

REVIEW ARTICLE

Artificial intelligence-based defect prediction in lithium battery manufacturing: A review in the context of Quality 4.0

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Abstract - Guided by the principles of Industry 4.0, the integration of artificial intelligence (AI), convolution neural networks into the lithium-ion battery manufacturing process for analysis and prediction is a significant advancement in the development of Quality 4.0. This review examines the methods that use AI to predict the state of health and state of charge of lithium-ion batteries. First, an overview of Industry 4.0, lithium-ion batteries, artificial intelligence, and convolutional neural networks is provided, followed by the discussion of key challenges in this field. Subsequently, these challenges are refined and the research objectives of this study are summarized. A matrix analysis of the relevant literature across six dimensions is conducted to identify areas of research that have the greatest value and significance to lithium-ion battery manufacturing. Furthermore, the process of lithium-ion battery manufacturing is introduced, the key steps and critical nodes involved are summarized, and digital and artificial intelligence technologies currently used in the production of lithium-ion batteries are reviewed. Finally, insights are given by responding to the refined research questions on the basis of a comprehensive synthesis of the literature to guide future research and innovation in the field of lithium-ion battery manufacturing and contribute to the high-quality and sustainable development of this field. In total, 200 representative articles published between 2004 and 2025 are analyzed in a 6×6 matrix of research objectives and methods, with approximately 50% of scholars adopting an optimistic view of AI integration and around 25% expressing concerns about its early-stage limitations.

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1. Introduction

With the global development of Industry 4.0, countries seek to position themselves as key players and leaders in various fields and investing resources to secure a competitive position internationally. In the field of new energy vehicles, especially electric vehicles and their related lithium-ion batteries, the production of lithium-ion batteries has emerged as a key field for advancing Quality 4.0, offering new possibilities for the evolution of this paradigm. Currently, Quality 4.0 remains in its formative phase, with no universally accepted definition or standardized approach to its implementation. Various industries are still exploring ways to operate this paradigm. In the field of lithium-ion battery manufacturing, research on artificial-intelligence-based analysis and prediction of big-data processes such as infiltration, formation, and aging remains limited. Studies that apply advanced artificial-intelligence algorithms such as convolutional neural networks to the formation process are rare, and their applicability to data types that can be analyzed with convolutional neural networks needs to be further investigated. Overall, the use of big data analysis and artificial intelligence to predict and diagnose defects in the lithium-ion battery formation process remains in its early stages. There is a clear need to systematically review existing research, summarize key advances, and identify challenges that will guide future developments in this field. This study will discuss the application of artificial intelligence in the manufacturing processes of lithium-ion batteries, comparing the similarities and differences between convolutional neural networks and other AI approaches such as recurrent neural networks, with the aim of addressing the gap in discussions on the application of convolutional neural networks in lithium-ion battery manufacturing processes.

1.1 Industry 4.0 and Quality 4.0

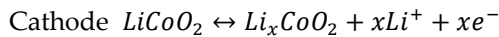
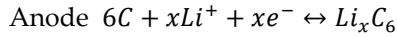
The advent of Industry 4.0, Quality 4.0 and digital quality management has created new opportunities for development in the manufacturing industry. Industry 4.0 has become the foundation for innovation and transformation in many sectors, which is reflected in the national industrial and economic strategies that have been adopted in 46 of the most industrially developed countries in the world [1]-[2]. The development of digital manufacturing has allowed the creation of the industry 4.0 framework, enabling sustainable digital ecosystems and smart manufacturing [3]. As businesses gradually become more digitalized, they are revising their existing quality-management models to adapt them to Quality 4.0 [4]. For small and medium-sized enterprises, the adoption of AI-driven approaches within the Industry 4.0 paradigm offers a more feasible route to developing Quality 4.0 models, particularly by strengthening the circular economy through big-data analysis [5]-[6]. Although the academic discourse on Quality 4.0 is still ongoing, the digital transformation is expected to refine and extend the scope of traditional quality-management methodologies such as IATF16949, total quality management, PDCA, quality inspection, and quality problem-solving frameworks [7]. A dominant trend in this evolution is the integration of big-data analytics and artificial intelligence to drive innovation across multiple industries.

The lithium-ion battery industry must align with this trend. The use of big data analytics and artificial intelligence applications in the industry 4.0 and quality 4.0 frameworks is essential for addressing persistent challenges in lithium-ion battery manufacturing and for improving production efficiency.

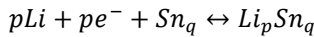
1.2 Lithium-Ion Battery

1.2.1 Overview of lithium-ion batteries

A lithium-ion battery is a type of secondary (rechargeable) battery that operates through the reversible migration of lithium ions between the positive and negative electrodes during charge and discharge cycles. The basic structure of a lithium-ion battery consists of a cathode (positive electrode), an anode (negative electrode), an electrolyte, a separator, and a casing. The cathode is typically composed of materials such as lithium cobalt oxide ($LiCoO_2$), lithium manganese oxide ($LiMn_2O_4$), and lithium nickel oxide ($LiNiO_2$), whereas the anode is typically made of carbon-based materials, such as graphite or silicon-based compounds. Using lithium cobalt oxide ($LiCoO_2$) as an example, the electrochemical reaction of a lithium-ion battery with graphite as the anode can be represented as follows:



Alternatively, tin (Sn), a commonly used anode material, serves as another example. Tin is cost-effective and widely available, and exhibits a high theoretical energy density and specific capacity, making it a promising candidate for lithium-ion battery anode applications. Unlike graphite, which is intercalated into and deintercalated from lithium ions, tin forms an alloy with lithium, allowing a reversible alloying and dealloying reaction. This process can be expressed as follows:



Besides the above reaction equations of lithium-ion batteries, Table 1 summarizes the key mathematical formulas for applying artificial intelligence to lithium-ion batteries, and Table 2 explains the purpose and source of the formulas. These formulations provide deeper insight into lithium-ion battery operation and support the development of AI-based methods for state-of-health and state-of-charge prediction. By using these equations, this study further examines how AI-driven predictive models align with the underlying principles and methodologies of the listed formulations, demonstrating their theoretical consistency and applicability.

Table 1. Key math formulas for using AI in lithium-ion batteries

Formula type	Formula	Source
SVM	$\min_{\omega, b} \frac{1}{2} \ \omega\ ^2 + C \sum_{i=1}^n \xi_i \text{ s.t. } y_i(\omega^T x_i + b) \geq 1 - \xi_i, \xi_i \geq 0. (1)$	[41]
Reinforcement learning	$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)]. (2)$	[53]
Molecular Generation models	$\min_G \max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p_z} [\log (1 - D(G(z)))] (3)$	[110]
GNN	$h_v^{(l)} = \text{AGGREGATE}^{(l)}(\{h_u^{(l-1)}, \forall u \in \mathcal{N}(v)\}) (4)$	[111]
Neural networks	$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}. (5)$ $a^{(l)} = \sigma(z^{(l)}). (6)$	[144]
Bayesian optimization algorithm	$x^* = \arg \max_{x \in \mathcal{X}} f(x). (7)$	[153]

Table 2. Table of math formula uses and origins

Purpose of the formula	Source of the formula	Source
Battery SOH Classification	Cortes & Vapnik,1995	[41]
BMS Dynamic Strategy Optimization	Watkins & Dayan,1992	[53]
Electrolyte molecular structure generation	Goodfellow et al.,2014	[110]
Materials Genomics and Interface Analysis	Kipf & Welling,2017	[111]
Input-output mapping in SOC estimation	Rumelhart et al.,1986	[144]
Efficient Battery Parameter Search and Optimization	Mockus,1975	[153]

In fact, from the early stages of R&D to the rapid advancement of lithium-ion batteries, the core focus of innovation has been the continuous optimization and advancement of safety and cost-effectiveness. Therefore, a deeper understanding of the development process of lithium-ion batteries is essential [8]-[9].

1.2.2 The development of lithium-ion batteries

The origins of lithium-ion batteries date back to 1970, when scientists, notably from Exxon, first utilized titanium sulfide as the cathode material and lithium metal as the anode material, producing the world's first lithium battery. However, lithium-ion batteries were not commercialized until 1990, when they became widely adopted as energy storage solutions for electronic devices such as mobile phones and computers [10]. This period marked the beginning of a steady rise in

market demand for lithium-ion batteries [11]. A significant advance was achieved when companies such as Sony introduced lithium-ion batteries with lithium compounds as the positive electrode and materials based on carbon as the negative electrode. Using lithium-ion intercalation with graphite effectively mitigated polarization effects and improved both reversibility and battery lifespan [12]. The rapid development of lithium-ion batteries by the early 2000s produced lithium-ion batteries with high energy density [13], long cycle life [14], long shelf life [15], relatively low cost [16], high discharge current capability [17], and no memory effect [18]. These advantages established lithium-ion batteries as the leading technology in the battery-pack market [19]. Today, lithium-ion batteries are a key technology in electric vehicles, providing new solutions for sustainable development and energy conservation [20]. This growing importance has further driven market demand, with the global market value of lithium-ion batteries exceeding USD 30 billion in 2020 and projected to reach USD 90 billion by 2027 [21].

The market growth rate of electric vehicles has risen steadily in recent years and is projected to continue increasing [22]. According to the predictions of international research institutions, electric vehicles were expected to account for 70% of the passenger-car market by 2024. At the same time, the proportion of renewable energy sources in the power grid is also increasing. By 2025, wind and solar energy are projected to surpass coal, natural gas, and hydropower in installed capacity. This shift highlights the need for large-scale energy-storage solutions, such as 'giant batteries', to stabilize regional grids and buffer fluctuations from intermittent energy sources [23]-[24]. Despite the development of different energy storage technologies around the world, lithium-ion battery technology remains the leading technology and is widely used in portable electronics, electric vehicles, and grid-scale energy storage [25]. However, as demand continues to grow, lithium-ion batteries must be further improved in performance and cost to meet market expectations [26]. In addition, factors such as service life, safety, and sustainable development require greater attention [27]. Moreover, the rising adoption of electric vehicles has produced a surge in lithium-ion battery production, with challenges in battery recycling, lifecycle safety and cycle-life improvements. Given that the expected lifespan of lithium-ion batteries is approximately 10–15 years, the recycling of decommissioned batteries remains a significant challenge, requiring continued improvements in battery safety and durability throughout their service life [28].

1.3 Artificial Intelligence And Convolutional Neural Networks

AI and CNNs, in the context of Industry 4.0 and Quality 4.0, offer effective solutions to the above challenges. Supervised learning is a widely used method in AI and is typically applied to train predictive models. These models are trained on historical process data and can predict product quality for items still in production. By continually comparing predictions with actual outcomes and refining the model through iterative calibration, high-accuracy predictions can be obtained [29-30]. In recent years, deep-learning algorithms have substantially benefited various industries through their advancement. As a class of versatile and powerful models, convolutional neural networks have demonstrated strong performance across several domains [31]-[32]. In the lithium-ion battery industry, data-driven methods have become increasingly popular. These methods enable lithium-ion battery degradation characteristics to be modeled from historical records alone, supporting systematic diagnostics and predictive analysis. However, despite their potential, these approaches remain at an early stage of development, with critical challenges still to be addressed. Therefore, a comprehensive review of the latest studies by leading scholars across various fields is needed to provide a practical basis for technological advances in lithium-ion batteries.

The applications listed in Table 1, including the use of machine learning for battery life prediction, the use of neural networks for state-of-charge detection, and the use of reinforcement learning for battery management, cover the main directions of artificial-intelligence applications in lithium-ion battery manufacturing currently being explored. However, in the lithium-ion battery manufacturing process, a clear gap remains in the application of artificial intelligence after the formation step. Based on this situation, this study's exploration of using convolutional neural networks to predict and screen defective cells after the formation process holds substantial practical value.

2. Materials and Methods

On the basis of the existing challenges in lithium-ion battery manufacturing, and consistent with the objectives of this study, the following key issues are identified for analysis and discussion:

- What is the current state of scholarly research on the industrial manufacturing of lithium-ion batteries?
- Is it feasible to predict defective cells after the formation process of lithium-ion batteries using big-data analysis in chemical manufacturing?
- Are artificial-intelligence-based analysis and prediction methods, such as convolutional neural networks, effective in the lithium-ion battery industry?

2.1 Research and analysis

To address the refined research questions, 200 representative articles on lithium-ion batteries were collected, and a cross-analysis of their research objectives and methods was conducted using matrix analysis. The research objectives were grouped into six dimensions: storage and recycling, quality assessment, review and discussion, state prediction, characteristic optimization, and process improvement of lithium-ion batteries. Similarly, the research methods were grouped into six dimensions: machine learning, new materials, advanced concepts, targeted experiments, digital models, and neural networks. A comprehensive review was conducted of the representative articles within these six research-

objective and six research-method dimensions. The findings from this classification and analysis are presented in Tables 3 and 4.

Table 3. Review of representative articles categorized into six dimensions based on their research objectives

Research Objective	Content summary	Source
Quality assessment	Utilizes convolutional neural networks to predict the reliability of lithium-ion batteries in real time.	[18]
State prediction	Investigates pyrometallurgical and hydrometallurgical processes for lithium-ion battery material recovery.	[19]
Review and discussion	Applies multivariable process capability metrics to ensure the quality and consistency of lithium-ion battery production	[23]
Process improvement	Employs lightweight deep residual networks and blockchain technology to enhance early defect detection and mitigate AI overfitting.	[28]
Storage and recycling	Reviews methods of ensemble learning and fault diagnosis for battery recycling and fault detection.	[33]
Characteristic optimization	Uses tandem battery detection to analyse cell-to-cell variation, aiding in the evaluation of battery quality and module integration.	[34]

Table 4. Review of representative articles categorized into six dimensions based on their research methods

Research method	Content summary	Source
Neural network	Utilizes transfer learning and self-supervised learning techniques to address the scarcity of labelled training data.	[10]
Digital model	Apply process models that systematically describe empirical knowledge about electrolyte filling in lithium-ion battery manufacturing.	[14]
Machine learning	Integrates experimental and computational methods incorporating machine learning, Internet of Things (IoT), and artificial intelligence to facilitate a smooth transition in lithium-ion battery manufacturing.	[17]
Targeted experiment	Develops a health prediction scheme for lithium-ion battery packs to overcome challenges related to requirements for extensive training data.	[20]
Frontier technology	Employs a high-precision deep convolutional neural network to predict the remaining service life of lithium-ion batteries.	[35]
New materials	Analyses research methodologies, development trends, and common challenges in data-driven forecasting methods for new battery materials.	[36]

For the matrix analysis, as shown in Figure 1, the distribution of 200 representative articles was analyzed across 6×6 dimensions. In the figure, the block distribution density is visualized with a color gradient, in which lighter colors indicate lower density and darker colors indicate higher density. This visualization helps identify key research objectives and methods and guides the subsequent analysis. The 200 collected papers were drawn primarily from databases such as Web of Science, Scopus, Google Scholar, and IEEE Xplore using "Industry 4.0", "Quality 4.0", and "lithium-ion batteries" as the main search terms. The search covered all relevant literature published between 2004 and 2025. Detailed screening was performed using inclusion and exclusion criteria based on key dimensions: storage and recycling, quality assessment, review discussion, state prediction, characteristic optimization, process improvement, machine learning, novel materials, cutting-edge concepts, targeted experiments, digital models, and neural networks.

In the matrix analysis, the blocks with the highest density correspond to state prediction as the research objective and neural networks as the research method. The preliminary conclusion is that state prediction using neural networks in the lithium-ion battery manufacturing process is currently the most prominent and impactful research focus. Accordingly, all articles categorized within this block are summarized in Table 5 for further analysis.

Next, the research objectives and methods of the 200 representative articles on lithium-ion batteries were systematically summarized and analyzed. To further examine the findings, the results and discussions in these studies were grouped into optimistic, neutral, and cautious perspectives, as illustrated in Figure 2. This classification provides insight into the progress made in addressing key challenges in lithium-ion battery manufacturing and highlights researchers' perspectives and recommendations regarding the future development of this field.

For the review presented in Table 5, the results and discussions of the articles in the most densely distributed block were also statistically analyzed, as illustrated in Figure 3. This analysis sought to consolidate the conclusions drawn from studies on state prediction in the lithium-ion battery manufacturing process using neural networks. These findings were synthesized to provide a comprehensive evaluation of the original assumptions of this study.

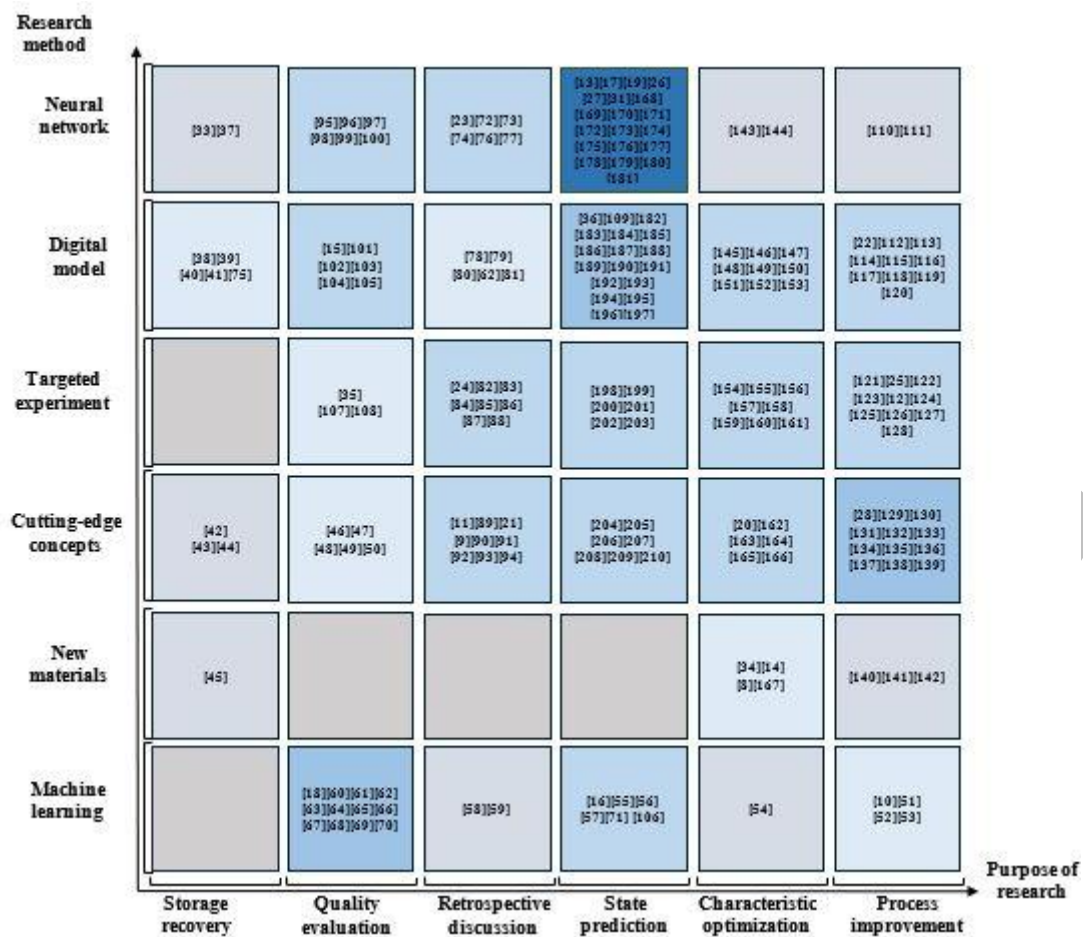


Figure 1. Cross-analysis matrix of research objectives and methods

Table 5. Review of articles in the most densely distributed blocks

Content summary	Source
Develops a rapid formation procedure for lithium-ion batteries, significantly reducing the total charging time.	[13]
Utilizes experimental and computational methods incorporating machine learning, IoT, and artificial intelligence to enable a smooth transition in lithium-ion battery manufacturing.	[17]
Investigates pyrometallurgical and hydrometallurgical processes of lithium-ion battery material recovery.	[19]
Reviews four types of machine learning (ML) algorithms for SOC and SOH estimation.	[26]
Proposes a domain attribute and feature transfer network to enhance adaptive fault diagnosis, enabling cross-domain fault detection from a single-source domain to a multi-source domain.	[27]
Examine the effectiveness of existing quality inspection systems in reducing battery production rejects.	[31]
Proposing LACF-YOLO, a lightweight adaptive network for detecting surface defects on lithium batteries.	[168]
Develops an evaluation system that enables users to quantitatively assess the impact of key technologies on battery performance and production costs.	[169]
A dual-task deep learning model was proposed to accurately detect lithium precipitation defects.	[170]
Reviews the application of artificial neural networks (ANNs) in estimating lithium-ion battery states.	[171]
Proposes a framework combining a process chain model and a battery cell model to quantitatively predict the impact of manufacturing processes on final battery cell performance.	[172]
Improves battery capacity estimation accuracy by mitigating uncertainties associated with SOC estimation and measurement.	[173]
Reviews advances in machine learning applications for improving battery material design and accurate battery state prediction.	[174]

Continuation of Table 5

Content summary	Source
Develops a data-driven method to automatically evaluate the effects of the formulation and liquid–solid ratio of the slurry on electrode heterogeneity in lithium-ion battery manufacturing.	[175]
Proposes a method for determining CB aggregate size in the anode and cathodic suspensions for lithium-ion battery electrodes.	[176]
Explored how the position of sensors affects an artificial neural network's (ANN) ability to classify engine misfires using vibration signals.	[177]
Analyses how material selection, processing methods, and system architecture impact the fabrication of lithium-based solid-state batteries.	[178]
Examines the prospects of soft sensors and sensor fusion for the data-driven modelling and prediction of battery product quality.	[179]
A new type of disc brake pad defect detection model has been proposed.	[180]
Conducts a systematic literature review on the latest research in machine learning for additive manufacturing.	[181]

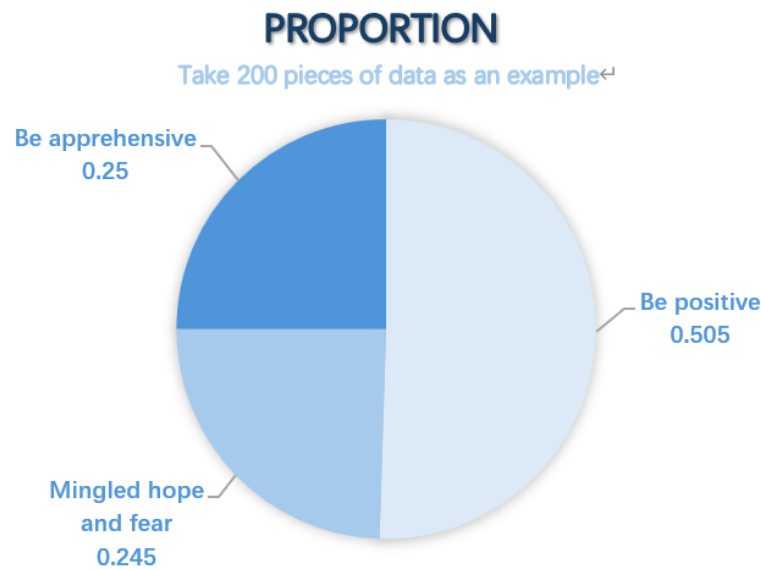


Figure 2. Proportional distribution of research results from articles analyzed in the matrix analysis

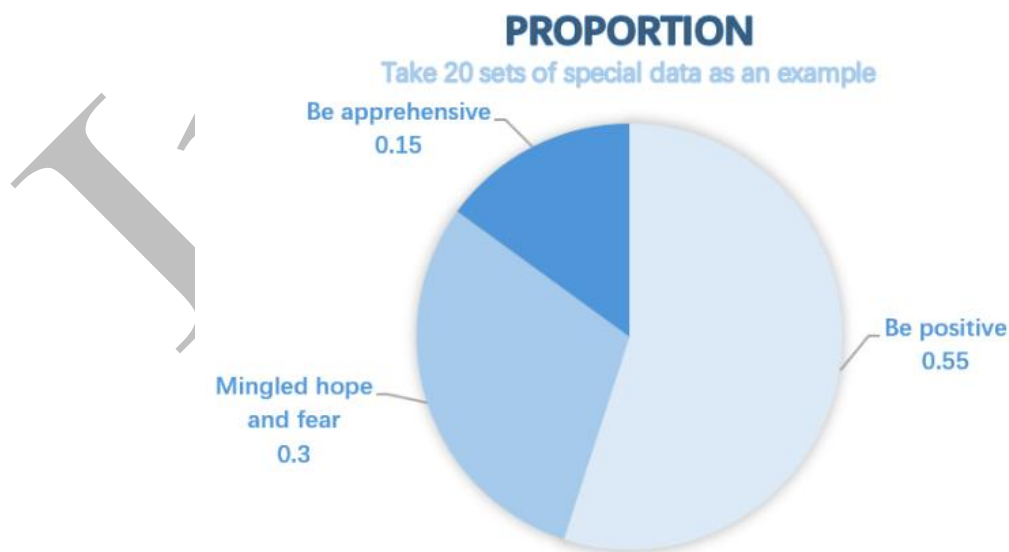


Figure 3. Statistical analysis of the results and discussion from the articles in the most densely distributed block

These findings indicate that significant progress has been made in the industrial manufacturing of lithium-ion batteries, with ongoing exploration of various innovative approaches. Scholars are actively using Industry 4.0 and Quality 4.0 to drive technological advancements in lithium-ion battery manufacturing. The conclusions of the 200 analyzed articles on AI integration in lithium-ion battery manufacturing were classified, and approximately 50% of scholars expressed

optimism, emphasizing the clear advantages of combining artificial intelligence with lithium-ion battery manufacturing, particularly in cost reduction and process optimization. They also note the high accuracy of neural networks in predicting the state of health in the lithium-ion battery manufacturing process. However, 25% of researchers expressed concerns, citing both the limitations of AI itself and the fact that its application in lithium-ion battery manufacturing is still at an early stage requiring cautious implementation and further validation. Overall, although these ideas offer clear benefits alongside considerable challenges, continued research, discussion, and analysis among scholars will be important for overcoming existing obstacles. Sustained contributions and advances in this field will shape the future of AI-driven lithium-ion battery manufacturing.

3. Results and Discussion

On the basis of the research questions raised above and the results obtained, several directions for discussion can be outlined. The application of convolutional neural networks in lithium-ion battery manufacturing is the most prominent area of study and research on post-formation processes remains relatively scarce. Therefore, it is necessary first to discuss in detail the digital applications used in lithium-ion battery manufacturing processes, second, to examine the application of different digital technologies to different stages of lithium-ion battery manufacturing, and finally to discuss, from multiple perspectives, the advantages and effects of convolutional neural networks compared with other digital approaches.

3.1 Digitalization of The Lithium-Ion Battery Formation Process

The manufacturing of lithium-ion batteries generally involves a series of sequential steps: mixing, coating, rolling, cutting, lamination or winding, liquid injection, infiltration, formation, aging, and inspection. Figure 4 summarizes the lithium-ion battery manufacturing process, introduces the key control elements of each step, and provides the basis for the subsequent integration of process flow and digital manufacturing.

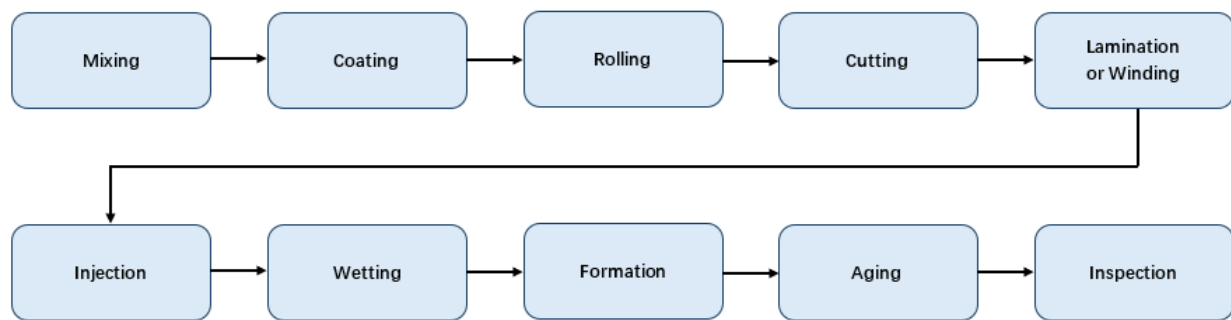


Figure 4. The manufacturing process of lithium-ion batteries

The first step in lithium-ion battery manufacturing is mixing, in which the active material, conductive agent, binder, and solvent are blended to form a homogeneous slurry. This step ensures the uniform dispersion of materials. Next, a metal foil is coated with the slurry to a uniform thickness and then dried to form the electrode sheet (coating step). After coating, the electrode sheet undergoes rolling, in which a high-pressure roller press compacts the material to improve its energy density and structural stability. In lamination, the positive and negative electrode sheets are alternately stacked with a separator into a prismatic structure, whereas in winding they are rolled into a cylindrical or oval-shaped core. During liquid injection, the electrolyte is introduced in a dry environment to provide a medium for lithium-ion transport. This is followed by infiltration, in which the battery is left to stand to allow full penetration of the electrolyte and ensure unobstructed ion channels. During the formation step, the battery is activated for the first time, and a solid-electrolyte interphase (SEI) film forms on the surface of the negative electrode; this layer is critical to battery performance and lifetime. During the aging step, the battery is stored in a temperature-controlled environment, and potentially defective cells are identified through static analysis or charge–discharge cycling. Finally, the inspection stage involves electrical performance testing, safety testing, and visual inspection. Only batteries that meet quality standards are released to the market.

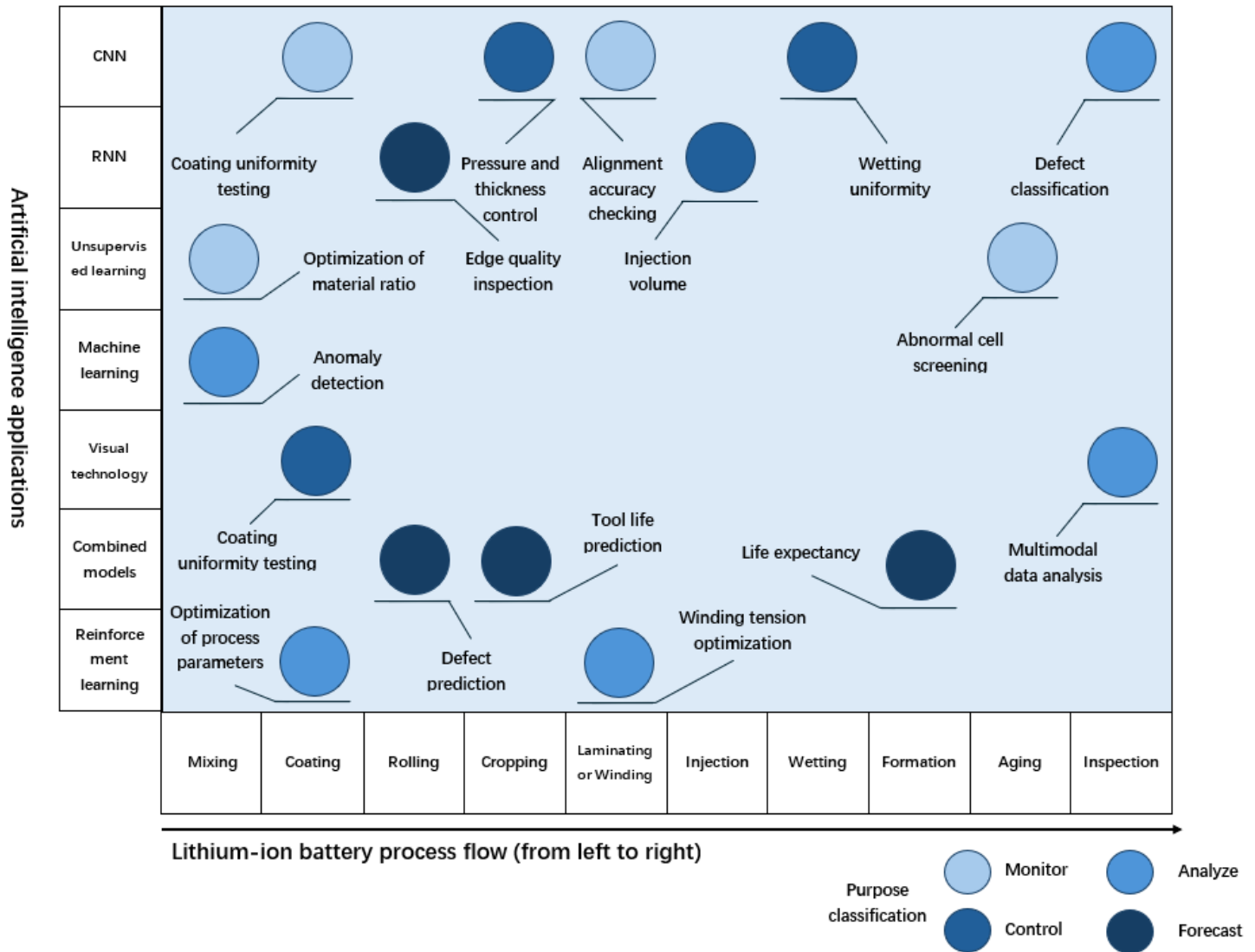


Figure 5. A summary of the integration of artificial intelligence technologies into various lithium-ion battery manufacturing processes

To meet battery performance, cost, and sustainability goals, advances in materials and battery manufacturing are essential. Currently, manufacturing processes for lithium-ion batteries have received limited research attention, pointing to opportunities for process optimization to improve efficiency, cost-effectiveness, and sustainability. Although lithium-ion battery production has reduced costs relative to earlier technologies, operational and quality-related challenges have become increasingly pronounced. Given that lithium-ion battery performance is highly sensitive to manufacturing variability, this sensitivity provides a viable basis for automated, digitally driven production. The development of digitalized super-factories makes it possible to optimize production in real time, thereby improving productivity, product quality, and reliability. Accordingly, Figure 5 summarizes the digital and artificial-intelligence technologies used at different stages of lithium-ion battery manufacturing, providing a clearer view of existing innovations and integration in the industry, and a basis for future advances.

In this context, data generated during battery manufacturing are used in system design, performance control, and maintenance, so that data collection and use are central to the digitalization of the production environment. Given the interdependence of manufacturing steps, the data volume needed to monitor processes and equipment is considerable. Comprehensive data collection is therefore key to ensuring process monitoring, quality control, cost-efficiency, and sustainability. The battery manufacturing process generally involves mixing, coating, rolling, cutting, lamination or winding, liquid injection, wetting, formation, and aging, among other steps. In addition, two rounds of open-circuit voltage testing are required to determine self-discharge rates and assign capacity classifications consistent with diverse product requirements. Several manufacturing stages have been optimized through big-data analytics and artificial intelligence, lowering defect rates and extending cycle life. This technological integration also supports digital quality management within the Quality 4.0 framework. Among these steps, wetting, formation, and aging are critical to achieving the uniform capacity, long cycle life, and safety required of high-quality lithium-ion batteries. However, the high cost of these steps remains a major challenge. The wetting and formation process alone takes 3–7 days, and aging continues for up to an additional 2 weeks. Although this is a significant improvement over the situation 20 years ago, these steps still account for a substantial portion of production costs, occupying almost 25% of the manufacturing floor space. Wetting and

formation play an essential role in establishing the anode solid-electrolyte interphase and the cathode–electrolyte interface. To optimize their thickness and minimize capacity degradation over the battery lifetime, formation charging and discharging must be performed at a slow rate. Enhancing the first-pass yield while using big-data and artificial-intelligence methods to analyze manufacturing data in real time could help identify defective batteries early in the wetting and formation steps. Such an approach would reduce losses in later open-circuit voltage testing, aging, and capacity classification, lower defect-related costs, and improve economic efficiency.

3.2 Lithium-Ion Batteries, Artificial Intelligence, and Convolutional Neural Networks (CNN)

With advances in computing technology, artificial-intelligence-based methods have been developed for estimating the state of health and state of charge of lithium-ion batteries. The widespread use of artificial intelligence and deep learning across different fields reflects their capacity to solve domain-specific problems. However, in battery research, many issues are highly technical and grounded in well-established physical principles, which makes it difficult to apply artificial intelligence to data processing and prediction. This is a major challenge for deep-learning algorithms, because battery data differ from those used in traditional AI applications. As a result, most studies on AI for lithium-ion batteries rely on machine-learning rather than deep-learning methods. Deep-learning algorithms are typically designed for three main types of big data: images, text, and time series. In contrast, battery data are usually collected from charge–discharge cycles, or from a combination of cycle time and aging time, producing records of current, voltage, and temperature. Among deep-learning techniques, RNNs have been widely used to predict capacity loss. However, this approach often yields unsatisfactory results because of the nonlinear nature of capacity degradation, which limits the ability of state-of-health tracking methods to predict or adapt accurately to such complex patterns. CNNs provide a feasible alternative for predicting capacity loss and addressing the above challenges. Under constant-current cycling conditions, electrochemical voltage spectrum data have similar characteristics as those of image data and therefore CNNs could effectively extract independent representations of capacity and voltage variations. CNN models show strong adaptability across different fields and offer high predictive accuracy. In addition, they can automatically detect distinctive patterns in the data, reducing the need for domain expertise. Thus, the use of CNN-based artificial-intelligence models to analyze and predict big data from the formation step of lithium-ion battery manufacturing is a feasible strategy for early defect detection. This approach not only reduces the costs associated with defective products but also has important theoretical and practical implications for technological advances in lithium-ion battery manufacturing.

4. Conclusions

In summary, this review first introduced the relevant concepts of Industry 4.0 and Quality 4.0, lithium-ion batteries, artificial intelligence, and convolutional neural networks. Drawing on the formulas already applied to artificial intelligence in lithium-ion battery manufacturing, we set out the ideas of this paper and posed three research questions, which laid the foundation for further investigation and discussion.

On the basis of the research and discussion above, sufficient evidence is available to address these questions. First, at the current stage, scholars have made significant progress in the application of artificial intelligence to the industrial manufacturing of lithium-ion batteries compared with previous research. However, within the broader context of industrial transformation, research on AI-based lithium-ion battery manufacturing remains at an early stage. Second, applying big-data analysis to predict defective cells during the formation step has clear theoretical significance, but the approach is still moving from discussion to practical implementation. Finally, methods that integrate artificial-intelligence analysis and prediction, such as convolutional neural networks, are clearly effective in the lithium-ion battery industry. When compared with recurrent neural networks, convolutional neural networks hold a clear advantage and have shown strong practical performance in other lithium-ion battery manufacturing processes.

Taken together, the answers to these questions and the results of this discussion suggest that AI-based methods for predicting the health status of lithium-ion batteries are theoretically feasible and efficient, and that practical implementation is needed to further strengthen the theoretical foundation.

Overall, the combination of AI and lithium-ion battery production represents an important direction in the development of the new-energy industry. AI-driven process optimization improves production efficiency, reduces manufacturing costs, and supports the development of next-generation battery technologies. This interdisciplinary convergence is expected to drive a substantial shift in the manufacturing industry.

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CRedit Author Contribution Statement

- J.L. (Formal Analysis; Investigation; Visualisation; Writing- Original Draft)
- H.W. (Conceptualization; Methodology; Formal Analysis; Writing-Review and Editing; Supervision)
- Y.X. (Formal Analysis; Visualisation)
- W.N. (Writing-Review and Editing)

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