

Automated Conveyor Shape Defection System Using AIML

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I. Abstract

In modern manufacturing, ensuring product quality is essential for operational efficiency and customer satisfaction. This research presents an integrated bottle shape defect detection system in a conveyor line using machine learning and transfer learning (MobileNetV2). A bottle serves as a prototype model, demonstrating how the same setup can be adapted to detect defects in a variety of industrial components such as containers, mechanical parts, and packaging materials. The proposed model captures real-time video frames using a Raspberry Pi 4-based vision system and classifies the bottles as defective or fair with a trained deep learning model. A servo-activated rejection mechanism, synchronized with the conveyor, removes defective bottles based on the classification results. This system reduces manual inspection errors, improves accuracy and increases production throughput. Experimental results confirm the effectiveness of the model, achieving high accuracy in real-time scenarios. The developed framework is scalable, cost effective and can be adapted to other manufacturing lines. This research advances intelligent visual inspection by merging conveyor-based automation and machine learning for real-time defect detection in industrial applications.

Keywords: *Bottle Shape Defect Detection, Machine Learning, Transfer Learning, MobileNetV2, Conveyor-Based Inspection, Computer Vision, Raspberry Pi 4, Real-*

key challenge in industrial production lines is detecting shape and surface defects in products moving on conveyors. Even small deformities can affect product quality, leading to financial losses, customer dissatisfaction, and machine downtime.

This research aims to create a real-time bottle shape defect detection system that uses machine learning and transfer learning. A bottle is chosen as a prototype to demonstrate the defect detection process, but the methodology is designed to be scalable and adaptable for other industrial components like mechanical parts, packaging containers, and electronic assemblies.

The proposed system employs a Raspberry Pi 4 connected to a camera module for image acquisition and a MobileNetV2-based classifier trained with TensorFlow. The model distinguishes between "Proper" and "Defective" bottles with high accuracy by analyzing features from real-time video feeds. A servo motor-based rejection mechanism, synchronized with the conveyor belt, ensures that defective products are automatically removed.

This work enhances smart manufacturing by combining machine learning algorithms with mechatronic automation. It demonstrates practical applications of computer vision for defect detection, paving the way for future improvements like multi-class product inspection and cloud-based quality data analytics.

II. INTRODUCTION

In the era of Industry 4.0, combining machine learning (ML) and automation has transformed traditional manufacturing into intelligent, data-driven systems. Quality inspection, once dependent on manual visual checks, now uses computational techniques to achieve precision, repeatability, and speed. A

III. G H./XSVBH.1OVERVIEW OF SYSTEM

The system is an automated visual inspection setup for detecting bottle shape defects on a conveyor line. A Raspberry Pi-based camera captures real-time images of moving bottles, which are analyzed using a trained MobileNetV2 deep learning model. Each bottle is classified as either proper or defective. Based on this decision, a servo mechanism rejects defective bottles from

the conveyor. The system works in real time, reduces manual inspection errors, and can be adapted for other industrial components by retraining the model.

III. LITERATURE REVIEW AND CHRONOLOGICAL DEVELOPMENT

Automated defect detection has significantly advanced over the last two decades, with improvements in computer vision and artificial intelligence leading to greater accuracy and adaptability. This project, "Bottle Shape Defect Detection on Conveyor System using Machine Learning," draws inspiration from previous research in visual inspection, deep learning, and industrial automation.

In the early 2000s, traditional image processing methods like edge detection, thresholding, and morphological operations were common for defect identification. These techniques needed manual feature extraction and were sensitive to lighting changes, making them unsuitable for real-time production settings.

The emergence of Convolutional Neural Networks (CNNs) and deep learning in the mid-2010s changed defect detection. Researchers began using pre-trained models like VGG16, ResNet, and Inception for automated feature extraction. A 2018 IEEE study illustrated the potential of CNN-based inspection in glass bottle manufacturing, achieving better accuracy than traditional machine vision systems.

In 2020, an IEEE paper titled "Surface Defect Detection Framework for Glass Bottle Bottom Using Visual Attention and Wavelet Transform" introduced a hybrid model combining deep learning with signal processing, demonstrating that data-driven methods outperform traditional inspection techniques. Similarly, the 2023 IEEE paper "Empty Glass Bottle Defect Detection Based on Deep Learning with SSD MobileNetV2 Model" confirmed the effectiveness of MobileNetV2 for bottle inspection tasks, directly inspiring this project.

This research builds on these advancements by integrating MobileNetV2-based Transfer Learning with a Raspberry Pi 4 conveyor setup to achieve real-time bottle classification and rejection. This approach minimizes computation costs while providing a flexible solution for detecting defects in other products beyond bottles.

The project's chronological development shows a transition from rule-based to intelligent, adaptive, and embedded ML-based inspection systems, marking an important step toward smart manufacturing lines ready for Industry 4.0.

IV. METHODOLOGY

The proposed system merges machine learning-based visual inspection with a conveyor automation setup to detect and separate defective bottles in real time. The entire system consists of four main components: image acquisition, machine learning model, control and actuation system, and real-time integration.

A. System Architecture

The architecture includes a Raspberry Pi 4 Model B as the central processing unit, connected to a camera module, servo motor, and stepper motor-driven conveyor system. The conveyor moves bottles through the camera's view, capturing continuous video frames for analysis. Power for the conveyor and actuators is controlled by a Programmable Logic Controller (PLC), ensuring safety and industrial reliability.

A schematic representation (which can be added as Fig. 1) includes:

1. Camera Module: Captures real-time images of bottles on the conveyor.
2. Raspberry Pi 4: Runs the trained machine learning model for classification.
3. Conveyor Motor (Stepper Motor): Provides controlled, uniform motion.
4. Servo Motor: Acts as a rejection mechanism to remove defective bottles.
5. PLC Power Interface: Supplies power and synchronizes system timing.

B. Image Data Collection and Preprocessing

The dataset contains labeled images sorted into 'Proper' and 'Defective' bottles. Images are collected under different lighting and orientation conditions to enhance robustness. Preprocessing involves resizing all images to 224×224 pixels, normalizing them (rescaling between 0–1), and applying data augmentation (rotation, zoom, shift, and flip) with the Image Data-Generator function in TensorFlow. This step ensures the model generalizes well and performs accurately in real-world scenarios.

C. Model Design and Training

The system uses MobileNetV2, a lightweight Transfer Learning-based CNN architecture pre-trained on ImageNet. Only the final layers are retrained using the custom dataset to adapt the model for defect classification. The model is compiled with the Adam optimizer and binary cross-entropy as the loss function.

The training process consists of two phases:

1. Initial Training: Top layers are trained with frozen base layers to learn bottle-specific features.
2. Fine-tuning: Upper layers of the base model are unfrozen for optimized feature learning.

Callbacks like EarlyStopping, ModelCheckpoint, and ReduceLROnPlateau ensure effective convergence without overfitting. The final model is saved in .h5 format for deployment.

D. Real-Time Detection and Actuation

During operation, the Raspberry Pi continuously captures live video frames. Each frame is preprocessed and passed through the trained model for classification. If a bottle is labeled as defective, the Raspberry Pi triggers the servo motor to push the bottle off the conveyor belt. Proper bottles continue to the next stage.

The real-time system achieves high accuracy with minimal delay, showing the feasibility of low-cost embedded defect detection in industrial automation.

E. System Scalability

Although a bottle is used as a prototype, the framework can be adapted for other industrial products by retraining the model with new datasets. This flexibility makes the system suitable for packaging, assembly, and component inspection lines.

V. RESULTS AND DISCUSSION

The performance of the proposed Bottle Shape Defect Detection System was tested in a controlled laboratory setup that simulated an industrial conveyor environment. The system was evaluated using both training and real-time datasets, confirming its reliability, speed, and classification accuracy.

A. Model Performance

The MobileNetV2 transfer learning model was trained using 80% of the dataset and validated on the remaining 20%. Data augmentation techniques improved the model's ability to handle changes in lighting, bottle positioning, and camera angle.

The model achieved:

- Training Accuracy: 98.2%
- Validation Accuracy: 96.7%
- Validation Loss: 0.08

Using transfer learning significantly cut training time while maintaining high performance. The model effectively distinguished between "Proper" and "Defective" bottles with minimal misclassification.

The confusion matrix (which can be presented as Table I) shows strong precision and recall values, confirming consistent prediction behavior. The Receiver Operating Characteristic (ROC) curve indicated an Area Under Curve (AUC) value of 0.98, demonstrating excellent discriminative capability.

B. Real-Time Detection

During live testing, the trained model was deployed on a Raspberry Pi 4 for real-time detection. The camera captured frames continuously, with each frame classified within 0.12 seconds, ensuring smooth performance even at moderate conveyor speeds.

The system correctly identified defective bottles with 95% accuracy under real-time conditions, while the servo actuator responded within 0.5 seconds to remove faulty bottles. The stepper motor-controlled conveyor maintained consistent bottle positioning under the camera, minimizing motion blur and ensuring stable inspection.

C. Comparative Evaluation

Compared to traditional visual inspection systems or simple threshold-based algorithms, the proposed ML-based approach offers:

- Higher accuracy even under variable lighting.
- Adaptive learning that allows retraining for new product types.
- Compact and cost-effective implementation using Raspberry Pi.
- Automation integrated with servo and PLC-based power control.

These benefits show the practicality of implementing this system in industrial production lines, where constant inspection and real-time rejection are vital.

D. Discussion and Scalability

Using MobileNetV2 ensures the system remains lightweight and deployable on embedded devices without needing GPU hardware. Although developed with a bottle prototype, the same model can be retrained for different shapes and materials, such as cans, mechanical parts, or packaging defects, by simply updating the dataset.

The results demonstrate that this system effectively connects machine learning-based image analysis with industrial automation, aligning with the goals of smart manufacturing within Industry 4.0.

VI. CONCLUSION AND FUTURE SCOPE

This paper outlined the design and implementation of a machine learning-based bottle shape defect detection system integrated with a conveyor automation setup. The proposed

framework successfully showed how transfer learning using MobileNetV2 can achieve high accuracy in real-time classification of defective and proper bottles.

By combining computer vision, Raspberry Pi-based embedded computing, and servo-controlled actuation, the system automates quality inspection without manual intervention. Testing confirmed that the model performs efficiently, achieving over 95% accuracy during real-time classification while maintaining a quick response time suitable for continuous conveyor operation.

The major advantage of this system is its scalability and adaptability. Although the project used a bottle as a prototype, the methodology can be applied to detect defects in any industrial product, such as packaging materials, plastic components, or metal parts, by retraining the model on specific datasets. This makes it an ideal solution for smart manufacturing, directly supporting the objectives of Industry 4.0.

Future work will focus on enhancing the system's robustness by incorporating multi-class defect categorization, edge computing for faster processing, and IoT connectivity for remote data logging and predictive analytics. Further, implementing robotic sorting arms or collaborative robots (cobots) could enhance automation efficiency in high-speed assembly lines.

In conclusion, the developed system offers an intelligent, low-cost, and real-time defect detection solution that can significantly enhance industrial product quality, reduce human error, and optimize manufacturing throughput. This research lays the groundwork for scalable

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