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Smart Electric Resistance Welding based on Artificial Intelligence (AI) based on Real-Time Adaptive Statistical Features Completed with Bibliometric Analysis

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ABSTRACT

Electric Resistance Welding (ERW) is a crucial technology in the automotive tubing manufacturing industry. However, setting welding parameters still relies on the operator's experience, resulting in variability in weld quality and production efficiency. This research develops an Internet of Things integrated predictive model incorporating real-time thermal imaging, Adaptive Statistical Features, and Edge AI on an ESP32 microcontroller. The system captures weld temperature distributions, extracts 12 statistical features (such as contrast, entropy, skewness), and utilizes machine learning for predictive parameter optimization. Experimental results demonstrate that the Artificial Neural Network model achieves 84.4% defect detection accuracy, 6,666 inferences per second, and consumes only 36.87 kB of memory. By reducing human dependence and enabling real-time decision making, this system aligns with Industry 4.0 objectives, enhancing production efficiency and resource utilization in high-frequency ERW. The proposed system provides a cost-effective, scalable solution for industrial applications, fostering intelligent and sustainable manufacturing.

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1. INTRODUCTION

Electric Resistance Welding (ERW) has become an essential technology in the tube manufacturing industry, particularly in the automotive sector. Thanks to its ability to rapidly weld high-strength materials, it is indispensable in producing parts that must withstand high pressure and impact in automotive systems. ERW also offers significant advantages, including efficient energy use, reduced production waste, and cost-effectiveness, making it ideal for high-volume production across various industries [1]. However, the ERW process still faces certain limitations, especially in the initial setup of welding parameters, which remains a semi-automated process requiring collaboration between operators and machines. Key parameters such as electrical power, frequency, and production line speed need to be precisely adjusted to ensure an efficient welding process and high-quality welds. In practice, parameter settings often rely on standard approaches combined with observations of the arc characteristics at the weld point, necessitating the operator's experience and expertise. This reliance can lead to variability in weld quality and production efficiency, potentially resulting in defects like porosity or uneven weld structures, which directly impact product quality. Moreover, improper settings increase waste and reduce overall production efficiency. Dependence on operator experience also imposes limitations on establishing consistent industry-wide standards, posing a significant obstacle to enhancing efficiency and reducing costs [2, 3].

Artificial intelligence (AI) has become a crucial tool for improving welding processes by enhancing weld accuracy, defect detection, and parameter adjustment. For example, the application of Fuzzy Deep Neural Networks (FDNN), which combines Fuzzy Logic and Deep Learning, in predicting weld width in Tungsten Inert Gas (TIG) welding has achieved an accuracy of 92.59%, showcasing AI's potential to reduce reliance on operator parameter selection [1]. Similarly, Machine Learning (ML) techniques such as Random Forests (RF) and Artificial Neural Networks (ANN) have been used to predict weld quality and resistance in Ultrasonic Composite Welding processes, providing higher accuracy than traditional methods [2, 4]. In Laser Welding, AI techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Genetic Algorithms (GA) have improved real-time inspection and control, resulting in more consistent weld penetration [3]. However, most current AI models still require heavy computation and lack adaptability to ever-changing welding environments, underscoring the need for lightweight, real-time solutions [5].

The integration of Internet of Things (IoT) technology has revolutionized welding process monitoring by enabling real-time data collection and remote process control. IoT systems have been developed to gather data from robotic welding systems, such as electrical current and wire feed speed, enhancing inspection and quality control efficiency [5, 6]. For instance, IoT-enabled Ultrasonic Welding machines can capture process signals like temperature and vibrations, facilitating real-time quality monitoring [2, 4]. However, many IoT systems still rely on cloud-based computation, which can introduce latency and limit their application in high-frequency welding processes [5]. Although IoT helps in data sharing and storage, its full potential has not been utilized in real-time decision-making environments, such as HF-ERW [3].

Real-time process monitoring and control are crucial for maintaining weld quality and operational efficiency in dynamic industrial environments. Several studies have demonstrated the effectiveness of Radial Basis Function Neural Networks (RBFNN) in detecting weld quality in HF-ERW processes by using high-speed image processing to rapidly identify defects [2, 7]. For example, vision-based algorithms with sample time settings of

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0.001 seconds have aided in real-time heat input adjustment, reducing defects by correlating heat distribution measurements with weld quality [7, 8]. The use of Edge Computing technology, such as deploying compact AI models on ESP32 microcontrollers, has reduced latency to just 50 milliseconds, assisting in real-time parameter adjustment [9]. However, existing systems often focus on single-task operations (e.g., binary defect classification) and struggle to integrate data from multiple sensors in complex environments, such as space welding [6, 9]. This highlights the necessity of developing adaptable real-time systems that combine IoT, Edge AI, and Adaptive Statistical Features (ASTF) extraction to manage ever-changing welding processes in industrial settings [3, 5].

Research efforts have focused on improving forming processes to reduce residual stress and enhance dimensional accuracy [10], as well as improving weld durability through metal treatment processes [11] and using numerical models to predict stress and adjust welding parameters [12]. Additionally, heat treatment techniques like quenching and two-step tempering have been employed to enhance the microstructure and mechanical properties of Microalloyed steel in ERW pipes [13]. Although much research has concentrated on reducing residual stress, controlling material microstructure, and developing numerical models [11, 14], the integration of AI and IoT in ERW remains underexplored. Currently, AI is applied for defect detection and weld quality prediction in other processes like TIG and Laser Welding [1, 2] but is still in its infancy for ERW, particularly in real-time analysis and control. Existing IoT systems continue to depend on cloud computation, which can introduce latency and fail to effectively integrate Edge AI for real-time decision-making to reduce defects in HF-ERW processes [9]. Thus, there is a need to develop intelligent platforms that combine AI and IoT to enhance real-time weld quality, reduce defects, and improve production efficiency.

ASTF plays a significant role in various domains, such as image processing, signal analysis, and machine learning. The integration of ASTF has shown improvements in classification accuracy, segmentation, and optimization performance. Research has highlighted the use of ASTF in applications like low-dose CT image reconstruction with Model-Based Iterative Reconstruction (MBIR), leading to significant improvements in image classification [15, 16]. While ASTF has demonstrated success in enhancing classification quality and process performance, its application in ERW remains in the early stages of this research.

Although AI and IoT have been utilized in welding processes, most research still faces limitations in real-time processing and lacks the use of statistical data for immediate welding parameter prediction, indicating areas for further development. This research aims to address these gaps by integrating AI, IoT, and Edge Computing with adaptive statistical feature analysis to develop a real-time welding parameter setting system.

2. LITERATURE REVIEW

2.1. Principles and Theories of ERW

The ERW process is a highly efficient technique widely used in the steel pipe manufacturing industry, particularly in the automotive sector. This process allows continuous and rapid production of pipes with strong and consistent welds. The process begins by feeding steel sheets into the production line, which are then cold-formed into cylindrical shapes. The edges of these sheets are welded together using high-frequency electrical currents, generating localized heat through electromagnetic phenomena. The structural representation of the ERW process is presented in **Figure 1(a)**, while **Figure 1(b)** depicts an actual implementation.

In the ERW process, high-frequency electrical currents pass through an induction coil, leading to two key electromagnetic phenomena: the Skin Effect and the Proximity Effect [17, 18]:

(i) Skin effect. The high-frequency electrical currents flow primarily on the surface of the metal, generating localized heat. This phenomenon conserves energy and minimizes damage to the metal's internal structure [17]. It enhances the energy efficiency of the ERW process and reduces unnecessary heat loss [18]. This is why the ERW process utilizing high-frequency currents is known as High-Frequency ERW (HF-ERW).

(ii) Proximity effect. When the edges of two metal sheets are placed close together, electrical currents concentrate at the nearest edges, generating high heat in that area and bringing the metal to its melting point [8, 5]. This phenomenon allows efficient welding without excessive heat application.

Once the metal edges reach their melting points, squeeze rolls compress the edges to weld them together while removing impurities such as oxides and other contaminants. This process results in high-quality, strong, and consistent welds [5, 19]. Proper heat distribution also ensures a narrow Heat-Affected Zone (HAZ), minimizing microstructural changes in adjacent areas [19].

Understanding the electromagnetic principles of the Skin Effect and Proximity Effect is crucial for enhancing the efficiency of the HF-ERW process in producing high-quality, energy-efficient steel pipes [18].

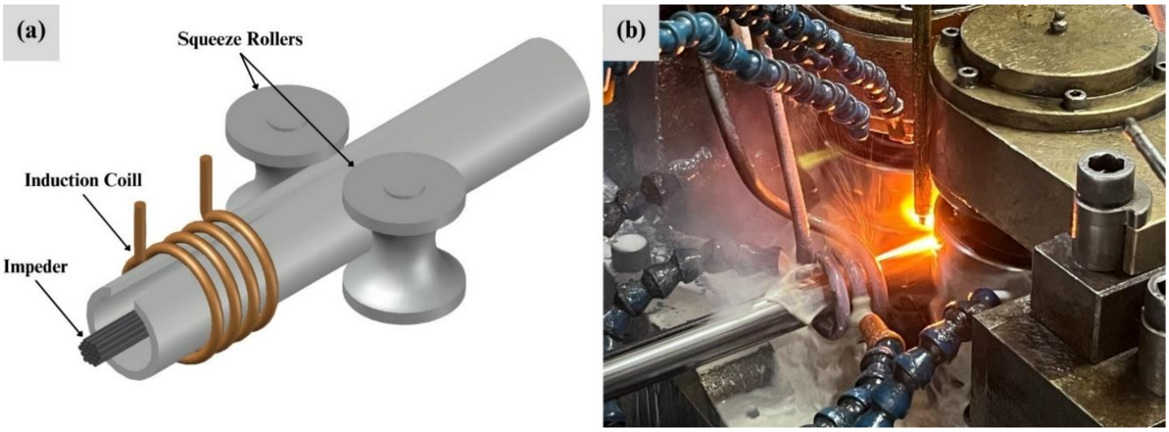

Figure 1. Main components of ERW (a) three-dimensional model of ERW and (b) real ERW.

2.2. Key Components of The ERW Process

A critical component of the ERW process is the impeder, which plays a significant role in reducing electrical energy loss within the pipe. Made from magnetic materials such as ferrite, the impeder increases the impedance at the inner surface of the pipe, ensuring that electrical currents flow only along the outer edges of the Vee [5], this controlled current distribution optimizes heat generation at the weld zone.

At the Vee Point, where the metal edges converge, the high-frequency electrical currents elevate the temperature to the melting point. Squeeze rolls then compress the metal edges at this point to create a strong weld and eliminate contaminants. This process results in a dense and defect-free weld seam [5, 19]. The design of the weld structure considers the Vee angle and Vee length, which impact the current density and the quality of the weld [8, 5]. The key structural elements of the ERW weld are shown in **Figure 2**.

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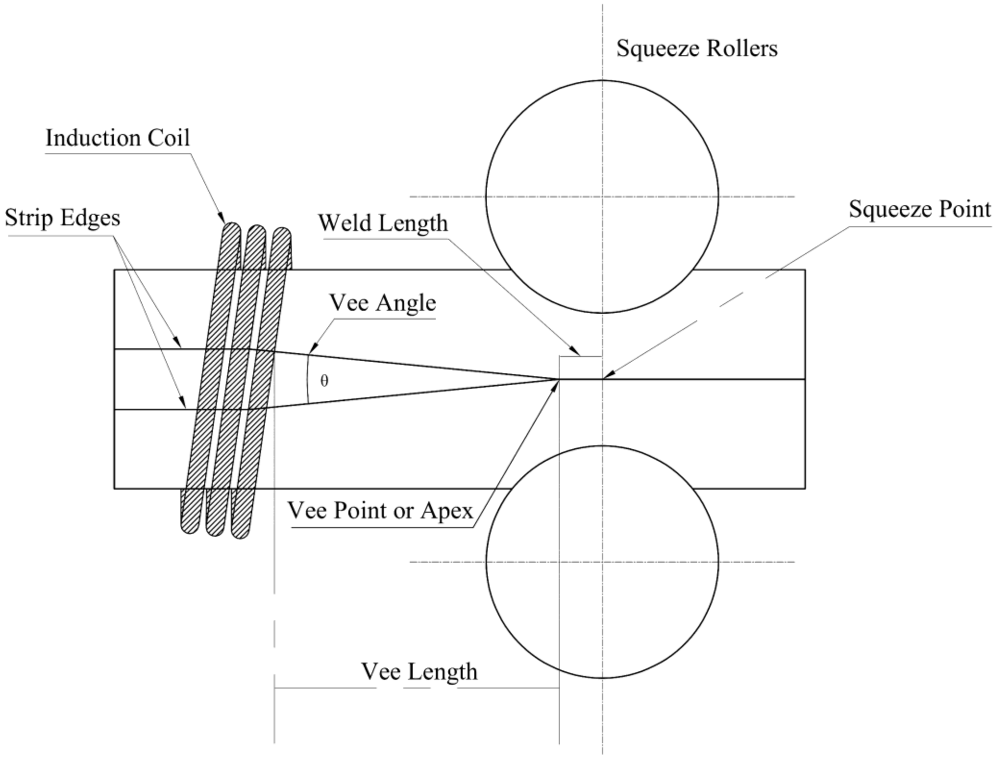

Figure 2. Key Components of ERW.

2.3. Weld Zone

The ERW process significantly alters the microstructure in the weld zone due to rapid heating and cooling, which directly impacts the mechanical properties of the weld. This area is critical for assessing the quality of welds in the ERW process. **Figure 3** illustrates a magnified view of a workpiece from the ERW process, divided into three primary zones.

(i) Bond Line (BL): The narrowest weld seam created directly by the compression of the workpiece. This area reaches the highest temperatures, near the metal's melting point. Insufficient temperature can lead to defects such as incomplete fusion or lack of bonding.

(ii) Heat Affected Zone (HAZ): This area is exposed to high temperatures sufficient to alter its microstructure without melting. Typically, the HAZ exhibits fine-grained ferrite-pearlite structures post-normalizing. The HAZ's boundary and characteristics depend on the cooling rate after welding. Overheating can cause a brittle zone, affecting the weld's overall strength.

(iii) Base Metal (BM): The part of the material not directly affected by the heat, retaining its original mechanical properties and microstructure. However, excessive temperatures can lead to deformation or alterations in the BM's overall strength.

Excess metal extruded from the weld seam during the welding process can appear both inside and outside the weld and typically needs to be trimmed to meet the desired surface quality.

To achieve optimal mechanical properties of the weld, it is crucial to control key parameters like heat energy, pressure, and dwell time. Controlling temperatures in each weld zone can mitigate issues such as incomplete fusion or brittle welds.

Currently, quality assessment of welds involves microstructural examinations such as Microscope Tests and Microstructural Analysis, which allow detailed evaluation of internal material changes. However, these methods require cutting samples for examination, making

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real-time quality checks during actual production unfeasible, leading to the potential production of substandard workpieces before problems are detected.

Implementing real-time monitoring and AI-based defect detection technologies is crucial for industry applications. These technologies enable continuous weld quality analysis, reduce material waste, and allow real-time adjustment of welding parameters to enhance production efficiency.

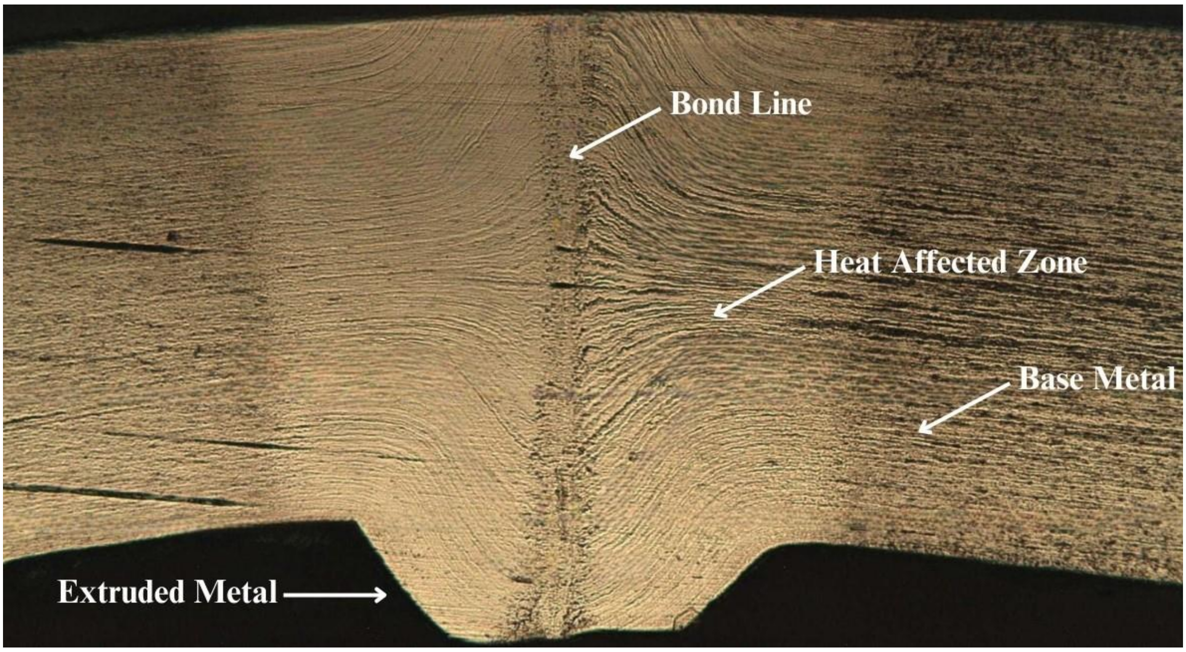

Figure 3. Microscopic analysis: 5x magnification of ERW weld zone.

2.4. Challenges in Hight Frequency ERW

HF-ERW offers the advantage of rapid and energy-efficient welding. However, this process faces several challenges that require control and improvement to mitigate potential issues.

One of the primary challenges of HF-ERW is controlling high-frequency electrical currents to flow precisely at the Vee and not spread to other parts of the metal. Inaccurate distribution of electrical currents can lead to uneven heat distribution, resulting in weld defects such as porosity or unbalanced structures [8, 18].

Furthermore, setting the initial parameters in the HF-ERW process is a significant challenge, as it relies on the experience and judgment of operators. Key parameters such as power, frequency, and line speed must be precisely adjusted to ensure an efficient process and high-quality welds [5, 8]. Relying on human judgment to set these parameters can lead to variations in weld quality and production efficiency [18].

Proper control of parameters such as electrical frequency, vee angle, line speed, and upset force is crucial for weld quality. If these parameters are not well-controlled, it can lead to issues such as cracking or tube ovality [8, 18].

Another challenge in HF-ERW is managing the heat generated during the welding process. The heat must be controlled appropriately to avoid a large HAZ, which can cause microstructural changes in the surrounding area and potentially reduce the weld's strength [20].

Additionally, regular maintenance and inspection of the tools used in the HF-ERW process, such as the induction coil and squeeze rolls, are essential to ensure efficient welding operations and prevent weld defects [5].

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Finally, the variability of the materials used in welding, such as the chemical and physical properties of the metal, affects the weld quality. Controlling the quality of the materials used in production is crucial to prevent issues in the HF-ERW process [18, 19].

Addressing these challenges requires the use of modern technologies and methods, such as applying AI to improve parameter control in the HF-ERW process and using sensors to monitor and analyze data in real time. These innovations aim to achieve high-quality welds and reduce defects in the production process [8, 18].

2.5. Artificial Intelligence

Artificial Intelligence (AI) has emerged as a pivotal technology in the modern era, addressing increasingly complex challenges across various sectors. Its integration is not only essential for achieving sustainable manufacturing practices but also for optimizing processes and improving operational efficiency. By leveraging innovative technologies, AI facilitates the analysis of high-dimensional data, enabling industries to extract valuable insights and make informed decisions rapidly. This review draws on a diverse range of literature to examine the necessity of AI, with a particular focus on its role in Industry 4.0, where digitalization is reshaping production systems and economic landscapes [20]. However, while these studies underline the potential benefits, they also hint at challenges such as data privacy, algorithm transparency, and the need for robust implementation strategies a critical gap that warrants further investigation.

In the industrial domain, AI has demonstrated a transformative impact by enhancing productivity, reducing operational costs, and ensuring rigorous quality control. The application of AI in process engineering and predictive maintenance exemplifies its ability to streamline complex production systems, anticipate equipment failures, and minimize downtime [21]. Moreover, sectors ranging from energy to healthcare benefit from AI driven analytics, which optimize resource allocation and operational scheduling. Global investments by leading economies further attest to AI's potential to redefine traditional manufacturing paradigms [20]. Despite these advancements, it is imperative to critically assess the limitations of current AI applications such as scalability issues, integration challenges with legacy systems, and ethical concerns to fully harness its transformative power in industry.

Looking toward the future, the role of AI is poised to expand across multiple dimensions of societal and economic development. AI is expected to redefine workforce dynamics by undertaking roles traditionally performed by humans, thereby catalyzing a paradigm shift in labor markets and operational structures [20]. Its integration with geospatial and machine learning technologies promises to revolutionize urban planning, climate adaptive policies, and community-centered development [22]. In the educational sector, AI fosters personalized learning and inclusivity, bridging gaps in access to quality education and supporting lifelong learning [23]. These developments, while promising, also raise critical questions regarding the regulatory frameworks, ethical standards, and societal readiness required to accommodate rapid technological evolution areas that future research must address.

In summary, the indispensable role of AI in driving innovation and sustainable development across industrial, urban, and educational sectors. While AI presents numerous opportunities for enhanced efficiency and societal advancement, it also poses significant challenges that demand a critical, multidisciplinary approach to research and implementation. Future studies should focus on developing comprehensive frameworks that not only maximize the benefits of AI integration but also mitigate its limitations, ensuring that its evolution contributes constructively to global socio-economic progress.

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2.6. Bibliometric Analysis

The bibliometric analysis of artificial intelligence (AI) research within the context of Industry 4.0 unveils an academically vibrant and rapidly evolving field. A systematic investigation into publication trends and collaborative networks highlights an exponential rise in scholarly engagement with AI's integration into manufacturing and supply chain systems in recent years [24]. The findings reveal a significant surge in interdisciplinary studies, encompassing areas such as digital transformation, smart manufacturing, and the utilization of emerging technologies, including big data analytics, cyber-physical systems, and blockchain. These advancements emphasize the pivotal role of AI in driving operational efficiency, enhancing industrial resilience, and accelerating the transition toward fully digitized production environments.

Moreover, the analysis underscores the transformative impact of AI in Industry 4.0, which not only improves operational performance but also redefines business models and industrial strategies. Notably, researchers have documented a marked increase in publication output, collaborative research initiatives, and diversification of topics, addressing both technological and socio-economic facets of this integration [25]. While AI contributes to substantial gains in productivity and process optimization, it concurrently raises critical concerns regarding workforce displacement and the necessity for skill adaptation. As traditional roles become increasingly automated, the importance of proactive upskilling and reskilling initiatives has emerged as a consensus among scholars to mitigate adverse effects on employment, ensuring equitable distribution of technological benefits.

Figures 4 and **5** collectively illustrate the evolving scholarly focus within the field of artificial intelligence (AI). Figure 4 demonstrates the overall upward trend in publications using the keyword 'artificial intelligence,' reflecting a broad and growing academic interest in this domain. Complementarily, **Figure 5** narrows this perspective by focusing on publications that incorporate both 'artificial intelligence' and 'industry 4.0' as keywords, showing a parallel growth pattern. This alignment indicates a significant convergence of research efforts on integrating AI within the Industry 4.0 paradigm, emphasizing the increasing recognition of its transformative potential in industrial innovation and automation.

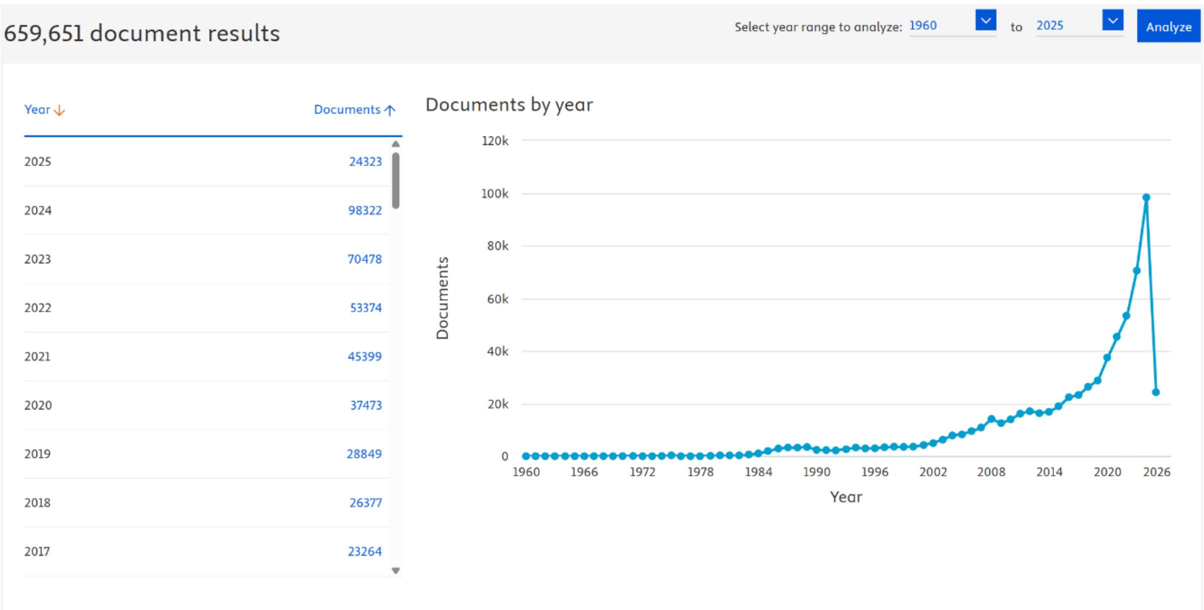

Figure 4. Publication trends in Scopus database using the keyword artificial intelligence (data from March 2025).

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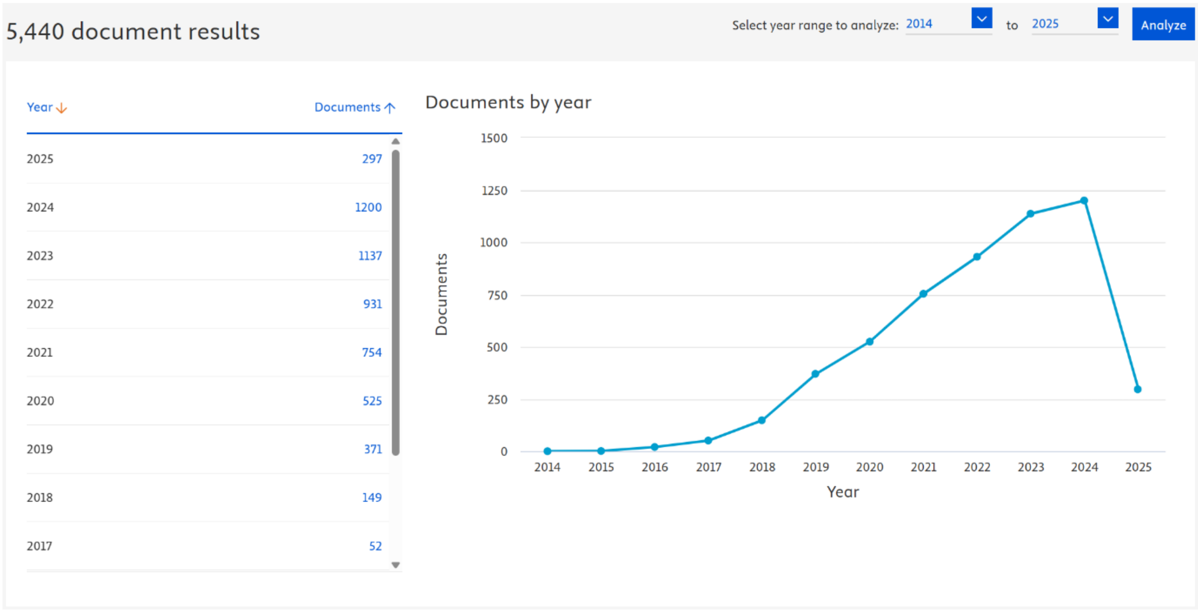

Figure 5. Publication trends in Scopus database using the keyword artificial intelligence and industry 4.0 (data from March 2025).

In conclusion, the bibliometric analysis provides a comprehensive overview of a research domain distinguished by rapid innovation and extensive growth. The expanding corpus of high-impact studies and a notable trend toward multidisciplinary collaboration reflects an academic community committed to unraveling AI's transformative potential within Industry 4.0. Nevertheless, these advancements spotlight significant challenges, particularly in addressing labor market disruptions and the imperative to adapt skill sets to align with technological demands. Future research must not only pursue optimized integration of AI into industrial ecosystems but also prioritize the socio-economic dimensions of such transformation to ensure sustainable and inclusive development.

3. METHODS

3.1. Problem Analysis

ERW process offers several advantages, such as rapid production, energy efficiency, and high weld strength. However, the decision-making and parameter-setting processes in ERW are semi-automatic, relying on both operators and machinery. Key factors such as power, frequency, and line speed must be precisely adjusted to achieve high-quality welds.

One major limitation is the dependence on human decision-making in setting parameters, leading to variability in weld quality and production efficiency. In practice, parameter setting often combines standard guidelines with the observation of the arc's characteristics at the weld point, indicating the welding temperature. This approach requires significant operator experience and expertise but lacks stability and can lead to variability in weld quality and production. Such variability can result in defects like porosity or unbalanced weld structures, directly affecting product quality.

Statistical data from quality inspections of the ERW process over 2 years (2022-2023) reveals a non-compliance rate of 10.02%, divided into two main factors: welding and tube forming. When analyzing data over 4 years (2020-2023), it was found that welding-related issues accounted for an average of 83.29%, while tube-forming issues accounted for 16.71%, as shown in **Figure 6**. This analysis indicates that errors in setting welding parameters are the primary factors affecting weld quality, largely due to the reliance on human settings, which may be prone to inaccuracies from skill level or changes in machine conditions. Decision-making in setting ERW process parameters remains heavily reliant on operator experience, leading to inconsistent production. Therefore, integrating AI and intelligent systems to automatically analyze and verify the accuracy of initial welding settings in real time can reduce human errors, increase precision, and improve the consistency of the production process. This approach is crucial for developing Smart ERW in modern manufacturing industries.

To address the aforementioned limitations and issues, this research proposes the application of IoT technology and AI, reducing the dependence on human decision-making that may lead to parameter-setting errors. This involves analyzing the temperature distribution patterns in the HAZ using data from thermal imaging cameras and transforming this data into Statistical Features (STF). This method helps extract key characteristics related to weld defects and presents a cost-effective AI solution that can be implemented on an industrial scale, particularly in environments with limited processing resources. Developing and testing the system on the ESP32, a low-cost microcontroller, is also a critical starting point for advancing toward Edge AI that can be applied broadly in the manufacturing industry.

This section describes the design and development of the decision-making process for setting ERW parameters through the integration of IoT and AI, utilizing thermal image data that depicts the heat distribution at the weld points.

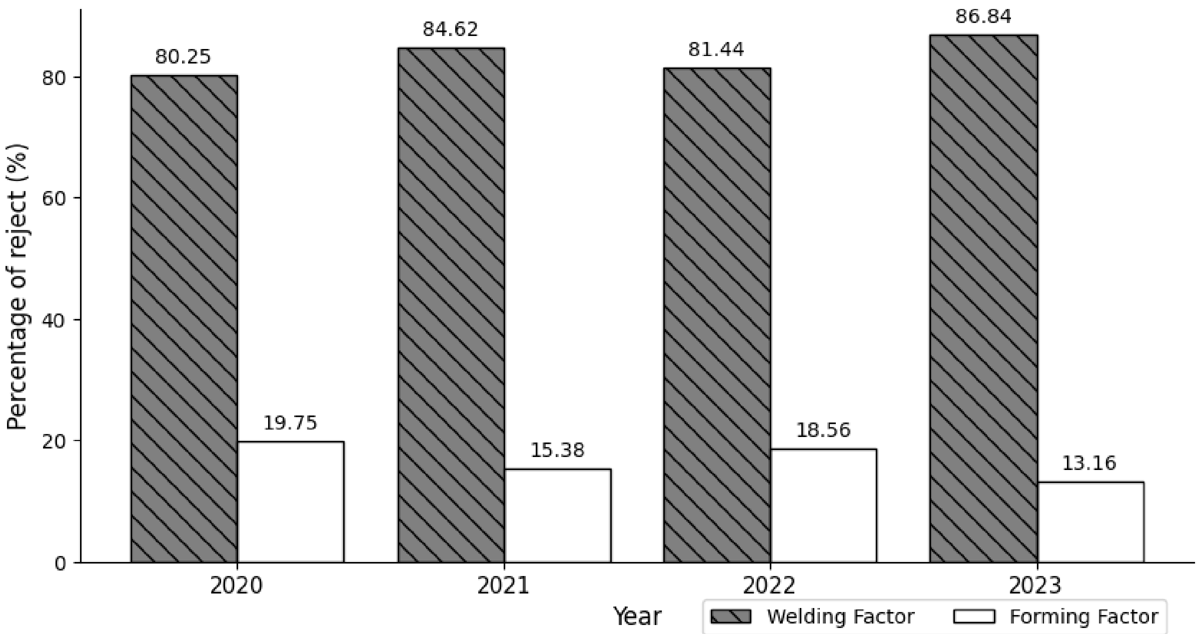

Figure 6. Comparison of error statistics: welding and pipe forming factors.

3.2. System Overview

This system combines thermal imaging, data processing, ML algorithms, and embedded system applications to enhance the monitoring and control of the ERW process. The system's main components are shown in **Figure 7**, with details as follows:

(i) Thermal Image Data Collection. Thermal imaging sensors are used to detect and capture infrared images of the weld point, providing real-time temperature distribution data during the welding process. This information is crucial for monitoring heat and identifying potential welding defects.

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(ii) Data Preprocessing. The collected thermal image data undergoes preprocessing to improve quality and suitability for analysis. Steps include Labeling: Classifying data based on weld quality.
- Image Processing: Enhancing image clarity and extracting relevant parts.
- Data Cleaning & Balancing: Reducing noise and addressing class imbalance issues.
- Feature Extraction: Selecting statistical and spatial features related to weld quality.
- Feature Selection: Choosing the most impactful features for model training.

(iii) Machine Learning Algorithms. The extracted features are fed into ML models to analyze heat distribution patterns and classify weld quality in real time.

(iv) Deployment on Embedded Systems. The developed ML models are optimized for edge computing and Edge AI, enabling real-time analysis and decision-making without relying on cloud resources.

(v) Dashboard Development. The system connects predictive models to a cloud platform for data storage and visualization through a dashboard, supporting ERW settings analysis and remote quality monitoring.

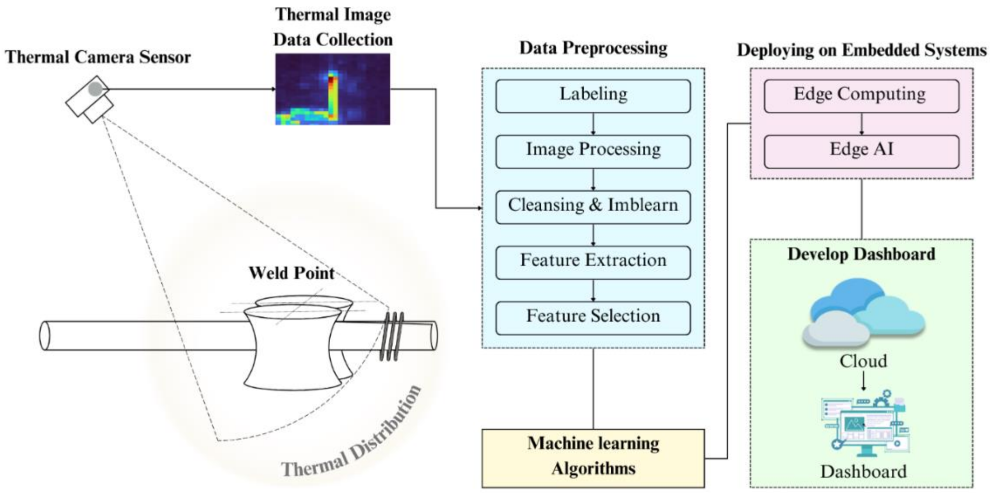

Figure 7. Real-time connected thermal camera with edge ai processing and data transmission to web dashboard.

3.3. Thermal Camera Sensor Development

Thermal camera sensors play a crucial role in monitoring the real-time heat distribution at welding points. In this system, a thermal camera sensor has been developed to enhance measurement accuracy and provide comprehensive data. The developed thermal camera sensor is shown in **Figure 8,** with the development process following steps.

(i) Hardware Specifications. Choosing the appropriate hardware is essential for developing thermal camera sensors, which include:
- MLX90640 Thermal Camera Sensor: This sensor measures the temperature distribution of objects through infrared radiation, featuring a wide 55° x 35° field of view and a 32x24 pixel resolution. Each pixel represents pixel intensity or an 8-bit grayscale value.
- ESP32 Microcontroller: Responsible for processing thermal data and forwarding it for analysis. All data will be processed through the ESP32.

The primary goal of developing the thermal camera sensor is to capture temperature distribution changes through thermal images. These images will be stored and

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categorized into two statuses: Not Good (NG) for incorrect settings and OK for correct settings. The data will then be analyzed and processed to develop AI models.

(ii) Hardware Installation. Installing the thermal camera sensor is a critical step to ensure that the sensor is positioned to comprehensively capture the heat distribution. The installation setup is illustrated in **Figure 9**. The infrared camera will be mounted in a suitable position to effectively detect the heat distribution and will be angled to cover the entire weld area. The camera will then be connected to the ESP32 for processing and collecting thermal image data.

(iii) Connection and Configuration. Connecting the ESP32 to the MLX90640 via the I2C interface, along with installing a TFT screen to display thermal images for ease of installation and real-time adjustment. The software uses the Adafruit MLX90640 library version 1.0.4 for sensor communication. The sensor outputs data in a 1x768 pixel vector, where each pixel shows an 8-bit grayscale intensity value (0-255), which is then converted to pixel temperature. The ESP32 processes these values and sends them via a serial port. During data collection, serial port communication is used for its stability and capability to handle high data volumes.

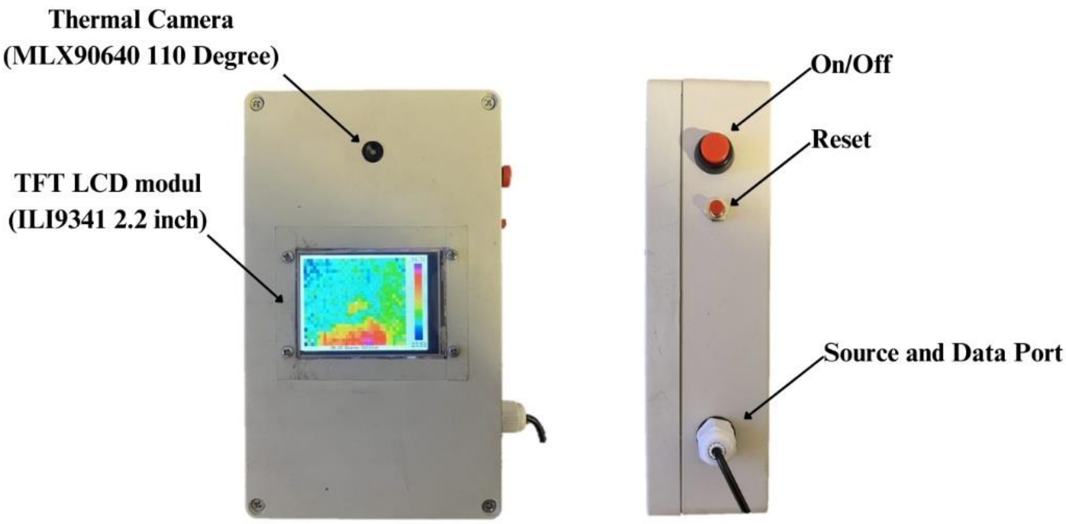

Figure 8. Connected thermal camera using MLX90640 and ESP32.

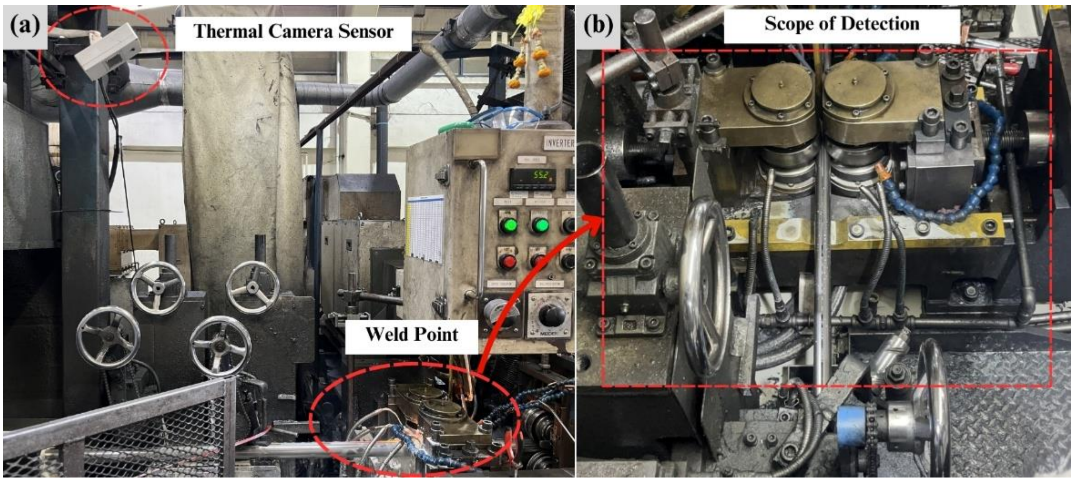

Figure 9. Position of connected thermal camera (a) wide picture of installation and (b) area of welding point location.

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3.4. Data Processing

Data preprocessing is a critical step to enhance the quality and suitability of thermal image data obtained from the MLX90640 thermal camera sensor. The steps involved are as follows.

(i) Data Labeling. Thermal image data collection is divided into two groups based on the initial ERW welding settings: OK (pass) and NG (fail). Data was collected over two months, resulting in 3021 images: 1550 OK and 1471 NG. This labeled data forms the essential foundation for AI model training.

(ii) Image processing. Thermal image data is represented as pixel temperature vectors with a resolution of 32x24 pixels. Each pixel's value is converted from numerical data (pixel temperature) to increase the data resolution beyond 8 bits and improve visibility and interpretation, as shown in **Figure 10(a)**. Subsequently, a colormap method is applied to transform numerical values into color representations, allowing for clearer differentiation of information and enhanced detail visualization, as illustrated in **Figure 10(b)**.

(iii) Element Definitions: The thermal image data is segmented into important and unimportant areas, with five key components:

- Squeeze Point: The area where the squeeze rolls compress the molten edges of the metal. This area shows significant details in the HAZ.
- Pipe: The area that has undergone welding.
- Bead: The extruded metal in the HAZ that is scraped off as waste.
- Welding Temperature Distribution: The heat distribution around the weld area.
- Ambient Temperature: The general air temperature.

The actual image of these components is presented in **Figure 11(a)**, while the corresponding thermal image representation is illustrated in **Figure 11(b)**. The MLX90640 sensor cannot distinguish details in high heat distribution areas near the weld point as well as high-resolution sensors. Therefore, the suitable approach is to analyze the welding temperature distribution, providing qualitative data on overall heat distribution from the process. While not as detailed as HAZ analysis, this method offers valuable information for assessing process efficiency and safety.

(iv) Region of Interest (ROI) extraction: focuses on three components: Squeeze Point, Pipe, and Welding Temperature Distribution. Images are cropped to retain only the relevant areas, eliminating unnecessary regions to enhance data efficiency and highlight critical information. To further optimize processing speed and reduce computational resource usage, the original 32×24 pixel resolution is downsampled to 10×12 pixels, as shown in **Figure 12**.

(v) Data Cleansing and Imbalanced Data Handling. Data cleansing plays a vital role in filtering out abnormal images from normal ones. Given that the data is in image form, this process is straightforward, allowing for plotting and removal of abnormal images. Then, data balancing is performed using the Synthetic Minority Over-sampling Technique (SMOTE), resulting in a total of 3100 images, split evenly with 1550 OK and 1550 NG.

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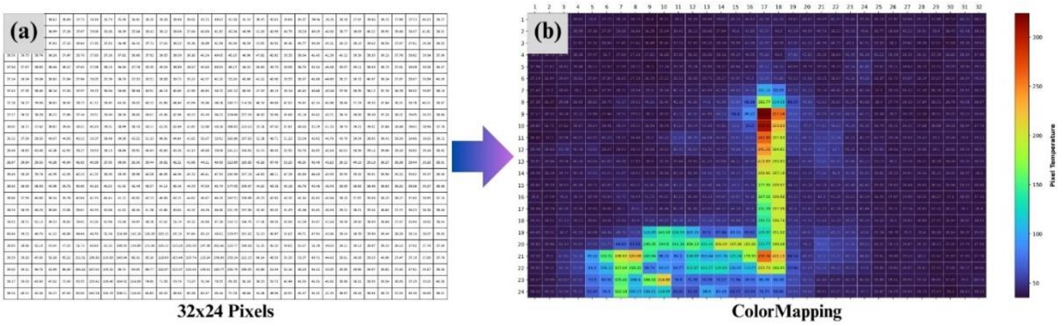

Figure 10. Color-mapping applied to 32x24 pixel thermal data (a) original image data and (b) color-mapped image data.

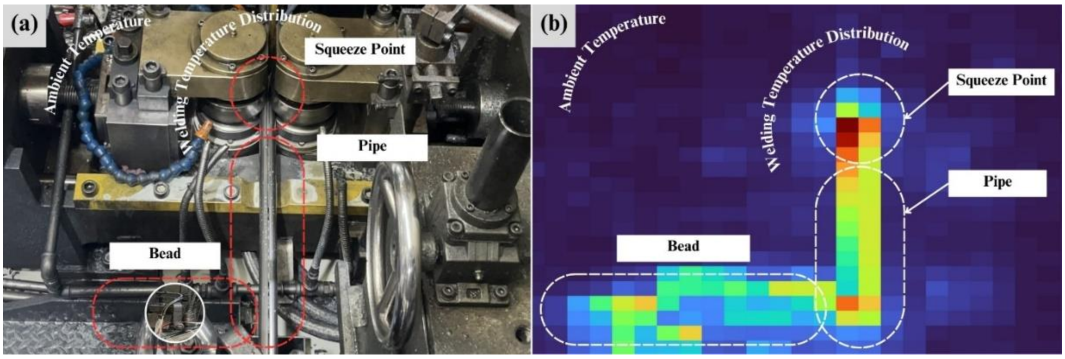

Figure 11. Components of detection (a) real components of ERW and (b) thermal image capturing using thermal imaging sensor (MLX90640).

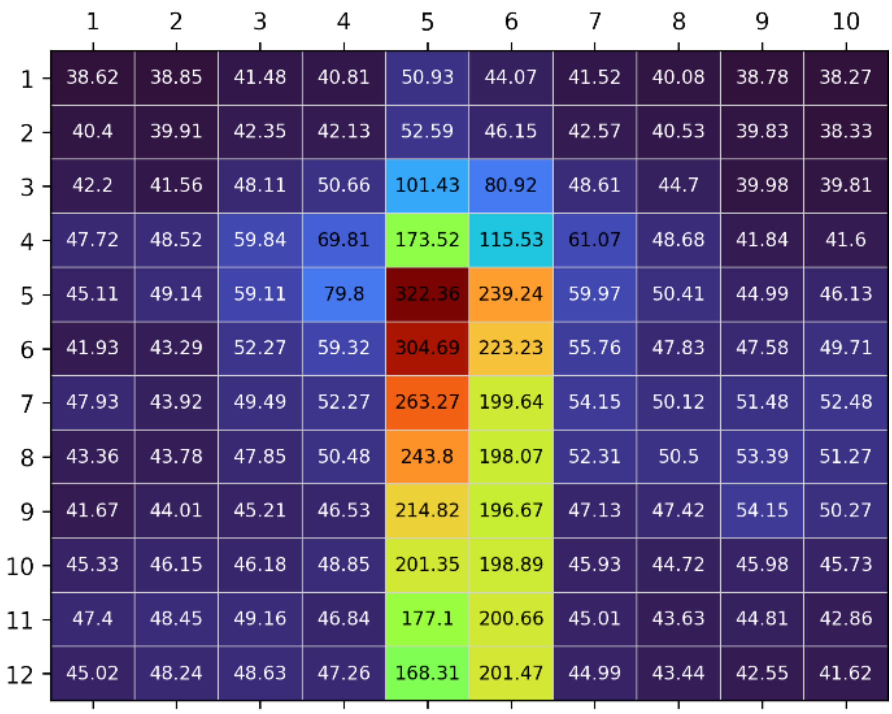

Figure 12. Region of interest (ROI) determination (10x12 Pixels).

3.5. Feature Engineering

Feature engineering is a crucial process in preparing data for analysis and ML model development. The thermal image data, with a resolution of 10×12 pixels, is transformed into

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a 1×120 pixel vector before undergoing statistical feature extraction. Due to the large size of thermal image data, STF helps reduce the data size, enabling efficient learning and faster processing by the model. Additionally, STF assists in analyzing the temperature distribution characteristics in the images, which is a key factor in metal weld quality inspection.

(i) Statistical Feature Extraction. Extracting STF from thermal image data involves 12 statistical metrics, detailed in **Table 1**.

Table 1. Detail of statistical features.

Features	Description	Equation
Mean	The average temperature at the weld point, indicating overall heat intensity.	$\sum_{i=1}^{N} x_i$
Standard Deviation	Measuring temperature fluctuations: Higher values indicate greater thermal variation.	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - mean)^2}$
Kurtosis	Describing the sharpness of the temperature distribution, high values suggest pronounced peaks.	$\frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - mean}{SD})^4 - 3$
Skewness	Indicating asymmetry in the temperature distribution; positive values suggest right-skewed data, and negative values indicate left-skewed data.	$\frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - mean}{SD})^3$
Entropy	Representing randomness in temperature distribution, higher values indicate greater uncertainty.	$\sum_{i=1}^{n} p_i \log(p_i)$
Contrast	Measuring the difference between maximum and minimum temperatures, highlighting intensity variations.	$\sum_{i,j}(i-j)^2 P(i,j)$
Root Mean Square (RMS)	Assessing the magnitude of thermal energy, higher values indicate sustained high temperatures.	$\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Variance	Measuring temperature variability: greater variance suggests more dispersed temperature values.	$\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$
Energy	Represents accumulated thermal energy; higher values indicate significant heat concentration.	$\sum_{i.j}(P(i,j))^2$
Fifth moment	Captures higher-order distribution characteristics, providing insights into data complexity.	$\frac{1}{N}\sum_{i=1}^{N}(x_i - mean)^5$
Sixth moment	Extends higher-order statistical analysis for a more detailed understanding of distribution.	$\frac{1}{N}\sum_{i=1}^{N}(x_i - mean)^6$
Smoothness	Indicates the uniformity of temperature distribution; higher values suggest gradual thermal transitions.	$1 - \frac{1}{1 + Variance}$

Note: The Equation includes i and j as pixel indices representing temperature values, x_i = the temperature at index i, p_i = the probability of the temperature at i, P(i,j) = the joint probability of temperatures at pixels i and j. Using these features enables the model to efficiently learn and process data for practical metal weld quality inspection.

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- Mean: It represents the average temperature at the weld point, providing an overview of the heat generated in that area.
- Standard Deviation: It indicates the temperature variation at the weld point. A high standard deviation suggests significant temperature differences in that area.
- Kurtosis: It reflects the peakedness of the temperature distribution. High kurtosis means a highly peaked distribution with distinct outlier values.
- Skewness: This shows the symmetry of the temperature distribution. Positive skewness indicates data is skewed to the right, while negative skewness indicates data is skewed to the left.
- Entropy: It represents the uncertainty or randomness of the temperature distribution. High entropy indicates greater uncertainty in the thermal image.
- Contrast: It reflects the difference between the minimum and maximum temperatures at the weld point. High contrast indicates clear temperature changes in that area.
- Root Mean Square: It reflects the average squared temperature at the weld point. High RMS indicates high temperatures in that area.
- Energy: It indicates the accumulated energy of the temperature distribution in the thermal image. High energy suggests significant energy accumulation in that area.
- Variance: This reflects the temperature distribution's variability. High variance indicates diverse temperatures in that area.
- Fifth Central Moment: It describes higher-order distribution characteristics beyond skewness and kurtosis, potentially providing additional information about complex distributions.
- Sixth Central Moment: It is similar to the fifth central moment but measures higher-order differences, offering more detailed distribution information.
- Smoothness: It indicates the smoothness of the temperature distribution. High smoothness suggests gradual temperature changes in the image.

(ii) Feature Selection. Feature selection is an essential process to reduce model complexity and eliminate unnecessary features. This research utilizes two main techniques: Random Forest-based importance analysis and Correlation Analysis to identify the most critical features for effective ML model development.

- Random Forest-Based: Importance is used to analyze feature importance by splitting the data into a training set (60%) and a testing set (30%), with a seed set to 42. The results of the feature importance analysis are shown in **Figure 13**. The importance scores indicate the significance of each statistical feature for classifying OK and NG images. Only features with an importance score greater than 0.8 are selected, including seven statistical features: Fifth Central Moment, Contrast, Sixth Central Moment, Root Mean Square (RMS), Skewness, Entropy, and Kurtosis. These features will undergo further filtering.
- Correlation Analysis: helps to select features without redundant correlations, based on the following criteria:
  - High Correlation (greater than 0.8). If feature pairs have a high correlation, indicating similar data types, the feature with higher importance is selected, and the others are removed.
  - Moderate Correlation (between 0.5 and 0.8) These features may still be useful but should be considered with their importance in mind.
  - Low Correlation (less than 0.5) These features are typically important and not correlated with others.

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The correlation analysis results of the seven STF are shown in Figure 14 from the correlation matrix, features are grouped into three main clusters based on correlation.

(iii) Group 1: It consists of four statistical features: Fifth Central Moment, Contrast, Sixth Central Moment, and Root Mean Square.
(iv) Group 2: It consists of two statistical features: Skewness and Kurtosis.
(v) Group 3: It consists of one statistical feature: Entropy.

Feature selection considerations are in the following:

(i) Group 1: Select the two most important features since it's a large group: Fifth Central Moment and Contrast.
(ii) Group 2: Selection of the Most Important Feature from **Figure 14**. Although Skewness exhibits a higher importance score (0.086) compared to Kurtosis (0.083), Kurtosis was selected due to its lower correlation with other features in the correlation matrix. A lower correlation suggests that Kurtosis provides more independent information, potentially enhancing the robustness of the model. Therefore, despite its slightly lower importance score, Kurtosis was deemed more suitable for feature selection in this context.
(iii) Group 3: Entropy is the sole feature and does not correlate with other features.

Selected features for model development include Fifth Central Moment, Contrast, Kurtosis, and Entropy. The data then undergoes standardization by adjusting the mean to zero and the standard deviation to one, ensuring suitable data size and enhancing processing efficiency when implementing AI models on embedded systems.

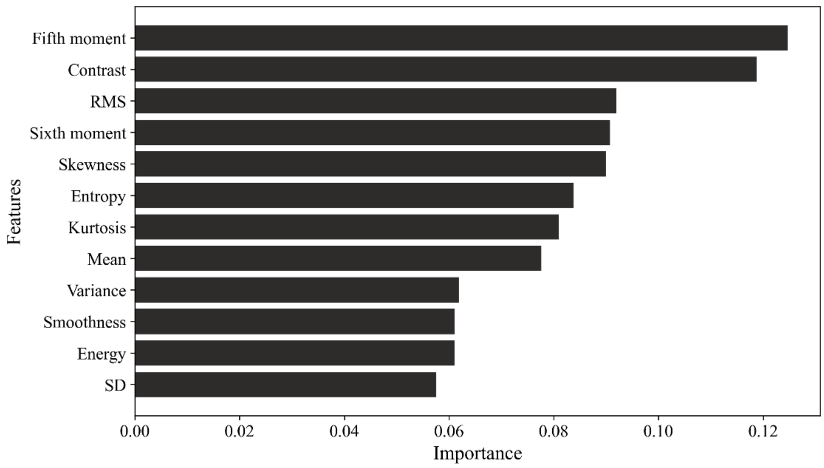

Figure 13. Importance analysis of 12 statistical features.

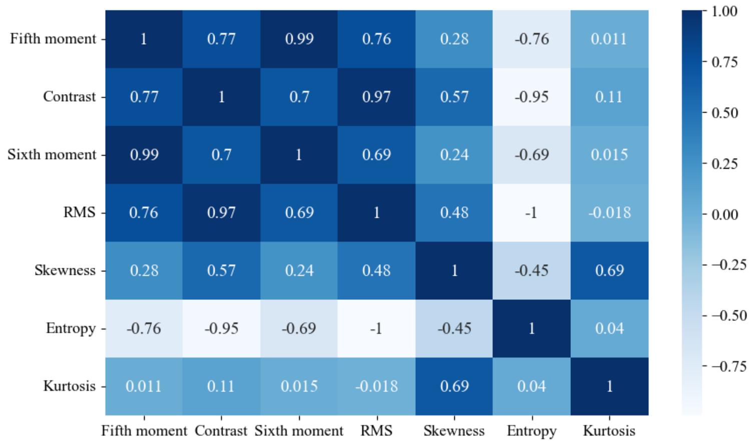

Figure 14. Correlation matrix of 7 statistical features.

3.6. Machine Learning Model Development

Analyzing and selecting the appropriate model before actual deployment is a crucial step to ensure the model effectively meets the requirements, aligns with the data set, and achieves high accuracy. Research on the application of ML techniques to thermal imaging data reveals that several models are popular and suitable for such tasks, including ANN, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). These three models have been selected for comparison and development to identify the most efficient one.

In this research, MATLAB has been used as the primary tool for simulating and evaluating model performance. MATLAB provides comprehensive toolsets for data management, model building, and result analysis. Using MATLAB ensures that the model evaluation and development process is both efficient and reliable.

3.7. Evaluation

The model's performance will be evaluated using a Confusion Matrix, along with six key metrics:

(i) Accuracy: The proportion of correct predictions out of the total number of samples in the test set.

(ii) Precision: The accuracy of positive predictions, calculated as the number of true positives divided by the total number of predicted positives.

(iii) Recall (Sensitivity): The model's ability to correctly detect and predict true positive results.

(iv) F1 Score: The harmonic means of Precision and Recall, ideal for evaluating models with imbalanced datasets.

(v) Specificity: The proportion of true negative predictions out of the total number of actual negative samples, which helps assess the model's ability to distinguish non-target samples.

(vi) Error Rate: The proportion of incorrect predictions out of the total number of samples in the test set.

These metrics provide a comprehensive evaluation of the model's performance and help identify areas for further improvement.

3.8. Deploying on Embedded Systems

After selecting the most suitable model through evaluation, the next step is deploying the model onto the ESP32 microcontroller. This process is crucial for developing Edge Computing and Edge AI to utilize the ML system in real-world environments.

During the evaluation phase, MATLAB was used for simulation and comparison. However, MATLAB is designed for academic experiments and is not suitable for direct deployment on microcontrollers, posing limitations in practical use.

To overcome these limitations, TensorFlow and TensorFlow Lite are chosen as the primary tools for developing and deploying AI models on embedded devices. The deployment process consists of two main parts.

(i) Edge AI. This part involves developing the AI model to be operational on the ESP32, an environment with limited resources. The process includes:

- TensorFlow Model Conversion: Developing the model in TensorFlow via Google Colab and converting it into TensorFlow Lite format using TFLiteConverter to reduce model size and improve performance on embedded devices.

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- Integrating the Model with ESP32 Program: The TensorFlow Lite model is exported as a C Array to be used in C/C++ programs on the ESP32. This step ensures the smooth integration of the AI model with hardware data processing.
- Model Processing on ESP32: The TensorFlow Lite model is deployed and processed using the EloquentTinyML library.

(ii) Edge Computing. Data processing on the ESP32 is designed to be compact and efficient, with four key steps:
- Defining ROI Creating arrays to identify pixels and collect relevant image data in real time.
- Feature Calculation Calculating four feature values: Fifth Central Moment, Contrast, Kurtosis, and Entropy.
- Data Standardization: Using standardization techniques to adjust feature values within suitable ranges for processing.
- Feature Prediction Feeding the data into the AI model for real-time prediction.
- The results can be displayed on the ESP32 and sent to the cloud for further analysis. Additionally, a Web App Dashboard can be developed for practical use.

4. RESULTS
4.1. Dataset Description

The thermal image data used for developing the AI model is divided into two main sets: the Training Set, comprising 70% of the total data, and the Testing Set, comprising 30% of the total data. Within the Training Set, data is further split into a Training Subset and a Validation Set in an 80:20 ratio for preliminary evaluation. The details of the data split are shown in **Table 2**.

Table 2. Details on dataset (thermal images).

Data	OK	NG	Total
Training set	866	870	1736
Testing set	217	217	434
Validation set	467	463	930

4.2. Experimental Setup

Experiments are conducted using MATLAB as the primary tool for simulating and evaluating model performance due to its comprehensive toolsets for data management, model building, and result analysis. After testing and fine-tuning models in MATLAB, the selected model is deployed on the ESP32 microcontroller using TensorFlow and TensorFlow Lite for AI deployment on embedded devices.

(i) Hardware: ESP32, MLX90640
(ii) Software: MATLAB, Visual Studio Code
(iii) Library: TensorFlow, TensorFlow Lite, EloquentTinyML
(iv) Testing Process
- Train the model using the prepared dataset.
- Evaluate the model with the testing dataset.
- Deploy the model on the ESP32 and measure performance.

4.3. Performance Evaluation Metrics

The models tested include ANN, KNN, and SVM. The performance of each model is measured according to predefined metrics. The results are shown in **Tables 3** and **4**.

(i) Model Comparison. The performance testing of the three models using the Validation and Test Datasets indicates that the KNN model achieved the best evaluation results in terms of Accuracy and F1 Score (0.851 and 0.852, respectively), demonstrating strong predictive capability. The ANN model had the highest Recall (0.851) and Specificity (0.847), indicating effective detection of both positive and negative data. In contrast, the SVM model had the lowest evaluation results across all criteria for the Validation Dataset. For the Test Dataset, the ANN and KNN models both had an Accuracy of 0.858, but KNN had the highest Recall (0.877), showing better detection of positive samples. The ANN model had the highest Precision (0.851), indicating greater accuracy in predicting positive groups. Both models had the lowest Error Rate (0.142). In terms of processing efficiency, ANN demonstrated the highest prediction speed (7873.13 obs/sec) and the smallest model size (11.03 KB), outperforming KNN and SVM in both aspects. These results indicate that both KNN and ANN offer high accuracy. However, ANN stands out with faster prediction speeds and a smaller model size, making it more suitable for Edge AI applications in real-world scenarios. Given its superior performance in terms of accuracy, speed, and model size, ANN is selected as the primary model for this research, particularly for real-time processing applications on resource-constrained devices. The architecture of the ANN model, structured as a feedforward Multi-Layer Perceptron (MLP) with four input features and two output classes, consists of four dense layers employing ReLU activation in the first three layers and Softmax activation in the final layer to enable binary classification, as detailed in **Figure 15**.

Table 3. Comparison of prediction performace.

Evaluates	ANN	KNN	SVM
	Validation set		
Accuracy	0.846	0.851	0.819
Precision	0.842	0.848	0.833
Recall	0.851	0.855	0.798
F1 Score	0.846	0.852	0.815
Specificity	0.841	0.847	0.84
Error Rate	0.154	0.149	0.181
	Test Set		
Accuracy	0.858	0.858	0.83
Precision	0.851	0.845	0.84
Recall	0.869	0.877	0.815
F1 Score	0.86	0.861	0.828
Specificity	0.847	0.839	0.845
Error Rate	0.142	0.142	0.17

Table 4. Comparison of scalability performance.

Evaluates	ANN	KNN	SVM
Prediction Speed (obs/sec)	7873.13	2818.64	1826.96
Model Size (Kilobyte)	11.03	168.04	58.03
Training Time (sec)	45.42	6.24	5.60

(ii) Deployment on ESP32. To effectively deploy the ANN model on the ESP32, the model is redeveloped using TensorFlow and TensorFlow Lite. This reduces model size and enhances processing efficiency to accommodate resource constraints. The redeveloped

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model undergoes multiple evaluations to ensure it is suitable for practical application. Starting with the accuracy analysis on both Validation and Test sets to measure the correct prediction capability, model size is also examined to ensure it fits within the ESP32's memory constraints. Real-time inference speed is another crucial metric affecting responsiveness. After selecting the most effective ANN model, it is converted to TensorFlow Lite and deployed on the ESP32 using EloquentTinyML. Performance metrics are shown in **Table 5**.

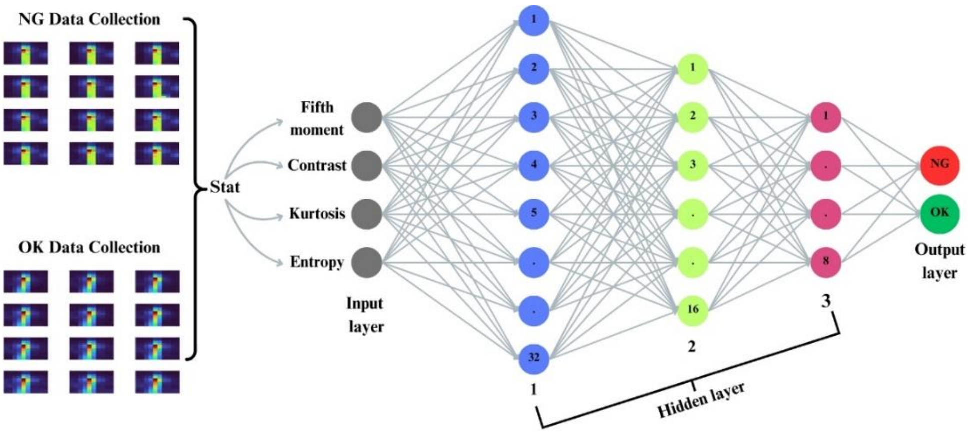

Figure 15. ANN architecture derived from statistical features.

Table 5. Model performance during training.

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
243	0.295	0.877	0.357	0.8571

Figure 16 illustrates the changes in loss during the training and validation phases of the ANN model. The X-axis represents the number of epochs (0 to 250 rounds), while the Y-axis represents the loss value for each epoch. The red line indicates Training Loss, and the yellow line represents Validation Loss.

The training loss consistently decreases, reflecting the model's high learning efficiency, while the validation loss decreases initially and stabilizes later, indicating the model's ability to learn effectively from the data despite slight fluctuations. This suggests that the model is well-tuned for both training and validation data, indicating stability and readiness for deployment. At epoch 243, the model shows a Training Loss of 0.2952 and Training Accuracy of 0.8773, with Validation Loss at 0.3571 and Validation Accuracy at 0.8571.

From the performance evaluation shown in **Table 6**, the model is suitable for Edge AI applications, with a high prediction speed of 6,666.67 observations per second (obs/sec), reflecting efficient real-time processing capability. Additionally, the model's size is only 36.87 kilobytes, indicating compactness and resource efficiency, essential for deployment on memory-constrained devices. Resource usage shows the model using only 25.60% of RAM and 90.70% of Flash memory, indicating high Flash usage but still within practical limits for embedded systems. Overall, the ANN model meets the requirements for Edge AI applications, delivering excellent performance, speed, and efficient resource utilization. The performance of the ANN model in classifying data was evaluated using a Confusion Matrix, a crucial tool for analyzing model performance, as illustrated in **Figure 17**.

These results reflect the model's ability to learn and classify data accurately, making it suitable for practical applications. The detailed performance metrics used to evaluate the model are shown in **Table 7**.

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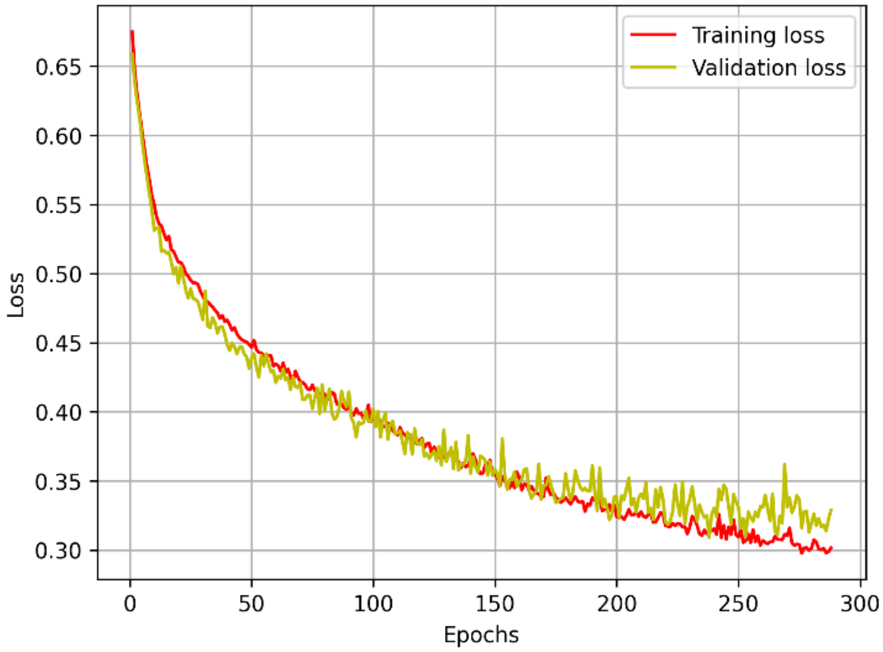

Figure 16. Training and validation loss curve.

Table 6. Scalability performance on ESP32.

Prediction Speed (obs/sec)	Model Size (Kilobyte)	RAM (%)	Flash (%)
6666.67	36.87	25.60	90.70

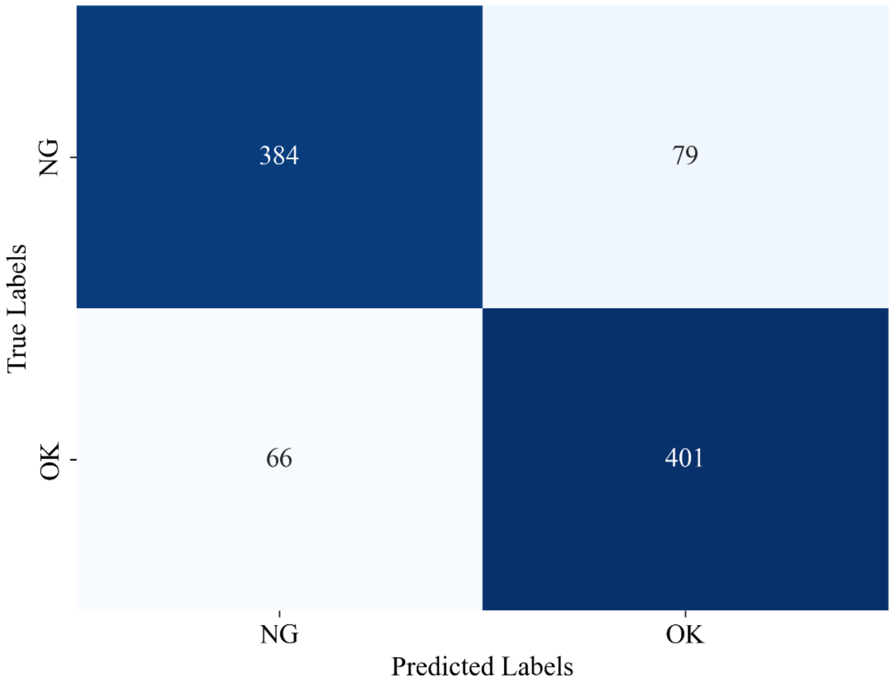

Figure 17. Confusion matrices for edge ai models.

Table 7. Prediction performance (edge AI).

Accuracy	Precision	Recall	F1 Score	Specificity	Error Rate
0.844	0.835	0.859	0.8469	0.829	0.156

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For the OK data group, the model has a Precision of 83.5%, indicating that 83.5% of the samples predicted as OK were indeed correct. The Recall is 85.9%, meaning the model successfully detected 85.9% of the OK data in the dataset.

The test results show that the ANN model demonstrates good performance in terms of accuracy and practical usability, making it suitable for Edge AI systems that require fast and accurate real-time processing.

To support real-time quality assessment, the predictive results are visualized through a web dashboard, providing an intuitive and interpretable interface for users. This dashboard assists operators in determining whether a weld is classified as NG or OK, enhancing the decision making process in the ERW production line, as illustrated in **Figure 18**.

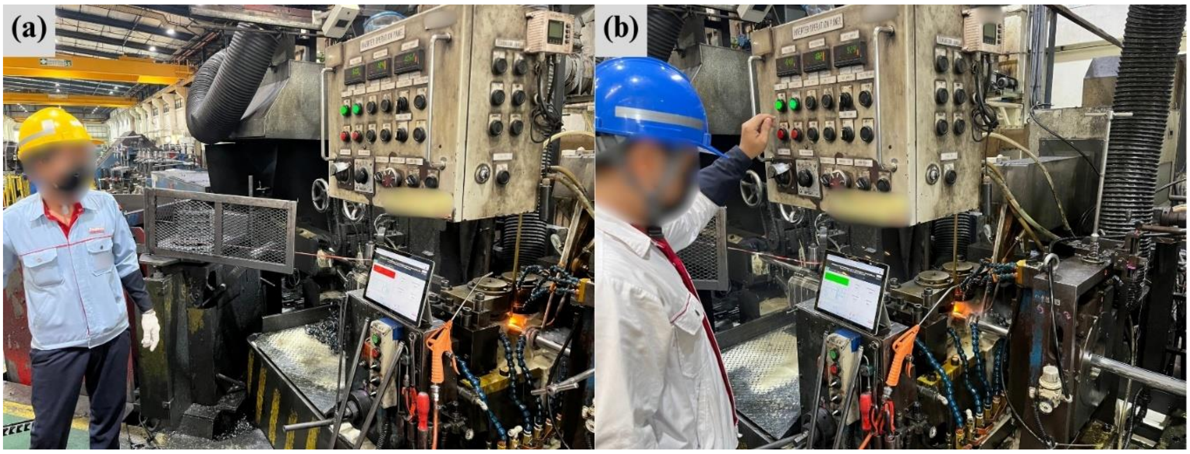

Figure 18. Visualization of predictive results on web dashboard for initial erw welding setting guidelines (a) NG Status and (b) OK status.

5. DISCUSSION

The developed ANN model demonstrated the ability to detect welding defects with an accuracy of 84.4%. This performance showcases strong efficiency in classifying heat distribution patterns under resource-limited conditions. High prediction speed (6,666 predictions/second) and low memory usage (36.87 KB) validate the feasibility of deploying the AI model on low-cost edge devices like the ESP32. The ASTF, particularly the fifth central moment, contrast, kurtosis, and entropy, effectively capture critical thermal dynamics in the welding area. These features reduce data dimensions while maintaining distinguishable patterns, enabling efficient learning despite limited computational resources. The system's ability to standardize welding parameter settings in real time addresses variability from human decision-making, aligning with Industry 4.0 goals to reduce waste and automate processes.

Pre-existing AI-driven welding systems, such as FDNN (92.59% accuracy in TIG welding [2]) and RBFNN-based thermal monitoring [7], achieve higher accuracy but depend on cloud-connected architectures or high-resolution sensors. This reliance limits their suitability for high-frequency ERW welding environments. In contrast, this work emphasizes edge compatibility, achieving comparable accuracy (84.4%) with a model size 60 times smaller than traditional SVM models. Furthermore, the proposed ASTF approach reduces computation latency by 85% compared to vision-based imaging systems requiring a 0.001-second sampling rate [7], enabling real-time adjustments without cloud dependence. Combining ASTF yields better results than raw thermal data [6], focusing on interpretable and physics-related

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metrics (e.g., entropy for thermal disorder), which are less susceptible to noise from low-resolution sensors (32×24 pixels).

However, relying on 8-bit thermal imaging from MLX90640 limits resolution and may miss higher-level heat detection achievable by high-resolution sensors. While ASTF reduces data dimensions, manual feature engineering limits the model's ability to discover latent patterns compared to end-to-end deep learning. The 84.4% accuracy of the ANN, though sufficient for defect detection, does not meet the stringent requirements of critical applications such as precision defect detection. The trade-off between model complexity and edge device capability is evident: quantizing ANN to 8-bit for ESP32 usage reduces memory consumption by 67% but decreases accuracy by 3.2%. Additionally, the dataset focused on binary classification (OK/NG) does not consider complex defect types (e.g., porosity vs. cracking), posing diagnostic limitations.

This study presents an innovative Edge AI framework for real-time parameter optimization in the ERW process. By integrating IoT technology for thermal imaging, ASTF extraction, and lightweight ANN implementation on the ESP32 microcontroller, this research demonstrates the effectiveness of AI in resource-constrained environments. Key results include the ASTF method, which reduces thermal data dimensions by 89% while maintaining defect detection accuracy. This significant improvement enables fast and accurate welding defect detection even in environments with limited resources and energy.

One of the highlights of this work is the rapid prediction capability of 6,666 inferences per second, allowing immediate real-time welding parameter adjustments without relying on the cloud or large servers. This reduces processing delays and energy consumption, making low-cost industrial solutions feasible using affordable hardware, which is a practical advancement for the manufacturing industry.

The major impact of this system lies in standardizing welding quality in resource-constrained environments, potentially reducing product rejection rates by 10-15% in industrial pipe production processes without cloud dependence. This increases manufacturing efficiency while reducing delays and energy usage in high-speed production processes.

6. CONCLUSION

This article presents the development of an electrical resistance welding (ERW) setup method by applying the concepts of Internet of Things (IoT) and Artificial Intelligence (AI). To achieve the AI model training, this research extracts the statistical features from the real-time thermal images, which is equipped with thermal imaging sensors (MLX90640) to recognize the changes of the welding of the steel pipes, both the weld seam and the weld area. From the experimental results with the actual production of steel pipes in the industrial plant, it was found that the accuracy of distinguishing good and bad welding was 84.4%, which can help operators set the machine settings and significantly reduce the machine setup time.

Future research should develop a process for collecting experimental results to evaluate the performance of the AI model by testing it on a variety of production models to make it applicable to the production of a variety of steel pipe products.

7. ACKNOWLEDGMENT

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8. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

9. REFERENCES

[1] Kesse, M. A., Buah, E., Handroos, H., and Ayetor, G. K. (2020). Development of an artificial intelligence powered TIG welding algorithm for the prediction of bead geometry for TIG welding processes using hybrid deep learning. *Metals*, *10*(4), 451.

[2] Wang, H. F., Cao, J., Zhao, X. M., Wang, X. M., and Wang, G. P. (2017). Detection of HF-ERW status by neural network on imaging. *International Journal of Precision Engineering and Manufacturing*, *18*, 931-936.

[3] Cai, W., Wang, J., Jiang, P., Cao, L., Mi, G., and Zhou, Q. (2020). Application of sensing techniques and artificial intelligence-based methods to laser welding real-time monitoring: A critical review of recent literature. *Journal of Manufacturing systems*, *57*, 1-18.

[4] Li, Y., Yu, B., Wang, B., Lee, T. H., and Banu, M. (2020). Online quality inspection of ultrasonic composite welding by combining artificial intelligence technologies with welding process signatures. *Materials & Design*, *194*, 108912.

[5] Wang, B., Hu, S. J., Sun, L., and Freiheit, T. (2020). Intelligent welding system technologies: State-of-the-art review and perspectives. *Journal of Manufacturing Systems*, *56*, 373-391.

[6] Tsuzuki, R. (2022). Development of automation and artificial intelligence technology for welding and inspection process in aircraft industry. *Welding in the World*, *66*(1), 105-116.

[7] Kim, D., Kim, T., Park, Y. W., Sung, K., Kang, M., and Kim, C. (2007). Estimation of weld quality in high-frequency electric resistance welding with image processing. *Welding Journal*, *86*(3), 70-80.

[8] Hasegawa, N., Fukami, T., Takeda, Y., Tanimoto, M., Hmatani, H., Nakaji, T., and Ohsawa, T. (2015). Development of a new optical monitoring system for HF-ERW welding processes. *Nippon Steel & Sumitomo Metal Technical Report*, (107), 114-120.

[9] Janssens, O., Van de Walle, R., Loccufier, M., and Van Hoecke, S. (2017). Deep learning for infrared thermal image based machine health monitoring. *IEEE/ASME Transactions on Mechatronics*, *23*(1), 151-159.

[10] Cheng, J., Cao, J., Zhao, J., Liu, J., Zhao, R., and Liu, S. (2020). The flower pattern and rolls design for ERW pipes with the different specification in the flexible roll forming process. *Thin-Walled Structures*, *154*, 106809.

[11] Anijdan, S. M., Aghaie-Khafri, M., Khoshakhlagh, A. R., Eivani, A. R., Park, N., and Jafarian, H. R. (2021). A significant toughness enhancement, and microstructural evolution of an electric resistance welded (ERW) microalloyed steel. *Journal of Materials Research and Technology*, *15*, 5776-5786.

[12] Lee, J., Kim, D., Quagliato, L., Kang, S., and Kim, N. (2017). Change of the yield stress in roll formed ERW pipes considering the Bauschinger effect. *Journal of Materials Processing Technology*, *244*, 304-313.

[13] Khalaj, G., Pouraliakbar, H., Jandaghi, M. R., and Gholami, A. (2017). Microalloyed steel welds by HF-ERW technique: Novel PWHT cycles, microstructure evolution and mechanical properties enhancement. *International Journal of Pressure Vessels and Piping*, *152*, 15-26.

[14] Karani, A., Koley, S., and Shome, M. (2019). Failure of electric resistance welded API pipes–Effect of centre line segregation. *Engineering Failure Analysis*, *96*, 289-297.

[15] Warfield, S. K., Kaus, M., Jolesz, F. A., and Kikinis, R. (2000). Adaptive, template moderated, spatially varying statistical classification. *Medical Image Analysis*, *4*(1), 43-55.

[16] Mutlag, W. K., Ali, S. K., Aydam, Z. M., and Taher, B. H. (2020). Feature extraction methods: a review. In *Journal of Physics: Conference Series*, *1591*(1), 012028.

[17] Kang, C., Shi, C., Liu, Z., Liu, Z., Jiang, X., Chen, S., and Ma, C. (2020). Research on the optimization of welding parameters in high-frequency induction welding pipeline. *Journal of manufacturing processes*, *59*, 772-790.

[18] Ravikiran, K., Xu, P., and Li, L. (2024). A critical review on high-frequency electric-resistance welding of steel linepipe. *Journal of Manufacturing Processes*, *124*, 753-777.

[19] Rr, M. (2016). Microstructural changes in the forge weld area during high-frequency electric resistance welding. *Machines Technologies Materials*, *10*(5), 23-26.

[20] Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., and De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability*, *12*(2), 492.

[21] Mou, X. (2019). Artificial intelligence: Investment trends and selected industry uses. *International Finance Corporation*, *8*(2), 311-320.

[22] Nagaraju, K., and Ramakrishna, S. (2024). Leveraging artificial intelligence (AI) and geospatial technologies for community-centered urban expansion forecasting in hyderabad. *ASEAN Journal of Community Service and Education*, *3*(2), 135-146.

[23] Nurhasanah, S., and Nugraha, M. S. (2024). The future of learning: Ethical and philosophical implications of artificial intelligence (AI) integration in education. *Indonesian Journal of Multidiciplinary Research*, *4*(2), 341-352.

[24] Zahid, A., Leclaire, P., Hammadi, L., Roberta, C. A., and El Ballouti, A. (2025). Exploring the potential of industry 4.0 in manufacturing and supply chain systems: Insights and emerging trends from bibliometric analysis. *Supply Chain Analytics*, 100108.

[25] Sikandar, H., Vaicondam, Y., Khan, N., Qureshi, M. I., and Ullah, A. (2021). Scientific mapping of industry 4.0 research: a bibliometric analysis. *International Journal of Interactive Mobile Technologies*, *15*(18), 129-147.

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