Smart Monitoring System for Bottle Breakage Detection in Production Lines

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Abstract

This project presents a smart monitoring system for bottle breakage detection in production lines. The system uses statistical analysis and real-time monitoring to evaluate machine performance and detect abnormal patterns. By combining event-level and accumulated metrics, the solution provides reliable insights and supports maintenance decision-making. The system improves operational efficiency and aligns with Industry 4.0 principles.

Introduction

Modern manufacturing relies on data-driven technologies to improve efficiency and reduce defects. Bottle breakage is a common issue that leads to production losses and operational delays. This project proposes a monitoring system that analyzes production data in real time to improve decision-making and system performance.

Background

Industry 4.0 integrates data analytics and real-time monitoring to improve manufacturing processes and operational efficiency. These technologies enable the continuous evaluation of production performance and support better decision-making in industrial environments. However, many production systems still rely on manual data interpretation and static monitoring approaches. This limitation highlights the need for more adaptive and data-driven solutions capable of analyzing performance trends and identifying abnormal patterns over time.

Problem

In bottle production lines, breakage events are recorded but not effectively analyzed. Operators must manually interpret the data, leading to delays and inconsistent decisions. Additionally, static thresholds do not adapt to different production conditions. There is a need for a system that analyzes breakage dynamically and provides automated recommendations.

Methodology

The proposed Smart Monitoring System was developed as a data-driven solution to monitor bottle breakage in production lines. The system was implemented using Python, leveraging the Flask framework to create a web-based application that allows real-time data entry and interaction.

The system architecture is composed of three main components: a Flask-based web application, a SQLite database for persistent data storage, and a visualization layer implemented using Chart.js. These components ensure efficient data processing and clear interpretation of system behavior.

Figure 1 shows the local execution of the system using Flask, where the application runs on a local server and enables user interaction through a web interface.

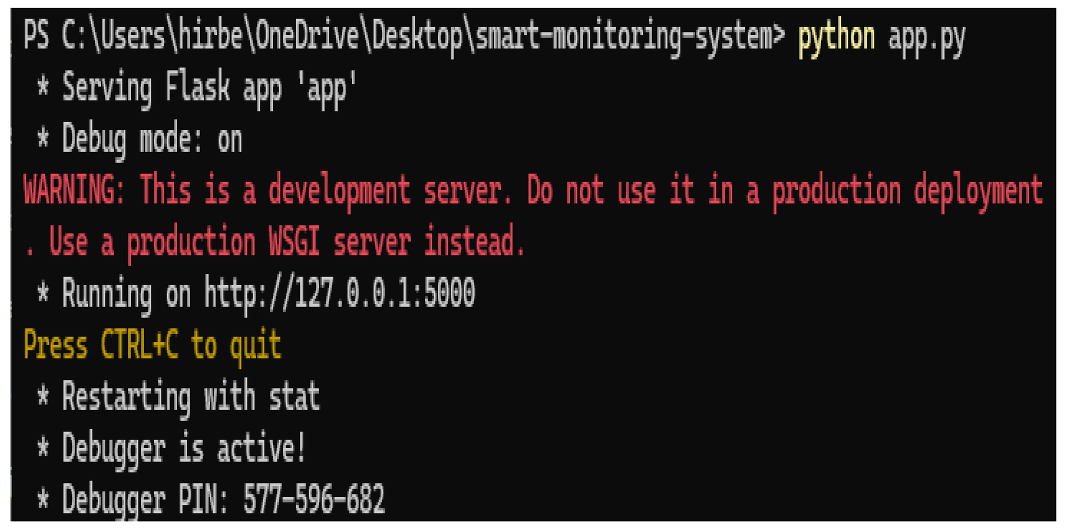


Figure 1
Flask Application Running Locally

The system operates by recording production events, where each event includes batch number, production stage, total bottles produced, and number of broken bottles. This event-based approach allows continuous data collection instead of relying on batch-level analysis.

For each event, the system calculates two key metrics: breakage rate at the event level and accumulated rate at the system level. While the breakage rate reflects immediate conditions, the accumulated rate provides a more stable indicator of long-term performance.

Based on predefined thresholds, the system classifies the machine condition into NORMAL, WARNING, or CRITICAL states and generates maintenance recommendations. Additionally, the system calculates Quantity Between Failures (QBF) to evaluate system reliability.

This methodology allows the system to continuously evaluate machine performance by combining immediate event data with accumulated historical behavior. As a result, the system avoids overreacting to isolated anomalies while still detecting meaningful degradation patterns over time. This improves the reliability of maintenance decisions and supports a more proactive approach to system monitoring.

Results and Discussion

The system was tested using simulated production data across multiple events and stages. Results show that the system successfully evaluates both event-level and accumulated performance, providing a more reliable assessment of machine behavior.

The user interface allows operators to input production data in real time, including batch number, stage, total bottles, and broken bottles. Once submitted, the system automatically calculates key metrics such as breakage rate, accumulated rate, system status (NORMAL, WARNING, CRITICAL), and maintenance recommendations.

The results demonstrate that the system avoids overreacting to isolated events by relying on accumulated performance. For example, a high breakage rate in a single event does not immediately trigger a critical condition if the accumulated rate remains within acceptable limits.

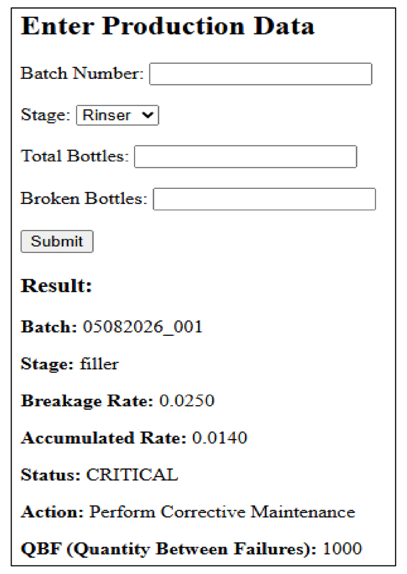
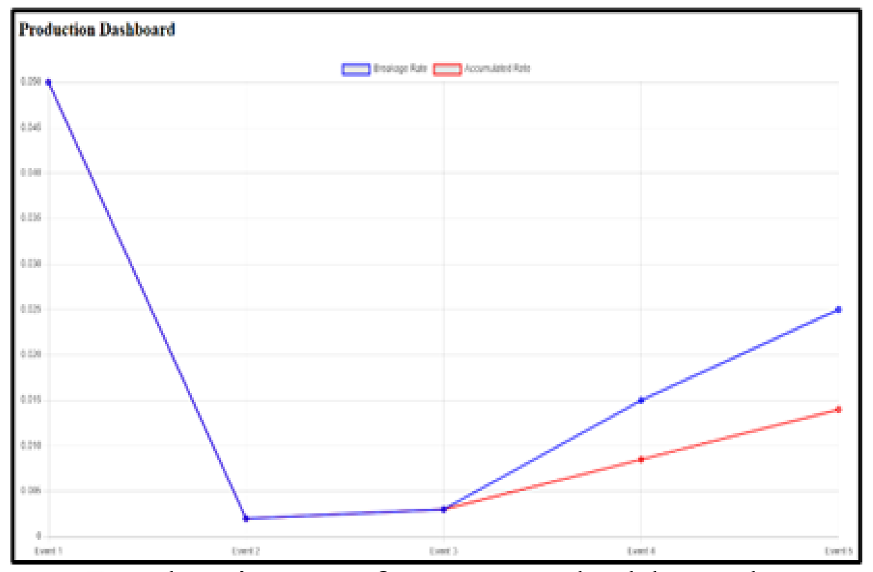


Figure 2
System Output in CRITICAL State

The dashboard visualization enhances system interpretability by displaying performance trends over time. The breakage rate (event-level) and accumulated rate (system-level) allow users to clearly observe system behavior and make data-driven decisions.

Overall, the system improves monitoring accuracy, reduces false alarms, and supports more consistent and efficient maintenance decisions compared to traditional approaches.



Production performance dashboard

Conclusions

The proposed Smart Monitoring System successfully integrates statistical analysis and real-time monitoring to evaluate machine performance in production lines. By combining event-level data with accumulated metrics, the system provides a more reliable understanding of system behavior.

The results demonstrate that the system effectively distinguishes between short-term variability and long-term degradation patterns. This reduces false alarms and supports more accurate and consistent maintenance decisions.

Overall, the system improves operational efficiency, enables proactive maintenance strategies, and aligns with Industry 4.0 principles for data-driven manufacturing.

Future Work

Future work may include the integration of machine learning and artificial intelligence techniques for predictive maintenance and anomaly detection. Additionally, the incorporation of automated data collection through sensors can enhance real-time monitoring capabilities. These improvements would enable the system to provide more accurate predictions, reduce manual input, and further optimize decision-making processes in industrial environments.

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