

Review

AI-Enabled Post-Process Surface Inspection in Laser-Welded Al–Cu Battery Interconnects: A Critical Review

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Abstract

The growth of electric vehicles has increased the need for reliable, low-resistance Al–Cu battery interconnects. Laser welding provides localized heat input, high productivity, and automation potential, but Al–Cu joining remains limited by thermophysical mismatch, unstable energy coupling, and brittle intermetallic compound formation, which can lead to visible defects, hidden discontinuities, and performance variability. This review focuses on artificial intelligence (AI)-enabled post-process surface inspection of laser-welded Al–Cu battery interconnects. Process–structure–property relationships, defect mechanisms, process enablers, and in-process monitoring are discussed as supporting context to distinguish surface-visible evidence from attributes requiring complementary validation. The review critically examines controlled imaging, illumination and reflectivity effects, defect taxonomy, annotation, dataset design, AI task selection, and risk-based quality decisions. Classification, detection, segmentation, and anomaly detection are compared in terms of annotation requirements, traceability, metrics, and limitations. The main contribution is a post-process inspection framework that links controlled image acquisition, defect taxonomy, weld-level datasets, AI inference, benchmarking, and accept–review–reject decision logic with functional validation. The framework supports reproducible, risk-sensitive, and functionally validated quality assurance for Al–Cu battery welds while preserving expert review for uncertain cases and for the acceptance of welding technologies, process windows, and critical quality decisions.

Keywords: aluminum–copper dissimilar joining; battery interconnects; laser welding; post-process surface inspection; surface defect taxonomy; computer vision; artificial intelligence; quality assurance



Academic Editor: Zhibin Yang

Received: 30 June 2026

Revised: 18 July 2026

Accepted: 21 July 2026

Published: 2 August 2026

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1. Introduction

1.1. Industrial Relevance

The expansion of electric mobility has increased demand for battery packs that combine high power capability, low mass, long service life, and reliable high-volume manufacturing. Within these systems, electrical interconnects provide the current path between cells, modules, terminals, and busbars. Their performance depends on maintaining low electrical resistance, limiting temperature rise, and ensuring sufficient mechanical integrity throughout assembly and service [1,2]. Because a battery pack may contain hundreds or thousands of individual connections, even a low defect rate can yield a substantial number of nonconforming joints, compromising pack-level efficiency, thermal uniformity, durability, and safety [1–3].

Aluminum and copper are widely used in battery interconnects because they offer complementary combinations of electrical conductivity, mass, cost, and compatibility with cell and busbar architectures. Their direct joining can reduce the need for intermediate connectors and simplify the electrical path. However, the required performance cannot be assessed from nominal conductivity alone. Joint geometry, effective bonded area, contact resistance, thermal contact resistance, failure location, and mechanical strength must be considered together because these responses do not necessarily evolve in parallel [1,3–5]. Recent battery-manufacturing reviews continue to identify joining and interconnect qualification as critical steps in the transition from cell production to reliable module and pack assembly [2,6].

Laser welding is attractive for these applications because it provides concentrated energy delivery, high processing speed, limited global heat input, flexible beam positioning, and compatibility with automated production [1,3,7]. Continuous-wave, quasi-continuous-wave, and pulsed laser sources can be combined with beam oscillation, tailored trajectories, beam shaping, and visible wavelengths to accommodate different sheet thicknesses and interconnect geometries [3–5,8]. Nevertheless, the benefits of high energy density are accompanied by strong sensitivity to surface condition, stack configuration, clamping, focal position, and local heat sinking.

1.2. Quality-Assurance Problem

Dissimilar Al–Cu laser welding is constrained by major differences in optical, thermal, and metallurgical behavior. Copper exhibits limited absorption at conventional near-infrared wavelengths before melting, while aluminum and copper differ substantially in thermal conductivity, melting temperature, and fluid-flow response. These differences can produce unstable energy coupling, melt ejection, keyhole fluctuations, incomplete bonding, and abrupt transitions between insufficient and excessive penetration [3–5,8,9].

At the interface, mutual melting and mixing promote the formation of Al–Cu intermetallic compounds. A limited reaction is required to establish metallurgical bonding, but excessive intermixing can generate thick or continuous brittle regions that increase crack susceptibility and degrade mechanical and electrical performance [3,9,10]. The process therefore involves a persistent compromise between obtaining sufficient bonded width and limiting excessive dilution, penetration, and intermetallic growth.

These coupled mechanisms narrow the operating window. Small changes in power, speed, focal position, beam trajectory, gap, surface oxidation, coating, or stack order may shift the result from inadequate bonding to spatter, porosity, underfill, undercut, cracking, burn-through, or excessive material interaction [3–5,8–11]. Beam shaping and oscillation can stabilize energy distribution and weld geometry [3,5,8]. Visible wavelengths, pulse shaping, and dual-beam control can improve coupling on Cu-rich surfaces [4,11,12]. Welding–brazing and interlayers primarily target mixing and control of intermetallic reactions [10]. These strategies reduce specific process risks but do not eliminate the need for inspection [3,4,10,12].

The resulting quality-assurance problem has two dimensions. First, critical conditions may develop during welding and may be reflected in transient optical, thermal, acoustic, or geometric signals. Second, the completed joint may contain visible surface anomalies whose location and severity can be assessed after welding. Neither source of evidence alone establishes complete joint conformity. A visually regular surface does not necessarily indicate adequate penetration, a hidden bonded width, limited porosity, controlled intermetallic formation, or low electrical resistance. Conversely, a surface irregularity does not necessarily imply functional rejection unless its size, position, and consequences have been validated [1,3,13].

Battery manufacturing therefore requires an inspection architecture that distinguishes observable surface defects from hidden joint attributes and that links both to electrical, thermal, mechanical, and metallurgical ground truth. This distinction is central to avoiding unsupported conclusions based solely on surface appearance or model confidence.

1.3. Why Post-Process Inspection Requires a Dedicated Review

Research on laser weld quality assessment has historically focused on in-process monitoring. Coaxial cameras, lateral high-speed imaging, photodiodes, spectroscopy, thermography, acoustic sensing, and optical coherence tomography have been investigated to estimate penetration, keyhole stability, material interaction, and seam width at the interface [14–17]. Recent reviews confirm continued growth in data-driven real-time defect diagnosis, multisensor learning, and machine learning-assisted process control [18,19].

This literature has established important links between process signals and weld-state variables. However, its transfer to manufacturing requires specialized optics, synchronization, calibration, protection from contamination, and validation across material and process changes. In-process sensing is therefore highly valuable when the target variable is strongly linked to process physics, but it may be difficult to retrofit or maintain in every production environment.

Post-process inspection addresses a distinct, complementary need. Images acquired after welding can document the final visible condition of every joint, including seam placement, continuity, spatter, surface pits, craters, cracks, undercut, underfill, excessive melting, and other geometric anomalies. The acquisition station can be separated from the welding optics and can use controlled illumination, fixed magnification, a calibrated scale, repeated views, and image reacquisition. Consequently, post-process inspection may be integrated into an automated line even though the evidence is collected after the laser–material interaction has ended.

Despite this practical potential, the evidence base remains fragmented. Most visual weld inspection studies address steels, conventional arc welds, radiographic images, battery housings, or general industrial surfaces rather than dissimilar Al–Cu battery interconnects [20–23]. Recent reviews of machine learning algorithms for weld-surface inspection identify recurring limitations, including small and heterogeneous datasets, inconsistent defect terminology, class imbalance, incomplete reporting, and limited evaluation under changes in illumination, geometry, and surface condition [20,21]. A visible-spectrum weld inspection study further illustrates the growing use of semantic segmentation for defect localization and shows that controlled datasets and application-specific definitions remain essential [24].

These limitations are amplified for Al–Cu joints. Highly reflective and heterogeneous surfaces can produce glare, false edges, intensity gradients, and apparent discontinuities unrelated to physical defects. Differences in alloy, coating, oxidation, roughness, weld trajectory, and stack geometry can alter the appearance of images and introduce domain shift. Moreover, the most critical battery-quality variables, including contact resistance, hidden-bond width, internal porosity, and intermetallic continuity, are not directly visible on the top surface.

A dedicated review is therefore needed to define what post-process imaging can defensibly measure, how images should be acquired and annotated, which AI tasks are appropriate, and how visual predictions should be linked to functional acceptance. The objective is not to position post-process vision as a replacement for in-process monitoring or destructive qualification, but as a scalable and traceable layer within a broader quality-assurance system. Human expertise remains essential in this framework. AI-assisted post-process inspection can improve consistency, traceability, and screening speed, but it

should not replace expert judgment when a weld lies outside the validated domain, when surface evidence is ambiguous, or when a new welding technology, parameter window, or acceptance criterion must be qualified. In such cases, expert review and complementary functional validation remain necessary to support sound manufacturing decisions.

1.4. Scope and Terminology

This review focuses on AI-enabled post-process inspection of surface-visible defects in laser-welded Al–Cu battery interconnects, while using process physics, process enablers, and in-process sensing as the technical context required to interpret the resulting surface morphology.

The terminology used throughout the review distinguishes the moment of evidence acquisition from the location of the inspection system. In-process monitoring refers to signals acquired during laser irradiation and material interaction. In-line integration refers to any inspection or monitoring operation physically integrated into the manufacturing line, regardless of whether it occurs during or after welding. Post-process inspection refers to examination of the completed joint after the welding interaction has ended. A post-process station may therefore remain fully in-line when it is installed downstream of the welding operation.

A surface-visible defect is an externally observable geometric or morphological condition that can be identified under a defined imaging protocol. This term does not include hidden lack of bonding, internal porosity, penetration depth, or intermetallic-layer characteristics unless an independently validated relationship has been established. Functional ground truth refers to electrical, thermal, mechanical, geometric, or metallurgical measurements used to determine whether an observable feature or model prediction is relevant to actual joint performance.

The primary application considered is the battery-relevant overlap interconnect, including tab-to-busbar, tab-to-terminal, and related thin-sheet configurations. Evidence from Al–Cu laser welding outside battery manufacturing and from general weld-surface inspection is included when it provides transferable principles, but such evidence is distinguished from studies performed directly on battery interconnects.

1.5. Positioning, Novelty, and Contributions of This Review

Several recent reviews have addressed topics adjacent to the present manuscript. These include dissimilar laser welding for electric-vehicle battery manufacturing [25] and the use of blue, green, and hybrid laser beams for welding highly reflective metals [26], together with reviews of battery-joining technologies, beam-shaping strategies for e-mobility components, in-process weld monitoring, machine learning in laser welding, weld-surface defect detection, and digital-twin-assisted manufacturing. These contributions have clarified important aspects of joining process development, sensor integration, model architectures, and quality monitoring. However, they generally treat these topics as separate domains. Battery-joining reviews often emphasize process selection, interconnect architecture, manufacturability, and functional requirements, but provide limited guidance on AI-ready post-process visual inspection. Al–Cu laser-welding reviews commonly focus on weldability, intermetallic compound formation, process stability, and mechanical or electrical performance, but rarely translate these mechanisms into image-based inspection protocols. Conversely, AI-oriented weld inspection reviews frequently discuss classification, detection, segmentation, and performance metrics, but are often weakly connected to Al–Cu metallurgy, battery-specific acceptance criteria, and functional validation.

The present review is positioned at the intersection of these fields. Its contribution is not merely to summarize AI models for weld inspection, nor to provide a general overview of Al–Cu laser welding. Instead, it develops a critical framework for AI-enabled post-process surface inspection of laser-welded Al–Cu battery interconnects. The novelty of this review lies in integrating Al–Cu joining metallurgy, post-process image metrology, AI-based surface defect inspection, and battery-oriented functional validation into a single quality-assurance framework.

Table 1 summarizes how the scope of this review differs from related review domains and identifies the specific gap addressed by the present work. Unlike previous reviews that separately address joining technologies, Al–Cu weldability, process monitoring, or AI-based defect recognition, this review connects surface-visible weld evidence with battery-specific defect risk, controlled imaging, weld-level dataset design, AI task selection, benchmarking, uncertainty handling, and functional acceptance. To the authors’ knowledge, no previous review has proposed an integrated post-process inspection framework specifically for laser-welded Al–Cu battery interconnects that links surface defect taxonomy, controlled image acquisition, AI-based inference, accept–review–reject decision logic, and validation through electrical, thermal, mechanical, and metallurgical evidence.

The main contributions of this review are fourfold. First, it organizes surface-visible defects according to battery-relevant risk while distinguishing observable surface evidence from hidden attributes that require complementary validation. Second, it proposes an AI-ready inspection workflow based on controlled image acquisition, image-quality validation, annotation rules, inter-annotator agreement, weld-level dataset construction, and data-leakage prevention. Third, it compares classification, detection, segmentation, and anomaly-detection tasks according to their annotation requirements, traceability, metrics, limitations, and false-negative risk. Fourth, it provides benchmarking and manufacturing-oriented decision guidance by linking model evaluation with cross-condition validation, uncertainty handling, functional ground truth, and accept–review–reject quality logic.

Unlike these reviews, the present work connects surface-visible weld evidence with battery-specific defect risk, image metrology, weld-level dataset design, AI task selection, benchmarking, uncertainty handling, and functional acceptance. To the authors’ knowledge, no previous review has proposed an integrated post-process inspection framework specifically for laser-welded Al–Cu battery interconnects that links surface defect taxonomy, controlled imaging, AI-based inference, accept–review–reject decision logic, and validation through electrical, thermal, mechanical, and metallurgical evidence. Figure 1 provides an overview of the review scope by linking battery-relevant Al–Cu interconnect geometries to the joining constraints, process enablers, inspection pathways, and AI-supported quality gates considered throughout the manuscript.

Table 1. Positioning of the present review relative to previous reviews on battery joining, Al–Cu laser welding, laser-process optimization, in-process monitoring, AI-based weld inspection, and smart manufacturing. The comparison is a synthesis based on representative reviews cited in Section 1.5.

Review Domain	Main Emphasis of Previous Reviews	Main Limitation for Al–Cu Post-Process Inspection	Gap Addressed by the Present Review
Battery-joining reviews	Joining technologies, interconnect architectures, manufacturability, and pack-level reliability	Post-process surface inspection and AI-ready quality gates are only marginally addressed	Links battery interconnect requirements with surface defect inspection, functional risk, and decision logic
Al–Cu laser-welding reviews	Weldability, IMC formation, process parameters, defect mechanisms, and joint performance	Metallurgical mechanisms are rarely translated into image-based inspection requirements	Connects Al–Cu defect formation with post-process visual signatures and functional validation

Table 1. Cont.

Review Domain	Main Emphasis of Previous Reviews	Main Limitation for Al–Cu Post-Process Inspection	Gap Addressed by the Present Review
Beam-shaping and laser-process reviews	Energy distribution, oscillation strategies, wavelength selection, hybrid routes, and process window enlargement	Process enablers are seldom related to post-process image appearance or AI inspection domains	Shows how process enablers modify surface morphology, defect prevalence, and model-transfer limits
In-process monitoring reviews	Coaxial imaging, photodiodes, spectroscopy, OCT, thermography, acoustic sensing, and real-time diagnosis	Focus on signals acquired during welding rather than completed-joint surface inspection	Distinguishes in-process proxies from post-process surface evidence and complementary validation needs
AI-based weld inspection reviews	Classification, object detection, segmentation, and defect-recognition metrics	Limited connection with Al–Cu defect mechanisms, battery reliability, and functional acceptance	Provides AI task selection, dataset rules, benchmarking metrics, and false-negative-oriented quality logic
Computer-vision and smart-manufacturing reviews	Generic visual inspection, automation, digitalization, prediction, and quality-control frameworks	Not specific to reflective dissimilar Al–Cu welds or battery interconnect requirements	Adapts transferable computer-vision principles to Al–Cu surface inspection, traceability, and risk-based decisions
Present review	AI-enabled post-process surface inspection of laser-welded Al–Cu battery interconnects	Not applicable	Integrates defect taxonomy, image acquisition, annotation, dataset design, AI task selection, benchmarking, uncertainty handling, and functional validation

Note: This table summarizes trends and gaps identified from the review literature discussed in Section 1.5; it does not report original experimental data.

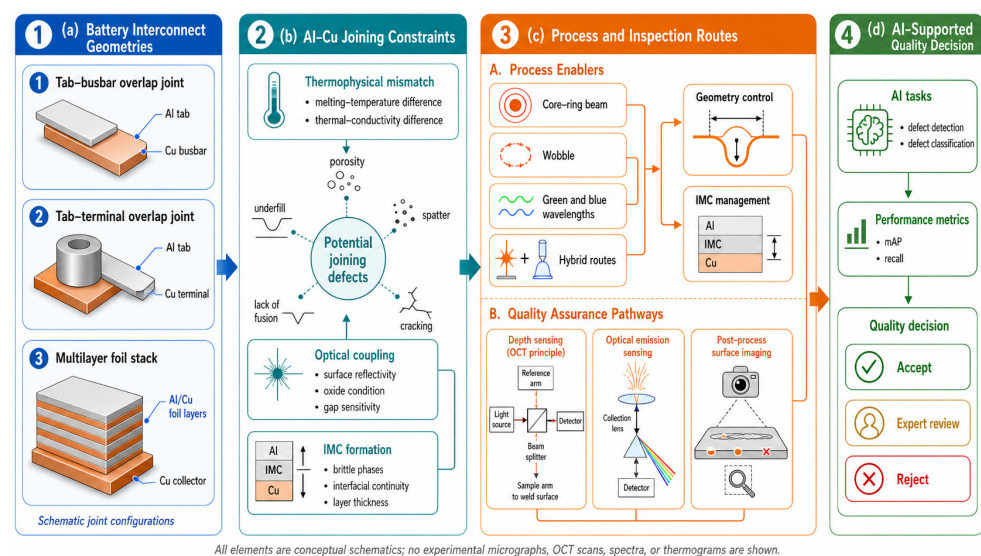


Figure 1. Scope of the review: battery interconnect geometries, Al–Cu joining constraints, process and inspection routes, and AI-supported quality decisions. (a) Representative tab–busbar, tab–terminal, and multilayer foil joints; (b) thermophysical, optical, and metallurgical constraints and potential defects; (c) process enablers and in-process and post-process inspection routes; and (d) AI tasks, performance metrics, and accept–review–reject decisions. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a four-panel scientific vector infographic linking Al–Cu battery interconnect geometries, joining constraints and defects, process and inspection routes, and AI-supported accept–review–reject decisions; use conceptual schematics only.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

Within this framework, the joint architecture and its functional requirements define both the relevant quality attributes and the surface region available for inspection. The following section therefore examines the principal battery interconnect configurations before addressing defect formation, process enablers, and quality-assurance strategies.

1.6. Review Approach and Evidence Hierarchy

This article was developed as a critical narrative review rather than as a PRISMA-based systematic review. The literature considered was published primarily from 2016 to July 2026, with earlier foundational sources included only when needed to support established concepts in welding metallurgy, image analysis, model evaluation, or quality assurance. The search was updated during the July 2026 revision of the manuscript. Peer-reviewed research articles were prioritized, while review papers and foundational sources were used to identify established concepts, major research directions, and additional primary studies.

Publications were identified through Scopus, Web of Science Core Collection, ScienceDirect, SpringerLink, IEEE Xplore, the MDPI journal platform, and Google Scholar. Database searches were complemented by backward citation tracking from relevant articles and reviews and by forward citation tracking of highly pertinent studies. Recently published reviews in adjacent domains were also screened to locate new primary evidence and to verify that major viewpoints had not been omitted.

Representative search blocks combined terms from four concept groups: (i) application and materials, including “Al–Cu,” “aluminum–copper,” “aluminium–copper,” “battery interconnect,” “tab-to-busbar,” “tab-to-terminal,” and “battery tab”; (ii) joining process and metallurgy, including “laser welding,” “dissimilar joining,” “intermetallic compound,” “beam shaping,” “beam oscillation,” “green laser,” “blue laser,” “welding–brazing,” and “interlayer”; (iii) inspection and sensing, including “post-process inspection,” “post-weld surface inspection,” “weld-surface imaging,” “in-process monitoring,” “coaxial imaging,” “photodiode,” “spectroscopy,” “thermography,” “acoustic sensing,” and “optical coherence tomography”; and (iv) artificial intelligence and data methodology, including “computer vision,” “machine learning,” “deep learning,” “classification,” “object detection,” “segmentation,” “anomaly detection,” “annotation,” “dataset,” “benchmarking,” “uncertainty,” “domain shift,” and “quality assurance.” The precise combination and syntax were adapted to each database’s indexing rules.

Screening was performed iteratively at the title, abstract, keyword, and full-text levels. A publication was included when it met at least one of the following criteria: (1) it reported direct evidence on laser-welded Al–Cu battery interconnects; (2) it provided closely related evidence on Al–Cu laser welding that was relevant to process physics, intermetallic compound formation, defect mechanisms, or joint performance; (3) it described transferable methods for weld imaging, sensing, defect localization, annotation, dataset construction, machine learning, model evaluation, or uncertainty assessment; or (4) it contributed contextual evidence on battery manufacturing, traceability, risk-based quality gates, or smart manufacturing. Publications were excluded when they lacked sufficient methodological detail, addressed unrelated materials or joining processes without a defensible transfer path, reported image-based models without usable information on data, labels, validation, or metrics, or did not contribute to the defined scope. When several publications reported substantially overlapping material, the most complete and informative account was prioritized.

The final synthesis comprised 124 references. Because the review was initially designed as a critical narrative synthesis, the numbers of initial database returns, duplicates, records excluded after title or abstract screening, and full texts excluded were not recorded prospectively. These quantities have therefore not been reconstructed or reported as if they

originated from a systematic-review protocol, and no PRISMA flow diagram is presented. This limitation is acknowledged explicitly. No quantitative meta-analysis was attempted because the studies differed substantially in material grade, thickness, stack order, joint geometry, laser source, beam-delivery strategy, surface condition, imaging system, defect definition, dataset structure, validation procedure, and performance metric.

To reduce the risk of selective narrative interpretation, every source was assigned to an evidence level according to its proximity to the target application, and each level was restricted to specific types of claims. Direct evidence from laser-welded Al–Cu battery interconnects was used to draw application-specific conclusions about joint performance, defect relevance, functional risk, and acceptance requirements. Closely related Al–Cu welding evidence was used to explain metallurgical and process mechanisms, but it was not treated as sufficient by itself to establish battery-specific acceptance criteria. Transferred welding and AI evidence were used to inform methodological recommendations on sensing, image acquisition, annotation, task selection, dataset design, benchmarking, uncertainty, and robustness, whereas contextual evidence was used for manufacturing traceability, quality-gate design, and digital-thread concepts. Whenever direct evidence was unavailable, the corresponding conclusion was framed as transferable evidence, a methodological recommendation, or a research need rather than as an established application-specific finding.

Conflicting or non-convergent findings were retained rather than excluded to support a preferred narrative. Differences were interpreted in relation to material stack, upper sheet, thickness, laser wavelength, beam profile, process regime, surface condition, clamping, imaging protocol, dataset partitioning, and functional test method. Table 2 summarizes the evidence hierarchy used to structure the review and to distinguish direct application-specific findings from broader methodological or contextual sources.

Table 2. Evidence hierarchy used to structure the critical review. The hierarchy was developed to classify the reviewed literature according to its proximity to laser-welded Al–Cu battery interconnect inspection.

Evidence Level	Literature Domain	Relevance to This Review	Typical Contribution	Main Limitation
Direct evidence	Laser-welded Al–Cu battery interconnects	Highest	Battery-relevant joint geometries, process windows, defect formation, electrical and mechanical performance	Limited number of studies combining post-process imaging with AI-based inspection and functional validation
Closely related evidence	Al–Cu laser welding outside battery applications	High	Al–Cu metallurgy, intermetallic compound formation, process instability, weldability, and defect mechanisms	Functional requirements and acceptance criteria may differ from battery interconnects
Transferred welding evidence	Laser weld inspection in other materials or joint configurations	Medium	Imaging strategies, defect localization, sensing concepts, and quality-monitoring workflows	Defect morphology and risk may not translate directly to reflective dissimilar Al–Cu joints

Table 2. *Cont.*

Evidence Level	Literature Domain	Relevance to This Review	Typical Contribution	Main Limitation
Transferred AI evidence	General computer vision and machine learning for weld inspection	Medium to low	Classification, detection, segmentation, annotation practices, and model-performance metrics	Often weakly connected to weld metallurgy, joint functionality, and manufacturing acceptance
Supporting contextual evidence	Battery-manufacturing quality assurance and smart manufacturing	Contextual	Reliability requirements, traceability, risk-based quality gates, and digital-thread concepts	May not address laser-welded Al–Cu joints or surface-visible defects specifically

2. Al–Cu Battery Interconnect Context: Requirements, Defect Formation, and Process Enablers

Laser-welded Al–Cu battery interconnects must satisfy electrical, thermal, mechanical, and manufacturing requirements simultaneously. From the perspective of post-process inspection, the key issue is not only whether a joint can be produced, but which quality-relevant features are externally visible, which remain hidden at the interface, and which require functional validation. Joint geometry, stack order, surface accessibility, seam trajectory, and the expected current path therefore define both the process window and the inspection logic.

2.1. Battery-Relevant Joint Configurations and Inspection Implications

Battery interconnects commonly use tab-to-busbar and tab-to-terminal overlap joints [1,2]. Thin-foil and dissimilar-sheet configurations are also reported in battery-related laser joining [27–30]. Patterned trajectories such as spiral or oscillated seams are used to manage local heat input and joint geometry [31]. These architectures differ in material thickness, heat sinking, electrical path length, accessible surface area, and sensitivity to seam placement. Consequently, inspection requirements cannot be transferred directly from one geometry to another without validation.

In tab-to-busbar overlap joints, the weld is commonly formed through the upper sheet and must provide sufficient bonded area at the hidden Al–Cu interface. Surface imaging can assess seam position, visible continuity, spatter, craters, undercut, underfill, and excessive melting. However, the visible upper bead does not necessarily represent penetration depth or seam width at the interface [1,3–5,30–32]. In copper-on-aluminum configurations, for example, the upper copper sheet may dominate the optical and thermal response, whereas the functionally critical bonded region is located below the visible surface. In aluminum-on-copper configurations, the optical coupling and heat-flow conditions change, and the same top-surface appearance may correspond to a different interfacial geometry.

Tab-to-terminal connections introduce additional constraints because the terminal feature may have greater thickness, local curvature, complex edge distance, and stronger heat sinking than thin tabs or busbars [27]. For post-process inspection, this means that seam placement, edge proximity, and incomplete overlap coverage become as important as local defect morphology. A weld that is visually continuous may still be functionally compromised if it is shifted away from the intended current-carrying region or if the effective bonded width is insufficient.

Foil stack and multilayer assemblies present a different inspection challenge. Multiple thin current collectors must be joined without excessive distortion, melt-through, or loss of stack integrity [28,29]. Surface defects may be small, repeated, or distributed across several weld locations. Patterned trajectories can improve local heat management, but they also create starts, stops, overlaps, and corners where craters, discontinuities, or local overmelting may occur. Inspection must therefore consider not only the presence of an isolated defect, but also its location relative to the intended seam path and current-flow region.

Figure 2 summarizes the principal battery interconnect configurations considered in this review and their associated functional requirements. Table 3 extends this overview by comparing representative Al–Cu joint and seam configurations reported in the literature, including their assembly location, thickness regime, joining purpose, process constraints, and evaluated outputs. As shown in Table 3, inspection requirements are geometry dependent. Surface accessibility, bonded-area distribution, stack order, seam trajectory, and heat sinking influence which defects can be detected visually and which hidden attributes must be validated through cross-sections, electrical resistance, thermal response, or mechanical testing.

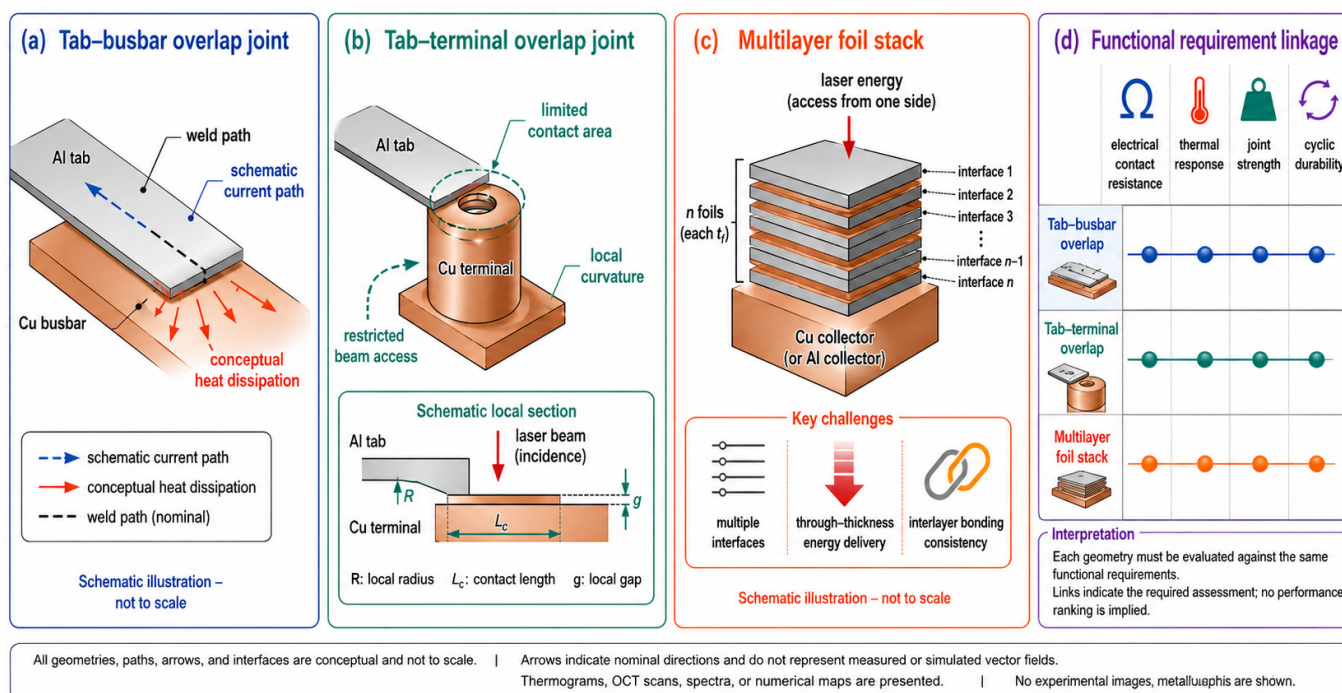


Figure 2. Representative battery interconnect geometries and associated functional requirements. (a) Tab-busbar overlap joint with nominal current path and heat dissipation; (b) tab-terminal joint showing local curvature, contact length, gap, and beam access; (c) multilayer foil stack and through-thickness joining challenges; and (d) electrical, thermal, mechanical, and durability requirements. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a four-panel scientific vector schematic comparing tab-busbar, tab-terminal, and multilayer foil Al–Cu battery joints and their electrical, thermal, mechanical, and durability requirements; show conceptual geometry and no measured fields.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

Table 3. Overview of geometries or assemblies in Al–Cu laser welding used for battery joints in the literature.

Assembly in Al–Cu Laser Welding for Battery Joints	Typical Battery Location	Stack and Joint Configuration	Typical Thickness Regime	Main Purpose	Key Process Considerations	Common Reported Outputs
Tab-to-busbar overlap seam [1,3,4,33]	Module and pack interconnects	Lap joint between a thin tab and a thicker busbar; Cu on Al or Al on Cu	Tabs: foils to sub-mm; busbars: sub-mm to a few mm	Low-resistance current path with high throughput	Strong sensitivity to stack order, surface condition, and heat sinking; IMC control and spatter minimization are critical	Contact resistance, temperature rise under load, seam width at interface, shear strength, IMC thickness, surface defect rate
Tab-to-terminal overlap seam [1,34]	Cell terminal connection	Lap joint between tab and terminal or collector plate	Sub-mm to mm scale	Reliable electrical connection at the cell level	Tight fit-up and repeatable clamping; controlling local melting and intermixing	Electrical resistance, pull or shear strength, visual seam quality, and porosity indicators
Multi-foil or multilayer lap joint [1,4,10]	High-power cell tabs and collectors	Multiple thin foils welded to a busbar or collector in a single joint	Foils: tens to hundreds of micrometers; busbar: sub-mm to mm	Combine current capacity and mechanical compliance	Risk of incomplete bonding between inner foils; tailored energy delivery and scan patterns are often required	Number of bonded layers, effective bonded area, resistance stability, local overheating, surface spatter distribution
Spot weld array on overlap [1,16,35]	Space-limited interconnect regions	Discrete spot pattern over an overlap area	Foils to mm scale	Reduce heat input while achieving sufficient bonded area	Spot spacing and pattern govern effective area and stress distribution; crater formation and expulsion can dominate	Button diameter or effective nugget area, spot-to-spot variability, resistance distribution, failure mode
Stitch seam weld [3,4]	Tab-to-busbar alternatives	A series of short seam segments separated by gaps	Foils to mm scale	Control heat accumulation and distortion	Segment length and spacing balance continuity versus overheating; defect clustering may occur at segment ends	Seam continuity, spatter and crater frequency, resistance uniformity, and mechanical strength
Spiral or circular scan spot [10,16]	Micro joining and foil joints	Spiral or circular scanning over a small region to create a nail-like joint	Foils and thin sheets	Increase effective interface area while limiting mixing	Scan strategy controls dilution and IMCs; useful for thin foils where a straight seam is unstable	Interface area proxy, IMC control, defect suppression, tensile or shear response

Table 3. Cont.

Assembly in Al–Cu Laser Welding for Battery Joints	Typical Battery Location	Stack and Joint Configuration	Typical Thickness Regime	Main Purpose	Key Process Considerations	Common Reported Outputs
Edge or corner lap joint [1,4]	Pack level constraints near edges	Lap seam placed near an edge or corner of the busbar or tab	Sub-mm to mm	Packaging-driven routing of current	Edge proximity increases the risk of underfill and edge melting; it needs robust fixturing and beam positioning	Edge undercut, distortion, seam placement accuracy, and resistance uniformity
Dissimilar stack with interlayer or coating [4,10,34]	Battery interconnect optimization	Lap joint with Ni-coated Cu or a thin interlayer to mitigate IMCs	Coatings: micrometers; base metals: foils to mm	Reduce brittle IMCs and stabilize coupling	Coating continuity and thickness influence wetting and reaction products; surface preparation becomes decisive	IMC morphology, resistance stability, crack tendency, seam appearance, and defect statistics
Bead on plate screening geometry [19,20]	Process window development	Single pass on one sheet used for rapid screening and image pipeline tuning	Any, typically thin sheet	Rapid parameter screening and imaging repeatability	Isolates spatter, morphology signatures, and sensitivity to focus and overlap before full joint trials	Surface morphology descriptors, spatter maps, bead width consistency, and imaging protocol robustness
Laboratory lap coupons [1,34,36]	Early-stage studies	Standardized small coupons in a lap with controlled overlap length	Sub-mm to mm	Repeatable datasets and microstructure sections	Strong control of overlap, pressure, and surface; ideal for microscopy and image labeling	Microstructure, IMCs, hardness mapping, surface defect labels, correlation to parameters

Note: References in the first column cite representative studies for each geometry or assembly.

2.2. Process–Structure–Property Relationships Relevant to Inspection

Laser welding of Al–Cu interconnects is governed by the interaction between energy coupling, heat flow, melt pool dynamics, material mixing, and interfacial reaction. Conduction-mode welding generally provides shallow, comparatively stable melting, whereas the transition to keyhole mode increases penetration [8,36,37]. Deeper keyhole operation is more susceptible to vaporization, pore formation, and melt pool instability [36–40]. Visible wavelengths and beam-control strategies can mitigate coupling-related instability on Cu-rich surfaces, but they do not remove the need for process-specific validation [41–44]. Evidence from thin Al–Cu sheets welded with a high-brightness single-mode fiber laser further shows that welding speed, stack order, and the irradiated upper material influence pore formation and joint morphology, confirming that heat input and material arrangement must be treated as inspection-relevant variables [36].

The selection of pulsed, quasi-continuous, or continuous-wave operation changes the thermal cycle and the time available for wetting, mixing, bubble escape, and solidification.

Pulsed or micro-pulsed conditions add control over pulse energy, pulse duration, frequency, overlap, and peak power, which may be useful for thin tabs and localized joints [12,45,46]. Continuous-wave processing, especially when combined with beam motion or beam shaping, can provide higher productivity and more stable seam formation in automated battery manufacturing [1,3–5,32,42].

A central metallurgical challenge is the formation of Al–Cu intermetallic compounds. Some interfacial reaction is necessary for metallurgical bonding, but excessive melting and mixing can produce brittle and continuous reaction zones that reduce mechanical tolerance and may increase electrical variability [10,11,38–42]. The relevant quality attribute is therefore not simply whether intermetallic compounds are present, but rather their continuity, thickness, morphology, spatial distribution, and relationship to the bonded area.

Process conditions also affect functional responses. Contact resistance depends on effective conductive cross-section, interfacial continuity, local constriction, and the presence of cracks or discontinuities [1,30–32,46]. Heat generation and temperature rise are influenced by electrical resistance and thermal contact conditions [31,33]. Mechanical strength depends on bonded area, intermetallic morphology, seam geometry, and stress-concentrating defects such as undercut, cracks, craters, or discontinuities [1,3,32,38,40–42,47]. These properties are coupled, but they do not necessarily vary in the same direction. A wider seam may improve load-bearing area while also increasing mixing and intermetallic growth if the energy input is excessive.

This coupling is central for inspection. Some process outcomes produce visible signatures, such as spatter, underfill, undercut, craters, burn-through, cracks, surface pits, or seam placement errors. Other critical attributes, including penetration depth, seam width at the interface, internal porosity, hidden lack of bonding, and intermetallic-layer continuity, are not directly observable from a top-surface image. Thus, not all critical joint attributes are externally observable.

2.3. Defect Mechanisms and Post-Process Signatures

Defect formation in Al–Cu laser welding is strongly linked to process-regime stability and interfacial mixing. In Al–Cu laser welding, spatter and melt ejection are associated with unstable energy coupling, recoil-driven expulsion, and melt-flow instability [3,32,37,40,47]. Studies of copper and Cu–Al welding further show that plume attenuation and wavelength-dependent coupling influence expulsion behavior [38,41–44]. In post-process images, spatter appears as detached or resolidified particles around the seam. Its functional relevance depends on particle size, density, adhesion, proximity to insulating regions, and potential for conductive contamination.

Surface pits and pores may be associated with unstable vapor dynamics, keyhole collapse, or gas entrapment during rapid solidification. However, surface pits should be treated only as visible risk indicators unless validated against volumetric inspection or metallography. A surface pit does not quantify internal pore volume or distribution.

Undercut and underfill are geometric defects related to excessive material displacement, insufficient filling, edge erosion, or unstable melt redistribution. In post-process inspection, undercut appears as a groove along the weld edge, whereas underfill is generally observed as a depression or loss of weld volume within the seam. Both may reduce the effective conductive cross-section and introduce mechanical stress concentrations, but their severity should be evaluated based on the physical dimensions and the length of the affected seam.

Discontinuities and visible lack of surface bonding are especially relevant for battery interconnects because they can reduce current-carrying area and create local hot spots. These defects may occur when energy input, wetting, coupling, or fit-up is insufficient. In

surface images, they appear as interrupted seam paths, missing segments, open interfaces, or severe local narrowing. In contrast, hidden lack of bonding cannot be assigned from surface appearance alone and requires independent validation.

Cracking in Al–Cu joints is commonly associated with brittle intermetallic regions, thermal contraction mismatch, and local stress concentrations [3,10,11,38,39,41,42]. Surface cracks can sometimes be detected visually, but subsurface cracking or cracks obscured by rough topography require complementary inspection. Craters and restart defects occur at transient thermal locations, especially seam starts, stops, and overlap regions in patterned trajectories. Burn-through or excessive melting indicates severe local loss of geometry and should normally be treated as a critical condition.

Table 4 summarizes the dominant defect mechanisms, their post-process visual signatures, and their functional risk in Al–Cu battery interconnect laser welds. The table is intended to distinguish observable surface evidence from hidden metallurgical or geometric conditions that require cross-sectional, electrical, thermal, or mechanical validation.

Table 4. Defect mechanisms, post-process visual signatures, and functional risk in laser-welded Al–Cu battery interconnects. The table is a synthesis based on reported Al–Cu welding mechanisms, battery interconnect studies, weld-defect literature, and inspection requirements cited in Sections 2.2 and 2.3.

Defect Mechanism	Typical Post-Process Visual Signature	Likely Process Origin	Primary Functional Risk in Battery Interconnects	Recommended Verification
Spatter deposition	Discrete droplets or clusters around the seam; scattered satellites near the toe region	Keyhole instability, recoil pressure fluctuations, and abrupt coupling transients on Cu-rich surface	Local shorts risk in dense assemblies; increased resistance scatters due to uneven effective area; contamination and debris	Standardized macro imaging plus spatter density metric; optional mass-loss or debris count
Underfill	Visible groove along seam centerline or depressed seam profile; reduced apparent bead volume	Melt ejection, insufficient filler volume in the melt pool, and excessive vaporization	Reduced effective cross-section and higher contact resistance; stress concentration and early mechanical failure	Cross-section of representative samples; 3D profilometry if available
Undercut	Linear notch at seam edges, often continuous along one side	Excessive local melting and edge erosion, beam positioning error, unstable melt flow	Stress concentration, crack initiation under vibration or cycling; potential increase in resistance due to reduced bonded width	Optical microscopy of seam edges; cross-section at worst location
Discontinuity or lack of bonding	Interrupted seam, unbonded segments, visible gaps, or incomplete fusion zones	Conduction regime with insufficient coupling, poor fit-up, excessive speed, surface contamination	Local current constriction and hot spots; high resistance and rapid heating under load	Four-wire resistance and current loading on suspect joints; destructive cross-section for confirmation
Surface porosity or pitting	Small pits or crater-like voids on the seam surface	Keyhole collapse, trapped vapor, hydrogen, and oxide-related effects in aluminum, fast solidification	Potential leak paths, reduced effective area, correlated internal porosity, resistance, and durability degradation	Metallography for internal porosity correlation; XCT in the qualification stage if available
End crater	Pronounced depression at the start or stop, sometimes with associated cracks	Improper ramp down, pulse overlap changes, termination instability	Local stress concentration and crack initiation; local resistance spike if the bonded area is reduced	Targeted imaging and rule-based rejection; optional microsection at stop point
Hot cracking in the mixed zone	Fine surface cracks, often transverse or longitudinal, sometimes emanating from a crater	Brittle intermetallic continuity, high thermal strain, and solidification cracking susceptibility	Mechanical integrity loss; long-term growth of crack under cycling; contact resistance drift	Cross-section and SEM if needed; correlate with IMC thickness and continuity
Excessive mixing and an IMC-rich surface appearance	Heterogeneous rough seam texture; brittle-looking ridge or granular appearance	High heat input, deep keyhole mixing, and insufficient control of energy distribution	Brittle interface, reduced ductility, increased resistance if IMC is thick and continuous	Cross-section thickness measurement; microhardness mapping in qualification

Table 4. Cont.

Defect Mechanism	Typical Post-Process Visual Signature	Likely Process Origin	Primary Functional Risk in Battery Interconnects	Recommended Verification
Misalignment or seam placement error	Seam offset from intended overlap region; inconsistent seam path	Fixturing issues, clamping variation, and beam positioning errors	Reduced effective overlap and bonded area; resistance scatter; mechanical peel sensitivity	Visual gauge with reference marks; image-based seam position tolerance

2.4. Process Enablers and Their Inspection-Relevant Outcomes

Process enablers aim to widen the Al–Cu operating window by stabilizing energy coupling, redistributing heat, controlling mixing, and reducing the probability of visible and hidden defects. Their relevance to this review lies in how they alter final surface morphology, seam consistency, defect prevalence, interface geometry, and functional variability.

Figure 3 maps the principal process enablers to their dominant physical levers and inspection-relevant outcomes. Table 5 complements this map by linking each enabler to its expected effect on seam geometry, intermetallic control, and functional benefit.

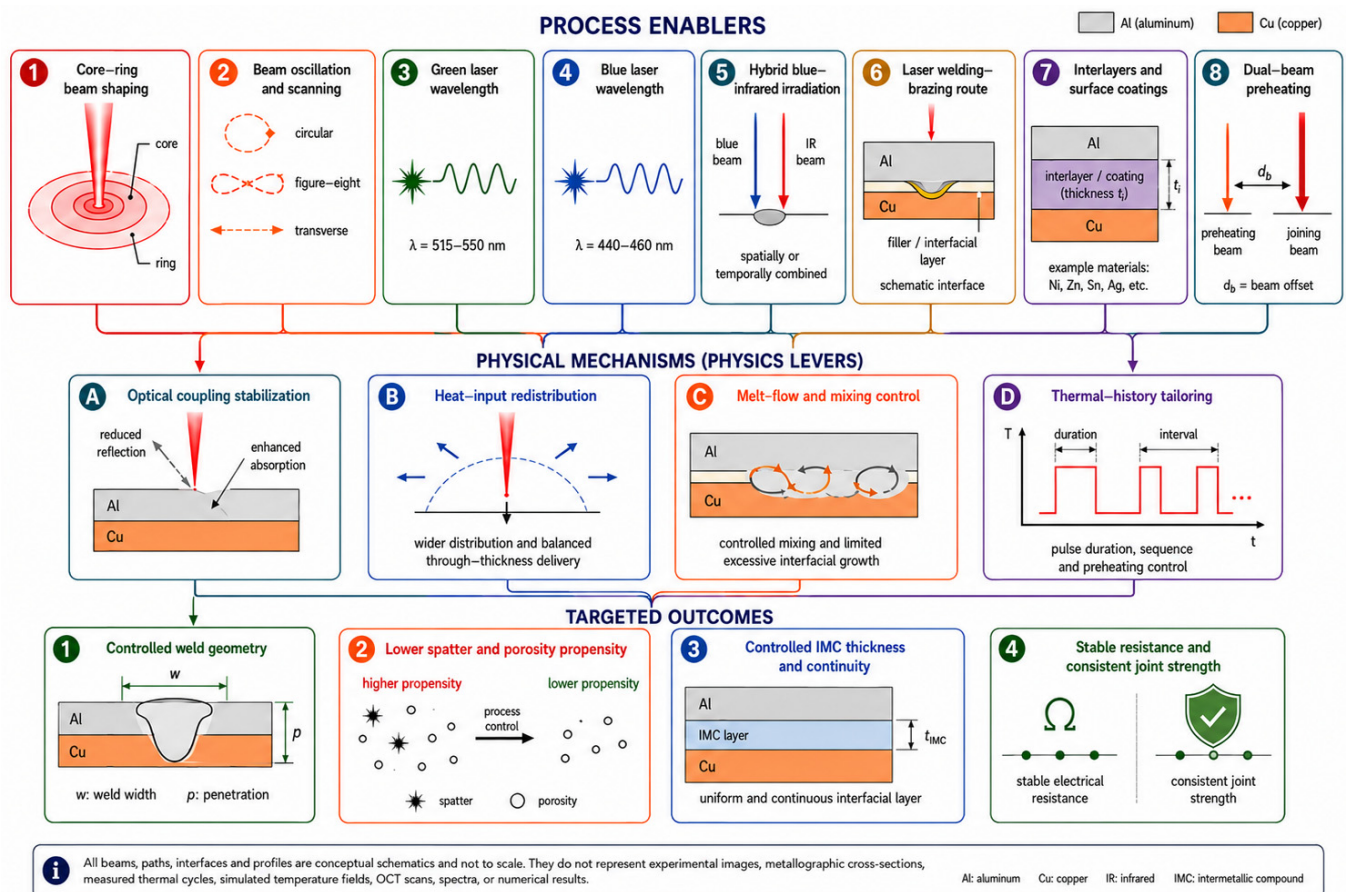


Figure 3. Process enablers, physical mechanisms, and targeted outcomes for laser joining of Al–Cu battery interconnects. The framework links beam shaping, beam oscillation, visible and hybrid wavelengths, welding–brazing, interlayers or coatings, and dual-beam preheating to coupling stabilization, heat redistribution, melt-flow control, thermal-history tailoring, weld-geometry control, defect reduction, intermetallic compound control, and functional consistency. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a vector map linking Al–Cu laser-joining enablers to optical coupling, heat redistribution, melt-flow control, thermal-history tailoring, defect reduction, IMC control, electrical resistance, and joint strength.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

Table 5. Relationship between process enablers, physical levers, geometry control, intermetallic control, and expected functional benefit.

Enabler	Physics Lever	Effect on Geometry	Effect on Intermetallics	Expected Functional Benefit
Core–ring and adjustable ring mode beam shaping	Irradiance redistribution and melt pool boundary stabilization [3,46]	Wider and more controllable seam width at the interface, improved placement tolerance [3,28]	Moderated mixing and reduced tendency for continuous brittle layers in optimized allocations [3,28]	Lower resistance scatter, improved strength consistency
Core–ring with multicore architectures for battery electrical contacts	Spatial power modulation and partial penetration control [29]	More repeatable bead shape in thin overlap assemblies	Improved control of mixed zone extent	Reduced variability under partial penetration constraints
Beam oscillation and wobble	Decoupling of width and penetration, redistribution of local heat input [35,40,47]	Increased bonded width at similar penetration, smoother profile, fewer crater-like defects	More distributed mixing, reduced localization of brittle phases [40,47]	Reduced spatter and underfill, improved electromechanical repeatability
Spiral and segmented scanning patterns	Controlled heat accumulation and start–stop management [40,41,47]	More uniform local bonding and reduced end crater severity	Indirect, via moderated thermal history	Improved durability and reduced reject rate in thin assemblies
Green wavelength welding	Higher copper absorption and more stable coupling [4,42,43]	More repeatable overlap seam morphology	Indirect, via reduced instability and moderated heat input	Reduced spatter and improved resistance stability
Blue wavelength welding	High copper absorption enabling stable conduction regimes [10,37,44,48]	Stable bead formation on copper-rich surfaces, reduced expulsion	Indirect, via reduced keyhole fluctuations	Lower defect rate, improved process stability, and yield
Blue-and-infrared hybrid welding	Blue preheating increases infrared absorption and stabilizes keyhole formation [48]	Spatter suppression and improved deep-penetration stability	Indirectly, through controlled thermal cycling and reduced instability	Improved quality consistency under high throughput conditions
Welding–brazing route	Modified mixing pathway and reaction time control [10,49]	Often smoother seam and reduced cracking tendency	Direct control of interfacial reaction products and continuity [10,49,50]	Improved ductility and reliability while maintaining low resistance
Coatings and interlayers, such as nickel-based interlayers	Modified wetting and diffusion and altered reaction pathways [50]	Improved wetting and seam uniformity in suitable thickness ranges	Reduced deleterious reaction products depending on interlayer design	Improved resistance stability and mechanical robustness
Dual-beam preheating plus welding	Coupling stabilization and reduced thermal gradients [12]	Reduced voids and undercuts, improved seam stability	Indirect, via improved stability and moderated mixing	Higher yield and improved electrical and mechanical outcomes

Beam shaping, including core–ring and adjustable ring mode strategies, modifies the spatial distribution of laser irradiance. The central core can promote penetration, while the surrounding ring can preheat, stabilize the melt pool boundary, widen the effective interaction zone, or reduce abrupt keyhole transitions [3,8,28–30,46]. In battery-relevant dissimilar joints, ring-shaped or multicore beams have been shown to influence weld formation, cross-sectional area, cracking tendency, electrical resistance, and mechanical performance [3,28–30]. From an inspection perspective, beam shaping can improve seam regularity and reduce spatter or cracking, but it can also generate different surface appearances for similar functional outcomes. Therefore, imaging models must be validated for each beam profile rather than transferred from Gaussian beam data without qualification. Broader Al–Cu laser-welding literature further supports the relevance of tailored energy delivery for controlling mixing, intermetallic formation, and defect sensitivity [31].

Beam oscillation and trajectory control redistribute energy over a wider footprint and can partially decouple seam width from penetration depth [35,40,47,51]. Wobble, spiral, segmented, and circular paths can improve wetting, increase effective bonded area, reduce local overheating, and manage start-and-stop behavior. These strategies are particularly useful for thin sheets and patterned battery joints, where excessive penetration or localized instability can lead to burn-through, craters, or discontinuities. For post-process inspection, trajectory control changes the expected seam geometry. A discontinuity, crater, or placement error must therefore be assessed relative to the intended path rather than relative to a generic straight seam.

Visible-wavelength strategies, especially green and blue lasers, address coupling limitations on copper-rich surfaces. Green wavelengths exhibit higher absorption than conventional near-infrared radiation and have been used for copper-to-aluminum battery tab connections [4,39,42,43]. Blue wavelengths can further enhance copper absorption and favor more stable conduction-mode behavior in copper and Cu–Al welding [26,37,44]. Hybrid blue-and-infrared concepts have also been reported to reduce spatter in deep-penetration copper welding [48]. These approaches can improve repeatability and reduce coupling-driven instability, but they also modify plume behavior, surface texture, heat distribution, and defect morphology. Consequently, wavelength is an important domain variable for both in-process monitoring and post-process image classification.

Hybrid routes, including laser welding–brazing, coatings, interlayers, and dual-beam preheating, target the reaction pathway and thermal history rather than only the surface shape. Welding–brazing approaches and filler or interlayer strategies can reduce full dilution and alter intermetallic formation at the interface [10,49,50]. Coatings and interlayers can influence wetting, diffusion, absorptivity, and reaction products. Dual-beam approaches separate preheating from welding, thereby stabilizing coupling and reducing abrupt thermal gradients [12]. These methods can improve joint reliability by limiting brittle intermetallic continuity while preserving bonded area, but their quality cannot be judged only by top-surface appearance.

The comparison across enablers shows that no single strategy optimizes all outputs. Beam shaping and spatial oscillation are primarily evaluated through weld geometry, electrical resistance, and mechanical response [3,5,29,35,47]. Visible-wavelength and hybrid-beam strategies mainly target optical coupling and process stability on Cu-rich surfaces [4,26,42,44,48,52,53]. Welding–brazing and interlayer approaches target the control of mixing and intermetallic reactions [10,49,50]. Therefore, each enabler should be qualified using the functional outputs associated with its intended mechanism rather than by surface morphology alone [1,3,4,10,35].

The implication of the inspection is clear: process enablers can reduce the occurrence of surface-visible defects and improve repeatability, but they also alter the relationship

between surface appearance and internal quality. Post-process AI models should therefore be trained and validated across the relevant process-enabler conditions or explicitly limited to the process domain from which the training data were obtained.

3. In-Process Monitoring as Complementary Evidence for Al–Cu Weld Quality

In-process monitoring provides temporally resolved information on laser–material interactions and can identify process deviations before the completed joint undergoes post-process inspection. This capability is especially relevant to Al–Cu battery interconnects because penetration, interface width, melt pool stability, and material mixing can change rapidly with surface condition, focal position, part-to-part gap, stack order, and absorbed energy. However, most sensing systems do not directly measure final weld quality. They record optical, thermal, acoustic, or geometric signals that must be calibrated against independent geometric, metallurgical, electrical, or mechanical evidence [13,54–57]. Figure 4 summarizes the in-process monitoring chain for laser-welded Al–Cu battery interconnects, linking process phenomena and sensor modalities to measured signals, inferred quality variables, validation methods, and final quality decisions.

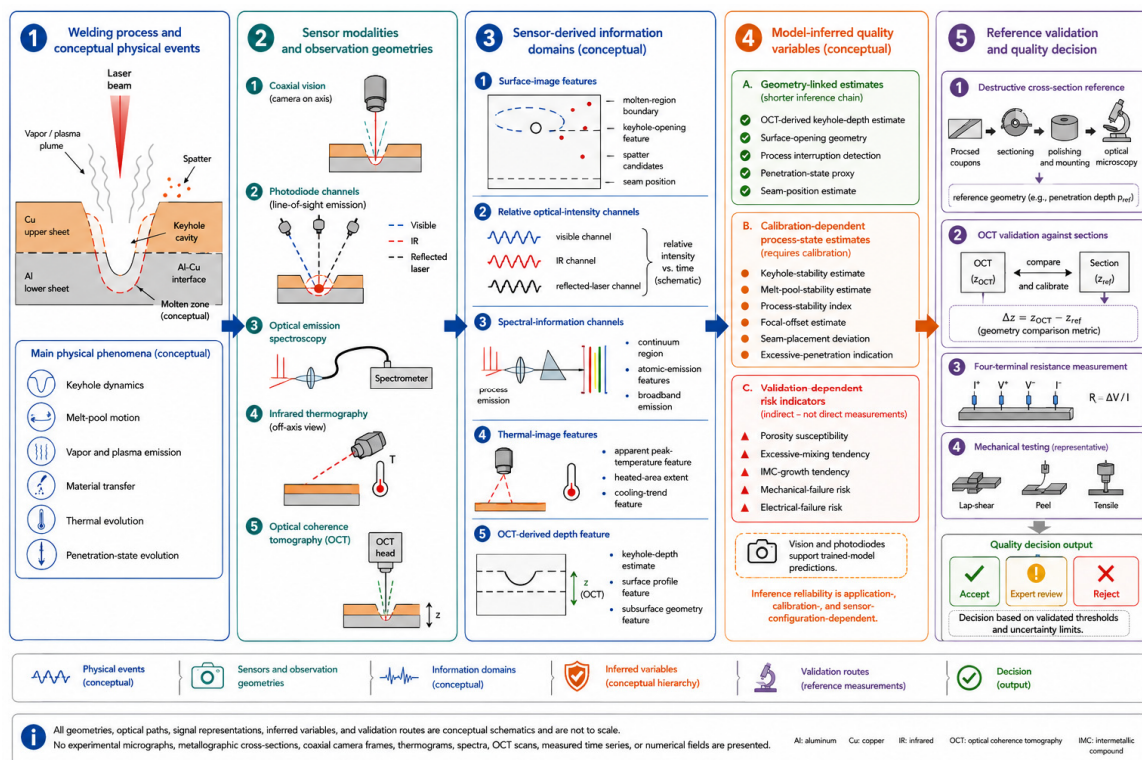


Figure 4. Multimodal in-process monitoring, inference, reference validation, and quality decision framework for laser-welded Al–Cu battery interconnects. The five linked stages comprise laser–material interaction and weld-pool events; sensor modalities and observation geometries; sensor-derived information domains; inferred quality variables with calibration and validation limits; and reference measurements leading to accept–review–reject decisions. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a five-stage vector workflow connecting laser–material interaction, multimodal sensors, sensor-derived information, validated inferred quality variables, reference measurements, and accept–review–reject decisions for Al–Cu battery welds.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

3.1. Sensor Modalities

3.1.1. Coaxial and Off-Axis Vision

Coaxial cameras observe the interaction zone through the processing optics, whereas lateral cameras provide an external view of the melt pool, plume, and ejected particles. High-speed imaging can resolve keyhole opening, melt pool dimensions, plume fluctuations, spatter trajectories, and process asymmetry [54,58–61].

These features support the detection of unstable coupling, intermittent keyhole collapse, melt ejection, process interruption, and changes in the penetration regime. In Al–Cu overlap welding, coaxial images have been combined with photodiode and spectrometer signals to estimate penetration depth using convolutional neural networks [14,62]. Such models can achieve low prediction error in under-represented conditions, but the relationship remains indirect because the visible keyhole opening and upper-surface melt pool geometry do not uniquely determine penetration or bonded width at the hidden interface.

Therefore, vision is the most defensible approach for estimating keyhole and melt pool stability, detecting spatter events, and classifying penetration states, provided it is calibrated to the process. Lateral imaging improves visualization of particle trajectories and plume geometry, but its interpretation is more sensitive to perspective, fixture obstruction, and changes in seam orientation.

3.1.2. Photodiodes

Photodiodes measure spatially integrated radiation within defined spectral bands. Monitoring heads may collect thermal emission, visible plasma radiation, ultraviolet radiation, or reflected process-laser light through separate channels. Their main advantages include high temporal resolution, compactness, moderate computational requirements, and compatibility with coaxial optical paths. They are therefore well-suited to detecting abrupt transitions, plume oscillations, changes in penetration state, misalignment, and process interruptions.

Photodiode signals are indirect and often nonunique. A similar change in amplitude may result from variations in penetration, contamination, gap, focal shift, surface oxidation, or plume attenuation. Frequency-domain analysis, wavelet features, and supervised learning can improve discrimination, particularly when multiple spectral channels are combined [63–68].

In Al–Cu and battery-related applications, photodiodes have been used both as standalone predictors and as complementary inputs. Deep neural network classification has been applied to Al–Cu penetration states using photodiode signals, and fusion with coaxial images or OCT improves interpretation when material reflectivity and process parameters vary. Brežan et al. showed that combining photodiodes with OCT can distinguish changes caused by laser power and focal offset during remote copper-to-aluminum welding. This fusion is valuable because photodiodes offer rapid event detection, whereas OCT provides more direct geometric information [14,15,69].

3.1.3. Optical Emission Spectroscopy

Optical emission spectroscopy detects radiation emitted by vaporized and excited species above the melt pool. Unlike broadband photodiodes, it can isolate elemental emission lines and provide information on plume composition, material transfer, vaporization, and interaction with the lower sheet [51,56,63,70,71]. Beyond diagnostic classification, spectroscopic monitoring has also been used for closed-loop control of penetration depth by relating plasma electron temperature to weld penetration and adjusting laser power accordingly [72]. Although this evidence was developed for CO₂ laser lap welding rather

than for Al–Cu battery interconnects, it supports the use of spectroscopy as a physics-based process proxy that requires process-specific validation.

This capability is relevant to Al–Cu overlap joints because aluminum emission can indicate that the laser interaction has reached the lower material when copper is placed above aluminum. Aluminum-specific emission bands have been used to distinguish insufficient, appropriate, and excessive interaction during spiral Cu–Al laser welding [51]. Spectrometer signals have also been combined with camera images and neural networks to predict penetration depth in Al–Cu joints [14].

Spectroscopy is best suited for detecting lower sheet interactions, compositional changes, contamination, and excessive mixing. It does not independently determine the intermetallic phase, the thickness of the intermetallic layer, the porosity, or the electrical resistance. These variables still require metallography, compositional analysis, diffraction, or functionally validated correlations.

3.1.4. Infrared Thermography and Pyrometry

Infrared cameras capture spatial and temporal variations in emitted thermal radiation. Relevant descriptors include the apparent thermal footprint, symmetry, peak intensity, cooling slope, hot-particle trajectories, and spatter temperature [73–76].

Thermal sequences have been used with machine learning and deep learning models to distinguish acceptable and defective laser welds [73]. Recent work has further shown that spatter temperature, trajectory, and cooling rate, extracted from infrared imaging, can provide discriminative information for defect prediction [76].

For Al–Cu joints, thermography can identify overheating, asymmetric energy deposition, abnormal cooling, and thermally intense spatter events. Quantitative temperature measurement is more difficult because emissivity varies with material, oxidation, coating, roughness, phase condition, and viewing angle. Because aluminum, copper, remelted material, and oxides may coexist in the same image, relative thermal descriptors are generally more reliable than absolute temperature unless material-specific calibration is performed.

3.1.5. Optical Coherence Tomography

OCT uses low-coherence interferometry to measure distance along the sensing beam. During laser welding, it can provide pre-weld surface position, keyhole-depth traces, penetration dynamics, and post-weld topography [17,77–82]. Among the modalities considered here, OCT provides the most direct geometric information.

OCT has been used for weld-depth monitoring in remote laser welding of automotive battery tab connectors [26], for closed-loop penetration control in aluminum components [77], for weld-depth determination during deep-penetration welding [78–80], and for continuous depth measurement during oscillation welding [81]. Its use in battery-related Al–Cu welding is particularly relevant because penetration and seam width at the interface cannot be reliably inferred from the visible top surface.

OCT measurements remain sensitive to probe-beam position, keyhole inclination, signal dropout, multiple reflections, speckle, and beam oscillation. The detected optical depth may not match the final metallographic weld depth if the probe beam does not reach the bottom of the keyhole. OCT should therefore be treated as a near-direct geometric measurement that still requires process-specific validation.

For adjustable ring mode Al–Cu welding, OCT has also been combined with plasma and optical signals to predict the seam width at the interface [16]. This variable is more closely related to the effective bonded area than to the visible top-bead width, but its estimation remains model-based and must be validated by cross-sections.

3.2. Quality Variables That Can Be Inferred Reliably

The reliability of an inferred quality variable depends on how directly it is related to the measured signal.

OCT provides direct depth-resolved measurements and has been applied to weld-depth monitoring in battery-related and metallic welding systems [17,77–80]. Photodiode, spectrometer, and camera signals are used to estimate penetration indirectly through calibrated models [14,15,62,69]. Because these mappings are empirical, they should be revalidated when the material batch, focal position, surface condition, beam profile, or joint geometry changes [14,15,62].

Keyhole and melt pool stability can be inferred from high-speed imaging, photodiode fluctuations, spectral emission, thermal behavior, acoustic signals, and OCT depth dynamics. High-speed cameras provide spatial evidence of melt pool, plume, and weld-state dynamics [58–61]. Photodiode and spectrometer signals provide high-frequency indicators of optical emission transients [68–71]. Acoustic sensing can detect process disturbances such as part-to-part gap or abnormal welding states [83–85]. OCT adds depth-resolved geometric information that is not available from intensity-only sensors [15,17,77–80].

Seam width at the interface is a particularly relevant variable for overlap joints because it is more closely associated with bonded area and current transfer than with visible surface width. Multisensor approaches that combine OCT and optical diagnostics have demonstrated the feasibility of estimating this hidden geometric descriptor during Al–Cu welding [16].

Gap, focal offset, and alignment disturbances can be detected using photodiodes, cameras, acoustic sensors, or combined OCT signals. These variables are often more reliably classified as process states than continuously quantified [15,29,68,83–86].

Porosity risk may be inferred from keyhole collapse, unstable depth traces, plume fluctuations, thermal anomalies, or spatter behavior. However, these signals indicate susceptibility rather than the final pore volume or spatial distribution. Volumetric or destructive validation remains necessary.

Intermetallic compound formation is not directly measurable with conventional in-process sensors. Spectroscopy can detect material transfer and composition-sensitive emissions, while monitored heat input and penetration can indicate conditions associated with excessive mixing. IMC phase, thickness, and continuity still require metallography, electron microscopy, diffraction, or validated physics-based models.

Recent studies are moving beyond single-signal classification toward multisensor and digital-twin architectures. For example, a laser-welding digital-twin approach has been proposed for real-time penetration-state prediction using Gaussian process-driven Markov modeling and online updating [87]. These developments signal a shift from isolated monitoring signals to continuously updated quality-state estimation, although direct evidence for Al–Cu battery interconnects remains limited. Table 6 compares the principal sensing modalities according to the physical signal acquired, the most defensible quality inference, the required validation route, and the main limitation for Al–Cu battery interconnect welding. References in the first column identify representative studies supporting the sensing capability, inference level, validation requirements, and principal limitations summarized in each row.

As summarized in Table 6, most in-process sensing modalities provide calibrated predictions or process proxies rather than direct measurements of final joint quality, making independent ground-truth validation essential.

Table 6. Compact comparison of the principal in-process sensing modalities used or proposed for laser-welded Al–Cu battery interconnects. The inference level distinguishes near-direct geometric measurement from calibrated data-driven prediction and indirect process proxies. All inferred variables require process-specific validation against independent geometric, metallurgical, electrical, or mechanical ground truth.

Modality	Primary Signal	Most Defensible Inference	Inference Level	Required Ground Truth	Main Limitation
Coaxial vision [14,59,60]	Spatially resolved images of the keyhole, melt pool, plume, and spatter	Keyhole stability, melt pool geometry, process interruption, and penetration state after calibration	Calibrated prediction	Cross-sections and validated OCT	Saturation, plume obstruction, high data volume, and sensitivity to illumination
Photodiodes [15,63,69]	Time-dependent broadband emission or reflected laser intensity	Process state changes, instability events, focal shift, and penetration class	Indirect proxy	Cross-sections, OCT, and defect labels	Limited spatial information and nonunique signal response
Spectroscopy [51,70,72]	Wavelength-resolved plume emission	Material transfer, lower sheet interaction, plasma state, and excessive mixing indicators	Physics-based proxy	Cross-sections, compositional analysis, and IMC characterization	Optical contamination, plume attenuation, and alloy-dependent calibration
Infrared thermography [73–76]	Spatial thermal radiation field	Thermal asymmetry, overheating, cooling behavior, and instability-related events	Relative thermal proxy	Calibrated thermal measurements, cross-sections, and defect labels	Variable emissivity and limited reliability of absolute temperature
OCT [15,17,81,88]	Optical path length and depth profile	Keyhole depth, penetration dynamics, surface topography, and geometry-related deviations	Near direct geometric measurement	Metallographic cross-sections	Signal dropout, multiple reflections, speckle, and beam position sensitivity

3.3. Calibration and Ground Truth

The credibility of an in-process monitoring system depends on the quality of its ground truth. Because most sensor outputs are proxies, calibration must map the acquired signal to a measured response in geometry, metallurgy, electrical systems, or mechanics.

Cross-sectional metallography remains the primary reference for penetration depth, interface width, fusion geometry, porosity location, and IMC morphology. Serial cross-sections or longitudinal sections are preferable when the monitored signal varies along the seam. A single cross-section may not capture transient events recorded at kilohertz frame or sampling rates. Therefore, accurate synchronization between signal time and physical seam position is essential.

OCT can serve as an intermediate ground truth for high-volume data generation once its depth measurements have been validated against metallographic sections. This strategy was used in Al–Cu penetration prediction research because OCT generated many

synchronized depth labels without sectioning each weld. However, OCT should not be treated as an unquestioned reference; beam position, signal dropout, oscillation pattern, and surface geometry must be validated for the specific process [14,17,77,79,81,88–90].

Electrical resistance and current-loading tests yield functional labels that are particularly relevant to battery interconnects. Penetration or interface width should not be automatically equated with acceptable electrical performance, as current constriction, IMCs, cracks, and incomplete bonding can independently alter resistance. Four-terminal resistance measurements, temperature-rise tests, and current cycling provide stronger evidence that a monitored geometric proxy is functionally meaningful.

Mechanical tests such as lap shear, pull, and peel testing should be included when the monitoring target is intended to assess joint integrity. For example, Garavaglia et al. correlated a coaxial back-reflected signal with the seam width at a hidden interface and with shear strength. This illustrates the value of linking process signals not only to geometry but also to mechanical performance [66].

Calibration datasets should span the anticipated production variability rather than being limited to nominal conditions. At a minimum, they should include variations in power, speed, focal offset, gap, surface state, stack tolerance, and sensor contamination. Validation should also be performed on batches or days not used for training. Randomly splitting adjacent frames from the same weld into training and test sets can lead to severe information leakage and unrealistically high performance.

3.4. Practical Constraints for Production Deployment

The transition from laboratory monitoring to production depends on robustness, latency, maintainability, and traceability. Battery manufacturing imposes additional constraints because short cycle times, reflective materials, complex fixtures, moving scanners, and high joint counts amplify even minor sensor or model instabilities.

Optical accessibility and contamination remain persistent limitations. Protective windows accumulate metal vapor and spatter, reducing signal amplitude and altering spectral transmission. Coaxial sensors share the process optical path and may be affected by scanner angle, focal changes, beam-shaping optics, and wavelength-dependent coatings. Off-axis cameras require a stable line of sight and may be obstructed by clamping systems.

Domain shift is especially severe in Al–Cu welding. Changes in supplier, alloy, coating, roughness, oxide condition, sheet thickness, stack order, and beam profile can alter signal distributions without necessarily affecting final quality. Models trained on a single material batch or a fixed setup may therefore fail after production changes. Recent work emphasizes the importance of transferable models, multisensor fusion, and calibration strategies that support generalization across conditions [91,92].

Data rate and latency vary significantly by modality. Photodiodes and point spectrometers produce compact signals that can be processed quickly. High-speed coaxial imaging and infrared video provide richer information but require more storage, synchronization, and computation. OCT produces relatively compact geometric signals, but reliable filtering and beam synchronization may introduce processing overhead. Production deployment, therefore, requires a clear distinction between real-time decision variables and data retained for traceability.

Sensor fusion can increase robustness but also raises integration complexity. Signals must be synchronized to a common spatial coordinate, normalized across operating conditions, and protected against missing channels. Fusion is justified when modalities provide complementary information, such as OCT geometry and photodiode dynamics, rather than when multiple correlated measurements of the same emission are available [14–16].

Model governance and quality-gate design are also essential. High overall accuracy is insufficient when rare, critical defects are present. The monitoring system should report class-specific recall, false-negative rate, calibration uncertainty, and an abstention state for signals outside the validated domain. In battery manufacturing, conservative escalation to post-process inspection or destructive sampling is preferable when sensor confidence is low.

Recent literature highlights two emerging directions. First, systematic analyses of machine learning in laser welding emphasize the need for clearer task definitions, comparable validation, and physically meaningful sensor selection [19]. Second, new battery-contact and thermographic studies confirm continued movement toward low-latency photodiode monitoring, image-based spatter analysis, and hybrid sensing architectures [29,76].

Accordingly, the most realistic production architecture is not a single universal sensor but a layered quality system. In-process sensors can identify instability and estimate penetration-related variables; OCT can provide direct geometric information for selected critical joints; and post-process imaging can verify final surface morphology, seam placement, and visible geometric defects. Periodic electrical, thermal, mechanical, and metallographic testing remains necessary to maintain the calibration between process signatures, visual evidence, and functional quality. The sensing modalities discussed above provide different levels of access to transient process behavior and hidden joint geometry. Table 7 maps the dominant defect mechanisms to the inspection pathway that provides the most defensible evidence, while distinguishing direct surface observations from process-based risk indicators.

Table 7. Preferred inspection pathway for dominant defect mechanisms in laser-welded Al–Cu battery interconnects. The table is a decision matrix based on the sensing, inspection, and validation literature discussed in Sections 3 and 4.

Defect Mechanism	Preferred Pathway	Observable Signature	Rationale
Keyhole instability and melt ejection leading to spatter	In-process plus post-process	In-process: melt pool fluctuations, optical emission spikes, process instability events; post-process: spatter clusters near the seam	In-process monitoring captures transient instability events; post-process provides decision-grade mapping of deposited spatter and its proximity to the seam
Keyhole collapse and vapor entrapment associated with porosity risk	Primarily in process, post-process as screening	In-process: keyhole instability proxies and depth-related signatures from optical diagnostics; post-process: surface pitting may appear, but is not a complete proxy	Internal porosity risk correlates more reliably with in-process dynamics; surface pits are an incomplete indicator and should be treated as screening only
Underfill and undercut from expulsion and edge erosion	Post-process	Visible groove along the seam centerline, edge notch features along the seam toe	These are geometric surface features that can be directly measured and standardized in post-process images
Discontinuity or lack of bonding due to insufficient coupling or fit-up	Post-process with functional spot checks	Interrupted seam, unbonded segments, seam offset from overlap region	Discontinuity is a direct accept or reject criterion; rapid post-process screening is effective, while occasional resistance checks support validation

Table 7. *Cont.*

Defect Mechanism	Preferred Pathway	Observable Signature	Rationale
Excessive mixing and continuous intermetallic-layer formation	In-process for stability proxies plus qualification cross-sections	In-process: stability and energy input proxies; post-process: heterogeneous rough seam texture may correlate, but is not definitive	Intermetallic thickness and continuity are not reliably inferred from surface appearance alone; in-process stability proxies and periodic destructive qualification are needed
Start and stop crater and restart defects	Post-process	Local crater depression at the start or end of the seam; possible local cracking	Deterministic location and high visual saliency make post-process inspection efficient and robust for quality gates
Seam placement error and insufficient overlap coverage	Post-process	Seam path offset, reduced overlap coverage, and inconsistent seam position	Geometry and tolerance checks are straightforward after welding, and support traceable acceptance criteria

The comparison confirms that in-process monitoring is most informative for transient instability and penetration-related behavior, whereas post-process imaging is better suited for traceable evaluation of final surface morphology, seam placement, and visible geometric defects. The following section examines these post-process requirements.

4. AI-Ready Post-Process Inspection: Metrology, Taxonomy, Annotation, and Functional Acceptance

Post-process visual inspection provides a scalable quality-assurance approach for laser-welded Al–Cu battery interconnects by evaluating the final visible condition of each completed joint. Unlike in-process monitoring, which captures transient optical, thermal, acoustic, or geometric signals during welding, post-process imaging documents the surface morphology that remains after solidification. This makes it suitable for assessing seam placement, visible continuity, spatter, craters, surface pits, undercut, underfill, cracks, burn-through, and other externally observable anomalies [1,13,22,34,35,66,93].

However, post-process inspection must not be interpreted as a direct substitute for internal or functional qualification. A visually continuous seam may still contain insufficient penetration, hidden lack of bonding, internal porosity, excessive mixing, or continuous brittle intermetallic regions. Conversely, some visible irregularities may remain acceptable if the effective bonded area, electrical resistance, temperature rise, and mechanical strength remain within validated limits [1,4,12,13,34,35,66]. Therefore, post-process vision is best understood as a surface-quality gate whose predictions must be calibrated against independent geometric, metallurgical, electrical, thermal, and mechanical evidence.

A robust AI-ready post-process framework requires six linked stages: controlled image acquisition, image and domain validation, a visually defensible defect taxonomy, weld-level dataset construction, AI inference with uncertainty assessment, and risk-based quality decision logic. Figure 5 summarizes this workflow by linking controlled imaging, defect annotation, construction of the independent-weld dataset, model inference, uncertainty handling, and functional validation.

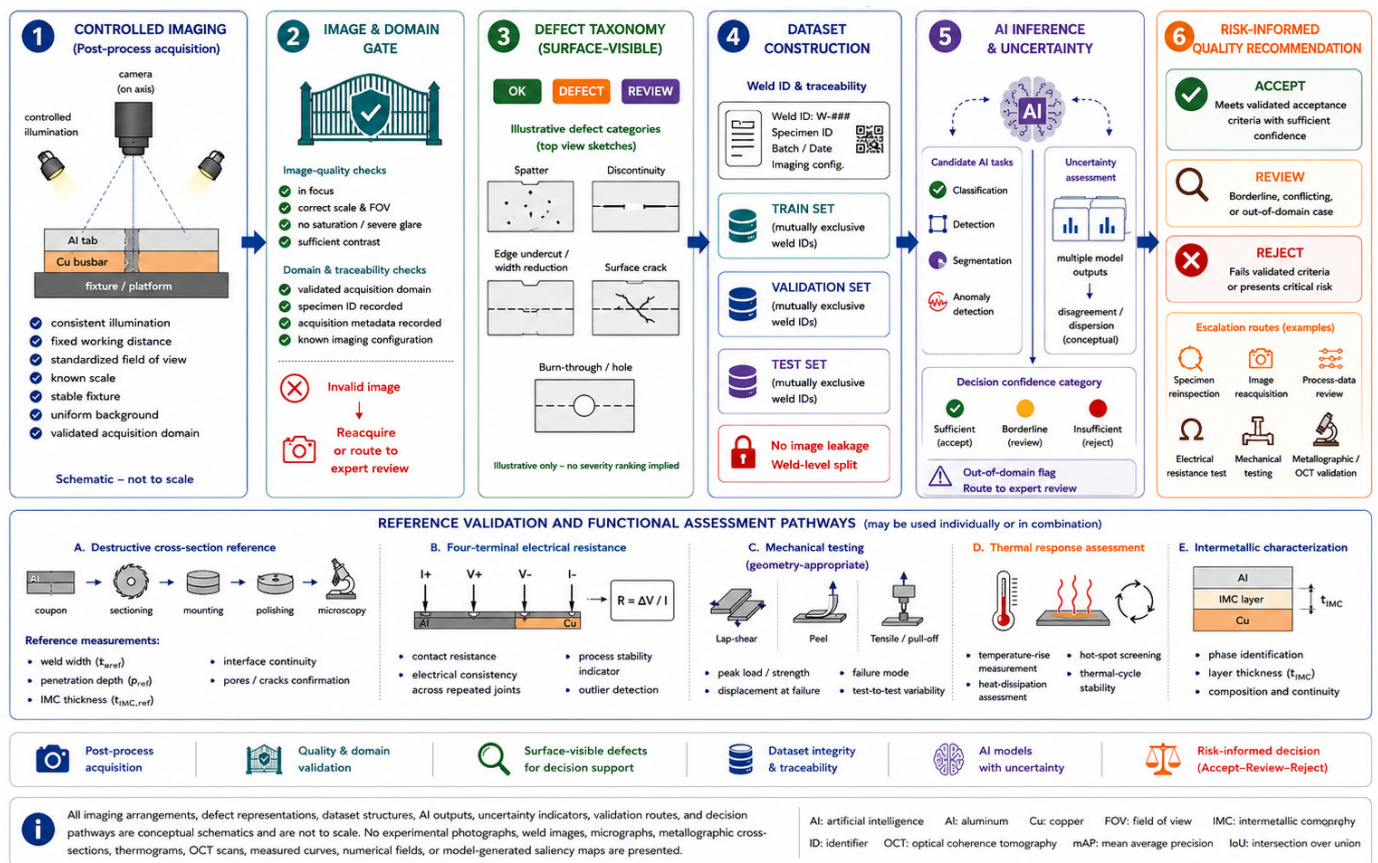


Figure 5. Conceptual AI-ready post-process inspection framework for laser-welded Al–Cu battery interconnects. The six stages comprise controlled imaging; image and domain validation; a surface-visible defect taxonomy; leakage-free weld-level dataset construction; AI inference with confidence, uncertainty, and out-of-domain assessment; and risk-informed accept–review–reject decisions supported by functional validation. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a six-stage vector workflow for controlled post-process imaging, domain validation, surface defect taxonomy, leakage-free weld-level datasets, uncertainty-aware AI inference, and functionally validated accept–review–reject decisions.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

4.1. Imaging as a Metrological System

A post-process imaging station should be designed as a measurement system rather than as a general photographic setup. The camera, lens, fixture, working distance, viewing angle, focus, field of view, illumination, and spatial scale must remain controlled, as variations in these factors can be learned by an AI model and confused with changes in weld quality [94–97]. This is particularly important for Al–Cu joints, where the appearance of aluminum, copper, oxides, coatings, deposited vapor, and remelted regions may vary strongly across batches and process conditions.

The complete weld and a standardized margin of surrounding material should be visible. This allows the system to assess seam placement, overlap coverage, spatter dispersion, surface contamination, and the relationship between defects and the intended current-carrying region. A rigid fixture should constrain specimen height, tilt, and rotation. When component geometry requires multiple views, the number of views, acquisition sequence, magnification, and illumination condition should remain fixed and linked to the same weld identifier.

Illumination is one of the dominant variables in post-process Al–Cu imaging. Diffuse illumination helps reduce directional glare and supports evaluation of global seam morphology. Low-angle illumination enhances topographical features such as spatter, pits, craters, edge grooves, undercut, and discontinuities. Coaxial or bright-field illumination may reveal planar changes but can cause severe reflections on smooth copper or aluminum surfaces. If multiple illumination modes are used, each image should remain stored separately rather than being irreversibly merged, so that the contribution of each optical condition can be audited.

After calibration, exposure, aperture, gain, white balance, focus, illumination intensity, image format, and compression should remain fixed. Automatic exposure and white balance should generally be avoided because they can normalize away the severity of defects or introduce batch-dependent contrast shifts. Images affected by defocus, motion blur, incomplete field of view, severe glare, or saturation should be reacquired or routed to review rather than silently processed as valid inputs.

Each image should include or be linked to a calibrated pixel-to-length conversion. Defect dimensions such as crater diameter, discontinuity length, undercut width, spatter area, seam offset, and affected seam fraction should be reported in physical units rather than only in pixels. The selected resolution should preserve the smallest defect relevant to the acceptance criterion while avoiding unnecessary sensitivity to scratches, sensor noise, or irrelevant background texture.

Measurement-system capability should also be considered. At minimum, repeated images of the same weld should be used to evaluate repeatability under fixed conditions, and images acquired across different operators, sessions, or fixture resets should be used to evaluate reproducibility. Spatial-calibration uncertainty, illumination stability, image-quality acceptance limits, and reacquisition criteria should be documented. This does not require imposing a formal industrial measurement-system analysis at the research stage, but it does require demonstrating that image variability is controlled well enough to support defect measurement and model validation.

The acquisition record should include camera and lens information, working distance, pixel scale, illumination geometry, exposure, gain, aperture, specimen orientation, material and coating condition, weld identifier, production batch, acquisition session, image format, and preprocessing version. These variables define the validated imaging domain. Changes in any of them should be treated as potential domain shifts [94–98].

4.2. Battery-Risk-Oriented Defect Taxonomy

The taxonomy should first be limited to features that are externally observable under the defined imaging protocol [20,22,93]. Each class should have an operational definition that can be applied consistently by different annotators [20,93]. Battery relevance should then be established independently through electrical, thermal, mechanical, or geometric evidence from Al–Cu joint studies [1,4,12,13,34,35]. Internal porosity, penetration depth, hidden lack of bonding, and intermetallic-layer thickness should not be assigned directly from surface appearance unless an independently validated relationship has been established.

The primary quality label should remain simple: OK: No visible anomalies exceed validated acceptance limits; the complete weld is visible; image quality is acceptable; and the image lies within the validated acquisition domain. Defect: At least one visible anomaly exceeds an acceptance threshold or poses sufficient risk to require rejection or secondary inspection. A third internal state, review, is strongly recommended. Review should be used when the image is outside the validated domain, acquisition quality is insufficient, the feature is visually ambiguous, or the model confidence is inadequate for an automatic

decision. This category is particularly important for reflective Al–Cu surfaces, where glare, oxidation, scratches, or deposited vapor may resemble physical defects. Optional subclasses may include spatter, surface pore or pit, underfill, undercut, discontinuity, visible lack of surface bonding, crater, surface crack, seam placement error, burn-through, and surface contamination. These classes should remain descriptive. For example, a surface pit should not be equated with internal porosity, and rough texture should not be interpreted as direct evidence of a specific intermetallic phase.

Visual class and risk level should be stored separately. A small isolated spatter particle and a dense cluster of conductive particles belong to the same visual family, but they do not necessarily have the same functional consequence. Risk levels may be defined as critical, major, or minor according to defect size, location, affected seam fraction, proximity to insulating regions, expected current path, and experimentally validated functional effect. Critical defects include severe discontinuity, open bonding, burn-through, gross seam misalignment, major cracking, and hazardous conductive debris.

The taxonomy should also account for task formulation [99–105]. Image-level classification is efficient for OK versus defect screening but provides limited traceability. Object detection is suitable for localized defects such as spatter particles, pits, craters, burn-through, and short cracks. Object detection is appropriate when the inspection output must localize discrete instances such as spatter particles, pits, craters, or short cracks [93,96,101,104]. Semantic or instance segmentation is preferable when the objective is to delineate irregular regions or quantify the affected area, including undercut, underfill, seam boundaries, or distributed spatter [24,99,102,103,105].

4.3. Annotation and Agreement

The annotation protocol should be established before training the definitive model. Each defect class should include an operational definition, inclusion and exclusion criteria, minimum resolvable size, severity descriptors, overlap-handling rules, representative positive examples, and visually similar negative examples. The protocol should explicitly define how to treat reflections, shadows, oxidation, scratches, dust, machining marks, plume deposits, coating irregularities, and pre-existing surface damage.

Bounding boxes should enclose the complete visible defect with minimal surrounding background. If spatter appears as a dense cluster, the protocol must state whether individual particles or complete clusters are annotated. Segmentation masks should follow only visible boundaries and should not infer hidden subsurface extension. Ambiguous cases should be assigned to review or uncertain rather than forced into OK or defect.

All images and labels associated with a single physical weld should share a unique identifier. This identifier should link full images, cropped images, multiple views, illumination conditions, welding parameters, material batch, acquisition session, functional measurements, metallographic observations, annotation version, and final adjudicated label. Such provenance is essential for auditing errors, avoiding data leakage, and linking visual features to functional performance.

At least two trained annotators should independently label a representative subset of images, including normal, defective, borderline, and poor-quality images. For binary OK versus defect labels, observed agreement should be reported along with a chance-corrected metric such as Cohen's kappa for two annotators [106]. Fleiss' kappa may be used when more than two annotators assign categorical labels [107], while Krippendorff's alpha is appropriate when missing labels or different measurement levels must be accommodated [108,109].

Agreement should be reported by class and, when possible, by severity level. A high global agreement value may conceal poor consistency for rare cracks, small pits, or borderline undercut. For object detection, localization agreement should include class consistency and intersection over union [110]. For segmentation, the Dice coefficient or intersection over union should be complemented by defect-level recall. Disagreements should be adjudicated by a welding or materials specialist using the original image, complementary illumination, pre-weld evidence when available, and functional or metallographic ground truth.

Persistent disagreement is not merely an annotation problem. It may indicate insufficient optical resolution, poor illumination, an unclear severity threshold, or a defect category that is not visually distinguishable. In such cases, the taxonomy or imaging protocol should be revised before expanding the dataset.

4.4. Dataset Design and Representativeness

No universal image count guarantees model reliability. Dataset adequacy should be evaluated against task complexity, defect diversity, acquisition variability, and deployment-domain coverage [94,95,103,104]. Class imbalance requires explicit sampling, weighting, or loss-design strategies [111–114]. Data augmentation increases training variation but does not create new independent welds [97]. Weld-level partitioning is required to prevent leakage between training and test sets [115,116]. Anomaly-detection studies additionally require representative normal variability and independent anomalous cases [98,117].

All images derived from the same weld, specimen, seam, illumination condition, or closely related production sequence should remain in the same dataset partition. Random image-level splitting can cause data leakage because nearly identical information may appear in both the training and testing sets. Such leakage can inflate apparent performance and lead to misleading conclusions regarding generalization [115,116].

Dataset size should be determined through learning-curve analysis, class-specific performance stabilization, defect and severity coverage, and cross-condition validation. Feasibility datasets may initially target controlled binary or limited-class tasks, whereas development datasets should progressively incorporate independent welds from multiple process conditions, material batches, surface states, and acquisition sessions. Deployment-oriented datasets require production-representative variability and at least one locked, temporally or externally separated test set.

Dataset provenance should be recorded at the weld level. Each image should be traceable to its material batch, sheet thickness, stack order, surface condition, weld parameters, acquisition session, illumination condition, annotation version, and available functional tests. This structure enables cross-batch testing, cross-session validation, model-drift analysis, and investigation of errors associated with specific materials or acquisition conditions.

Public benchmark datasets are desirable for scientific comparison, but their absence does not prevent industrial implementation of the proposed framework. In battery manufacturing, deployment can begin with private, well-documented datasets if each image is linked to a unique weld identifier, material batch, process condition, acquisition session, annotation version, and available functional measurements. Under this approach, feasibility is first established within a controlled internal dataset, then tested across batches, operators, acquisition sessions, and surface conditions, and finally evaluated on a locked deployment-oriented test set. Public or multi-institutional benchmark datasets would still be valuable for community-level comparison, but traceable private datasets can support process-specific qualification when acquisition, annotation, validation, and reporting are standardized.

Class imbalance should be addressed first through data collection. Controlled variation in power, speed, focus, gap, clamping, contamination, trajectory, and overlap can generate physically plausible defects. Artificially edited defects should not replace authentic weld examples in validation or testing. During model training, class-aware sampling, balanced batches, weighted losses, focal loss, hard-negative mining, transfer learning, self-supervised pretraining, and anomaly detection may be used to mitigate imbalance [111–114,117].

Augmentation should reproduce plausible changes in illumination, orientation, scale, blur, and sensor noise without altering the defining morphology of the defect. Synthetic data may enrich rare defect classes during training, provided that synthetic images are not included in final test sets and that their contribution is verified using real weld images. Transfer learning can reduce data requirements by initializing models with features learned from larger visual datasets, while active learning can make annotation more efficient by prioritizing uncertain, borderline, or high-impact samples for expert review. Foundation models may support feature extraction, pre-annotation, or representation learning, but their outputs should not be accepted without task-specific validation, weld-level testing, and functional ground truth.

Two complementary test sets are recommended. A prevalence-preserving test set estimates operational behavior at expected production frequency, while a balanced challenge set enables comparison across rare-defect subclasses. Performance should include defect-class precision, recall, false-negative rate, specificity, F1 score, average precision by class, confusion matrix, confidence intervals, and inference time. Precision–recall analysis is particularly informative when defects are rare [118]. Detection studies should specify the intersection-over-union threshold, while segmentation studies should report the Dice coefficient or intersection over union together with instance-level defect recall [24,101,102,119].

4.5. Functional Acceptance Logic

The main value of post-process inspection lies not only in visual recognition but also in converting surface evidence into conservative, reproducible quality decisions. This requires a validated relationship between visible morphology and battery-relevant functional responses [1,4,12,13,34,35,66].

A three-layer structure is recommended. The first layer is visual observation: defect class, location, size, affected seam fraction, image quality, and prediction confidence. The second layer is validated risk relationship: correlation with electrical resistance, voltage drop, current-induced heating, mechanical strength, bonded width, penetration, porosity, cracks, or intermetallic morphology. The third layer is the production decision—accept, review, or reject—based on predefined and functionally validated thresholds.

Visible seam width, continuity, and placement may correlate with bonded area and electrical performance, but the relationship depends on material stack, thickness, seam trajectory, penetration, mixing, and intermetallic formation [1,4,12,34,35,66]. Therefore, thresholds established for one Al–Cu configuration should not be transferred automatically to another geometry, stack order, or beam-delivery strategy.

Gross seam misplacement, open interfaces, burn-through, severe cracking, missing seam sections, and extensive material loss generally support direct rejection. In contrast, isolated pits, moderate undercut, minor underfill, discoloration, and small spatter particles require size-dependent and application-specific thresholds. Surface pits should not be treated as a quantitative measure of internal porosity. Surface texture or color should not be treated as a direct indicator of intermetallic phase or thickness. Similarly, an apparently normal surface should not be assumed to have adequate penetration.

Post-process visual AI should be integrated with complementary nondestructive evaluation or destructive validation when the relevant quality attribute is hidden beneath the surface. Optical coherence tomography can support geometric verification when surface profile, seam position, or depth-related information is accessible. X-ray computed tomography can reveal internal porosity, voids, and hidden discontinuities, although its use is generally more suitable for laboratory validation, sampling, or failure analysis than for every production weld. Ultrasonic testing may contribute to internal-discontinuity assessment in appropriate geometries, but its sensitivity must be validated for thin Al–Cu stacks and small interconnect features. Electrical resistance measurements and thermal imaging provide functional evidence of current-carrying capability, local heating, and hot-spot formation, while metallographic cross-sections remain essential for periodic validation of bonded width, fusion quality, intermetallic compound morphology, porosity, and cracking. Therefore, post-process surface inspection should be interpreted as a traceable quality gate rather than as a standalone proof of internal joint conformity.

A conservative acceptance framework should follow a hierarchical sequence. First, an acquisition-validity gate should verify focus, spatial calibration, field of view, exposure, and absence of severe glare or saturation. Second, a domain-validity gate should confirm that material appearance, coating condition, joint geometry, and illumination fall within the validated dataset's domain. Third, a critical-defect gate should automatically reject welds with severe discontinuity, visible lack of bonding, major cracking, burn-through, gross seam misalignment, or hazardous spatter. Fourth, a severity-assessment gate should evaluate undercut, underfill, craters, pits, and distributed spatter against calibrated dimensional and affected-area thresholds. Fifth, uncertain cases should be routed to a functional-risk gate involving electrical, thermal, geometric, nondestructive, or metallographic verification. Final acceptance should be granted only when image acquisition is valid, the weld lies within the validated domain, and all critical and major acceptance criteria are satisfied.

Threshold selection should reflect the unequal consequences of errors. A false negative allows an unacceptable joint to proceed and may result in excessive resistance, local heating, mechanical weakness, or conductive debris. Therefore, defect-class recall and subclass-specific false-negative rate should take precedence over overall accuracy. Nevertheless, excessive false positives may increase reinspection, scrap, and production interruption. The final operating point should be selected using validation data and a cost-sensitive analysis that considers defect prevalence, secondary-inspection capacity, scrap cost, and missed-defect risk.

The review category provides a controlled path for handling uncertainty. It may trigger image reacquisition, higher magnification, expert inspection, electrical resistance measurement, thermography, OCT, or destructive sampling. This is preferable to forcing uncertain or out-of-domain images into an OK or defect label.

Post-process vision should ultimately operate within a layered quality architecture. In-process sensing can identify instability and penetration-related deviations; post-process imaging can document visible morphology and seam placement; electrical and thermal measurements can assess current-carrying behavior; and periodic metallographic or mechanical testing can maintain the relationship between appearance and function [1,4,12,13,34,35,66]. Within this framework, AI-assisted inspection improves consistency, traceability, and the escalation of high-risk or uncertain joints, but its industrial reliability depends on acquisition control, a defensible taxonomy, annotation quality, independent dataset design, and functionally validated acceptance rules rather than on the neural network architecture alone.

The preceding section defined the metrological, taxonomic, and decision-making requirements for AI-ready post-process inspection. The next step is to select the appropriate AI task and evaluation strategy based on the required levels of localization, quantification, and risk traceability for the manufacturing decision. Table 8 presents a functional decision matrix that maps representative surface-visible defects to measurable image descriptors, potential functional risks, required validation methods, and the most suitable AI inspection task.

Table 8. Functional decision matrix linking surface-visible evidence, measurable image descriptors, functional risk, validation route, and suitable AI task. The matrix is a synthesis based on the defect taxonomy, functional acceptance logic, and inspection literature discussed in Section 4.

Surface-Visible Indication	Measurable Image Descriptor	Possible Functional Risk	Recommended Validation Route	Recommended AI Inspection Task
Weld discontinuity or interrupted bead	Discontinuity length, affected bead fraction, number of interrupted segments, location along the weld path	Increased electrical resistance, local current constriction, hot-spot formation, reduced load-bearing area	Electrical resistance measurement, thermal response under current loading, cross-sectional metallography, mechanical testing	Object detection for localization; segmentation for affected-area quantification
Undercut or edge recession	Apparent undercut width, length, continuity, position relative to the weld toe, local bead-width reduction	Stress concentration, reduced effective section, premature mechanical failure, possible current-density localization	Optical profilometry, cross-sectional metallography, shear or pull testing, electrical resistance measurement	Segmentation for boundary extraction and severity estimation
Spatter cluster or adhered particles	Spatter count, projected area, particle-size distribution, density, distance from weld centerline, spatial clustering	Conductive debris, local contamination, short-circuit risk in compact battery assemblies, unstable process indication	Extended visual inspection, electrical safety inspection, surface-cleanliness assessment, correlation with process records	Object detection for particle localization; instance segmentation for particle counting and area estimation
Surface pit, open pore, or small cavity	Diameter, projected area, depth proxy from shading, pit density, spatial distribution, proximity to bead centerline	Possible porosity, keyhole instability, local loss of section, moisture or electrolyte trapping risk	Cross-sectional metallography, X-ray computed tomography when justified, profilometry, electrical resistance measurement	Object detection for screening; segmentation for size and density quantification
Crater or end-of-weld depression	Crater diameter, area, apparent depth, position at weld start or stop, surrounding radial cracks if present	Crack initiation, reduced end-joint integrity, local thermal instability, incomplete termination quality	Cross-sectional metallography, optical profilometry, mechanical testing, end-region electrical resistance measurement	Detection for localization; segmentation for area and shape quantification
Seam misplacement or weld-path offset	Offset from nominal trajectory, bead centerline deviation, distance from overlap edge, affected length	Reduced effective overlap, insufficient bonded area, asymmetric heat input, increased electrical resistance	Geometric inspection, cross-sectional metallography, electrical resistance measurement, mechanical testing	Geometric measurement combined with object detection

Table 8. Cont.

Surface-Visible Indication	Measurable Image Descriptor	Possible Functional Risk	Recommended Validation Route	Recommended AI Inspection Task
Excessive bead-width variability	Mean bead width, standard deviation, coefficient of variation, local narrowing or widening, bead-width uniformity index	Unstable energy coupling, variable penetration, inconsistent bonding area, local overheating or underheating	Cross-sectional metallography, electrical resistance mapping, mechanical testing, correlation with process parameters	Segmentation for bead-boundary extraction; regression for width prediction
Surface oxidation, discoloration, or heat tint	Color intensity, hue variation, affected area, distance from weld centerline, oxidation uniformity	Surface contamination, altered contact condition, possible shielding instability, reduced reproducibility of image-based inspection	Surface chemistry analysis when needed, visual inspection under controlled illumination, electrical contact assessment, process-log correlation	Classification for screening; segmentation for affected-area quantification
Lack of surface continuity at the overlap region	Gap-like feature length, apparent separation width, bead interruption, continuity index along the joint line	Lack of bonding, high contact resistance, weak mechanical interlock, risk of local heating during service	Electrical resistance measurement, cross-sectional metallography, peel or shear testing, thermal response under current loading	Detection for localization; segmentation for continuity assessment
Irregular bead morphology or excessive roughness	Texture descriptors, bead-edge irregularity, roughness proxy, local intensity variation, contour tortuosity	Process instability, inconsistent heat input, variable bonding quality, and reduced reproducibility of visual acceptance criteria	Optical profilometry, cross-sectional metallography, and correlation with electrical and mechanical performance	Classification for quality screening; segmentation and texture-based analysis for severity estimation

To translate post-process surface inspection into a quality-assurance tool, surface-visible defects must be interpreted through measurable descriptors and linked to plausible functional risks. This step is essential because an AI model can classify, detect, or segment visual anomalies, but it cannot by itself determine whether a weld is electrically, mechanically, or metallurgically acceptable. For laser-welded Al–Cu battery interconnects, the same surface feature may have different implications depending on its size, location, density, continuity, relation to the weld path, and correlation with electrical resistance, mechanical strength, cross-sectional geometry, or intermetallic compound distribution. Therefore, AI-enabled inspection should be coupled with validation routes that connect visual evidence with functional performance.

5. AI Methods for Post-Process Inspection: Detection, Classification, and Segmentation

Building on the metrological, taxonomic, and functional requirements defined in Section 4, this section compares the AI task formulations most relevant to post-process surface inspection. AI methods for post-process inspection convert controlled images of completed welds into quality labels, localized defect predictions, or pixel-level defect maps. In laser-welded Al–Cu battery interconnects, the model should not be selected only because it is recent or computationally efficient. The appropriate task depends on the manufacturing decision, the required level of traceability, the size and morphology of the target defects, and the available annotation effort. Binary classification is suitable when the manufacturing decision is limited to weld-level screening [20,93,105]. Localizing discrete defects such as spatter, pits, craters, or short cracks requires object detection [96,101,104].

Measuring undercut length, defect area, or the fraction of a seam affected by discontinuity requires segmentation [24,99,103]. Figure 6 summarizes the selection and validation of AI tasks for post-process inspection, linking classification, object detection, and segmentation to their annotation requirements, model families, evaluation metrics, robustness tests, and risk-based quality decisions.

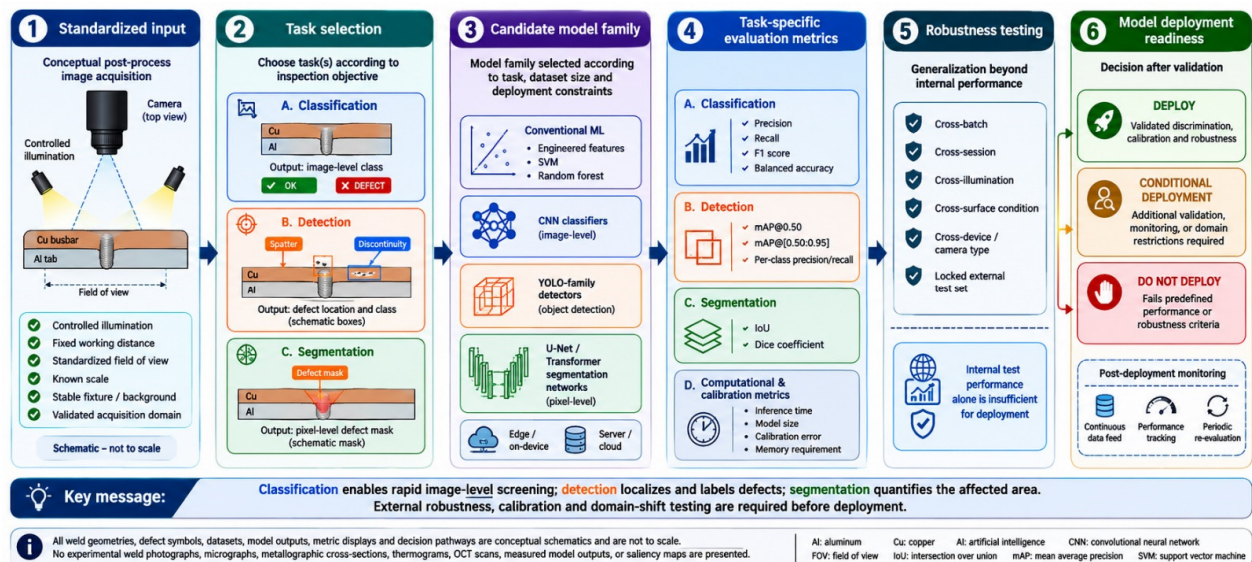


Figure 6. Task selection, model evaluation, robustness testing, and deployment readiness for AI-based post-process weld inspection. The six stages cover standardized imaging; selection of classification, detection, or segmentation; representative model families; task-specific performance, calibration, and computational metrics; cross-condition and external-domain robustness testing; and deployment decisions based on predefined validation criteria. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a six-stage vector framework for imaging standardization, AI task and model selection, task-specific metrics, cross-condition and external robustness testing, uncertainty assessment, and deployment-readiness decisions in weld inspection.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

5.1. Task Selection

Image classification assigns one or more labels to the complete image, such as OK, defect, or a dominant defect class. It is the simplest annotation task and can be useful as a first screening step. Its main limitation is limited traceability: the model may classify a weld as defective without identifying which feature caused the decision. In reflective Al–Cu surfaces, this poses the risk that the classifier learns illumination patterns, surface texture, fixture marks, or material boundaries rather than defect morphology [93–96,105].

Object detection predicts defect class, location, and confidence through bounding boxes. This task is more appropriate for localized anomalies such as spatter particles, surface pits, craters, burn-through, short cracks, and isolated discontinuities. Detection supports traceability because the predicted box can be reviewed by an operator and can be linked to size, count, and distance from the seam or critical current path. However, bounding boxes represent irregular features approximately and may include background, which limits their usefulness for accurate area or length measurement [101,104,110,119].

Semantic segmentation assigns a class to each pixel and is preferable when the defect is elongated, irregular, or area-dependent. Undercut, underfill, distributed spatter, seam-boundary deviation, and affected seam fraction are better represented by masks than by boxes. Instance segmentation is useful when individual overlapping defects must be separated, for example, multiple spatter particles or adjacent pits. These tasks provide

higher metrological value but require more expensive and less reproducible annotations, especially when defect boundaries are visually ambiguous [24,99,100].

Anomaly detection is useful when defective examples are rare, incomplete, or difficult to classify into stable subclasses. These models learn the appearance of normal welds and flag deviations from that distribution. This makes them attractive for early industrial deployment, but anomaly scores do not automatically indicate defect type, severity, or functional consequence. Therefore, anomaly detection should be treated as a review trigger unless its outputs are linked to validated defect classes and functional risk [98,117].

A practical strategy is hierarchical: classification can remove clearly acceptable images, detection can localize discrete defects, segmentation can quantify geometry-dependent features, and anomaly detection can identify unexpected or out-of-domain cases. Each stage must be evaluated independently because errors made by an early classifier may prevent later localization or measurement. Figure 6 provides a workflow for selecting and validating AI inspection tasks, whereas Table 9 summarizes the main task families, annotation requirements, metrics, and limitations. The comparison highlights that task selection should be driven by the required inspection output: weld-level screening, defect localization, pixel-level measurement, separation of overlapping defects, or detection of unexpected anomalies.

Table 9. Compact comparison of AI tasks for post-process inspection of laser-welded Al–Cu battery interconnects. The comparison is based on AI-based weld inspection, industrial surface defect detection, object-detection metrics, segmentation metrics, and anomaly-detection literature cited in Section 5.

AI Task	Recommended Use	Minimum Annotation	Typical Models	Core Metrics	Main Limitation
Image classification	Weld-level OK or defect screening	Image-level label	Engineered features with SVM or random forest; CNN classifiers	Precision, recall, F1 score, specificity, confusion matrix	No defect localization
Object detection	Localization of discrete defects such as spatter, pits, craters, short cracks, and burn-through	Class-labeled boxes	YOLO-family detectors; Faster R-CNN	IoU, AP50, AP50–95, class-specific recall	Approximate boundaries and limited small-defect sensitivity
Semantic segmentation	Pixel-level quantification of undercut, underfill, seam continuity, and affected area	Class masks	U-Net, DeepLab, and related networks	IoU, Dice coefficient, defect-level recall	High annotation cost and uncertain boundaries
Instance segmentation	Separation of individual overlapping defects	Instance masks	Mask R-CNN and related models	Mask AP, IoU, Dice coefficient, instance recall	Higher annotation and computational complexity
Anomaly detection	Screening when defective examples are scarce or incomplete	Mostly normal images	Autoencoders, one-class methods, deep anomaly detection	AUROC, average precision, defect recall	Limited defect-class and functional interpretation

Note: The metrics listed in Table 9 should be used for task-specific reporting rather than for cross-study ranking, unless the evaluated models share the same images, labels, data partitions, and acceptance criteria.

5.2. Model Families

Classical machine learning with engineered features remains useful as a baseline, particularly when datasets are small and imaging conditions are controlled. Features such as intensity statistics, edge density, local binary patterns, gray-level co-occurrence matrices, Gabor filters, geometric descriptors, and morphological measurements can be combined with support-vector machines, random forests, logistic regression, or shallow neural networks [100,105]. These approaches are interpretable and computationally inexpensive, but they depend heavily on feature design and may lose robustness when illumination, surface conditions, or defect morphology change.

In addition to the selected inspection task, the learning strategy determines the type of data required and the expected deployment risk. Supervised learning remains the most direct option when representative defect labels are available, but it depends strongly on annotation quality and class balance. Semi-supervised learning can reduce labeling effort by combining a limited number of labeled weld images with larger unlabeled datasets. Self-supervised learning can be useful for pretraining on unlabeled post-process weld images and may improve robustness to surface appearance variations, but its benefit must be verified through downstream classification, detection, or segmentation tasks. Anomaly-detection approaches are attractive when defect examples are scarce, although their outputs should generally be used as review triggers unless defect class and functional relevance are independently validated.

Convolutional neural networks learn image features directly and are widely used for weld classification. Transfer learning from pretrained CNNs can reduce data requirements and improve performance when weld datasets are limited [24,103,105]. However, CNN classifiers should not be reported without localization or error analysis. A high classification score does not prove that the model is using the weld region or the defect itself. Visual explanations, occlusion tests, and external-condition validation are needed to reduce this risk.

YOLO-family detectors and related one-stage detectors are attractive for industrial inspection because they provide fast localization and classification of defects in a single model. They are suitable for spatter, pits, craters, burn-through, and short cracks when throughput is important [96,101,110]. Two-stage detectors may improve localization in some small or low-contrast cases but usually require more computation. Detector comparisons should use the same dataset partition, image resolution, augmentation policy, confidence threshold, and matching rule.

Segmentation models, including U-Net-type architectures, fully convolutional networks, DeepLab-like models, and instance-segmentation networks, are appropriate when the output must support physical measurement. They are particularly useful for affected-area estimation, seam-boundary analysis, undercut or underfill quantification, and irregular discontinuities [24,99]. Their main limitations are annotation cost, boundary ambiguity, and sensitivity to changes in illumination and surface texture.

Model selection should therefore be justified by the required inspection output. For example, classification may be sufficient for coarse OK versus defect screening, detection is preferable for traceable localization of discrete defects, and segmentation is more defensible when the acceptance rule depends on area, length, or the affected seam fraction.

From a deployment perspective, learning strategies should evolve with dataset maturity: supervised models are appropriate once reliable labels exist, transfer learning is useful when labeled data are limited, active learning can prioritize expert annotation, semi-supervised and self-supervised approaches can exploit unlabeled production archives, and anomaly detection can support early screening or out-of-domain detection when critical defects are rare.

5.3. Metrics and Reporting Standards

Evaluation metrics must match the task and the manufacturing risk. Overall accuracy is insufficient for post-process weld inspection because defective welds are often rare and critical defects may represent only a small fraction of the dataset [112–114,118]. A model can achieve high accuracy by correctly classifying most OK welds while missing small cracks, discontinuities, or hazardous spatter.

For image classification, the minimum reporting set should include class-specific precision, recall, F1 score, specificity, false-negative rate, and confusion matrix. Recall for the defect class is particularly important because it measures the proportion of defective welds the model detects. The false-negative rate should be reported for the complete defect class and separately for critical subclasses.

For object detection, the intersection-over-union threshold used to match predictions and annotations must be specified. AP50 is useful as a tolerant screening metric, whereas AP50–95 is more demanding and better reflects localization consistency across multiple thresholds [102,119]. Mean average precision should not be reported alone. Average precision and recall should also be reported by class, defect size, and risk level, because high aggregate performance may conceal missed small cracks or low-contrast pits.

For segmentation, intersection over union and Dice coefficient should be reported by class. These pixel-level metrics should be complemented by instance-level recall, since a model may achieve a high mask score over large regions while missing a small but critical defect. For all tasks, confidence intervals should be calculated at the independent-weld level rather than at the crop or image-augmentation level.

A direct quantitative ranking of classification, detection, segmentation, and anomaly-detection models remains difficult for laser-welded Al–Cu battery interconnects because no widely adopted public benchmark dataset exists for post-process weld-surface images in this application. Reported performances in the broader weld inspection literature are often obtained using different materials, weld geometries, image resolutions, defect definitions, annotation protocols, class distributions, data splits, augmentation strategies, and metrics. Consequently, accuracy, F1 score, AP50, AP50–95, IoU, Dice coefficient, and AUROC values reported in separate studies should not be interpreted as directly comparable unless the same dataset, labels, train–validation–test partitions, and evaluation thresholds are used. This lack of comparability is one of the main methodological gaps addressed in this review through the proposed weld-level dataset design, cross-condition validation, and reporting framework.

The operating threshold should be selected using validation data and evaluated once on a locked test set. Reporting should include image resolution, preprocessing, augmentation, model initialization, loss function, class weighting, confidence threshold, hardware, inference time, and dataset split strategy. Without these details, comparisons among CNNs, YOLO-family detectors, segmentation models, and anomaly-detection methods are not reproducible.

5.4. Robustness, Uncertainty, and Failure Analysis

Robustness is essential because post-process Al–Cu inspection is exposed to strong domain shifts. A model trained under one imaging condition may fail when illumination, focus, surface oxidation, coating, material batch, seam trajectory, magnification, or background changes. Therefore, evaluation should include internal testing, cross-session testing, cross-batch testing, and, when possible, a locked external set representative of deployment conditions [20,93–97,103,104].

Out-of-distribution detection is needed when the model receives images outside its validated domain. Examples include severe glare, missing weld regions, new coatings, unfamiliar geometries, unusual oxidation, excessive blur, or surface finishes absent from training. These cases should not be forced into OK or defect. They should be routed to review, reacquisition, or complementary inspection. Anomaly-detection scores, confidence-based rejection, embedding-distance methods, or dedicated out-of-distribution classifiers can support this step, but they must be validated on realistic out-of-domain examples [98,117].

Confidence calibration is equally important. A predicted probability of 0.90 does not necessarily mean that the prediction is correct with 90 percent reliability. Overconfident models are risky in manufacturing because they may assign high confidence to incorrect OK predictions. Calibration should be assessed on validation data, and uncertain predictions should trigger review rather than automatic acceptance. Calibration is especially relevant when class imbalance, small datasets, or transfer learning are used.

Interpretability and failure analysis help determine whether the model is learning meaningful weld features. Class-activation maps, occlusion tests, predicted boxes, segmentation masks, and counterfactual illumination or background tests can reveal whether decisions depend on the weld region, defect morphology, or irrelevant acquisition artifacts [120]. Recent laser-welding studies also show the value of physically interpretable features, such as spatter area, spatter temperature, spatter count, and weld-zone temperature, for defect prediction; although these examples are mainly in-process rather than post-process, they support the broader principle that AI decisions should be linked to observable physical evidence whenever possible [76]. Visual explanations should be treated as diagnostic evidence, not as proof of physical causality.

False negatives require the most careful analysis because they allow unacceptable welds to proceed as OK. They should be stratified by defect class, defect size, location, material batch, illumination condition, and risk tier. Common failure modes include small or low-contrast cracks, scratches mistaken for cracks, glare mistaken for pits, undercut hidden by shadows, merged spatter clusters, incomplete field of view, and unseen surface conditions.

A human-in-the-loop strategy is recommended for borderline, uncertain, or out-of-domain predictions. The review state can trigger expert visual inspection, reacquisition under alternative illumination, higher magnification, electrical resistance measurement, thermography, OCT, or metallographic sampling. This approach is more appropriate for battery interconnect manufacturing than an uncontrolled binary output, because it acknowledges uncertainty and preserves traceability.

For industrial deployment, robustness should be evaluated against the main sources of variation expected in production. These include changes in illumination, surface oxidation, roughness, coating condition, material lot, stack geometry, camera replacement, focus drift, fixture positioning, and background appearance. A model trained under controlled laboratory conditions should therefore be tested using cross-session, cross-batch, and cross-condition validation sets that remain disjoint at the weld level. In addition, out-of-distribution detection, confidence calibration, and drift monitoring should be implemented to identify images that no longer belong to the validated acquisition domain. When such cases occur, the output should be routed to review rather than automatic acceptance. This requirement is particularly important for reflective Al–Cu surfaces, where changes in glare, texture, or oxidation can resemble physical defects or mask critical discontinuities.

In summary, the most credible AI system for post-process inspection is not defined by a single model architecture. It requires an inspection task aligned with the manufacturing decision, a representative dataset, task-specific metrics, cross-condition validation, calibrated confidence, out-of-distribution handling, and systematic false-negative analysis.

For laser-welded Al–Cu battery interconnects, these requirements are essential to translate image recognition into risk-sensitive quality assurance. Table 9 summarizes the main AI task formulations for post-process inspection of laser-welded Al–Cu battery interconnects. The comparison highlights that task selection should be driven by the required inspection output: weld-level screening, defect localization, pixel-level measurement, separation of overlapping defects, or detection of unexpected anomalies.

6. Benchmarking and Reporting Guidelines for the Field

Because model performance depends strongly on data partitioning, reporting detail, and validation conditions, the methodological choices discussed above must be translated into benchmarking rules for the field.

The literature on AI-assisted inspection of laser welds reports promising classification and detection performance, but direct comparisons among studies remain difficult. Differences in imaging conditions, defect definitions, dataset splitting, class prevalence, preprocessing, model selection, and evaluation metrics can produce substantial variation in reported results. In addition, high performance on images acquired under a single laboratory condition does not necessarily demonstrate robustness to the material, surface, and production variability encountered in battery manufacturing [13,95,104,121]. For Al–Cu battery interconnects, benchmarking should therefore assess not only predictive performance but also data independence, functional relevance, domain coverage, and the consequences of false-negative decisions. The following guidelines are proposed as a minimum framework for reproducible post-process inspection research.

6.1. Minimum Reporting Checklist

A complete study should report four groups of information: image acquisition, annotation, dataset construction, and model evaluation.

Image acquisition

The acquisition system should be described in sufficient detail to reproduce the imaging domain. At a minimum, authors should report: camera and lens specifications; working distance and viewing angle; image resolution and physical pixel scale; illumination type and geometry; exposure, aperture, and gain; material stack, coating, and surface condition; field of view and specimen orientation; and image format and preprocessing operations. Representative unprocessed images should be provided for normal welds, each defect class, and challenging cases involving glare, oxidation, contamination, or low contrast. Reporting only enhanced or cropped examples prevents assessment of the original acquisition quality.

Annotation

Studies should define each class using explicit inclusion and exclusion criteria. The annotation format should be specified as image-level labels, bounding boxes, semantic masks, or instance masks. The handling of ambiguous cases, overlapping defects, spatter clusters, reflections, scratches, and pre-existing damage should also be documented. When multiple annotators are involved, the study should report the number and expertise of annotators, the adjudication procedure, and an agreement metric appropriate to the annotation task. Class-level agreement is preferable to a single global value because abundant normal images can mask disagreement on rare defects.

Dataset construction and splitting

The number of independent physical welds should be reported separately from counts of images, crops, frames, and augmented samples. All images from the same weld or specimen should remain in a single partition. Improper splitting of correlated images can substantially inflate performance and should be treated as a form of data leakage [115]. The following information should be reported: independent welds per class; natural and

sampled class prevalence; material batches and acquisition sessions; train, validation, and test splits; grouping variable used for splitting; augmentation applied only to training data; treatment of synthetic data; and whether the test set was locked before model selection.

Model and metrics

The model architecture, initialization, input resolution, preprocessing, augmentation, training schedule, loss function, class weights, confidence threshold, and matching criteria should be reported. Model comparisons should use identical dataset partitions and evaluation conditions. For classification, the minimum set of metrics is class-specific precision, recall, F1 score, specificity, false-negative rate, and the confusion matrix. For detection, studies should report intersection over union, AP50, AP50–95, average precision per class, class-specific recall, and the number of missed critical instances. Segmentation studies should report intersection over union, Dice coefficient, and defect-level recall [119]. Overall accuracy or mean average precision alone is insufficient when defect prevalence is low, or class severity is unequal. Precision–recall analysis is generally more informative for imbalanced inspection datasets because it reveals the trade-off between missed defects and false alarms [118].

6.2. Recommended Benchmarking Protocol

A common benchmarking protocol would improve comparability across Al–Cu battery interconnect studies. However, a meaningful quantitative comparison among AI models requires a shared or locked dataset, weld-level data partitioning, harmonized annotation rules, and task-specific metrics reported under the same evaluation thresholds. Without these conditions, reported values of accuracy, F1 score, AP50, AP50–95, IoU, Dice coefficient, or AUROC should be interpreted as study-specific results rather than as evidence that one model family is intrinsically superior. Therefore, the proposed benchmarking protocol contains three evaluation levels.

Level 1: Internal benchmark

The dataset is split into training, validation, and test subsets at the independent-weld level. A practical allocation may use approximately 60 to 70 percent for training, 10 to 20 percent for validation, and 20 percent for testing, provided that all images associated with a single weld remain in the same subset. The validation set is used for model selection, hyperparameter tuning, and defining the confidence threshold. The test set is evaluated only after the complete pipeline has been fixed. This level measures performance under the acquisition and material conditions represented during development. It should be regarded as necessary but not sufficient evidence of generalization.

Level 2: Cross-batch and cross-session validation

At least one material batch or acquisition session should be excluded from training and reserved for evaluation. This test assesses sensitivity to changes in surface finish, oxidation, coating condition, material supplier, illumination, camera recalibration, and specimen handling. Performance should be compared with the internal benchmark using absolute and relative degradation in defect recall, precision, F1 score, and average precision. Reporting only the best-performing condition can mask severe domain dependence. This validation level should intentionally include variations in illumination, surface condition, material batch, fixture positioning, and acquisition session, because these factors are common sources of domain shift in post-process Al–Cu weld imaging.

Level 3: External or deployment-oriented validation

An external set should be locked after model development and collected using specimens, batches, or production conditions not represented during training. Where possible, this set should reflect the natural prevalence of defects expected in manufacturing. The external benchmark should include: normal production variability; borderline defects; rare

critical defects; image-quality failures; out-of-domain surface conditions; and welds with electrical or mechanical ground truth. Models should not be retrained or recalibrated using the external set. When adaptation is later performed, performance before and after adaptation should be reported separately. For fair model comparison, all candidate algorithms should use identical images, labels, partitions, augmentations, and decision thresholds. Computational performance should also be reported, including inference time, hardware, image throughput, and memory requirements. This is particularly important when a highly accurate model cannot meet the production cycle time. Public industrial datasets such as MVTec AD have demonstrated the value of standardized images and fixed evaluation partitions for anomaly-detection research [98]. However, they do not capture the optical, metallurgical, or functional complexity of Al–Cu battery welds. Therefore, a dedicated benchmark should include weld-specific metadata, multi-condition images, functional test results, and explicit risk levels.

6.3. Suggested Acceptance Criteria Aligned with Manufacturing

Model acceptance criteria should reflect the consequences of each error type rather than maximizing a single aggregate metric. In battery interconnect inspection, false negatives are generally more consequential than false positives because an undetected defective joint may exhibit excessive resistance, local heating, inadequate bonded area, conductive debris, or reduced mechanical integrity [4,13,34,35].

A manufacturing-oriented evaluation should therefore prioritize: recall for the complete defect class; recall for each critical subclass; false-negative rate; number of missed critical welds; false-positive rate and review burden; and inference time relative to the production cycle time. No universal numerical threshold can be recommended without considering joint design, defect prevalence, current demand, and the available secondary-inspection route. Nevertheless, a model intended for production should demonstrate stable critical-defect recall across the internal, cross-batch, and external test sets, rather than achieving high recall only under development conditions.

In a manufacturing line, the proposed accept–review–reject framework can be implemented as a downstream post-process inspection station placed after laser welding and before module-level assembly or electrical qualification. Such a station may combine an industrial camera, fixed illumination, calibrated fixturing, local inference on an industrial computer or an edge graphics processing unit, and automatic storage of the weld image, weld identifier, model output, confidence score, and final decision. This architecture allows post-process inspection to remain compatible with high-throughput production while preserving traceability at the individual-weld level.

The three decision states should be interpreted as manufacturing actions rather than only model labels. Accept should be assigned only when image acquisition is valid, the weld lies within the validated domain, no critical defect is detected, and the prediction confidence is above the selected threshold. Review should be triggered by uncertain predictions, out-of-domain images, borderline severity, acquisition-quality problems, or disagreement between model output and process metadata. Reject should be assigned when a critical defect is detected or when a validated severity threshold is exceeded. Review cases may be routed to image reacquisition, expert inspection, electrical resistance measurement, thermal verification, OCT, X-ray computed tomography, ultrasonic testing when geometrically appropriate, or periodic metallographic validation, depending on whether the suspected risk is surface-visible, geometric, internal, or functional.

Acceptance should also depend on calibration and uncertainty. Images with confidence near the decision threshold, incomplete field of view, severe glare, defocus, saturation, or out-of-domain characteristics should not be forced into a binary OK or defect output. A

three-state decision system is therefore preferable to an unconstrained binary classifier because it provides a controlled path for uncertainty and reduces the risk of accepting nonconforming welds.

The operating threshold should be selected using validation data and a cost-sensitive criterion that accounts for the risk of missed defects, false-reject cost, production takt time, and secondary-inspection capacity. The chosen threshold and its associated confusion matrix should then be evaluated once on the locked test set. For practical deployment, inference time should be reported along with image acquisition time, preprocessing time, reacquisition rate, review rate, and hardware requirements. A model with high offline performance but excessive latency, unstable hardware demands, or an unmanageable review burden may be unsuitable for production even if its classification or detection metrics are favorable.

The review state preserves the role of human expertise by routing uncertain, borderline, or out-of-domain welds to expert evaluation or complementary testing instead of forcing automatic acceptance.

7. Research Gaps and Roadmap

7.1. Remaining Gaps for Al–Cu Battery Interconnects

Research on laser-welded Al–Cu joints has advanced considerably in process optimization, beam oscillation, wavelength selection, and in-process monitoring [4,14,15,17,34,35]. In contrast, systematic post-process visual inspection remains relatively underdeveloped.

The main gaps are outlined below. First, no widely adopted public dataset focuses specifically on surface-visible defects in laser-welded Al–Cu battery interconnects. Existing industrial inspection datasets do not capture the reflectivity, mixed-material appearance, small seam dimensions, or functional constraints of these joints [95,98,104]. Second, defect taxonomies are inconsistent. Terms such as pore, pit, lack of fusion, discontinuity, underfill, and burn-through are not always defined by observable criteria. Some studies also infer subsurface or metallurgical conditions directly from surface appearance without sufficient validation. Third, the relationship between surface morphology and functional performance remains poorly quantified. Few studies pair controlled post-process images with four-terminal resistance, current-induced heating, bonded width, mechanical strength, porosity, and intermetallic morphology. Consequently, many AI studies predict visual labels rather than manufacturing-relevant acceptance. Fourth, generalization is rarely demonstrated across material batches, surface states, illumination systems, joint geometries, or acquisition sessions. Models may therefore learn laboratory-specific optical patterns instead of robust defect features. Domain adaptation and anomaly-detection methods can address part of this problem, but their value must be confirmed using independent real welds [117,122]. Fifth, reporting remains heterogeneous. Differences in dataset splitting, class prevalence, image resolution, augmentation, and metrics prevent reliable comparison among models. False-negative analysis is also frequently absent despite its importance for battery safety and reliability. Finally, uncertainty and out-of-domain recognition are seldom integrated into the final decision. A model that always produces an OK or defect label may express unjustified confidence when presented with a new coating, geometry, or reflection pattern.

7.2. Short-Term Roadmap: One to Two Years

The immediate priority is to establish reproducible data and evaluation foundations. A multi-institutional dataset should be developed using standardized imaging protocols and weld-level identifiers. The dataset should include normal welds, controlled defects, borderline conditions, multiple material batches, complementary illumination, and independent functional measurements. Original images and acquisition metadata should be

retained. A consensus taxonomy should distinguish visible morphology from inferred internal mechanisms. The primary label may remain OK versus defect, with optional subclasses for spatter, surface pits, undercut, underfill, discontinuity, craters, cracks, placement error, and burn-through. Each class should include dimensional descriptors and a preliminary battery-risk category.

Benchmark partitions should be fixed at the weld, batch, and acquisition-session levels. Baseline results should include classical texture and geometric features, CNN classification, YOLO-family detection, segmentation, and anomaly detection. Standardized metrics and confidence intervals should be reported for each baseline. Short-term studies should also identify which visual features correlate reproducibly with electrical resistance, thermal response, and mechanical strength. These correlations are necessary to convert image recognition from cosmetic inspection to functional acceptance. Reproducibility should be supported by publishing annotation manuals, metadata dictionaries, dataset partitions, preprocessing routines, and evaluation scripts whenever industrial confidentiality permits. When raw images cannot be released, representative subsets or benchmark servers should be considered.

7.3. Mid-Term Roadmap: Three to Five Years

The mid-term objective should be a layered, multimodal, and uncertainty-aware quality architecture integrating in-process sensing, post-process imaging, process history, and functional validation. Future approaches may combine post-process surface imaging with thermal imaging, acoustic emission, spectroscopy, OCT, process metadata, and electrical measurements, provided that each modality contributes nonredundant information and that missing-sensor or low-quality-sensor conditions are explicitly validated. Emerging technologies such as vision transformers, self-supervised pretraining, multimodal foundation models, edge AI, and digital twins may support robustness, data efficiency, and industrial deployment. However, their use should remain tied to weld-specific validation, domain-shift testing, inference-time constraints, and functional ground truth rather than being adopted only because of model novelty.

In-process cameras, photodiodes, spectroscopy, thermography, and OCT provide information on coupling, penetration, keyhole stability, material interaction, and seam width at the interface [14,15,17,121]. Post-process imaging provides traceable evidence of the final surface morphology and seam placement. Combining these sources can reduce ambiguity associated with any single modality.

Multimodal models should be developed around physically meaningful intermediate variables rather than relying on unrestricted signal fusion. Examples include penetration depth, interface width, instability score, surface defect area, and electrical resistance. Validation should include missing-sensor conditions so that the failure of one channel does not invalidate the entire system.

A digital thread should link the material lot, welding parameters, in-process signals, post-process images, model outputs, electrical measurements, and destructive-sampling results for each weld. These records can support drift detection, root-cause analysis, maintenance decisions, and continuous recalibration.

Digital twins may add a physics layer by linking beam delivery, heat flow, mixing, seam geometry, and functional response. Their most realistic near-term role is not to replace inspection but to constrain inference, generate physically plausible hypotheses, and identify combinations of process signals and surface features that require verification. The current battery-manufacturing literature likewise positions AI-enabled digital twins as tools for quality prediction, process optimization, and traceable decision support rather than as independent substitutes for experimental evidence [123]. Consistent with this direction,

Lyu recently demonstrated a multimodal neural network framework that fused electrical, infrared-thermal, and visible-image data to classify dissimilar weld quality and map reject probability across the process window [124]. Figure 7 integrates the proposed benchmarking framework with the main research gaps and the short- and mid-term roadmap required to translate AI-assisted inspection of Al–Cu battery interconnects from laboratory demonstrations to functionally validated manufacturing systems. Table 10 summarizes the minimum information required to make AI-assisted Al–Cu weld inspection studies reproducible, comparable, and relevant to manufacturing. The framework extends conventional model reporting by requiring independent-weld partitioning, cross-condition validation, risk-sensitive metrics, and functional ground truth. The goal is not to replace post-process inspection with increasingly complex models, but to build validated quality architectures in which visual evidence, process signals, functional tests, and uncertainty estimates support traceable manufacturing decisions.

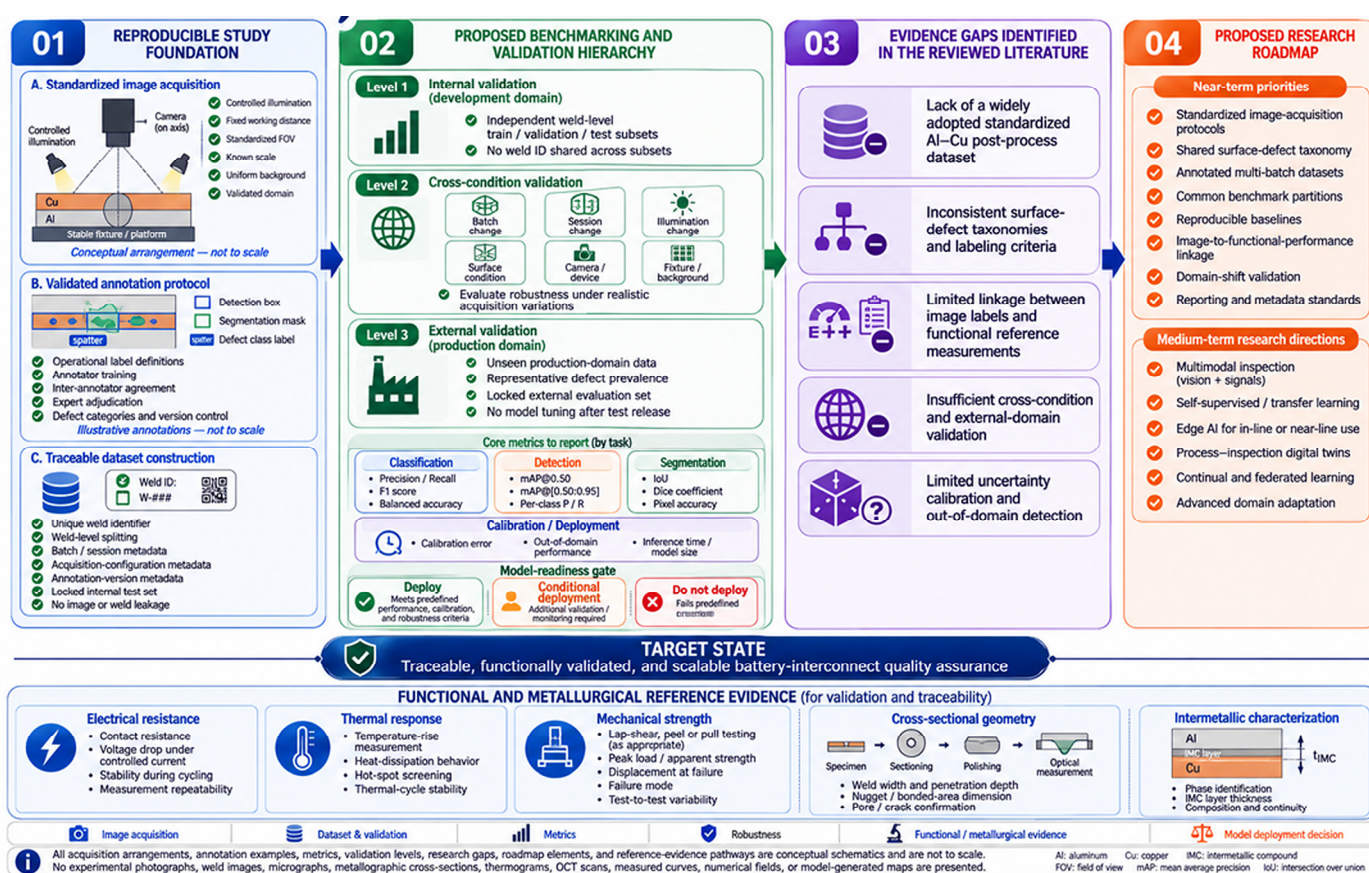


Figure 7. Roadmap for reliable and scalable AI-supported post-process inspection of laser-welded Al–Cu battery interconnects. The roadmap integrates reproducible study foundations; internal, cross-condition, and external validation with deployment gates; principal evidence gaps; and short- and medium-term research priorities supported by electrical, thermal, mechanical, geometric, and metallurgical reference measurements. AI-use disclosure: Created and graphically refined using ChatGPT Images 2.0 (OpenAI, ChatGPT web interface; accessed on 15 July 2026). Reconstructed prompt (verbatim log unavailable): “Create a four-part scientific roadmap covering reproducible study foundations, validation and deployment gates, evidence gaps, and short- and medium-term priorities for AI-supported Al–Cu battery-weld inspection.” The authors reviewed and edited the output; no experimental, measured, simulated, or model-output data are shown.

Table 10. Recommended reporting checklist for AI-enabled post-process inspection of laser-welded Al–Cu battery interconnects. The checklist was developed based on the reviewed literature on image acquisition, annotation, dataset partitioning, class imbalance, model evaluation, benchmarking, and manufacturing quality assurance.

Reporting Domain	Minimum Information	Recommended Validation Evidence
Image acquisition	Camera, lens, illumination, working distance, pixel scale, exposure, surface condition, and material stack	Representative unprocessed images from all classes and acquisition conditions
Annotation	Operational class definitions, annotation format, ambiguity rules, and annotator expertise	Class-specific agreement and expert adjudication
Dataset	Independent-weld count, class prevalence, batches, sessions, and metadata	Weld-level splitting with no correlated-image leakage
Internal evaluation	Train, validation, and locked test partitions	Class-specific precision, recall, F1 score, and confusion matrix
Detection and segmentation	Confidence and matching thresholds	AP50, AP50–95, class recall, IoU, and Dice coefficient
Generalization	Unseen batches, sessions, illumination, and surface conditions	Performance degradation relative to the internal benchmark
Manufacturing decision	Accept, review, and reject thresholds	Critical-defect recall, false-negative rate, and review burden
Functional relevance	Electrical, thermal, mechanical, and metallurgical measurements	Experimentally validated relationship between image features and joint performance
Production deployment	Camera and illumination setup, hardware, inference time, reacquisition rate, review rate, decision thresholds	Demonstration on disjoint welds under representative takt time, batch, surface-condition, and acquisition-session variability

7.4. Critical Synthesis and Unresolved Tensions

The reviewed evidence reveals several unresolved tensions that should guide future research and industrial implementation. First, a visually regular weld surface cannot be considered equivalent to functional conformity, as penetration, internal porosity, bonded width, intermetallic continuity, and electrical resistance may remain hidden. Second, in-process monitoring and post-process inspection provide complementary evidence and should not be treated as interchangeable quality-assurance routes. Third, controlled image acquisition, consistent annotation, weld-level dataset partitioning, and representative domain coverage may influence model reliability more strongly than marginal differences between neural network architectures. Fourth, high performance on an internal test set does not demonstrate robustness across changes in material batch, surface condition, illumination, camera settings, joint geometry, or process window. Finally, binary accept–reject decisions are inadequate for uncertain or out-of-domain cases; a dedicated review state is required to preserve expert oversight and prevent confidence-based false acceptance.

8. Conclusions

The main conclusions of this review can be summarized as follows:

1. Laser welding offers the energy localization, processing speed, and automation capability required for Al–Cu battery interconnect production, but its operating window remains intrinsically narrow. Differences in optical absorption, thermal transport, melting behavior, and intermetallic compound formation make joint quality highly sensitive to the material stack, surface condition, heat input, focal position, gap, and fit-up. These factors govern spatter, porosity, underfill, discontinuity, excessive mixing, and variability in electrical, thermal, and mechanical performance.
2. Process enablers such as beam shaping, adjustable core–ring distributions, beam oscillation, visible wavelengths, welding–brazing routes, interlayers, and dual-beam strategies can improve robustness by stabilizing coupling, redistributing heat, and controlling mixing. However, their effectiveness must be evaluated through functional outputs, including resistance stability, bonded width, strength consistency, thermal response, and intermetallic continuity, rather than through surface appearance alone. In-process monitoring provides valuable evidence on dynamic events and penetration-related behavior, but it remains complementary to post-process inspection and does not independently establish final joint conformity.
3. Post-process surface inspection is particularly relevant because it provides traceable evidence of the completed weld condition, including seam placement, visible discontinuities, spatter, craters, undercut, underfill, cracks, burn-through, and other surface-visible anomalies. Nevertheless, surface appearance must be interpreted cautiously. A visually acceptable weld may still contain hidden lack of bonding, internal porosity, excessive intermetallic growth, or insufficient interface width. Therefore, post-process inspection should be linked to functional ground truth through electrical resistance, thermal response, mechanical testing, cross-sectional geometry, nondestructive evaluation, and metallurgical characterization.
4. The main contribution of this review is a framework for AI-enabled post-process surface inspection of laser-welded Al–Cu battery interconnects. The proposed framework integrates a battery-risk-oriented taxonomy of surface-visible defects, controlled image acquisition, annotation and agreement rules, weld-level dataset design, task-specific metrics for classification, detection and segmentation, cross-condition benchmarking, uncertainty handling, and accept–review–reject decision logic.
5. AI-assisted inspection should support, not replace, expert judgment. Human expertise remains essential for interpreting uncertain or out-of-domain cases, validating new welding technologies and parameter windows, defining acceptance criteria, and deciding when complementary electrical, thermal, nondestructive, or metallographic verification is required. The review state is therefore a critical element of the proposed framework because it preserves expert oversight for borderline or high-risk welds.
6. Future progress will depend less on marginal improvements in neural network architecture and more on standardized datasets, independent validation, uncertainty management, transparent reporting, and experimentally verified links between visual features and functional performance. Multimodal inspection, self-supervised learning, foundation models, edge AI, and digital twins may support future deployment, but their value must be demonstrated through weld-specific validation, domain-shift testing, inference-time assessment, and functional ground truth.

Author Contributions: Conceptualization, M.H.-H. and A.G.-M.; methodology, M.H.-H. and A.G.-M.; formal analysis, M.H.-H. and A.G.-M.; investigation, M.H.-H. and A.G.-M.; resources, M.H.-H.; writing—original draft preparation, M.H.-H.; writing—review and editing, M.H.-H. and A.G.-M.; visualization, M.H.-H. and A.G.-M.; supervision, M.H.-H.; project administration, M.H.-H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors gratefully acknowledge support from the Secihti—Investigadores por México program. During the preparation and revision of this manuscript, the authors used OpenAI ChatGPT (web interface; exact conversational and image-generation model versions were not displayed or retained across all revision sessions; accessed June–July 2026) for structural editing and the development and graphical refinement of conceptual scientific illustrations. The OpenAI ChatGPT image-generation feature was used to generate or graphically refine the conceptual schematics in Figures 1–7. No generative AI tool was used to create, alter, analyze, or interpret experimental data, micrographs, metallographic cross-sections, thermograms, OCT scans, spectra, numerical simulations, measured fields, or quantitative results. Because verbatim prompt logs were not retained, the prompts reported in the figure captions were faithfully reconstructed from the authors’ design instructions and revision history and are explicitly identified as reconstructions rather than verbatim records. The authors critically reviewed and edited all AI-assisted outputs, verified their scientific meaning, corrected labels and graphical elements, and take full responsibility for the accuracy, integrity, and final content of the manuscript and figures. The authors have reviewed and edited the output and take fully responsible for the content of this publication.

Conflicts of Interest: Authors Maricruz Hernández-Hernández and Adriana Gallegos-Melgar were employed by the Secihti-InnovaBienestar de México. They declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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