High-Precision AI-Based Vision Inspection for Defect Detection in PEMFC MEA Manufacturing

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This study aims to develop an artificial intelligence (AI)-based vision inspection system for the effective detection of defects in the membrane electrode assembly (MEA), a critical component that directly impacts the performance and durability of polymer electrolyte membrane fuel cells (PEMFCs). The MEA is the site of electrochemical reactions within the fuel cell, and even minor defects, such as electrode damage or gasket failure, can lead to significant performance degradation or complete system failure. Therefore, a high-precision, automated inspection system capable of rapid and accurate defect detection is essential for large-scale manufacturing.

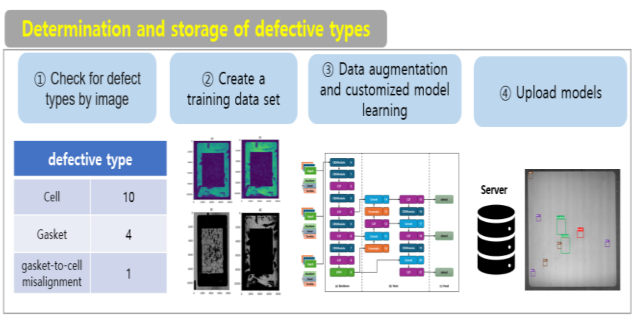

Figure 2. Components for detecting fuel cell defects

Figure 1 illustrates the defect types in PEMFC systems and the essential components involved in the inspection workflow. A typical fuel cell consists of electrodes, gaskets, and the interface region between them, referred to as the gasket-to-electrode alignment area. Defects in the cell (electrode region) are categorized into ten types, including electrode line defects, electrode junction defects, dents, and wrinkles. Gasket-related defects are classified into four major categories: bubble defects, lamination and delamination issues, contamination by foreign materials or dust, and serial number(S/N) marking text defects. Additionally, the alignment region between the gasket and electrode is susceptible to electrode bonding misalignment, which represents a critical defect type [1].

In this study, raw images are preprocessed to construct a training dataset, which is then used to train an AI-based defect detection model. The trained model is stored on a server

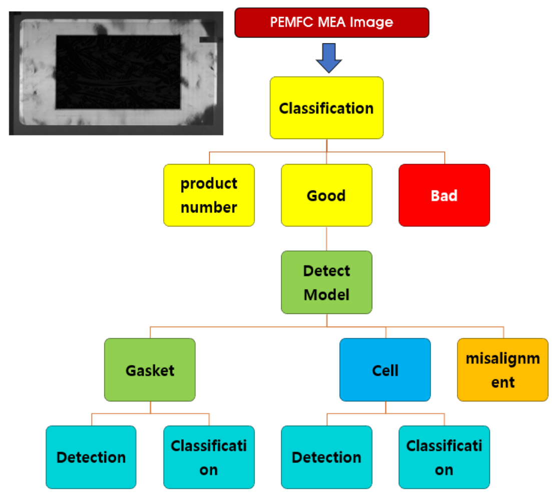

Figure 1. Fuel cell failure detection scenario using AI models

and deployed in the manufacturing process for real-time quality inspection and defect classification. The goal is to automate the inspection of membrane electrode assemblies (MEAs), which are critical to the performance and longevity of PEMFCs [2], [3].

Figure 2 presents the complete workflow for defect classification in fuel cell images following preprocessing. The original image of the fuel cell has a high resolution of 11,000 × 8,134 × 24, which imposes significant computational and memory challenges when used directly in conventional AI models [4]. Therefore, the initial step involves resizing the image. For visually identifiable defects, a classification model is applied to the resized image to selectively detect major defect types. During this stage, product numbers are also extracted for traceability.

In the subsequent stage, a detection model is employed to accurately segment the gasket, electrode, and misalignment regions. These segmented regions are then sliced into small image patches with a defined overlapping ratio. Each patch is analyzed using either a DETR (DEtection TRansformer) model [5] or an additional classification model to identify fine-grained defects. To enhance the precision of detecting small-scale defects—such as bubbles or micro-cracks—a customized DETR model incorporating the Tailing SAHI (Slicing Aided Hyper Inference) technique [6] is adopted. This approach enables accurate detection of minute defects even in high-resolution images without omission, optimizing the balance between detection accuracy and computational efficiency.

The developed system encompasses AI model management, training dataset generation and version control, and a user interface (UI) for real-time visualization of defect detection results. It is designed to be readily deployable in real manufacturing environments. The system automatically logs inspection outcomes, defect rates by product, and daily reports by defect type, supporting informed decision-making and enhanced traceability in the production process [7], [8].

This study establishes a high-precision, vision-based AI defect detection framework tailored for the PEMFC MEA manufacturing process. It significantly contributes to ensuring both reliability and economic feasibility in fuel cell production [9]. Future developments will include integration with real-time control systems for immediate feedback during defect detection and expansion to multi-camera environments and 3D analysis technologies to enable full-cycle quality control across the entire manufacturing line [10].

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