International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 06 | Jun 2024 www.irjet.net p-ISSN: 2395-0072

Real-time quality control monitoring should be facilitated by artificial intelligence.

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Abstract - *Computer Vision (CV) is a field of artificial intelligence (AI) that enables computers to interpret and process visual data from the world, emulating human vision. By using digital images from cameras and videos, along with deep learning models, computers can be trained to perform tasks such as image recognition, object detection, and image generation.*

Machine Vision (MV), closely related to CV, is a technology used in industrial automation that employs cameras and image processing software to inspect and analyze objects automatically. While CV is more focused on algorithms and the science behind visual recognition, MV is typically application-driven and focuses on integrating hardware and software for specific industrial tasks.

Key Words: Artificial Intelligence, machine learning, deep learning, DL, Industry 4.0, Quality 4.0, real-time quality management, and computer vision.

1.Introduction

In recent years, computer vision (CV) technologies have seen significant advancements, becoming integral to many industrial processes. According to the latest Gartner Hype Cycle 2023, CV is nearing its peak productivity, particularly in the realm of artificial intelligence (AI) tools. This trend signals a forthcoming expansion of CV applications across various industries. Presently, CV plays a crucial role in the industrial sector, especially in automated inspection functions as part of quality control procedures. However, the growing complexity of automation, driven by Industry 4.0, the Internet of Things (IoT), cloud computing, AI, machine learning (ML), and other technologies, presents significant challenges for users and developers of CV systems in selecting the most suitable technology for specific applications.

1. Evolution and Integration of Computer Vision in Industry

With rapid advancements in numerous fields—such as CV techniques, CMOS sensors, integrated machine vision (MV), ML, deep learning (DL), robotic interfaces, data transfer standards, and MV functionality—new MV technologies are unlocking new application potentials. For instance, hyperspectral imaging can provide information on the chemical composition of processed materials, and computer imaging can combine a series of images to highlight details not visible using traditional MV techniques. Additionally, polarization cameras can visualize stresses in materials. These advancements enable improved performance, integration, and automation in the manufacturing industry. The high demands of Industry 4.0 necessitate varying levels of integration, from supporting manual assembly to full integration with original equipment manufacturers.

2. Importance of Quality in Industry 4.0

To ensure continued customer satisfaction, the industry must continuously innovate, accelerate, and improve. Crucially, the evolution of the sector must be accompanied by the evolution of the quality function. Neglecting "Quality 4.0" could jeopardize the apparent progress, potentially compromising product quality and the customer experience. Quality controls must transition from paper-based to cloud-based systems, aligning with the technological advancements of Industry 4.0 while maintaining their core purpose. Digital tools now enable companies to connect more directly with their contractors, suppliers, and customers, fostering stronger relationships across the entire ecosystem. The growth enabled by AI can significantly bolster business operations, facilitating real-time collaboration, enhanced client engagement, and optimized reporting. This interconnectedness contributes to overall quality and risk prevention.

3. Role of Machine Vision in Quality Control

Machine vision (MV) systems offer unparalleled speed, precision, and consistency in the quantitative assessment of structured scenes. For example, an MV system on a production line can inspect hundreds or even thousands of components per minute. With appropriate optics and camera resolution, such systems can easily detect defects that are invisible to the naked eye. MV excels in quantitative tasks, while human inspection is better suited for qualitative interpretation of complex and unstructured scenes. By leveraging both human and machine capabilities, industries can achieve comprehensive quality control.

4. **Objective and Organization of the Study**

This research study aims to provide the scientific community with an overview of the use of CV and MV in real industrial applications. The rest of this paper is organized as follows:

5. **Section 2: Background**
    - We will provide an overview of AI, CV, MV, and the main technologies and techniques used in CV, such as ML, DL, and color detection and measurement, while describing the design of an MT (machine vision technology) system.
6. **Section 3: Industrial Applications**
    - We present two industrial applications of CV and discuss their results through critical analysis. The first application focuses on real-time quality monitoring, while the second examines bolt and screw testing.
7. **Section 4: Conclusion**
    - We conclude the study by offering new insights into potential future research directions.

2. Artificial Intelligence History

Artificial intelligence (AI) is a branch of computer science focused on developing intelligent agents or autonomous systems capable of thinking, learning, and acting. AI has been instrumental in creating effective methods for addressing a wide range of problems, from game playing to medical diagnosis. Among the most significant advancements in AI are machine learning (ML) and deep learning (DL) algorithms. These algorithms enable AI systems to learn from data without the need for explicit programming.

Today, AI is applied across various fields, including manufacturing, transportation, healthcare, retail, and customer service. In manufacturing, AI facilitates the automation of industrial processes, enhances quality assurance, and predicts maintenance needs. For instance, AI-equipped robots can undertake repetitive or hazardous tasks, improving safety and efficiency in the workplace.

2.1 *Machine vision (MV) versus computer vision (CV))*

The field of Computer Vision (CV) is a branch of artificial intelligence that enables computers and systems to derive meaningful information from digital images, photos, videos, and other visual inputs. By processing this visual data, CV systems can take actions or make recommendations based on the information extracted. CV relies heavily on large datasets to perform analyses that lead to image discrimination and recognition. One of the most effective types of machine learning (ML) algorithms used in CV is deep learning (DL), particularly convolutional neural networks (CNNs).

Machine Vision (MV) is a subset of CV, focusing on the practical application of CV techniques to solve real-world industrial problems. The goal of MV is to reduce costs, increase efficiency and productivity, minimize errors, improve quality, and collect data, all of which contribute to significant advancements in industrial processes. MV systems can also address the shortage of skilled workers and relieve workers from hazardous or demanding tasks. Over time, MV has evolved to become synonymous with the practical implementation of CV technologies in industrial settings.

The integration of MV and ML has revolutionized the field, bringing CV capabilities closer to human vision. This milestone, long sought after since the inception of CV in the 1960s, has only recently been achieved due to significant advancements in AI.

1. **2.2 Design of Machine Vision Systems (MVS)**

Machine Vision Systems (MVS), commonly used in manufacturing applications such as quality control, employ image processing techniques governed by a set of rules and parameters. The primary components of an MVS include lighting, optics, image sensors, image processing, and communication.

2. **Illumination**:
    - **Lighting** is crucial as it makes objects visible and highlights features for accurate recognition by the camera. The system's efficiency depends significantly on proper illumination.
    - **Lighting Configurations**:
        - **Front Lighting**: Provides focused light on the object, enhancing the visibility of surface details.
        - **Backlighting**: Illuminates the background of the object, highlighting its outline and silhouette.
    - **Types of Lighting**: Includes incandescent lamps, fluorescent lamps, lasers, X-ray tubes, and infrared light.
3. **Image Acquisition**:
    - This involves capturing images of the sample using various instruments or sensors such as scanners, ultrasound, X-rays, and near-infrared spectroscopy.
    - **Image Sensors**:
        - Solid-state devices like CCD (charge-coupled device) cameras are commonly used.
        - Digital cameras have eliminated the need for separate components to convert captured images into a

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
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computer-readable format, maintaining high resolution and minimal noise.

4. **Image Processing**:
   - Digital images are processed by computers, which convert them into numerical data that can be manipulated and analyzed. These images, although appearing as pictures on the screen, are composed of pixels or small dots that represent real objects.
   - Processed digital images can be used in various applications, such as authentication systems.
   -

MVS systems are designed to perform specific tasks in industrial environments, utilizing the components mentioned above to achieve accurate and efficient image processing and analysis. The integration of illumination, image acquisition, and image processing components ensures that MVS systems can effectively address the needs of various industrial applications.

Diagram1. Machine-Vision-System

2.3 Used methods & technologies in CV

The three main technologies accelerating computer vision (CV) development are Machine Learning (ML), Deep Learning (DL), and Convolutional Neural Networks (CNNs). Here's an overview of each:

3. Machine Learning (ML)

Machine Learning (ML) is a branch of artificial intelligence and computational science that focuses on the development, analysis, and implementation of automated methods allowing machines to learn and evolve through a learning process. These methods are primarily grounded in algorithms. In practice, ML algorithms can be broadly classified into two types: black box algorithms and interpretable algorithms. When choosing an ML algorithm, it is crucial to consider the specific requirements of the application and find a balance between "accuracy" and "interpretability."

1. **Black Box Algorithms**

Black box ML algorithms are often highly accurate but can be difficult or impossible to understand. These algorithms are typically developed using sophisticated mathematical models and trained on large datasets. They are capable of producing impressive results, but in situations where it is important to understand how decisions are made, their lack of interpretability can be problematic. Examples of black box algorithms include:

2. **Deep Learning (DL) Algorithms**: Such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).
3. **Support Vector Machines (SVM)**
4. **Random Forest**
5. **Gradient Boosting Machines (GBM)**
6. **K-Nearest Neighbors (KNN)**
7. **Naive Bayes**
8. **Interpretable Algorithms**

In contrast, interpretable ML algorithms are easy for humans to understand and interpret. These algorithms are usually developed using less complex mathematical models and often require smaller datasets. While interpretable algorithms are generally less accurate than black box algorithms, they are more reliable in applications where interpretability is critical, such as financial and medical diagnostics for decision-makers. Examples of interpretable algorithms include:

1. **Class Association Rules (CAR)**
2. **Refined Class Association Rules (RCAR)**

RCARs, in particular, demonstrate high performance and accuracy in various domains, especially in cybersecurity for profiling and preventing security attacks. Compared to black box algorithms, interpretable algorithms like CARs and RCARs are better suited for applications where understanding the reasoning behind decisions is essential, such as in finance, security, and medicine.

9. **Balancing Accuracy and Interpretability**

When selecting an ML algorithm, it is essential to consider:

1. **Application Requirements**: Whether the application demands high accuracy or high interpretability.
2. **Data Availability**: The size and quality of the available dataset.
3. **Decision-Making Context**: The criticality of understanding how decisions are made.

In summary, while black box algorithms excel in accuracy and handling complex tasks with large datasets, interpretable algorithms offer transparency and are better suited for critical applications where decision understanding is paramount. The choice between these types of algorithms should be informed by the specific needs and constraints of the application at hand.

3.1 Deep Learning (DL)

Deep Learning (DL) is a subset of Machine Learning (ML) where tasks are divided and distributed across multiple algorithms organized into successive layers. Each layer builds upon the output of the previous one, forming an artificial neural network that mimics the distributed problem-solving approach of neurons in the human brain. A prominent subset of DL includes Convolutional Neural Networks (CNNs). Consequently, while all CNNs are DL algorithms, not all DL algorithms are CNNs.

CNNs are especially prevalent in classification and computer vision (CV) tasks. By breaking down images into pixels with labels or tags, CNNs enable ML or DL models to "see." A convolution is a mathematical operation involving two functions that produces a third function. In the context of CNNs, convolutions are used to process input data with labels, enabling the network to make predictions about what it "sees." The neural network iteratively performs convolutions and evaluates the accuracy of its predictions, refining its ability to identify or interpret images, similar to human vision.

3.2 Color Detection & Measurement

The concept of color recognition in image processing is integral to various fields, especially in food quality control where color is a primary indicator of quality and freshness. Let's delve into how color recognition works, particularly in the context of food dyes, and explore different methods of color measurement.

- **Understanding Color Recognition**

Color recognition is based on the human eye's ability to perceive different wavelengths of light. This perception is enabled by three types of photoreceptor cells (cones) in the retina, each sensitive to different wavelength ranges:

- **Short wavelengths (S-cones)**: Sensitive to bluish light, with peak sensitivity around 420-440 nm.
- **Medium wavelengths (M-cones)**: Sensitive to greenish light, with peak sensitivity around 530-540 nm.
- **Long wavelengths (L-cones)**: Sensitive to reddish light, with peak sensitivity around 560-580 nm.

These three types of cones allow humans to perceive a wide range of colors through the additive mixing of these primary colors: red, green, and blue (RGB).

- **Color Coding and Measurement**

In digital imaging and display technologies, colors are often coded using the RGB color model. Each color is represented as a combination of the three primary colors:

- **Red (R)**
- **Green (G)**
- **Blue (B)**

By varying the intensity of each primary color, a vast spectrum of colors can be produced. When all three colors are combined at full intensity, the result is perceived as white.

- **Methods of Color Measurement**

In industry and science, precise color measurement is crucial to ensure consistency and quality. Here are the three main methods of color measurement:

1. **Visual Measurement by Trained Personnel**:
    - Relies on human perception.
    - Subjective and may vary between individuals.
    - Used for quick assessments but lacks precision.
2. **Traditional Measurement with Colorimeters and Spectrometers**:
    - **Colorimeters**: Measure the intensity of colors based on standard lighting conditions. Suitable for basic color matching and quality control.
    - **Spectrometers**: Provide detailed spectral data by measuring the intensity of light at different wavelengths. Highly accurate and used for detailed color analysis.
3. **Computer Vision (CV) Measurements**:
    - Utilizes digital imaging and algorithms to analyze colors.
    - Offers rapid and automated color measurement.
    - Ensures reproducibility and objectivity, making it ideal for industrial applications.

- **Color Spaces and Calibration**

To achieve consistent color representation across different devices and contexts, color spaces and calibration methods are employed:

- **Color Spaces**: Systems for organizing colors. Common examples include RGB, CMYK (used in printing), and LAB (used for color correction and analysis). Each color space defines colors in relation to a specific white point and set of reference colors.
- **Color Calibration**: Adjusts the color response of devices (e.g., monitors, cameras, printers) to match a standard color space. Ensures that colors are represented accurately across different devices.

- **Application in Food Quality Control**

In food quality control, rapid and accurate color measurement is essential. For instance, the color of a dessert can indicate its flavor (e.g., yellow for vanilla) or the freshness of meat (red color indicating freshness). By employing color measurement techniques, manufacturers can ensure that products meet quality standards and consumer expectations.

In conclusion, color recognition and measurement are fundamental to various applications, particularly in food quality control. Through the use of visual inspections, traditional instruments, and advanced computer vision techniques, industries can achieve accurate and reproducible color measurements, ensuring product quality and consistency.

Diagram 2. HEX Color Codes

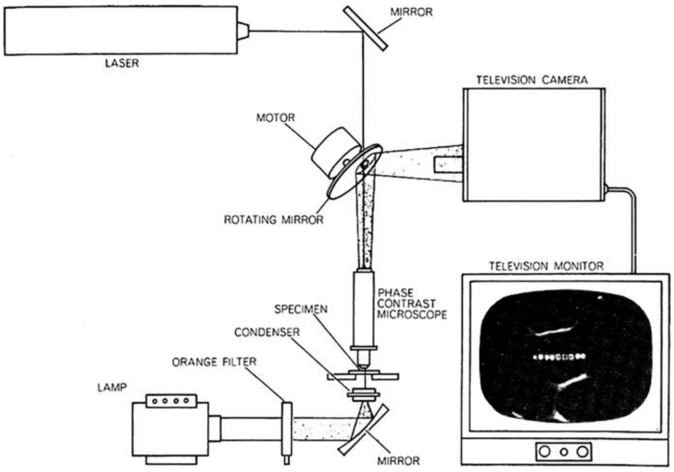

Diagram 3 Ion laser microbeam microscope

4. Industrial CV applications: Outcome and critical evaluation

4.1 Real-time quality monitoring during robotic building construction

In this section, we will discuss the use of computer vision (CV) for quality control in robotic building construction. The effectiveness of this method is tested using a laboratory-scale concrete printer with an extrusion process. Data capture and processing are facilitated by a Logitech 720p camera that records extrusion films. The camera is securely mounted on the extruder using a 3D printed bracket, ensuring it faces the top of the product layer. The top surface of the extruded layer is positioned 40 cm from the camera lens, as illustrated in Fig. 3.

A Raspberry Pi 3 Model B is employed to process the extrusion material in real time. The CV method described by Kazemian et al. is used to identify over- or under-extrusion situations. In Fig. 4, the width of the newly extruded layer is compared to the width of the desired layer. Over-extrusion is easily detected by observing if the layer is wider than intended. However, under-extrusion can manifest in three ways: a reduced layer width, cracking and discontinuity of the extruded layer, or complete absence of deposit.

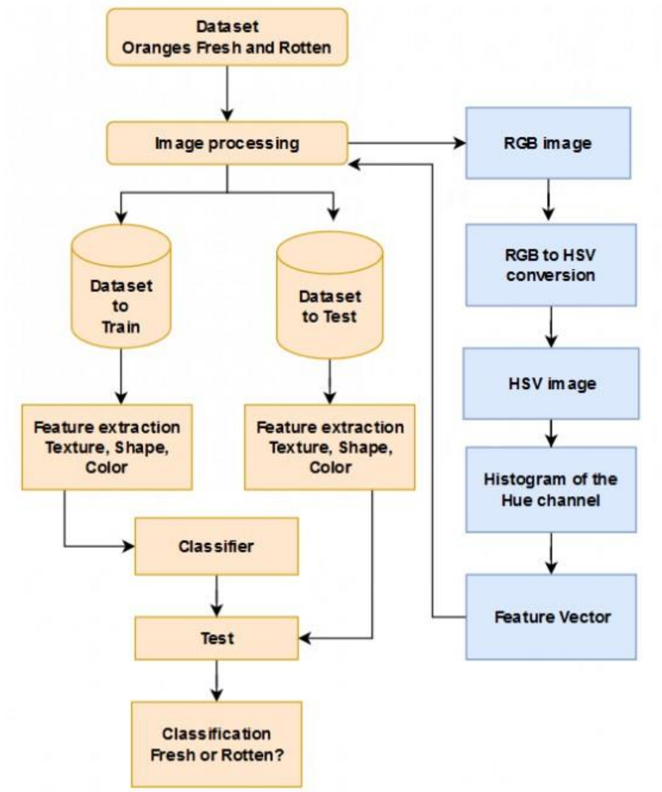

Diagram 4. Suggested algorithm for computer vision

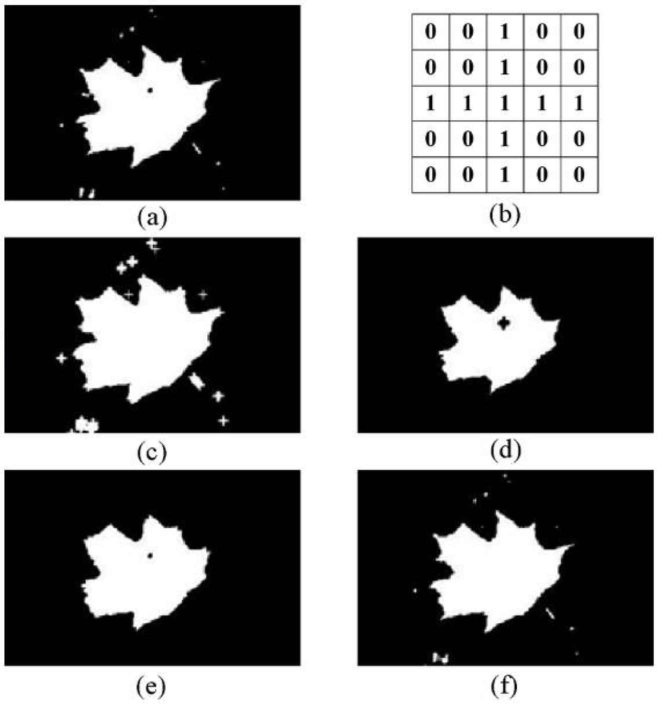

Diagram 5. An image of the extrusion process that was prepared: Top view (a) and the matching binary image (b)

Diagram 6. Color Defect

The video processing technique described in the passage employs a shape-based approach for detecting subtle objects, as opposed to color- and texture-based methods. The process begins simultaneously with the extrusion process for each test, using a video recording and processing setup. To facilitate the subsequent steps, the image undergoes blurring with a Gaussian filter and is then transformed using binary thresholding. This technique distinguishes the foreground (extruded plane) from the background (print plane) by rendering the "extruded layer" in white and the "background" in black, resulting in a binary image.

The next step involves locating and confirming the boundary of a layer using a shape discrimination method, after which the layer's width is determined. This method is exemplified in Fig. 4 by the feedback-controlled extrusion system developed using the computer vision (CV) algorithm described by A. Kazemian et al. The aim is to create an extrusion system capable of automatically adjusting extrusion settings to maintain a consistent layer width, without prior calibration and despite variations in the printing medium.

The preliminary results indicate that it is feasible to develop a vision-based extruder that can automatically print layers of a specified size in any printable combination, eliminating the need for calibration. However, further research is required to enhance the functionality of this vision-based closed-loop extrusion system, particularly in refining the control algorithm.

Computer Vision Systems (CVSs) are advantageous because their integration into Machine Vision Systems (MVSs) allows them to adapt to real-time changes during the process. The experimental results have shown that the developed extrusion monitoring system is highly accurate and responsive. Despite the limitations imposed by using a single-board computer, such as increased reliability but difficulty in repairs due to fewer connectors, the performance of the implemented system is promising. Improvements could be achieved by using embedded computers, which would enhance processing speed and the quality of extrusion by handling larger sample sizes. Embedded systems, although often limited in real-time computing capabilities, control many devices today. For better visual quality in real-time imaging, the system proposed by B. Kerbl et al., which employs three-dimensional (3D) Gaussian splatting for real-time radiation field rendering, could be utilized.

4.2 *Inspection of bolts and screws in production line based on CV*

The study by J. Rajan et al. delves into the application of computer vision (CV) in inspecting bolts and screws, employing AI cameras for image capture. The process involves converting analog images into digital ones through sampling and quantization, followed by preprocessing to ready the image for segmentation. Utilizing an Intel Neural Compute Stick (NCS) for edge processing, the study combines Python and C++ for programming. To detect defects, infrared light-emitting diodes and SolidWorks for hardware case creation are employed.

The camera input undergoes binary translation for processing akin to human visual data recognition. This process, executed on a machine with Intel NCS, a vision sensor, and a microcontroller, enables defect detection, leading to removal of defective screws. Defects are categorized into color defects, orientation errors, and cracking defects.

Color defects often stem from manufacturing issues or data flow degradation during neural model use. Misorientation in bolts is detected using Convolutional Neural Network (CNN) techniques, while cracks are identified by sending bolt images through a neural model after grayscale conversion and edge detection.

Despite the efficacy of the active contour method, it poses limitations such as susceptibility to local minima, detail loss, accuracy dependent on convergence criteria, slow processing for large images, inability to segment adjacent objects, and unsuitability for video operations. These limitations necessitate solutions like simulated annealing for local minima, stringent convergence criteria for accuracy, and considerations for processing speed in large images.

5. Conclusion

This article provides a comprehensive overview of the integration of artificial intelligence (AI), particularly machine/deep learning and neural networks, along with computer vision (CV) technologies in real-time industrial quality control. It delves into two specific use cases: real-time quality monitoring during robot construction and inspection of bolts and screws in the production line. The findings highlight the current integration of CV into industrial processes, emphasizing its role in enhancing real-time perception of product quality and enabling more accurate anticipation of deviations, thereby reducing costs. The critical analysis of the results from these CV applications in industrial settings aims to pinpoint the primary limitations of commonly employed techniques and methods. This is crucial for advancing the field and overcoming challenges. The article recognizes the diverse applications of CV, ranging from assisting operators in identifying non-compliant parts to aiding autonomous mobile robots in navigation and analyzing object behavior within specific environments.

Looking ahead, the article advocates for conducting analyses of real-world cases closely aligned with existing industrial processes to address the limitations of future intelligent vision systems effectively. Future research directions outlined include studying various machine learning (ML) and deep learning (DL) algorithms within CV and exploring their potential application in automotive component manufacturing to enhance real-time quality control further. By focusing on practical applications and acknowledging existing limitations, the article provides valuable insights into the current state and future prospects of integrating AI and CV technologies into industrial quality control processes.

REFERENCES

[1] https://sciotex.com/how-to-use-ai-for-quality-control/
[2] https://blog.allplan.com/en/construction-monitoring-by-robots
[3] Artificial Intelligence: A Modern Approach - by Russell/Norvig
[4] Artificial Intelligence: A Modern Approach, Global Edition - by Stuart Russell
[5] https://www.ibm.com/topics/machine-learning