TOOL WEAR SEGMENTATION USING YOLOv11 FOR ENHANCED MACHINING EFFICIENCY

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ABSTRACT

Tool wear monitoring is crucial to ensure machining accuracy and extend tool life in turning operations. This study presents a novel method using YOLOv11 for tool wear segmentation in turning processes. Unlike traditional wear detection methods that rely on manual inspection or indirect sensor-based techniques, our method leverages deep learning to accurately identify and segment wear zones from images captured during machining. The proposed model is trained on a tool wear image dataset and optimized for real-time performance. Experimental results demonstrate that YOLOv11 achieves high segmentation accuracy, effectively distinguishing wear zones during machining. The study enhances tool wear assessment, helping machining engineers and improving production efficiency.

Keywords: *Tool wear monitoring, YOLOv11, deep learning.*

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1. INTRODUCTION

Tool wear is an issue that occurs during the machining process, directly affecting product quality, tool life and overall production efficiency. During the turning process, tool wear occurs due to the continuous friction between the cutting tool and the workpiece, along with high temperatures generated in the cutting zone [1] . When the wear level exceeds the allowable limit, it can cause many serious problems such as poor surface finish, product dimensional errors, increased cutting force, unwanted vibration, and even tool damage [2]. These problems not only affect product quality but also reduce the overall efficiency of the production process. Using an excessively worn tool can lead to sudden failures, interrupting the machining process [3]. This not only increases operating costs due to tool replacement and machine repair, but also affects production progress and overall productivity. Conversely, replacing a tool too early before it reaches its maximum wear limit will also increase tool costs unnecessarily. Therefore, accurate and timely monitoring of tool wear is a key factor in optimizing the machining process, ensuring product accuracy and extending tool life [4].

Traditional methods for monitoring tool wear often rely on manual inspection or indirect sensor systems such as measuring cutting forces, vibrations or acoustic signals [5]. However, these methods have some limitations such as the accuracy depends on the experience of the operator. In particular, the method requires additional hardware, or is susceptible to interference from the machining environment. With the rapid development of artificial intelligence and computer vision, image processing and deep learning-based methods are emerging as a potential approach to improve the accuracy and automation of tool wear monitoring [6]. In recent years, advances in computer vision [7] and deep learning [8] have paved the way for automated, data-driven solutions for tool wear assessment. Machine vision and deep learning are widely used in robotics, in manufacturing [9], medical and transportation workshops [10].

This study presents an improved method that leverages YOLOv11 [11] for tool wear segmentation in turning processes. YOLOv11 [11], an advanced object detection and segmentation model, is used to accurately identify and segment wear zones from images. The proposed method eliminates the need for additional sensors and manual intervention, providing a more efficient and scalable solution for real-time tool wear assessment. The study is a first step to develop further problems related to the assessment and automatic detection of tool wear in direct machining processes. Real-time tool wear segmentation using YOLOv11, provides continuous monitoring and maximum support for machinists. The study is the first step for optimization problems for tool classification or management problems in the workshop.

2. MATERIALS AND METHODS

2.1. YOLOv11

YOLOv11 is designed with three main components: Backbone, Neck and Head as shown in Fig. 1. Each part plays an important role in extracting, merging and predicting information from the input image.

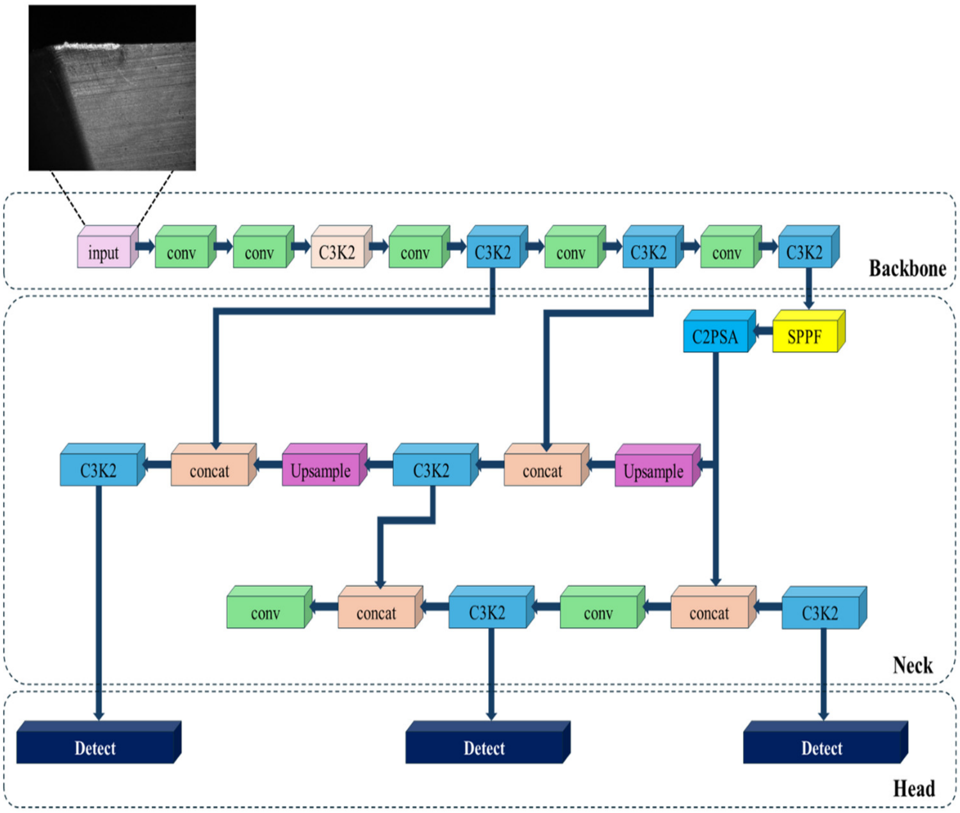

Fig. 1. The architecture of YOLOv11 [11]

Backbone - Image Feature Extraction: YOLOv11 uses CSPDarknet, a pre-trained convolutional neural network, to efficiently extract image features. Utilizing the weights from the pre-trained model not only saves computational resources but also speeds up training on new tasks. In addition, using these weights allows the model to learn universal features, giving it better generalization ability. When applied to new problems, simply re-adjusting the existing weights, the model can adapt faster to the input data, while improving processing performance. Moreover, this approach also helps to minimize overfitting when working with small-scale datasets.

Neck - Feature fusion from multiple scales: This component plays the role of combining information from features at different scales, helping the model recognize objects of various sizes. YOLOv11 improves the PANet architecture to enhance the ability to combine features between layers. Thanks to the horizontal connection mechanism, information is transferred effectively between feature levels, allowing higher layers to take advantage of the details of lower layers. This improves the ability to recognize and accurately locate objects, especially in scenes with large changes in size and shape.

Head - Category and Bounding Box Prediction: This is the part responsible for determining the object category and generating bounding boxes. YOLOv11 uses a multi-branch architecture in the output to improve the ability to recognize objects of different sizes. In addition, the model is equipped with two more DWConv convolutional layers with depth-separable capabilities, which reduces the number of parameters and saves computational resources without sacrificing prediction performance. With this improved architecture, YOLOv11 not only improves recognition and segmentation accuracy but also optimizes computational efficiency, making it a suitable choice for real-time applications.

2.2. Dataset Preparation

In this study, we used a publicly available dataset of tool wear during the turning process. To prepare the data for the model, we used the Roboflow platform to accurately and consistently label the data. In addition to labeling, Roboflow also supports data augmentation techniques, which increase the diversity of the input data, thereby improving the generalization ability of the model. The dataset is also removed from noisy or unclear data samples to avoid affecting the training process. Finally, the data is normalized to the same size and format to optimize the performance of the YOLOv11 model.

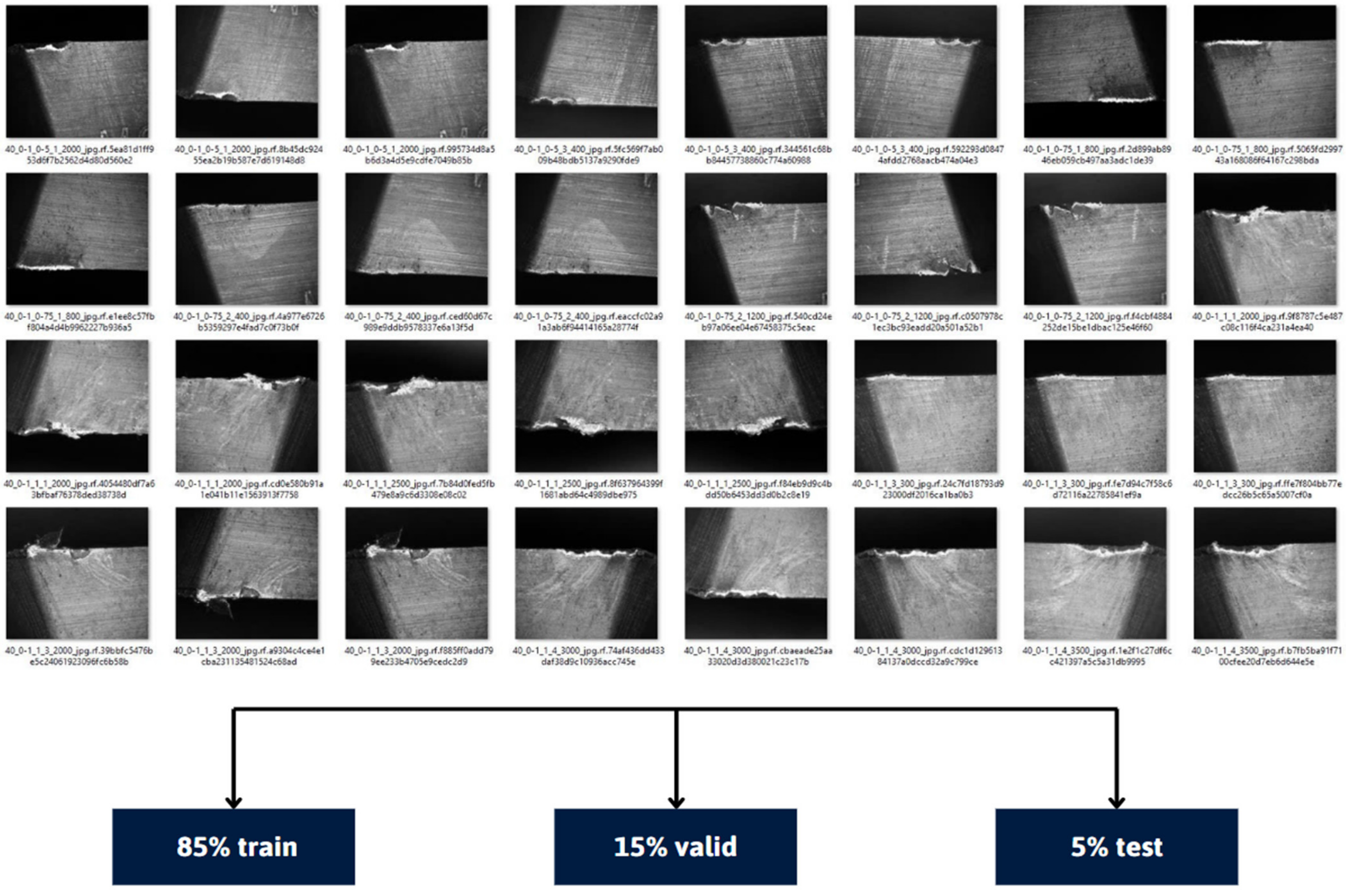

Fig. 2. Dataset after labeling and increasing diversity

The processed dataset is divided into three separate sets: 80% for training, 15% for validation, and 5% for testing. This division ensures that the model has enough data to learn, and also helps to objectively evaluate its performance before deploying it in practice. Fig. 2 shows the dataset after labeling and increasing diversity.

In this study, we used the YOLOv11 compact version (YOLO11n) model to perform the tool wear segmentation task. The model was trained and evaluated in a Python 3.9.16 environment, with the PyTorch library as the main platform for deploying and optimizing the deep learning model. The hardware configuration includes an Intel i7-11700 @2.50GHz processor, 32GB RAM, and a GeForce GTX 1660 SUPER 6GB graphics card, ensuring good computational performance during training and inference. Windows 10 Pro operating system is used to ensure stability and compatibility with supporting tools. YOLO11n has an input size of 640x640 pixels, achieving a mAP accuracy of 39.5. The processing speed on CPU (ONNX) is 56.1 ± 0.8ms, while on GPU T4 (TensorRT10) it only takes 1.5 ± 0.0ms. The model has 2.6 million parameters (M) and requires 6.5 billion floating point operations (FLOPs), which balances accuracy and processing speed.

3. RESULTS AND DISCUSSION

After training, YOLOv11 achieved good performance on the tool wear dataset, with a Precision of 88.3%, indicating that the model is capable of correctly predicting the majority of tool wear cases out of the total number of positive predictions. At the same time, the model achieved a Recall of 91.5%, demonstrating its ability to detect most of the actual tool wear cases. In addition, the mean accuracy value mAP@0.5 reached 92.8%, reflecting the high overall performance of the model in identifying and segmenting wear traces. These results show that YOLOv11 is an effective and reliable method for tool wear monitoring, providing effective support for maintenance and quality control applications in the mechanical processing process.

Fig. 3 shows the test results of the YOLOv11 model when detecting and segmenting wear marks on a lathe blade. Each pair of images includes the original image (left) and the model's prediction result (right), in which the wear mark area is delimited by a bounding box and a blue segmentation mask. The results show that the model is capable of accurately identifying wear marks on the tool surface with high confidence, ranging from 0.77 to 0.85. The wear mark areas are clearly identified, even when there are differences in the degree of wear. In particular, for samples with clearer wear marks, the model achieves the highest confidence (0.85), showing good adaptability to many different surface conditions. In addition, the model is capable of accurately identifying the contour of the wear mark, providing more detailed information than traditional detection methods. This shows the strong application potential of the system in real-time monitoring of tool quality, supporting the optimization of the production process.

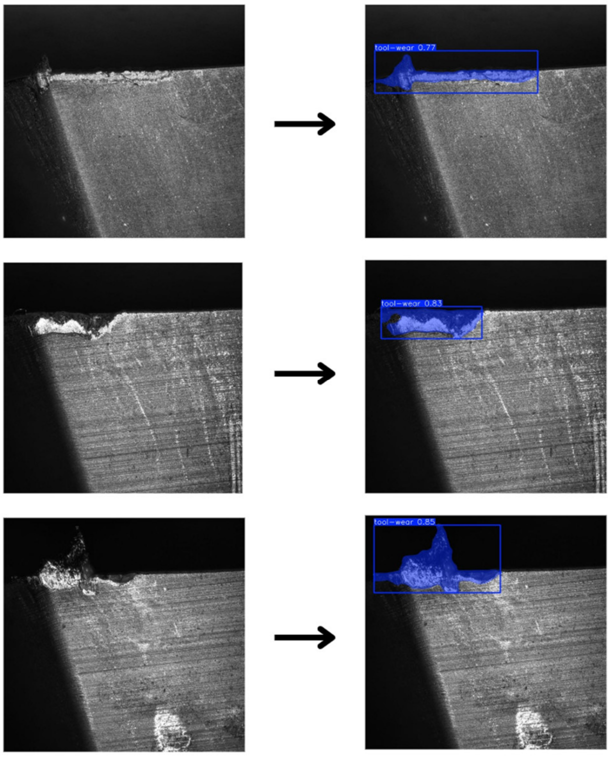

Fig. 3. Yolov11 model testing for wear detection and segmentation

4. CONCLUSION

This study proposes a method using YOLOv11 to segment lathe tool wear in real time, which helps to monitor tool condition more accurately than traditional methods. The model achieves high accuracy, ensuring continuous monitoring without affecting the machining process. The experimental results are the first step to show the potential application of the method in tool inventory management and cutting tool classification, contributing to production optimization. In the future, the study will expand the training dataset and integrate a tool life prediction system to improve monitoring performance.

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