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# Utilizing Machine Vision and Deep Learning for Quality Control in Pharmaceutical Lab Tools Manufactured Via Injection Molding

*Jenil* Patel[1*], and *Vedang* Chauhan[2]

[1]Mechanical Engineering, Western New England University, Springfield, MA, USA
[2]Mechatronics Engineering, California State University Channel Islands, Camarillo, CA, USA

**Abstract.** This research presents a machine vision inspection system for quality control of injection molded parts used in pharmaceutical lab tools. Industries demand fast and accurate inspection systems, and machine vision offers automation, consistency, precision, and high-speed capabilities, making it an ideal solution. The system integrates National Instruments Vision Builder for Automated Inspection (VBAI) and MATLAB to perform defect detection, dimensional verification, and feature validation. Eppendorf's TipOne® Filter Tip Refills, known for precision and contamination prevention, were inspected to demonstrate the system's utility. The hardware setup features top and front view cameras, LED boards for uniform lighting, and opaque covers to minimize external interference, ensuring consistent image quality. Six inspection programs utilize traditional algorithms and deep learning models to measure dimensions, detect missing features, and identify surface irregularities, achieving 95% accuracy across all tasks. These results highlight the system's potential to replace manual inspections, enabling real time, high throughput quality control. Future enhancements include integrating high resolution cameras and advanced machine learning to improve defect classification. This research emphasizes the transformative potential of machine vision in advancing manufacturing quality assurance and automation across industries like pharmaceuticals, automotive, and consumer goods.

Keywords: Injection Molding, Inspection, Machine Vision, Pharmaceutical Lab Tools, Quality Tools.

## 1 Introduction

The quality assurance of injection molded parts is a critical aspect of manufacturing, ensuring that products meet design specifications and function reliably. Traditional inspection methods often rely on manual labor or basic tools, which can be time consuming, error prone, and unsuitable for large scale production. To address these challenges, machine vision technologies offer automated, accurate, and efficient solutions for defect detection and dimensional verification, making them essential tools in modern manufacturing.

Corresponding author: [1*]jenilkamlesh.patel@wne.edu ; [2]vedang.chauhan@csuci.edu

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Machine vision systems have gained prominence due to their ability to perform consistent inspections, minimize human intervention, and enhance productivity. By employing tools such as image processing, pattern recognition, and feature extraction, these systems can detect a wide range of defects, including dimensional deviations, missing components, and surface irregularities. Additionally, machine vision systems integrate seamlessly with automation technologies, enabling high throughput production lines to maintain stringent quality standards. Advanced software platforms, such as National Instruments Vision Builder for Automated Inspection (VBAI) [1] for industrial applications and MATLAB [2] for academic and research innovations, further enhance the precision and versatility of machine vision systems in addressing complex inspection requirements.

Beyond general manufacturing, machine vision technologies have significant applications in specialized fields like the pharmaceutical industry. In pharmaceutical laboratories, quality tools such as Eppendorf's TipOne® Filter Tip Refills [3] are widely used for precision liquid handling, where contamination prevention and accuracy are paramount. The integration of machine vision in such scenarios allows for real time monitoring of defects, ensuring the reliability of critical laboratory tools. This capability is especially valuable in industries where compliance with stringent regulatory standards is required, such as healthcare and biotechnology.

This project focuses on designing and implementing a machine vision inspection system for injection molded parts, highlighting its utility in addressing diverse industrial needs. By combining VBAI's industrial grade capabilities with MATLAB's advanced algorithmic flexibility, the system delivers a comprehensive inspection solution. A specific product was used as a case study to evaluate the system's effectiveness; however, the methodologies developed are highly adaptable to a wide range of injection molded components across industries such as automotive, pharmaceuticals, and consumer goods. The system's scalability, combined with its precision and automation, positions it as a vital tool for the future of manufacturing quality assurance.

Moreover, this project emphasizes the broader role of machine vision in enabling automation, reducing production errors, and fostering innovation in industrial practices. With the growing complexity of modern manufacturing systems, the adoption of machine vision technologies ensures that industries can achieve faster production cycles without compromising on quality. These technologies not only optimize manufacturing workflows but also set a new standard for reliability and efficiency, making them indispensable for maintaining competitive advantage in global markets.

## 2 Product

Eppendorf's TipOne® Filter Tip Refills as shown in Fig. 1 are indispensable tools in laboratory liquid handling operations, offering precision and contamination prevention during pipetting. Widely used in scientific research, diagnostics, and industrial applications, these filter tips are engineered to deliver exceptional accuracy and reproducibility, meeting the demands of sensitive processes like molecular biology, chemistry, and clinical diagnostics.

The tips use filters that prevent aerosols and liquid from contaminating the pipette shaft. This innovation effectively eliminates cross contamination between samples, a critical requirement in environments where data integrity is paramount. These tips are particularly beneficial in PCR (polymerase chain reaction) and DNA or RNA research applications, where even minor contamination can compromise experimental outcomes. The presence and position of the filter is very important for proper functioning of the tips.

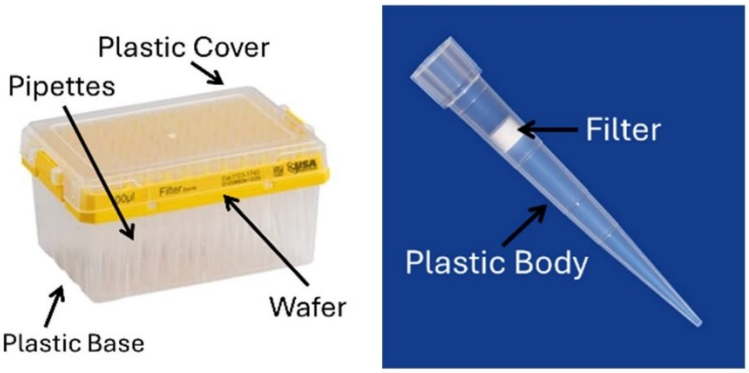


**Fig. 1.** Product Sample

## 3 Defects

In the manufacturing process of TipOne® Filter Tip Refills, several potential defects can compromise the quality and functionality of the product, directly impacting laboratory precision and safety. Identifying and addressing these defects is crucial to ensuring that the filter tips meet industry standards and laboratory requirements. Below are the key defects that have been observed by the manufacturer.

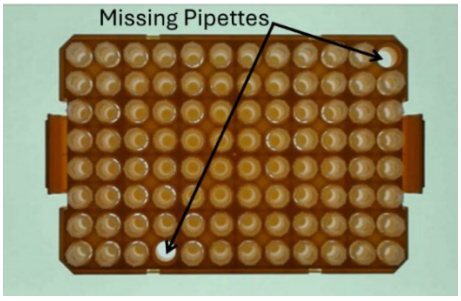


**Fig. 2.** Missing Pipettes

Missing Pipettes: Fig. 2 shows a critical defect in which some pipette tips may be absent from the packaging, leading to shortages in the expected quantity.

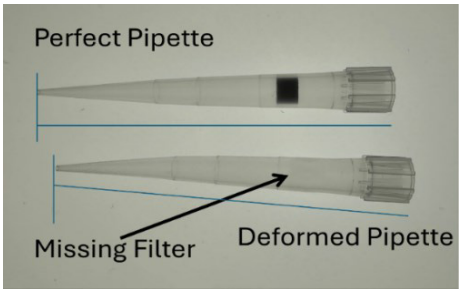


**Fig. 3.** Pipette Distortion

Pipette Distortion: As shown in Fig. 3 deformation of the pipette tips, which can affect the accuracy of liquid handling and lead to improper sample measurements.

Missing Filter: Fig. 3 shows the absence of the filter inside the pipette tips can cause contamination during pipetting processes, compromising sample integrity.

Pipette Dimensions: This defect includes variations in the overall dimensions of the pipette tips, which can lead to improper fitting with pipettes and reduced performance.

Filter Position and Height: This defect defines misalignment or incorrect height of the filter within the pipette tips, which can interfere with functionality and lead to sample contamination.

Dimensions of Plastic Cover and Base: Variations in the overall dimensions of the plastic top cover and bottom base as shown in Fig. 4, either at the top or bottom, can compromise sterility and integrity during packaging.

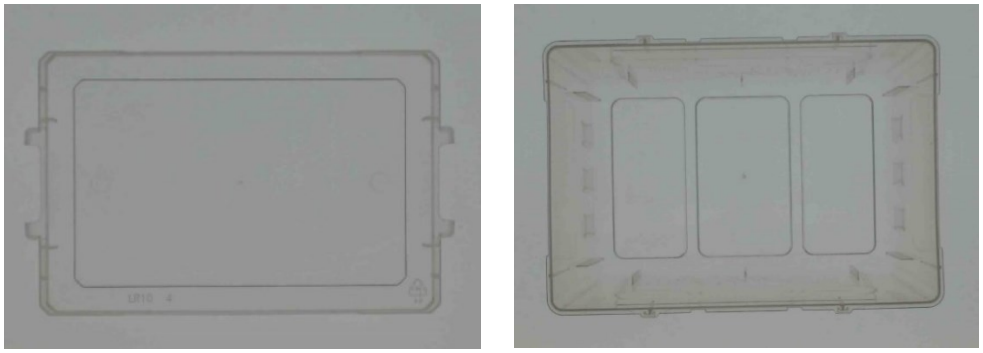

**Fig. 4.** Top Cover and Bottom Base

Missing Printed Text: Defective or missing printed text defect is shown in Fig. 5, which can lead to misidentification of products or issues in traceability.


**Fig. 5.** Printed Text

To ensure the highest quality, these defects must be systematically inspected and addressed during the production and quality assurance stages. Our approach will focus on deploying advanced machine vision technology to detect and rectify these issues in real time, ensuring that only defect free products reach the end users.

## 4 Literature Review

Machine vision technology has emerged as a robust solution for automating detection and quality control across various industries. Recent advancements highlight its versatility and effectiveness in addressing challenges in manufacturing and inspection tasks.

For instance, a machine vision system for bearing defect inspection demonstrated its potential in detecting deformations, rust, scratches, and cracks using novel image acquisition setups and image processing algorithms. This system achieved high precision and recall metrics compared to human inspectors, showcasing its reliability for industrial applications [4]. Similarly, automated methods for fabric defect detection have been categorized into various approaches such as statistical, spectral, model based, learning, structural, hybrid, and motif based. These methods address challenges like defect background similarity and emphasize the need for generalized solutions to improve detection rates [5]. In the cotton ginning industry, machine vision systems have been employed to detect plastic contamination, integrating real time image processing and pneumatic removal to significantly improve product purity without compromising quality [6].

In the pharmaceutical manufacturing sector, machine vision plays a critical role. Deep convolutional neural networks like ResNet50 have achieved an accuracy of 96.6% in identifying defective tablets, demonstrating the efficiency of deep learning in large scale inspections [7]. Reviews of machine vision applications have emphasized the integration of spectroscopic methods and real time monitoring for continuous manufacturing, enabling improved quality control [8]. These systems ensure compliance with stringent regulations, supporting tasks such as blister packaging and label verification [9].

Machine vision systems have also been instrumental in detecting dimensional defects in glass vials and film coated tablets. Techniques like heuristic segmentation coupled with fuzzy inference systems effectively address challenges such as glass reflectivity and non-uniform lighting [10]. Another application involved using YOLOv5 for real time detection and coating thickness measurement in film coated tablets, achieving an accuracy of 98.24% [11].

For high-speed manufacturing environments, machine vision systems employing Otsu thresholding and Hough transformations have enabled real time object counting with high accuracy and flexibility [12]. Additionally, a system for plastic bottle inspection utilized simple algorithms, achieving 95% accuracy in detecting common defects while offering a cost-effective solution for fast paced production [13].

Reviews comparing traditional and modern approaches have highlighted the evolution of defect detection techniques. Ren and Zhang noted the shift from classical image processing methods like Otsu thresholding and SVMs to advanced deep learning approaches such as Convolutional Neural Networks (CNNs) and YOLO. These methods significantly enhance accuracy, localization, and defect segmentation in complex industrial environments, showcasing the importance of integrating machine vision with automation [14].

Recent advancements have also explored fault detection in automated assembly machines. Chauhan and Surgenor developed a system using Gaussian Mixture Models (GMMs) and optical flow to enhance fault detection, achieving reduced downtime and improved efficiency [15]. Another breakthrough in flexible inspection systems is FlexMVS, which combines supervised and semi-supervised machine learning techniques to classify parts with over 95% accuracy, showcasing scalability and adaptability for diverse applications [16].

Machine vision systems have also been integrated with smart conveyor systems to detect and classify material loads while optimizing energy efficiency through real time adjustments [17]. In the context of Industry 4.0, machine vision is becoming a vital component of workforce training programs, helping students understand complex concepts like automation and robotics [18]. Finally, a system for part metrology and defect detection using National

Instruments Vision Builder achieved 96% classification accuracy in sorting automotive blade fuses, highlighting machine vision's reliability for high-speed quality assurance [19].

These advancements underscore the transformative potential of machine vision in modern manufacturing, enabling scalable, precise, and versatile solutions for real time, high throughput industrial applications.

The proposed research work demonstrates how machine vision systems developed using NI Vision Builder and MATLAB can detect defects in injection molded parts. Early detection can save expensive recalls and enhance productivity. The work includes both traditional computer vision tools and modern AI based tools for inspection. The paper is organized into the following sections: Machine Vision System Setup, experimental setup, methodology, machine vision algorithms, results, discussion, and conclusion.

## 5 Machine Vision System Setup

The machine vision system employed a Logitech C920 HD PRO camera with a maximum resolution of 1920 x 1080 pixels and a sensor size of 4.8 mm x 3.6 mm or 6 mm diagonal. The Field of View (FOV), measuring 10.04" X 5.71" or 11.55" diagonal, determines the area captured by the camera in a single image. The camera operates at a working distance (WD) of 5", ensuring the object remains in focus for accurate inspection.

The smallest number of pixels required for the vision algorithm to detect edges is 2 pixels, ensuring sufficient accuracy for edge-based detections. These parameters collectively influence the camera's setup and calculations, ensuring precision in the machine vision inspection process. The following set of equations are used to calculate the vision system resolution and required focal length of the lens.

$$Camera\ Resolution\ (in\ megapixels) = \frac{Width\ in\ pixels\ \times Height\ in\ Pixels}{1{,}000{,}000} \tag{1}$$

$$Camera\ Resolution\ (in\ megapixels) = \frac{1920 \times 1080}{1{,}000{,}000} = 2.07 = 2\ MP$$

$$Camera\ Resolution\ (in\ inches/pixel) = \frac{FOV\ Width\ in\ inches}{Image\ Width\ in\ Pixels}\ OR\ \frac{FOV\ Height\ in\ inches}{Image\ Height\ in\ pixels} \tag{2}$$

$$Camera\ Resolution\ (in\ inches/pixel) = \frac{10.04}{1920}\ OR\ \frac{5.71}{1080}$$

$$= 5.22\ X\ 10^{-3}\ OR\ 5.28\ X\ 10^{-3}$$

$$MV\ system\ resolution\ in\ inches = camera\ resoluion\ \left(\frac{inches}{pixel}\right) \times Smallestt\ \text{number}\ of\ required\ pixels \tag{3}$$

$$= 5.28\ X\ 10^{-3} \times 2\ = 0.0105\ in.$$

$$WD\ \times sensor\ size = focal\ length\ \times FOV \tag{4}$$

$$focal\ length\ = 2.59 = 3\ mm$$

To build a robust and precise machine vision inspection system, the following hardware components were employed:

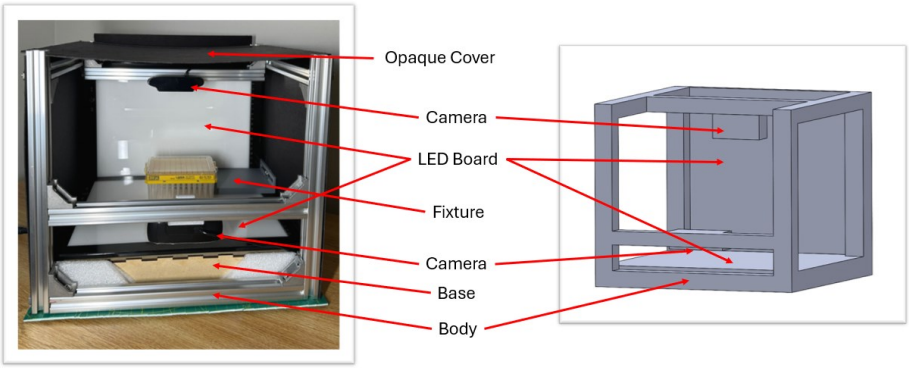


**Fig. 6.** Experimental Setup

Body: As shown in Fig. 6 the framework was constructed using 80/20 Aluminum Extrusions, ensuring a sturdy and lightweight structure for the setup.
Cameras: Two cameras were strategically mounted to capture the front view and top view of the product, ensuring comprehensive visual inspection.
LED Boards: Two LED boards were installed to provide uniform illumination, facilitating high quality imaging of the product [20].
Opaque Covers: Opaque covers were utilized to block external light interference. This ensured consistent lighting conditions for the cameras, resulting in uniform image quality throughout the inspection process.

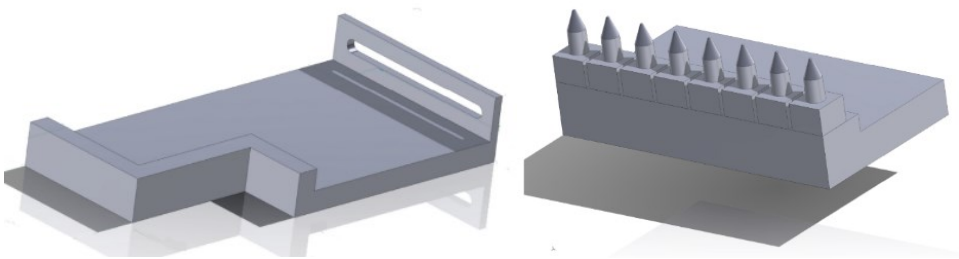

**Fig. 7.** Fixture A and Fixture B

Fixtures: Two fixtures were incorporated into the setup. Fixture A: As shown in Fig. 7 secures the product in a fixed position to ensure accurate and repeatable results. Fixture B: Specifically designed for pipette inspection, enhancing the precision of the inspection process for pipette products.

## 6 Methodology

The machine vision inspection system utilized two primary software tools: National Instruments Vision Builder for Automated Inspection (VBAI) and MATLAB.

VBAI is robust industrial grade software widely used in manufacturing for automated quality assurance. Its user-friendly graphical interface allows developers to configure complex vision tasks without requiring extensive programming skills. Key features include pattern matching, object detection, dimensional measurements, and defect inspection. These functionalities enable real time image processing, ensuring quick and reliable decision

making, making VBAI an essential tool for high throughput production environments. Its reliability and efficiency make it ideal for implementing standardized inspection tasks in manufacturing.

On the other hand, MATLAB provides advanced capabilities for designing and simulating custom algorithms, offering a more research driven approach. With tools like the Image Processing Toolbox and Deep Learning Toolbox, MATLAB supports feature extraction, classification, and algorithm development, enabling innovative image analysis techniques. This flexibility is especially valuable for exploring solutions to complex inspection challenges that go beyond standard industrial requirements. MATLAB's ability to tailor inspection processes complements VBAI's robust industrial application, bridging the gap between practical manufacturing needs and advanced research methodologies.

The integration of VBAI's industrial grade precision and MATLAB's algorithmic flexibility ensured a versatile and efficient machine vision inspection system. This combination allowed the system to meet the immediate demands of real time manufacturing while also supporting exploratory enhancements for future innovations, effectively balancing reliability with adaptability.

The following sections explain, using flow charts algorithms, various programs used to detect defects on various parts of the product.

# 7 Machine Vision Algorithms

## 7.1 Base Inspection (VBAI)

This program measures the length, width, and height of the product using both the front view and top view images.

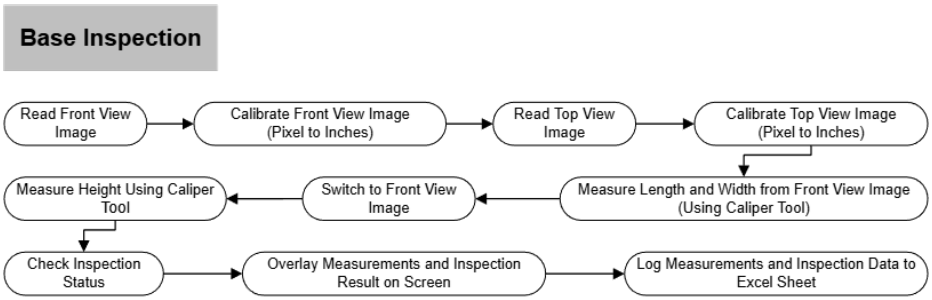


**Fig. 8.** Base Inspection Algorithm Flowchart

As shown in Fig. 8 The inspection process begins by reading the front view image and calibrating it to convert pixel dimensions into real world units (inches). This calibration step is then repeated for the top view image. Subsequently, the system utilizes the caliper tool to measure the width and length from the front view image and the height from the top view image. After completing these measurements, the inspection results are evaluated, and a pass or fail status is determined based on predefined criteria. To enhance usability, custom overlays display the measurement data and inspection results directly on the screen. Additionally, all results, along with corresponding image data, are systematically logged into an Excel sheet for documentation and further analysis.

### 7.2 Cover Inspection (VBAI)

This program inspects the length and width of the product's cover using the top view image.

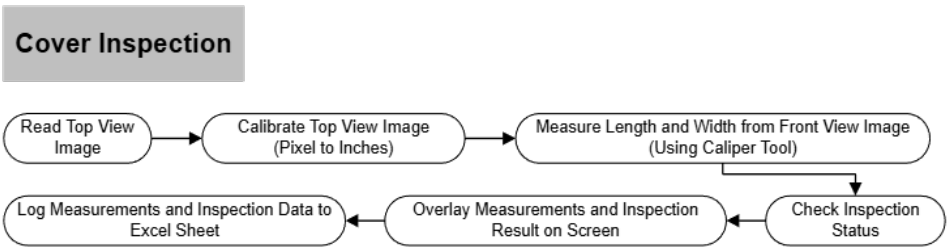


**Fig. 9.** Cover Inspection Algorithm Flowchart

As shown in Fig. 9 the inspection process begins by reading the top view image, which is then calibrated to convert pixel measurements into real world units (inches). Using the caliper tool, the system measures the length and width of the object. The inspection results are subsequently evaluated to determine a pass or fail status based on the measurements. To provide immediate feedback, custom overlays display the measurement data and inspection results on the screen. Additionally, all inspection data and results are logged into an Excel sheet for record keeping and analysis.

### 7.3 Missing Pipettes Inspection (VBAI)

This program identifies any missing pipettes in the product using the top view image.

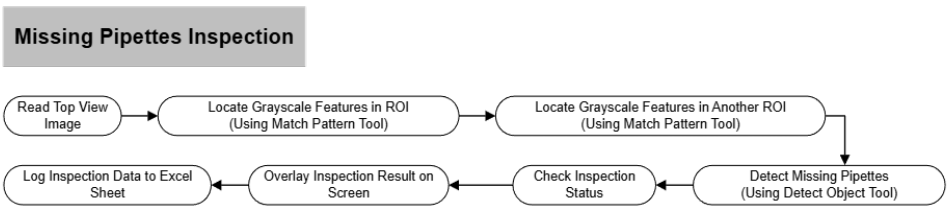


**Fig. 10.** Missing Pipettes Inspection Algorithm Flowchart

As shown in Fig. 10 the inspection process begins by reading the image, after which the system utilizes the Match Pattern tool to locate grayscale features within specified regions of interest (ROIs). This process is repeated across multiple ROIs to ensure comprehensive inspection. The Detect Object tool is then employed to determine the presence or absence of pipettes by identifying regions of homogeneous intensity. Based on these analyses, the inspection results are evaluated, and a pass or fail status is determined. Custom overlays are used to display the results on the screen, while all inspection data and results are logged into an Excel sheet for documentation and further analysis.

### 7.4 Missing Pipettes Inspection (MATLAB)

As shown in Fig. 11 a MATLAB based program utilizing machine learning was developed to inspect pipettes for defects, leveraging the AlexNet deep learning model for feature extraction and a Support Vector Machine (SVM) for classification. The process works as follows.

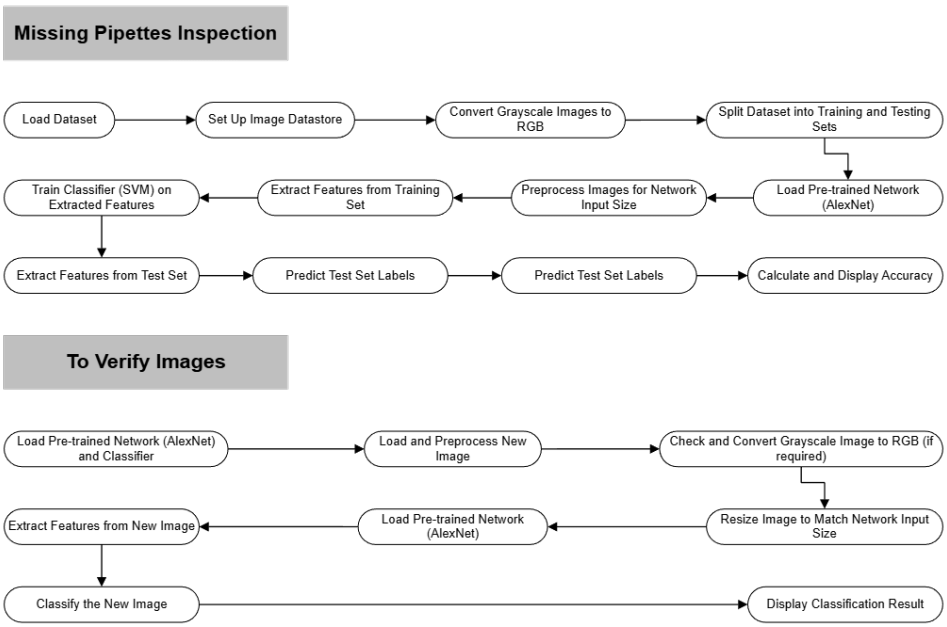


**Fig. 11.** Missing Pipettes Inspection Algorithm Flowchart using MATLAB AI Tools

### *7.4.1 Data Preparation*

Images of pipettes were organized into two categories: "Perfect" and "Defective." These were loaded into a datastore, and grayscale images were converted to RGB for compatibility with the pre-trained AlexNet network. The dataset was split into 80% training and 20% testing subsets to train and validate the model.

### *7.4.2 Feature Extraction and Training*

The pre-trained AlexNet model was used to extract features from the fc7 layer for the training images. These features, representing high level patterns in the images, were then used to train an SVM classifier.

### *7.4.3 Testing and Evaluation*

Features from the test set were extracted using the same process, and the classifier predicted their labels. The system achieved high accuracy, validated by the confusion matrix, demonstrating the robustness of the classification process.

### *7.4.4 Testing/Verification of New Images:*

To classify a new pipette image, the system preprocesses the image by resizing and converting it to RGB if necessary. Features are extracted using AlexNet, and the classifier predicts whether the image belongs to the "Perfect" or "Defective" category. The result is displayed along with the image, providing a visual confirmation of the classification.

This MATLAB program complements traditional inspection methods by offering a scalable and accurate solution for identifying pipette defects. The integration of deep learning for feature extraction and SVM for classification enhances the system's ability to detect subtle imperfections and improve overall inspection efficiency.

### 7.5 Missing Text Inspection (VBAI)

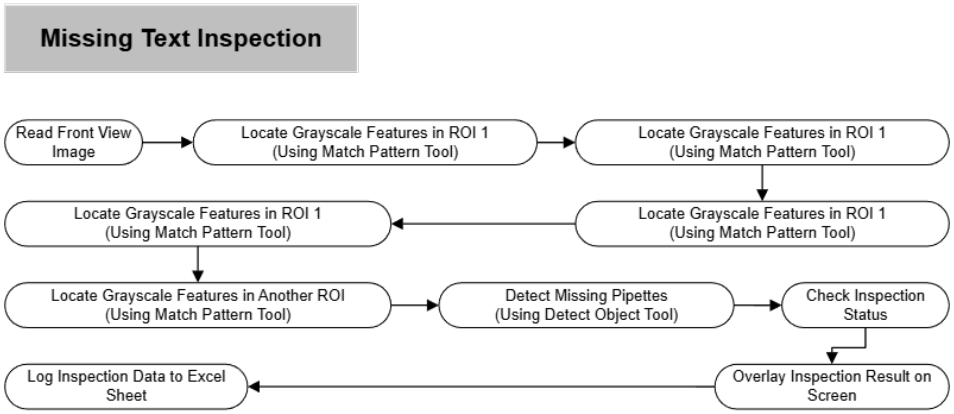


**Fig. 12.** Missing Text Inspection Algorithm Flowchart

This program ensures that all printed text is present on the product using the front view image. As shown in Fig. 12 the inspection process begins by reading the image, followed using the Match Pattern tool to locate grayscale features within multiple regions of interest (ROIs) to verify the presence of text. This process is repeated across various ROIs on the product to ensure complete text verification. Once all ROIs are inspected, the results are reviewed, and a pass or fail status is assigned based on the findings. Custom overlays are employed to display the inspection results directly on the screen, and all relevant data is systematically logged into an Excel sheet for documentation and further analysis.

### 7.6 Pipettes and Filter Inspection (VBAI)

This program evaluates the height, damaged surface, and filter position of the pipettes using the front view image. As shown in Fig. 13, the pipette inspection process begins by capturing and analysing an image using the Match Pattern tool to verify the filter position. The system then calibrates the image, converting pixel measurements into real world units (inches) for precise dimensional analysis. The Caliper Tool measures the heights of eight individual pipettes, while the Advanced Straight Edge Tool draws lines along the pipette's right and left sides to ensure alignment. The Geometry Tool calculates midpoints and evaluates angles to check for concentricity, ensuring accurate geometric alignment. Surface defects are identified using the Match Pattern Tool, completing a thorough inspection. Based on the findings, the system generates a pass or fail status, displaying measurement data and inspection results through custom overlays in real time. All data is logged onto an Excel sheet for comprehensive documentation and analysis, supporting a detailed and efficient quality control process.

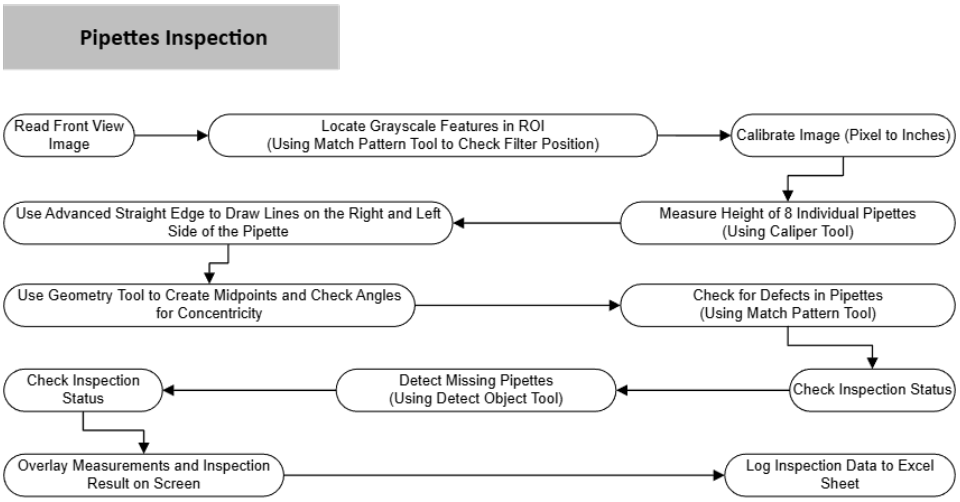


**Fig. 13.** Pipettes and Filter Inspection Algorithm Flowchart

## 8 Results

The machine vision inspection system demonstrated exceptional accuracy across all inspection tasks, as highlighted below.

### 8.1 Base Inspection

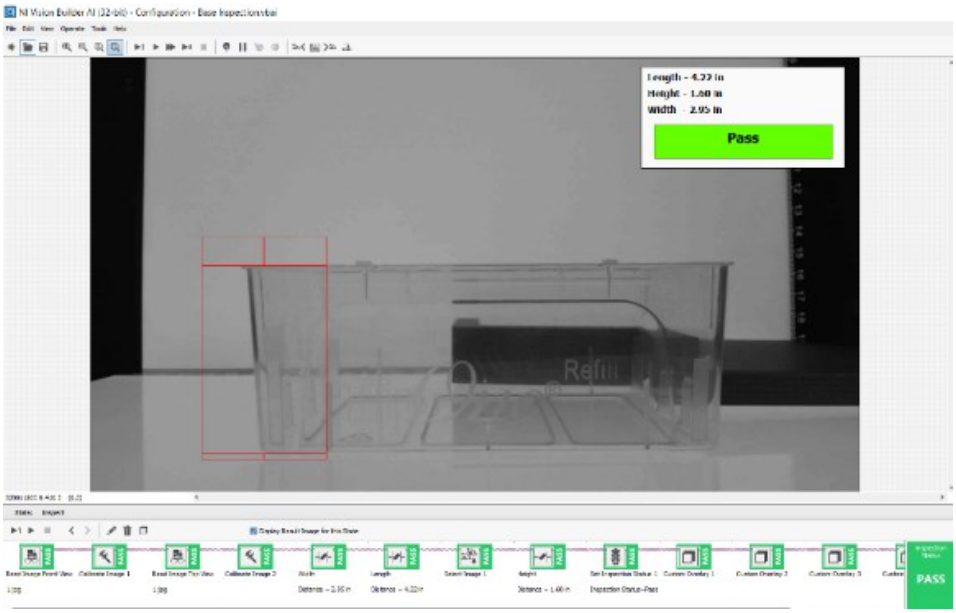


**Fig. 14.** Base Inspection

As shown in Fig. 14 the program consistently measured the product's dimensions (length, width, and height) with 100% accuracy. To validate the inspection process, 500 physical

boxes were used, ensuring that the system's performance was evaluated across a diverse set of real-world samples. Since all products were pre-built and defect free in size, the results confirmed that the system is both reliable and highly precise. As shown on Fig. 15 the confusion matrix indicated no false positives or negatives, further validating the robustness of the inspection system. Additionally, all measured results fell within the typical range of injection molding tolerances, which typically range from ±0.1 mm to ±0.5 mm (±0.004″ to ±0.020″). This ensures that the inspection system is capable of adhering to industry standards for dimensional accuracy, reinforcing its effectiveness for quality control in manufacturing.

| n = 1000 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 500 | FN = 0 | 500 |
| Actual: Defactive | FP = 0 | TN = 500 | 500 |
| | 500 | 500 | |

**Fig. 15.** Base Inspection Confusion Matrix

### 8.2 Cover Inspection

Like the Base Inspection, this program also achieved 100% accuracy in measuring the cover's dimensions. As shown in Fig. 16 and Fig. 17, the results confirm that the inspection system is highly reliable for dimension-based evaluations. The program used the Caliper Tool in VBAI to measure the cover's length and width precisely after image calibration. Each measurement was automatically compared with predefined tolerance limits to ensure dimensional consistency. The consistent accuracy across multiple samples demonstrated the system's ability to maintain precision under repeat tests. Overall, the results validated that the cover inspection module performs as a dependable component of the overall machine vision system.

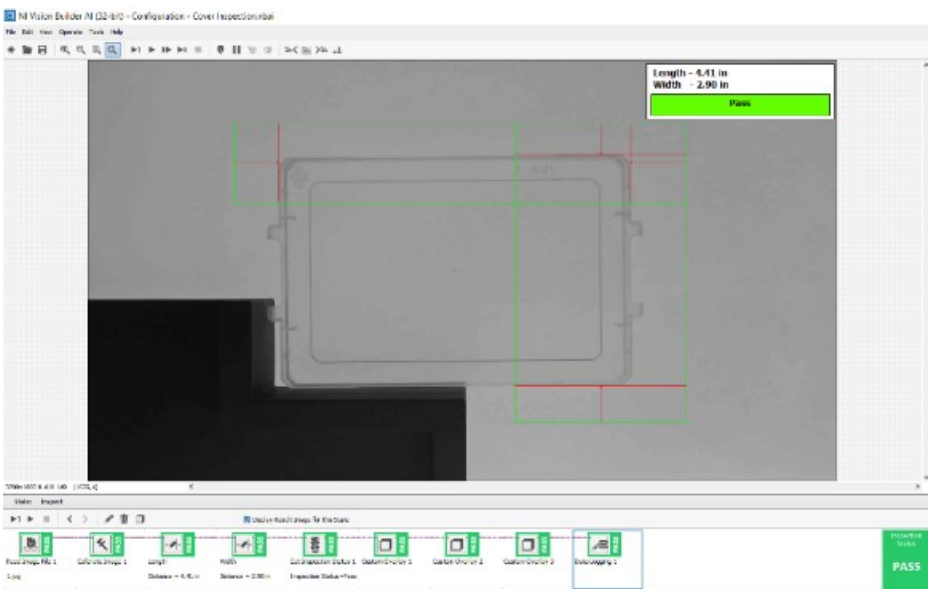


**Fig. 16.** Cover Inspection

| n = 1000 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 500 | FN = 0 | 500 |
| Actual: Defactive | FP = 0 | TN = 500 | 500 |
| | 500 | 500 | |

**Fig. 17.** Cover Inspection Confusion Matrix

### 8.3 Missing Pipettes Inspection (VBAI)

As shown in Fig. 18 the VBAI based inspection effectively identified all missing pipettes with 100% accuracy. To validate the system, 500 perfect and 500 defective physical boxes were used, ensuring comprehensive testing across both ideal and defective scenarios. As shown in Fig. 19 the confusion matrix reinforced this result, confirming the system's capability to detect missing parts with high confidence.

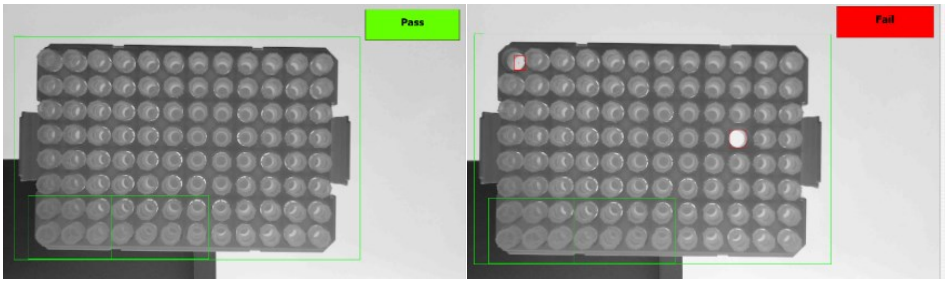


**Fig. 18.** Missing Pipettes Inspection with VBAI

| n = 1000 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 500 | FN = 0 | 500 |
| Actual: Defactive | FP = 0 | TN = 500 | 500 |
| | 500 | 500 | |

**Fig. 19.** Missing Pipettes Inspection Confusion Matrix with VBAI

### 8.4 Missing Pipettes Inspection (MATLAB)

The MATLAB based inspection program, powered by machine learning, achieved 100% accuracy in detecting missing pipettes. As shown in Fig. 20, this approach utilized the AlexNet deep learning model for feature extraction and a Support Vector Machine (SVM) for classification between “Perfect” and “Defective” samples. Images were pre-processed, resized, and split into training and testing sets to ensure balanced learning. The resulting model accurately identified missing components by analysing visual and geometric features from pipette images. The confusion matrix in Fig. 21 confirms perfect classification performance, validating the robustness of the method. This demonstrates MATLAB’s capability to perform deep learning based inspection efficiently. Overall, the results highlight how AI assisted analysis can significantly improve accuracy and reliability compared to traditional rule-based inspection systems.

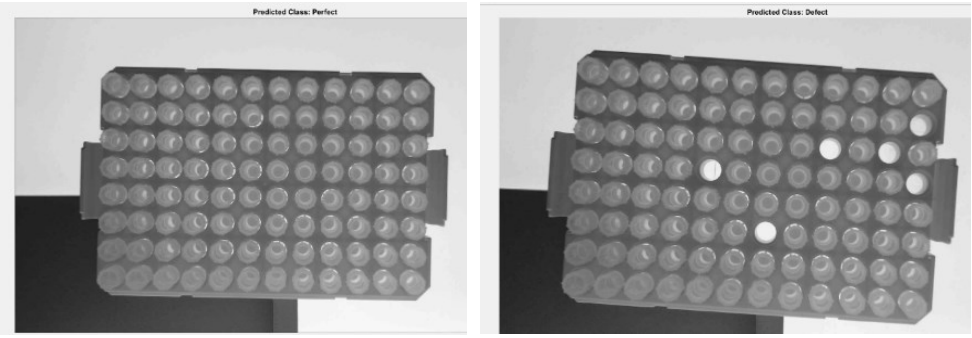


**Fig. 20.** Missing Pipettes Inspection with MATLAB

| n = 200 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 100 | FN = 0 | 100 |
| Actual: Defactive | FP = 0 | TN = 100 | 100 |
| | 100 | 100 | |

**Fig. 21.** Confusion Matrix for Missing Pipettes Inspection with MATLAB

### 8.5 Missing Text Inspection

As shown in Fig. 22, the system accurately detected missing or incomplete text on the product with 100% accuracy, ensuring reliable inspection of printed markings. To validate the system, 500 perfect and 500 defective physical boxes were used, covering a wide range of variations in print quality and alignment. The inspection utilized the Match Pattern tool in VBAI, which compared grayscale intensity and texture patterns within predefined regions of interest to verify the presence of printed text. The algorithm effectively identified faint or missing characters, smudged areas, and inconsistent font spacing that could lead to misidentification. As shown in Fig. 23, the confusion matrix confirmed the system's efficiency and repeatability with zero false detections. This high precision underscores the reliability of the method even under varying lighting conditions. The approach proved particularly useful for ensuring proper labelling and traceability of pharmaceutical lab tools, where text clarity is essential for compliance and quality assurance. Overall, the system demonstrated excellent performance in verifying printed text and ensuring consistent marking accuracy during production.

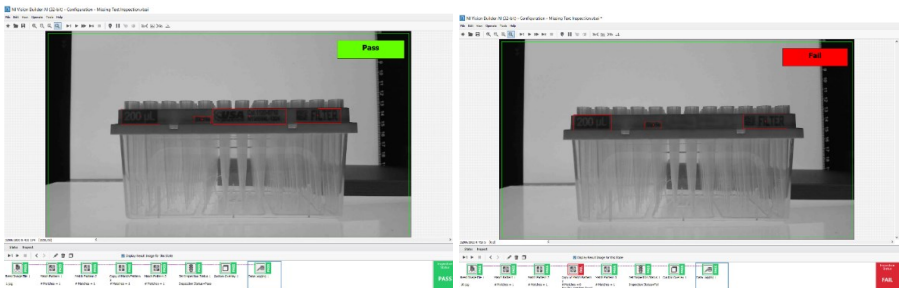


**Fig. 22.** Missing Text Inspection with MATLAB

| n = 1000 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 500 | FN = 0 | 500 |
| Actual: Defactive | FP = 0 | TN = 500 | 500 |
| | 500 | 500 | |

**Fig. 23.** Confusion Matrix for Missing Text Inspection

### 8.6 Pipettes and Filter Position Inspection

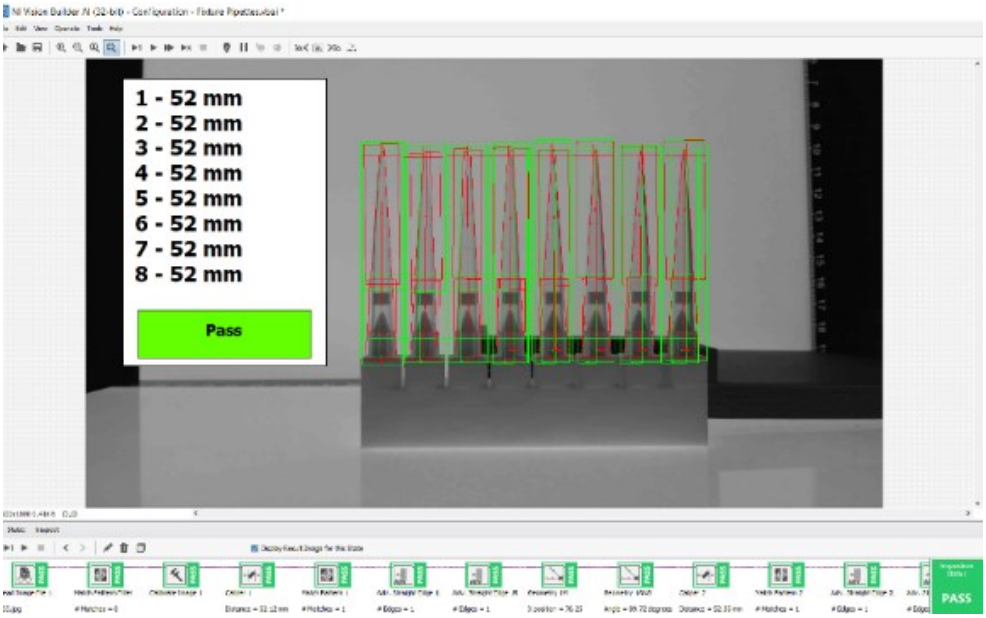


**Fig. 24.** Pipettes and Filter Position Inspection with VBAI

| n = 1000 | Predicted: Perfect | Predicted: Defactive | |
|---|---|---|---|
| Actual: Perfect | TP = 500 | FN = 0 | 500 |
| Actual: Defactive | FP = 0 | TN = 500 | 500 |
| | 500 | 500 | |

**Fig. 25.** Confusion Matrix for Pipettes and Filter Inspection

As shown in Fig. 24, the inspection program accurately measured the pipettes' height, identified defects (such as bending or surface irregularities), and checked the filter position, all with 100% accuracy as shown in the confusion matrix in Fig. 25. This preliminary result was achieved due to the small batch size used for testing. However, the accuracy may decrease if a larger number of products are used, and real time analysis is performed. Despite this, the results underscore the system's versatility in handling both dimensional and defect-based inspections.

## 9 Discussion

All programs provide reliable and repeatable results. Below are key points from the discussion:

Lighting Interference: External light initially caused inconsistencies in image quality. Adding Opaque covers effectively resolved this issue by standardizing the lighting conditions.
Low-Cost Cameras: The use of budget cameras posed a challenge in capturing high quality images, potentially affecting inspection accuracy. Adjusting tolerance levels based on focal length calculations mitigated this limitation.
Strengths of the System: The system excelled in texture defect inspection and missing part detection using VBAI, delivering accurate results even during the initial stages of program development.

Tasks like detecting missing pipettes and printed text were efficiently handled, with VBAI providing consistent and reliable outcomes.

## 10 Improvements and Future Work

Upgrading to higher quality cameras could enhance image resolution, reducing potential errors in inspection. Developing a custom LED lighting system would ensure uniform illumination and provide flexibility for future modifications. Further integration of machine learning models in MATLAB could improve defect detection and accommodate more complex inspection requirements.

In the context of Eppendorf, the company whose products were used in this study, they generate approximately 1,209,600 products per day. Inspecting such a high volume of products manually would be prone to errors, resulting in inefficiencies and potential quality issues. Machine vision, in contrast, offers an ideal solution in high-speed, real-time environments, where large quantities of products need to be inspected consistently and accurately. This system's ability to handle large volumes and environmental variables, such as fluctuating lighting and varying product characteristics, makes it an invaluable tool for ensuring quality control in high demand production settings.

Overall, the system demonstrated exceptional accuracy and efficiency in its current state while providing a foundation for future enhancements. These improvements could extend its applicability to a broader range of industrial inspection tasks, helping to optimize quality control processes in various manufacturing environments.

## 11 Conclusion

This project developed a robust machine vision inspection system to address the quality control needs of injection molded parts. By combining National Instruments Vision Builder for Automated Inspection (VBAI) and MATLAB, the system successfully performed dimensional verification, defect detection, and part verification with 100% accuracy. While the study demonstrated its effectiveness using a specific product, the methodologies and programs are broadly applicable to various injection molded components across industries. The system excelled in detecting dimensional deviations, missing features, surface defects, and verifying printed text, ensuring products adhered to design specifications.

The integration of VBAI and MATLAB proved critical for creating a flexible and efficient system. VBAI, with its user-friendly interface and real time image processing capabilities, is ideal for industrial applications requiring speed and consistency. MATLAB complemented this by providing advanced algorithm development, feature extraction, and

deep learning capabilities, making it suitable for research driven innovations. Together, these tools enabled the system to handle both standard industrial tasks and complex research challenges, demonstrating adaptability and reliability in real world manufacturing environments.

Future work aims to enhance precision by integrating high resolution cameras, developing custom LED lighting systems for consistent illumination, and expanding machine learning capabilities for advanced defect detection and classification. The project highlights the transformative potential of machine vision inspection systems in improving manufacturing efficiency and product reliability across diverse industries. The combination of VBAI and MATLAB ensures a scalable, practical, and innovative solution for the future of quality assurance in high-speed production environments.

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