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Design and Development of Real-Time Vision AI Welding Analyzer

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ABSTRACT

Welding training needs simple, reliable tools that give quick feedback on bead quality to help learners improve skills and meet industry standards. The main purpose of the study was to develop a real-time vision AI welding analyzer, specifically describing its technical features, its accuracy, sensitivity, response time, and acceptability in terms of technical features, composition, operating performance, and safety features. The research used a developmental method, and the evaluation was conducted using a researcher-made questionnaire, validated by the members of the panel. Thirty (30) evaluators, comprising professors, welders, Technology and Livelihood Education (TLE) instructors, and end-users, assessed the developed device, providing valuable insights for its proper utilization in welding training. The device provided real-time feedback on weave and stringer beads via a web dashboard with pass/fail metrics and safety features. The findings showed that the device delivered reliable weld bead evaluation with advanced technical features, strong operating performance, and comprehensive safety measures. It achieved 90% accuracy in classifying acceptable stringer and weave beads, 100% precision with no false positives, and instant response times within the 10 second threshold. It was very acceptable, confirming its effectiveness as a supportive tool for welding education and training.

INTRODUCTION

Welding is one of the most important joining processes in modern industry, serving as the foundation of infrastructure in construction, automotive, aerospace, energy, and marine sectors (Sazonova *et al.,* 2021). The global demand for skilled welders is expected to continue increasing due to expanding infrastructure projects, growing manufacturing needs, and an aging workforce, with approximately 45,600 annual openings projected through 2034 (Bureau of Labor Statistics, 2018). In response, international organizations such as the European Commission (2020) and the World Bank (2020) have emphasized the modernization of vocational education to meet workforce requirements. Effective training programs, as noted by Khorshidikia *et al.* (2026), are essential to ensure welders acquire the technical skills needed for safety, structural integrity, and cost efficiency in industries such as shipbuilding.

To achieve welding proficiency, learners must master fundamental bead techniques, particularly weave beads and stringer beads. A stringer bead is formed by moving the electrode in a straight line along the joint, producing a narrow and uniform deposit. In contrast, a weave bead is created by oscillating the electrode side to side, resulting in a wider deposit with improved fusion at the joint edges. Mastery of these bead patterns requires control of parameters such as travel speed, arc length, electrode angle, and puddle manipulation. The American Welding Society (AWS) recognizes these skills as core competencies for entry-level welders (Ahmad & Rofiq, 2020).

Vocational and technical institutions worldwide adopt the American Welding Society (AWS) Guide for the Training of Welding Personnel: Level I – Entry Welder as a curriculum framework. Students are required to demonstrate proficiency in producing consistent, defect-free beads before qualifying for certification. However, in the Philippines, welding education faces challenges such as limited resources, insufficient hands-on practice, and gaps in safety compliance. These issues, present from senior high school technical-vocational tracks to industry-level training, often result in a mismatch between graduate skills and industry expectations (TOTC Inc., 2025).

Assessment practices further complicate training outcomes. Traditional evaluation methods rely heavily on instructor-led visual inspection, which is prone to subjectivity and inconsistency due to human factors such as fatigue, experience, and workload (Ranganayaklu *et al.,* 2017). Without timely corrective feedback, students may continue to use incorrect techniques, weakening skill development. More importantly, inadequate assessment has consequences beyond the classroom, as weld quality directly affects the safety and reliability of infrastructure such as bridges, pipelines, and transportation systems. Even minor undetected defects can lead to catastrophic failures, resulting in economic losses, environmental damage, and loss of life (Bhardwaj *et al.,* 2022; Naddaf-Sh *et al.,* 2022).

Welding defects such as cracks, porosity, and spatter compromise structural strength and service life, acting as stress concentration points that may cause fatigue failure, stress corrosion cracking, or complete system malfunction (Sun *et al.,* 2025; Chandra *et al.,* 2019). Historical failures in pipelines, pressure vessels, and structural components highlight the dangers of undetected flaws (Jeremic *et al.,* 2020). While Non-Destructive Testing (NDT) methods

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such as X-ray radiography, ultrasonic testing, and magnetic particle inspection can detect defects, they are costly, time-consuming, and rarely applied in vocational training environments. Visual inspection, the most basic NDT method, remains vulnerable to subjectivity, making it insufficient for consistent evaluation.

Recent advances in Artificial Intelligence (AI) and machine learning provide promising solutions by enabling automated defect detection with greater accuracy and speed than manual methods (Bansal *et al.,* 2023; Dogra, 2018). However, most AI systems are designed for industrial production lines and do not address the specific needs of educational settings, which require portable, cost-effective, and user-friendly tools for real-time feedback. This gap highlights the need for a Vision AI welding analyzer designed to assess weave and stringer bead quality in student outputs.

This study directly supports Sustainable Development Goal 4: Quality Education, specifically Target 4.4, which aims to substantially increase the number of youth and adults with relevant technical and vocational skills for employment and decent jobs (United Nations, 2015). Globally, it aligns with international efforts to modernize vocational education through technology-enhanced training (European Commission, 2020; World Bank, 2020). Nationally, it supports the Philippine government's push for stronger technical-vocational education under the Technical Education and Skills Development Authority's (TESDA's) framework (TESDA, 2021). Locally, it addresses the pressing need for accessible, standardized, and technology-driven training tools in schools and training centers across Western Visayas (Western Visayas Regional Development Council, 2022).

The device assessed whether students' weld joint outputs pass quality standards. To make accurate results, it was embedded with datasets of good and bad welding samples, enabling it to learn and evaluate properly. The study focused on the design and development of a real-time Vision AI welding analyzer for weave and stringer bead. It employed dataset preparation, YOLO-based model training, model conversion to TensorFlow Lite (TFLite), and embedded deployment on a Raspberry Pi platform with camera-based input. The system served as an assessment aid rather than a replacement for instructor expertise, helping institutions implement scalable, technology-enhanced training programs that align industrial-grade quality standards with student learning needs.

This study aimed to develop a real-time vision AI welding analyzer for weave and stringer bead. Specifically, this study sought to describe the technical features of the real-time vision AI welding analyzer; determine the operating performance of the real-time vision AI welding analyzer in terms of accuracy, precision, and response time; and determine the acceptability of the real-time vision AI welding analyzer in terms of technical features, composition, operating performance, and safety features.

LITERATURE REVIEW

Recent research has made impressive advances in AI systems that use cameras to monitor welding in real time, detecting defects and assessing quality with high accuracy. However, these systems face significant limitations that make them unsuitable for classroom training, particularly for high school students learning proper welding techniques. All these systems worked well for factories, but could not help students check their own welding practice. They require costly hardware, internet connections, and teacher assistance, which creates additional work for instructors. The new Real-Time Vision AI Welding Trainer addressed this by operating on affordable Raspberry Pi computers equipped with batteries and Wi-Fi hotspots. Students could assess stringer and weave beads themselves through a simple web dashboard at any time, from anywhere, without an internet connection, finally giving them independent practice while reducing teachers' checking workload.

Liang *et al.* (2025) developed a WELD-DETR, a sophisticated transformer-based deep learning model, specifically designed for weld defect detection. Their system processes video at 58 frames per second while achieving 98.2% accuracy on an RTX 2060 graphics card, using specialized layered feature extraction and wavelet filters to identify extremely small cracks and microscopic porosity even in complex weld geometries. This represents a breakthrough for industrial quality control, where speed and precision directly impact production efficiency and safety standards. The system's ability to handle challenging lighting conditions and irregular weld shapes makes it ideal for automated factory environments. However, its critical limitation lies in the requirement for expensive, high-performance GPU hardware that costs thousands of dollars and demands constant electrical power and cooling infrastructure. For classroom deployment, particularly in resource-limited developing country schools, this hardware remains completely inaccessible. Additionally, the system requires continuous network connectivity for model updates and data logging, preventing any possibility of standalone student use without internet access or teacher supervision.

Pan *et al.* (2023) created the WD-YOLO, a YOLO-based detection system enhanced with a gray value curve enhancement (GCE) module specifically engineered for low-contrast weld X-ray images. Their approach achieved 92.6% mean average precision (mAP@0.5) while processing 98 frames per second, effectively addressing longstanding challenges in radiographic inspection where defects often blend into surrounding material due to poor image contrast and varying defect sizes. This made the WD-YOLO exceptionally valuable for post-weld quality assurance in manufacturing facilities, where non-destructive testing must balance thoroughness with production throughput. The specialized preprocessing innovation represents genuine technical progress in handling real-world imaging challenges. However, the system operates exclusively on stored X-ray images captured after welding completion, offering no capability for live video analysis during active welding practice. Students cannot receive immediate feedback on their technique execution, and the centralized server infrastructure required for processing eliminates portability. Independent assessment becomes impossible without teacher intervention and reliable internet connectivity, perpetuating traditional supervision workflows.

Yamane *et al.* (2025) engineered a hybrid system combining ResNet50 deep learning vision analysis with proportional-integral (PI) process control specifically for CO_2 arc welding applications. This integrated approach monitors molten pool behavior in real time, accurately tracking weave bead patterns, seam geometries, and droplet transfer dynamics across varying welding parameters. The combination of visual feature extraction with active process feedback adjustment demonstrates robust generalization capabilities, making it highly reliable for automated robotic welding systems in industrial settings. The system's ability to maintain stable performance under dynamic conditions represents a significant engineering achievement. However, its design optimization for fully automated factory robots creates fundamental incompatibilities with human welder training scenarios. The system demands constant communication with central factory controllers, eliminating portability for classroom deployment. Students cannot use it independently to evaluate their own stringer bead or weave bead techniques, as it lacks any standalone assessment functionality or battery operation capability.

Dold *et al.* (2022) conducted a comprehensive testing of cascaded sensor fusion architectures for laser welding defect inspection, achieving 95.96% accuracy while reducing computational requirements by nearly 50% through intelligent decision-making. Their approach used photodiode signals for initial screening, activating high-speed cameras only when necessary, which represents smart resource allocation for production-line efficiency. This cascaded methodology balances detection accuracy with processing speed, particularly effectively in high-volume manufacturing environments where every millisecond counts. The sensor prioritization strategy marks genuine innovation in industrial inspection systems. Nevertheless, the multi-sensor hardware configuration, including photodiodes, specialized cameras, and supporting electronics, creates substantial cost barriers for educational applications. The system's dependence on online data pipelines for real-time processing further undermines classroom portability, making independent student assessment without teacher supervision and internet connectivity entirely unfeasible.

Dosari and Abouellail (2023) asserted that the advantages of integrating AI into control systems include energy savings, greater product quality, increased process effectiveness, and adaptive and predictive control. Various AI approaches, including machine learning methods like decision trees, neural networks, and support vector machines, are extensively studied for system identification, modelling, and adaptive control.

The study of Alhammadi (2023) found that AI-enhanced chatbots in facilities management improve communication, responsiveness, and operational efficiency. They automate workflows, handle manual tasks, predict failures, and respond to customer queries. However, challenges include technical issues, limited human-human interaction, system quality and security, and user adoption. Chatbots deliver productivity gains and are used for automated reporting, identifying hazards, conducting briefings, managing meetings, providing training, supporting teamwork, ensuring well-being, and enhancing customer service.

MATERIALS AND METHODS

Design Criteria

The key design criterion was the real-time automated assessment of weld bead quality using computer vision and artificial intelligence. It can analyze weave and stringer bead patterns captured by a high-resolution camera and classify them into acceptable or non-acceptable; however, this function operates entirely offline without requiring an internet connection. The device included Wi-Fi hotspot capability, allowing students to connect their laptops or tablets directly to the system, and a web-based dashboard interface accessible through any standard browser for seamless interaction.

The device also offered hands-on educational training for welding students since they could practice their welding techniques and receive immediate feedback on their bead quality. Students could view live camera feeds, trigger analysis with a single button press, and generate printable assessment reports without waiting for instructor evaluation. This accelerated the learning process by enabling rapid iteration and self-paced skill development.

The device prioritized portability and field deployment by incorporating features such as a rechargeable lithium-ion battery pack and a compact 3D-printed enclosure to enable operation in workshop environments without fixed power sources. Furthermore, the device offered robust power management, integrating a DC barrel jack for external power and an adjustable buck step-down module to ensure a stable voltage supply. This flexible approach ensured reliable performance and extended operation time in various training settings. The system emphasized safety and thermal management through active cooling provided by a DC cooling fan that prevented overheating of the Raspberry Pi processor during continuous analysis sessions.

Additionally, the device included an illuminated HALO push button switch for clear power status indication and user control, reducing the risk of accidental operation. The tubular steel stand and broad platform base provided mechanical stability and vibration resistance during image capture

Design Plan, Preparation, and Fabrication

A detailed presentation was made on the device's design and the fabrication of all its parts and accessories. In assembling the Real-time vision AI welding analyzer, a step-by-step process was followed that conformed to the occupational health and safety program, which was done as follows:

Step 1 involved designing the schematic diagram and 3D digital prototype of the device. A schematic diagram was a simplified, easy-to-understand visual representation of a project plan, created using lines and approved symbols (Freeman, 2016).

The development process started with 3D digital design using Autodesk Fusion 360. All structural parts, including the enclosure, camera mount, vertical stand, and base plate, were modeled to ensure correct alignment, rigidity, and safe placement of electronics. During this stage, the design was improved several times to enhance stability, cable routing, and ease of assembly.

Dimensional checks were done digitally to confirm that the Raspberry Pi, camera module, and internal components could fit properly, allowing space for screws, vents, and access openings. For the electronics subsystem, a circuit schematic was designed using the EasyEDA platform. The schematic included power distribution, interface wiring, and connection headers needed for the Raspberry Pi, camera, optional indicators, and peripheral devices.

Step 2 involved the gathering of all materials and tools

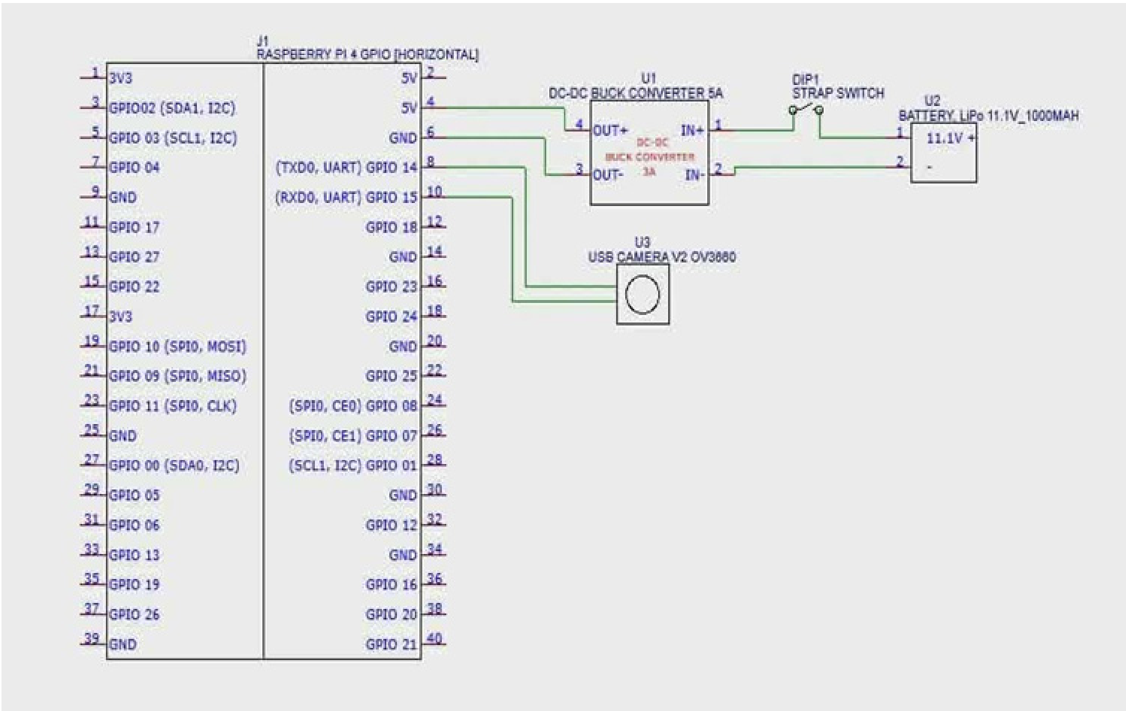

Figure 1: Schematic diagram of the real-time vision AI welding analyzer

required for device construction. The physical parts were then fabricated, with tools carefully tested and calibrated to ensure user safety. These tools included cutting implements such as hacksaws, driving tools like standard and Phillip screwdrivers, boring tools such as electric drills, various pliers for wire management, and a soldering station for electronic components and connections.

Following the finalization of the Fusion 360 design, the physical housing was produced using two methods. First, laser CNC cutting was employed for the main wooden panels and structural body components, utilizing exported 2D profiles from the CAD design to achieve clean edges, consistent dimensions, and repeatable assembly. Second, 3D printing was applied for functional plastic parts, including brackets, spacers, mounts, standoffs, and protective covers, enabling rapid prototyping and refinement of complex or tight-fitting shapes with industrial-grade printers.

Step 3 involved PCB fabrication and installation of the operating system and software framework into the Raspberry Pi. Once the schematic design was completed, the PCB layout was generated in EasyEDA and prepared for fabrication. Subsequently, the board was produced using a chemical etching process, where the copper-clad board was coated, patterned, and etched using etching chemicals to remove unwanted copper traces. Drill holes were created for through-hole components and connectors as required.

The operating system used was the Raspberry Pi OS (64-bit), which was a Debian-based Linux distribution optimized for the Raspberry Pi hardware. The Raspberry Pi Imager tool was used to flash the OS onto a high-speed microSD card (minimum 32GB, Class 10), which served as the boot and storage medium. Following the OS installation, the Python development environment was configured with Flask for the web application framework, OpenCV for camera capture and image preprocessing, and TensorFlow Lite runtime for model inference. The system software was developed using a combination of Python for camera handling, backend processing, model inference, and system-level functions, and Node.js for handling web services and UI integration. A browser-based dashboard was implemented so that users can connect via Wi-Fi, view camera output, run analysis, and generate reports without installing special client applications.

Step 4 involved the assembly of the different components of the controller and hardware integration. After PCB fabrication, the board was assembled using a soldering station. Components such as resistors, capacitors, pin headers, connectors, and supporting modules were soldered in place. After soldering, the board was visually inspected to verify solder joint integrity and reduce the risk of cold joints or shorts.

The assembly process began with the installation of the XL4015 buck converter module, which was mounted and secured with appropriate hardware inside the main enclosure. The rechargeable lithium-ion battery pack was positioned in the lower compartment with proper padding to prevent movement. Terminal blocks for power input and output connections were installed, followed by the HALO switch push button for power control and the DC barrel power jack for external charging. The wiring harness was fabricated with appropriate gauge wires: 18 AWG for main power lines and 22 AWG for signal connections.

The assembled power circuit was then tested using a 12V DC power supply, verifying that the XL4015 output was stable at 5.0V ±0.1V and capable of delivering the required 3A current for Raspberry Pi operation. The Raspberry Pi 4 was mounted on the 3D-printed mounting tray using M2.5 nylon screws and standoffs to prevent electrical short circuits. The PCB was secured inside the main enclosure with nylon spacers providing clearance from the case. The assembled PCB and electronic modules were mounted inside the enclosure.

Cable management was performed to avoid loose wiring that could interfere with airflow, mechanical movement, or camera alignment. The DC 2-pin mini 3010 cooling fan was mounted adjacent to the Raspberry Pi processor for effective heat dissipation. Power connections between the buck converter and Raspberry Pi were established via the USB-C port or GPIO pins. The PK-910H 1080P camera was tested for functionality by connecting it to the Raspberry Pi USB 3.0 port and verifying device detection using the lsusb command. The 5V 1W high-power LED was connected to the 5V GPIO pin with a current-limiting resistor. Power and signal lines were checked using basic continuity tests to ensure stable interconnections before applying full system power.

Step 5 involved downloading the trained AI model and configuring the inference application. For the AI component, the weld classification/detection model was trained using the YOLO framework, following a typical computer vision workflow: collection and preparation of weld image samples, annotation of weld regions using bounding boxes and class labels, dataset splitting into training and validation sets, and model training and tuning based on accuracy and detection stability.

After training, the YOLO-based weld bead classification model, which detects three categories: Stringer Bead, Weave Bead, and Rejected, was converted to TensorFlow Lite format for optimized edge deployment. This conversion process included post-training quantization to reduce model size and improve inference speed while maintaining acceptable accuracy levels. The TFLite model was configured for 320x320 input resolution with confidence filtering and Non-Maximum Suppression (NMS) per class, then transferred to the Raspberry Pi and organized in a dedicated directory.

Step 6 involved the meticulous assembly of the complete device system, followed by system testing, calibration, and iteration. The final assembly process integrated all subsystems, including the Raspberry Pi 4 with loaded software, the XL4015 buck converter with rechargeable lithium-ion battery pack, the PK-910H 1080P camera mounted in the 3D-printed camera holder, the 5V 1W high-power LED lighting system, the DC 2-pin mini 3010 cooling fan, and the HALO switch push button. The tubular steel stand was assembled with vertical square tube support, ensuring the camera housing remained properly elevated at the correct working height, while the large flat platform base provided stable support and prevented tipping.

The full mechanical assembly was then performed using fasteners and mounting hardware to create a rigid and portable prototype frame. After deployment, the prototype underwent functional testing to validate Wi-Fi hotspot connectivity and dashboard access, live camera preview stability, proper inference results and output formatting, correct grading logic and confidence threshold behavior, successful PDF generation and printing workflow, and reliability of offline operation without internet.

Testing was performed using repeated weld capture sessions to ensure that detections were consistent across multiple runs, with mechanical alignment rechecked during testing, especially camera distance and angle, since these directly affect detection quality. Based on test outcomes, adjustments were made to the mounting geometry, dashboard behavior, confidence thresholds, and report layout.

Evaluation Procedure

The device was evaluated based on actual observations and evaluations by evaluators using a researcher-made questionnaire. The questionnaire underwent validation by experts and members of the research advisory committee. The steps in evaluating and rating the device according to the observation and analysis were as follows:

To determine the accuracy of the real-time vision AI welding analyzer, weld beads that have already been classified by the researcher was used. The device's camera captured 5 frames for every sample and used them to analyze the quality of the weld bead. If the device correctly classified an acceptable weave bead and string bead, a score of one (1) was given, and zero (0) if not. A total of 30 weld beads were used: 10 acceptable weave beads, 10 acceptable string beads, five reject weld beads, and five reject string beads.

To determine the precision of the device, the data collected in assessing the accuracy was used. The weld beads labeled as acceptable and classified by the device as acceptable were regarded as true positive (TP), while the bead samples labeled as reject and classified by the device as acceptable were regarded as false positive (FP). The value of precision was calculated as the number of true positives (TP) divided by the sum of true positives (TP) and false positives (FP). For the response time, the time taken for the device to analyze the bead samples was recorded. The timer began right after clicking the analyze button and ended once the result came out. If the device gives the result within 10 seconds, a score of one (1) was given, indicating minimal to no delay. If the device took more than 10 seconds to analyze the bead samples, a score of zero (0) was given, indicating a delayed response.

To test the general acceptability of the device in terms of technical features, composition, and operating performances, a researcher-made questionnaire was utilized. A total of 30 evaluators, comprising professors, welders, Technology and Livelihood Education (TLE) instructors, and end-users.

Instrumentation

The research instruments used in the study were actual observations. Before the evaluation, the researcher presented the questionnaire to the advisory committee and the research committee for validation. Feedback and suggestions were recorded for making necessary revisions. Different bead samples were analyzed to test their accuracy, precision, and response time. A total of thirty (30) weld beads were analyzed by the device, comprising ten (10) acceptable string beads, ten (10) acceptable weave beads, five (5) reject string beads, and five (5) reject weave beads. The testing and observation were done in ten (10) second intervals per weld bead to determine if the device can correctly classify weld beads. For the level of acceptability of the device, there are three (3) factors, namely: technical features, composition, and operating performance, which were rated using the evaluation sheet.

Tools and Equipment

Table 1 presents the tools needed for the development of a real-time vision AI welding analyzer for weave and stringer bead. It includes the description and usage of each tool and piece of equipment in the study.

Table 1: Materials and supplies used in making the real-time vision AI welding analyzer

Description	Use and Function
3D Camera Holder	Its purpose is to securely hold the camera module in place while keeping its orientation fixed toward the target area.
PK-910H 1080P Camera	It serves as the main image-capturing component of the system
5V 1W High Power LED	It is positioned near the camera assembly to provide illumination for the viewing area
Rechargeable Lithium-Ion Battery Pack	It allows the prototype to operate without being continuously connected to an external power supply.
HALO Switch Push Button	It acts as a user input or power control button.
Raspberry Pi	It serves as the main controller that handles image processing, data management, program execution, and communication between the camera and other electronic components.
XL4015 4V–38V Adjustable Buck Step Down Module	Its role is to reduce a higher input voltage from the battery or external power source down to a stable lower voltage required by the Raspberry Pi or other electronics.
DC 2Pin Mini 3010 Cooling Fan	A component that provides airflow and removes excess heat.
DC Barrel Power Jack	It provides an external power input connection for the system.
Tubular Steel Stand	It provides mechanical stability and maintains the correct height and viewing position of the camera system
Tubular / Square Tube	It serves as the main support column and helps bear the weight of the upper assembly.

Table 2: Tools and equipment used in making the real-time vision AI welding analyzer

Description	Uses
Bench Power Supply	Supplies adjustable DC voltage/current to power and test circuits.
Solder Station	Melts solder to join electronic components.
Multi Tester Universal	Measures voltage, current, resistance, and continuity.
Multi Tester AMP V W TEMP	Measures amps, volts, watts, and temperature.
AVR Power Regulator	Stabilizes AC voltage to protect equipment.

Metal Cutter	Cuts metal sheets, rods, or pipes.
Power Grinder	Grinds, sharpens, or smooths metal surfaces.
Rotary Tool	Drills, cuts, engraves, or sands small materials.
Drill Press	Drills precise holes at set angles and depths.
Bench Grinder	Sharpens tools or polishes metal on a fixed bench.
3D Printer	Prints plastic parts from digital models layer by layer.
Micro Screw Set	Tightens tiny screws in electronics.
Mid-Range Screw Set	Fastens medium screws in devices.
Standard Screw Set	Secures larger screws in enclosures.
Calipers	Measures precise dimensions of parts.
Fit Clippers	Trims thin wires, plastics, or soft metals.
Wire Stripper	Strips insulation from wire ends.
Wire Socket Crimping Tool	Crimps connectors onto wires for secure joints.

Data Gathering Procedure

The data gathering procedure was through a series of actual observations with manipulation of the real-time vision AI welding analyzer. The observation process was conducted to determine the accuracy, precision, response time, and general acceptability of the device in classifying weld beads as acceptable or non-acceptable.

To evaluate the accuracy of the device, a set of pre-classified weld beads, which were verified by the researcher, served as the validation dataset. The device's integrated camera captured five sequential frames per sample to assess weld bead quality.

Correct classification of acceptable weave and string beads yielded a score of 1, while incorrect classification yielded a score of 0. The dataset comprised 30 weld beads: 10 acceptable weave beads, 10 acceptable string beads, 5 reject weave beads, and 5 reject string beads.

For the precision of the device, the data set collected in assessing the accuracy was used. The weld beads labeled as acceptable and classified by the device as acceptable were regarded as true positive (TP), while the bead samples labeled as reject and classified by the device as acceptable were regarded as false positive (FP). Precision was determined by dividing the number of true positives (TP) by the total of true positives (TP) plus false positives (FP). Moreover, the response time was measured by recording the duration from activation of the analyze button to the output of results. An analysis completed within 10 seconds received a score of 1, indicating negligible delay, while an analysis exceeding 10 seconds received a score of 0, indicating delayed response.

To test the general acceptability of the device in terms of technical features, composition, and operating performances, a researcher-made questionnaire was utilized. A total of 30 evaluators, comprising professors, welders, Technology and Livelihood Education (TLE) instructors, and end-users.

Parameters for Analysis

In scoring the accuracy of the device in correctly classifying weave and string bead as acceptable or non-acceptable, the researcher used binary scoring:

In scoring the precision of the device in classifying weave and string beads as either acceptable or non-acceptable, the researcher used the collected data in testing the accuracy and determined its value using the formula adapted from the study of Chen *et al.* (2026):

Precision (%) = (True Positive)/(True Positive+False Positive) x 100

In scoring the response time of the device, the researcher used binary scoring as follows:

Table 3: Accuracy Rating and Interpretation of the Device

Rating	Interpretation	Description
1	Accurate	The device correctly classifies the weave and string beads as either acceptable or non-acceptable.
0	Inaccurate	The device incorrectly classifies the weave and string beads as either acceptable or non-acceptable.

Table 4: Response Time Rating and Interpretation of the Device

Rating	Interpretation	Description
1	No Delay Response	The device delivers the result within 10 seconds.
0	Delayed Response	The device delivers the result after 10 seconds.

In determining the general acceptability of the device in terms of technical features, composition, and operating performance, the five (5) response categories were used.

The mean was calculated, which was used to determine the level of general acceptability of the real-time vision AI welding analyzer.

Table 5: Mean Score and Verbal Interpretation for General Acceptability

Score	Mean Score	Verbal Interpretation
5	4.21-5.00	Very Acceptable
4	3.41-4.20	Acceptable
3	2.61-3.40	Moderate Acceptable
2	1.81-2.60	Less Acceptable
1	1.00-1.80	Least Acceptable

Testing and Evaluation

Industrial experts, academic professors, and end-users carried out the testing. Multiple rounds of testing were conducted to achieve optimal performance of the real-time vision AI welding analyzer. A trial-and-error approach was employed, and the insights of the experts were integrated.

RESULTS AND DISCUSSION

Technical Features of Real-Time Vision AI Welding Analyzer

Figure 2 presents the technical features of the real-time vision AI welding analyzer. The device was developed as a portable, offline-capable weld assessment system that integrates both hardware and software into a unified design. At its core, the system employed a Raspberry Pi controller, which functions simultaneously as the central processing unit and a standalone Wi-Fi hotspot.

This configuration allowed the device to establish a localized network, enabling the students to connect directly via their laptops or tablets without requiring external internet connectivity. Once connected, the users accessed a web dashboard interface that provides live camera previews, analysis controls, and utility functions, ensuring a streamlined environment for instructional and inspection purposes.

Furthermore, the imaging subsystem of the device was anchored by a USB camera integration (PK-910H 1080P camera) mounted within a custom 3D-printed holder, complemented by a high-power LED for controlled illumination. The captured frames were pre-processed and passed into a YOLO TFLite AI model optimized for weld detection.

The backend pipeline incorporated the confidence filtering, non-maximum suppression, and cross-frame merging, producing structured outputs that classified welds into categories, such as stringer bead, weave bead, or rejected. Each detection was accompanied by confidence scores, grading logic, and cropped image thumbnails, which were displayed in real time on the dashboard.

To enhance usability, the system included a password-protected settings panel, allowing instructors to adjust parameters, such as confidence thresholds, frame sampling iterations, and grading offsets. A fully integrated PDF report generation feature enabled offline printing of detailed weld analysis reports, complete with student information, synchronized timestamps, and structured grading summaries. Additional utility functions, such as time synchronization and shutdown control, provided accurate reporting and secure device management.

Moreover, from a hardware perspective, the analyzer incorporated a rechargeable battery pack for portability, an XL4015 buck step-down module for voltage regulation, and a cooling fan integration to maintain thermal stability during extended use. The mechanical design, supported by a steel stand and platform, ensured structural stability and durability. A DC barrel power jack provided flexibility for the external power input or battery charging.

Collectively, these features established the real-time vision AI welding analyzer as a robust educational tool that delivers autonomous, high-fidelity weld analysis in classroom and workshop environments. Its combination of offline operation, embedded AI vision, and portable IoT-style deployment made it a cutting-edge solution for training and assessment in welding education.

Figure 2: Technical features of real-time vision AI welding analyzer

Technical Features:
1. Raspberry Pi Controller
2. Standalone Wi-Fi Hotspot
3. Web Dashboard Interface
4. USB Camera Integration
5. YOLO TFLite AI Model
6. Confidence Threshold & Grading Logic
7. PDF Report Generation
8. Shutdown Control
9. Offline Operation

10. Cooling Fan Integration
11. Rechargeable Battery Pack
12. External DC Power Jack

Accuracy of Real-Time Vision AI Welding Analyzer

Table 3 presents the accuracy of the real-time vision AI welding analyzer. The device accurately classified acceptable stringer beads correctly in nine out of ten trials with a 90% success rate, with only one misclassification. Similarly, for acceptable weave beads, the device classified them correctly in nine out of ten trials, achieving a success rate of 90%. Notably, the device demonstrated perfect accuracy in classifying reject beads, obtaining a 100% success rate.

The results imply that the device can accurately classify different bead samples. This further showed its strong capability to distinguish weld quality variations reliably, supporting its use in diverse training scenarios, typical of the high school vocational programs.

The findings aligned with Liang *et al.* (2025), who developed a WELD-DETR framework for real-time weld defect detection in manufacturing settings using an RTX 2060 GPU. Their system achieved 98.2% accuracy at 58 frames per second for tiny cracks and holes, leveraging layered features and wavelet filters. This supported the use of fast, accurate AI vision tools for instant feedback in vocational training.

Table 6: Accuracy of real-time vision AI welding analyzer

Bead	**Bead Samples**										**Total**	**Success Rate**
	1	2	3	4	5	6	7	8	9	10		
Acceptable Stringer Beads	1	1	1	1	0	1	1	1	1	1	9	90 %
Acceptable Weave Beads	1	1	1	1	1	1	0	1	1	1	9	90 %
Reject Beads	1	1	1	1	1	1	1	1	1	1	10	100 %

Legend: 1 –Accurate - If the device correctly classifies the weave and string beads as either acceptable or non-acceptable, 0 –Not Accurate - If the device incorrectly classifies the weave and string beads as either acceptable or non-acceptable.

Precision of Real-Time Vision AI Welding Analyzer

Table 4 presents the precision of the real-time vision AI welding analyzer. Based on the results, the device demonstrated excellent precision in classifying stringer beads, achieving a rate of 100%. Similarly, the device achieved 100% precision in classifying weave beads.

The real-time vision AI welding analyzer exhibited excellent precision in classifying stringer and weave beads, with zero false positives across all samples. This implies reliable identification of acceptable beads. The limited sample size, however, restricted broader application. The device's 100% precision in classifying stringer and weave beads directly aligned with the research of Szőlősi *et al.* (2024), who evaluated the YOLO family of algorithms and identified YOLOv7 as the most effective model for automatic weld checks. The alignment between the device's performance and the standards established confirmed that the software is optimized for the precise detection of acceptable weld shapes.

Table 7: Precision of real-time vision AI welding analyzer

Bead Sample	**True Positive**	**False Positive**	**Precision (%) TP/(TP+FP) * 100**
Stringer Beads	9	**0**	**100%**
Weave Beads	9	0	100%

Legend: True Positive - If the bead labeled as acceptable is classified as acceptable by the device, False Positive - If the bead labeled as reject is classified as acceptable by the device

Response Time of Real-Time Vision AI Welding Analyzer

Table 5 presents the response time of the real-time vision AI welding analyzer. The result revealed that using a 10 second threshold to define "no delay," the system classified all 10 samples of acceptable stringer beads, acceptable weave beads, and reject beads within the time limit, indicating 100% success in meeting the real time criterion. The result implies that the real-time vision AI welding analyzer is operationally responsive and can classify weld bead samples fast enough to support immediate feedback during training or inspection.

The findings were supported by Seabery (2024), whose work demonstrated that systems incorporating an analysis module for instant feedback enable trainees to correct errors immediately. This approach enhances learning reinforcement and knowledge retention compared to traditional methods with delayed feedback.

Table 5: Response time of real-time vision AI welding analyzer

Bead	Bead Samples										Total	Success Rate
	1	2	3	4	5	6	7	8	9	10		
Acceptable Stringer Beads	1	1	1	1	1	1	1	1	1	1	10	100 %
Acceptable Weave Beads	1	1	1	1	1	1	1	1	1	1	10	100 %
Reject Beads	1	1	1	1	1	1	1	1	1	1	10	100 %

Legend: 1 –No Delay - If the device delivers the result within 10 seconds, 0 – Delayed - If the device delivers the result after 10 seconds

Acceptability of Real-Time Vision AI Welding Analyzer in Terms of Technical Features

The overall mean rating was 4.65, classified as "very acceptable". Users rated the high-resolution camera system for providing clear and detailed visualization of weld beads as "very acceptable" with a mean of 4.70, highlighting its effectiveness in delivering precise imagery essential for training. Similarly, the camera positioning and viewing angle, which effectively capture weld bead details was rated "very acceptable" with a mean of 4.70, ensuring comprehensive coverage without blind spots.

The LED illumination for consistent image capture received a "very acceptable" rating with a mean of 4.60, demonstrating its reliability in maintaining optimal lighting conditions across sessions. The vision system's consistent performance across different welding positions was also viewed as "very acceptable" with a mean of 4.50, indicating robustness in varied practical scenarios.

The YOLO TFLite model, providing accurate quality assessments comparable to expert human evaluators, earned a "very acceptable" score with a mean of 4.60. This showed that the system evaluates welds as well as experts, building confidence in its feedback. Users further appreciated how the system effectively distinguishes between acceptable and unacceptable weld quality, rated "very acceptable" with a mean of 4.70, which supports reliable feedback for skill improvement.

The web-based dashboard interface, noted for being intuitive and easy to navigate, was rated "very acceptable" with a mean of 4.70, reflecting strong user satisfaction with accessibility. The visual feedback displayed effectively, communicating weld quality, achieved the highest rating of "very acceptable" with a mean of 4.80, emphasizing its clarity in real-time guidance.

Additionally, the system's clear pass/fail indicators for weld assessments were seen as "very acceptable" with a mean of 4.60, demonstrating that the simple pass or fail indicator makes progress tracking straightforward.

The reliable passing percentage for accepted weld beads also received a "very acceptable" rating with a mean of 4.73, highlighting the effectiveness of giving a score overview in motivating students.

Sun *et al.* (2025) strongly supported the high acceptability of the device's technical features, emphasizing that smart, flexible layers and advanced feature-combination techniques enabled systems to outperform standard models in industrial monitoring. Their findings confirmed that this design delivered the expert-level accuracy, real-time weld quality assessment, and intuitive interface that users valued.

Acceptability of Real-Time Vision AI Welding Analyzer in Terms of Composition

The overall mean rating was 4.63, classified as "very acceptable". Users rated the tubular steel stand for providing adequate stability for the camera system as "very acceptable" with a mean of 4.63. This implies reliable support for consistent imaging in training setups. Similarly, the platform base, which effectively prevents tipping during normal use, was rated as "very acceptable" with a mean of 4.60, demonstrating its safety in training environments.

The overall height and viewing position of the camera, appropriate for welding training, received a "very acceptable" rating with a mean of 4.63, demonstrating ergonomic suitability. The structural design, allowing convenient placement of weld plates in the viewing area, was also viewed as "very acceptable" with a mean of 4.60, highlighting its efficiency during hands-on practice sessions.

The rechargeable lithium-ion battery pack, providing sufficient runtime for training sessions, earned a "very acceptable" score with a mean of 4.63. This showed its practicality for extended use without interruptions. Users further appreciated the power system, allowing both battery-only and wired operation as needed, rated "very acceptable" with a mean of 4.60, which supports flexible integration in varied training setups.

The DC 2Pin Mini 3010 cooling fan, effectively managing operating temperature, was rated "very acceptable" with a mean of 4.63, reflecting sustained performance during prolonged sessions. The enclosure design, allowing adequate airflow for component cooling, achieved a "very acceptable" rating with a mean of 4.60, highlighting the device's longevity during its operation.

Additionally, the overall assembly quality, meeting expectations for an educational prototype, was seen as "very acceptable" with a mean of 4.70, demonstrating professional craftsmanship. Lastly, the wiring and internal cable management, noted for being neat and secure, also received a "very acceptable" rating with a mean of 4.70, highlighting the durable construction details of the device.

The findings were supported by the work of Sun *et al.* (2025), who emphasized that the integration of robust, adaptive physical components is a foundational requirement for any system aimed at reliable, real-time industrial monitoring.

Acceptability of Real-Time Vision AI Welding Analyzer in Terms of Operating Performance

The overall mean rating was 4.62, classified as "very acceptable". Users rated the system's reliable operation without frequent crashes or errors as "very acceptable" with a mean of 4.50, highlighting its stability for uninterrupted training. Similarly, the ease of connecting laptops/tablets to the Weld Analysis network was rated as "very acceptable" with a mean of 4.53, demonstrating its capability for quick student access.

The system's consistent analysis speed across multiple consecutive runs received a "very acceptable" rating with a mean of 4.70, demonstrating efficiency in high-volume sessions. The classification results, correlating well with actual weld quality, was also viewed as "very acceptable" with a mean of 4.43, highlighting its accuracy in classifying weld beads.

The system's effective operation without internet connectivity earned a "very acceptable" score with a mean of 4.70. This showed its suitability for offline environments. Users further appreciated the battery-powered operation, allowing flexible placement in training areas, rated "very acceptable" with a mean of 4.73, implying classroom versatility.

The print report option, becoming available promptly after successful analysis, was rated "very acceptable" with a mean of 4.70, implying its capable of facilitating record-keeping. The immediate feedback, helping trainees identify and correct welding errors promptly, achieved a "Very Acceptable" rating with a mean of 4.60, demonstrating that it promotes real-time learning.

Additionally, the system's ability to reduce the instructor's workload in evaluating practice welds was seen as "very acceptable" with a mean of 4.63. This implies that is reliable in reducing the workload of instructors in checking the weld bead outputs of students. Lastly, the objective AI assessment complementing the instructor's subjective evaluation also received a "very acceptable" rating with a mean of 4.70, highlighting its accuracy and precision in classifying weld bead samples.

The findings regarding the high acceptability of the real-time vision AI welding analyzer's operating performance were supported by the research of Kesse *et al.* (2020), who established that AI-driven algorithms effectively integrate fuzzy logic and deep neural networks to provide consistent and predictable assessments of weld bead samples. This aligned with the current study's results, where evaluators confirmed that the system maintained consistent analysis speeds and provided objective, real-time feedback that effectively complemented traditional instructor evaluations.

Acceptability of Real-Time Vision AI Welding Analyzer in Terms of Safety Features

The overall mean rating was 4.68, classified as "very acceptable". Users rated the system's electrical components, properly enclosed to prevent accidental contact, as "very acceptable" with a mean of 4.70, indicating robust protection against electrical hazards. Similarly, all internal wiring, securely managed to avoid short circuits or damage, was rated as "Very Acceptable" with a mean of 4.50. This affirms the system's electrical integrity during prolonged use.

The tubular steel stand, providing a stable base that resists accidental tipping, received a "very acceptable" rating with a mean of 4.70. This demonstrated the physical stability of the device, reducing the risk of accidents in dynamic training settings. The battery management system, effectively preventing overheating during operation, was also viewed as "very acceptable" with a mean of 4.70. This implies that the device effectively addresses thermal risks for safe, continuous operation.

The DC cooling fan, maintaining safe operating temperatures for all internal components, earned a "very acceptable" score with a mean of 4.67. This demonstrated reliable heat dissipation under operational loads. Users further appreciated all exterior surfaces being free from sharp edges that could cause injury, rated "very acceptable" with a mean of 4.60. This implies that the device promotes user safety during handling and maintenance.

The system, emitting no harmful radiation or light beyond standard operating levels, was rated "very acceptable" with a mean of 4.70. This highlights that the device confirms emission safety for trainee health. The power system, including appropriate safeguards for both battery and wired modes, achieved a "very acceptable" rating with a mean of 4.70. This demonstrated that the device has versatile, secure power options without compromise.

Additionally, the assembly quality, ensuring components remain fixed and do not detach unexpectedly, was seen as "very acceptable" with a mean of 4.73, indicating durable construction. Lastly, the device design, minimizing the risk of pinched fingers during setup and adjustment, also received a "Very Acceptable" rating with a mean of 4.70. This showed safe handling and adjustments in instructional contexts.

The findings aligned with the study of Alsharabi (2023), who emphasized that robust hardware protection is essential for managing risks in welding environments. The study's results align with this, as the device's secure electrical enclosures, organized wiring, and thermal safeguards effectively mitigate hazards like electric shocks and overheating.

CONCLUSION

The real-time vision AI welding analyzer demonstrates strong technical features, solid construction, reliable performance, and effective safety measures. It supports objective weld quality assessment through a user-friendly web dashboard that provides instant feedback, pass/fail results, and key metrics, while ensuring user safety and instructional efficiency.

The real-time vision AI welding analyzer exhibits outstanding accuracy in reliably classifying acceptable stringer and weave beads while achieving perfect detection of reject samples. This affirms its effectiveness for objective weld quality evaluation in training applications. The device achieves 100% precision in classifying stringer and weave beads with zero false positives, confirming its reliability in identifying quality welds without misclassifying acceptable samples. It is beneficial for instructors in quality control by reducing workload through automated evaluation and for facilitating students' self-assessment of welding performance.

The real-time vision AI welding analyzer demonstrates operational responsiveness, enabling seamless integration into welding training and inspection workflows that demand immediate feedback. The device demonstrates excellent performance in technical features, composition, operating performance, and safety, confirming its ability to function reliably and securely in its intended environment. The positive evaluations indicate that experts regard the device highly.

The real-time vision AI welding analyzer can be a transformative tool that combines advanced technical performance, outstanding accuracy, and operational responsiveness with educational and institutional value, enabling objective weld quality assessment, reducing instructors' workload, empowering student self-assessment, and aligning training practices with global standards.

REFERENCES

Ahmad, Z., & Rofiq, Z. (2020). Development of competency-based assessment model welding practices for vocational school students. *American Journal of Educational Research, 8*(1), 29–34. https://doi.org/10.12691/education-8-1-5

Alhammadi, M. (2023). Optimising Customer Service Delivery and Response Time through AI-Enhanced Chatbots in Facilities Management-A Mixed-Methods Research. *American Journal of Smart Technology and Solutions, 2*(2), 43-54. https://doi.org/10.54536/ajsts.v2i2.2206

Alsharabi, N. (2023). Real-time object detection overview: Advancements, challenges, and applications. *Journal of Advanced Urban Studies, 3*(6), 73. https://doi.org/10.59145/jaust.v3i6.73

Bansal, A., Vettivel, S. C., Kumar, M., & Agarwal, M. (2023). Weld defect identification and characterization in radiographic images using deep learning: Review. *Engineering Research Express, 5*(4), 042005. https://doi.org/10.1088/2631- 8695/acdf3f

Bhardwaj, S., Ratnayake, C., Efthymios Polatidis, & Čapek, J. (2022). Experimental investigation of residual stress distribution on girth welds fabricated at proximity using neutron diffraction technique. *The International Journal of Advanced Manufacturing Technology, 121*(5-6), 3703–3715. https://doi.org/10.1007/s00170-022-09574-6

Bureau of Labor Statistics. (2018). *Occupational employment projections data: Welders, cutters, solderers, and brazers.* U.S. Department of Labor. https://www.bls.gov/emp/tables/occupational-separations-and-openings.htm

Chandra, H., Nukman, & Sianturi, B. (2019). Analysis of fatigue life and crack propagation characterization of gray cast iron under normalizing process. *Journal of Physics: Conference Series, 1198*(3), 032006. https://doi.org/10.1088/1742-6596/1198/3/032006

Chen, Z., Tan, K., Shi, Y., Liu, M., Yi, L., Chen, T., & Bai, Y. (2026). Computational Discovery of Novel SGLT2 Inhibitors from Eight Selected Medicine Food Homology Herbs Using a Multi-Stage Virtual Screening Pipeline. *Pharmaceuticals, 19*(2), 246. https://doi.org/10.3390/ph19020246

Dogra, V. (2018). Application of welding process parameters using AI algorithm. *Türk Bilgisayar ve Matematik Eğitimi Dergisi, 9*(2), 632–642. https://doi.org/10.17762/turcomat.v9i2.13866

Dold, P. M., Bleier, F., Boley, M., & Mikut, R. (2022). Multi-stage inspection of laser welding defects using machine learning. *DAGM German Conference on Pattern Recognition* (pp. 1–15). https://doi.org/10.58895/ksp/1000151141-3

Dosari, F. H. M. A., & Abouellail, S. I. A. D. (2023). Artificial Intelligence (AI) Techniques for Intelligent Control Systems in Mechanical Engineering. *American Journal of Smart Technology and Solutions, 2*(2), 55-64. https://doi.org/10.54536/ajsts.v2i2.2188

European Commission. (2020). *Council Recommendation on vocational education and training (VET) for sustainable competitiveness, social fairness and resilience* (2020/C 417/01). *Official Journal of the European Union.* https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32020H1202(01)

European Commission. (2020). *Vocational education and training modernization.* https://ec.europa.eu/social/main.jsp?catId=1415&langId=en

Freeman, J. (2016). *Schematic diagram – A complete tutorial with free examples.* Edraw Software. https://www.edrawsoft.com/schematic-diagram.html

Jeremić, L., Sedmak, A., Petrovski, B., Đorđević, B., & Sedmak, S. (2020). Structural integrity assessment of welded pipeline designed with reduced safety. *Tehnicki Vjesnik, 27*(6), 1839–1845. https://doi.org/10.17559/TV-20200413142538

Kesse, M. A., Buah, E., Handroos, H., & 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. https://doi.org/10.3390/met10040451

Khorshidikia, S., Rismanchian, M., Popov, G., & Habibi, E. (2026). Determining training needs of welders in equipment manufacturing industry: A systematic approach using Delphi fuzzy method and FAHP for traditional and immersive trainings. *WORK: A Journal of Prevention, Assessment & Rehabilitation.* https://doi.org/10.1177/10519815251408O3

Liang, Y., Yu, B., Ding, M., Hu, W., Jin, Y., & Yuan, Y. (2025). WELD-DETR: A real-time welding defect detection framework with multi-scale feature fusion and multi-kernel perception optimization. *Sensors, 25*(22), Article 7024. https://doi.org/10.3390/s25227024

Naddaf-Sh, S., Naddaf-Sh, M.-Mahdi, Zargarzadeh, H., Dalton, M., Ramezani, S., Elpers, G., Baburao, V. S., & Kashani, A. R. (2022). Real-time explainable multiclass object detection for quality assessment in 2-dimensional radiography images. *Complexity, 2022,* 1–17. https://doi.org/10.1155/2022/4637939

Pan, K., Hu, H., & Pan, G. (2023). WD-YOLO: A more accurate YOLO for defect detection in weld X-ray images. *Sensors, 23*(21), Article 8677. https://doi.org/10.3390/s23218677

Ranganayakulu, S., Burra, S., & Ravi, S. (2017). Characterization of weldment defects through non-destructive evaluation techniques. *Indian Journal of Science and Technology, 10*(16), 1–9. https://doi.org/10.17485/ijst/2017/v10i16/109603

Sazonova, S. A., Nikolenko, S. D., Osipov, A. A., Zyazina, T. V., & Venevitin, A. A. (2021). Weld defects and automation of methods for their detection. *Journal of Physics: Conference Series, 1889,* 022078. https://doi.org/10.1088/1742-6596/1889/2/022078

Seabery. (2024). *Soldamatic augmented reality welding training: Hyper-realistic simulation with instant feedback*. Seabery Augmented Technology. https://www.seabery.com

Szőlősi, J., Szekeres, B., Magyar, P., Adrián, B., Farkas, G., & Andó, M. (2024). Welding defect detection with image processing on a custom small dataset: A comparative study. *IET Collaborative Intelligent Manufacturing, 6*. https://doi.org/10.1049/cim2.70005

Sun, Y., Xie, Y., Peng, R., Zhang, Y., Chen, W., & Guo, Y. (2025). DEIM-SFA: A multi-module enhanced model for accurate detection of weld surface defects. *Sensors, 25*(20), 6314. https://doi.org/10.3390/s25206314

TOTC Inc. (2025). *How to hire a skilled welder: Challenges and best practices.* TOTC Inc. https://www.totc.com.ph/whats-new/blogs/how-to-hire-a-skilled-welder/

United Nations. (2015). *Sustainable Development Goal 4: Quality education.* https://sdgs.un.org/goals/goal4

Western Visayas Regional Development Council. (2023). *Regional development plan 2023–2028.* https://pdp.depdev.gov.ph/wp-content/uploads/2023/07/Western-Visayas-RDP.pdf

World Bank. (2020). *Strengthening teacher quality in vocational education and training: Professional standards for VET teachers.* World Bank Open Knowledge Repository. https://openknowledge.worldbank. org/handle/10986/34588

Yamane, S., Wang, C., Nakamura, T., Nagai, T., & Ishizaki, K. (2025). Detection of molten pool state using ResNet50 and control of molten pool penetration in CO2 gas shielded arc welding. *Welding in the World, 69*. https://doi.org/10.1007/s40194-025-02020-7