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AI-Supported Video-Based Maintenance for Unknown Systems

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Abstract

Traditional industrial maintenance depends on comprehensive documentation, historical data, and explicit system models—resources often absent for legacy, proprietary, or acquired machinery. This paper introduces a novel paradigm termed Zero-Knowledge Maintenance Ziane et al. [6], which enables diagnostic reasoning for completely unknown systems without any prior technical information.

Our approach relies solely on multiview video Donato et al. [1] observations of equipment operation. During an initial learning phase, a vision-enhanced Large Language Model (LLM) Zhou et al. [5] analyzes synchronized video streams from fixed perspectives, autonomously constructing a behavioral blueprint—a structured textual description of normal operational patterns, component interactions, and sensor-event correlations. This blueprint serves as emergent, machine-generated documentation.

Upon fault occurrence, an identical multiview recording is captured. The LLM then performs comparative spatiotemporal analysis, detecting subtle deviations in motion sequences, timing, and relational logic between components. Rather than matching pre-defined fault patterns, the system engages in physical-abductive reasoning to generate plausible root-cause hypotheses and actionable maintenance suggestions.

This method fundamentally reframes maintenance from a data-driven prediction task into a multimodal reasoning and explanation challenge. It eliminates dependency on labeled failure datasets, system-specific training, or manual expert input. We present the conceptual architecture of the framework, detail the infer-

ence pipeline from perception to recommendation, and discuss critical challenges regarding operational safety, robustness in noisy environments, and the explainability of AI-generated diagnostic narratives. Wang et al. [4], Du et al. [2]

The proposed framework establishes a new direction for maintaining true black-box systems, with immediate relevance for legacy industrial sites, critical infrastructure with lost documentation, and rapid-response scenarios in field service and disaster recovery.

1. Description from process

In our research, we are investigating the operation of a bagging machine. The first step is to describe the process in natural language. We record videos from multiple positions while the bagging machine is in operation. From these, we create a description based on the videos. Our algorithm takes into account key moments and changes. During the description, we use a technique called clustering. The video recording points are pre-marked so that it can be reproduced. In addition, we predetermined the length of the videos to suit the given position, fully covering the processes.

2. Maintenance and fault detection method

The algorithm describes a basic, well-functioning bagging machine. This description will be the starting point for our system. The next step is to create videos of a malfunctioning bagging process, from the original designated positions. The resulting good and bad process descriptions are compared with our algorithm. The algorithm then compares the clusters and lists the differences. Taking the differences into account, we receive a solution and maintenance and fault detection Lang et al. [3] proposal from the system.

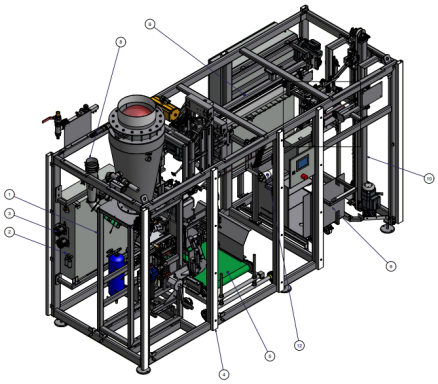

Figure 1. Overview of bagging machine

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