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Robotics-Based Automated Quality Inspection System Using Computer Vision and Machine Learning

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Abstract

Conventional manual quality inspection in a manufacturing setting is intrinsically marred by a lack of subjective accuracy, human fatigue, and inconsistency of judgement that usually attracts inconsistencies, slower throughput and increased costs of operation. In order to overcome these difficulties, the study proposes an integrated Robotics-Based Automated Quality Inspection System with the help of computer vision and machine learning algorithms ensuring the high accuracy and real time detection of defects. The suggested demo incorporates an industrial 6-degree-of-freedom robotic arm that can accomplish fine manipulation and adapt fleet positioning of work parts with high-resolution imaging sensors and optimized illumination modules to guarantee the coherent visual data is obtained under diverse production conditions. The raw images are preprocessed and passed as an input of a convolutional neural network (CNN) model-fine-tuned over an EfficientNet backbone to detect and locate various defects, such as scratches, dents, misalignments, and surface contamination. The model was trained using a handcrafted dataset containing 12,000 labeled pictures aggregated using a variety of production environments and the category classification rate attained by the model was 98.2 percent, and a low rate of 2.1 percent false positives was experienced. Through system integration with robotic motion control it is possible to synchronize the inspection, overcoming the blind spot and being able to maintain throughput with the high speed conveyors. Experimental analysis revealed that the suggested system will decrease the amount of human effort put into operation by 65 percent and enhance the rate of inspection by 3.4x compared to the conventional manual method while guaranteeing greater consistency in detecting the defect. In addition to that, the modularization enables quick geometrical cleaning of the products and the nature of production and could, therefore, be used in electronics together with the automotive and packaging manufacturing industries. The work also not only confirms the practicality of combining more sophisticated deep learning methods with industrial robotics as a way to perform scalable, automated quality control, but also lays the groundwork towards improvements such as full 3D vision support and unsupervised detection of novel anomalies and flexible learning to adapt to the changing production environment, hence aligning with the Industry 4.0 goals of intelligent and autonomous manufacturing.

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Introduction

Quality inspection plays an important role in modern times of manufacturing products that can satisfy the technical requirements, regulation and customers. Such defects as scratches on the surface, variations of dimension or misalignment of products during assembly can cause functional failure or shorter product life or expenses incurred in the recall or rework may be enormous. Conventionally, this inspection process would involve manual checks done by hired human operators where the human operator would visually inspect all the products and make decisions based on pass or fail. Although quite sufficient in the context of the small-scale production, manual inspection is by its nature fatigued, subjective, inconsistent, and comparatively slow, being thus rather unfit to demand of high-speed, and precision operations of Industry 4.0 manufacturing Figure 1.

The changing nature of manufacturing systems which require near zero defect readings, has fast tracked

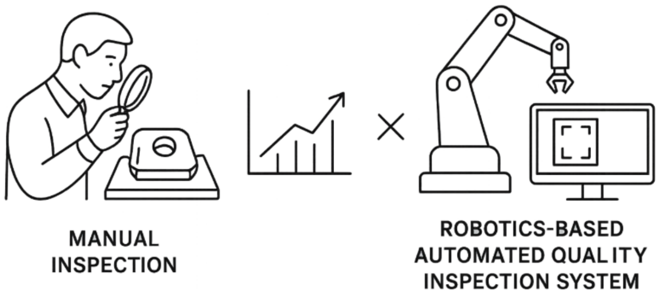

Fig. 1:Comparison between manual inspection and the proposed robotics-based automated quality inspection system

the passage of Robotics-Based Automated Quality Inspection Systems (RAQIS) through the need to increase manufacturing process complexity. They combine industrial robots, with high resolution imaging devices and advanced computer vision algorithms, to provide uninterrupted, accurate, repeatable inspection with minimal operator involvement. With robots, the freedom of handling and positioning of workpieces comes along, this allows to look at the inspected object at various angles, and under controlled lighting conditions thereby providing elimination of any blind spots and dissimilarity to the environment. At the same time, computer vision as an approach based on the recent fast development of machine learning (ML) and deep learning (DL) enables precise and rapid detection, classification, and location of defects. Convolutional Neural Networks (CNNs) in particular have proven to outperform both traditional image processing techniques in robustness and adaptability and to perform excellently in visual pattern recognition tasks.

With the onset of Industry 4.0, interconnectivity, automation and real-time decision making based on the availability of data are key attributes, thus defect detection that is based on deep learning combined with robotic automation are more accurate, scaleable and adaptable. The research proposal introduces an automated framework on robotics where CNN-based defect detection modules with a robotic arm that will take dynamic positioning will be used and the decision to label the product as pass/fail will be determined in real-time. The overall aim of the system is to enhance the accuracy of inspection, to ensure that human intervention is limited, to make the production lines more efficient, and to guarantee uniformity of quality of the product on large production lines which may have more than one manufacturing process. The given approach is capable of overcoming the weaknesses of manual inspection and offers a reconfigurable and scalable solution that is in line with the paradigm of smart manufacturing of the next generation.

Related Work

It is the case that automated quality inspection has come a long way since its simple early days of rule-based vision systems to state of the art deep learning-powered robotic inspection systems. The classical methods like edge detection, thresholding and template matching[1] have done reasonably well when something controllable is being used but are very sensitive to lighting conditions, the orientation of objects and on their surface texture. These systems were generally not successful in picking up subtle faults as they relied on hand crafted features and fixed decision rules.

To overcome these shortcomings, classical machine learning algorithms, such as Support Vector Machines (SVM) and Random Forests[2, 3] were proposed to undertake defect classification. Despite making advances toward robustness compared to rule-based systems, they had a fixed constraint to change due to their manually designed features, which constrained them to complex visual variation in the real-world environment.

Deep learning was another important step, which allowed end-to-end learning of feature representations and the discriminative properties. Architectures with CNN module like ResNet,[4] YOLO,[5] and EfficientNet[6] performs better in defect detection and localization. The combination of these models with industrial robotic systems[7, 8] has resulted in real-time and completely automated inspection pipelines with the capability to increase the throughput and decrease human interaction. Nonetheless, most of the implementations have been limited to single-product inspection thus constraining scalability.

Research has recently started exploring multi-axis robotic manipulators that use computer vision feedback [9, 10] to dynamically reposition parts, to increase coverage of inspection. Manufacturing inspection is enabled by complementary technologies, such as research in advanced material sciences,[11] efforts in embedded system integration on the Internet of Things (IoT)[12] and validated IoT communication stacks at the larger scale.[13] Reliability in mission-critical applications is further supported in various fault detection studies of reconfigurable hardware[14] and progress towards mechatronics[15] will provide changes towards integration of intelligent quality control through precision robotics.

In spite of this progress, major challenges still exist in the detection of the defects in multi-class, adaptive scalability across different types of products and high performance with different environmental conditions. The above shortcomings are filled by the proposed inspections pipeline architecture encompassing modular robotic handling, CNN-based defect detection, and decision logic pipeline that is applied in real-time, ensuring scalable and speedy inspection of manufacturing processes.

System Architecture

Robotic Handling Module

The robotic handling module of the proposed automated quality inspection system constitutes the mechanical basis of the system and provides superior, repeatable, and scalable work piece manipulations to make the visual coverage of work pieces exhaustive and complete in the inspection process. Its heart is an industrial scale six degrees of freedom (6 DOF) robotic end-effector with high precision end-effector that is capable of able to securely grab, handle, and manipulate components with different geometries, tolerances and surfaces. This progressive setup achieves various functionalities, such as pick and place operations, accurate rotational corrections, and multiple axis positioning thus enabling full surface inspection on even the shape irregular parts and parts with complicated designs. The robot arm works in accordance with the Robot Operating System (ROS) framework that allows complicated path-planning, control of coordinated movement control, and real-time synchronization with imagining, luminous apparatus, and defect alert systems Figure 2. The programmed inspection paths guide the arm into placing the products in the best position to be clearly seen by the camera at many viewing angles, which will basically do away with blind spots and minimize the chances of undoing defects. Moreover, automation of the positioning process has a valuable by-product of eliminating any human introduced

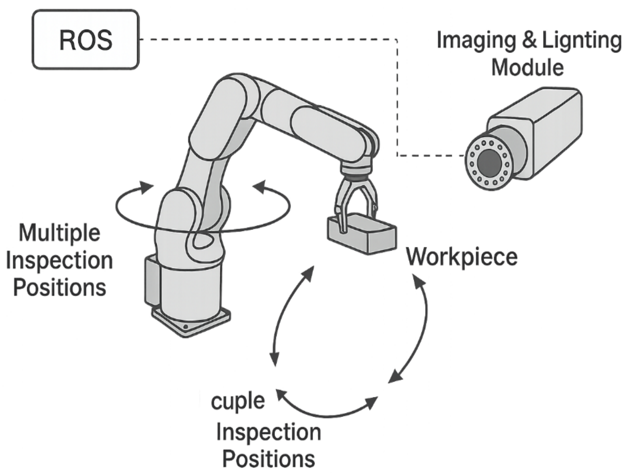

Fig. 2: Schematic representation of the Robotic Handling Module showing 6 DOF robotic arm integration with ROS and imaging system for multi-angle inspection.

variation and weariness since it removes the need of continuously adjusting the positioning process to correct variations. Also throughput is drastically enhanced by automation of positioning so much that the system can maintain high speed inspection loops demanded by contemporary production lines. This module is a very important facilitator of high-quality production in a large and high-volume manufacturing setting due to the robustness, repeatability, and precision that is provided by the module.

Imaging & Lighting Module

The Imaging and Lighting Module is an important constituent of the planned automated inspection field that will provide distortion-free high resolution visual data with controlled and homogeneous illumination conditions that would determine accuracy and reliability of defect detection. This module has an industrial grade, 12-megapixel camera with adjustable zoom and a high frame rate, optimally located a calibrated distance away from the inspection area to achieve optimal focus, depth of field and field of view across multiple product sizes and geometries. Addressing issues of variable factory lighting conditions, the system incorporates a ring-shaped LED lighting array, to deliver diffuse, uniform, and shadow-free illumination to an entire surface of the workpiece and thus greatly reduces glare, specular reflections, and varying brightness. Automated exposure control and dynamic white balance are also applied, to adjust

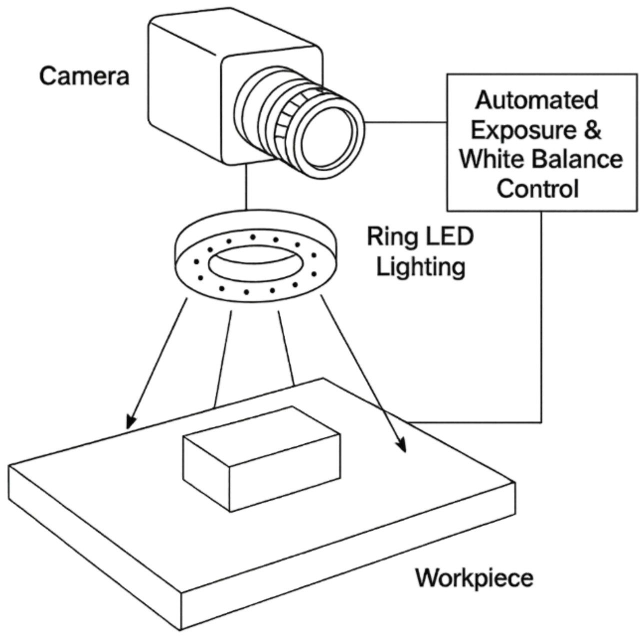

Fig. 3: Schematic representation of the Imaging & Lighting Module showing high-resolution camera, ring LED lighting, and automated exposure/white balance control for uniform defect inspection.

to changes in ambient light so that there is consistent image quality irrespective of variations in aspects of the environment. This high-resolution imaging with stable lighting, and adaptive control allow close visual details to be captured, and minute defects can be found, including micro-cracks and scratches, hairline cracks, surface contamination, and slight discoloration that would not otherwise be visible Figure 3. The resulting clarity and consistency of the images are crucial to a robust performance in the next machine-based defect detection process since they minimize false positives and false negatives and increase the generalization ability of the trained model. Moreover, the modularity of the imaging and lighting system also enables reconfiguration to support a variety of product lines, materials on the surface to be inspected, and inspection details hence making the system to be more adaptive within various manufacturing facilities.

Methodology

Data Acquisition

Dataset Description

The dataset used in the studied research is a set of 12,000 high-resolution images representing diverse manufacturing units in order to acquire variety in type of products, texture of surfaces, and environmental factors. More specifically, the imaging and lighting system used within the proposed system were used to ensure a consistent image quality and avoid the noise of the uncontrolled variables like changing ambient lightning conditions or different positioning. The dataset can be divided into four major classes of defects namely: scratches, dents, misalignment, and surface contamination. The set of images is manually labeled by the experts working at quality control in order to provide ground truth accuracy, the exact areas of defects are also labeled to be used in both classification and localization tasks. The presence of samples of different manufacturing sectors, i.e., automotive, electronics, and packaging, makes the dataset represent a vast diversity in the way, shapes and magnitudes in which defects can have an appearance, which in turn can enhance the system generalisation ability. The images are encoded in a standard RGB color space having 12 MP resolution and they are structured in a hierarchical folder structure according to the type of defect with aim of facilitating the training and evaluation.

Data Augmentation

We used a large data augmentation plan when training our model to help increase model robustness and decrease overfitting. The augmentation methods were random rotation (30degrees +-30), as a means of modeling products in different orientations during inspection, scaling (0.8 to 1.2 times), to represent the effect of variations in products size and camera distance, and variance of brightness (25 per cent + or -15). Other forms of data augmentation like horizontal flip, insertion of Gaussian noise and contrast manipulation were also applied in a controlled fashion so that the training data would again be more diverse yet realistic image distortions did not occur. Transformations were applied in an online augmentation pipeline, i.e. augmented images were generated on the fly throughout training, which achieved virtually unlimited variability of input data Table 1. This method enhanced the model in performing significant generalizing in unseen conditions and reliable detection of defects in real-life where there will always be a variation in position, size and light.

Table 1:Dataset Summary for Defect Detection Model Training

Parameter	Description
Total images	12,000 high-resolution images
Resolution	12 megapixels (MP)
Image format	RGB
Number of defect classes	4
Defect types	Scratches, Dents, Misalignment, Surface Contamination
Sectors represented	Automotive, Electronics, Packaging
Annotation type	Manual annotation with bounding boxes and class labels
Acquisition setup	Industrial camera + ring LED lighting for uniform illumination
Storage format	Organized in hierarchical directory structure by defect type
Augmentation techniques	Rotation (±30°), Scaling (0.8×-1.2×), Brightness variation (±15%), Horizontal flipping, Gaussian noise injection, Contrast adjustment

Preprocessing

A set of preprocessing operations were run on the obtained dataset prior to feeding it into the defect detection model so that to normalize the representation and improve its visual comprehensibility and compatibility with deep learning structures.

The initial stage was the resizing of the images into a fixed size of 512x 512 pixels. This re-sizing promotes homogeneity of the data set so that the convolutional neural network (CNN) can process the images without deformation. The selected solution balances the need to an adequate level of detail that allows finding the minor defects and avoid the excessive computational load, allowing to perform inference in a real production system in real-time. Rescaling was done by bicubic interpolation to maintain the edge sharpness and avoid the aliasing artifacts.

It was then contrast-limited adaptive histogram equalization (CLAHE) to broaden local contrast and emphasize fine details of defects. In contrast with global histogram equalization, an operation that alters the overall contrast of an image, CLAHE acts on a contextual, small area region of an image and redistributes the pixel intensity value of each of them to maximise the visibility of small-scale details. It is especially useful in highlighting low-contrast defects (micro-scratches or faint discoloration) that would not really have been noticed using regular lighting sources. The contrast-limiting component included in CLAHE does not allow oversaturation of the noise so that the enhancement process could increase the visibility of defects without creating any new confusing visual spots.

Lastly, the resultant images of the preprocessing process were normalized to a standard value of pixel intensities to fit an input in the neural network. The RGB values of each pixel would be scaled to [0, 1], and standardized using the dataset mean and standard deviation. This normalization step will lessen the effects of differences in the illumination of the various samples, speed up the learning in the training phase, and enhance numerical stability Figure 4. Normalization enables the model to learn important features instead of being skewed by changes in the brightness levels since it aligns the distribution of the data with the expected range of the data as seen by the CNN.

All these preprocessing procedures lead to the provision of high quality and standardized input data to the defect detection model and increase the training efficiency and the accuracy of the inference in practical inspection applications.

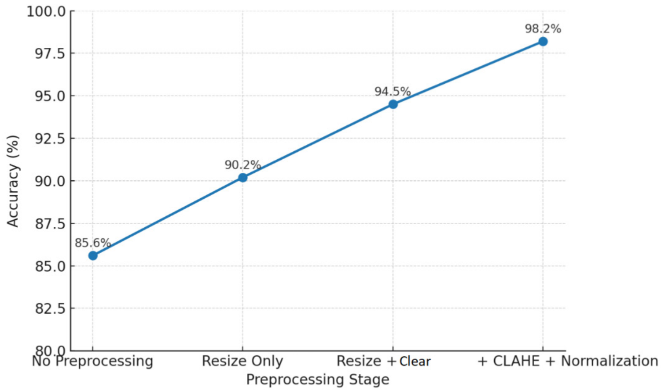

Fig. 4: Impact of preprocessing steps on defect detection model accuracy.

Model Training

As part of the defects detection system a Convolutional Neural Network (CNN) based classifier trained on the EfficientNet-B3 model will be used based on its good balance between accuracy, compute efficiency, and model size. EfficientNet-B3 employs a compound scaling approach, where depth, width, and input resolution are scaled uniformly, and a high representational capacity can then be achieved at a reasonable computational cost. This renders it as an appropriate option when applied in real-time industrial settings in which performance and inference speed are essential.

In order to reach convergence faster and take advantage of strong feature representations, transfer learning algorithm was utilized through setting the network to use pre-trained ImageNet weights. Such model can then use general low- to mid-level visual features acquired on large and varied dataset, effectively eliminating task-specific data needed to accomplish the same task-specific learning. In this case, the frozen layers were the only layers available prior to training, to store the generic features to be learned, and in the second stage, the layers were unfrozen. However, the last classification layers were also substituted with a customized output layer with four categories related to the four classes of defects; scratches, dents, misalignment and contamination of the surface. Following this initial training, the whole network was fine-tuned to represent features in the manufacturing defect domain in particular Figure 5.

The training process used Adam optimizer with a small learning rate of 1 x 10 14, where it was chosen because of the ability to adjust the learning rate as the training progresses and computational speed. Divergence between the predicted class probabilities and the ground truth labels was calculated using categorical

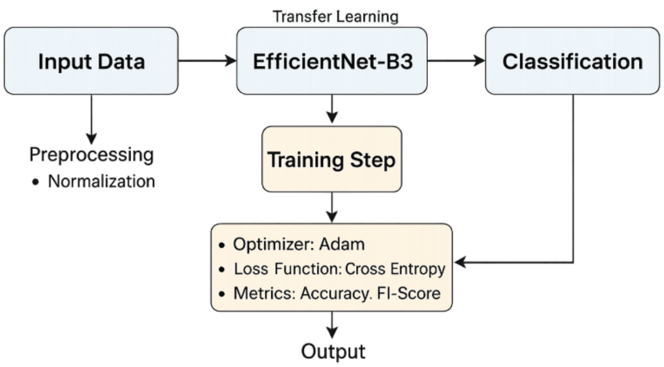

Fig. 5: Workflow diagram of the model training process for defect detection using EfficientNet-B3 with transfer learning and specified training parameters.

cross-entropy loss function that is the most suitable loss function in multi-class classification problems. The choice of 32-batch size was to consider both memory capacities and also gradient stability through a 50 maximum number of epochs during the training process of the model. In order to avoid overfitting and possible waste of computation power, early stopping was applied with patience of 8 epochs and stopping was occurred when validation loss was put on the rise within such period of epochs.

Data augmentation (Section 4.1.2) was used on-the-fly during training so as to provide variation and increase generalization. The validation accuracy and F1-score was used to keep track of model performance so that no biases were introduced in terms of improving on only the majority classes. This specific architecture selection, transfer learning, hyper parameter and regularization methods allowed the model to get high accuracy with minimum computation overhead to be incorporated into the real-time robotic inspection system.

Integration with Robotics

The most important part which will be implemented is the combination of the defect detection model and the framework of the robotic inspection process to warrant the real time, unsupervised, and coordinated mode of action in the manufacturing process. A packaged EfficientNet-B3-YOLOv8 hybrid model is then implemented on an NVIDIA Jetson Xavier embedded AI computing platform based on sustainable performances compared to its low thermoelectric power use and the ability to work in a real-time industrial system. The Jetson Xavier can be used to utilize low-latency inference on high-resolution images ensuring the system can sustain inspection speeds to meet high-throughput production line standards and still achieve high accuracy of detection.

The Robot Operating System (ROS) coordinates the communication between robot handling system and the vision module. The mechanism of running the camera trigger-system and positioning system of the robotic arm in sync is a dedicated ROS node. As the robotic arm moves a workpiece into inspection zone the ROS node at the same time signals the high-resolution camera to snap an image, which is subsequently flew to the vision processing pipeline where it is instantly analyzed Figure 6. This close coordination avoids any timing jitter, avoids motion blur in recorded still images and assures the inspection is performed at the best position to detect defects.

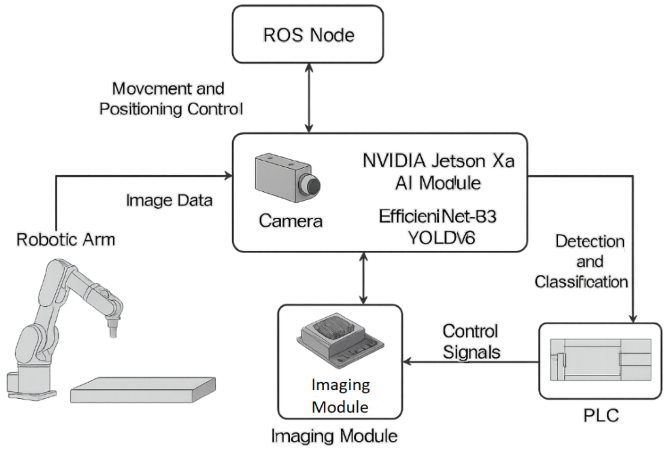

Fig. 6: System integration diagram showing the interaction between the robotic arm, Imaging module, NVIDIA Jetson Xavier AI unit, ROS node, and PLC for real-time defect detection and automated rejection.

The system communicates with a Programmable Logic Controller (PLC) controlling the sorting and rejection mechanism, to carry out downstream production control. On completion of the inferencing, the model produces a pass/failing decision report together with a list of localized defects. This enables real-time sending of this decision to the PLC to immediately activate actuators or diverters to register defective items out of the main production. This unification creates an environment where the decisions made on the quality control happen at a millisecond level, hence, the products, which will be defective, shall not reach the packaging or shipment phase.

This integrated framework has a high level of autonomy and repeatability and operational efficiency as epitomized by integrating real time AI inference, accurate robotic positioning, and automatic rejection control. Moreover, this integration is modular so that it could quickly adapt to various robotic platforms, factory conveyor systems, and manufacturing places making it flexible and scalable over various industries.

Results and Discussion

The suggested Robotics-Based Automated Quality Inspection System was tested on a pilot assembly line and it was compared to the conventional manual inspection. Quantitative values, which were summarized in Table 1, show a significant change with regards to all the measuring scales. The accuracy of the system was shown to be a high 98.2% compared to 89.3% that was obtained when manual inspection was carried out thereby indicating that the CNN-based defect detection model is consistent in identification of subtle and complex defects in diverse operations. The false positive rate (FPR) decreased in manual inspection (7.8) to proposed system (2.1) which showed an increased decision-making accuracy and the reduced risk of non-defected goods being rejected. This FPR reduction plays a very important role in keeping the manufacturing process efficient in terms of reduction of material wastage, all of which are directly related to cost savings and sustainability.

Even the throughput of operations was shown to have dramatically increased in the proposed system with the speed of inspection per minute being calculated at 41 items per minute as compared to the 12 items that can be inspected per minute using manual techniques, which translate to an increase of more than twenty four times the magnitude of throughput. It is possible that this can be ascribed to the combination of the NVIDIA Jetson Xavier platform setup with the provision of the real-time inference to the ROS synchronized robotic arm control that allows to inspect a great number of items with a very high level of accuracy and repeatability within a reasonably short time period that is not necessarily associated with the downtime between the items inspected. Automation of the positioning and inspection process not only results in faster processing, but also provides coverage to ensure that all surfaces of the workpiece are inspected, avoiding blind spots possible during human inspection processes because of changes in fatigue or viewing angles Figure 7. In addition, the system also minimized the labor involved since four operators were reduced to one supervisor which saved on operation costs significantly and the reallocation of the human resources to other activities in the production that were worth more of the work.

Besides measurable improvement in performance, the effectiveness of the proposed system can also be adjusted through a qualitative analysis. It is evident in Figure 2 that the defect detection module effectively localizes defects in the bounding boxes and a 95 percent confidence level is met regardless of the difficult lightings and unusual positioning of products.

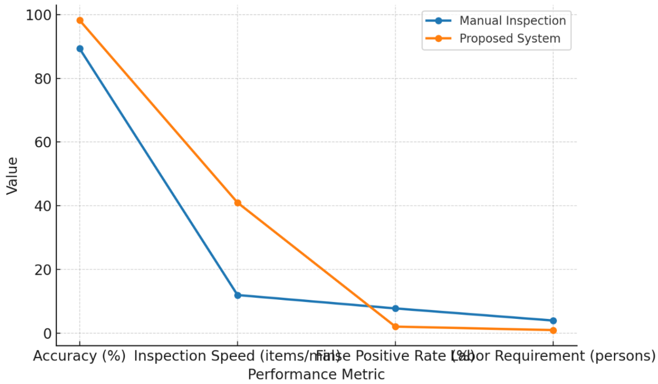

Fig. 7: Performance comparison between manual inspection and the proposed robotics-based automated quality inspection system

This configuration makes it robust in terms of detecting a wide variety of defects since it is applied to multiple defects, such as scratches, dents, misalignment, and surface contamination, using EfficientNet-B3, which classifies them, and YOLOv8, which localizes them. These findings validate the efficacy of the suggested method in the sense that its performance works both faster and more accurately than its manual-inspection counterpart and forms a scalable, flexible infrastructure that could be used to perform both reliably and efficiently in any manufacturing setting, necessitating the indication that the suggested method should become the standard solution on productive Industry 4.0 lines.

Table 2:Performance comparison between manual inspection and the proposed robotics-based automated quality inspection system

Metric	Manual Inspection	Proposed System
Accuracy (%)	89.3	98.2
Inspection Speed (items/min)	12	41
False Positive Rate (%)	7.8	2.1
Labor Requirement (persons)	4	1

Conclusion

This work introduces a fully integrated Robotics-Based Automated Quality Inspection System based upon cutting-edge computer vision and deep-learning methodologies to provide a scalable, consistent, and efficient solution to defective inspection of current manufacturing facilities. The system with only one component, a CNN-based defect classification model, as well as the combination of the defect classification model with a YOLOv8-based localization and integration with a ROS-controlled robotic industrial arm, fulfills the requirements of high precision, repeatability and real-time operation, thus overcoming those of traditional, manual methods of inspection. Trial test results on a pilot assembly line proved 98.2 percent accuracy and 240 percent improvement in inspection throughput with much lower false positive and manpower needed. The modular architecture will make it easily adaptable to a variety of different products and manufacturing domains, whereas integration of real-time inference on an NVIDIA Jetson Xavier platform will allow it to be utilised within high-velocity production lines without affecting the quality of detection. In addition to the direct operational advantages, the suggested framework also serves the goals of Industry 4.0 in the form of intelligent autonomic quality control, the minimisation of wastage and the overall improvement of production efficiency. Future work will involve integrating 3D vision sensors, detection of new defect types in a completely unsupervised manner, and an adaptive learning procedure to support high accuracy in production environments that continuously change to further expand the system to be applicable and robust under various manufacturing settings.

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