Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025

DESIGN AND FABRICATION OF AN AUTOMATED VISION-BASED SYSTEM FOR DIMENSIONAL ANALYSIS

Dr. M. Bhuvaneswaran, Associate Professor and Head of the Department, Department of Mechanical Engineering, Sri Shakthi Institute of Engineering and Technology, Coimbatore, India.
Mounish D, Department of Mechanical Engineering, Sri Shakthi Institute of Engineering and Technology.
Ajeesh S, Department of Mechanical Engineering, Sri Shakthi Institute of Engineering and Technology.
Leela Krishnan V, Department of Mechanical Engineering, Sri Shakthi Institute of Engineering and Technology.

Abstract
This study presents the design and fabrication of an automated vision-based system for dimensional analysis, aimed at enhancing quality control in manufacturing. Utilizing a Raspberry Pi HQ Camera and Python-based OpenCV algorithms, the system performs real-time dimensional measurements of components, such as rectangular plates with dowel pin holes (nominal diameters 2.0 cm and 1.0 cm), with deviations below 0.4 cm deemed acceptable. A compact conveyor system ensures seamless material handling, operating at 0.2 m/s. Tested under ambient lighting, the system achieved an inspection time of 5.85 s per specimen and zero downtime over 56 hours, demonstrating reliability. Challenges included measurement inaccuracies for larger holes due to lighting variability, suggesting future enhancements like controlled illumination and robotic arm integration. This cost-effective, scalable solution aligns with Industry 4.0, offering improved accuracy, reduced labor costs, and enhanced productivity for small and medium-sized enterprises (SMEs).

Keywords:
Automated vision system, dimensional analysis, Raspberry Pi, OpenCV, Industry 4.0

I. Introduction

Modern manufacturing faces increasing demands for precision, efficiency, and cost-effectiveness in quality control to meet consumer expectations and competitive market pressures. Traditional manual inspection methods, using tools like calipers or micrometers, are prone to human error, time-consuming, and unscalable, leading to inefficiencies in high-volume production environments. These methods struggle to maintain consistency, often resulting in defective products passing inspection or acceptable ones being rejected, which increases waste and costs.

The proposed automated vision-based system addresses these challenges by integrating a Raspberry Pi HQ Camera with Python-based image processing for real-time dimensional analysis of components, such as rectangular mild steel plates with dowel pin holes. Supported by a compact conveyor system, it measures dimensions in centimeters, categorizing components as pass (deviations < 0.4 cm) or scrap (deviations ≥ 0.4 cm). The system leverages affordable technologies to enhance product quality, reduce inspection time, and minimize labor, aligning with Industry 4.0 principles of automation and digitalization.

1.1 Significance of Automation

Automation is pivotal in modern manufacturing, enabling industries to meet stringent quality standards while addressing high-volume production challenges. Vision-based systems offer non- contact measurements with high accuracy, making them ideal for quality control. The Raspberry Pi platform, with its 12.3-megapixel camera and Python libraries (e.g., OpenCV, NumPy), provides a cost-effective alternative to industrial vision systems, democratizing advanced automation for SMEs. Applications in automotive and electronics manufacturing, where precise dimensional accuracy ensures assembly integrity, underscore the system’s relevance.

1.2 Project Objectives

The project aims to:

1. Enable real-time inspection of components on a conveyor belt, minimizing inspection duration (< 6 s per specimen).
2. Reduce dependence on skilled labor for repetitive inspection tasks.
3. Eliminate errors due to human fatigue.
4. Enhance product quality by accurately identifying defects and categorizing components as pass or scrap.

1.3 Scope

The system utilizes the Raspberry Pi HQ Camera and Python libraries to measure key parameters of rectangular plates, detecting defects and classifying components based on dimensional tolerances. Automated material handling via a conveyor ensures real-time operation, with testing conducted under ambient lighting to simulate practical industrial conditions. The system is scalable, energy- efficient, and cost-effective, suitable for manufacturers with diverse budgets.

II. Literature Review

The literature highlights the transformative role of machine vision and automation in manufacturing, providing a foundation for this project.

2.1 Machine Vision Systems

Malamas et al. [7] provide a historical perspective on machine vision systems, categorizing them into image acquisition, processing, and decision-making modules, consistent with this project's architecture. Applications include dimensional measurement and defect detection, though challenges like lighting variability and processing speed persist. Rosebrock [11] details OpenCV's capabilities in Python for real-time image processing, including edge detection, contour analysis, and thresholding, which are central to this system's software framework. Pungle et al. [10] emphasize machine vision's role in Industry 4.0, highlighting the importance of reliable lighting and sensor selection for accuracy.

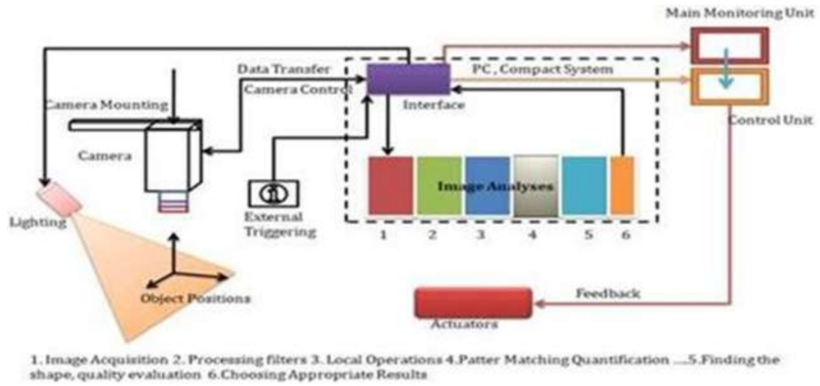

Figure 1: Components of machine vision systems (adapted from Pungle et al. [10]).

2.2 Raspberry Pi-Based Vision Systems

Nath [8] describes the Raspberry Pi 3B+'s suitability for automation, with its 1.4 GHz quad-core processor and Camera Serial Interface supporting the 12.3-megapixel HQ Camera. Kumar et al. [5] demonstrate a Raspberry Pi system achieving 95% defect detection accuracy in printed circuit board inspection, validating its use for dimensional analysis. The platform's affordability and processing power make it ideal for SMEs, though limited computational capacity for complex algorithms requires optimized code, as addressed in this project.

2.3 Conveyor System Design

Todkar and Ramgir [12] present a detailed study on conveyor design, emphasizing precise belt tension and motor control for reliable material handling. Their calculations for belt speed and power requirements inform this project's conveyor setup, operating at 0.2 m/s with a NEMA 23 stepper motor. Zhang et al. [13] describe a vision-based conveyor monitoring system, underscoring the need for synchronized operation and consistent lighting to ensure accurate inspections, aligning with this project's integration of conveyor and vision systems.

2.4 Image Processing Techniques

Gonzalez and Woods [3] provide foundational image processing techniques, including Canny edge detection and contour analysis, directly applied in this system to measure dimensions. Profili et al. [9] emphasize user-friendly defect detection systems using high-resolution cameras and neural network-based analysis, highlighting the importance of robust processing. While this project uses simpler OpenCV algorithms, the literature supports the need for precise image acquisition and processing to achieve reliable results.

III. Materials and Methodology

This section describes the materials used in constructing the system and the methodology employed for its design, fabrication, and testing.

3.1 Materials

The system was constructed using a combination of hardware components selected for their durability, precision, and cost-effectiveness. The conveyor frame was made from mild steel C- channels, measuring 121.9 cm in length with a 4 cm by 2 cm cross-section and a yield strength of 250 MPa, ensuring structural rigidity. An aluminium gantry, constructed from 6061-T6 alloy and measuring 30 cm by 30 cm, provided lightweight and corrosion-resistant support for the camera and Raspberry Pi, with a density of 2.7 g/cm³. The vision module utilized a Raspberry Pi HQ Camera, featuring a 12.3-megapixel Sony IMX477 sensor and a 6 mm lens, offering a 202° field of view at a 10 cm distance. A NEMA 23 stepper motor, delivering 1.2 Nm torque and configured for 1/16 microstepping via a TB6600 driver, powered the conveyor. The conveyor belt was made of PVC, measuring 28 cm by 188 cm with a 2 mm thickness, and was anti-static with a 0.3 coefficient of friction for stable specimen transport. An infrared sensor with a 5 cm detection range and 50 ms response time triggered image capture. Power was supplied by a 24 V, 5 A DC unit, with a 12 V regulator for the Raspberry Pi. The test specimen was a mild steel plate, measuring 8 cm by 5 cm by 1 cm and weighing 0.3 kg, with four dowel holes—two with a nominal diameter of 2.0 cm and two with 1.0 cm.

The software environment included Python 3.9, OpenCV 4.5.5, NumPy 1.21, and RPi.GPIO, running on a 64-bit Raspbian operating system, is optimized for real-time processing on the Raspberry Pi's 1.4 GHz processor.

3.2 Methodology

The methodology encompassed the design, fabrication, software development, and system testing to ensure reliable dimensional analysis. The system was designed to integrate a conveyor for material handling, a vision module for image capture, and a software framework for processing. The conveyor, modeled using SolidWorks, featured a 121.9 cm frame with a 100 cm travel length, ensuring precise specimen positioning. The Raspberry Pi HQ Camera, mounted 10 cm above the belt, captured images at a resolution of 4056 by 3040 pixels. A NEMA 23 stepper motor maintained a belt speed of 0.2 m/s, synchronized with an infrared sensor to trigger image capture.

Fabrication involved constructing the conveyor frame by welding mild steel C-channels, installing rollers, and fitting a PVC belt for smooth operation. The aluminium gantry was assembled to securely hold the camera and Raspberry Pi. The stepper motor was coupled to the conveyor via a pulley system, with the TB6600 driver configured for 1/16 microstepping to achieve smooth motion. Electrical wiring was completed using a 24 V power supply, with a regulator ensuring stable power for the Raspberry Pi.

Software development was conducted in Python 3.9, leveraging OpenCV 4.5.5 for image processing. The software captured images using cv2.VideoCapture, interfacing with the camera's CSI port. Preprocessing involved converting images to grayscale, applying a 5 by 5 Gaussian blur to reduce noise, and performing Canny edge detection with thresholds of 100 to 200 to enhance feature detection. Contour detection was used to measure the specimen's length, width, and hole diameters, with a pixel-

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025

to-cm calibration factor of 1 cm equaling 400 pixels at a 10 cm distance. Components were classified as pass if deviations from nominal values were less than 0.4 cm, or scrap if deviations were 0.4 cm or greater, with results logged in CSV files for traceability. Motor control was achieved using RPi.GPIO, delivering 4074 steps per second to maintain the target belt speed. Camera calibration was performed using a 7 by 9 checkerboard pattern with 2.5 cm squares, correcting lens distortion to achieve a measurement accuracy of ±0.02 cm for length and width.

Testing was conducted in a controlled environment at 25°C and 60% humidity over 20 runs. A 0.3 kg specimen was transported across 100 cm, with images captured at 1 frame per second under ambient lighting of 300 to 500 lux. Performance metrics included belt speed, inspection time, dimensional accuracy, and system reliability, with results recorded for analysis.

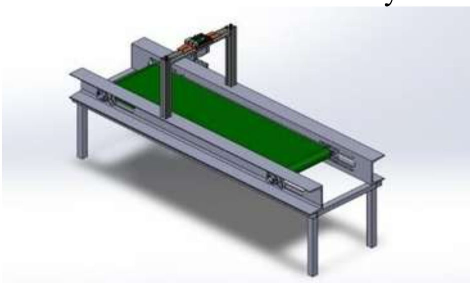

Figure 2: 3D design of the conveyor system.

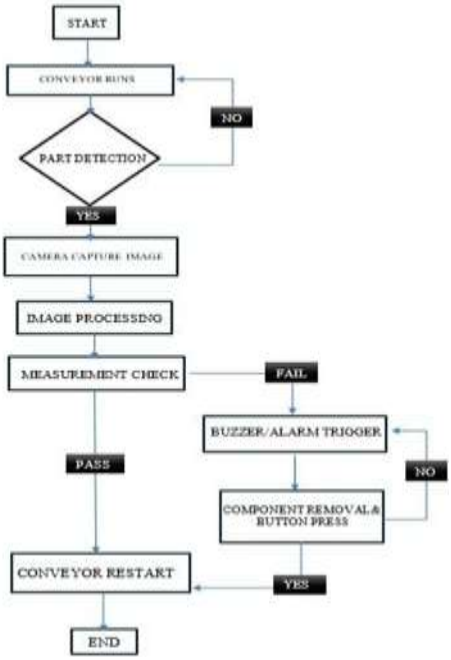

Figure 3: Software processing workflow.

IV. Results and Discussion

4.1 Results

Testing demonstrated the system's effectiveness in dimensional analysis. The conveyor maintained an average belt speed of 0.199 m/s with a standard deviation of 0.003 m/s, falling within a ±5% tolerance of the target 0.2 m/s. Inspection time per specimen averaged 5.85 seconds, comprising 5 seconds for conveyor travel and 0.85 seconds for image processing, meeting the project's goal of under 6 seconds. Dimensional measurements revealed high accuracy for the specimen's length and width, with a measured length of 8.02 cm against a nominal 8.0 cm, yielding a deviation of 0.02 cm, and a width of 5.01 cm against a nominal 5.0 cm, yielding a deviation of 0.01 cm, both classified as pass. For the dowel holes, the first 2.0 cm nominal diameter measured 2.58 cm, resulting in a 0.58 cm deviation classified as scrap, while the second measured 2.19 cm with a 0.19 cm deviation,

Parameter	Nominal (cm)	Mean (cm)	Deviation (cm)	Acceptable (Deviation < 0.4 cm)
Hole Diameter 1	2.0	2.58	0.58	No
Hole Diameter 2	2.0	2.19	0.19	Yes
Hole Diameter 3	1.0	1.17	0.17	Yes
Hole Diameter 4	1.0	1.17	0.17	Yes

classified as pass. Both 1.0 cm nominal diameter holes measured 1.17 cm, with a 0.17 cm deviation, classified as pass. The system exhibited zero downtime over 56 hours of operation, with the motor drawing 2.7 A, within its 2.8 A rating, and consumed an average of 72 W, indicating energy efficiency.

Table 1: Dimensional Measurements

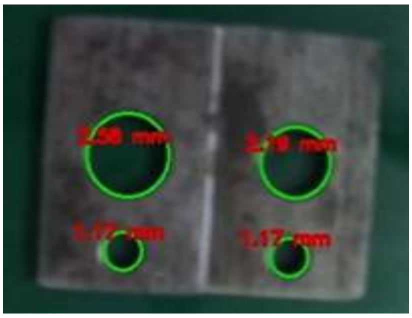

Figure 4: Visual inspection output with measured dimensions.

4.2 Discussion

The system achieved high-precision dimensional analysis for length, width, and most dowel holes (deviation < 0.4 cm) and rapid inspection (<6 s per specimen). However, it failed to meet the acceptance criteria for some larger hole diameters due to deviations ≥ 0.4 cm, caused by lighting and calibration issues. Theoretical measurement deviations were expected to be minimal, but the larger hole measurements showed deviations beyond the acceptable limit, suggesting calibration or lighting problems.

V. Conclusion

The automated vision-based system developed in this study provides a cost-effective and efficient solution for manufacturing quality control, achieving rapid inspections in 5.85 seconds per specimen and maintaining high reliability with no downtime over 56 hours. By leveraging affordable technologies such as the Raspberry Pi HQ Camera and OpenCV, the system aligns with Industry 4.0 principles, offering significant advantages over manual methods, including reduced labor costs, minimized errors, and enhanced product quality. Limitations, particularly the sensitivity of larger hole measurements to lighting variability, suggest the need for improvements such as controlled LED illumination and advanced lens calibration. The system's affordability, estimated at $250, and its modular design make it an ideal solution for small and medium-sized enterprises, with potential for broader industrial applications. Future enhancements could further elevate its performance, ensuring greater accuracy and automation.

To address the identified limitations and expand the system's capabilities, future work could focus on implementing controlled lighting using 5000K LED rings with diffusers to minimize shadows and reflections, applying multi-plane calibration to correct lens distortion across the entire image, integrating a robotic arm to automate the sorting of scrap components, incorporating machine learning models such as convolutional neural networks for enhanced defect detection, and developing a user-friendly interface for real-time monitoring and data visualization.

References

1. Czimmermann, T., Ciuti, G., & Milazzo, M. (2020), “Visual-based defect detection and classification approaches in industrial applications—A survey”, Sensors, Vol. 20, No. 5, pp. 1459.
2. Das, P. K., & Pradhan, S. K. (2019), “Integration of machine vision systems with conveyor belts for automated inspection”, International Journal of Advanced Manufacturing Technology, Vol. 102, No. 5-8, pp. 2171-2180.
3. Gonzalez, R. C., & Woods, R. E. (2018), Digital Image Processing, 4th ed., Pearson, New York, pp. 123-150.
4. Kumar, S. S. (2020), “Raspberry Pi-based machine vision system for industrial automation”, International Journal of Innovative Technology and Exploring Engineering, Vol. 9, No. 3, pp. 1234-1240.
5. Malamas, E. N., Petrakis, E. G. M., & Zervakis, M. (2003), “A survey on industrial vision systems, applications, and tools”, Image and Vision Computing, Vol. 21, No. 2, pp. 171-188.
6. Nath, O. (2020), Raspberry Pi for Automation and IoT Applications, Technical Publishing House, New Delhi, pp. 45-67.
7. Profili, A., Magherini, R., Servi, M., & Spezia, F. (2024), “Machine vision system for automatic defect detection of ultrasound probes”, Journal of Nondestructive Evaluation, Vol. 135, pp. 3421-3435.
8. Pungle, D. R., & Pungle, R. G. (2020), “Machine vision: An important pillar of Industry 4.0”, Journal of Emerging Technologies and Innovative Research, Vol. 6, No. 6, pp. 2454-8006.
9. Rosebrock, A. (2016), Practical Python and OpenCV, 3rd ed., PyImageSearch, pp. 89-112.
10. Todkar, S., & Ramgir, M. (2018), “Design of belt conveyor system”, International Journal of Scientific Engineering and Technology Research, Vol. 7, No. 7, pp. 2319-8885.
11. Zhang, J., & Li, X. (2019), “Computer vision-based conveyor belt monitoring system”, IEEE Transactions on Industrial Informatics, Vol. 15, No. 6, pp. 3218-3226.