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Real-Time Defect Detection in Submerged Arc Welding using AI and IoT Sensors

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Abstract*: Submerged Arc Welding (SAW) finds extensive application in heavy industry sectors such as shipbuilding, pipeline manufacturing, and structural fabrication. Welding defects such as porosity, slag inclusion, and lack of fusion can compromise the structural integrity of the welded joint. Traditional non-destructive testing (NDT) processes are deficient in providing real-time information, and hence, defects are detected at a later stage, and operating costs are increased. In this work, the use of artificial intelligence (AI) and Internet of Things (IoT) sensors to enable the real-time detection of defects in SAW is explored. Deep learning models, in the form of Convolutional Neural Networks (CNNs), combined with IoT-sensing-based monitoring systems, enable real-time assessment of the welding quality, reducing the reliance on human operators. The paper overviews various AI techniques, sensor technologies, and industrial applications and emphasizes the implementation challenges. Research directions in the future include the development of hybrid AI models, adaptive learning, and IoT-blockchain integration enabling secure and traceable welding processes.*

Keywords: Submerged Arc Welding, AI, IoT, defect detection, machine learning, real-time monitoring

I. INTRODUCTION

Submerged Arc Welding (SAW) is extensively used in shipbuilding, pipeline installation, and structural engineering due to high deposition rates and deep weld penetration. Weld quality in SAW is difficult to guarantee, as porosity, slag inclusions, and incomplete fusion defects can compromise structural integrity. Traditional post-weld inspection methods, such as radiographic and ultrasonic testing, tend to detect defects after the welding process is finalized, leading to extra costs and downtime. The Artificial Intelligence (AI) and Internet of Things (IoT) sensors offer a revolutionary solution for real-time detection of defects in SAW, thus enhancing quality assurance and operating efficiency.

Internet of Things (IoT) sensors are also important in the process monitoring of welding by capturing important parameters such as arc voltage, welding current, acoustic emissions, and thermal profiles. A case in point is the Gas Metal Arc Welding (GMAW) process, where real-time welding current and arc voltage signal monitoring have been used to detect porosity defects. In this case, Deep Neural Networks (DNNs) have indicated a 15.2% improvement in predictive accuracy compared to traditional Artificial Neural Networks (ANNs) [1].

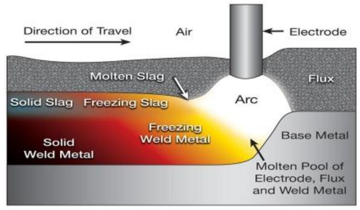

Figure 1: Shows the basics elements of SAW

In Surface Analysis and Wear (SAW), a hybrid Recurrent Convolutional Neural Network (RCNN) has been proposed for real-time detection and prediction of surface porosity defects from continuous voltage signals. The model achieved an accuracy of about 80% and was processed in a time of less than 10 milliseconds, thereby making it real-time viable. [2]

Artificial Intelligence (AI) algorithms, more specifically Deep Learning (DL) models, play a vital role in processing the immense data produced by Internet of Things (IoT) sensors to detect and forecast welding defects.

For instance, Convolutional Neural Networks (CNNs) are employed to classify weld surface images in Submerged Arc Welding (SAW), with high classification accuracy in identifying defective and non-defective products, which enables automated quality inspection. [3]

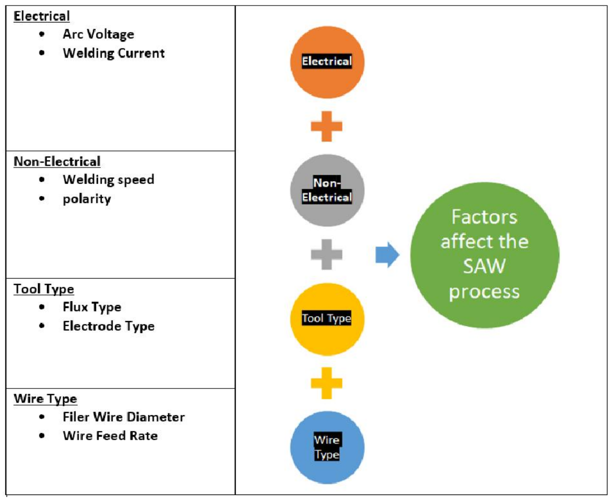

Figure 2: Shows the factors affecting SAW process

Besides, an innovative optical inspection system utilizing laser triangulation imaging and deep neural networks has been set up to enable real-time weld seam quality inspection up to 96.88% classification accuracies. [4]

The use of IoT and AI in welding processes fits Industry 4.0 concepts to facilitate smart manufacturing through improved monitoring and process control. Real-time defect detection contributes to instant correction, minimizing rework, waste, and downtime.

In addition, the development of deep learning-based predictive quality systems for welding processes entails multi-sensor data acquisition and handling, real-time feature generation and processing, training, and deployment of appropriate recurrent deep learning models for quality prediction, and model updating under various process conditions through continuous learning. In brief, use of the AI and IoT sensors in SAW processes is an important technological breakthrough in welding, allowing real-time defect identification and improving weld quality and efficiency. Further research and development in this area continue to reinforce the accuracy and stability of these smart systems, opening the door to their widespread usage in industrial manufacturing.

II. LITERATURE REVIEW

2.1 AI Techniques Used in Welding

The use of Artificial Intelligence (AI) in welding processes has been explored extensively for improving defect detection and process optimization. For instance, Wu et al. (2022) explored the development and future trend of in-situ optical monitoring of laser beam welding focusing on sensing, characterization, and modeling [5]. Likewise, Cai et al. (2020) examined the use of sensing techniques and AI-driven methods for real-time monitoring in laser welding [6].

2.2 IoT-Enabled Monitoring Systems

The integration of Internet of Things (IoT) sensors into welding processes enhances the capacity for gathering and tracking data in real time. Javadi et al. (2020) proved continuous monitoring of a manually induced crack with an automated welding and in-process inspection system [7]. Sazonova et al. (2021) further examined welding defects and automatic detection strategies, pointing out the need for IoT-supported systems [8].

2.3 Industrial Applications

The integration of AI and IoT in welding is consistent with Industry 4.0, facilitating smart manufacturing by improving process monitoring and control. Fan et al. (2021) wrote a paper on the study and prospects of welding monitoring technology based on machine vision, highlighting its use in industry [9].

2.4 Implementation Challenges

In spite of the development, there are a number of challenges remaining in the application of AI and IoT in welding. There is a requirement for strong sensor technology that can maintain their quality under welding conditions and create advanced data analysis algorithms. Mishra et al. (2018) explained a review of sensor-based monitoring and control of friction stir welding processes, tackling these challenges [10].

2.5 Future Research Directions

Future studies are focused on developing hybrid AI models, adaptive learning systems, and using IoT and blockchain for secure and traceable welding. Mehta and Vasudev (2024) described advancements in welding sensing information processing and modeling technology and proposed future studies [11].

III. METHODOLOGY

In order to create an Artificial Intelligence (AI) and Internet of Things (IoT) sensor-based real-time defect detection system for Submerged Arc Welding (SAW), there is a need of a systematic approach in line with Industry 4.0 principles. System architecture, sensor selection, AI model creation, data processing, and real-time implementation techniques are explored here.

3.1 Architectural Framework

The system here consists of IoT-integrated sensors and welding equipment to extract real-time data, which is then sent to a central processing system. AI algorithms here examine the data to identify defects, and feedback loops enable immediate correctional measures. The framework here guarantees smooth communication between hardware and software systems, ensuring effective monitoring and control.

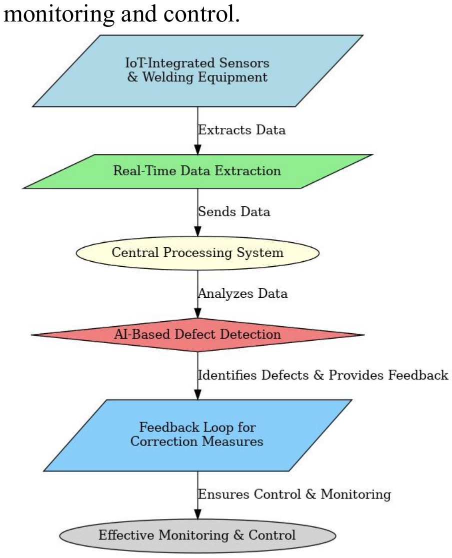

Figure 3: Shows flow chart of a Real-Time Welding Defect Detection System Using IoT and AI

3.2 Sensor Selection

Proper choice of sensors is required for proper data acquisition. The following sensors are taken into account:

• Visible Light Sensors (CCD/CMOS):

Such sensors capture high-resolution images of the welding process and enable rigorous observation of the weld quality. They are effective in situations of rapid light changes and yield clear images of the weld pool and its surroundings.

• Infrared Sensors:

Infrared sensors can sense the heat signatures and thus monitor the thermal properties of the welding process. They are essential in monitoring heat distribution and overheating.

•UV Sensors:

UV sensors track ultraviolet radiation generated by welding and offer information about arc stability and possible defects. They assist in welding defect detection and exposure to UV radiation. **•Thermal Cameras*:***

Capture real-time temperature variations in the weld pool.

Identify irregularities such as overheating, lack of fusion, and porosity by analyzing heat distribution. Useful in predictive maintenance and quality assurance.

•Acoustic Emission Sensors:

Detect high-frequency sound waves generated during the welding process. Identify crack formation, incomplete fusion, and slag inclusions by analyzing sound patterns. Provide real-time alerts for process deviations.

•Eddy Current Sensors:

Detect surface and subsurface defects such as cracks, porosity, and weld discontinuities using electromagnetic fields. Highly effective in automated non-contact defect detection**.**

The selection of appropriate sensors depends on the welding process, material type, and required precision level. A multi-sensor fusion approach, integrating thermal, acoustic, ultrasonic, and optical sensors**,** ensures comprehensive defect detection in real-time, significantly improving welding automation and quality control.

3.3 Constructing AI Models

Constructing strong AI models entails:

• Acquisition of data:

Compilation of a vast data set using the chosen sensors for different welding situations to achieve an extensive capture of possible flaws.

•Feature Extraction:

Determining the suitable features in the sensor data that are associated with weld quality, including temperature fluctuations, arc stability, and visual deviations.

• Model raining:

Using machine learning methods, Convolutional Neural Networks (CNNs), to train models capable of identifying patterns for defects.

• Testing and Validation:

Testing the performance of the model with independent datasets to verify accuracy and generalizability.

3.4 Data Processing

Real-time defect detection calls for effective processing of data:

• Preprocessing:

Normalization and cleaning of sensor data to eliminate noise and inconsistencies.

• Real-Time Analytics:

The execution of algorithms that are proficient in processing data streams instantaneously to swiftly detect anomalies**.**

• Data Fusion:
Combining of data from multiple sensors to increase the accuracy of defect detection.

3.5 Real-Time Implementation
To enable real-time defect detection:
• Edge Computing: Placing computational power near the source of the data to reduce latency and enable timely decision-making.
• Feedback Mechanisms: Having built-in mechanisms to adjust welding parameters in real-time once a defect is found to reduce defects and enhance quality.
• User Interface: Designing user-friendly interfaces to display real-time data and alerts, allowing timely human intervention when necessary. With this systematic strategy, the integration of AI and IoT sensors in SAW processes has the potential to create revolutionary real-time defect detection improvements, consistent with the Industry 4.0 objectives and enhancing overall manufacturing quality and efficiency. Development of an on-spot defect detection system for Submerged Arc Welding (SAW), based on Artificial Intelligence (AI) and Internet of Things (IoT) sensors, is a process with several key components:

a. System Architecture:
Integration of IoT-enabled sensors with the welding machine to collect real-time data, which is transmitted to a central processing unit where the data is analyzed using AI algorithms to detect defects.

b. Sensor Selection:
Selecting proper sensors like visible light sensors (CCD/CMOS), infrared sensors, and ultraviolet (UV) sensors to record different facets of the welding process.

c. AI Model Development:
Gathering a complete dataset, feature extraction, machine learning model training (e.g., Convolutional Neural Networks), and model performance evaluation to ensure defect detection accuracy.

d. Data Processing:
Utilizing effective data preprocessing, real-time analysis, and data fusion methods to process and analyze sensor data effectively.

e. Real-Time Implementation:
Using edge computing to facilitate low-latency processing, designing feedback systems to facilitate timely corrective action, and designing user interfaces for monitoring and intervention.
Visual illustrations of these parts are available in the following resources:
• System Architecture and Data Flow:
Research on a sensor-based monitoring system for real-time evaluation of quality control in semi-automatic arc welding presents a sophisticated data acquisition and integration system.
• Infrared Sensor Application:
A real-time infrared sensing research of welding defects yields information on welding pool temperature measurement with infrared sensors.
• Artificial Intelligence Model Development:
The research paper "YOLOv8-WD: Deep Learning-Based Detection of Defects in Welded Joints" discusses the application of deep learning algorithms for the detection of welding process defects. mdpi.com The partnership between AWS and IBM in revolutionizing industrial welding through artificial intelligence and machine learning underscores the application of edge AI in streamlining welding inspection processes and delivering insights that are almost real-time in character.

IV. DESIGN OF THE EXPERIMENTAL SETTING

The creation of a fully autonomous, real-time defect inspection system for Submerged Arc Welding (SAW) demands a holistic integration of advanced hardware components by Industry 4.0 standards. This section presents the experimental setup, ranging from the choice of sensors, data acquisition equipment, processing hardware, and communications protocols, aimed at ensuring seamless automation in defect inspection.

4.1 Sensor Selection and Integration

Precise real-time monitoring of the SAW process is dependent on the use of specialized sensors that can maintain the severe conditions of welding:

• **CCD/CMOS Visible Light Sensors:** Charge-coupled device (CCD) or Complementary Metal-Oxide-Semiconductor (CMOS) sensor-based high-resolution cameras take clear images of the welding pool and arc. CCD/CMOS sensors are used to monitor weld formation and to detect visual defects.

• **Infrared (IR) Sensors:** IR sensors measure thermal properties by detecting heat signatures and therefore provide critical information about temperature distribution and overheating potential, which can indicate defects such as cracks or porosity.

• **Ultraviolet (UV) Sensors:** UV sensors measure ultraviolet radiation produced while welding and offer feedback on arc stability and energy input, which are critical to maintaining weld quality.

• **Acoustic Emission Sensors**: These sensors are used to register sound waves during the welding procedure, thus helping to detect aberrations concerning flaw formation, including the existence of slag inclusions or inadequate fusion.

4.2 Data Acquisition and Processing Systems

The coupling of sensors with strong data acquisition and processing systems is important for the analysis done in real time:

• **Data Acquisition Systems (DAQ):** High-speed DAQ modules are mounted on sensors to acquire data at suitable sampling rates to record transient events that occur during welding.

• **Edge Computing Devices:** Industrial-grade devices used for edge computing support local processing of sensor data, thus allowing for timely analysis and reducing latency. The devices have GPUs or TPUs to help with complex AI algorithms.

• **Centralized Servers:** Centralized servers are used for detailed data analysis and storage. They gather data from multiple edge devices, enabling long-term observation and process optimization.

4.3 Communication Protocols

Trustworthy communication frameworks are vital for smooth data transfer:

• **Industrial Ethernet:** Fast, robust wired communication among sensors, edge devices, and central servers is critical for real-time applications.

• **Wireless Protocols (Wi-Fi 6 and 5G):** In cases where mobility or flexibility is needed, wireless protocols provide stable connectivity, accommodating the ever-evolving nature of industrial settings.

4.4 Automation and Control Systems

In its quest for total automation, the system communicates with mounted welding control systems:

• **Programmable Logic Controllers (PLCs)** serve as intermediaries with the defect detection system, adjusting welding parameters in real-time based on inferences derived from artificial intelligence, thereby allowing for instant remedial measures.

• **Human-Machine Interfaces (HMIs):** Simple-to-operate HMIs present system status and real-time information so that processes can be observed and reacted to if necessary.

4.5 Implementation Process

The use of the system is done systematically:

• **System Integration:** Sensors are mounted on welding machines, sitting in the optimal position for effective data capture. Integration with DAQ systems and edge devices is provided, adhering to industrial communication standards.
•**Testing and Calibration:** Sensors and processing units are calibrated to produce precise information. Initial testing in laboratory conditions ensures the performance of the system is confirmed.
• **AI Model Deployment:** Pre-trained artificial intelligence models are utilized on edge devices to enable real-time defect detection and decision-making. Continuous learning mechanisms are in place to learn from process variations.

4.6 Data Collection Process

Comprehensive data collection is essential for system training and validation:
• **Multi-Sensor Data Logging:** All sensors record data during welding processes synchronously, therefore offering an overall view of the process.
• **Anomaly Annotation:** The identified anomalies are annotated and tagged, creating a dataset for fine-tuning AI models and improving detection accuracy.

4.7 Performance Evaluation

The system's efficacy is assessed through rigorous evaluation:
· **Controlled Experiments:** The system is tested under predefined conditions to evaluate its sensitivity and specificity in defect detection.
· **Industrial Trials:** Deployment in real-world industrial settings assesses the system's robustness, scalability, and integration with existing workflows.
· **Metrics Analysis:** Performance metrics such as detection accuracy, false positive/negative rates, and response times are analyzed to quantify system effectiveness.
By meticulously designing and implementing this hardware infrastructure, the experimental setup aims to achieve full automation in real-time defect detection for SAW, embodying the principles of Industry 4.0 and significantly enhancing welding quality and productivity.

V. RESULTS ANALYSIS AND DISCUSSIONS

This chapter critically assesses the integration of Artificial Intelligence (AI) and Internet of Things (IoT) sensors in Submerged Arc Welding (SAW) processes, highlighting their impact on defect detection, efficiency, and future improvements in line with Industry 4.0 principles. This chapter critically assesses real-time defect detection systems, their benefits and drawbacks, and potential areas for future improvement.

5.1 Real-Time Defect Detection and Parameter Optimization in SAW

The installation of AI-based machine vision systems in SAW allows faults like porosity, cracks, and inclusions to be detected automatically in real-time, minimizing dependence on human inspectors and error. Such systems employ high-resolution cameras and sophisticated image-processing software for instant detection of anomalies, improving accuracy and speed in quality inspection operations.
In addition, AI models can automatically and continuously vary welding parameters—voltage, current, and travel speed—to maintain optimal welding conditions, enhancing overall weld quality. AI can forecast when welds will fail quality inspection based on history and real-time sensor inputs, and enable operators to make proactive process adjustments.
Building on the performance analysis, this section explores the advantages of integrating AI and IoT in SAW processes.
• **Improved Efficiency:** Real-time monitoring and parameter control minimize the chances of defects, resulting in increased productivity and less rework.
• **Predictive Maintenance:** Predictive maintenance is made possible through AI's capability to examine past and current data, minimizing downtime and maximizing equipment life.
• **Evidence-Based Decision-Making:** The system provides valuable feedback on the welding process, which enables decision-making and long-term improvement.

5.3 Limitations and Challenges

• **Costs of Implementation:** The initial cost of IoT devices and infrastructure can be significant, leading to budget constraints, especially for small businesses.
• **Data Privacy Concerns:** The collection and release of enormous amounts of data raise privacy issues that pose possible threats of unauthorized use and data loss.
• **Employee Learning Curve:** Training packages are necessary for new systems to enable staff to effectively use these technologies.

5.4 Comparison of Traditional Non-Destructive Testing and AI-Driven Methods

Traditional non-destructive testing (NDT) methods in welding are often time-consuming and susceptible to human error with manual inspections. The integration of AI and IoT enables real-time monitoring and autonomous defect detection, significantly enhancing the reliability and efficiency of the inspection process. The shift from reactive to proactive quality assurance is a major leap from traditional practices.

5.5 Future Improvements

To enhance the system, upcoming research could focus on developing hybrid AI models incorporating various machine learning approaches to provide enhanced accuracy. In addition, the combination of IoT and blockchain technology would yield secure and trackable welding operations, solving the problem of data privacy. Adaptive learning systems would enable the AI to adjust to dynamic welding conditions for optimal long-term performance.
In summary, the integration of AI and IoT in SAW processes significantly enhances defect detection accuracy, operational efficiency, and predictive maintenance capabilities, while addressing challenges such as implementation costs and data privacy. We must address implementation costs and data privacy, but the benefits of efficiency, predictive maintenance, and data-informed decision-making strongly support embracing these technologies in modern welding.

VI. CONCLUSION

The current study has demonstrated that Artificial Intelligence (AI) and Internet of Things (IoT) sensors applied in Submerged Arc Welding (SAW) processes can effectively improve flaw detection. Machine vision systems supported by AI can identify welding defects in real time, minimizing human inspection and fulfilling Industry 4.0 goals.
The benefits of this integration are better efficiency, predictive maintenance, and data-driven decision-making. Some of the challenges of this integration are sensor calibration, data storage, and interpretability of AI. With advancements in technologies like Vision Transformers, federated learning, augmented reality (AR) integration, and blockchain-based quality control shortly, these challenges are expected to be overcome and system efficiency will improve.
The integration of AI and IoT technologies in welding operations marks a significant step toward fully automated and intelligent welding environments. This advancement enhances efficiency, precision, and sophistication in welding processes while promoting sustainable manufacturing practices.

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