JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

COMPUTER VISION BASED QUALITY CONTROL IN MANUFACTURING

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Abstract

Quality control (QC) in manufacturing processes is critical to ensuring consumers receive products with proper functionality and reliability. Faulty products can lead to additional costs for the manufacturer and damage trust in a brand. A growing trend in QC is the use of machine vision (MV) systems because of their noncontact inspection, high repeatability, and relatively low cost. This paper presents a robust MV system developed to perform comparative dimensional inspection on diversely shaped samples, including additive manufacturing products. The algorithm used performs dimensional inspection on a base product considered to have acceptable dimensions. The perimeter, area, rectangularity, and circularity of the base product are determined using blob analysis on a calibrated camera. These parameters are then used as the standard with which to judge additional products. Each product following is similarly inspected and compared to the base product parameters. A likeness score is calculated for each product, which provides a single value tracking all parameter differences. Finally, the likeness score is considered on whether it is within a threshold, and the product is considered to be acceptable or defective. The proposed MV system has achieved satisfactory results, as discussed in the results section that would allow it to serve as a dependable and accurate QC inspection system in industrial settings.

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1. INTRODUCTION

In today's rapidly evolving manufacturing landscape, ensuring product quality is paramount for maintaining competitiveness and meeting customer expectations. Traditional quality control methods often involve manual inspection processes, which are time-consuming, prone to errors, and lack scalability. To address these challenges, this project proposes the implementation of a computer vision-based quality control system in manufacturing processes. The primary objective of this project is to develop and deploy a robust computer vision solution capable of automating the quality control process in manufacturing environments. By leveraging advanced image processing techniques and machine learning algorithms, the system aims to detect defects, anomalies, and deviations from desired specifications with high accuracy and efficiency.

The system consists of three main components: image acquisition, processing, and decision-making. Initially, high-resolution images or videos of the manufacturing components or products are captured using industrial-grade cameras. These images are then processed using sophisticated computer vision algorithms to extract relevant features and identify potential defects. Machine learning models trained on labelled data are utilized to classify defects and make real- time decisions regarding the acceptance or rejection of the inspected items.

The adoption of computer vision-based quality control systems promises multifaceted benefits for manufacturers. Firstly, it facilitates the early detection of defects, enabling timely corrective actions to be taken before defective products progress further along the production line or reach the hands of consumers. This not only minimizes the likelihood of costly rework, scrap, or recalls but also enhances overall product quality and reliability. Moreover, by automating and streamlining the quality control process, computer vision technology can contribute to significant improvements in manufacturing efficiency, throughput, and cost-effectiveness. By reducing the need for manual inspection and accelerating defect detection, manufacturers can optimize their production processes, reduce cycle times, and enhance resource utilization.

1.1 DESCRIPTION

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1.2 PROBLEM STATEMENT

"Requirement to build a document summarization product to save time and efforts of people and to use human resources efficiently."

The amount of information is increasing every day. Thus finding relevant data becomes hectic and time consuming, more over not all the data is relevant to the user's topic of interest. In order to find relevant data for user's search and to save time is it necessary to have a small summary of the documents. Summary made by humans is time consuming and tedious. Thus there is a need for automatically summarizing the text document to save time and to get quick results. Automatic Summarization can be defined as the art of condensing large text documents into few lines of summary, giving important information

1.3 SCOPE AND MOTIVATION

The scope of computer vision-based quality control in manufacturing is poised to revolutionize production processes, offering unparalleled precision, efficiency, and adaptability. In the coming years, automation will play a pivotal role, with advanced algorithms and hardware driving the seamless integration of computer vision systems into manufacturing lines. Real-time monitoring capabilities will enable swift detection of defects, empowering manufacturers to take immediate corrective actions and minimize wastage. Moreover, the evolution of computer vision technology promises to elevate quality assurance standards to new heights. By harnessing the power of artificial intelligence and machine learning, these systems can analyse vast amounts of visual data to identify even the most subtle defects, ensuring that only products of the highest caliber reach consumers .

1.4 OBJECTIVES

- This system aims to revolutionize traditional quality control methods by leveraging advanced image processing techniques and machine learning algorithms to automate defect detection, classification, and decision-making
- The overarching objectives of the project include Enhancing Product Quality the primary goal is to improve product quality and reliability by implementing a more efficient and accurate quality control system.
- By detecting defects at an early stage of the production process, the system can prevent faulty products from reaching consumers, thereby minimizing warranty claims, recalls, and reputational damage.
- Computer vision quality control in manufacturing serves as a pivotal cog in the wheel of modern production processes, aiming to fortify quality assurance measures through automated visual inspection

2. LITERATURE REVIEW

Here we will elaborate the aspects like the literature survey of the project and what all projects are existing and been actually used in the market which the makers of this project took the inspiration from and thus decided to go ahead with the project covering with the problem statement.

2.1 Literature Survey

Computer vision-based quality control systems have become integral to modern manufacturing, leveraging advancements in artificial intelligence (AI) and machine learning (ML) to enhance inspection processes. These systems offer numerous benefits over traditional manual inspections, including increased accuracy, efficiency, and the ability to operate continuously without fatigue.

2.2 Key Components and Techniques

1. **Image Processing and Machine Learning**:

- **Image Acquisition**: High-resolution cameras and sensors capture detailed images of products. Proper lighting and image acquisition setups are critical for accurate inspection.
- **Preprocessing**: Techniques like noise reduction, contrast enhancement, and normalization are applied to prepare the images for analysis.
- **Feature Extraction**: Algorithms identify relevant features (e.g., edges, textures) from images. Traditional methods include edge detection and histogram analysis, while modern approaches often utilize convolutional neural networks (CNNs) for more complex feature extraction.

2. **Defect Detection**:

- **Classification**: ML models classify images into categories such as "defective" or "non-defective." This process can involve supervised learning where models are trained on labeled datasets.
- **Localization**: Advanced systems not only detect defects but also pinpoint their exact locations on the product. This is especially useful in identifying specific areas that need rework or repair .

3. **System Integration**:

- **Real-Time Processing**: Modern systems process images in real-time, providing immediate feedback and enabling quick corrective actions. This is crucial in high-speed manufacturing environments.
- **Interconnectivity**: Integration with other Industry 4.0 technologies allows for seamless data exchange and better decision-making across the production line.

2.3 EXISTING SYSTEM

Manual Inspection: Trained inspectors visually examine manufactured components or products for defects, anomalies, or deviations from desired specifications. This process typically involves physically inspecting each item, which can be slow and tedious, particularly for large production volumes. Subjectivity and Variability. Manual inspection is subjective and can vary between inspectors, leading to inconsistencies in defect detection and classification. Factors such as fatigue, distractions, and individual judgment can impact the reliability and accuracy of inspection results.

Limited Scalability: Manual inspection processes are often not scalable to meet the demands of high-volume manufacturing environments. As production volumes increase, the need for additional inspectors and inspection resources becomes a bottle neck, limiting overall production efficiency. High Labour Costs: The labour-intensive nature of manual inspection processes results in significant labour costs for manufacturers. Employing trained inspectors and dedicating resources to manual inspection can be a significant expense, particularly for industries with stringent quality standards or complex production processes. Delayed Detection: Manual inspection may only detect defects after they have occurred, leading to delays in identifying quality issues and implementing corrective actions. This delay can result in the production of defective products reaching customers, leading to customer dissatisfaction, warranty claims, and potential recalls.

2.4 METHODOLOGY

Initial Investment: Implementing a computer vision-based quality control system requires a significant upfront investment in hardware, software, and personnel training. The cost of cameras, processing units, sensors, and other equipment can be substantial, particularly for small or medium-sized manufacturers with limited resources.

Complexity of Implementation: Integrating computer vision technology into existing manufacturing processes can be complex and time-consuming. It may require expertise in image processing, machine learning, and software development, as well as collaboration with external vendors or consultants to design and deploy the system effectively.

Data Requirements: Training machine learning models for defect detection and classification requires large amounts of labelled data, which may not always be readily available. Collecting and annotating training data can be labor-intensive and may require specialized expertise, particularly for complex or rare defect types.

Algorithm Tuning and Optimization: Developing and fine-tuning computer vision algorithms for specific manufacturing environments and defect types can be challenging. It may require iterative testing, validation, and optimization to achieve the desired level of accuracy, which can prolong the development process and increase implementation costs.

Environmental Variability: Manufacturing environments can be dynamic and unpredictable, with variations in lighting conditions, background clutter, and object orientation. Computer vision systems may struggle to perform reliably in such environments, leading to false positives or false negatives in defect detection.

Maintenance and Support: Once deployed, computer vision-based quality control systems require ongoing maintenance, updates, and technical support to ensure optimal performance. This may involve regular calibration of cameras and sensors, software updates to address bugs or vulnerabilities, and troubleshooting issues as they arise.

3.REQUIREMENT ANALYSIS AND PLANNING

To develop an effective computer vision-based quality control system, a thorough requirement analysis and meticulous planning are essential. This ensures that the system meets the specific needs of the manufacturing process and achieves the desired quality control objectives.

1. **Define Objectives and Scope**

- **Quality Standards**: Identify the specific quality standards and metrics that the system must adhere to. These could include defect detection rates, accuracy, and inspection speed.
- **Product Characteristics**: Understand the physical and visual characteristics of the products to be inspected, such as size, shape, color, texture, and symmetry.

2. **Stakeholder Requirements**

- **User Needs**: Gather input from all stakeholders, including production managers, quality control inspectors, and IT staff. Determine user expectations, interface requirements, and any specific functionalities needed.
- **Regulatory Compliance**: Ensure that the system meets industry-specific regulatory requirements and standards.

3. **Technical Requirements**

- **Hardware**: Specify the types of cameras, lighting, and other imaging equipment required. High-resolution cameras and appropriate lighting are crucial for capturing clear images.
- **Software**: Determine the software requirements for image processing, machine learning models, and user interfaces. Include considerations for data storage and processing capabilities.
- **Integration**: Plan for integration with existing manufacturing execution systems (MES), enterprise resource planning (ERP) systems, and other relevant software.

4. **Environmental Considerations**

- **Operational Environment**: Analyze the manufacturing environment where the system will be deployed. Consider factors such as lighting conditions, temperature variations, and potential sources of interference.
- **Maintenance and Scalability**: Define requirements for system maintenance, scalability for future expansion, and adaptability to different production lines or products.

Planning

1. **System Design**

- **Architecture**: Develop a detailed system architecture that includes hardware and software components, data flow, and communication protocols.
- **Algorithm Development**: Plan the development of image processing and machine learning algorithms. This includes selecting appropriate models, training datasets, and performance metrics.
- **User Interface**: Design a user-friendly interface for system operators to interact with the quality control system. This should include visualization tools for defect analysis and reporting features.

2. **Project Management**

- **Timeline and Milestones**: Establish a project timeline with clear milestones for each phase of development, including requirement gathering, system design, implementation, testing, and deployment.
- **Resource Allocation**: Allocate resources, including personnel, budget, and equipment. Ensure that there is a dedicated team with expertise in computer vision, software development, and quality control.

3. **Implementation Plan**

- **Prototype Development**: Develop a prototype to validate the system design and algorithms. Conduct initial testing in a controlled environment to identify and address any issues.
- **Pilot Testing**: Implement the system on a small scale in the actual production environment. Gather feedback from operators and make necessary adjustments.
- **Full Deployment**: Gradually scale up the deployment to cover all relevant production lines. Ensure continuous monitoring and support during the initial phase of full deployment.

4. **Evaluation and Optimization**

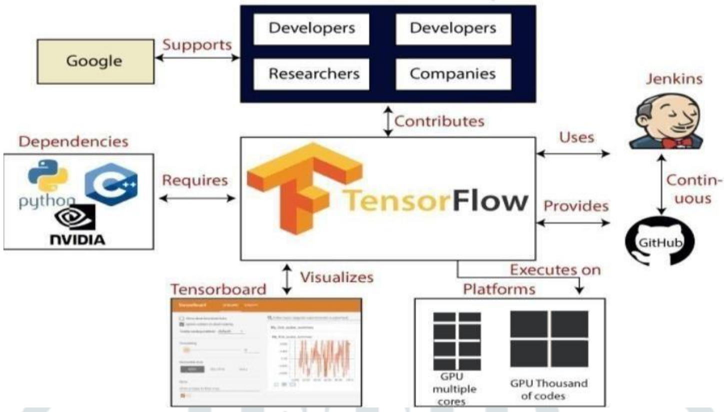
- **Performance Metrics**: Define key performance indicators (KPIs) to evaluate the system's effectiveness. Regularly review these metrics to identify areas for improvement.
- **Continuous Improvement**: Implement a feedback loop for continuous system improvement. Regularly update the algorithms and system components based on performance data and user feedback.

5. **Training and Documentation**

- **User Training**: Provide comprehensive training for system operators and maintenance personnel. Ensure they understand how to use the system effectively and troubleshoot common issues.

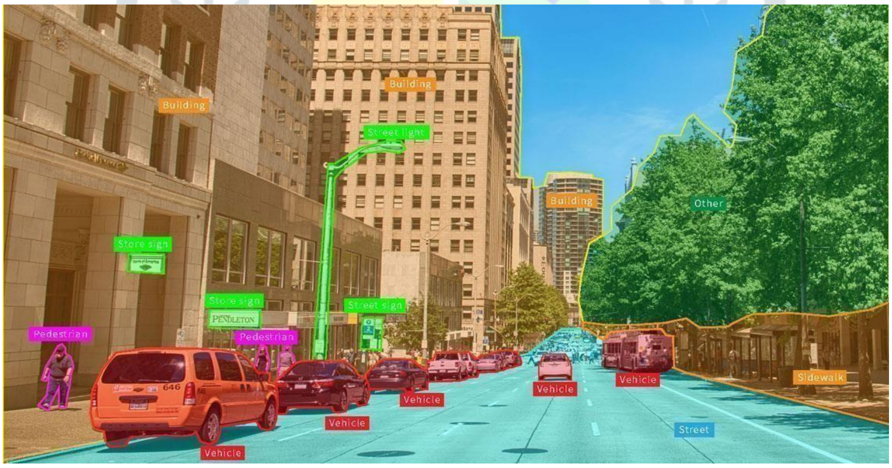
• **Documentation**: Develop detailed documentation for all aspects of the system, including installation guides, user manuals, and maintenance procedures.

4. ARCHITECTURE



Tensor Flow is a popular framework of machine learning and deep learning. It is a free and open- source library which is released on 9 November 2015 and developed by Google Brain Team. It is entirely based on Python programming language and use for numerical computation and data flow, which makes machine learning faster and easier. TensorFlow can train and run the deep neural networks for image recognition, handwritten digit classification, recurrent neural network, word embedding, natural language processing, video detection, and many more. TensorFlow is run on multiple CPUs or GPUs and also mobile operating systems.

5. RESULT



TRAFFIC IMPLEMENTATION

DEFECT IMAGE PREPROCESSED DEFECT IMAGE

IMAGE PREPROCESSING OUTPUT

FEATURE EXTRACTIO

DEFECT DETECTION EXTRACTION

PRODUCT INSPECTION

CONCLUSION

In conclusion, computer vision technology has emerged as a powerful tool with diverse applications across industries, from healthcare and automotive to retail and agriculture. By enabling machines to interpret and understand visual information, computer vision systems have revolutionized processes, enhanced efficiency, and facilitated innovative solutions to complex problems. However, the widespread adoption of computer vision technology is not without its challenges and considerations. From data quality and algorithm robustness to ethical implications and regulatory compliance, navigating these challenges is essential for ensuring the responsible development and deployment of computer vision systems.

Despite these challenges, the potential impact of computer vision technology is profound. From improving medical diagnostics and autonomous vehicles to enhancing retail experiences and environmental monitoring, computer vision has the power to transform industries, drive innovation, and improve quality of life. Moving forward, addressing the challenges and considerations associated with computer vision requires a multidisciplinary appoach, involving

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