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Production Process Quality Inspection with Machine Learning Approach

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ABSTRACT

Technological developments in the industrial world encourage innovation in the inspection process, one of which is the application of artificial intelligence with machine learning. CV. XYZ is a palm oil machine component fabrication workshop that still applies manual quality inspection. Manual inspections are prone to errors, depend on human skills, and take a long time. This research aims to develop an automated inspection system using the YOLO (You Only Look Once) model which is a convolutional neural network (CNN) based algorithm for product defect detection. The manual inspection used is considered inconsistent, error-prone, and time-consuming. The use of machine learning is able to identify product defects such as geometry defect, porous defect, and surface defect. Evaluation of model performance using confusion matrix, loss graph, and precision recall curve. The results obtained show that the model has detection accuracy with a mAP50-95 value of 74.5%, mAP50 of 88.5%, and detection time of 0.0084 seconds per image.

Keyword: Quality Inspection, Machine Learning, Convolutional Neural Network (CNN)

ABSTRAK

Perkembangan teknologi pada dunia industri mendorong inovasi pada proses inspeksi, salah satunya dengan penerapan kecerdasan buatan dengan *machine learning*. CV. XYZ merupakan *workshop* fabrikasi komponen mesin kelapa sawit yang masih menerapkan inspeksi kualitas secara manual. Inspeksi manual rentan terhadap kesalahan, ketergantungan terhadap keterampilan manusia, dan memerlukan waktu lama. Penelitian ini memiliki tujuan dalam mengembangkan sistem inspeksi otomatis menggunakan model *YOLO (You Only Look Once)* yang merupakan algoritma berbasis *Convolutional Neural Network (CNN)* untuk deteksi kecacatan produk. Inspeksi manual yang digunakan dinilai tidak konsisten, rentan tehadap kesalahan, dan memakan waktu. Penggunaan *machine learning* mampu mengidentifikasi cacat produk seperti cacat geometri, cacat keropos, dan cacat permukaan. Evaluasi peforma model menggunakan *confusion matrix*, grafik *loss*, serta kurva *precision-recall*. Hasil yang dipeoleh bahwa model memiliki akurasi deteksi dengan nilai mAP50-95 sebesar 74,5%, mAP50 sebesar 88,5%, dan waktu deteksi sebesar 0,0084 detik pergambar.

Keyword: Inspeksi Kualitas, Machine Learning, Convolutional Neural Network (CNN)

1. Introduction

The rapid development of technology in the industrial world has driven significant transformations in innovation, efficiency, and productivity. The application of automation technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) makes the production process faster and more accurate. The use of technology can reduce operational costs and minimize errors caused by humans so that the industry is now facing global challenges and increasingly competitive market competition [1]. In modern industry, the implementation of artificial intelligence technology can diagnose and predict product quality more quickly and accurately. One of the branches of artificial intelligence that can do this is machine learning. In the manufacturing industry, one of the applications of machine learning is to improve quality through the results of analysis and predictions given based on experience gained [2].

In the competitive industrial world, innovation is needed in improving the quality provided to customers. Companies can pay special attention to customer satisfaction such as offering the best prices, responding to market demand, and innovating to improve the quality of products is one of the determinants in determining competitiveness in the industrial world [3]. Quality in the production process plays an important role in increasing customer satisfaction, reducing production costs, and increasing process efficiency. By maintaining good quality, companies can reduce the number of defective products that require rework so that there is no waste of costs. Products with high quality standards will meet customer expectations because they meet the desired specifications. So that this more stable and high-quality process not only saves costs but provides a competitive advantage for a company [4]. In improving product quality, companies are expected to establish an efficient quality assurance mechanism [5].

Product defects have a significant impact on the company, especially in terms of reputation and cost. Products with poor quality can cause the company to experience financial losses which require repairing defective products or replacing them with new materials [6]. Product defects are also a trigger for late delivery. Quality control and assurance are needed to prevent defects, reduce cost waste, and guarantee the quality of the products provided. Products that have good quality are basically products that are produced from a production process that is expected to meet predetermined specifications. Products that cannot meet predetermined specifications can cause cost losses to the company such as rework, excess energy usage, additional materials, additional labor costs, and additional machine working hours.

Geometric Defect Porous Defect Surface Defect

Figure 1. Type of defective products

In Figure 1, the types of product defects in the workshop that can be seen directly are classified as geometric defects, porous defects, and surface defects. Geometric defects are conditions where the physical shape of the product is not in accordance with predetermined specifications or part of the material is not exposed to the cutting in the machining process. Porous defects are small holes or pores in the material that cause empty cavities in the material structure. Surface defects occur in the surface layer which affects the appearance and functionality of the product.

Table 1. Product Inspection Time

Part Name	Inspection Time Per Part (Minutes)
Cone Hydrocyclone	10
Shaft Digester	8
Outer Gear Coupling	10
Casing Pump 30 Inch	15
Cover Wear Plate Ripple Mill	7
Housing Bearing Centrifuge	12
Adjusting Cone Press	8
Cone Guide Press	10
Flexible Coupling	7
Outlet Piece	10
Sprocket 6 Inch x 13T	12
Center Piece Coupling	7

CV. XYZ is a fabrication workshop engaged in the production of palm oil machine components such as threser machine parts, digester machine parts, screw press machine parts, vibrating machine parts, sludge centrifuge machine parts, decanter centrifuge machine parts, ripple mill machine parts, and many more. Manual inspection methods in the industry are increasingly considered inefficient due to their dependence on human expertise, susceptibility to error, and lengthly processing time [7], [8]. Based on Table 1, inspection times for various components ranging from from 7 to 12 minutes per part highlighting the significant time investment required by this manual process. These manual inspection limitations, such as reliance on quality control staff expertise, limited speed, and errors due to fatigue, directly impact costs and company reputation. Therefore, applying technology to the product inspection process is crucial to increase defect detection speed and reduce reliance on human roles for quality assurance.

The use of machine learning technology in the quality inspection process has an important role with a number of significant advantages over manual methods. The application of technology in the quality inspection process can increase precision, efficiency, and speed in defect detection as well as reduce quality inspection time and produce consistent results without dependence on quality control staff [9].The implementation of Artificial Intelligence (AI) machine learning can significantly improve the accuracy and efficiency of product quality inspection and reduce dependence on manual inspection. The advantage of using machine learning in the quality inspection process is the increased performance in the inspection process applied on the production floor in a user-friendly and seamless manner. The limitation of using machine learning algorithms is that the accuracy of the inspection process depends on the quality of the data used to train the model if the data is not representative, the inspection results can be inaccurate [10]. The application of this technology is expected to improve the company's ability to handle product defects and speed up inspection time which has a direct effect on the company's finances and reputation. Although previous studies have applied CNN models for quality inspection, limited research has specifically evaluated the application of YOLO for defect detection in palm oil machine components in small to medium-scale industries. Furthermore, comparative studies quantifying detection time and class-wise performance metrics remain scare.

Based on the problems that have been stated, further research is needed in providing solutions to product defect problems in companies by using artificial intelligence technology by training machine learning algorithm models to be representative so that the inspection results issued by machine learning are accurate.

2. Method

Exploratory research is research conducted to find causes or things that influence the occurrence of something [11]. Exploratory studies are conducted to gain a clear and detailed understanding of certain phenomena of concern and develop knowledge through theory building [12]. Exploratory research aims to discover and understand phenomena or problems that have not been thoroughly studied.

This research uses a Convolutional Neural Network (CNN) algorithm model specifically designed in object detection in various image processing tasks. Convolutional layers are an integral part of an artificial neural network that can make classification decisions by training it and then implementing it into a multi-layer network in order to evaluate visual images [13]. CNNs enable automatic classification based on appearance, replacing manual inspection that relies on human expertise [14]. The generalization ability of CNN can be trained on various defect images such as cracks, holes, and scratches and is able to recognize similar patterns in new data. Furthermore, CNN is able to achieve high accuracy in defect image classification with limited datasets and inconsistent labels [15] . Real-time detection capabilities can be implemented in systems such as Intellegent Visual Scanner or machine learning-based inspection tools with the incorporation of hardware such as cameras will provide solutions in quality inspection and quality control automatically [16]. The implementation of machine learning with the implementation of YOLO (You Only Look Once) which is a CNN-based algorithm model can reduce the need for error-prone and time-consuming manual inspections.

The datasets consists of 511 images in total, specifically designed for defect detection in palm oil machine components. This dataset was meticulously annotated with bounding boxes to define various defect types observed in the components. For model development and evaluation, the dataset was systematically divided into three sets namely training set, validation set, and test set [17]. A training set comprising 447 images for model training and development, a validation set with 43 images used for optimization during training to ensure generic pattern recognition and generalization, and a test set containing 21 images for evaluating the model's performance after the training process was completed. The images were primarily sourced from CV. XYZ's production line.

The model employed in this study is YOLOv8 which is released in January 2023, represents the latest evolution in the YOLO series of object detection algorithms [18]. It was implemented using the PyTorch framework via Ultralytics, specifically version 8.2.1.03 of the Ultralytics library. Ultralytics develops advanced, leading-edge YOLO models, leveraging extensive foundational research in computer vision and AI. These models are continuously updated to ensure high performance, flexibility, and user-friendliness, excelling in tasks such as object detection, tracking, instance segmentation, image classification, and pose estimation while maintaining speed and accuracy [19]. Key parameters used during the training process included a batch size of 16 and a total of 50 epochs. The learning rate was set to 0,01. To enhance the model generalization capabilities, various data augmentation techniques inherently applied by Ultralytics YOLOv8 were utilized, such as mosaic augmentation, random horizontal/vertical flips, and HSV transformations [20]. The input image size for training, validation, and test was set to 800 pixels. The training process utilized a NVIDIA 1080Ti GPU equipped with 16GB of RAM, resulting in an average duration of 0,224 hours for each run.

3. Result and Discussion

In the results evaluation stage, analyses are conducted to measure the performance and accuracy of the model that has been developed. This evaluation is presented through various forms of visualisation to facilitate interpretation of the model's performance in detecting and classifying objects. The visualisations used include confusion matrix to show the classification accuracy of each class, box loss graph during training and validation to illustrate the convergence of the model towards object detection, class loss graph that shows the classification performance during training and validation, and precision-recall graph to evaluate the balance between precision and sensitivity of the model towards each class. Each of these visualisations is used as a basis for discussion to comprehensively understand the strengths, weaknesses, and potential improvements of the model [21].

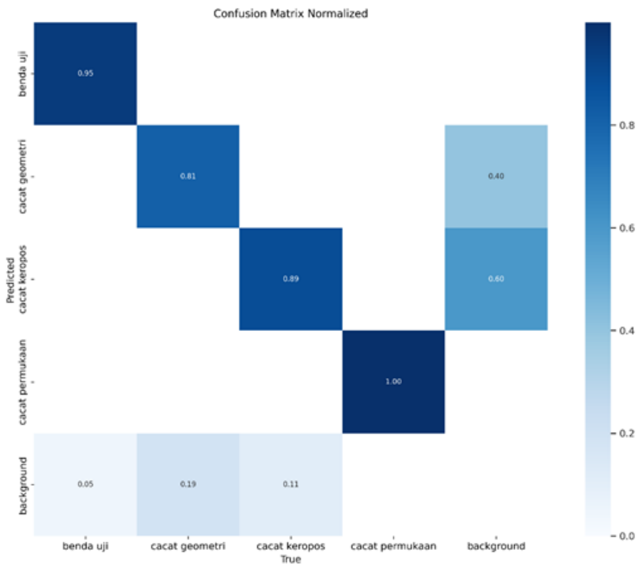

Figure 2. Confusion Matrix

The normalized confusion matrix is a representation of a matrix that has been normalized between a value of 0 and a value of 1. Each value shows the proportion of data classified into each class based on the number of samples in the actual class or ground truth. Analysis of model performance has a positive performance with excellent performance in the surface defect class which has a value of 1.00 or 100% correct while on the part of the object tested it has 95% accuracy. There is a slight error in the classification of geometry defects and porous defects due to the fact that the visual results are almost the same. The normalized confusion matrix provides an overview of model performance to identify the strengths and weaknesses of the model [22].

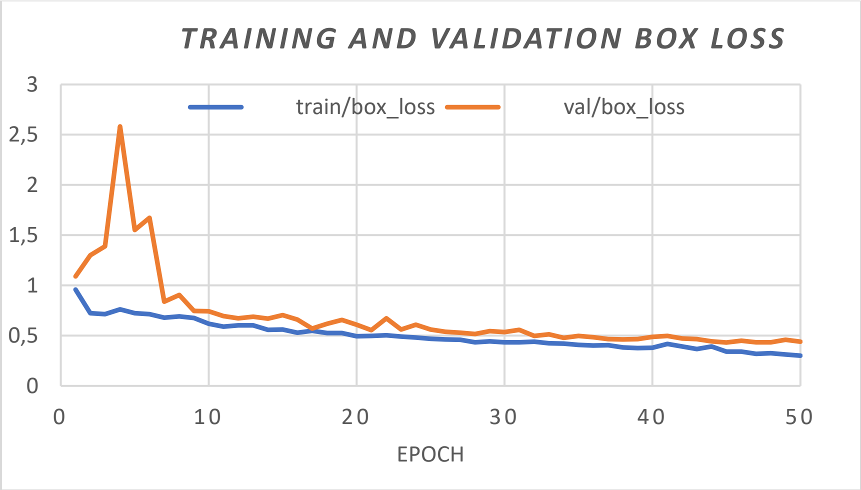

Figure 3. Graphic Training and Validation Box Loss

Based on the training and validation box loss graph at the beginning of the training epoch and validation box loss shows a significant decrease, this means that the model is learning quickly in minimizing the bounding box of training and validation data. The stability of the values of some training on both losses (training and validation) is stable which shows the same downward trend, indicating that the model does not experience underfitting and overfitting [23]. The difference in validation box loss values is slightly higher than the training box loss but the difference is small, which indicates good generalization ability in the validation data. At the end of training, both losses are close to low and stable values, indicating that the model has converged [24].

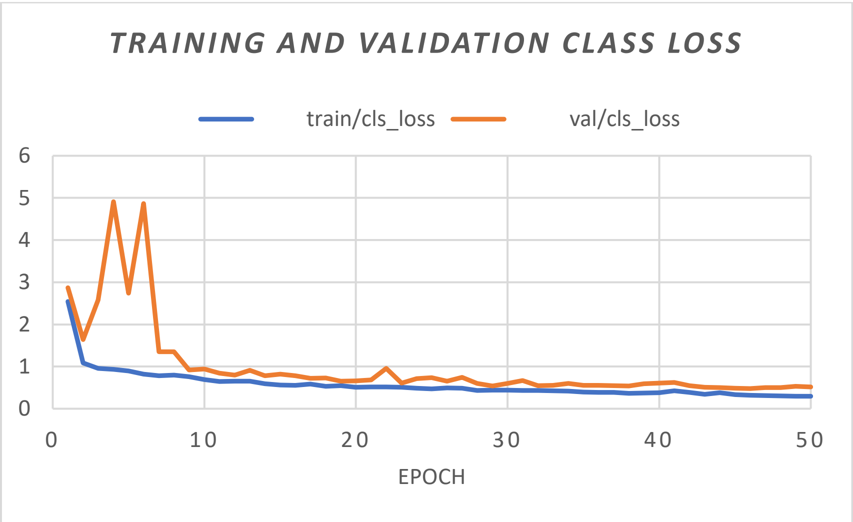

Figure 4. Graphic Training and Validation Box Loss

The result of the training and validation class loss graphs is a gradual and stable decrease in the training class loss value after a few epochs which shows the model learns well on the training data, while the validation class loss value also decreases at the beginning which has higher fluctuations than the training class loss although the validation class loss is stable [25]. The trend shows that the model has learned from the training data well and started to stabilize its performance on the validation data. The gap difference between training class loss and validation class loss is small after the 20th epoch which indicates that the model does not experience significant overfitting, if the gap between the two is large there could be an indication of overfitting. Overall, the model is good enough based on the graph in the figure above for the final assessment to check other evaluation metrics to ensure the model is capable of object detection and classification with high accuracy [24].

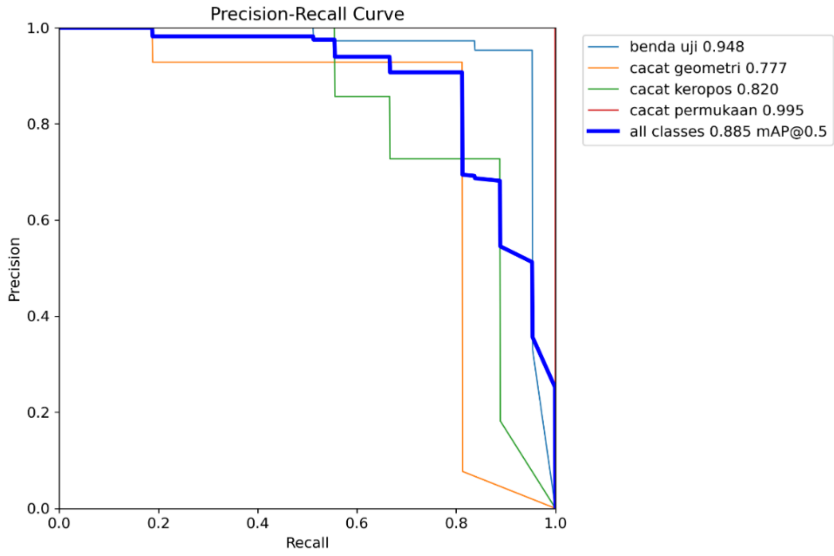

Figure 5. Graphic Precision-Recall

The results of the precision-recall graph provide information on the relationship between precision and coverage for each class in the trained model. The red surface defect curve performs well with high precision at all recall levels, but the geometry defect and porous defect curves are lower than the surface defect curve. Overall, the model performed well with a mAP 0.5 (Mean Average Precision) value of 0.885 with stable and consistent performance [26].

Table 2. Model Evaluation Results

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
All	43	72	0,868	0,941	0,885	0,745
Benda Uji	41	43	0,941	0,953	0,948	0,944
Geometric	12	16	0,925	0,812	0,777	0,538
Porous	8	9	0,721	0,889	0,82	0,58
Surface	4	4	0,885	1	0,995	0,952
Speed: 0.3ms preprocess, 6.7ms inference, 0.0ms loss, 1.4ms postprocess per image						

The performance of the model (mAP50: 88,5%, recall: 94,1%, precision: 86,8%) is evaluated in relation to previous/CNN-based visual inspection research, along with local industrial studies in similar contexts. The evaluation was conducted on 43 images from the validation dataset, containing a total of 72 annotated objects. Specifically, the model achieved a mean Average Precision at 50% IoU (mAP50) of 88,5% indicating quite good object detection capability. A more comprehensive metric, mAP50-95 (Mean Average Precision from 50% to 95% IoU at 5% interval), was 74.5%, signifying good overall model performance across varying detection thresholds. The model demonstrated strong recall, successfully detecting 94.1% of all coverage objects in the data, implying high success in identifying most instances of each defect class. Precision, which represents the proportion of correct predictions among all positive predictions, stood at 86.8%, confirming the model's accuracy in object detection.

While deep learning approaches, including CNNs, have demonstrated significant success in visual inspection across various manufacturing sectors. For example, studies have applied YOLO for fabric defect detection, solar cell surface defect detection, and steel surface defect detection. Furthermore, Fu et al. proposed a CNN model for the high-precision defect inspection of USB components [27]. A comprehensive review by Hussain details the evolution of YOLO variants, including YOLOv8, highlighting their real-time and high-classification performance in industrial defect detection [18]. Despite these broad applications and advancements in CNNs for various industrial contexts, limited research has specifically evaluated the application of YOLOv8 for defect detection in palm oil machine components, particularly concerning complex geometric, porous, and surface defects. Our tailored YOLOv8 approach demonstrates particular efficacy for identifying these specific defects in palm oil machine components, evidenced by its robust mAP50 of 88.5%

and strong per-class performance. This positions our model competitively within the broader field of industrial visual inspection, while critically addressing a gap in the existing literature.

Crucially, the automated inspection system exhibited remarkable speed, with a total detection time of 0.0084 seconds per image. This includes 0.0003 seconds for preprocessing, 0.0067 seconds for inference, and 0.0014 seconds for postprocessing. This represents a significant improvement compared to the manual inspection times at CV. XYZ, which typically range from 7 to 12 minutes per part. This quantitative comparison highlights the substantial efficiency gains and reduction in processing time offered by the proposed automated system over traditional human-dependent methods, especially in a local SME industrial context where such detailed performance metrics are often unmeasured.

The model exhibits several limitations, including inadequate performance in differentiating between geometric defects and porosity (as indicated by low mAP50-95 values for these classes: 53.8% for Geometry and 58.0% for Porous). This limitation is likely attributed to the subtle visual similarities between these two defect types and potentially the current dataset's size and balance for these specific categories. Furthermore, the model's susceptibility to variations in lighting and camera angles, along with a lack of comprehensive validation under real-world production conditions, poses challenges for full-scale deployment. Future enhancements may encompass the application of transfer learning utilizing larger, more diverse, and industry-specific datasets to improve differentiation between challenging defect types. The implementation of real-time deployment accompanied by live monitoring, and the integration of the model into automated production systems, are critical steps forward.

This study demonstrates a significant improvement in detection accuracy (mAP50 of 88.5% compared to manual inconsistency) and a substantial reduction in inspection time (0.0084 seconds per image versus 7-12 minutes manually) using our YOLO-based model, validating its practical potential for real-world quality control in the palm oil machine component fabrication industry. This efficiency gain translates into a considerably faster inspection process, moving from minutes to milliseconds per part. We recommend phased implementation beginning with high-value or high-volume components like Cone Hydrocyclone or Outer Gear Coupling combined with comprehensive operator training programs and technician certification to ensure seamless adoption and effective utilization within CV. XYZ. This immediate deployment for specific machinery parts can lead to an estimated detection speed-up factor of over 67000 in these initial phases.

Critical next steps should include comparative analysis with other state-of-the-art object detection architectures, such as Faster R-CNN, EfficientDet, or more recent transformer-based architectures like DETR, particularly focusing on their performance in differentiating between geometric and porous defects. Rigorous 6-month production-line trials under real-world conditions, encompassing multiple production shifts and varying environmental factors (e.g., dynamic lighting, dust, vibration), must be conducted to assess the model's robustness and long-term reliability. Furthermore, there is an urgent need for the development of standardized and expanded defect datasets through industry partnerships and cross-industry collaboration to achieve >50,000 annotated images covering diverse failure modes, which will significantly enhance model accuracy and generalizability for broader adoption.

4. Conclusion

Based on the research findings, it can be concluded that the machine learning approach proves effective in handling product defects through the design of a multi-camera detection system prototype. The machine learning model as a whole effectively detects product defects with a detection time of 0.0084 seconds per image, significantly minimizing inspection time compared to manual methods which require 7 to 12 minutes per part. The model achieved a mAP50 (Mean Average Precision at 50% threshold) of 88.5%, indicating good object detection capability, and an mAP50-95 of 74.5%. By implementing the YOLO (You Only Look Once) algorithm based on a Convolutional Neural Network (CNN), the system not only detects but also classifies defect types (such as geometric defects, porous defects, and surface defects), providing crucial information for further quality improvement and remediation. The application of this machine learning algorithm in the inspection process enables automated operations, thereby substantially reducing the risk of errors caused by human fatigue or lack of concentration inherent in manual inspection methods. This ensures the consistent quality of manufactured products adheres to established standards, while strengthening the company's competitiveness.

Although the existing model demonstrates encouraging outcomes, it encounters several limitations that need to be addressed. These include (1) inadequate efficacy in differentiating geometric flaws (mAP50-95: 53.8%) from porosity (mAP50-95: 58.0%), as indicated by their relatively low mAP50-95 scores; (2) dependence on a restricted and potentially unbalanced dataset; (3) vulnerability to variations in lighting conditions and camera angles; and (4) absence of comprehensive validation in genuine production settings. To address these constraints and enhance practical relevance, future advancements should concentrate on three primary domains: (1) employing transfer learning with more extensive and industry-specific datasets; (2) refining the model for real-time implementation with ongoing monitoring capabilities; and (3) investigating seamless integration with current automated production systems to facilitate closed-loop quality assurance.

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