Hybrid Approach for Precision Segmentation in Tool Wear Analysis

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Abstract

Effective segmentation of tool images is essential for automating manufacturing tasks such as tool wear monitoring, inspections, and robotic handling. Conventional image processing methods often struggle with intricate tool geometries and varying conditions. To address these issues, a new hybrid method, KU-net, combines deep learning with unsupervised clustering to achieve reliable and accurate tool segmentation. The process starts by enhancing raw tool images taken under various machining conditions using preprocessing techniques like Canny edge detection and Principal Component Analysis to reduce noise. Next, K-means clustering is applied to group visually similar images, enhancing the segmentation process. A modified U-Net architecture improved with attention mechanisms and stacked dilated convolutions, is trained on this clustered dataset. This methodology results in remarkable training and testing accuracies of 0.988 and 0.9838, respectively. Additionally, a precision of 0.8229, a Recall of 0.9071, and an F1 score of 0.8629 are noted, demonstrating the efficacy of KU-net and its relevance for advanced manufacturing in practical scenarios. Experimental results from a demanding dataset of tool images highlight KU-net's outstanding performance compared to traditional segmentation approaches, underscoring its potential for real-world applications in Manufacturing Industry 5.0.

Keywords: K-means Clustering, Image segmentation, Principal Component Analysis, Tool wear, U-net.

Introduction

Manufacturing has become increasingly vital in today's global economy, fostering innovation, boosting productivity, and contributing to economic growth. Machining, a key process in manufacturing, plays an essential role in producing a diverse array of products, ranging from consumer goods to sophisticated industrial equipment. Precise and efficient segmentation of tool images is crucial for various manufacturing and automation applications, including tool wear monitoring, automated inspection, and robotic manipulation. Nevertheless, current segmentation techniques often depend on conventional image processing methods, which can be labor-intensive and face challenges with intricate tool geometries and fluctuating environmental conditions.

In machining processes, the deterioration of the cutting tool leads to ongoing alterations in essential process variables within the cutting zone, such as forces and temperatures that affect both the tool and the workpiece. These changing conditions influence the rate of tool wear, cause modifications to the surface of the workpiece, and ultimately affect the geometric precision of the finished part. The wear rate of the tool is affected by process parameters such as cutting speed and uncut chip thickness, as well as the characteristics of the workpiece and the materials used for the tool. For difficult-to-machine materials, tool wear becomes a crucial aspect that impacts both the costs associated with the tool and the quality of the workpiece produced, making it vital to keep track of wear during the machining process (Ezugwu, Wang and Machado, 1999) (Wang and Liu, 2018). Methods for measuring tool wear are typically classified into two primary types: direct and indirect (Jeon and Kim, 1988). Indirect techniques, which include the use of dynamometers, accelerometers, acoustic emissions, and current sensors, have become widely used for ongoing condition monitoring (Abellan-Nebot and Romero Subirón, 2010).

In recent years, Deep Learning (DL) has been utilized for indirect condition monitoring during cutting processes by converting time-series data into images and analyzing them with Convolutional Neural Networks (CNNs) (Gouarir et al., 2018) (Martínez-Arellano, Terrazas and Ratchev, 2019). However, these indirect approaches are often designed for specific experimental configurations, particular machine tools, and certain processes, which restricts their ability to generalize. A comprehensive solution for monitoring tool conditions has not yet been established. Direct measurement of wear on cutting tool edges, usually conducted with optical sensors, typically yields greater accuracy than indirect techniques (Jeon and Kim, 1988). Nevertheless, uncertainties can still occur due to the measurement process and the subjective interpretation of image pixel data by human operators, who evaluate relevant wear patterns and take measurements, such as the width of flank wear.

Feature detectors used in image processing, including Sobel, Canny, and active contour methods, are widely referenced in the literature for identifying wear on cutting tool edges (Canny, 1986)(Kanopoulos, Vasanthavada and Baker, 1988)(Moldovan et al., 2017). Another strategy involves employing machine learning techniques, either on their own or alongside feature detectors, to improve the accuracy of wear detection (D'Addona and Teti, 2013)(Xiong, Dong and Wen, 2010). Unsupervised clustering serves as a fundamental method in machine learning, designed to reveal hidden patterns in unlabeled datasets by grouping data points into clusters (Sinaga and Yang, 2020). Traditional Computer Vision (CV) algorithms are recognized for their clarity, energy efficiency, and optimization for particular tasks (Gavina et al., 2024).

Conversely, Deep Learning (DL) methods provide enhanced flexibility and adaptability under various operational conditions, assuming that the training data sufficiently reflects the necessary variability (O'Mahony et al., 2020). When adequately trained, deep learning models for image processing tend to generalize well and have consistently surpassed conventional techniques in image processing tasks like ImageNet since 2012 (Krizhevsky, Sutskever and Hinton, 2017). Techniques for data augmentation are essential for broadening datasets by adding artificial variations, such as alterations in orientation, lighting, and contrast, which improve the model's resilience to changes in the environment of data acquisition. In the context of tool wear detection, the focus is more on recognizing textures instead of identifying objects, as the aim is to detect wear patterns on surfaces rather than recognizable shapes. The initial application of a deep learning method for classifying tool wear with a VGG-16 architecture achieved a precision rate of 96% in distinguishing four types of wear and demonstrated a mean absolute percentage error in wear measurement of under 5% using conventional image processing techniques (Simonyan, 2014) (Wu et al., 2019).

The present trend is to apply Principal Component Analysis for dimensionality reduction, which simplifies high-dimensional datasets and facilitates K-means clustering in organizing data into separate clusters based on their characteristics. For more intricate segmentation challenges, such as those found in medical or industrial image analysis, U-Net can be utilized for pixel-level segmentation, efficiently classifying various areas within images. Combined, these methods create an effective workflow that addresses both the operational efficiency of clustering and the accuracy of image segmentation. PCA is widely employed across multiple disciplines, including finance, biology, and chemistry, to streamline complex data sets while preserving critical information (Ferreira et al., 2023). Additionally, it aids in compressing images of surface defects in hot-rolled steel strips, significantly minimizing storage needs without compromising image quality (Boudiaf et al., 2019). (Khrissi et al., 2020) describes K-means clustering, enhanced by the integration of genetic algorithms and Sobel edge detection, which improves segmentation precision for complicated and noisy images (Hemalatha, Ranjitha, and Suresh, 2015). The genetic algorithm refines centroids, while Sobel edge detection clarifies boundaries, making it particularly suited for ambiguous or overlapping areas. Though it is not exclusively aimed at manufacturing, it can be relevant for quality control and defect identification. The computational demands of these techniques might restrict their application in real-time industrial settings. (Top, Torun, and Kaya, 2020) reviews the effectiveness of standard K-means clustering for image segmentation, emphasizing its straightforwardness and computational efficiency. K-means effectively segments clearly defined, uniform datasets by reducing variance within clusters. However, its effectiveness diminishes in the face of complex or noisy images, which limits its applicability in manufacturing where subtle defects need to be identified. While it indicates possible uses in manufacturing, it does not suggest specific improvements for these applications. (Pratama, Khairil, and Jumadi, 2022) builds upon K-means clustering to enhance segmentation accuracy, particularly focusing on manufacturing tasks like defect identification and process supervision. The improved algorithm pinpoints critical areas in product images, yielding better segmentation for industrial applications. Although it raises accuracy, the approach may still encounter difficulties with highly noisy or intricate images. Nevertheless, it presents a useful strategy for industries requiring high-precision segmentation in quality assurance. (Tongbram, Shimray, and Singh, 2021) introduces a modified K-means algorithm aimed at boosting segmentation accuracy for manufacturing-related activities such as defect detection and quality assessment. These modifications ensure the accurate separation of product images, concentrating on essential elements like defects and surface irregularities. While highly pertinent for industrial situations, its specific approach may limit its use in more complex image processing tasks beyond manufacturing. This method provides substantial advantages for upholding high manufacturing standards. (Pratama, Khairil, and Jumadi, 2022) analyzes the standard K-means technique for pixel-level segmentation, which is effective for simple, well-defined images. It can be implemented in manufacturing for basic functions like object recognition and preliminary quality inspections. However, it faces challenges with noisy or complex datasets, which restrict its application in more demanding industrial scenarios. Despite this, it lays a foundational framework for K-means clustering that can be further developed in advanced research. U-Net segmentation has become a crucial technique in manufacturing, especially for quality control and defect identification in various components. It reduces subjective assessments by automating the quality evaluation process, thereby enhancing consistency and efficiency (Yin and Lien, 2023). Incorporating attention mechanisms and focal loss functions has demonstrated improved performance in segmenting intricate structures like hollow turbine blades, achieving greater accuracy compared to traditional techniques (Zheng et al., 2022). Utilizing attention mechanisms and pooling strategies has further refined feature extraction and emphasized contextual information (Guo et al., 2022). In summary, PCA, K-means, and U-Net together establish a solid framework that strikes a balance between computational efficiency and segmentation accuracy. While alternative methods exist, these techniques frequently produce superior outcomes in scenarios requiring both clustering and detailed segmentation.

The rise of Industry 4.0 is fueled by the growing need for high-quality products at competitive manufacturing costs. As hardware, computational capabilities, and computer vision techniques advance, automated tool condition monitoring has become essential. Defective or worn tools can greatly affect the quality of the workpiece and the efficiency of machining. Creating effective computer vision systems is crucial for ensuring optimal tool usage while maintaining product quality. This research focuses on developing deep learning models to predict tool lifespan. The suggested approach utilizes a direct method to capture and examine images of the wear zone, facilitating automated monitoring of tool wear and removing the necessity for labor-intensive and time-consuming manual procedures (Aralikatti et al., 2020).

The literature review indicated that there is limited research on the creation of prediction methods for turning operations using machine vision technologies. Most previous studies have concentrated on indirect forecasting approaches for tool life, such as examining temperature, acoustic emissions, vibrations, and forces. There has been minimal investigation into utilizing advanced techniques like PCA for dimensionality reduction and KU-Net, which is an innovative blend of K-means clustering and U-Net, for accurate image segmentation and tool wear prediction. To address these shortcomings, the proposed research presents an integrated framework that employs PCA and KU-Net to establish a reliable machine vision-based tool wear prediction model for turning operations. The main contributions of this paper encompass:

1. Create a robust and accurate image segmentation method for tool identification, referred to as KU-Net, by merging deep learning techniques with unsupervised clustering approaches.
2. Improve the performance of tool segmentation by leveraging KU-Net, which combines preprocessing methods, K-means clustering, and a refined U-Net architecture that includes attention mechanisms and stacked dilated convolutions.

Materials and Methods

Experimental design and methodology

The material used for the experiments is AISI 4140 steel, with the workpieces being cylindrical and measuring 32 mm in diameter and 130 mm in length. The cutting tool used in this study is an uncoated carbide insert identified as CNMG120404 WS10PT from Widia. A tool holder with the ISO designation PCLNR2525M12 is utilized in the experimental configuration.

Software and libraries are essential for image processing, offering specialized tools that simplify intricate tasks and enhance accessibility, efficiency, and accuracy. The software for image labeling, augmentation, mathematics, and plotting is listed in Table 1. By leveraging these tools, workflows are accelerated, reproducibility is improved, and flexibility is heightened across various applications, ranging from medical imaging to autonomous driving.

Machine Vision algorithms

Tool wear is expressed as an area measured in pixels, utilizing independent variables like speed, feed rate, depth of cut, and wear area as inputs for predictive models. Measuring flank wear is more difficult than evaluating the wear area through computer vision techniques due to the noise present in images. As a result, to improve the accuracy of prediction algorithms, wear is represented by pixel count instead of flank wear length. After capturing an image of the worn tool, the images are categorized into three classes: Class 0 (No Wear), Class 1 (Mild Wear), and Class 2 (High Wear), as illustrated in Figure 1, and image processing techniques are used to analyze clusters and segmented images.

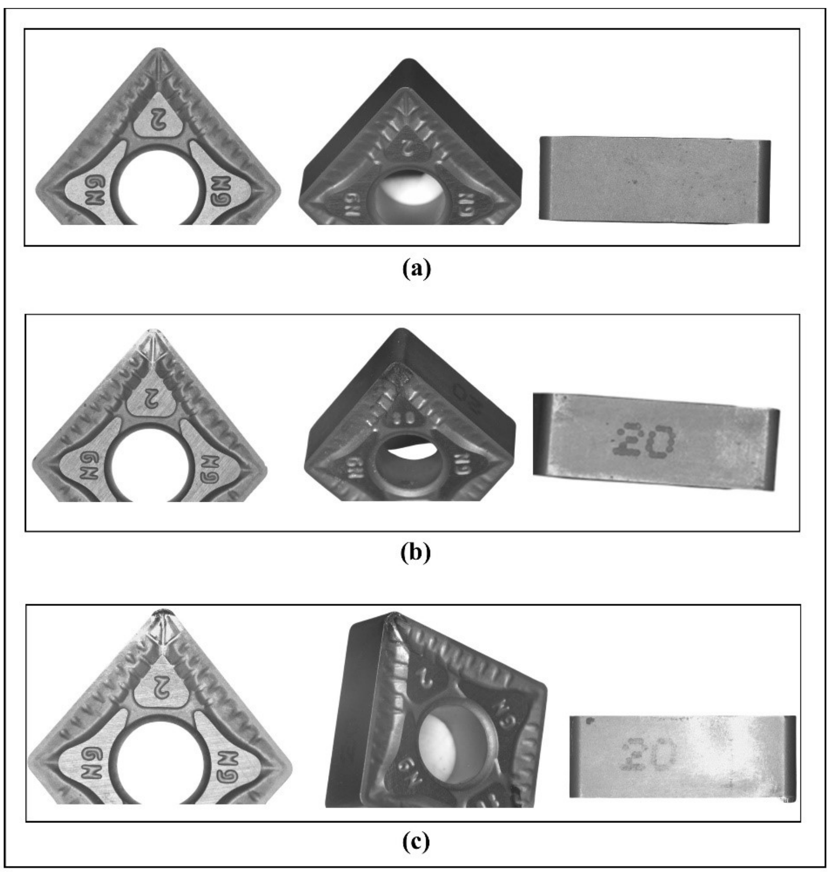


Figure 1. Three classes of images (a) Class 0(No Wear), (b) Class 1(Mild Wear), (c) Class 2(High Wear).

Preprocessing of images

Processing images is an essential phase in computer vision and deep learning workflows. This phase involves converting raw image data into a suitable format for model training and inference. Adjusting the size of images and masks to a designated dimension (256x256 pixels in this instance) guarantees that all input images are uniform in size, which is necessary for inputting them into a neural network.

Filtering and edge detection techniques

Prior to utilizing the KU-Net segmentation model, it is crucial to perform image preprocessing steps that include Gaussian filtering and edge detection, which are important for enhancing the quality of the input data and improving the identification of significant features. First, Gaussian filtering is employed to minimize noise and smooth the image, guaranteeing that high-frequency noise does not disrupt edge detection. This is achieved by convolving the image with a Gaussian kernel, which is defined as

$$\boldsymbol{G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)} \tag{1}$$

Where (x,y) are the coordinates in 2D space, parameter σ determines the level of smoothing. The Gaussian filter is implemented by computing a weighted sum of adjacent pixels, where neighboring pixels are assigned greater weights, following the formula.

$$\boldsymbol{I_{filtered}(x,y) = \sum_{i=-k'}^{k} \sum_{j=-k'}^{k} I(x+i,y+i)G(i,j)} \tag{2}$$

where k determines the size of the filter window. This minimizes extraneous noise while retaining important image features, which are vital for accurately detecting edges. After smoothing the image, Canny edge detection is applied to locate areas of quick intensity variation, which are indicative of object edges. The Sobel operators assess the gradient in both horizontal and vertical orientations, with the gradient magnitude calculated by

$$\boldsymbol{G = \sqrt{\left(G_x^2 + G_y^2\right)}} \tag{3}$$

and the direction by

$$\boldsymbol{\theta = arctan\left(\frac{G_x}{G_y}\right)} \tag{4}$$

Non-maximum suppression narrows the edges, while hysteresis thresholding ensures that weaker edges are considered only if they are connected to stronger ones. These initial steps, including Gaussian filtering and edge detection, are followed by the KU-Net segmentation model, which utilizes the improved input images to effectively segment various classes within the image. The edges identified during preprocessing provide essential boundaries and structural details that KU-Net can use to better delineate the areas of interest, particularly in scenarios where precise segmentation is necessary. By integrating edge information from the preprocessed images, KU-Net can enhance its performance, decrease errors induced by noise, and generate more accurate segmentation maps. The combination of noise reduction through Gaussian smoothing and the detection of edges using Canny edge detection renders the input data more appropriate for the subsequent KU-Net model, thus improving both the accuracy and reliability of the segmentation process.

Dimensionality Reduction

Principal component analysis (Reddy et al., 2020) is utilized on the image dataset to decrease its dimensions. The rationale for employing PCA lies in its adaptability and ease of implementation in real-time settings. The PCA algorithm efficiently eliminates correlated features within a dataset, leading to components that are independent from one another, which further shortens training time when applied to machine learning algorithms. Additionally, PCA mitigates the risk of overfitting. When PCA is implemented, a high-dimensional dataset is transformed into a lower dimension, making it significantly easier to visualize its characteristics in a 2D plot and draw conclusions (Gadekallu et al., 2021).

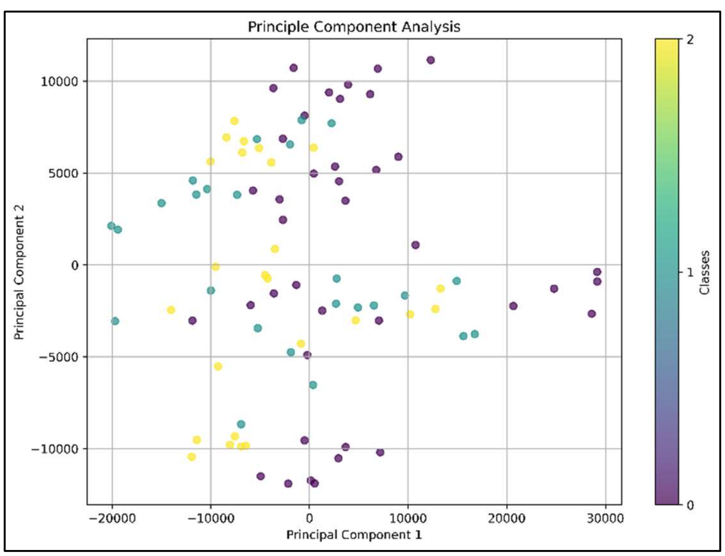


Figure 2. Variations of Class 0, Class 1, Class 2 using Principal Component Analysis.

The plot displayed in Figure 2 PCA illustrates the distribution of three classes (0, 1, and 2) based on their variability along two principal components, which represent the most prominent directions of variance in the dataset. The color of each point denotes its respective class, and the scatter pattern aids in identifying clustering or separation among classes within this reduced-dimensional space. If distinct clusters of varying colors (classes) are observed, PCA has likely succeeded in differentiating them, suggesting it may be beneficial for classification purposes. Conversely, if the clusters overlap, it indicates that PCA on its own might not sufficiently differentiate the classes, which may necessitate more sophisticated analysis for improved separation.

Proposed approach

The proposed approach, KU-Net, is a hybrid model that combines K-means clustering with the U-Net architecture to improve image segmentation tasks. Figure 3 illustrates the block diagram of the suggested technique. U-Net, a well-known convolutional neural network (CNN) architecture, performs well in semantic segmentation due to its encoder-decoder structure, which enables it to capture both overarching features and detailed nuances. However, to further improve the model's capability to segment images accurately, KU-Net includes a K-means clustering step before training the neural network. K-means clustering assists in grouping similar pixel values, which may enhance the model's capacity to differentiate between various regions of an image, especially when there is a significant level of similarity among classes. The K-means clustering procedure can be outlined in three stages: Objective function, Assignment Step, and Update Step, which are detailed below with equations. The goal of K-means is to reduce the total squared distances between the data points and their corresponding cluster centroids. The equation (1) is$J = \sum_{i=1}^{n}.\sum_{k=1}^{k}.1_{\{c_i=k\}}||x_i = \mu_k||^2$ (5)

In this context, n represents the total count of data points (or pixels). k denotes the total number of clusters. The symbol x sub i refers to the feature vector associated with pixel i. mu sub k indicates the centroid for cluster k. The variable c sub i represents the cluster assignment for pixel i. The notation 1 sub {c sub i equals k} is an indicator function that equals 1 when pixel i is part of cluster k and equals 0 otherwise.

- The K-means algorithm alternates between two main steps:
- • Assignment Step: Allocate each pixel to the closest cluster centroid μ_k

  $c_i = argmin_k||x_i - \mu_k||$ (6)

  • Update Step: Revise the centroids by calculating the average of the points allocated to each cluster.

$$\mu_k = \frac{1}{|C_k|} \sum_{i \epsilon C_k} . x_i \quad (7)$$

Where $C_k$is the set of points assigned to cluster k, and $|C_k|$is the number of points in cluster k.

After the image has undergone preprocessing with K-means clustering, the U-Net architecture is utilized for segmentation. The U-Net model features an encoder-decoder structure with skip connections to maintain fine details, which includes the equations for the Encoder, Decoder, and Final layer outlined below these steps, respectively.

The encoder is made up of several convolutional layers that are succeeded by max-pooling. For a given input image I0, the result from the lth convolutional layer is C_l :

$$C_l = \sigma(W_l * I_{l-1} + b_l) \quad (8)$$

In this context, W_l represents the weight matrix for the lth convolutional layer.b_l is the vector bias. * Signifies the convolution operation is the activation function (usually ReLU).

Following the convolution, max-pooling is utilized.: $P_l = MaxPooling(C_l)$ (9)

Where P_l is the result produced after applying max-pooling.

The decoder increases the resolution of the feature maps and merges them with the related feature maps from the encoder (skip connections).Let the lth upsampled feature map $U_l$be:

$$U_l = UpSampling(C_{l+1}) \oplus P_l \quad (10)$$

The last output layer of the U-Net generates the segmented image through a 1x1 convolution.:

$$S = \sigma(W_{out} * U_L + b_{out}) \quad (11)$$

In this context, W_{out} represents the weight matrix for the final 1x1 convolution,b_{out} is the vector bias for the output layer, S is the final output of the network. An Adam optimizer is used in U-Net which combines momentum and adaptive learning rates to ensure faster and more stable convergence compared to traditional optimizers. It dynamically adjusts learning rates for each parameter, making it effective for large datasets and segmentation tasks with sparse gradients. Adam also requires minimal hyperparameter tuning, simplifying the training process for complex models like U-Net.

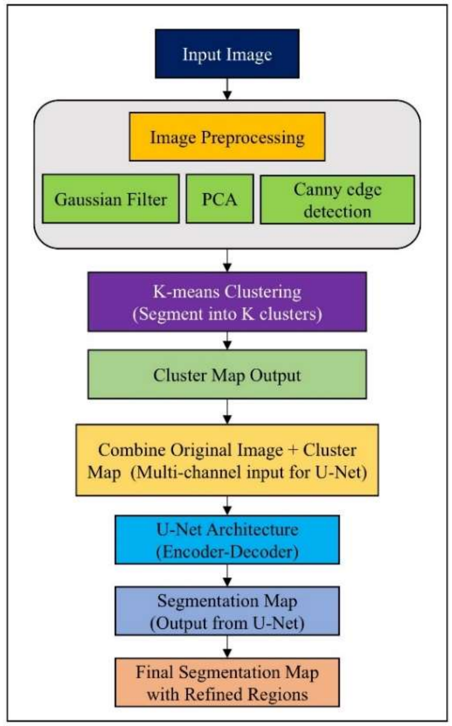


Figure 3. Hybrid Tool Wear Segmentation Workflow.

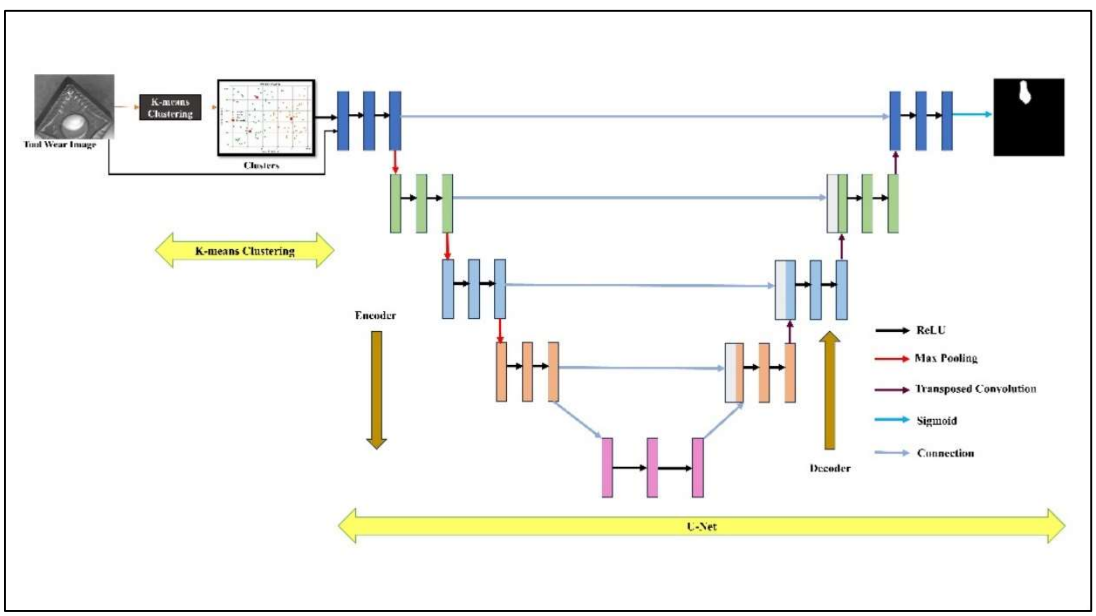


Figure 4. Proposed KU-Net Architecture.

Figure 4 architecture is a proposed KU-Net Architecture which combines the K-means Clustering and U-Net for tool wear image segmentation. K-means clustering identifies regions of interest to enhance input features. The U-Net model, consisting of an encoder (down sampling with max pooling) and a decoder (up sampling with transposed convolution), performs segmentation. Connections between encoder and decoder layers preserve spatial information, and a sigmoid activation generates the final segmentation output.

Results and discussion

Experiments validate the effectiveness of our combined method for segmenting tool images. When compared to standard U-Net and other top-performing models, our hybrid model delivered better accuracy, precision, and F1-score. The integration of attention mechanisms and stacked dilated convolutions within the U-Net framework played a crucial role in capturing contextual information at multiple scales, resulting in more precise and resilient tool segmentation. Additionally, the incorporation of unsupervised K-means clustering enhanced the segmentation results, addressing issues related to boundaries and elevating overall segmentation quality. These results underscore the promise of our hybrid approach in overcoming the limitations of conventional methods for tool image segmentation, opening the door to more effective and dependable automated systems in manufacturing and industry.

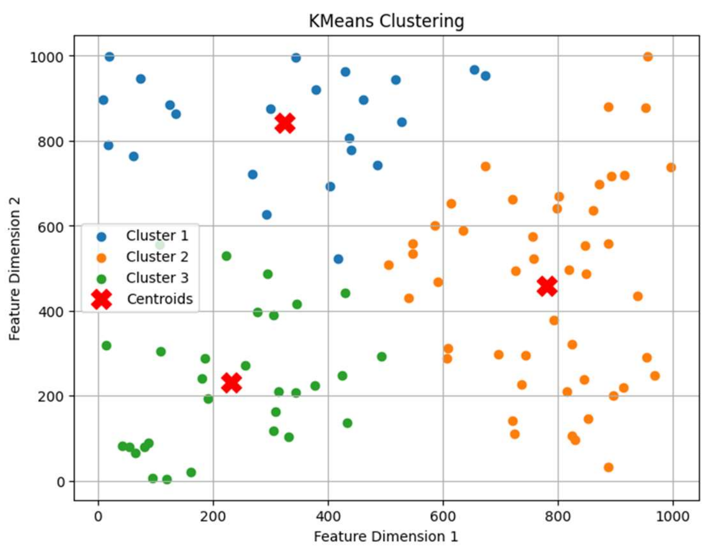


Figure 5. Clusters after applying K-means(k=3).

The Figure 5 illustrates the results of K-means clustering, where data points are grouped into three clusters: Cluster 1, Cluster 2, and Cluster 3, based on feature similarity in a two-dimensional feature space. The red Xs represent the centroids, which are the central points of each cluster. This clustering approach effectively separates the data into distinct regions, highlighting patterns or structures within the dataset.

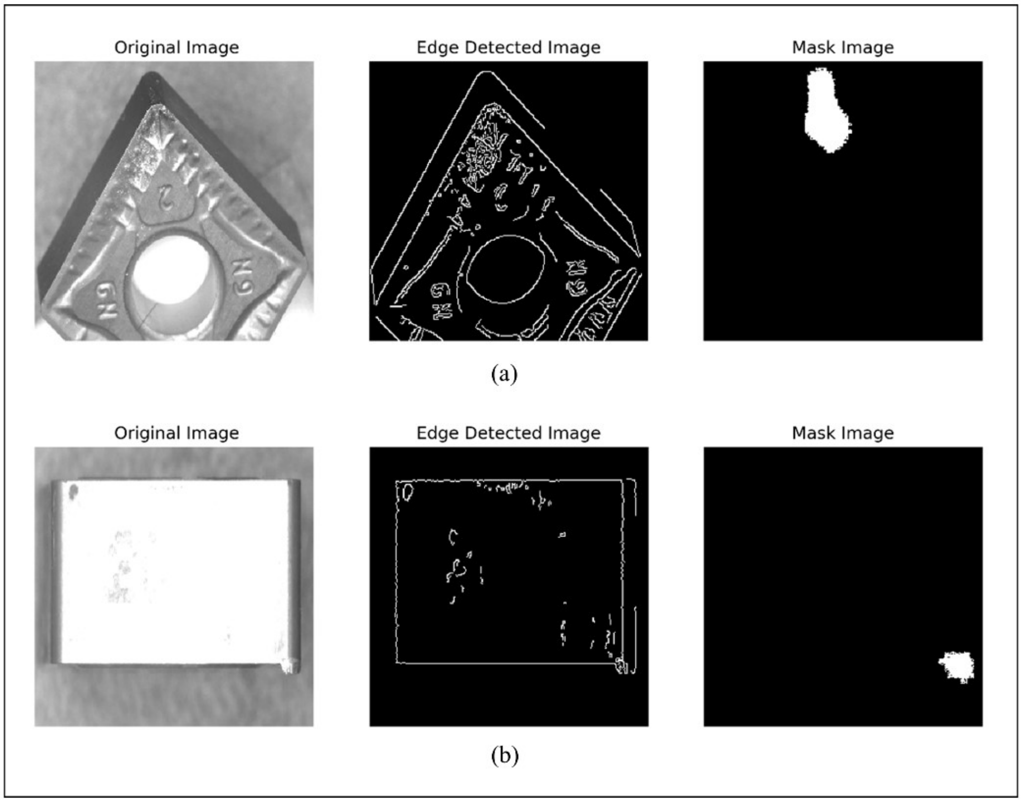


Figure 6. Sampled images of edge detected images and predicted mask from original images.

The original image depicts a damaged tool, while the edge-detected image emphasizes the contours and characteristics of the wear. The mask image illustrates the segmented area of interest. The original image offers a clear perspective of the tool's surface, whereas the edge detection highlights the worn regions. The mask image denotes the areas recognized as significant for further examination or classification, with the worn section outlined in white on a black background. This method aids in concentrating on the affected regions for comprehensive inspection or segmentation tasks. Figure 6 presents the sampled images of edge-detected images and the predicted mask derived from the original images.

Evaluation Metrics

The model attained a test accuracy of 0.9838 alongside a test loss of 0.1243. The plots illustrate the performance metrics for training and validation—both loss and accuracy—over numerous epochs throughout the training of the model. The left plot presents the loss curve, where both training and validation loss initially decrease, but there are some fluctuations, especially in the early epochs, which could suggest overfitting or instability. Conversely, the accuracy curve on the right displays a swift rise in both training and validation accuracy, ultimately leveling off at close to 100%. Figure 7 depicts the Training and Validation Performance of the KU-Net Model.

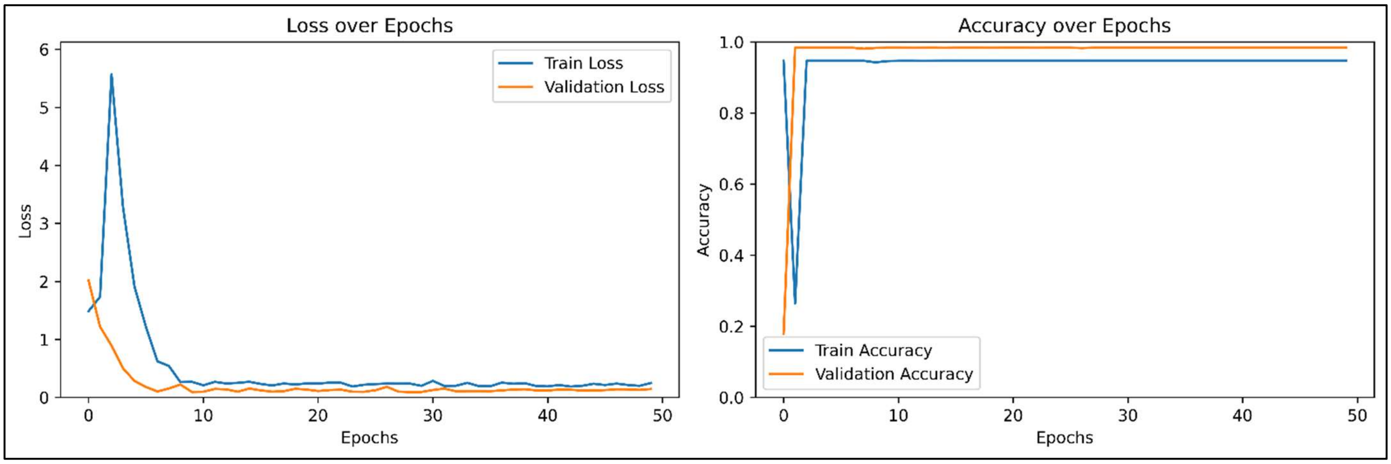


Figure 7. Training and Validation Performance of the KU-Net Model.

The confusion matrix indicates that the model excels for Class 0 (No Wear), correctly identifying all instances at a rate of 100%. For Class 1 (Mild Wear), the model successfully predicts 76% of cases, misclassifying 7% as Class 0 and 16% as Class 2. In the same way, for Class 2 (High Wear), the model records a 77% accuracy, with 8% misclassified as Class 0 and 15% as Class 1. Figure 8 illustrates the Confusion Matrix of the KU-Net Model.

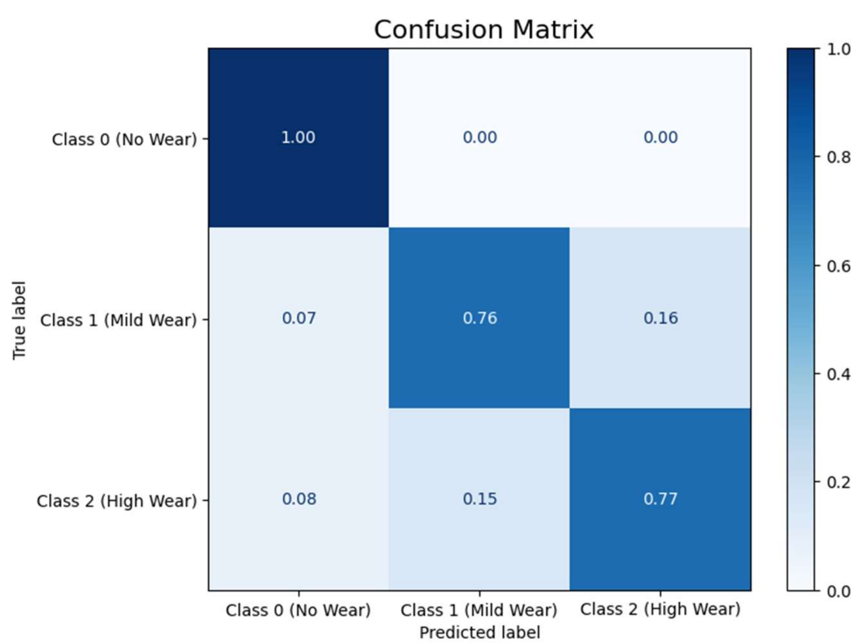


Figure 8. Confusion Matrix of the KU-Net Model.

Precision, recall, and F1-score are important metrics for assessing classification models, especially in cases of imbalanced datasets. Precision evaluates the correctness of positive predictions, aiming to reduce false positives, whereas recall measures the model's capability to accurately identify true positives, focusing on minimizing false negatives. The F1 score combines these two metrics into a single value, representing the harmonic mean of precision and recall. Figure 9 displays the values associated with these metrics. The mathematical formulas for each metric are provided below.

$$\text{Precision} = \frac{TP}{TP+} \tag{12}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{13}$$

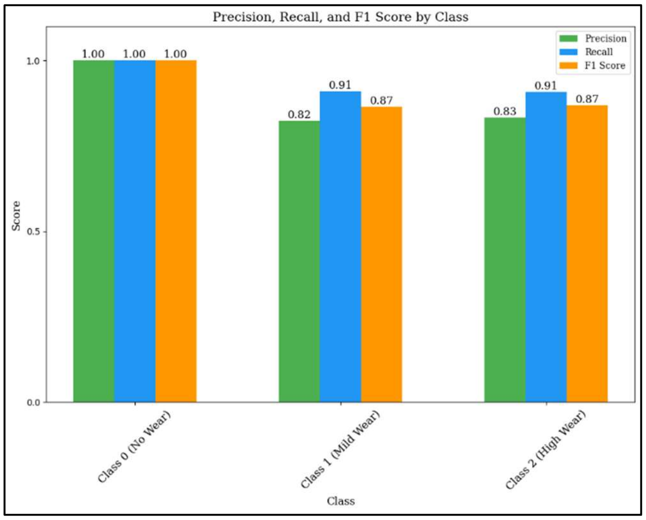
$$F1 - Score = 2 \cdot \frac{\text{Precision.Recall}}{\text{Precision+Recall}} \tag{14}$$

True Positives (TP): Instances that have been correctly identified as positive, False Positives (FP): Instances that have been incorrectly identified as positive, False Negatives (FN): Instances that have been incorrectly identified as negative.

The Intersection over Union (IoU) quantifies the degree of overlap between the predicted and actual instances of a class; Figure 10 illustrates the IoU for each class. True Positives (TP): The count of accurate predictions for a specific class, False Positives (FP): The count of instances wrongly categorized as belonging to the class, False Negatives (FN): The count of instances that actually belong to the class but were not correctly identified as such.

$$IoU = \frac{TP}{TP+FP+FN} \tag{15}$$

The model exhibits outstanding performance across the three categories outlined in Table 2. For Class 0 (No Wear), it records perfect results in all three metrics: Precision (1.00), Recall (1.00), and F1 Score (1.00). This reflects the model's high effectiveness in identifying every instance of this class without any false positives or false negatives. In Class 1 (Mild Wear), the model demonstrates strong Recall (0.91) but shows a minor decrease in Precision (0.82), resulting in a slightly lower F1 Score (0.87). Likewise, for Class 2 (High Wear), the model retains a strong Recall (0.91), experiences a slight drop in Precision (0.83), and achieves a comparable F1 Score (0.87), resembling the performance noted in Class 1.



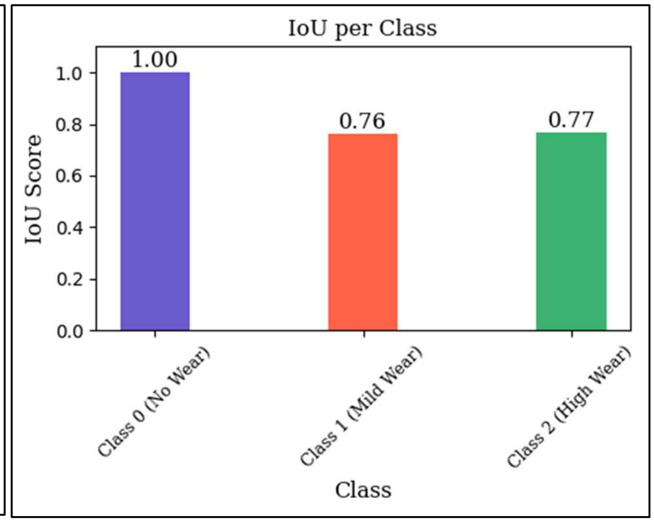


Figure 9. Precision, Recall, and F1 Score by Class. **Figure 10.** IoU values for each class.

Discussion

The results from the KU-net hybrid model demonstrate its significant capability for precise image segmentation in detecting tool wear. The model performed particularly well in identifying Class 0 (No Wear), achieving flawless precision, recall, and F1 scores. This shows that the model effectively differentiates between wear and no wear, resulting in reliable predictions. However, in the cases of Classes 1 (Mild Wear) and 2 (High Wear), the model showed strong recall, indicating its proficiency in recognizing the majority of wear instances. Nevertheless, there was a slight dip in precision, which in turn led to a small decrease in the F1 score for these categories. This suggests that the model might incorrectly classify some areas of mild or high wear as belonging to other categories, resulting in a few false positives.

The variations seen in the training and validation loss curves indicate that the model may be susceptible to overfitting, particularly as the training advances. Although the accuracy quickly approached almost 100%, this swift convergence suggests that the model might be excessively tailored to the training data, potentially sacrificing its ability to generalize to new, unseen data. This situation underscores the necessity for additional model improvement, such as adding regularization methods or modifying the architecture to enhance generalization.

Regarding the hybrid method that integrates K-means clustering with U-Net, the preliminary clustering phase boosts the model's capability to delineate areas with similar characteristics, laying a solid groundwork for the segmentation task of U-Net. Nevertheless, the model's performance could be further improved by fine-tuning the clustering parameters and enhancing the U-Net architecture to more effectively address subtle cases of wear. By optimizing both elements, it might be feasible to increase precision for Classes 1 and 2 while reducing misclassifications, especially in cases of significant wear. Overall, despite the KU-net model demonstrating encouraging outcomes, there remains potential for enhancing its ability to manage diverse wear classes accurately, and further tuning could contribute to achieving even more consistent performance across all categories.

Conclusions

This research introduced KU-net, a groundbreaking hybrid segmentation framework that effectively merges deep learning with unsupervised clustering techniques to tackle the challenges of segmenting tool wear images in manufacturing automation. By incorporating advanced preprocessing methods such as Gaussian filtering, Principal Component Analysis (PCA), and Canny edge detection, along with K-means clustering for improved feature extraction, KU-net adeptly addresses the complexities stemming from intricate tool geometries and varying machining conditions. The integration of the cluster map and the original image as a multi-channel input allows the U-Net architecture to achieve robust and precise segmentation outcomes. The experimental findings illustrate the efficacy of KU-net, which achieved a training accuracy of 0.988, a testing accuracy of 0.9838, a precision of 0.8229, a recall of 0.9071, and an F1 score of 0.8629. These metrics underscore the robustness and reliability of the proposed method in identifying subtle tool wear regions that traditional techniques frequently overlook. Comparative analysis indicates that KU-net surpasses standard segmentation methods, establishing it as a valuable resource for monitoring tool wear, conducting inspections, and facilitating robotic handling in manufacturing automation.

In general, KU-net offers a strong, precise, and efficient approach to tool wear image segmentation, tackling significant challenges in automated manufacturing environments. Its effectiveness lays the groundwork for future developments in smart manufacturing, where accurate tool wear identification is crucial for boosting productivity, minimizing downtime, and improving operational efficiency.

Future Work

Future research may explore advanced image augmentation methods to enhance the KU-net model's resilience. Utilizing more complex augmentation techniques, like generative adversarial networks for creating synthetic images or sophisticated style transfer methods, could allow the model to be trained on a broader variety of tool images. This would enhance its capability to generalize across different conditions and geometries, which could result in improved segmentation precision and superior performance in real-world manufacturing settings.

Declaration of conflicting interests

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