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EV BATTERY HEALTH MONITORING

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Abstract: The increasing global demand for Electric Vehicles (EVs) has placed unprecedented emphasis on the health, safety, and lifespan of lithium-ion batteries, which serve as the core energy storage units in these systems. Among various battery formats, cylindrical cells are widely used due to their high energy density, robustness, and ease of manufacturing. However, their operational reliability is highly dependent on internal structural integrity, which, if compromised, can lead to performance degradation, safety hazards, and costly failures. It proposes an automated, non-destructive methodology for detecting anomalies within cylindrical EV batteries using X-ray imaging combined with advanced computer vision and anomaly detection techniques.

The developed system leverages **PaDiM (Patch Distribution Modeling)**, a state-of-the-art anomaly detection algorithm, integrated with image processing libraries such as **OpenCV** and **NumPy** for preprocessing, contour detection, and spatial analysis. The process begins with the acquisition of high-resolution X-ray images of cylindrical batteries under test. These images undergo preprocessing to normalize intensity values, suppress noise, and enhance structural details. The PaDiM model, trained exclusively on defect-free battery images, learns a statistical representation of normal cell structures in a multi-scale embedding space. During inference, any deviation from this learned normal distribution is flagged as a potential defect.

In addition to anomaly classification, the system generates **heatmaps** that visually highlight the spatial location and severity of detected defects. These heatmaps provide interpretable feedback to engineers, enabling precise localization of structural irregularities such as electrode misalignment, separator damage, or manufacturing inconsistencies. A thresholding mechanism is applied to prediction scores to differentiate between "healthy" and "defective" cells, producing quantitative metrics for decision-making in quality control pipelines.

Index Terms: anomaly detection, electric vehicle, X-ray images, PaDiM, spatial analysis, heatmap, thresholding mechanism

I.INTRODUCTION

The rapid adoption of electric vehicles (EVs) has driven exponential growth in lithium-ion battery production, where cell-level quality inspection is paramount for ensuring safety, performance, and longevity. Internal defects such as electrode misalignment, electrolyte leakage, dendrite formation, and foreign particle contamination can lead to catastrophic failures including thermal runaway. X-ray imaging provides a powerful non-destructive testing (NDT) modality for inspecting internal battery structures without disassembly. However, a fundamental challenge arises in applying machine learning to battery X-ray inspection defective batteries are inherently dangerous to scan. Cells exhibiting internal damage—the very samples needed for training a defect classifier—pose risks of thermal runaway, gas venting, or explosion when subjected to X-ray radiation This creates a severe class imbalance problem where normal (good) samples are readily available while anomalous (bad) samples are extremely scarce and hazardous to acquire.

Traditional supervised binary classifiers require representative samples of both classes and thus are ill-suited for this domain. Instead, we adopt a one-class learning paradigm—training the model exclusively on normal battery images and detecting anomalies as deviations from the learned normal distribution. This approach offers two key advantages:

1) It eliminates the need for labeled defective samples during training.
2) It can detect novel, previously unseen defect types, since any deviation from normality triggers detection.

II. OJECTIVES:

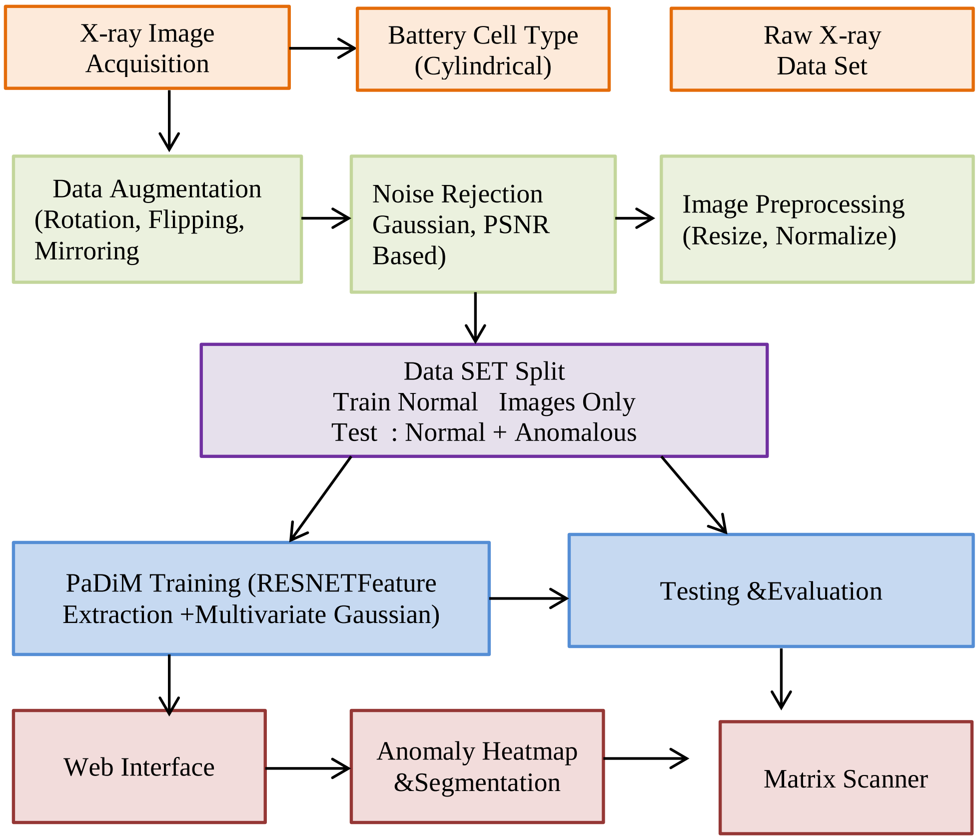
The primary objective of the proposed work is to design and develop an automated, non-destructive EV battery health monitoring system using X-ray imaging and machine learning–based anomaly detection techniques.

The specific objectives are:

1. To develop a non-destructive inspection framework for evaluating the internal structural integrity of cylindrical lithium-ion EV batteries using high-resolution X-ray images.

2. To implement unsupervised anomaly detection model (PaDiM) that learns the normal internal structure of healthy battery cells without requiring large labeled defect datasets.
3. To detect and localize internal battery defects such as electrode misalignment, winding irregularities, separator damage, or material inconsistencies at an early stage.
4. To generate interpretable heatmap visualizations that highlight the exact location and severity of detected anomalies within the battery cell.
5. To extend single-cell analysis to battery pack-level inspection, enabling automated scanning of large battery matrices and identification of defective cells within a pack.
6. To reduce dependency on manual inspection, thereby improving inspection speed, consistency, and accuracy in EV battery manufacturing and quality control processes.
7. To enhance EV battery safety, reliability, and lifespan by ensuring early defect detection and preventing defective cells from entering service.

III. ARCHITECTURE OF THE SYSYEM



IV. **RELATED WORK**

A. Battery Inspection Methods

Non-destructive testing methods for battery cells include ultrasonic testing, computed tomography (CT), and X-ray radiography [3]. X-ray imaging offers a favorable balance between resolution, throughput, and cost for production-line inspection. Recent works have explored automated X-ray analysis using deep learning for detecting internal defects in pouch and cylindrical cells [6].

B. Anomaly Detection in Manufacturing

Anomaly detection in manufacturing has evolved from traditional statistical process control to deep learning-based approaches [7]. Auto encoders [8], generative adversarial networks (GANs) [9], and knowledge distillation methods [10] have been applied to defect detection. However, these methods often require careful architecture design and extensive hyper parameter tuning.

C. Patch-based Anomaly Detection

PaDiM [5] and PatchCore [11] represent state-of-the-art approaches that leverage pre-trained CNN features for patch-level anomaly detection. PaDiM models the distribution of normal patch features using multivariate Gaussians and detects anomalies via Mahalanobis distance. Its advantages include: no need for neural network training (only statistical modeling), efficient inference with pre-computed feature statistics, and pixel-level anomaly localization without segmentation labels. The Anomalib library [12] provides standardized implementations of multiple anomaly detection algorithms, which we utilize as our primary framework.

V. DISCUSSION

A. Advantages of One-Class Learning

The one-class learning paradigm offers critical advantages for battery inspection:

Safety: By requiring only normal samples for training, the approach eliminates the need to repeatedly X-ray potentially hazardous defective cells. This directly addresses the core safety concern that motivates this work.

Generalization to novel defects: Since the model learns the distribution of normality rather than specific defect patterns, it can detect previously unseen defect types—a crucial capability given the diverse failure modes in battery manufacturing.

Reduced annotation burden: No defect-specific labels or segmentation masks are required for training, significantly reducing the annotation effort compared to supervised methods.

B. Robustness through Augmentation

The data augmentation strategy proved essential for achieving robust performance from limited data. PSNR-based noise injection is particularly valuable as it simulates realistic imaging condition variations. The structural symmetry exploitation for prismatic cells leverages domain-specific knowledge to generate physically plausible augmented samples.

C. Limitations

- The anomaly threshold (τ) requires calibration for each cell type and imaging setup.
- Performance may degrade for subtle defects that fall within the normal distribution margin.
- The limited availability of anomalous test samples constrains comprehensive quantitative evaluation.
- The current system assumes relatively consistent imaging conditions; significant variations in X-ray energy or orientation may require recalibration.

D. Industrial Deployment Considerations

The matrix scanning capability enables integration into production-line workflows where multiple cells are imaged simultaneously. The Gradio web interface provides an accessible deployment option that does not require specialized software on the inspection workstation. OpenVINO model export further enables deployment on edge hardware for low-latency inspection.

VI. CONCLUSION

We presented a comprehensive anomaly detection framework for EV battery cell X-ray inspection that addresses the fundamental challenge of scarce anomalous training data. By leveraging PaDiM's one-class learning capability, our system is trained exclusively on normal battery images, eliminating the safety risks associated with repeatedly scanning defective cells. The framework supports cylindrical, pouch, and prismatic cell form factors through tailored preprocessing and augmentation strategies.

Our data augmentation pipeline—combining geometric transforms, PSNR-calibrated noise injection, and structural symmetry exploitation—effectively mitigates the limited dataset constraint. The batch matrix scanning system and web-based deployment interface bridge the gap between research and industrial application.

Future work will explore: (1) active learning strategies to safely incorporate the few available anomalous samples
(2) transfer learning across cell types to leverage shared defect patterns;
(3) integration with production-line CT scanning systems for 3D defect analysis;
(4) continual learning to adapt to evolving manufacturing variations over time.

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