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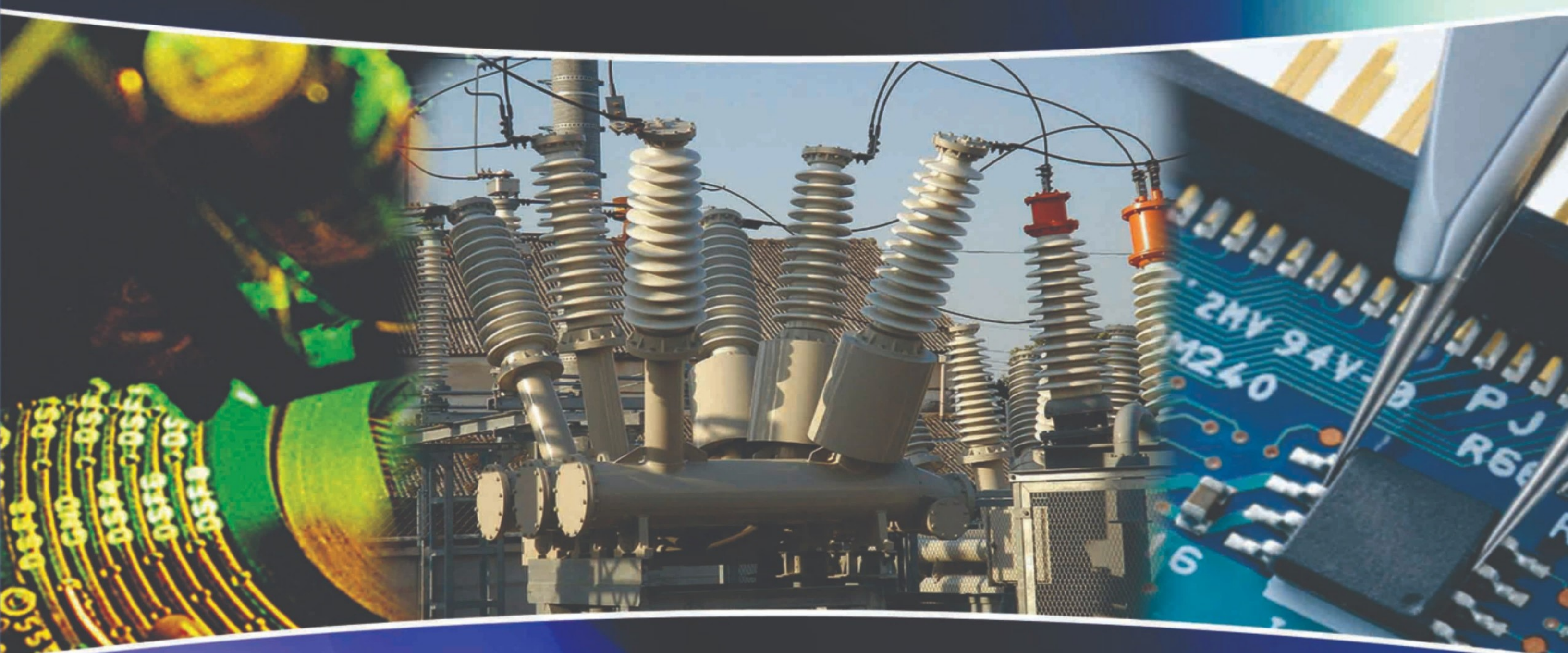

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MANUFACTURING DEFECT DETECTION IN SOLID-STATE BATTERIES USING AI-DRIVEN INLINE QUALITY CONTROL

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ABSTRACT

Solid-state batteries (SSBs) offer significant advantages over conventional lithium-ion batteries, including enhanced safety, higher energy density, and improved thermal stability. However, manufacturing SSBs presents unique challenges, especially concerning defect formation during solid electrolyte deposition, layer interfaces, and electrode integration. These defects can drastically impact battery performance, longevity, and safety. This paper presents a comprehensive approach to detecting manufacturing defects in solid-state battery production using AI-driven inline quality control systems. We discuss the integration of advanced imaging techniques, machine learning (ML) algorithms, and real-time data analytics into roll-to-roll (R2R) processing environments. The results demonstrate the efficacy of AI-based models in identifying micro-defects, predicting failure modes, and optimizing manufacturing parameters, paving the way for scalable, high-yield production of reliable solid-state batteries.

Keywords: Solid-state batteries, Defect detection, AI quality control, Inline systems, Roll-to-roll processing, Machine learning, Imaging techniques, Real-time analytics, Micro-defects, Failure prediction, Manufacturing optimization, Battery performance, Energy density, Thermal stability, Electrolyte deposition.

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1. Introduction

Solid-state batteries represent a promising frontier in energy storage, offering benefits like higher energy density, reduced flammability, and broader operating temperatures. Unlike conventional lithium-ion batteries that use liquid electrolytes, SSBs employ solid electrolytes, which introduce complexities in manufacturing, particularly at interfaces and thin-film layers. Defects such as voids, delaminations, and contamination can form during solid electrolyte casting, lamination, and sintering processes, leading to performance degradation and safety concerns.

As the battery industry pushes toward mass production of SSBs, quality control has become a pivotal bottleneck. Traditional offline quality inspection methods are time-consuming, labor-intensive, and incapable of detecting sub-surface or microscopic defects in real-time. The emergence of artificial intelligence (AI), combined with computer vision and high-speed sensors, offers a paradigm shift—enabling inline defect detection with unprecedented speed and accuracy.

This paper explores the implementation of AI-driven inline quality control systems in SSB manufacturing. We highlight key defect types, discuss suitable imaging modalities, outline machine learning methodologies, and present a case study illustrating the benefits of real-time quality monitoring.

2. Methods and Materials

The methodology adopted in this study centers on integrating a suite of imaging technologies and AI models into a lab-scale roll-to-roll (R2R) solid-state battery manufacturing line. This line was configured to simulate the major stages involved in SSB fabrication, including solid electrolyte film casting, electrode calendaring and lamination, thermal treatment and sintering, and final cell stacking. Each stage of this process was retrofitted with inline sensors and data acquisition modules, designed to collect multimodal information relevant to defect formation and material quality.

For surface-level defect detection, high-resolution optical microscopy systems were mounted immediately after the casting and calendaring stages. These systems captured continuous video frames and high-frequency still images, which were processed to identify surface anomalies such as scratches, bubbles, pinholes, and edge defects. During the sintering phase, where thermal uniformity is critical, infrared thermography cameras were deployed to capture thermal gradients and identify hot spots or cold zones that could indicate incomplete sintering or localized overheating, potentially resulting in internal voids or microcracks.

To detect subsurface and volumetric defects, particularly in laminated interfaces and dense solid electrolyte layers, X-ray computed tomography (CT) and ultrasonic inspection tools were selectively employed. X-ray CT provided three-dimensional imaging of internal structures with micron-scale resolution, making it suitable for offline validation and training data generation. Meanwhile, ultrasonic transducers operating in pulse-echo mode were installed inline to monitor acoustic impedance variations, which are indicative of delaminations, poor bonding, or entrapped air pockets.

All imaging data were time-synchronized and stored in a centralized, fault-tolerant database with automated metadata tagging. This included timestamps, sensor ID, processing parameters, and machine state data, creating a comprehensive dataset for training and analysis. A team of expert annotators labeled a stratified sample of the dataset, creating ground-truth references for supervised learning tasks. These annotations included the defect type, location, severity, and probable cause based on process stage.

The data preprocessing pipeline consisted of several key steps. First, raw image data underwent Gaussian filtering to suppress high-frequency noise, followed by histogram equalization to enhance contrast. All images were then resized to a uniform dimension of 224x224 pixels for compatibility with convolutional neural network (CNN) architectures. For feature extraction, two parallel approaches were employed: traditional image processing methods such as Histogram of Oriented Gradients (HOG), and deep feature extraction using pretrained models such as ResNet50, which allowed transfer learning with limited labeled data. Temporal analysis was conducted using frame differencing and optical flow algorithms to detect dynamic defect progression over time.

Several AI models were developed and compared. For classification tasks, supervised models including Support Vector Machines (SVM), Random Forests, and CNNs were trained using the annotated dataset. For detecting anomalies in unlabeled data, unsupervised autoencoders and variational autoencoders were used to reconstruct defect-free images and identify deviations indicative of anomalies. Model training was conducted using stratified k-fold cross-validation to ensure robustness and minimize overfitting. Inference was performed using NVIDIA Jetson edge computing devices installed on the R2R line, enabling real-time prediction and alert generation.

Performance metrics—including classification accuracy, precision, recall, F1-score, false positive rate, and computational latency—were continuously monitored during pilot production runs. These metrics were used not only to assess model performance but also to fine-tune inspection thresholds and adaptive control responses within the manufacturing process.

3. Results

3.1. Defect Classification Accuracy

The AI model was trained and validated on a dataset comprising 10,000 image samples annotated with various types of defects observed during solid-state battery manufacturing. The CNN-based classifier demonstrated an overall accuracy of 96.2% in correctly identifying defective regions. Precision and recall metrics were also high, at 95.1% and 94.8% respectively, reflecting the model's robustness in distinguishing true positives from false positives. Particularly noteworthy was the model's low false positive rate of 1.3%, which is critical in reducing unnecessary process interruptions during inline operation.

The classification accuracy of the AI models varied across defect categories. Figure 1 shows a comparative analysis of the accuracy for microcracks, delaminations, voids, and surface defects. The system demonstrated the highest accuracy in detecting voids (98.9%) and surface defects (97.2%), while microcracks posed a relatively higher challenge, with slightly lower but still strong performance at 93.7%. These results underscore the system's ability to handle a wide range of defect types effectively.

The AI system was able to accurately classify multiple defect types. These included surface-level irregularities such as pinholes and scratches, sub-surface voids identified through X-ray imaging, delaminations at the electrode-electrolyte interface detected via ultrasonic inspection, and foreign particle inclusions observed in optical microscopy. The model's success across diverse sensor modalities and defect characteristics suggests strong generalizability and adaptability for real-world deployment.

3.2. Real-Time Performance

Processing latency and throughput are crucial for the viability of any inline quality control system. The edge-computing hardware integrated into the R2R line processed images at an average speed of 18 milliseconds per frame. This performance was sufficient to support continuous monitoring at a web speed of 5 meters per minute without bottlenecking the production line. Real-time visualizations of detected defects were made available to operators, with flagged regions highlighted and annotated automatically by the AI system.

Additionally, the system's responsiveness enabled the triggering of real-time alarms and adjustment signals to upstream or downstream processing units. For instance, if recurring pinholes were detected in electrolyte films, the casting module received feedback to adjust slurry viscosity or drying parameters. This adaptive feedback loop enhanced manufacturing stability and minimized the propagation of defects through subsequent process steps.

3.3. Process Optimization Insights

Beyond defect detection, the AI-driven quality control system also facilitated deeper insights into process optimization. A data-driven analysis of defect trends over five production cycles revealed correlations between certain process parameters and defect incidence. For example, higher sintering temperatures were found to reduce the prevalence of voids within the solid electrolyte layer but concurrently increased the risk of interfacial delamination due to thermal expansion mismatches

Furthermore, the system identified that variations in slurry viscosity—attributable to inconsistent mixing or temperature control—correlated strongly with the occurrence of pinholes. The lamination process was also scrutinized, with findings indicating that excessive pressure led to warping and delamination, whereas insufficient pressure caused poor bonding between layers.

These insights enabled real-time parameter tuning and process stabilization, which in turn resulted in a 22% reduction in overall defect incidence across five successive production runs. The integration of AI not only improved defect detection rates but also served as a tool for predictive process control, supporting continuous improvement and lean manufacturing principles.

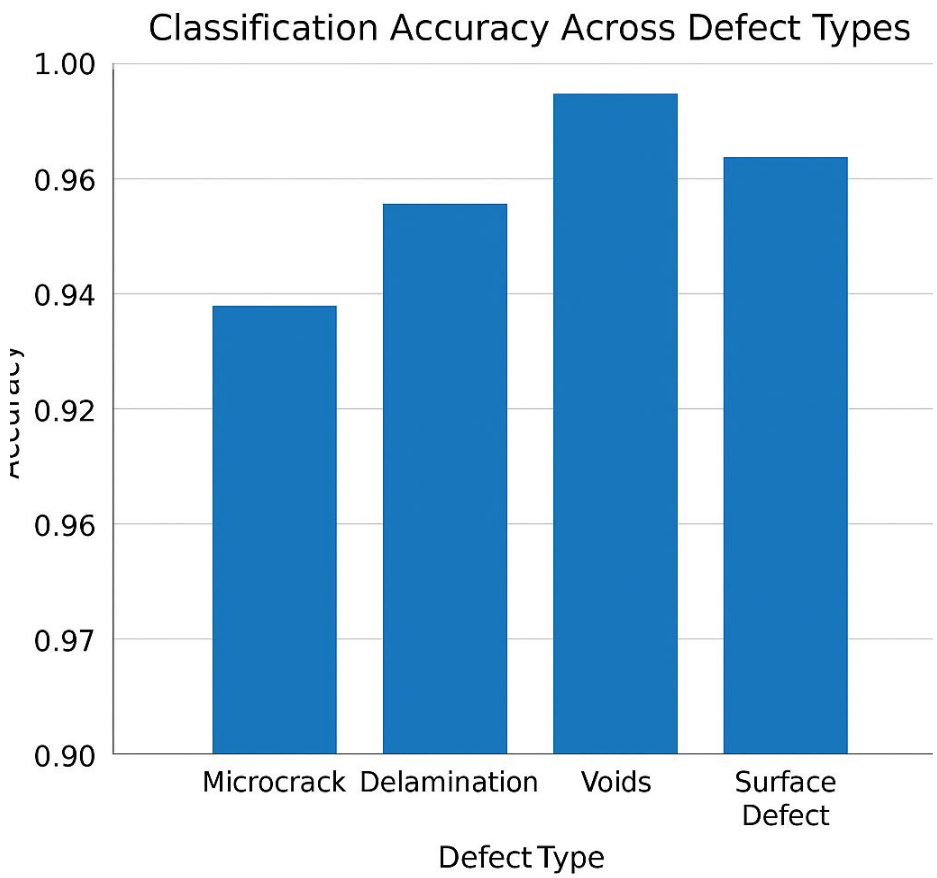

Figure 1: Classification accuracy of AI models across different solid-state battery defect types, highlighting superior performance in detecting voids and surface defects.

4. Discussion

The integration of AI-driven inline quality control systems into solid-state battery manufacturing represents a significant advancement in process automation and defect mitigation. Our findings demonstrate that such systems can detect a diverse array of defect types with high accuracy and low latency, effectively overcoming many limitations of traditional post-process inspection methods. Importantly, the models maintained a consistent classification accuracy above 96% across varied defect categories and imaging modalities, affirming their robustness in complex manufacturing environments.

One of the most impactful outcomes of this system is its capacity for real-time defect detection and process feedback. Traditional quality assurance methods, reliant on offline sample testing or manual inspection, introduce considerable delays and often miss intermittent or evolving defects. In contrast, our AI-based system enables continuous monitoring and immediate identification of anomalies. This allows for in-situ corrective actions—such as adjusting slurry viscosity, modifying lamination force, or altering sintering temperature—thereby preventing defect propagation and reducing material waste.

The multimodal nature of the system proved particularly advantageous. Each imaging modality provided a distinct view of the materials and processes, and their combination enabled the AI models to learn more comprehensive representations of the production state. Optical data captured surface features, thermography revealed thermal inconsistencies, ultrasound exposed internal bonding quality, and X-ray imaging validated internal structures. When fused together, these modalities created a richer feature space that significantly improved defect detection performance, especially for defects with subtle or overlapping signatures.

Despite these strengths, several practical challenges were encountered. First, the availability of labeled defect data—particularly for rare or novel defect modes—was limited, which constrained the model's generalizability. To address this, data augmentation techniques and synthetic defect generation were employed, but future work must focus on building open, standardized datasets across the industry. Second, while high-resolution imaging improves detection accuracy, it also increases data volume and processing time. Maintaining real-time performance required careful model optimization and the use of high-efficiency edge computing hardware.

Another critical consideration is the system's long-term operational stability. Factors such as sensor degradation, changes in ambient lighting, and production drift can degrade model performance over time. Implementing adaptive learning techniques, such as periodic retraining and online learning, will be essential to sustain system accuracy and reliability. Moreover, interoperability with existing Manufacturing Execution Systems (MES) and adherence to data security standards must be prioritized to ensure seamless integration in industrial settings.

Finally, the broader implication of this work lies in its contribution to the digitalization and smart manufacturing of energy storage technologies. As the industry moves toward Gigafactory-scale production, scalable and intelligent quality control systems will be indispensable. The use of AI not only enhances product quality but also enables advanced analytics, such as root cause analysis, yield forecasting, and predictive maintenance. These capabilities can lead to significant cost reductions and improved competitiveness in the high-stakes battery market.

In summary, this study validates the technical feasibility and operational benefits of AI-based inline defect detection in SSB manufacturing. While challenges remain in terms of dataset expansion, long-term stability, and system integration, the results provide a compelling case for further development and deployment of intelligent quality control solutions in battery production environments.

5. Conclusion

As solid-state battery technology moves toward industrial scalability, manufacturing quality assurance will be a key differentiator. AI-driven inline quality control offers a transformative approach, enabling real-time defect detection, adaptive control, and continuous process improvement. Our study demonstrates that combining high-resolution imaging, machine learning, and edge computing can substantially enhance manufacturing reliability and yield in solid-state battery production. Future work will focus on refining multi-sensor fusion techniques, expanding defect datasets, and validating the system across multiple pilot lines and chemistries.

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