An advanced product inspection and sorting system using artificial intelligence

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Abstract. The manufacturing sector is experiencing a notable transformation due to the incorporation of Industry 4.0 and the emerging concepts of Industry 5.0. Artificial intelligence (AI) plays a significant role in driving this transformation, particularly in the domain of product inspection and sorting systems. Incorporating digital computer vision, high accuracy and resolution sensors, and bigdata-driven simulations into manufacturing processes, the vision of smart manufacturing becomes tangible. These technologies offer practical solutions for automating product inspection and sorting processes, providing non-destructive and cost-effective alternatives. This ongoing research aims to develop a real-time product inspection and sorting system utilising artificial intelligence, specifically focusing on convolutional neural networks (CNNs) and machine learning algorithms. The proposed approach adopts a dynamic methodology, leveraging the synergistic capabilities of CNNs and machine learning algorithms. To extract features from images, CNN is trained on datasets containing both none-defective and defective product samples. These features are then further refined and classified by machine learning algorithms. Through rigorous training on diverse datasets, the system developed a robust ability to distinguish between none-detective and defective products and achieving an accuracy close to 98.10%

Keywords: Smart Manufacturing, Quality Control, Artificial Intelligence, Convolutional Neural Networks, Machine Learning, Deep Learning

1 Introduction

Quality control is critical to manufacturing processes, ensuring products meet specified design specifications and standards requirements. In automotive, aerospace, and railway industries, detecting and sorting defects in manufactured components are essential to maintain product quality, reduce waste, and prevent costly recalls [1]. Ensuring the quality of products is paramount to maintaining competitiveness and customer satisfaction [2]. One critical aspect of quality control is inspecting key systematic components for defects, as even minor imperfections can lead to significant failures in the final product. Hex nuts, commonly

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used in various industrial applications, are no exception to this requirement for meticulous inspection. The traditional methods of product inspections often rely on manual labour, and this is time-consuming, prone to human error, and suffers from a lack of the precision necessary to detect subtle defects reliably [1]. This research programme proposes developing a real-time product inspection and sorting system using Artificial Intelligence (AI) and advanced image processing techniques to address these challenges. This automated and close to real-time system inspects and sorts hex nuts based on their surface finish using Artificial Intelligence (AI). The goal is to improve precision, competence, and safety while ensuring product quality and reliability and preventing costly recalls.

2 State of the art of technology

Manufacturing is a critical sector that contributes significantly to the world's economy, and accounting for 16% of the global GDP in 2019 and 2022 respectively [3]. Manufacturing processes are continually evolving to enhance product quality and yield with the development of new technologies. One such technology revolution that has emerged is smart manufacturing, which integrates AI, automation, Internet of Things (IoT), bigdata, Edge and Cloud Computing, and Information Technology (ICT) to optimise manufacturing processes, resulting in improved efficiency, quality, and agility [4]. The industrial product inspection and sorting sector is currently undergoing a significant evolution, mainly driven by advancements in AI. Its heavy reliance on AI technologies sets the advanced industrial product inspection and sorting system apart from its counterparts in the manufacturing industry. Unlike traditional inspection systems based on predetermined rules and thresholds, this advanced system leverages AI's capabilities to adapt and learn from bigdata [5].

AI-based inspection systems have revolutionised quality control processes across manufacturing sectors, offering automated, precise, and efficient defect detection capabilities. Notably, [6] demonstrated the efficacy of artificial intelligence in enhancing the quality of vibrating fruit harvesting mechanical operations, achieving an impressive recovery rate of up to 95%. One of the key technologies driving this progress is Convolutional Neural Networks (CNNs), which have demonstrated remarkable success in image-based defect detection tasks. CNNs automatically learn hierarchical representations of visual data, enabling them to identify complex patterns and features associated with defects in manufactured products [7].

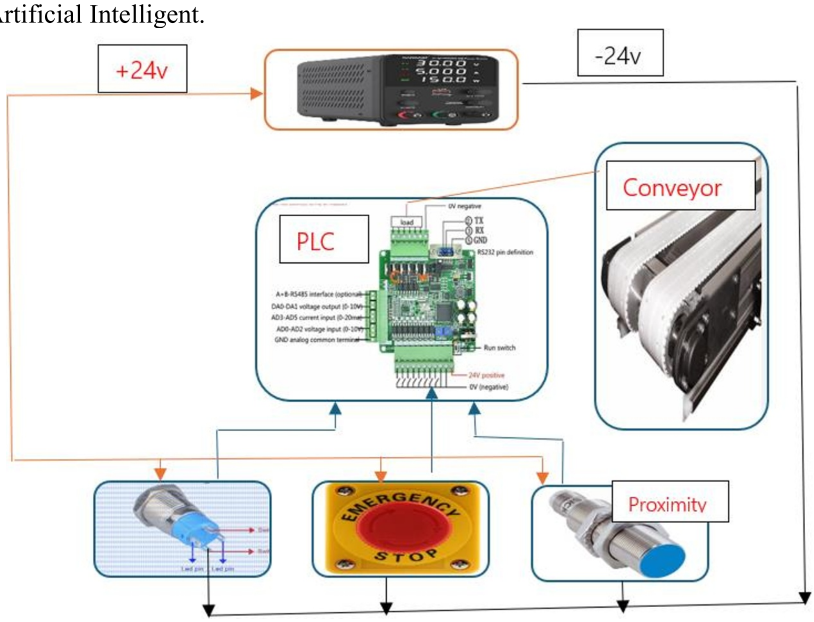
Several advanced methods have been adopted to inspect and sort products in a manufacturing line. In [8], an intelligent system using a Programmable Logic Controller (PLC) and vision system was implemented. This system employs a conveyor belt, image sensors, vision cameras, and a PLC for control. While effective, this approach relies on pre-programmed rules and human expertise to identify defects. These rules can be time-consuming to develop and may require manual tuning for different scenarios. A machine learning-based approach offers a powerful alternative. CNNs can be trained on vast image datasets, allowing them to identify features and patterns automatically. This reduces dependence on manually defined rules and streamlines the process of adapting to different product variations.

Furthermore, machine learning algorithms like Support Vector Machines (SVMs) and Random Forests have gained widespread adoption for defect classification [9]. By training on extensive datasets of labelled defect images, these algorithms develop robust models capable of accurately categorising defects in real-time production environments. Combining data from various sensors such as high-resolution cameras, laser scanners, and infrared sensors, AI-based inspection systems gain a comprehensive understanding of the manufacturing environment. This multi-modal approach allows for the identification of defects that may elude detection through visual inspection alone.

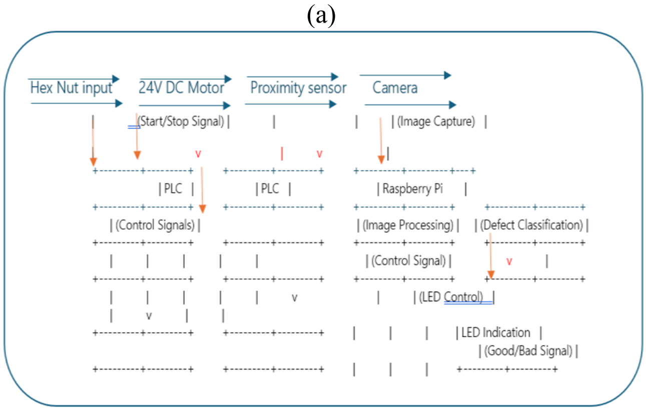
AI-based inspection systems, driven by technologies such as CNNs, machine learning algorithms, and sensor data fusion techniques, represent the state of the art in industrial product inspection and sorting. These systems offer unprecedented levels of accuracy, efficiency, and adaptability, making them indispensable tools for ensuring product quality in manufacturing industries.

3 Proposed inspection and sorting system architecture

Figure 1 illustrates the proposed inspection and sorting system architecture and design flow using Artificial Intelligent.



(a)



(b)

Fig. 1. Inspection and sorting system architecture and design workflow.

The system comprises several interconnected units, each playing a crucial role in the overall functionality and performance. These units include the conveyor belt control unit, sensor integration unit, image processing unit, defect classification unit, and sorting unit. The conveyor belt control unit oversees the movement of the product along the conveyor belt, ensuring synchronised operation with other system components. It interfaces with the PLC to start, stop, and control the speed of the conveyor belt. Additionally, it coordinates with the proximity sensor to halt the conveyor belt when a product reaches the inspection area. The sensor integration unit incorporates various sensors into the system architecture to gather real-time data about the product. This includes proximity sensors for detecting the presence of the product on the conveyor belt and cameras for capturing high-resolution images of the product.

The integration of these sensors enables precise monitoring and inspection of each product as it passes through the inspection zone. The image processing unit is responsible for analysing the captured images to identify and classify defects in the product. Leveraging deep learning techniques, such as CNNs, this unit processes the images to extract relevant features and detect anomalies indicative of defects. It employs pre-trained models and custom algorithms to achieve high accuracy in defect detection. The defect classification unit categorises the inspected product into "none-defective" or "defective" based on the results obtained from the image processing unit. It utilises the output from the CNNs model to make real-time decisions about the quality of each product. This classification is crucial for subsequent sorting operations. Finally, the sorting unit is responsible for segregating the product based on their classification, and controls mechanical actuators to divert the nuts into separate bins for further processing or disposal.

4 Model training and accuracy evaluation

The CNNs algorithm developed for the hex nut inspection system was designed and trained using MATLAB. To ensure the algorithm's effectiveness and accuracy several steps were followed for training and deployment. Data Preparation: A dataset consisting of an equal number of non-defective and defective hex nuts was obtained from Kaggle, a subsidiary of Google and an online community of data scientists and machine learning engineers. The dataset was split into 80% for training and 20% for testing, selected randomly. This partitioning ensured a robust training process and accurate model performance evaluation.

CNN Training: MATLAB's Deep Learning Toolbox was utilised to design and train the CNN. As seen in Figure 2, the first layer of the input layer, followed by the convolutional layers, ReLU activation layers, max-pooling layers, a fully connected layer, a softmax layer, and a classification output layer, the convolutional network is the convolutional layer as the input is a coloured image. It consists of a matrix of 3D pixels. Data augmentation was applied to the training set to improve the model's robustness, using techniques like random reflections and rotations to create variations of the training images.

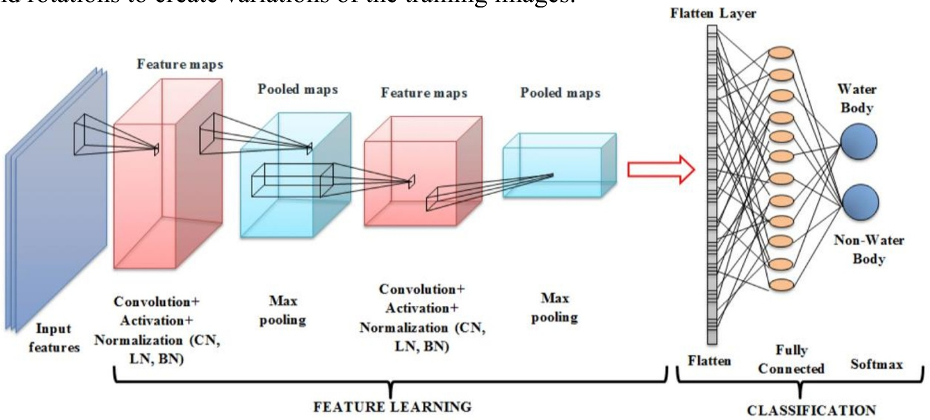


Fig. 2. Convolutional neural networks model training [10].

Training options were specified for the Adam optimiser, including initial learning rate, learning rate schedule, maximum epochs, mini-batch size, and validation data as seen in figure 3.

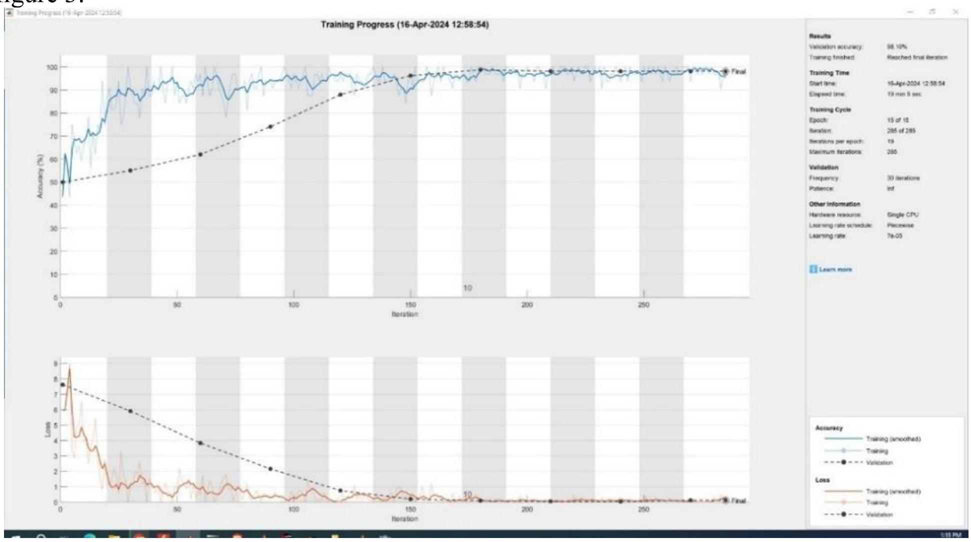


Fig. 3. Convolutional neural networks training progress showing accuracy and error.

These settings controlled the training process and helped optimise the model performance. The CNN model was then trained using the augmented training set. The accuracy of the trained model was calculated by comparing the predicted labels with the actual labels of equation 1 [11].

$$Accuracy = \frac{\text{sum(predictedLabels == testLabels)}}{\text{numel(testLabels)}} \tag{1}$$

The trained model's classification capability was evaluated using new images, as seen in Figure 4 below. These images were not used during training, ensuring an unbiased evaluation, these images were resized, classified, and displayed with their predicted labels.

Fig.4. Samples used for verification and validation of the developed inspection and sorting system using AI.

Conclusion

This paper presented a real-time hex nut defect inspection and sorting system using artificial intelligence. The system leverages computer vision techniques for image pre-processing and a CNNs for image training and classification to inspect hex nuts on a moving conveyor belt. The system provides sorting functionality, distinguishing between non-defective and defective products, and has achieved an accuracy close to 98.10%. This showcases the potential of AI to revolutionising manufacturing processes, as it can significantly enhance product quality, reduce waste, and optimise resource utilisation in various industrial settings.

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