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Automated Quality Inspection for Submersible Pump Impellers Using Deep Learning Techniques

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Abstract

Quality assurance has become vital for modern industrial systems, because even a single failure in delivering substandard products can drag down brand image and customer satisfaction as well as cause an economic loss. It is very difficult to measure quality in mass production with high precisionand manual inspec-tion work often involves such errors, discrimination errors and low efficiency. With the rapid development of intelligent manufacturing, computer-vision-based automated inspection has become an effective approach for reliable and large-scale quality assessment. Here, we examined acasting component dataset called submersible pump impellers to enable efficient pumping machine. The study concentrated on defect identification ofthe casting components. We used defect-free as well defective images to train deep learning models, taking advantage of OpenCV ViT (Vision Transformer) and YOLO-based architectures. The exper-imental results show that the Vision Transformer significantly outperforms all other modelswith impressive 99.9% accuracy. Because of this, it is an extremely effective model for automatically detecting cast defects. This study shows how AI-based estimate techniques can increase industrial productivity, lower human error, and improve quality control in large-scale manufacturing.

Keywords: Quality control,Intelligent manufacturing,Computer vision,Deep learning, Vision Transformer (ViT), YOLO, OpenCV, Automated inspection

1 Introduction

It is not possible to win trust loyalty of consumers without delivering high qual-ity products, which makes concepts like Six Sigma Total Quality Management vital elements for Manufacturing Industries.[1] Kagzi et. al have stated in their research work regarding importance of Predictive Maintenance is also crucial for Manufacturing industries which will help in assisting on-site engineers to repair machineries only when it is time.[2] In their research, it is stated that finding real time data from industries which exhibits various operations are quite difficult and also emphasized that condition monitoring data should be used to identify patterns and determine defects in manu-facturing line. [3] Despite this, due to a lack of knowledge, many industries continue to be reluctant to implement sophisticated quality control procedures, instead depending on antiquated manual inspection techniques that are ineffective and prone to mistakes. These restrictions can be successfully addressed by automated inspection systems that can learn intricate patterns, textures, colors, forms, and structural irregularities that are challenging for humans to recognize, thanks to the development of artificial intel-ligence and smart manufacturing. Hasan et al. emphasized the necessity for AI- and computer-vision-based methodologies in quality control by pointing out that manual inspection, static imaging, and traditional sampling procedures are no longer appro-priate in contemporary production contexts.[4] This technological change is supported by recent study. Raghunadh et al. used image-based comparison to show how well YOLOv8 detects flaws.[5] However, Loukas et al. used the same method to create an AI-driven vision system for online shop-floor assembly inspection.[6]. Sundaram et al. deployed a CNN model for casting defect detection [7] Amusan et al. documented the growing acceptance of intelligent manufacturing among industrial personnel[8], and The importance of data analytics and system-level communication in facilitating smart production was highlighted by Alexandros et al.[9] Further, Saeid et al. success-fully integrated ResNet-18 with an OPC-UA-based injection molding setup.[10] When taken as a whole, these studies show that automated AI-based defect detection sys-tems are becoming essential for attaining precise, dependable, and expandable quality control in contemporary manufacturing.

2 Proposed System

2.1 Submersible pump impeller Cast image dataset

The dataset utilized in this study consists of casting images of submersible pump impellers, sourced from Pilot Technocast, a small and medium-sized enterprise (SME) engaged in casting manufacturing in Gujarat, India. The dataset has been curated, updated, and publicly released by Gyan Shashwat on Kaggle for open research use.[11] It comprises 6,000 top-view images of submersible pump impellers, representative samples of both defective and acceptable impellers are illustrated in Figure 1

2.2 Deep Learning Models

This study employs three prominent computer vision techniques—OpenCV, YOLO, and Vision Transformer (ViT)—to detect defects in casting images.

(a) Acceptable images of pump impeller

(b) Defective images of pump impeller

Fig. 1: Representative samples of the casting dataset used for the study

2.2.1 OpenCV

OpenCV (Open Source Computer Vision Library) is a widely used open-source library designed for image processing and computer vision tasks. It provides efficient algo-rithms for operations such as edge detection, filtering, segmentation, and feature extraction. [12]

2.2.2 YOLO (You Only Look Once)

YOLO is a real-time object detection framework based on a single-stage deep neural network. Instead of generating region proposals, YOLO predicts bounding boxes and class probabilities directly in a single evaluation of the image, making it extremely fast and suitable for industrial applications. [13]

2.2.3 Vision Transformer (ViT)

The Vision Transformer applies transformer-based self-attention mechanisms, origi-nally developed for natural language processing, to computer vision tasks. An input image is divided into patches that are processed as token embeddings, enabling the model to capture long-range spatial dependencies more effectively than convolutional networks.[14]

2.3 Training Process

The dataset was divided into three subsets following the proportion of 70% for train-ing, 15% for validation, and 15% for testing, ensuring balanced distribution of defective and acceptable samples. For the Vision Transformer (ViT), a pretrained ViT model was used for feature extraction, leveraging transfer learning to improve learning effi-ciency and reduce training time. Also, conversion of all grayscale casting images into RGB (three-channel) format is done, enabling standardized feature representation The extracted feature representations were passed to a classification head for final predic-tion. 10 epochs completed in approximately 7-8 minutes with GPU support on Google Colab Platform.

Several performance indicators were calculated to evaluate how well the models detected casting flaws. Classification accuracy served as the main comparison param-eter. To assess robustness against false positives and false negatives, precision, recall, F1-score, Training Loss, and Validation Loss were also computed.

3 Experimental Results & Discussion

Three methods were used to assess the suggested system: OpenCV feature-based detec-tion, YOLOv8, and Vision Transformer (ViT). Using loss, accuracy, precision, recall, and F1-score over ten epochs, the chosen model's training performance was evaluated. Figure 2a shows how key performance parameters change over time. While accu-racy, precision, recall, and F1-score stayed near 1.0 during the training, the training and validation loss steadily decreased as the number of epochs increased. This behavior demonstrates the model's dependability by showing steady learning, quick
convergence, and little overfitting.

The accuracy curves of YOLOv8 and ViT across ten epochs are shown in Figure 2b to compare deep learning architectures. While ViT maintains near-perfect accuracy from the first epochs with little variance, YOLOv8 exhibits considerable changes dur-ing the early stages of training and subsequently stabilizes. A similar pattern can be seen in Figure 2c, where YOLOv8 shows a slow and progressive fall whereas ViT's training loss drastically drops to nearly zero by the third epoch. These findings con-firm that ViT learns more effectively and converges more quickly than YOLOv8. Our ViT-based model achieves a substantially lower initial loss (below 0.1), implying faster and more stable convergence throughout training, while Sundaram et al. used a CNN to obtain 99.86% model accuracy in 13 epochs with initial training and validation loss around 0.6.[7]

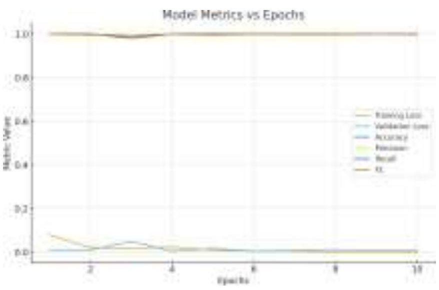
Figure 2d shows a comparison of the three methods. With an accuracy of 50.1%, OpenCV feature-based detection performs noticeably worse, demonstrating its limita-tions in intricate and varied real-world contexts. With an accuracy of 93.8%, YOLOv8 performs well, while ViT outperforms both CNN-based and traditional approaches with the maximum accuracy of 99.9%.

Overall, compared to YOLOv8 and conventional OpenCV-based techniques, the experimental findings demonstrate that ViT is the most efficient architecture for the suggested system, providing faster convergence, higher classification accuracy, and greater robustness.

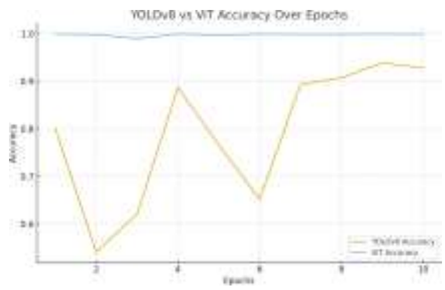
4 Conclusion

This work presents an automated quality management and inspection method for pump

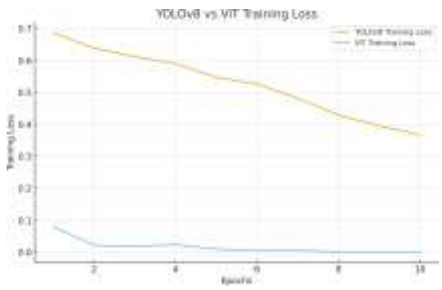
peller casting components using computer vision-based algorithms to solve the flaws of manual inspection carried out by workers in shop floors. Deep learn-ing techniques like ViT YOLO greatly outperform conventional OpenCV technique for accurate quality flaw detection. The Vision Transformer (ViT) proved to be the most successful model with 99.9% accuracy, and shown stability across epochs, while YOLOv8 produced outstanding results with 93.8% accuracy. However, YOLOv8 showed fluctuation in the early stages of training. Overall, the results show that ViT



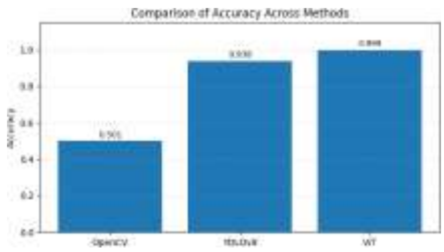
(a) ViT Model Metrics



(b) YoLov8 vs ViT Accuracy Comparison



(c) YoLov8 vs ViT Training Loss Comparison



(d) Various Model Accuracy Comparisons

Fig. 2: Performance Metrics of Proposed Model

offers a very reliable and effective industrial defect detection system that improves consistency and lowers human error in quality control procedures.

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