

Review

A Review of Research Progress on Surface Defect Detection Methods for Battery Shells of New Energy Vehicles

Dongdong Ge ^{1,2,*}  and Guiyang Jin ¹¹ Intelligent Equipment Research Institute, Ningbo Polytechnic University, Ningbo 315800, China; 2019030@nbpu.edu.cn² Ningbo AOMATE High Precision Power Press Co., Ltd., Ningbo 315800, China

* Correspondence: 2023043@nbpu.edu.cn

Abstract

Driven by the dual-carbon target strategy, the new energy vehicle industry has achieved large-scale and rapid development. As the core protective component of power batteries, the surface quality of battery shells directly determines the operational safety and reliability of batteries. However, defects such as scratches, pits, and cracks easily occur on battery shells during forming processes, including stamping and deep drawing. Traditional manual detection suffers from bottlenecks, such as high labor intensity, low detection efficiency, and high false detection rates, making it difficult to adapt to the large-scale and high-cycle production requirements of modern industry. Firstly, this study systematically elaborates the material system, preparation process, and defect formation mechanism of battery shells, and clarifies the coupling mechanisms of material properties, process parameters, and equipment and environmental conditions for defect evolution. Subsequently, it compares and analyzes the principles, advantages and disadvantages, and applicable scenarios of traditional machine-vision- and deep-learning-based detection technologies, and focuses on analyzing the application performance and optimization paths of single-stage and two-stage object detection algorithms in shell defect recognition. Furthermore, it addresses the core challenges of deep-learning-based battery shell defect detection technologies in data, algorithm deployment, detection dimensions, and other aspects, and proposes targeted optimization strategies. Finally, the development directions, such as system integration and online learning, are forecasted. This study can provide theoretical support and technical references for the intelligent manufacturing of battery shell stamping and forming, as well as for surface defect detection.

Keywords: power battery shell; surface defect detection; machine vision; deep learning; intelligent manufacturing



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1. Introduction

Guided by the global dual-carbon targets and the accelerated energy structure transition, the new energy vehicle (NEV) industry has entered a stage of large-scale explosive growth and become the core force driving green and low-carbon development of the transportation sector [1,2]. As the power core of NEVs, the performance and safety of lithium-ion batteries (Libs) directly determine the vehicle's driving range, service life, and driving safety. Its technological iteration and quality control have always been research focuses of both industry and academia [3,4]. Since 2014, the installed capacity of Libs in global electric vehicles has grown at a rate of over 40% per year. In 2024, the global installed

capacity of power batteries exceeded 1500 GWh, with a year-on-year increase of more than 35%. Among them, square batteries have gained a market share of over 80% and become the mainstream technical route, owing to their advantages of 15–20% higher space utilization rate than cylindrical batteries, excellent assembly efficiency, and high structural strength [5,6].

As a key structural component and safety barrier of the power battery system, the battery shell undertakes core functions such as cell protection, heat dissipation, mechanical protection, and insulation isolation [7]. Its manufacturing quality directly affects the sealing performance, structural stability, and electrochemical performance of the battery. Under the working conditions of high-frequency charging and discharging, complex road vibrations, and extreme environments of NEVs, surface defects of the shell easily induce potential safety hazards; defects such as scratches, pits, and cracks not only reduce the structural strength of the shell but also damage the sealing performance, cause electrolyte leakage, and even form stress concentration points that can induce shell rupture, eventually leading to an internal short circuit of the battery and triggering a thermal runaway chain reaction [8,9]. Therefore, realizing the accurate detection and strict control of surface defects of battery shells is a key link to ensure the safe operation of power batteries, improve product consistency, and reduce after-sales risks, which have important theoretical research significance and engineering application value.

Early defect detection of battery shells mainly adopts manual visual inspection and manual touch. Although this method is flexible in operation, it has inherent limitations, such as high labor intensity, low detection efficiency, and strong subjective dependence. Affected by factors such as personnel experience and fatigue, the false detection rate is as high as 20–30%, which is difficult to meet the large-scale and high-takt production requirements of the modern industry [10]. Eddy current testing demonstrates superior robustness in detecting surface-breaking flaws in ferromagnetic materials due to their high magnetic permeability [11]. With the iterative upgrading of intelligent manufacturing technology, automated detection methods based on machine vision have gradually replaced manual detection as the mainstream technical path in the industry due to their advantages of fast detection speed, high accuracy, and good repeatability [12,13].

At present, machine vision detection for surface defects of battery shells is mainly divided into two technical systems: traditional machine vision and deep learning [14]. Traditional machine vision extracts defect features through manually designed algorithms, such as edge detection, threshold segmentation, and morphological processing, which is applicable in scenarios with stable illumination and regular defect shapes. However, it has shortcomings, including feature design relying on professional experience, weak generalizability, and poor adaptability to complex defects and environmental interference [15,16]. Deep learning realizes automatic learning of defect features and end-to-end detection through neural networks; shows significant advantages in the detection of multi-type, subtle, and morphologically variable defects; and has become a research hotspot in recent years [17,18]. However, many urgent challenges remain in this field: firstly, defect samples are scarce and category-imbalanced, and key defects, such as microcracks and local thinning, occur with low probability, limiting the generalizability of the model [19]; secondly, most battery shells are made of metal with strong surface reflection and complex textures, which easily blur defect features [20]; thirdly, industrial scenarios have strict requirements for the real-time performance, lightweight, and robustness of detection systems, and existing algorithms still have room for improvement in balancing accuracy, speed, and edge device deployment [21]; and fourthly, detection technology mostly focuses on two-dimensional surface defect recognition, and lacks the quantitative detection capability for three-dimensional geometric tolerances, such as scratch depth and pit volume [22].

In response to the above problems, this study systematically sorts out the technological evolution and research status of surface defect detection for NEV battery shells, and conducts an in-depth analysis focusing on defect formation mechanisms, detection method innovations, and engineering applications. The main contributions of this paper are as follows:

1. Comprehensively analyze the defect formation mechanism in the production process of battery shells, clarify the characteristics and key influencing factors of various defects, and provide a theoretical basis for the design of detection methods.
2. Systematically compare the technical principles and detection processes of traditional machine vision and deep learning detection methods, and focus on analyzing the application performance and optimization directions of single-stage and two-stage object detection algorithms in battery shell defect recognition.
3. Deeply explore the key challenges faced by current detection technologies, such as data scarcity, insufficient environmental robustness, and lack of three-dimensional detection; and propose targeted solutions, including data augmentation, multimodal fusion, and lightweight deployment, combined with industrial practical needs.
4. Prospect the future development trends of this field, including online learning, integration of digital twins and virtual simulations, and construction of detection–diagnosis–decision closed-loop systems; and provide references for relevant research and engineering practice.

The specific structure of this paper is as follows: Section 1 introduces the study; Section 2 analyzes the preparation process of battery shells and the formation mechanisms and characteristics of surface defects; Section 3 elaborates the process and core methods of machine vision defect detection; and Section 4 discusses the technical challenges and future development directions.

2. Defect Formation Mechanism and Characteristic Analysis

2.1. Classification and Preparation Process of Battery Shells

The structural design and preparation process of power battery shells for NEVs directly determine their mechanical properties, sealing performance, and safety characteristics. Classified by their geometric form and application scenarios, mainstream products are divided into two categories—cylindrical and square, as shown in Figure 1. The two types have significant differences in material selection, forming processes, and performance priorities.



Figure 1. Deep-drawn battery shells.

Cylindrical battery shells are mainly made of BDCK cold-rolled steel, as specified in GB/T34212-2017. This material has a tensile strength of 275 MPa and a hardness of 40–56 HRB, which can not only meet the stamping and forming requirements but also

provide reliable mechanical protection [23]. Its core preparation process is steel sheet stamping forming, in which a cold-rolled steel sheet is stamped into a cylindrical shell one at a time through a die. Some shells are treated by sandblasting or shotblasting to improve wear resistance and electrochemical compatibility, but improper process parameter controls will easily introduce micro-pits or texture damage [24]. This type of shell has mature technology and low cost, but its space utilization is limited, and its market share in the power battery field of NEVs has dropped to less than 20%.

Square battery shells have become the mainstream choice for NEV power batteries due to their high space utilization, excellent assembly efficiency, and strong structural stability. To meet the lightweight demand of NEVs, square shells mostly adopt six-series or seven-series aluminum alloy materials. These materials have both high strength and good formability, and can meet the preparation requirements of high-aspect-ratio structures with a depth ≥ 100 mm and wall thickness ≤ 1 mm [25]. Its core preparation process is deep drawing, which gradually forms an aluminum alloy flat blank into an open hollow part through a die. Complex structures require multi-pass deep drawing or ironing drawing processes. Deep drawing is easy to realize continuous automatic production, with a single production-line speed of up to 80–120 m/min. However, the process parameters are highly sensitive, and the material flow state directly affects the surface quality of the shell [26,27].

In addition to traditional deep drawing processes, a variety of advanced forming technologies have been developed in the industry to meet higher performance requirements: multi-point forming technology adapts to the forming needs of complex curved surfaces through flexible dies and reduces local stress concentrations [28]; pulsating deep drawing improves the uniformity of material flow through periodic pressure changes [29–31]; and peripheral pressurized liquid-filled deep drawing uses liquid pressure to achieve uniform material extension, effectively reducing the risks of wrinkling and cracking [32]. For ultra-high-aspect-ratio shells, multi-pass ironing drawing composite technology has become a key technology [33,34]. Du Bing et al. proposed a scheme combining multi-pass deep drawing and single-die ironing drawing. By reasonably distributing the deformation of each process, thin-walled high-box parts with high dimensional accuracy and excellent surface quality can be prepared, with a wall thickness reduction rate of more than 30% and no obvious defects [35].

2.2. Defect Formation Mechanism and Key Influencing Factors

The formation of surface defects on battery shells is affected by the coupling of multiple factors, such as material properties, process parameters, equipment status, and environmental conditions. The defect formation mechanisms vary greatly between different preparation stages.

2.2.1. Material Properties

Raw material quality is the basis for determining the surface quality of the shell. Defects including impurities, pores, and oxide inclusions in aluminum alloy or cold-rolled steel materials can be directly inherited in the finished shell. Fe and Si impurity particles in the form of hard and brittle phases in aluminum alloy ingots will become stress concentration points in the subsequent deep drawing process, resulting in microcracks on the surface; meanwhile, oxide scale that is not completely removed from the surface of cold-rolled steel will be pressed into the matrix during stamping and form pits or scratches [36]. The uniformity of a material's mechanical properties is also critical. When the yield strength fluctuation of aluminum alloy exceeds 5%, local excessive deformation easily occurs during deep drawing, leading to wrinkling or cracking defects [37]. In addition, the surface roughness of the material needs to be strictly controlled, as excessively high roughness

will increase die friction, and excessively low roughness will easily lead to insufficient lubrication, both of which will induce surface scratches. The influence of material properties on defect formation is shown in Table 1.

Table 1. The influence of material properties on defect formation [23,25,36,37].

Influencing Factors	Key Control Indicators	Defect Induction Mechanisms	Typical Defect Types	Prevention and Control Measures
Raw material purity	Aluminum alloy shells: impurity content $\leq 0.05\%$ (Fe, Si, etc.); Steel shells: mass fraction of non-metallic elements (S, P) $\leq 0.03\%$	Impurity particles become stress concentration points, leading to local material fracture or bulging during the deep drawing process	Cracks, bulges, pits	Select high-purity raw materials; incoming inspections performed per national standards
Uniformity of mechanical properties	Yield strength fluctuation $\leq 5\%$	Local strength differences lead to uneven material flow, causing stress concentration	Wrinkling, cracking	Optimize the heat treatment process of materials to ensure consistency in mechanical properties
Surface quality (for general grade)	Surface roughness Ra: 0.8~1.6 μm (aluminum alloy), 1.0~1.6 μm (steel shell)	Oxide scale is pressed into the matrix, forming pits and surface scratches that expand during deep drawing	Pits, scratches	The surface of raw materials should be polished, and moisture and oxidation protection measures should be taken during storage
Plasticity index	Elongation rate $\geq 15\%$ (aluminum alloy)	Insufficient plasticity leads to insufficient material extension during the deep drawing process, making it prone to fracture	Cracks, fissures	Select high-plasticity aluminum alloy materials

2.2.2. Process Parameters

Precise cooperative control of process parameters is the core to avoiding defects. Taking the deep drawing process as an example, the matching degrees of deep drawing coefficient, blank holder force, deep drawing speed, and lubrication conditions directly determine the material flow state. The deep drawing coefficient is a core index to measure the deformation degree. When the single-pass deep drawing coefficient exceeds the material limit, the stress in the force transmission area exceeds the material strength limit, and tensile cracks easily occur in weaker parts, such as the punch fillet; meanwhile, an excessively small deep drawing coefficient will lead to excessive tangential compressive stress on the outer edge of the blank and cause flange wrinkling.

The setting of the blank holder force (BHF) is critical for wrinkling suppression. An excessively small BHF cannot constrain material flow, while an excessively large BHF increases frictional resistance, leading to surface scratching or cracking. BHF is dynamically adjusted according to the material's thickness and deep drawing coefficient, and is usually controlled at 15–30% of the material's yield strength [31]. The matching of deep drawing speed and lubrication conditions also directly affects surface quality. Low-speed deep drawing (5–10 mm/s) facilitates sufficient material flow but features low production efficiency; high-speed deep drawing (15–25 mm/s) can improve productivity but requires matching with high-performance lubricants. Otherwise, lubrication failure caused by frictional heat accumulation will easily occur, leading to die aluminum adhesion and surface scratching [38].

In the multi-pass deep drawing process, inter-process annealing treatment is a critical step. The work hardening caused by aluminum alloy deep drawing reduces material plasticity, and failure to perform annealing treatment in a timely manner will easily lead to crack propagation in subsequent processes. The ironing deep drawing process has higher

precision requirements for matching of the die's cone angle, clearance, and drawing speed. A cone angle deviation exceeding 0.5° will result in uneven material thickness, causing surface protrusions or depressions [39]. The influence of process parameters on defect formation is shown in Table 2.

Table 2. The influence pattern of process parameters on defect formation.

Process Type	Key Parameters	Reasonable Value Range	Defect Induction Mechanism	Typical Defect Types
Single-pass drawing [25,31] (aluminum alloy shells)	Drawing coefficient	0.5~0.8	An excessively large coefficient leads to stress exceeding the strength limit in the force transmission area; an excessively small coefficient leads to excessive tangential compressive stress	Cracking, wrinkling
	Blank holding force	15~30% of the material's yield strength	Too small and it cannot constrain the flow of material; too large and the frictional resistance increases	Wrinkling, scratching, tearing
	Deep drawing speed	5~25 mm/s,	Too low results in low production efficiency; too high leads to lubrication failure and accumulation of frictional heat	Scratching, aluminum adhesion
Multi-pass drawing [25,38] (aluminum alloy shells)	Inter-process annealing	300~350 °C, with heat preservation for 1~2 h	Failure to anneal causes work hardening, leading to a decrease in plasticity	Crack propagation, fracturing
Thinning drawing	Cavity cone angle [23,39,40]	Aluminum alloy shells: 10~20°; Steel shells: 8~18°	If deviation of the cone angle exceeds 0.5° , the material's thickness is uneven	Convex, concave
	Mold clearance [23,39]	Aluminum alloy shells: 1.05 to 1.1 times the thickness of the material; Steel shells: 1.03~1.08	Too small a gap increases friction; too large a gap causes material rebound	Scratching, deformation

2.2.3. Equipment and Environment

The status of forming equipment has a direct impact on the surface quality of battery shells. Die precision and surface conditions are the core factors. The die's surface roughness R_a should be controlled within 0.02–0.05 μm . If the die is worn, scratched, or adhered with metal chips, then corresponding scratches or indentations will be formed on the shell's surface. The uniformity of die clearance is also critical. A unilateral clearance deviation exceeding 0.01 mm will lead to uneven material stress, causing mouth deformation or side wall inclination. The precision of the stamping machine affects the force stability during the forming process. When the slider parallelism deviation exceeds 0.02 mm/m, local stress concentration occurs in the shell, which tends to produce crack or deformation defects.

The cleanliness, temperature, and humidity controls of the production environment cannot be ignored. When the dust concentration in the workshop exceeds 0.5 mg/m³, dust particles enter the contact surface between the die and the material, forming pits or scratches. Environmental temperature fluctuations exceeding $\pm 5^\circ\text{C}$ will change the mechanical properties of the material, affecting the adaptability of process parameters. When the relative humidity is below 40%, the material surface is prone to electrostatic dust adsorption, increasing defect risks. In the transportation and turnover stages, collisions and friction between shells or improper contact with fixtures will cause subsequent defects, such

as dents and scratches. The influence of equipment and environment on defect formation is shown in Table 3.

Table 3. The influence pattern of equipment and environment on defect formation [17,41,42].

Impact Type	Key Control Indicator	Defect Induction Mechanism	Typical Defect Type
Mold status	Surface roughness is $Ra \leq 0.05 \mu\text{m}$, with no wear or material adhesion	Mold scratches/adhesive residues are directly transferred to the surface of shells; insufficient precision leads to uneven stress distribution	Scratching, indentations, deformations
Stamping machine accuracy	Slider parallelism $\leq 0.02 \text{ mm/m}$, guide rail clearance $\leq 0.01 \text{ mm}$	Local stress concentration in the housing caused by out-of-tolerance parallelism/clearance	Cracking, deformations, mouth inclinations
Environmental cleanliness	Dust concentration $\leq 0.5 \text{ mg/m}^3$	Dust particles enter the contact surface between the mold and material, forming indentation defects	Pitting, indentations
Temperature and humidity controls	Temperature: $20\sim 28^\circ\text{C}$; Relative humidity: $40\sim 60\%$	Temperature fluctuations exceeding $\pm 5^\circ\text{C}$ can cause changes in the mechanical properties of materials; excessively low humidity can lead to electrostatic adsorption of dust	Wrinkling, cracking, pitting
Turnover transportation	Surface hardness of fixture: $28\sim 35 \text{ HRC}$ (aluminum alloy shell), $48\sim 58 \text{ HRC}$ (steel shell)	Collision and friction cause surface damage	Bruising, scratching

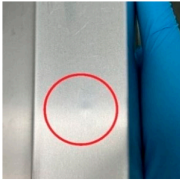
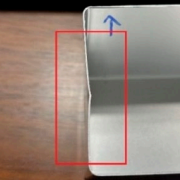
2.3. Typical Defect Types and Characteristics of Battery Shells

Combined with industrial production practices, the typical surface defects of battery shells can be divided into eight categories [43]. The morphological characteristics, formation stages, and causes of each defect are shown in Table 4. Among these defects, perforation, cracking, and severe deformation are fatal defects that directly lead to product scrapping. Scratches and pits exceeding the allowable range (scratch depth $> 0.05 \text{ mm}$, pit diameter $> 1 \text{ mm}$) will significantly reduce the corrosion resistance and structural stability of the shell, and easily evolve into serious potential safety hazards during battery charge–discharge cycles or vehicle driving vibration. When the surface scratch depth exceeds 10% of the wall thickness, the shell fatigue life will be reduced by more than 40%, and corrosion cracking is more likely to occur in high-temperature and high-humidity environments. Therefore, the accurate identification of various defects and analysis of their formation mechanisms are the basis for formulating detection strategies and process optimization schemes.

Table 4. Typical defect characteristics and formation reasons on the surface of battery shells.

Defect Type	Schematic Diagram	Morphological Characteristics	Main Formation Stage	Possible Causes
Pit		Circular or irregular depressions, with a depth ranging from 0.02 to 0.3 mm and a diameter spanning from 0.1 to 5 mm, exhibiting no discernible pattern in their distribution	Deep drawing, stamping	Impurities in raw materials, impurities pressed into the mold surface, and local plastic deformation of materials during the deep drawing process

Table 4. Cont.

Defect Type	Schematic Diagram	Morphological Characteristics	Main Formation Stage	Possible Causes
Protrusion		Localized bulging protrusions, with a height ranging from 0.01 to 0.2 mm, and are mostly distributed in a punctate or small-area pattern	Deep drawing, annealing	Impurities in raw materials, material accumulation during the deep drawing process, and uneven oxidation during the annealing process
Scratch		Linear or strip-shaped grooves, with widths ranging from 0.01 to 0.5 mm and varying lengths, and are distributed along the forming direction or circumferential direction	Deep drawing, transportation, surface treatment	Mold surface scratches or material adhesion during turnover process, improper surface treatment process parameters
Punching		Irregular-shaped holes, with hole diameters ranging from 0.1 to 2 mm, and a complete absence of material	Deep drawing, cutting	Local stress exceeding the tensile strength of materials, deviation in cutting process, and material deficiency
Gap		The material on the inside of the shell mouth is missing, appearing as white dots or short stripes, with a length of 0.5~3 mm	Cutting, stamping	Wear of cutting tools, defects in the cutting edge of stamping dies, and process positioning deviations
Damage		Multiple small through-holes in a regional pattern appear on the surface	Transportation, surface treatment	Exposure to impacts, corrosion, etc., during processing, transportation, or use
Shell deformation		The shell is twisted and deformed	Stamping, transportation	External force compression or uneven stress distribution at various parts during the molding process
Mouth deformation		Deformation occurs in the material of the small surface of the shell	Deep drawing, assembly	Wear of the mold, improper assembly, or unreasonable temperature control during the molding process

3. Surface Defect Detection Methods for Battery Shells

Surface defect detection technology for battery shells has evolved from traditional manual identification to an automated detection paradigm with machine vision as the core. Technically, it can be divided into two core systems of traditional machine vision

and deep learning, both of which follow the basic logic of “image acquisition–image preprocessing–image recognition”.

3.1. Machine-Vision-Based Defect Detection Process

The machine-vision-based defect detection process mainly consists of five steps: image acquisition, image preprocessing, model training, model evaluation, and result output.

Step 1: Image acquisition

Image acquisition is the first critical step of the detection process, and its quality directly determines the upper limit of subsequent analysis and recognition. This step requires rational configuration of light sources, industrial cameras, optical lenses, and other hardware to build an imaging system adapted to the material and defect characteristics of battery shells, thus obtaining images with high contrast and clear defect features, as shown in Figure 2.

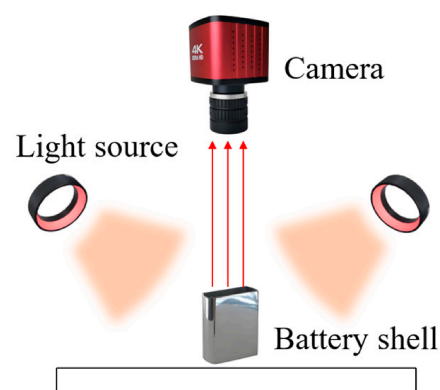


Figure 2. Schematic diagram of image acquisition.

The light source arrangement is a key factor affecting imaging quality, which should be designed according to the reflectivity, texture characteristics, and defect geometry of the shell material. It mainly includes three technical dimensions.

(1) Illumination mode and angle. According to the geometric relationship between the light irradiation direction and the camera observation direction, illumination is mainly divided into bright-field illumination and dark-field illumination. Bright-field illumination places the light source on the same side as the camera, which is suitable for highlighting surface color changes, stains, and defects with obvious reflectivity differences from the background. Dark-field illumination adopts low-angle or lateral irradiation, so that the reflected light from the flat surface does not enter the lens. Minor defects, such as scratches and depressions, are highlighted due to the light scattering effect, which has an excellent effect on detecting subtle textures and contour defects.

(2) Illumination intensity and uniformity. The intensity should ensure the image has a sufficient signal-to-noise ratio to avoid overexposure or underexposure. For large-area shell detection, diffuser plates or multi-light source arrays should be adopted to achieve uniform illumination, eliminate brightness gradient artifacts, and ensure detection stability and consistency.

(3) Light source color. Selecting a light source color matching the spectral reflection characteristics of the shell and defects can effectively enhance the contrast between defects and the background. For aluminum alloy shells, wavelength-specific light sources are more sensitive to oxidation spots; by using colored light sources or combining these with multispectral imaging, they can better distinguish defects, such as oil stains and watermarks, that are similar in color to the material.

Typical industrial inspection systems adopt targeted hardware configurations for different shell types. For prismatic power battery aluminum shells, a typical surface defect detection station is equipped with a 12-megapixel global shutter industrial camera paired with a bi-telecentric lens, and integrates coaxial diffuse illumination and dual-sided strip light sources to suppress specular reflection on metal surfaces, enabling full-surface imaging of the four side walls and bottom face [44]. For high-speed cylindrical steel shell production lines, a 4K line-scan camera paired with an annular low-angle dark-field illuminator is widely adopted to achieve unwrapped cylindrical surface imaging and accommodate high-speed stamping throughput [45].

Step 2: Image preprocessing

The main purpose of image preprocessing is to eliminate or suppress the interference of irrelevant information, enhance key features related to defects, and thus improve the robustness and accuracy of subsequent defect recognition and classification algorithms. Affected by industrial camera performance, ambient light interference, uneven light sources, and even the reflective characteristics of the battery shell material itself, battery shell images often encounter problems, such as noise, uneven illumination, low contrast, and background texture interference. Image preprocessing can effectively improve image quality and provide stable and reliable inputs for model training and evaluation. A typical preprocessing process follows the logic of “denoising–enhancement–segmentation”.

Image filtering is a core method for suppressing noise. Common spatial domain filtering methods include mean filtering, median filtering, and frequency domain filtering. Mean filtering smooths the image through local neighborhood averaging, which can effectively suppress Gaussian noise but easily cause edge blurring. Median filtering replaces pixels with the median value sorted by the gray values in the neighborhood, which can effectively remove salt-and-pepper noise while retaining edge information, and is more conducive to protecting defect contours. Frequency domain filtering converts the image to the frequency domain and designs filters for the targeted removal of periodic noise or interference fringes at specific frequencies.

Image enhancement aims to improve visual contrast and detail expression. For the problem of uneven illumination, the Retinex algorithm or homomorphic filtering can be used to enhance local contrast while compressing the brightness range. For images with insufficient overall contrast, histogram equalization or contrast-limited adaptive histogram equalization can be used to limit the amplification of local contrast and avoid excessive noise enhancement, which are suitable for processing large-area brightness changes in battery shells.

Threshold segmentation preliminarily separates potential defect regions from the background. When the battery shell background is relatively uniform, global threshold segmentation is computationally efficient. If there is an illumination gradient, adaptive threshold segmentation can dynamically calculate the threshold according to the local characteristics of the pixel neighborhood. For cases where the gray values of the background and defects overlap greatly, edge detection, region growing and other methods can assist in complex defect segmentation.

In recent years, preprocessing research has shown a development trend of integration with deep learning and adaptive optimization. Lightweight neural networks directly learn end-to-end mappings from low-quality original images to optimized images so as to achieve more intelligent and task-specific preprocessing. Adaptive preprocessing can automatically adjust preprocessing algorithms and parameters according to the quality of real-time collected images, improving system generalizability and detection stability.

Step 3: Model training

The goal of model training is to drive neural networks to automatically learn the essential features of defects from labeled data through optimization algorithms, and establish an accurate mapping from input images to defect categories, positions, and pixel-level masks. It is the core link that determines the detection accuracy, robustness, and generalizability of the model. The core challenge is to achieve the accurate identification of subtle defects in complex backgrounds with limited and unbalanced defect samples while resisting environmental disturbances, such as illumination and angle changes.

The training process generally first adopts transfer learning with a pre-trained model on a large general dataset to accelerate convergence and improve small-sample performance. Then, a data flow pipeline is constructed, and online data augmentation is implemented to expand data diversity. Subsequently, a loss function and optimizer suitable for the task are configured. Network parameters are iteratively updated through forward propagation and backpropagation. In this process, training loss and validation set indicators are monitored, and an early stopping strategy is adopted to prevent overfitting.

Mainstream training methods include supervised learning, unsupervised learning, and semi-supervised learning. Supervised learning trains models based on labeled data and is the mainstream in industrial applications. Unsupervised learning is trained on the normal sample distribution of unlabeled data, thereby identifying defects deviating from the distribution. Semi-supervised learning combines a small amount of labeled data with a large amount of unlabeled data to reduce labeling costs. To ensure efficient model training, a multi-level optimization strategy is required, as shown in Table 5. These techniques differ significantly in industrial maturity, applicable scenarios, and practical constraints, which are further detailed in the table. At the algorithm level, knowledge distillation and self-supervised pre-training can improve model lightweight and generalization capabilities; at the computational level, mixed-precision training and distributed parallelism can significantly improve training efficiency. Future research will further develop towards self-supervised learning with reduced labeling dependence, automated and intelligent training processes, and lightweight training for extreme edge scenarios.

Table 5. Comparison of key optimization techniques for model training efficiency.

Optimization Category	Core Technology	Principle and Function	Maturity and Limitations
Algorithmic strategy	Knowledge distillation	We transfer the knowledge of large and complex teacher models to lightweight student models, significantly reducing model size and inference latency while maintaining high accuracy.	Industrial adoption—Widely applied to lightweight edge deployment and model compression for production-line inspection systems; inherent accuracy loss exists, and performance depends on the alignment between the teacher model and target scenarios.
	Self-supervised pre-training	Utilizing a vast amount of unlabeled battery shell images, we design a proxy task to pre-train a model by learning a robust and general visual representation, thereby significantly reducing the reliance on labeled data.	Technology development—Rapidly validated in few-shot defect scenarios and gradually piloted in leading production lines; requires heavy computational investment for pre-training, and a domain gap exists between general pre-trained models and metal surface inspection scenarios.
	Automated hyperparameter optimization	We utilize Bayesian optimization, evolutionary algorithms, and other techniques to automatically search for the optimal combination of hyperparameters, replacing time-consuming manual parameter tuning and enhancing experimental efficiency.	Academic demonstration—Primarily used for hyperparameter tuning during algorithm R&D, and rarely deployed online for frozen production models; incurs high computational overhead for searching, and industrial parameters are mostly fixed based on process experience.

Table 5. Cont.

Optimization Category	Core Technology	Principle and Function	Maturity and Limitations
Computing hardware	Mixed precision training	Forward/backward propagations use FP16 floating-point numbers while weight updates utilize FP32, fully harnessing the computational power of modern GPU tensor cores to achieve 1.5–3 times speedup in training.	Industrial adoption—A standard technique natively supported by mainstream training frameworks and universally adopted in industrial model training; numerical stability degrades at extremely low bit widths, and acceleration gains are insignificant for small-scale models.
	Distributed data parallelism	We split the data into multiple GPU slices, with each card holding a complete copy of the model. After independent gradient computation, we synchronize and average the results to achieve a near-linear speedup ratio.	Industrial adoption—A de facto standard for large-scale dataset training and a default configuration for production-line model iteration; introduces communication overhead across multi-node clusters, and the speedup ratio decays noticeably for small-batch datasets.
	Gradient communication optimization	By adopting technologies such as gradient compression and sparse transmission, the communication bandwidth pressure between nodes in distributed training is reduced, thereby enhancing overall efficiency.	Technology development—Only applicable to ultra-large-scale training clusters and rarely used in general industrial scenarios; features high implementation complexity, with negligible performance gains for small- and medium-scale clusters.

Step 4: Model Evaluation

Model evaluation is a core link connecting algorithm research and industrial application. It aims to quantify the generalization performance, robustness, and practicality of models on independent datasets, providing a scientific basis for model selection, performance comparison, and optimization direction while ensuring that industrial accuracy, speed, and stability requirements are met. Model evaluation is divided into classification tasks, detection tasks, and segmentation tasks according to task types, and the calculation methods for each core indicator are as follows.

(1) Classification task

This type of indicator measures the model's ability to distinguish "defective or not" battery shells and their defect types. Based on the confusion matrix, accuracy, precision, recall, F1-score, and ROC-AUC are used to measure the model's classification ability.

Accuracy represents the proportion of correctly predicted samples in the total samples, which is an intuitive reflection of overall performance, as shown in Equation (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where true positive (TP) and false positive (FP) represent the number of correct and incorrect predictions, respectively, for samples belonging to the category; while true negative (TN) and false negative (FN) represent the number of correct and incorrect predictions for samples not belonging to the category.

Precision refers to the proportion of actual defective samples in all samples predicted as defects by the model. The high-standard requirement aims to reduce false rejects, as shown in Equation (2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall rate represents the proportion of all real defective samples correctly identified by the model. The high-standard requirement aims to strictly control missed detections, as shown in Equation (3).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score represents the weighted average of precision and recall, used to comprehensively evaluate the balance between the two. Its value ranges from 0 to 1, where 1 indicates perfect model performance and 0 indicates the worst model performance, as shown in Equation (4).

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

Receiver operating characteristic (ROC) refers to the receiver operating characteristic curve. The abscissa of the curve is the false positive rate (FPR), and the ordinate is the true positive rate (TPR). A classifier can obtain a TPR and FPR point pair according to its performance on test samples, which is mapped to a point on the ROC plane.

TPR refers to the proportion of samples truly classified as positive in all actual positive samples, as shown in Equation (5).

$$TPR = \frac{TP}{TP + FN} \quad (5)$$

FPR represents the proportion of samples incorrectly classified as positive in all real negative samples, as shown in Equation (6).

$$FPR = \frac{FP}{FP + TN} \quad (6)$$

Area under the curve (AUC) refers to the area under the ROC curve, which is used to evaluate the overall ranking and discrimination ability of the model. The AUC value usually ranges from 0.5 to 1, and the closer to 1, the better the model performance, as shown in Figure 3.

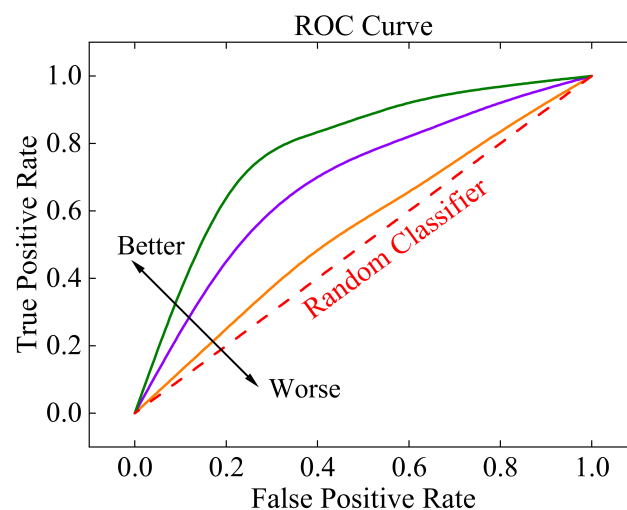


Figure 3. Schematic of ROC curve.

(2) Detection task

Based on Intersection over Union (*IoU*), this type of indicator uses average precision (*AP*) and mean average precision (*mAP*) to evaluate the comprehensive performance of positioning and classification, and is the core evaluation standard for object detection algorithms.

IoU is the ratio of the intersection area to the union area between the predicted bounding box and the real bounding box, and is used to measure the positioning overlap degree, as shown in Equation (7).

$$IoU = \frac{P \cap GT}{P \cup GT} = \frac{TP}{TP + FP + FN} \quad (7)$$

For a single defect category, average precision (*AP*) calculates the precision at different recall thresholds and obtains the area enclosed by the precision–recall (P-R) curve. The calculation methods include discrete sampling interpolation and full-point integration.

The discrete sampling interpolation method selects 11 equally spaced sampling points on the recall axis for precision interpolation and averaging. For each recall point, the maximum precision corresponding to all recall points greater than or equal to its position is calculated, which is called right-side maximum interpolation, as shown in Equation (8), where r is the discrete point and $P(r)$ is the precision value. *AP* is the arithmetic mean of 11 interpolated precisions, as shown in Equation (9).

$$P_{\text{interp}}(r_i) = \max_{\tilde{r} \geq r_i} P(\tilde{r}) \quad (8)$$

$$AP = \frac{1}{11} \sum_{r \in \{0,0.1,\dots,1.0\}} P_{\text{interp}}(r) \quad (9)$$

To further improve the accuracy of *AP* calculation, the full-point integration method is used to calculate the exact area under the P-R curve; that is, the continuous integration for all recall points. Firstly, the precision value of each recall point is replaced with the maximum precision value of all recall points on its right side; that is, the P-R curve is smoothed, as shown in Equation (10). Then, the area of the P-R curve is calculated by discrete summation to obtain the *AP*, as shown in Equation (11), where n is the number of discrete rectangles.

$$P_{\text{smooth}}(r) = \max_{\tilde{r} \geq r} P(\tilde{r}) \quad (10)$$

$$AP = \sum_{i=1}^n (r_i - r_{i-1}) \cdot P_{\text{smooth}}(r_i) \quad (11)$$

Mean average precision (*mAP*) refers to the average value of *AP* for all defect categories, and has become a standard evaluation indicator for mainstream detection models, such as You Only Look Once (Yolo) v8.

(3) Segmentation task

This type of indicator uses mean Intersection over Union (*mIoU*) and Dice coefficient to measure pixel-level segmentation accuracy. The Dice coefficient is more sensitive to tiny defects and is suitable for the quantitative evaluation of micro-defects in shells.

The *mIoU* is calculated by separately calculating the *IoU* of each category and then averaging all categories, as shown in Equation (12), where C is the total number of categories.

$$MIoU = \frac{1}{C} \sum_{C=1}^C \frac{TP_C}{TP_C + FP_C + FN_C} \quad (12)$$

The Dice coefficient is a pixel-level similarity metric used to measure the similarity between the predicted segmentation region and the real region, as shown in Equation (13).

$$Dice = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (13)$$

Compared with the *IoU* indicator, the Dice coefficient contributes equally to the intersection and union of predicted results and real labels, while *IoU* pays more attention

to the intersection. Therefore, the Dice coefficient is more sensitive to the evaluation of tiny defects, while *IoU* is more suitable for large-target detection and segmentation tasks.

In summary, in the practical application of battery shell defect detection, it is necessary to select an indicator combination according to the detection task requirements, simultaneously consider engineering indicators, such as inference speed and model complexity, and complete the comprehensive evaluation and deployment selection of the model.

Step 5: Output the results

The core of result output is to convert model predictions into standardized, executable structured industrial control information. The system outputs structured data (JSON/XML format), such as defect category, position, confidence, and quantitative features, and generates defect annotation through visual images for manual review and quality traceability.

This link can realize the closed-loop intelligent manufacturing of detection–execution–feedback. In actual production, according to the detection results, the robotic arm is triggered to sort defective shells, the inkjet printer performs position marking, and the data are synchronized to the manufacturing execution system. Through statistical analysis of defect patterns, early warnings are fed back to upstream processes, such as stamping and welding, to realize adaptive parameter adjustment. Finally, a full life cycle digital quality file of battery shells is formed, providing data support for process optimization and predictive maintenance. The overall process of machine-vision-based defect detection is shown in Figure 4.

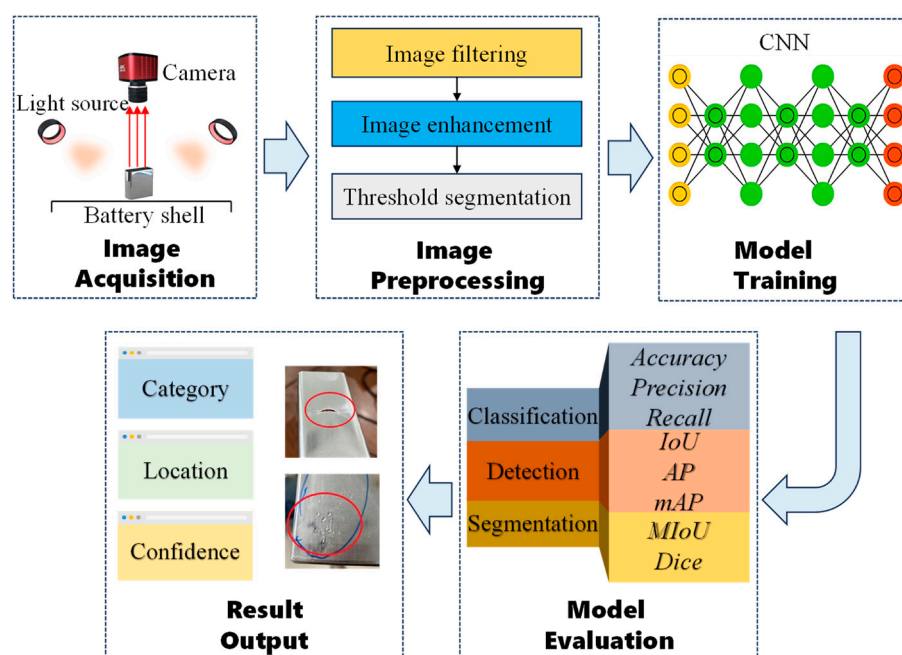


Figure 4. Flowchart of shell defect detection based on machine vision.

In mass-production applications, the aforementioned prismatic aluminum shell inspection system achieved a mean average precision of 97.2–98.1% across eight typical defect categories, with a false positive rate below 1.2% and a single-shell inspection cycle of less than 2 s, matching a line throughput of 80–120 parts per minute [44,46]. For cylindrical steel shell production lines, the high-speed vision system delivered a 100% recall rate for fatal defects, including perforation and cracking, with an overkill rate lower than 2%, fully satisfying the quality requirements of full online inspection [45,47].

3.2. Defect Detection Methods

At present, battery shell surface defect detection technology mainly evolves and integrates along two paths: traditional machine vision and deep learning. The two have generational differences in feature extraction and defect discrimination mechanisms, which can adapt to the needs of different industrial scenarios.

3.2.1. Traditional Machine Vision

The core of traditional machine vision methods is to realize defect detection based on manually defined rules and features. Technicians design algorithms, such as edge detection, threshold segmentation, and template matching, to extract features and make judgments based on prior knowledge of defect morphology [48,49]. This method features a transparent workflow and deterministic logic, delivering high detection efficiency in scenarios with stable illumination, regular defect shapes, and uniform backgrounds. For prismatic aluminum battery shell inspection under controlled constant lighting, a typical scheme combining improved Canny edge extraction and support vector machine (SVM) classification yielded 92–94% classification accuracy for three common defect types at 30–40 frames per second [50,51]. However, its accuracy dropped by more than 15% under illumination fluctuations or diverse defect morphologies, showing pronounced environmental sensitivity.

Table 6 compares the advantages and disadvantages of common traditional machine vision algorithms. However, such methods have some limitations in industrial applications: feature extraction relies on manual design, requires professional experience, and mostly stays at extracting low-level features, making it difficult to describe the high-level semantic information of complex and subtle defects; environmental robustness is poor, so the original rules easily fail when production conditions change, requiring re-tuning parameters and high maintenance costs; and in the face of small-sample, small-target, and multi-type defect scenarios, detection accuracy and recall rates have difficulty meeting the safety requirements of power batteries.

Table 6. Advantages and disadvantages of common traditional machine vision algorithms.

Category	Methods	Advantages	Limitations	Adoption Status and Industrial Applicability	Ref
Filtering and smoothing	Improved anisotropic diffusion filtering	Significant edge preservation and enhancement for microcracks	Complex parameter tuning; weak generalization for diverse defects	Technology development: Applied in customized high-precision microcrack inspection scenarios; poor universality for variable defect types, requiring line-specific parameter calibration.	[52]
	Mean shift technique	Effectively smooths background & preserves defects in complex color/texture images	High computational load; hard to meet real-time demands of high-speed online inspection	Academic demonstration: Restricted to laboratory theoretical verification; excessive latency makes it inapplicable to high-takt battery shell production lines.	[53]
	Gaussian filtering	Simple and efficient; effectively suppresses Gaussian noise	Causes edge blurring; weakens subtle defect features	Industrial adoption: Universally configured as a standard denoising module in industrial vision systems; inherent edge blurring limits detection performance for ultra-fine scratches.	[54]

Table 6. Cont.

Category	Methods	Advantages	Limitations	Adoption Status and Industrial Applicability	Ref
Feature extraction and classification	RBF + SVM	Strong classification for nonlinearly separable defect features; high recognition rate for partial defects	Low training efficiency on large-scale datasets; kernel function & parameter selection relies on experience	Industrial adoption: A classic classification scheme widely deployed in scenarios with stable features and few defect categories; performance degrades sharply as defect diversity and sample complexity increase.	[55]
	KAZE + SVM	Stable detection of subtle defect textures via nonlinear scale space	High computational cost for feature extraction/matching; slow detection speed	Technology development: Adopted in a small number of offline high-precision detection scenarios; low extraction efficiency prevents application in high-speed production lines.	[56]
	DBF + SVM	Deep features from pre-trained models; more discriminative than hand-crafted features	Performance limited by pre-trained model domain relevance; requires traditional classifiers	Technology development: A transitional scheme combining deep features and traditional classifiers; mostly verified in academic research, with less industrial penetration than end-to-end deep learning models.	[57]
Clustering and segmentation	Uniform distribution clustering	Requires few labeled data; adaptively detects abnormal regions	Sensitive to initialization parameters; prone to noise-induced missegmentation	Academic demonstration: Poor stability under complex industrial backgrounds and noise interference; rarely integrated into mass-production full-inspection systems.	[58]
	Otsu global threshold segmentation	Fast computation; effective segmentation for images with distinct foreground–background gray contrast	Sharp performance degradation under uneven illumination or high gray overlap	Industrial adoption: A standard segmentation algorithm for uniform background scenarios; fails to maintain stability under illumination fluctuations or defect background gray overlap.	[59]
	CPICS-LBP + SVM	Improved local texture descriptor; robust to defects under uneven backgrounds	Belongs to hand-crafted features; limited expression for complex variable defects	Technology development: Optimized for specific texture backgrounds; weak generalization to variable defect morphologies, requiring targeted calibration for different shell materials.	[60]
Local features and visual attention	Visual attention mechanism	Simulates human visual saliency; quickly locates suspected defects	Complex mechanism; for auxiliary positioning only; hard to achieve precise classification & segmentation	Academic demonstration: Only serves as an auxiliary positioning module with high implementation complexity; cannot independently complete classification and segmentation.	[61]
	Canny edge detection	Accurate edge localization; classic for contour defects (scratches, cracks)	Sensitive to noise; prone to broken/false edges; requires post-processing	Industrial adoption: A classic contour detection algorithm widely deployed in industrial systems for scratch and crack inspection; false edges under noise require additional post-processing modules.	[59]

3.2.2. Deep Learning

Deep learning methods have realized a paradigm shift in battery shell defect detection from experience-driven to data-driven. Its core is to construct a multi-layer nonlinear neural network; automatically learn the high-dimensional mapping relationship between defects and backgrounds through end-to-end training; abandon manual feature engineering; and adaptively extract high-level semantic features, such as defect texture, topology, and context. It exhibits excellent generalizability and robustness in industrial scenarios with fluctuating illumination, background interference, and variable defect morphologies [62,63]. The surface smoothness, color, and reflectivity variations in aluminum alloy shells can interfere with the stable recognition of traditional machine vision, while deep learning can automatically model optical heterogeneity through end-to-end feature learning, achieving highly robust defect detection. Comparative experiments on the same prismatic battery shell dataset demonstrated that optimized single-stage detection models achieved a mean average precision of 97.2–98.5% across eight defect types while maintaining less than 3% accuracy loss under $\pm 20\%$ illumination variation [64,65], which empirically confirmed the comprehensive performance advantage of deep learning in complex industrial conditions.

According to the output granularity and task objectives, deep-learning-based defect detection networks have mainly evolved into three categories: image classification networks, object detection networks, and image segmentation networks.

The image classification network [66] has a simple structure and high computational efficiency, but it only outputs the image defect category without providing specific defect location information, and is mostly used for rapid initial screening or qualification judgment in production lines. To tackle the few-shot defect classification scenario in industry, Yang et al. [67] adopted a self-supervised contrastive learning method for pre-training on a million-scale industrial dataset covering lithium batteries and other scenarios, significantly improving the generalization performance of downstream classification tasks.

The object detection network [68] simultaneously completes defect category recognition and spatial positioning by generating bounding boxes in the image. Its annotation cost only requiring box-level annotation is much lower than that of pixel-level annotation, and the model inference speed can meet the beat requirements of most online detections. Therefore, it is most widely used in the simultaneous detection and positioning of various defects such as scratches, pits and stains on battery shells. To address the challenge of detecting small-scale surface defects on lithium battery end faces, Xing et al. [69] proposed an algorithm based on the Transformer architecture, which effectively improves the detection accuracy of small-scale defects through adaptive feature fusion.

The image segmentation network [70] assigns category labels to each pixel in the image to realize pixel-level defect contour delineation. By quantifying the defect area and analyzing morphological characteristics, its impact on battery performance and safety can be evaluated. However, pixel-level annotation has a high cost and slow model inference speed, making it suitable for offline precision analysis or key defect precision detection requiring quantitative in-depth analysis. To overcome the foreground–background imbalance in lithium battery surface defect images, Sun et al. [71] proposed a Mask-Space Optimized Transformer, which achieves highly precise semantic segmentation of irregular surface defects on lithium batteries. To meet the demand for rapid deployment of surface defect detection on lithium battery electrodes, Qiao et al. [72] proposed a self-supervised Wavelet Adaptive Restoration Module, which achieves efficient anomaly detection through frequency domain feature refinement.

As the most widely used object detection network in industrial applications, it is divided into two technical paths—two-stage and single-stage—focusing on the balance between detection accuracy and inference speed.

Two-stage detection algorithms, represented by faster Region-Based Convolutional Neural Networks (R-CNNs) and its variants, follow the refined process of “proposal first, detection later”. In the first stage, candidate regions that may contain targets are extracted from the image through a Region Proposal Network (RPN) or selective search mechanism; then, in the second stage, deep feature extraction, classification, and regression are performed for each candidate region. This two-stage design enables the model to re-examine candidate regions with more refined feature discrimination, so it has the advantage in detection accuracy for small targets and complex defects. However, the step-by-step processing mechanism also brings more computation and slower inference speed. Table 7 summarizes the cases and the advantages and disadvantages of two-stage detection algorithms. Quantitative comparisons indicate that two-stage detectors generally deliver superior localization accuracy for small- and micro-sized defects but suffer from limited inference speed; they are more applicable to offline high-precision inspection scenarios rather than high-takt online production lines.

Table 7. Summary of two-stage detection algorithm cases.

Methods	Advantages	Limitations	Ref
Improved Faster R-CNN	Integrates ResNet101, FPN multi-scale fusion, and CBAM; accurate localization for small blister defects; significantly boosts detection accuracy	Needs large annotated datasets; sometimes missed detection of ultra-small blisters (<3 μm)	[73]
Region Pyramid RPN + Faster R-CNN	Integrates dual-coordinate attention, retains defect location information, and embeds channel attention; significantly improves detection accuracy for small defect ratios (scratches, wrinkles)	Slightly reduced inference speed under complex backgrounds; depends on high-performance computing hardware	[14]
Mask R-CNN	Combines ResNet50+FPN for multi-scale feature extraction; realizes simultaneous defect detection & segmentation; supports defect contour quantification	Needs pixel-level annotated data; large model size; slow inference speed	[74]
Cascade R-CNN	Deformable convolution boosts defect feature learning; OHEM reduces missed detection of weak-feature defects; multi-stage optimization enhances classification accuracy	Long multi-stage inference; insufficient real-time performance; sensitive to imbalanced datasets	[75]
R-FCN (Multi-scale Feature Fusion)	Full-convolution structure cuts parameter redundancy; enables efficient multi-scale defect detection; higher localization accuracy than traditional two-stage detectors	Limited recognition for low-contrast defects; generalization depends on data augmentation	[76]

Single-stage detection algorithms, represented by the YOLO series and Single Shot MultiBox Detectors (SSDs), input the entire image into the network all at once, and directly perform category prediction and bounding box regression on preset dense anchor frames. By eliminating the independent candidate region generation stage, these have fast inference speed and are suitable for real-time detection. In recent years, through a series of optimization methods, such as introducing feature pyramid networks to enhance multi-scale perception ability, integrating attention mechanisms to focus on key feature regions, and designing more advanced loss functions to optimize bounding box regression, their detection accuracy has been greatly improved. Table 8 summarizes the advantages and disadvantages of single-stage detection algorithm cases. Quantitative comparisons show that single-stage detectors feature outstanding inference speed and lightweight deployability, making them the mainstream solution for high-takt online full inspection;

their detection accuracy for ultra-fine weak-feature defects is slightly lower than that of two-stage architectures. Figure 5 illustrates the procedural differences between single-stage detection and two-stage detection.

Table 8. Summary of single-stage detection algorithm cases.

Methods	Advantages	Limitations	Ref
YOLOv3 (Weight Transfer + CIoU)	Weight transfer accelerates training convergence; CIoU loss optimizes target localization; high accuracy for common lithium battery defects	Large model size & high computation; high large-scale deployment cost; insufficient response to ultra-small defects	[77]
YOLOv4 (Dilated Convolution + ECA Attention)	Dilated convolution expands receptive field; ECA attention enhances defect features; balances accuracy–speed; adapts to multiple lithium battery defects	Large model parameters; relies on high-performance hardware for deployment; high missed detection rate for low-contrast defects	[13]
YOLOv5 (DDCNet + CAM + AD – Head)	Deformable down-sampling convolution adapts to large-aspect-ratio defects; context enhancement module improves small-sample sensitivity; lightweight with fewer parameters	Prone to false detection of weak-feature defects under complex backgrounds; relies on data augmentation to alleviate sample imbalance	[78]
YOLOv5	Lightweight backbone reduces deployment cost; CBAM attention enhances defect feature expression; adapts to edge devices	Limited small-target detection accuracy; insufficient generalization in complex defect scenarios	[79]
YOLOv8	GhostConv lightweight design reduces computation; CA attention improves feature extraction efficiency; EIoU optimizes regression performance; excellent real-time performance	Vulnerable to interference from defects on highly reflective surfaces; model generalization relies on calibration of large-scale datasets	[80]
YOLOv8-EB	EIEM strengthens defect contour extraction; semantic detail fusion improves tiny defect recognition; fast detection speed	Susceptible to interference under strong illumination; slight accuracy drop for defects on large battery edge areas	[46]
SSD	MobileNetV3 lightweight backbone improves inference speed; optimized anchors adapt to battery defects of different sizes; low deployment cost	Poor accuracy for small targets; high false detection rate in complex backgrounds	[81]
YOLO-MDD	Adopts normalized Wasserstein distance loss; improves detection sensitivity for tiny defects; adapts to end-face defects of lithium battery shells	Slightly higher computation than vanilla YOLO; reduced efficiency for large-area defects (>10 mm)	[15]
SimYOLOv5s (SimSPPF + Attention)	SimSPPF simplifies computation for fast inference; embedded attention improves accuracy by 6.9% compared to YOLOv5s	Easily misses ultra-tiny defects; insufficient adaptability to diverse defect types	[82]
YOLOv7	Adaptive illumination preprocessing fits highly reflective battery surfaces; achieves 98.1% detection accuracy; supports synchronous detection of multiple defect types	High model complexity and parameter volume; high requirement on dataset scale	[47]

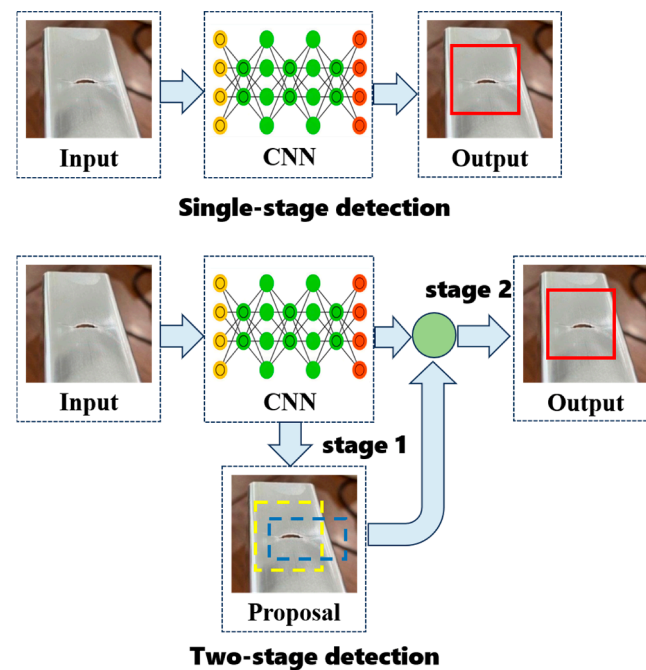


Figure 5. Flowcharts of single-stage detection and two-stage detection.

At present, the industrial sector has increasingly stringent requirements for the real-time performance of defect detection systems, driving lightweight single-stage technologies represented by YOLOv8 to become a research hotspot. At the same time, the two technologies integrate and learn from each other, such as incorporating a more refined feature reassignment strategy into the single-stage network or optimizing the efficiency of RPN in the two-stage network, which continuously promotes the performance improvement of battery shell defect detection.

4. Challenges and Prospects

Deep-learning-based battery shell defect detection technology has shown great potential, but its large-scale industrial deployment still faces core challenges due to the complexity of industrial sites. This is driving the field to evolve from pursuing single performance breakthroughs to building a robust, efficient, and continuously evolving intelligent detection system.

4.1. Challenges at the Data Level

The scarcity, class imbalance, and high cost of high-quality annotation of battery shell defect samples constitute the primary data bottleneck for visual defect detection of battery shells. On mature production lines, qualified products account for the vast majority of production output, while shell defects, such as perforation, severe local deformation, and wall thinning induced by deep drawing and ironing processes, occur at extremely low frequencies and exhibit diverse morphologies, severely limiting the generalization performance of purely supervised-learning-based methods. No single strategy can fully address this challenge, as data generation alone carries inherent risks of model bias arising from domain gaps between synthetic and real samples, and the effectiveness of all mitigation strategies is highly contingent on the underlying data engineering architecture and training paradigms. A combinatorial framework integrating data generation and augmentation, learning paradigm innovation, and automated annotation assistance is therefore widely adopted to tackle the data bottleneck from complementary dimensions.

(1) Data generation and augmentation. Generative adversarial networks and diffusion models are adopted to synthesize defect samples with realistic physical features and varied backgrounds; alternatively, controllable defect implantation is applied to normal samples to expand the training set in a cost-effective and low-risk manner. Conventional geometric augmentation (rotation, flipping, and cropping) improves *mAP* by only 3–5%, whereas generative augmentation yields an 8–12% *mAP* gain under extreme sample imbalance. Nevertheless, the domain gap between synthetic and real samples typically leads to a 1–2% increase in the false positive rate. Notably, such data-side optimizations impose no additional computational overhead during model inference.

(2) Learning paradigm innovation. Few-shot learning, zero-shot learning, and unsupervised/self-supervised anomaly detection are employed to reduce reliance on labeled samples and enable recognition of previously undefined defects. Schemes based on self-supervised pre-training can retain over 96% of the fully supervised baseline accuracy with only 10% of the labeled data, reducing annotation workload by more than 80%. Unsupervised anomaly detection achieves a recall rate above 85% for known defect categories, but it presents higher false positive rates for defects with previously unseen morphologies.

(3) Automated annotation assistance. Weakly supervised technologies including interactive segmentation and foundation model prompt segmentation enable automatic fine-grained defect annotation, which substantially improves labeling efficiency and reduces the cost of pixel-level annotation. Relevant benchmarks indicate that interactive assisted annotation boosts pixel-level labeling efficiency by a factor of 3–5 with annotation consistency exceeding 92%, effectively alleviating the labor cost burden of data preparation.

Despite these optimization approaches, the quantitative findings noted above are mostly derived from proprietary in-house datasets of individual studies. The lack of unified public benchmark datasets and standardized evaluation protocols for battery shell surface defects remains a fundamental challenge at the data level, as it hinders cross-study comparisons and objective evaluation of different detection methods.

4.2. Challenges at the Algorithm and Deployment Levels

Industrial scenarios impose comprehensive constraints on defect detection models, covering not only detection accuracy and real-time performance but also deployment cost, compatibility with existing production lines, and deployment scalability. At present, prominent shortcomings remain in the engineering deployment of deep-learning-based detection algorithms, which are mainly reflected in two dimensions: lightweight edge deployment and production-line integration adaptability.

4.2.1. Lightweight Edge Deployment and Cost–Performance Trade-Off

The deployment of detection systems on industrial edge terminals requires a balance among three core metrics—detection accuracy, inference latency, and hardware cost—which are mutually constrained. At the algorithm level, lightweight technologies, represented by neural architecture research, knowledge distillation, structured pruning, and integer quantization, constitute the mainstream optimization path. These technologies can compress model parameters and computational load by 40–70% while limiting *mAP* loss to within 2–3%, enabling deployment on edge computing platforms with limited computing power.

In terms of hardware deployment, current mainstream industrial solutions fall into a gradient selection hierarchy ranging from high-performance industrial personal computers (IPCs) to embedded advanced reduced instruction set computer machine platforms and field-programmable gate arrays. The hardware cost per station varies widely, with corresponding differences in inference performance and operational and maintenance overhead. For high-takt stamping and deep drawing production lines with a production rate of

80–120 parts per minute, the lightweight scheme combining model quantization and edge GPUs can meet the real-time detection requirement of single-frame inference latency below 50 ms, and effectively reduces unit deployment cost compared with IPC-based solutions.

4.2.2. Production-Line Integration and Deployment Scalability

The scalable application of detection systems across multiple production lines and multi-product scenarios is subject to two core constraints: environmental robustness and system compatibility. In terms of environmental adaptability, the reflective properties of metal shell surfaces and variations in illumination conditions across production lines tend to cause model performance degradation after cross-line deployment migration. Technologies such as multimodal data fusion of visible light and three-dimensional (3D) point clouds, unsupervised domain adaptation, and online self-calibration of imaging parameters can mitigate the model's reliance on specific production-line environments and shorten the commissioning cycle of cross-line deployment.

In terms of system integration, the detection system must enable data interconnection and signal interaction with existing on-site programmable logic controllers, manufacturing execution systems, and sorting actuators. The standardization of communication interfaces and the stability of closed-loop feedback latency are key factors affecting deployment effectiveness. Currently, the lack of unified technical specifications for detection systems results in high secondary development costs for cross-scenario migration, which restricts the widespread adoption of relevant technologies in the battery shell manufacturing industry.

Overall, the optimization of battery shell defect detection algorithms must move beyond the single performance-oriented paradigm that prioritizes only accuracy and speed, and incorporate deployment cost, production-line compatibility, and deployment scalability as key dimensions of algorithm evaluation, thus facilitating the deep integration of detection technology and industrial manufacturing scenarios.

4.3. Challenges in Detection Dimensions and Standards

During the imaging process of metal battery shells, interference such as reflective spots and overexposed highlighted regions frequently occurs, and shallow scratches exhibit high visual similarity to the inherent metal texture of the shell substrate. As a result, two-dimensional (2D) vision technology faces inherent limitations in stably extracting subtle defect features such as shallow scratches. With the continuous improvement of battery safety standards, the demand for battery shell defect detection is extending from 2D surface defects to three-dimensional (3D) geometric tolerances and internal structural integrity, which has promoted the integrated application of 3D vision detection technologies.

Three-dimensional vision detection approaches, including line laser scanning, structured light imaging, and binocular stereovision, reconstruct high-precision point cloud data of the shell to realize quantitative detection of 3D parameters, such as scratch depth, pit volume, and surface flatness, compensating for key metrics that are difficult or even impossible to capture and quantify via traditional 2D vision. On this basis, multimodal information fusion technology combines the rich texture information of 2D images with the precise geometric information of 3D point clouds to construct multimodal feature representations, enabling more comprehensive and reliable identification and classification of complex defects. Nevertheless, the joint annotation of multimodal data is far more complex than that of pure 2D images, representing a prominent data bottleneck that restricts the large-scale deployment of such solutions. Empirical results have demonstrated that an interactive automatic annotation framework based on weakly supervised prompt segmentation improved 2D–3D cross-modal defect annotation efficiency by 65–75% and achieved

annotation consistency of more than 88% [71,72], effectively alleviating the data annotation cost pressure of multimodal detection schemes.

4.4. Prospects of System Integration and Intelligence

Looking forward, battery shell surface defect detection technology will evolve from isolated algorithmic modules to closed-loop intelligent systems deeply integrated into intelligent manufacturing frameworks. Driven by continuous breakthroughs in sensing dimensionality and distributed collaborative paradigms, it will enable full-process intelligent quality control throughout production.

(1) Form a detection–diagnosis–decision closed loop. The machine vision detection system for battery shell defects will be deeply integrated with manufacturing execution systems. It can trace process parameters according to detected defect types and automatically output adjustment suggestions for upstream processes, such as stamping and deep drawing, shifting quality control from post-event detection to in-process prevention. On the sensing side, multimodal sensing frameworks that combine visual inspection with acoustic emission and infrared thermal imaging signals will further overcome the inherent limitations of single-modal vision. Complementary multi-source signals can capture sub-surface microcracks and internal stress anomalies that are undetectable by two-dimensional vision, providing more comprehensive quality evidence for process diagnosis and adaptive parameter adjustment.

(2) Digital twin and simulation verification. Digital twin models of production lines and products will be constructed to simulate various defect morphologies and their imaging processes in a virtual space. This approach effectively reduces the cost of algorithm verification, extreme scenario testing, and personnel training, and provides a low-risk, high-efficiency verification platform for process optimization and detection scheme iteration.

(3) Sustainable online learning ability of the model. Defect detection models deployed on production lines require continuous learning capability, which can safely and efficiently absorb newly emerging defect samples and enable iterative model updates without catastrophic forgetting of existing knowledge, thus adapting to product iterations and new defect modes. On this basis, federated learning provides a feasible paradigm for cross-factory model collaboration. Under the premise of safeguarding process data privacy and intellectual property, multiple manufacturing entities can jointly optimize the detection model by sharing model parameters rather than raw defect data. This effectively alleviates the issue of insufficient sample diversity at individual manufacturing sites and extends the generalization boundary of the model.

In summary, battery shell surface defect detection technology is evolving towards high-precision perception, intelligent decision-making, and autonomous operation and maintenance, constituting a systematic engineering framework that integrates machine vision, intelligent sensing, edge computing, and industrial big data. Future research needs to strengthen interdisciplinary cooperation to further promote the deep integration of core algorithms for visual defect detection with industrial scenarios.

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Abbreviations

The following abbreviations are used in this manuscript:

NEV	New Energy Vehicle
Lib	Lithium-Ion Battery
BHF	Blank Holder Force
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
ROC	Receiver Operating Characteristic
FPR	False Positive Rate
TPR	True Positive Rate
AUC	Area Under the Curve
IoU	Intersection Over Union
AP	Average Precision
mAP	Mean Average Precision
mIoU	Mean Intersection Over Union
R-CNN	Region-Based Convolutional Neural Network
Yolo	You Only Look Once
SSD	Single Shot MultiBox Detector
IPC	Industrial Personal Computer
SVM	Support Vector Machine
2D	Two-Dimensional
3D	Three-Dimensional

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