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Smart Manufacturing With Industrial Internet of Things: Advances in TIG Welding for SS304 Stainless Steel

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ABSTRACT

Data are most important for any manufacturing processes in decision-making. It is important to monitor this data to improve the productivity of processes. Industrial Internet of Things (IIoT) is a very effective tool for capturing process information. This work focus on implement of IIoT in TIG welding processes. We developed an IIoT-enabled TIG welding setup that tracks key parameters like current, travel speed, gas flow rate, and arc gap in real time. This data is sent to a cloud platform and displayed through an easy-to-use mobile app, giving welders and engineers clear visibility into the process. This work also explore the potential application of IIoT in inspection to improve the inspection process. By capturing and processing weld images, we could measure bead width and detect any visible surface defects using edge detection and contour analysis. Also, Mobile based application is developed to store the inspection results of LPT, UT and metallography for proper documentation and analysis. The implementation of machine learning using XGBoost algorithm is discussed to predict the mechanical properties like, Ultimate tensile strength and hardness of HAZ and weld. The model performed very well, achieving over 95% accuracy, and was further explained using SHAP tools so we could understand not just what the model predicted, but why. For example, we could see how changing travel speed or gas flow affected the final weld quality. In short, this work demonstrates how combining IIoT, machine learning, and image processing can make TIG welding smarter, more reliable, and easier to control. It turns raw.

1 | Introduction

In recent times, rates of the internet have dropped significantly. Also, high computing devices are available at lower rates. In view of this economic internet connectivity and high computing devices, many consumer products are converted into Internet of Things (IoT) based products. Air conditioning, water purifiers, washing machines, etc. are some examples of in which IoT is already applied for remote controlling and monitoring products. But still, the implementation of IoT in the industries is very low. There are many challenges to implementing IoT in the industry. Industrial equipment is used in a very harsh environment, to sustain the environment robust hardware is required. Also, the industries are required high accuracy, precision and repeatability is require mainly for safety, quality, and uninterrupted production, and that why the implementation of IoT in industry is totally different sector known as Industrial Internet of Things (IIoT). Due to recent experience of pandemic, humans understand the importance of remote monitoring and controlling of the industry operation. So, nowadays government and private agencies are investing a high amount in developing IIoT based products for industries.

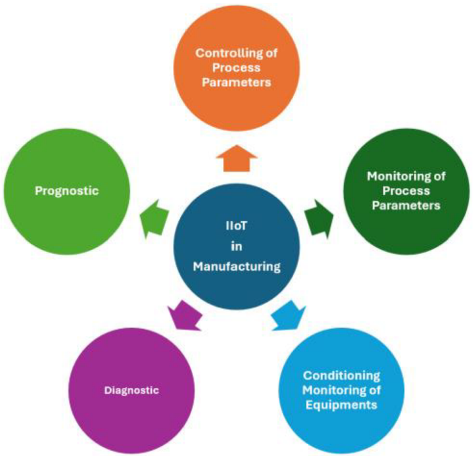


FIGURE 1 | Potential area of implementation of IIoT in industry.

Tungsten Inert Gas (TIG) welding is a metal joining process that provides excellent weld quality in terms of appearance as well as strength. India wants to become self-reliant in areas like aerospace, defense, nuclear, biomedical, etc., and TIG welding is a key metal joining process in this sector. It is not possible to be competitive in the world with conventional industrial infrastructure. It is necessary to upgrade the existing industrial infrastructure to improve the quality and productivity of industries.

Manufacturing is the most important function of industries. Controlling and monitoring the manufacturing process helps in achieving the desired quality, cost reduction, and on time delivery of the products. Figure 1 illustrates the role of IIoT (Industrial Internet of Things) in manufacturing. It highlights five interconnected functions: controlling process parameters, monitoring process parameters, condition monitoring of equipment, diagnostics, and prognostics. These functions collectively enhance manufacturing efficiency, predictive maintenance, and real-time decision-making by integrating sensors, data analytics, and automation.

This work upgrades conventional TIG welding to an IIoT-enabled system, allowing remote monitoring and control of the welding process. The integration of sensors and connectivity ensures real-time data acquisition and process optimization. This enhances efficiency, precision, and accessibility in TIG welding operations.

2 | Literature Survey

2.1 | TIG

Austenitic stainless steels demonstrate remarkable characteristics, including exceptional formability even under cryogenic conditions, elevated mechanical properties, and excellent corrosion resistance. Serindag, et al. examined 316 L stainless steel plates employed in the fabrication of LNG tanks through gas tungsten arc welding. Their findings revealed that the welded joint displayed elevated yield and tensile strength values, specifically 329 MPa and 630 MPa, surpassing the base plate values of 308 MPa for yield strength and 603 MPa for tensile strength [1]. The elevated corrosion resistance of these steels can reduce the necessity for maintenance. Stainless steels find primary applications in civil engineering structures, notably in reinforced concrete and structural steels. In these scenarios, stainless steels can serve as substitutes for carbon steels Shojaati, and colleagues determined that employing a duplex filler metal resulted in a weld with high strength. The outcomes of mechanical tests on the 316 L welded specimen are deemed acceptable, particularly when considering cost as a significant factor in welding [2]. Different fluxes namely, TiO2, MnO2, SiO2, MoO3, and Cr2O3 influence on several properties, including surface appearance, weld morphology, angular distortion, ferrite/austenite content, and mechanical properties of 6 mm thick grade 2205 stainless steels under Tungsten Inert Gas (TIG) welding process in detail, to evaluate the influence of different fluxes on welding outputs. Thus, in a systematic consideration of all such factors, the present work in detail investigates how each contribution of flux leads to enhanced performance and properties of welded material. All the results showed dual enhancement with respect to the process when utilizing SiO2, MoO3, and Cr2O3 fluxes. Not only did these fluxes substantially increase the penetration capability of the welds, but they also led to a notable improvement in the mechanical strength of the grade 2205 stainless steel welds when compared to conventional TIG welds. This double advantage infers that these fluxes might be an idea for the optimization of the performance of welding and the mechanical properties after welding [3]. Attarah, M. made a 3D finite element simulation. for Gas Tungsten Arc Welding (GTAW) on three joints two similar and one dissimilar consisting of thin plates of AISI type 304 stainless steel and St37 carbon steel the study reveals nonlinear temperature decrease in weld pieces that gives insight into the HAZ microstructure prediction [4]. The impact of repetitive TIG (tungsten inert gas) welding passes, involving the melting and remelting of the same material volume, on the microstructure and corrosion resistance of 2507 (EN 1.4410) super duplex stainless steel. Reduced secondary phases observed in the Fusion Boundary Zone (FBZ) and Zone 2 were observed when employing fewer weld passes with higher heat input, as opposed to a greater number of passes with lower heat input [5].

2.2 | IoT

Kevin Ashton introduced the word Internet of things (IoT) in 1999 [6]. With the help of IoT, it is possible to connect all the physical devices through the internet [7]. Cloud computing can offer the virtual infrastructure necessary for utility computing, which combines monitoring devices, storage systems, analytics tools, visualization platforms, and client delivery. Its cost-based model facilitates end-to-end service provisioning, allowing businesses and users to access applications on demand from any location [8]. The applications of IoT are in agriculture, smart cities, and industrial control [9]. Techniques like privacy-by-design, differential privacy, and lightweight public-key cryptography will serve as foundational elements for security in IoT middleware [10]. Around 30 years after the advent of IoT, society faces substantial challenges concerning IoT security. The pervasive interconnectivity and widespread use of IoT devices mean that cyberattacks can have extensive effects on many stakeholders. Historical incidents reveal numerous vulnerabilities within the IoT domain, which have been exploited to cause physical, economic, and health-related damage. Despite these threats, manufacturers still find it difficult to adequately secure IoT devices [11]. The biggest challenge in the implementation of IoT is cybersecurity. Machine Learning and Deep Learning can help to build the system for a cybersecurity system for IoT systems [12]. Integration of IoT in healthcare devices can improve the healthcare systems. Wearable devices help to monitor the movement of body parts. Collected data through IoT helps to diagnose the disease and customized treatment for the patient [13].

2.3 | IoT In Manufacturing

Smart machines play a crucial role within a smart factory [14]. Enabled by advanced IoT technologies, smart machines should possess the capability to operate autonomously [15]. This suggests that smart machines need the capacity to make independent decisions without relying on human instructions. They should also be able to communicate and collaborate with each other and with smart products [16]. In the context of a mechanical system, self-awareness involves the machine's capability to evaluate its own condition and respond accordingly to the assessment output [17]. Brizzi et al. explores the use of the Internet of Things (IoT) to collect real-time data during manufacturing, enabling responsive production management, maintenance, and monitoring of energy and water usage. It utilizes the ebbits platform to seamlessly integrate industrial sensors into mainstream business systems like MES and ERP [18]. Zhong et al. presents a real-time machine status monitoring platform enabled by the Internet of Things (IoT), utilizing technologies like RFID and wireless communications to capture and provide real-time information on resource availability [19].

Implementation of IoT in manufacturing makes it more powerful and efficient. The key issues in the implementation of IoT in manufacturing are data acquisition, preprocessing, latency, etc. [20]. The IoT is widely recognized as a revolutionary paradigm capable of transforming the manufacturing industry. It enables the seamless integration of various manufacturing devices equipped with sensing, identification, processing, communication, actuation, and networking capabilities. This highly integrated smart cyber-physical space paves the way for entirely new business and market opportunities in manufacturing. Tao et al. proposed the five-layer architecture for manufacturing systems. The architecture consists of the resource layer, network layer, perception layer, service layer, and application layer [21]. In the realm of IoT, a key advantage stems from the integration of cyber-physical interactions, where computer-based sensors and devices help initiate or facilitate changes in the physical world. The surge of smart devices entering the market acts as a catalyst for this new revolution, poised to significantly transform manufacturing practices worldwide [22]. Pan et al. provide the guidelines to protect the IoT-based manufacturing systems from cyber-attacks [23]. Trakadas et al. proposed the architecture to integrate all the assets of manufacturing systems [24]. Cloud-based technologies like remote data collection, interconnectivity, intelligent algorithms, and remote monitoring have improved the efficiency of all manufacturing operations, including the rapidly growing 3D printing process [25].

Beliatis et al., implemented IoT in an electronic company for digital traceability. Digital traceability helps to improve transparency in manufacturing, also helps to reduce manufacturing lead time and bottlenecks [26]. Real-time manufacturing efficiency is enhanced by advancements in production processes, supply chains, robotic facilities, embedded systems, and interconnected equipment. These factors collectively contribute to risk reduction and foster innovation. As automated factories become more productive, driven by the proliferation of low-cost, reliable, and connected sensors, IIoT can soon enable self-diagnosing and repairing of manufacturing equipment and assembly lines. This capability can reduce downtime, optimize asset usage, lower overall costs, boost workforce productivity, improve result measurability, enhance product effectiveness, and achieve greater efficiencies, including increased energy efficiency. Consequently, businesses can cut operating expenses and develop new revenue streams [27]. AI-based intelligent systems are the most important development in industrial manufacturing, which helps to develop smart manufacturing systems [28]. Nowadays, industries are highly dynamic and complex due to constant changes in customer requirements, which bring uncertainty in industrial operations. There are many uncertainties in industrial operations; to overcome these uncertainties, AI can be helpful [29]. Manufacturing is evolving from large, monolithic production floors to geographically distributed, internet-connected, medium-scale smart factories. The advantages of smart manufacturing include enhanced productivity, cost savings, market-specific product customization, resource efficiency, and reduced environmental impact [30]. Ghahramani et al., proposed the utilization of neural networks and genetic algorithms to build intelligent systems for the semiconductor industry. PCA is not capable of recognizing the nonlinear relationships among the variables. The genetic algorithm and artificial neural networks can solve this problem [31]. Customized manufacturing not only requires automation, but its assets must be intelligent and flexible, which is possible through technologies like remote sensing, cloud storage and computing, self-diagnostics, and preventive maintenance [32]. The advanced artificial intelligence algorithms find applications in areas like automated visual inspection, fault detection, and maintenance. Reinforcement learning can be implemented in material handling and production scheduling [33].

2.4 | IoT In Welding

Chen, et al. developed the data driven system for welding process using IoT based system. The various data collected using the optical, electrical and sound sensor to monitor welding process [34]. In the oil and gas industry continuous production is very important so it is essential to reduce the downtime due to maintenance. Welding is an important process in the maintenance of oil and gas industries Yusof et al., proposed the welding monitoring system for oil and gas industries using IoT based monitoring system [35]. In the era of Industry-4.0 all the manufacturing process is transforms including welding process. The technologies like IoT, AI, Big Data, Cloud Computing etc. helps to build the intelligent welding system for remote monitoring, controlling [36]. It is essential to store the welding related data in cloud, which is connected to high-speed internet, so that whenever require welding machine ask the cloud to provide the essential parameters for different customers' requirements [37]. It is challenging to connect and collect data from various type of equipment due to the heterogeneous characteristic and enormous connection in IoT based system. Ke et al. proposed the solution for the networking issues in monitoring system of robot welding [38]. The concept of lean manufacturing was introduced after the World War 2 in Japan. Lean manufacturing helps to improve the productivity of industries using scientific management techniques. Poka yoke is one of lean manufacturing tool which helps to avoid human error in operation in industries. Wijaya et al., developed IoT based poka yoke system for spot welding machine for production line of automotive components [39]. Qiang et al. proposed multi agent system which consist of several agent like, macro monitoring agent, welding pool monitoring agent, spectrum monitoring agent arc sound monitoring agent arc voltage and current monitoring agent, tracking control agent, and infrared thermal agent for welding monitoring system [40]. To control the cost of the product is very essential in today's competitive world. In the welding process, generally inspection is carried out after completion of welding run. If welding runs fail in quality inspection it wastes of welding resources which ultimately increases the cost of the product. To overcome this issue, Barot et al. proposed the IoT based online process monitoring system for the submerged arc welding process [41]. The Internet of Things (IoT) involves connecting any powered device to the internet and to each other, while artificial intelligence (AI) refers to machines, particularly computer systems, simulating human intelligence. AI encompasses learning (acquiring data and rules for using it), logic (applying rules to reach conclusions), and self-correction. Many automatic welding machines are now networked and connected to computers, allowing them to be accessed from anywhere in the world at any time. The primary application of this connectivity is the evaluation and configuration of the equipment, which requires regular network interfacing. Future IoT technology in the welding sector is expected to integrate extensively with AI networks, enhancing the ability to control and monitor functions even when the system is not connected to the internet [42]. Liu, Q proposed the intelligent welding manufacturing system which integrates IoT technology and MAS to seamlessly merge the cyber-physical system with the welding manufacturing process, advancing the system towards digitization and Intelligence [43]. Predictive maintenance is important in industries to improve the over equipment efficiency. It is used overtime in the industries, but IoT also transform the predictive maintenance with the help of edge device, machine learning and cloud computing [44].

3 | Methodology

3.1 | Architecture

Architecture of IIoT enabled TIG welding is shown in Figure 2. IIoT module consists of sensors, data acquisition system (DAS) and controller. IIoT module is connected to conventional TIG welding machine for capturing the process information. All the process information is sent to the cloud for storage and processing purposes. Smart devices are connected with cloud for controlling and monitoring purposes. The above architecture can be used for monitoring and controlling TIG welding process. Developing a data acquisition system for an IIoT-enabled TIG welding machine involves a sophisticated integration of sensors data, processing units, and communication protocols to ensure real-time monitoring and control of the welding process. It contains several sensors, of which the first is the current sensor to detect the welding current, and the rest include the gas flow sensor, which shows the flow rate, and the speed sensor for determining the speed of the welding. This data, therefore, gets fed to a hardware in terms of high-speed data acquisition, while the process data managed through a microcontroller or embedded system would perform an initial processing step and run through control algorithms. This microcontroller communicates through protocols like MQTT or OPC UA with an IIoT gateway, ensuring data is transferred securely to the cloud.

The IIoT gateway will connect the local system with the cloud. Therefore, operations can be remotely monitored and controlled.

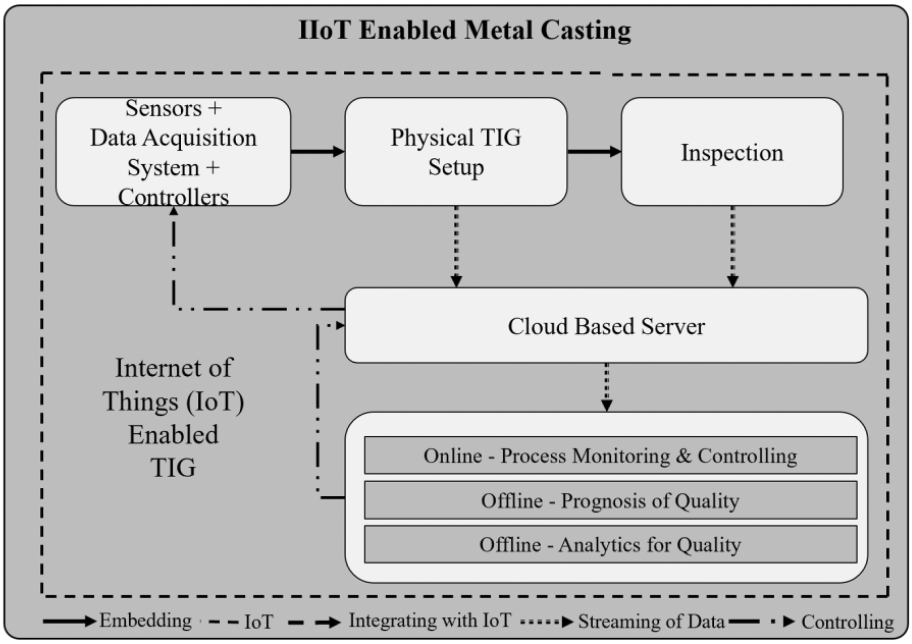


FIGURE 2 | Architecture of IIoT enabled TIG welding.

In the cloud, data storage and more advanced analytics are carried out by machine learning models to predict welding defects and optimal operational parameters. The architecture of the system ensures that data from sensors are properly synchronized and calibrated to provide a total look at welding process through techniques of data fusion. Real-time data processing also allows for the implementation of closed-loop control where welding parameters such as current, voltage, and gas flow can be adjusted for optimal welding conditions. The integration extends to developing user interfaces, including web or mobile applications that provide operators with real-time dashboards for monitoring and controlling the welding process. These interfaces offer alerts and notifications for any detected abnormalities, immediate corrective actions. The cloud platform also facilitates historical data analysis, helping in process improvement and decision-making.

It provides historical analysis and pattern recognition through machine learning, as well as process optimization. It will enable operators to interact with the system through user interfaces, with real-time alerts and adjusting parameters as required, all supported by detailed reports and analytics for continuing improvement.

This holistic approach to sensor integration, data acquisition, cloud computing, and user interfaces in an IIoT-enabled TIG welding machine greatly promotes weld quality, operational efficiency, and above all, marks a significant step forward in industrial welding processes.

3.2 | IIoT Enabled TIG Welding Machine (Physical Machine)

With IIoT-enabled TIG welding, the welding process is completely transformed by taking advantage of advanced sensors for real-time data acquisition along with cloud-based analytics in order to enhance precision, efficiency, and quality. The most important parameters like welding current, torch speed, gas flow rate, and arc gap are measured continuously through high-precision sensors. The gathered data is communicated with the cloud using an IIoT gateway, where in real time, machine learning algorithms decode the patterns, and hence, the best conditions for welding are optimized. This system enables dynamic adjustments, such as modifying current or speed, ensuring optimal weld quality and minimizing defects. The main parts of the IIoT enabled TIG welding are welding power supply, IIoT module and 3-axis CNC machine as shown in Figure 3.

3.3 | IIoT-Enabled TIG Welding Machine (Physical Machine)

3.3.1 | Welding Power Source

Constant current output type and air-cooled welding power source is used. The specifications of the machine are shown in Table 1.

3.3.2 | IIoT Module

An IIoT module for TIG welding enhances the process by integrating sensors, real-time data acquisition, and cloud-based analytics. It consists of the current sensor, speed sensor, gas flow rate sensors, and arc gap sensor to capture the process parameters like current, speed, gas flow rate, and arc gap. It also consists of

TABLE 1 | Specification of power source.

Specification	SW400PT
Rated input voltage	3 ϕ, 415 V, ± 15%, 50HZ
Power (KVA) @ 100%	12KVA
Duty cycle @ 40 C	100% @ 300 Amps
Open circuit voltage	65 Volts
Output current range amperes	8–400 Amps
(W × D × H) mm	360 × 650 × 560
Weight	45 Kgs

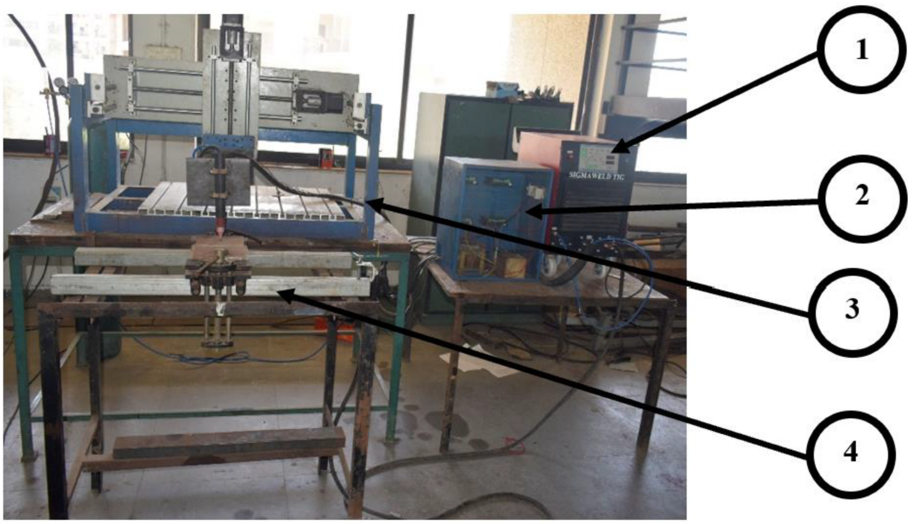


FIGURE 3 | IIoT enabled TIG Welding Machine. (1) Weldpower source, (2) IIoT module, (3) CNC welding machine, (4) Work holding table.

motor drivers, a controller, a DC power supply, and a communication module to transfer the captured data to the cloud. This smart integration allows for remote control and continuous process improvement, transforming traditional TIG welding into an efficient and adaptive system.

3.3.3 | Current Sensor

An open-loop current sensor uses the Hall effect to measure current based on the detection of the magnetic field about a conductor. Current flow through the conductor produces, due to its flow, a magnetic field perpendicular to the direction of the flow. The Hall effect sensor within the open-loop sensor detects the magnetic field produced and converts it into an output directly proportional to the magnitude of the current flowing. These transducers are famous for being simple, of wide bandwidths, and for their use in the measurement of huge currents without saturation. Applications include automotive applications, industrial automation, power electronics, and renewable energy systems in which large current measurements and relevant functions of the considerable current function.

3.3.4 | 3-Axis Welding Machine

A stepper motor-driven 3-axis CNC welding machine automatically welds with precise control over the X, Y, and Z axes using stepper motors and linear guides. A CNC controller can read G-code correctly for even the most complex repeatable welding patterns. The system includes a TIG welding torch, power supply, and limit switches and emergency stop for safety. This configuration enhances weld quality, efficiency, and consistency to make it suitable for complex welding tasks without human intervention and predictive maintenance through advanced data analytics.

3.3.5 | Work Holding Table

A TIG welding machine work holding table is a strong and safe place to mount and position workpieces as they are welded. This table, made of a heat-resistant material, contains moveable clamps, fixtures, and slots to accommodate varied sizes and shapes of the metal parts. It accurately holds the parts in one place, allowing minimal movement for excellent welds. Grounding points are provided to increase electrical conductivity. This welding configuration enhances precision and consistency in welding but also enhances safety and efficiency in the welding process.

3.3.6 | Smart Devices

The use of IIoT-based TIG welding machines makes flexible interfaces for monitoring and control, using smart device mobile. It offers the ability to access real-time data, alerts, and remote diagnostics on the go to enhance responsiveness and flexibility. In-depth data analysis, simulation, and system management for robust processing power are made ideal for in-depth process optimization and reporting. Tablets come with the mobility of a screen but bigger, and easy field operations and on-site changes through touch-sensitive controls. These devices collectively ensure seamless integration, comprehensive oversight, and enhanced productivity in managing advanced TIG welding systems. Smart devices help users in interaction with physical machines and cloud-based servers for monitoring, controlling, inspection, and analysis of the process. The home page of the mobile application is shown in Figure 4a. Through this home page, users can navigate to Process Monitoring and Controlling or Inspection and Quality Control parts as shown in Figure 4b.

3.3.7 | Process Monitoring and Controlling

Realtime process monitoring and controlling is possible with the help of smart devices like, mobile tablet and desktop. Before setting the parameters the position of torch is set using Position tab as shown in Figure 4c. User interface is designed to control and monitor the process parameters of TIG welding machine. User interfaces contain the input field to enter the value of current, speed, arc gap and gas flow rate for controlling them on physical

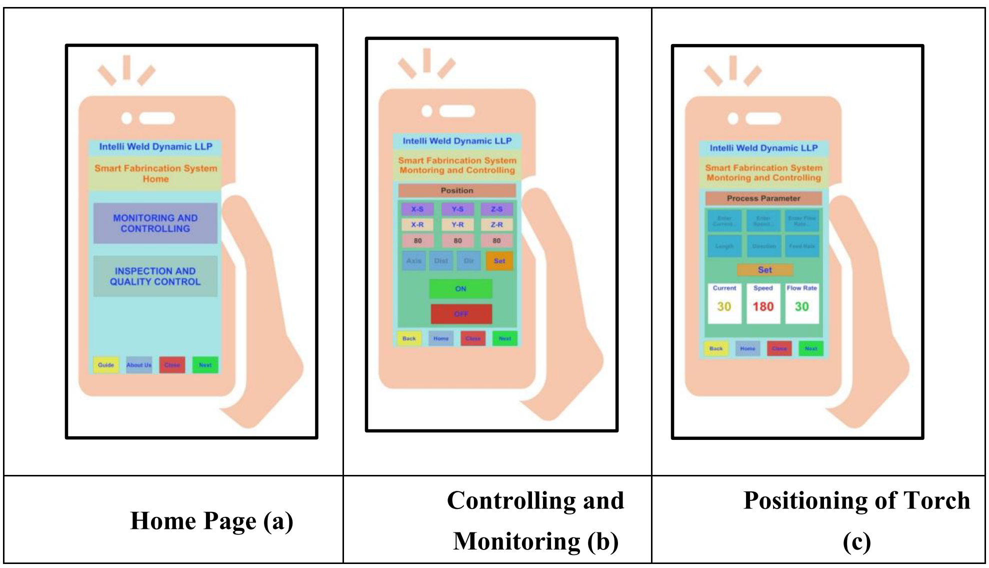


FIGURE 4 | Controlling and monitoring user interface.

machines. Also, from the monitoring interface the Realtime data of process parameters can be monitored. User interface also consists of button for ON/OFF the welding machine.

4 | Experimentation

Conducting experiments on an IIoT-enabled TIG welding machine involves controlling and monitoring critical welding parameters such as current, speed, gas flow rate, and arc gap to optimize the welding quality on SS304 stainless steel. The composition of SS304 as provided by the supplier is mentioned in Figure 5. The primary objective of the study is that experiment is real-time data acquisition and analysis are facilitated by integrating various sensors that measure and record the parameters with high precision.

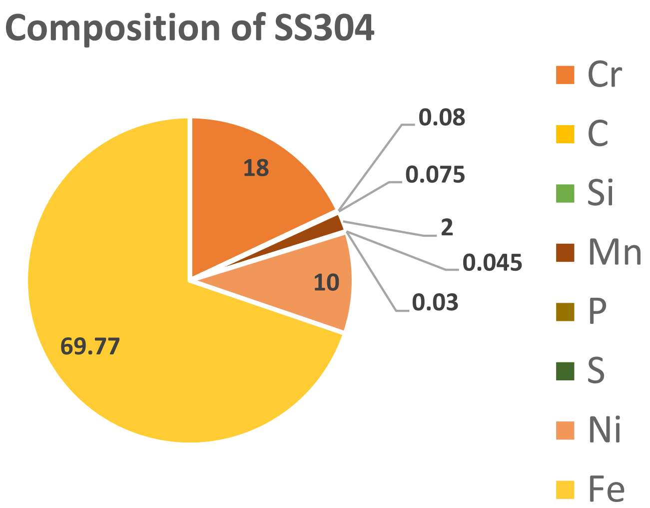


FIGURE 5 | Composition of SS304.

The experiments are conducted on an SS304 1.5 mm thin sheet using an enabled TIG welding machine. The SS304 is widely used in food processing, chemical containers etc., due to its excellent corrosion resistance properties. The input parameters are set using the mobile application. The desktop and mobiles are used to monitor the process parameters. The welded sample images of SS304 are provided in Figure 6.

The current, a vital parameter, is adjusted to determine its effect on the penetration depth and heat input. Experiments vary the welding current, weld speed, arc gap, and gas flow rate to monitor their impact on the microstructure and mechanical properties of SS304. Higher currents typically increase penetration but can also lead to defects like excessive grain growth or burn-through, whereas lower currents might result in inadequate penetration. Speed, or the travel speed of the welding torch, is another crucial factor. By altering the speed, the heat input per unit length of the weld is controlled. Slower speeds usually enhance penetration and bead width but risk overheating and warping the material. Conversely, faster speeds might lead to shallow welds and poor fusion.

This includes the study of gas flow rates, crucial to protecting the weld pool from atmospheric impurities. Inert gas flow variability can be set at minimum, which may cause oxidation and porosity, to extreme levels that can give rise to turbulence and contamination. Under ideal gas flow conditions, there would be a smooth arc and weld cleanliness. The arc gap or distance from the tungsten electrode to the workpiece has also been observed.

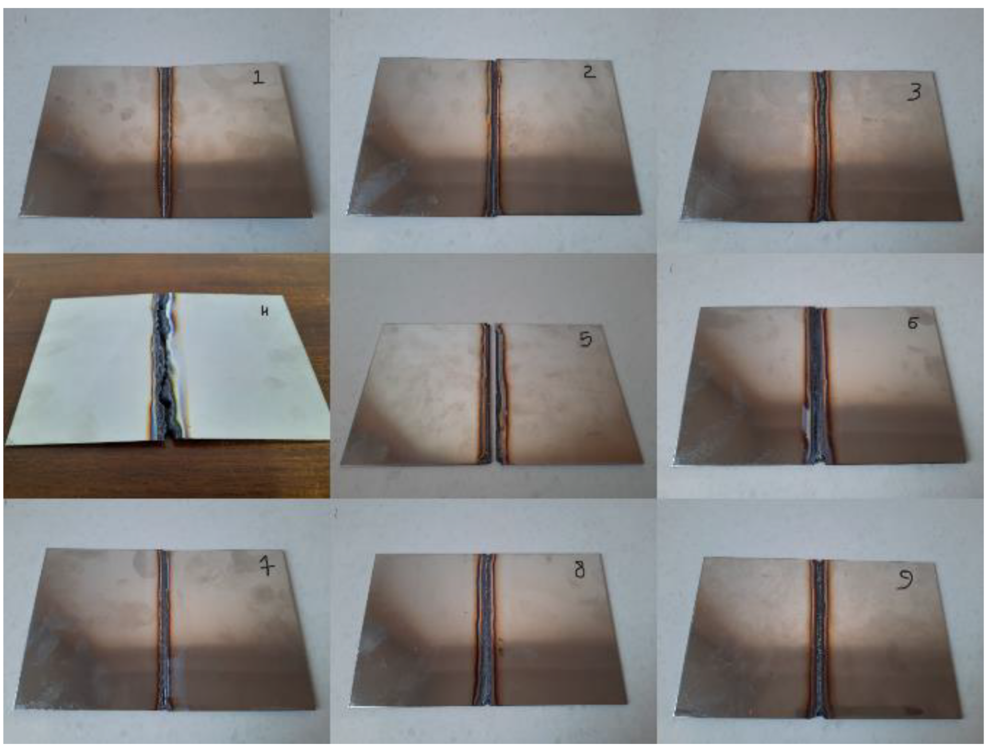


FIGURE 6 | Welded sheet of SS304.

A longer gap between arcs will have a larger heat affected zone and more unstable arcs; whereas a smaller gap increases stability of arcs but must be carefully maintained to prevent short circuits or contamination.

In the experiments carried out, the system gathers real-time data on current, speed, gas flow rate, and arc gap using sensors. These are forwarded to the cloud for analysis, and then the data are processed using machine learning algorithms in the cloud to obtain patterns and correlations. From these patterns and correlations, parameters are dynamically altered for obtaining the quality weld as required. For instance, when excess heat input is identified, it can self-correct the current or enhance the speed to avoid defects.

Additionally, the user interface of the system is capable of real-time process monitoring with informed adjustment for operators. Alerts and notifications about abnormalities allow proactive intervention to ensure reliability in the welding process. Systematic testing of these parameters will result in finding the optimal combinations that work well for welding SS304 and produce strong welds with desirable mechanical properties free of defects. Experiment conducted on SS304 using IIoT-enabled TIG welding machine. Table The parameters and their range are tabulated below.

5 | Inspection Results

Other experiments also include post-weld analysis, such as NDT, metallographic examination, and mechanical testing, such as tensile, test, and Hardness tests, to validate the quality of welds. The gathered data from successful welds are stored and used in making predictive models, to improve future welds and to provide a solid knowledge base for SS304 welding processes. The results of liquid penetrant and ultrasonic tests may be uploaded in the cloud for access through any app across the world by a quality team for accessing such data, as shown in Figure 7. Similarly, visual inspection and metallography results can also be uploaded into the cloud and accessed globally to carry out advanced analysis at any location in Figure 7. The result of metallography is shown in Figure 8.

The machine's user interface provides operators with real-time dashboards and alerts, allowing for immediate intervention and fine-tuning of parameters. The cloud-based platform not only facilitates remote monitoring and control but also stores historical data for trend analysis. This capability helps in preventing potential failures and improving the overall reliability of the welding process. Additionally, post-weld analysis and

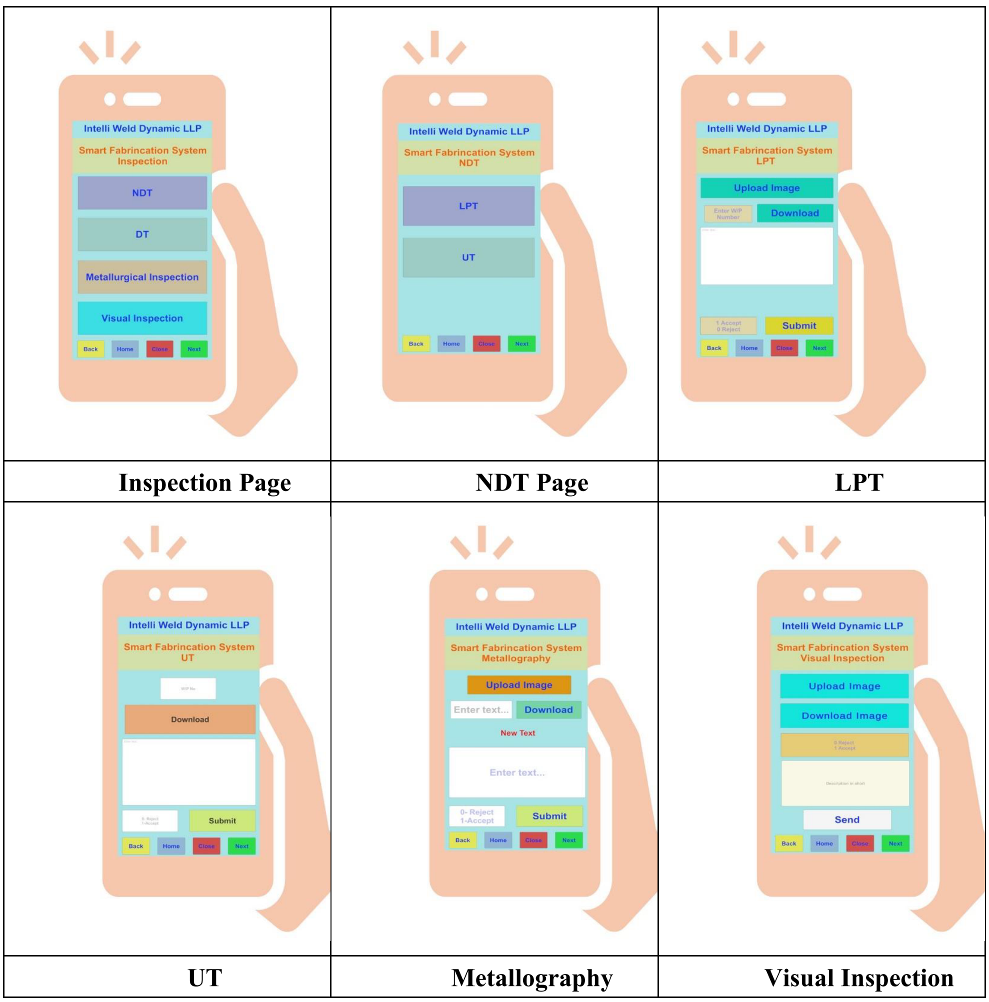
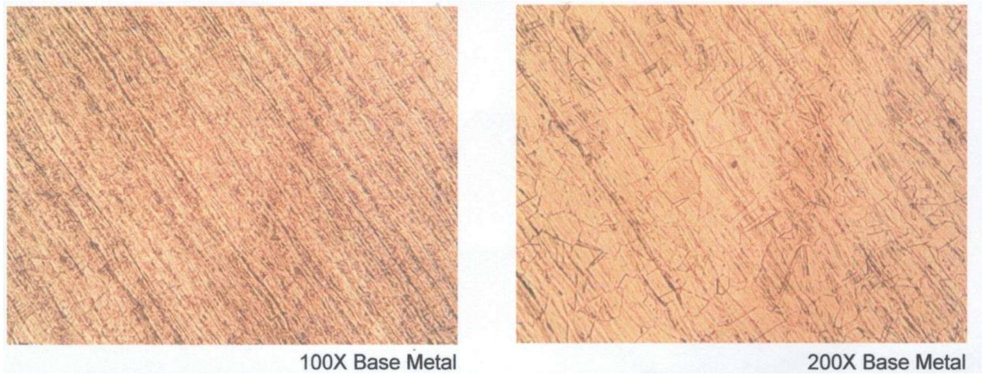
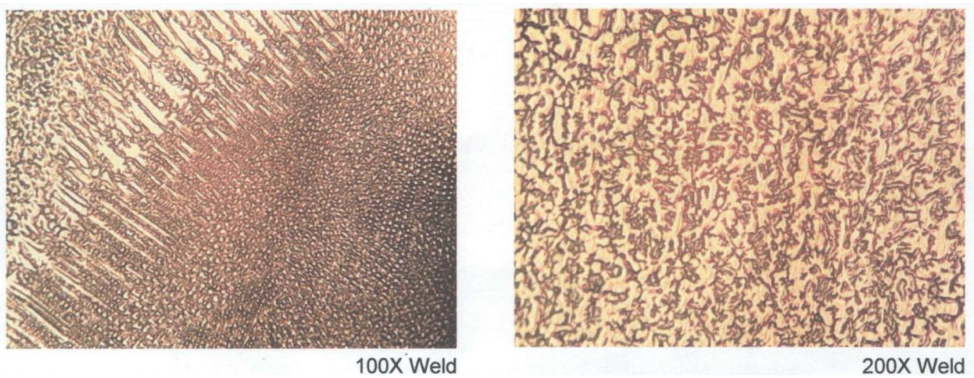


FIGURE 7 | User interface for inspection result.



(a)



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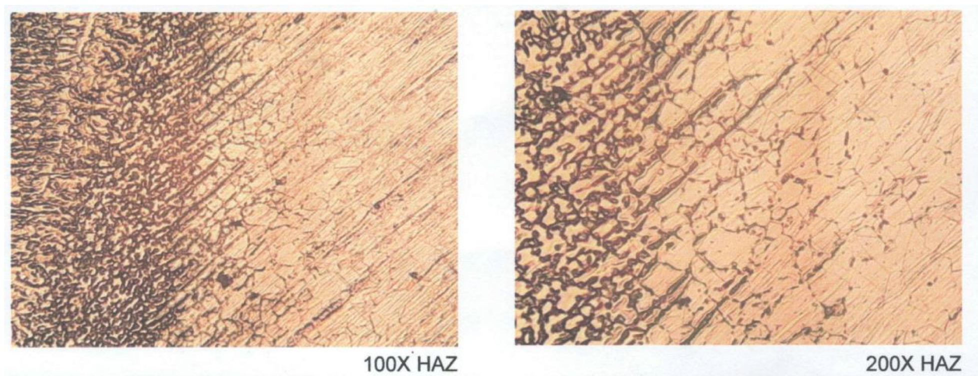

(c)

FIGURE 8 | (a) Microstructure of base metal. (b) Microstructure of weld bead. (c) Microstructure of heat affected zone (HAZ).

data-driven insights contribute to refining welding procedures and achieving consistent, high-quality welds. By leveraging IIoT technology, the TIG welding machine transforms traditional welding into a smart, adaptive process, significantly enhancing productivity and weld integrity.

Mechanical properties are very important in welded joints. Mechanical properties are mainly determined by destructive testing. The tensile test and hardness test of the weld and HAZ are measured. It is challenging to develop IIoT-enabled destructive testing methods. So, on the smart device, a separate user interface is designed to enter the results of destructive testing, like ultimate tensile strength (UTS), hardness of the weld bead, and hardness of the HAZ. Figure 9 represents the user interface for inspection of destructive testing.

6 | Data Analysis

On collected data of process parameters like current, speed, gas flow rate, and collected mechanical property data such as tensile strength, weld hardness, and hardness of the heat-affected zone (HAZ), welding processes can be optimized for enhanced quality and performance using machine learning. ML can identify the complex relationship between input process parameters and output mechanical properties. It supports process optimization by adjusting parameters to achieve desired mechanical properties and minimize defects. Additionally, in welding, lots of time is wasted in finding out the best parameters in the trial-and-error method. ML can reduce experimentation efforts, enhance quality control, and ensure consistent weld strength and integrity across varied conditions.

FIGURE 9 | User interface for inspection result of destructive testing.

An artificial welding inspector can be developed by implementing ML on collected images of LPT and visual inspection and ultrasonic frequency charts. ML can identify defects in images, such as cracks, porosity, or improper fusion. The use of image datasets in combination with parameters substantially enhances the understanding of how different variations in current, speed, or flow of gases impact weld quality and defectiveness. This approach promotes the design of adaptive control systems that automatically adjust parameters to achieve uniformity. Still, this policy is associated with several problems that include the need for good datasets and heavy computational resources. This strategy ensures a complete evaluation of the weld quality, leading to data-informed decision-making towards optimizing welding processes and regular, defects-free outcomes. Offline prognosis of weld quality using ML combines historical parameter data and image datasets to predict outcomes without real-time monitoring. By analyzing past trends, defect patterns, and mechanical properties, ML models can provide accurate quality predictions. This approach enables preemptive adjustments to processes, reducing defects and enhancing efficiency in future welding operations.

Offline Analytics of weld quality: ML is used to analyze the stored data by parameters, images, and mechanical properties to detect trends or defects. That way it knows performance and will refine future welding operations, and with historical information, it is optimized, and hence ensures consistent quality without real-time dependency.

7 | Conclusion

Implementation of the IIoT in TIG welding of SS304 stainless steel has a transformative impact on the quality, productivity, and control capabilities involved in welding. It allows the welding parameters, including the current, speed, gas flow rate, and arc gap, to be controlled and monitored in real time. This improves the welding process's precision and consistency. Since these data are stored on clouds for easier analysis, the technology guarantees predictive quality assessments as well as data-driven optimization parameters. This integration aids improvements in mechanical properties-including ultimate tensile strengths and hardness of both welded and heat-affected regions. Moreover, because accessible user interfaces are made "smart device-compatible", making remote process management relatively smoother, IIoT here plays a pivotal role in high-quality efficient welding procedures. This study highlights the possibility of using IIoT to transform conventional welding systems into smart, adaptive operations that meet modern manufacturing's demand.

Author Contributions

Mukhtar Sama: conceptualization, methodology, validation, writing – original draft, writing – review and editing, data curation, investigation. **Amit Sata:** conceptualization, writing – original draft, validation, software, formal analysis, visualization, investigation. **Gaurang Joshi:** investigation, validation, software, formal analysis, data curation, resources, writing – review and editing. **Dhanesh G. Mohan:** methodology, writing – review and editing, funding acquisition, validation, visualization, project administration, formal analysis, supervision, data curation.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All the data from this research are included in this article.

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