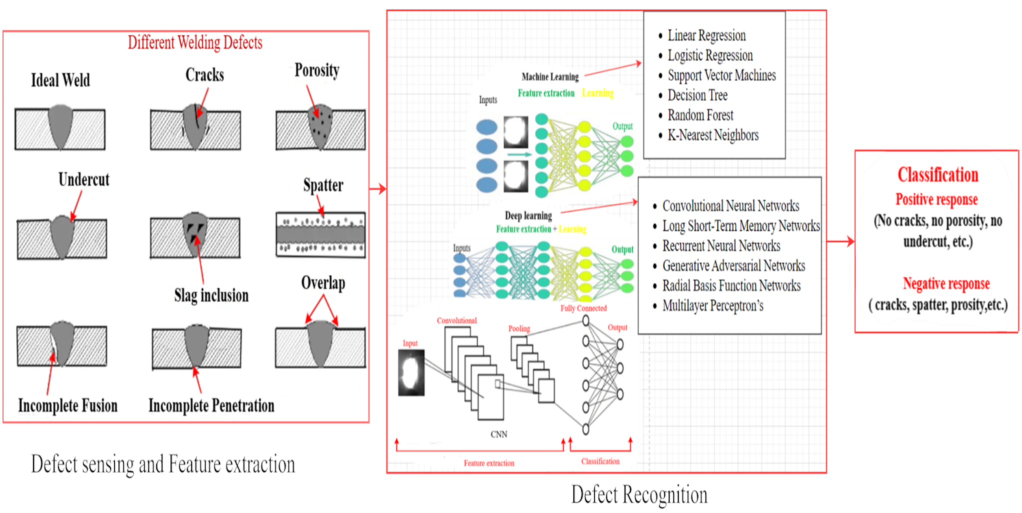

Figure 4: Structure of defect recognition using machine learning

model achieved high accuracy, with over 95% of estimations having a 1 mm error or less. The study also found that the estimation accuracy varied locally based on the quality of the training data. Additionally, the researchers observed that the image size used in the model did not significantly affect the estimation accuracy. The model demonstrated short calculation times, making it suitable for real-time monitoring applications. Kumaresan, Samuel, *et al*. [77] proposed an object detector-based method for detecting casting defects in aluminum components used in automobiles. The method involved modifying key elements of existing detectors and utilizing a defect classifier. The process included applying sliding windows on images of different scales, extracting regions of interest (ROIs), and employing non-maxima suppression. The approach utilized welding seam radiography as input and involved predicting defect labels. However, the method may not achieve the performance of deep learning-based detectors due to potential slowdown in real-time detection and the inability to perform end-to-end training [81–83].

As shown in Table 2 and Table 3, the performance of machine learning (ML) algorithms for welded joint defect detection reveals a diverse landscape of approaches with varying strengths and limitations. Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), Support Vector Regression (SVR), hybrid ML approaches, Support Vector Machines (SVMs), and other deep learning methods collectively revolutionize inspection, monitoring, and optimization processes across various welding methodologies. CNNs specialize in image-based defect detection and classification [77, 103–106], while DBNs excel in modeling intricate relationships within high-dimensional welding data, facilitating real-time anomaly detection [94, 106–108]. SVR models leverage historical data to predict critical welded joint quality parameters with robust generalization, thereby enhancing process optimization. The hybrid ML approach synergistically integrates multiple techniques to address diverse challenges [90], enabling adaptive control strategies and real-time adjustments. SVMs efficiently classify welding defects, ensuring stringent quality control across different welding processes [109–111]. Deep Learning methods, encompassing various neural network architectures, contribute significantly to feature learning, anomaly detection, and predictive modeling, further augmenting the capabilities of ML in welded joint quality analysis [75, 112–114].

Figure 5 illustrates the accuracy of classification and defect detection across various machine learning (ML) algorithms applied to welding processes. The legend identifies different welding processes. Insights from the plot reveal that Hybrid CNN-ELM achieves the highest accuracy among all algorithms, followed by DBN and Deep Learning. Such observations facilitate the comparison of ML algorithms' performance across various welding processes, aiding stakeholders

Table 2: Summary of Welded Joint Quality Monitoring through AI/ML in Laser Welding Methods

Welding type and [Papers]	Algorithm	Advantages	Disadvantages	Defect detection	Accuracy
Laser welding [47, 84, 85]	CNN	High accuracy, Multi-sensing signal analysis	Detection accuracy for small porosity is limited due to subtle features, Requires labeled data	Porosity, penetration depth	Classification accuracy ranging from 95.67% to 99.38%
Laser welding [86, 87]	Support Vector Machine and Regression	Fast and efficient classification, Can handle high-dimensional and noisy data	Requires careful feature selection	Welding quality prediction	The classification accuracy rate was higher than 90%
Laser welding [88, 89]	EMD-PNN	Real-time detection, Uses laser-induced plasma signals	Limited to specific defects, Requires specific signal processing	Weld seam, weld defects	The average prediction accuracy range of 90.16% to 94%
Laser welding [90, 91]	Hybrid ML, CNN, MLP for real-time welding quality prediction	Real-time control, Improved welded joint quality	Complex system integration, Requires expertise in multiple ML techniques	Adaptive welding speed control	–
Laser welding [92, 93]	Gradient Boost (GB)	Combines acoustic emission with ML for monitoring	Mis-classifications occur between neighbor categories, Requires acoustic emission data	Stable keyhole, unstable keyhole, and spatter	Accuracies ranging from 74% to 95%
Laser welding [36, 94]	DBN	Online monitoring, Facilitates real-time process adjustments	Limited to monitoring, Requires specific network architecture	Welding status, Laser keyhole penetration state	with average accuracies ranging from 93.80% to 98.85%

Table 3: Summary of Welded Joint Quality Monitoring through AI/ML in Plasma and Gas Metal Arc Welding Methods

Welding type and [Papers]	Algorithm	Advantages	Disadvantages	Defect detection	Accuracy
Plasma arc welding [95, 96]	Hybrid CNN-ELM	Excellent feature learning ability, Improved accuracy	The training process of the CNN model remains a challenge	Penetration recognition	Classification accuracy of 98.18%
GMAW [97, 98]	Deep learning	Insightful process understanding, Potential for defect prediction	Requires diverse data sources	GMAW process analysis	Achieved 97.24% correct test image classification with a loss value of 0.10
GMAW [99, 100]	Supervised Deep Learning (SDL)	Real-time monitoring, Potential for defect detection	Requires labeled data, Limited to back-bead monitoring	Back-bead monitoring	Approximately 93.5%
GMAW [101, 102]	Decision tree and Support vector machine (DT and SVM)	Suitable for classifying welded joint defects, Cost-effective	Requires diverse training data	Weld defect classification	Decision tree classifier achieved a classification efficiency of 96.428%

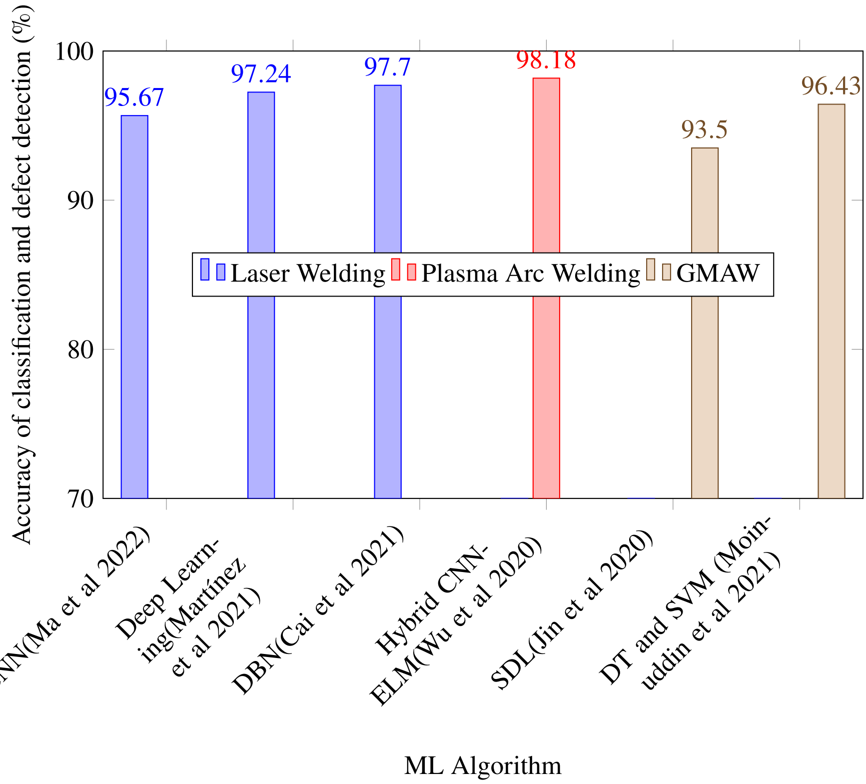

Figure 5: Machine learning algorithms for welding defect detection display varying accuracies

in selecting suitable algorithms for classification and defect detection tasks. It's important to note that the accuracy values presented may vary based on dataset characteristics and other factors, highlighting the need for comprehensive evaluation using additional performance metrics.

4. Application of Digital Twin Technology in Welded Joint Quality Monitoring

A digital twin is a virtual model of a system or item that follows its life cycle, is updated based on real-time data, and aids in decision-making through reasoning, simulation, and machine learning. Digital twin technology is used in many different industries, such as aerospace, automotive, healthcare, and manufacturing [12, 115]. A significant portion of the military and aerospace industries use the digital twin concept, which was first proposed by Grieves [116]. Due to its properties of full-factor data drive, virtual-real integration and real-time interaction, and iterative operation and optimization, digital twin technology gained a lot of attention and practical application. Digital twins are virtual models of physical entities that are constructed digitally to mimic their behavior in the actual world using data, according to Tao *et al*. [117]. This allows for more intelligent, efficient, and real-time services that are focused on the full life cycle of a product.

Digital twin technology offers several potential benefits for welded joint quality monitoring. Firstly, it enables the monitoring of the welding process in real-time, allowing for immediate detection of defects and the optimization of manufacturing and product design [118]. Additionally, digital twins can reduce product development costs and improve the functionality of products by speeding up the achievement of appropriate product quality [119]. However, there are also challenges associated with digital twin technology for welded joint quality inspection. These challenges include the need for accurate data acquisition and processing systems, as well as the development of effective models and identification methods [120].

Aminzadeh, Ahmad, *et al*. [43] provided an extensive assessment on process monitoring using computer-aided inspection in light metal blanks that have been laser-welded. The study provided a real-time monitoring and a novel digital model based on computer-aided inspection (CAI) and cloud manufacturing is proposed to improve welding efficiency and guarantee product quality. Wang *et al*. [18] proposed to improve real-time quality assurance during welding processes and provided a deep learning-powered digital twin framework for visualized welded joint joint growth monitoring and penetration control. The digital twin uses CNNs and traditional image processing to estimate welding parameters, with CNN model excelling in 2-channel composite images. It develops decision-making strategies for welding penetration and quality, with a GUI for user control. Franciosa, Pasquale, *et al*. [121]demonstrated the possibility for ongoing manufacturing process optimization with the presentation of a deep learning augmented digital twin centered on Closed-Loop In-Process quality improvement. The digital twin framework combines sensors, deep learning, and Computer-Aided Engineering(CAE) simulations to improve assembly system quality, achieving over 96% right-first-time rate in testing. Similarly, the Closed-Loop In-Process (CLIP) approach, utilizing stochastic process capability space, integrates in-process data and physics-driven simulation to diagnose and prevent defects, also achieving a 96% right-first-time rate in a production pilot study. The approaches streamline parameter selection, automate adjustments, and reduce the need for physical experiments. Ji, Tao, and Norzalilah Mohamad Nor [122] offered a Deep Learning-Enabled Digital Twin that uses acoustic signals for welding quality inspection, demonstrating the potential of deep learning methods for fault identification. The paper presents a digital twin system for welding robots that uses acoustic signals to examine welded joint defects. It uses wavelet filtering to remove machine noise and uses an SeCNN-LSTM model for recognition. The model achieved a verification accuracy of 91% and was compared with other models. The paper also discusses wavelet thresholding for removing noise signals, comparing different threshold functions and demonstrating its efficacy in noise reduction. It proposes a modified threshold value to improve signal recovery. Dong, Jianwei, Jianming Hu, and Zhen Luo [119] researched resistance spot welding quality monitoring using a digital twin technique, providing insights into process optimization and welded joint quality improvement. Additionally, focus on employing digital twin technology for monitoring the resistance spot welding process of aluminum plates, specifically 2219/5A06 aluminum plates with varying thicknesses. They introduce a data acquisition system for resistance spot welding and real-time data processing techniques utilizing wavelet threshold analysis for noise reduction. Contact resistance calculation during welding incorporates factors like contact surface pressure, rheological stress, and material resistances. The digital twin model is utilized to simulate the welding temperature field and analyze nugget formation and size evolution. Comparative analysis with experimental measurements demonstrates the practicality of digital twin technology for real-time monitoring of resistance spot welds.

Digital Twin technology, coupled with machine learning, as shown in Figure 6, offers a comprehensive workflow for monitoring welded joint quality in hybrid welding [119, 121, 123]. The process begins with data acquisition and preprocessing. A network of sensors captures real-time data of various parameters [124]. This raw data is then cleaned and formatted to ensure quality and consistency. The digital twin model which combines physics-based simulations of heat transfer and material behavior with machine learning algorithms is developed and trained on historical welding data. The ML algorithms, like CNNs,

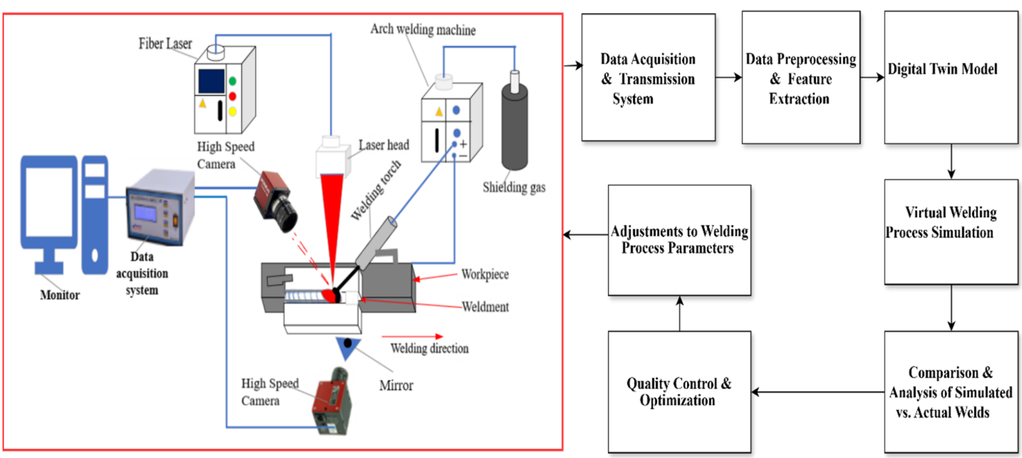

Figure 6: Workflow: Welded Joint Quality Monitoring with a Digital Twin

learn to identify relationships between process variables and welded joint quality. As the welding process unfolds, real-time sensor data continuously feeds into the digital twin model. The model then analyzes this data using the physics simulations and different ML algorithms to provide real-time process visualization, defect detection, and predictive maintenance capabilities [125, 126] as shown in Figure fig:digital. The digital twin's analysis can be used to make real-time adjustments to welding parameters (laser power, travel speed, etc.) to maintain optimal welded joint quality. Additionally, the "what-if" scenario capability of the digital twin allows simulating different welding parameters within the virtual model [119, 127]. This helps determine the optimal settings for achieving desired welded joint quality before actual welding begins [128, 129]. Finally, the workflow incorporates continuous improvement. Data from both the welding process and the resulting welded joint quality are collected and fed back into the digital twin model. This ongoing feedback loop refines the model's accuracy and ensures it remains an accurate reflection of the real-world welding operation.

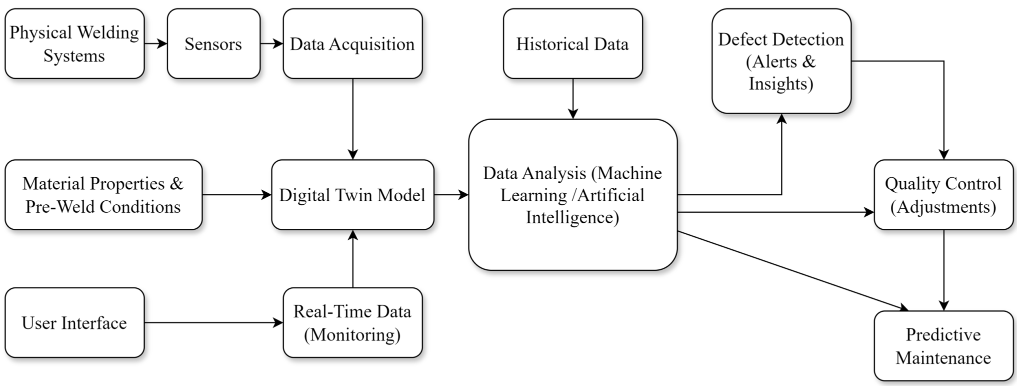

Figure 7: Structure of digital twin for welding process

At the heart of a digital twin system for welded joint quality monitoring lies the concept of data-driven decision making as shown in Figure 7. Monitoring welded joint quality relies on real-time sensor data captured during the welding process, feeding it into a virtual model alongside pre-defined parameters and historical data [18, 119, 130]. Machine learning algorithms analyze this information to detect patterns and predict defects, triggering alerts for deviations. Insights from the analysis inform quality control measures, facilitating adjustments to welding parameters and predictive maintenance scheduling [122, 127, 131]. A user interface enables real-time monitoring, data visualization, and limited process control, ultimately optimizing weld quality and process efficiency through comprehensive data analysis and insights.

5. Conclusions

In conclusion, hybrid welding processes have gained considerable traction in the manufacturing industry due to their ability to enhance process efficiency, control, and weld quality. By combining various welding techniques and energy sources, such as plasma arc or laser with MAG welding, hybrid welding offers significant advantages in welded joint integrity and processing speed. However, challenges persist in ensuring the stability and consistency of hybrid welds, particularly due to the complex interactions of physical phenomena and the need for real-time monitoring and analysis.

Significant advancements have been made in the development of monitoring techniques for hybrid welding, especially with the integration of sensing technologies, artificial intelligence (AI),and machine learning (ML). These advancements enable real-time monitoring and analysis of welding parameters, facilitating prompt defect detection and optimization of key factors such as welding speed, voltage, and current. These optimizations enhance weld quality by reducing defects and ensuring consistent fusion, with critical quality measures including penetration depth, heat-affected zone size, weld bead geometry, and porosity.

Digital twin technology has emerged as a promising approach for welded joint quality monitoring, offering virtual models of physical entities that mimic their behavior in the real world. By integrating real-time data and simulation models, digital twins enable proactive identification of potential issues and optimization of manufacturing processes.

Future advancements in digital twin technology for welded joint quality monitoring include the application of data-driven models, improved detection methods, and integration of virtual and real data. These advancements have the potential to enhance the efficiency and accuracy of welded joint quality monitoring, ultimately leading to improved welded joint quality and production outcomes in the manufacturing industry. In addition to the advancements in monitoring techniques and digital twin technology, researchers have also explored innovative approaches to defect detection and process optimization in hybrid welding. ML algorithms, such as CNNs, DBNs, and SVMs, have been employed to analyze welding signals and predict welded joint quality in real-time. These algorithms have shown promising results in accurately detecting defects and optimizing welding parameters to ensure high-quality welds.

The integration of advanced sensing technologies, such as voltage and current sensor, acoustic sensors, vision systems, and vibration sensors, has enabled comprehensive monitoring of the welding process. These sensors capture a wide range of welding signals, including sound waves, visual information of the welded joint pool, and vibration patterns, which are then analyzed using signal processing techniques and machine learning algorithms to assess welded joint quality and detect defects. Furthermore, the development of hybrid models that combine different ML algorithms has demonstrated improved accuracy and robustness in welded joint quality monitoring.

Overall, the combination of advanced sensing technologies, ML algorithms, and digital twin technology holds great promise for revolutionizing welded joint quality monitoring in the manufacturing industry. By leveraging these technologies, manufacturers can achieve higher efficiency, greater automation, and improved welded joint quality.

Nomenclature

ANN	Artificial Neural Network
BPNN	Backpropagation Neural Network
CNN	Convolutional Neural Network
DBN	Deep Belief Network
EMD-PNN	Empirical Mode Decomposition Probabilistic Neural Network
ELM	Extreme Learning Machine
GMAW	Gas Metal Arc Welding
MLP	Multi-Layer Perceptron
LMHW	Laser Metal Active Gas Hybrid Welding
LSTM	Long-Short Term Memory
RNN	Recurrent Neural Network
SVM	Support Vector Machine
SVR	Support Vector Regression

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