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Tool Wear Classification Based on Convolutional Neural Network in Micro Drilling

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ABSTRACT

Tool wear significantly impacts both machining performance and product quality. While sensor-based approaches are prohibitively expensive and manual verification is prone to human error, this study proposes a cost-effective computer vision-based classification system using Convolutional Neural Networks (CNN). High-resolution images of tool wear were acquired using a CMO Stereo Microscope at high magnification, with the tool positioned vertically to allow for a 90° top-down image recording of the rake face. The dataset consists of two primary wear categories: Built-up Edge (BUE) and Chipping. To evaluate the system's robustness, the study acknowledges a real-world class imbalance within the dataset, specifically noting that light chipping samples are underrepresented compared to BUE. These images were processed via four distinct frameworks: Gray_Edge, Gray_MorphEdge, RGB_Enhanced, and ContourOnly. The CNN model, adapted from the AlexNet architecture and optimized using the Adam optimizer, was evaluated based on precision, recall, and F1-score. Performance results, including a validation accuracy of up to 99.26% for the ContourOnly method, demonstrate that proper image preprocessing is essential for accurate, low-cost tool wear classification in smart manufacturing environments.

1. Introduction

In modern manufacturing, the condition of the tools during machining processes has become very vital. Tool wear may cause problems such as poor quality or defective products, increased cost of production, among others. As tools wear over time, identification of the condition is a necessary factor to ensure smoothness and efficiency of operations. Failure to detect tool wear in good time will lead to material waste, delays, and costly repairs. Thus, effective tool monitoring is a vital tool for maintaining industry efficiency, which relies on precision and high production. Most factories today use manual inspection methods to spot wear on tools. However, these manual methods are time-consuming, prone to human error, and impractical for continuous monitoring in high-throughput automated manufacturing systems [1]. Therefore, reliable and accurate real-time

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monitoring of tool wear is crucial for improving productivity, ensuring workpiece quality, and optimizing tool life in subtractive manufacturing processes [2,3].

Traditional manual inspection typically involves workers performing visual assessments and taking basic measurements of worn components. Beyond being labor-intensive, this approach is highly subjective, as it relies heavily on the individual inspector's expertise and is susceptible to fatigue. Although some industries have implemented advanced sensor-based systems to address these limitations, such hardware is often prohibitively expensive and requires complex integration. This high barrier to entry often leads to conservative or premature tool changes, resulting in underutilized tool life and inflated operational costs [4]. Conversely, delaying tool changes beyond optimal wear levels compromises workpiece integrity, necessitates rework, and incurs substantial financial losses [5].

To address these challenges, researchers have explored both traditional computer vision and artificial intelligence techniques. Early methods relied on manual feature engineering—such as edge detection, thresholding, shape descriptors, and texture analysis via Gray-level co-occurrence matrices (GLCM) to classify wear types [6,7]. However, these traditional approaches are inherently limited by their reliance on predefined, hand-crafted features, which often fail to generalize when wear patterns evolve or when machining conditions change. Furthermore, these techniques lack the adaptability to distinguish between complex, multi-modal wear features, often overlooking how specific visual representations such as subtle geometric boundary shifts versus fine-grained textural details that influence the classification of distinct wear types like built-up edge (BUE) and chipping. While deep learning has emerged to overcome these manual constraints, current CNN-based models still face significant hurdles in real-world industrial deployment. These models are frequently constrained by the 'black-box' nature of their decision-making, the necessity for massive, high-quality labelled datasets, and a persistent susceptibility to environmental noise, fluctuating lighting conditions, and non-stationary machining dynamics, all of which critically limit their robustness and industrial scalability [8-10].

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNN) offer a more robust approach by automatically extracting intricate features from raw image data, thereby mitigating the limitations of traditional methods [11-13]. This capability of deep learning models to automatically learn hierarchical representations from images reduces the dependency on labor-intensive feature engineering and enhances their adaptability to diverse operational conditions [14]. For instance, Ambadekar and Choudhari [15] employed a CNN to classify flank wear progression into low, medium, and high states from tool microscope images under dry cutting conditions, attaining 87.26% accuracy for life prediction with modest datasets, while similar approaches have discerned crater wear, chipping, and built-up edge [16] , thereby establishing the superiority of CNN for robust, end-to-end image-based wear classification in real-time industrial monitoring owing to its automated feature learning and noise resilience. The objective of this study was to develop a simple, practical CNN-based system designed for resource-limited industrial settings. By utilizing the AlexNet architecture and evaluating multiple preprocessing strategies, this study explores the creation of a robust tool wear classification model that balances computational efficiency with high accuracy.

2. Methodology

2.1 Image Acquisition

The acquisition of images was done through a CMO Stereo Microscope to get the close-up pictures on tool wear from the rake face. The tool was placed in a vertically positioned CMO Stereo Microscope, with the rake face pointing upward to allow image recording at 90° (top-down) relative to the surface. This technique was capable of observation of wear characteristics of chipping and BUE using high magnification. The microscope was connected to a computer, allowing real-time observation as well as saving through dedicated imaging software. The images give visual clear data of the wear conditions which are very necessary in generating the actual and replicated dataset. This data was then cropped and labelled to train the CNN model successfully. After the images are collected, these were labelled by naming the wear types of the images. This process normally involves the manual work of observing and cropping each image and labelling its wear type such as BUE and chipping. Labelled data is crucial because the CNN learns from the labels to create the mapping of relationships between the visual features in an image and the wear type. This dataset should be curated with care, and every image should be correctly labelled since any mislabels would mean poor model performance. Labelling was done by saving the cropped image in a folder which was named as "Chipping" and "BUE" accordingly. Then, the next step is image preprocessing which prepares the data for training the CNN model. Fig. 1 shows the process of cropping the wear pattern from the raw image.

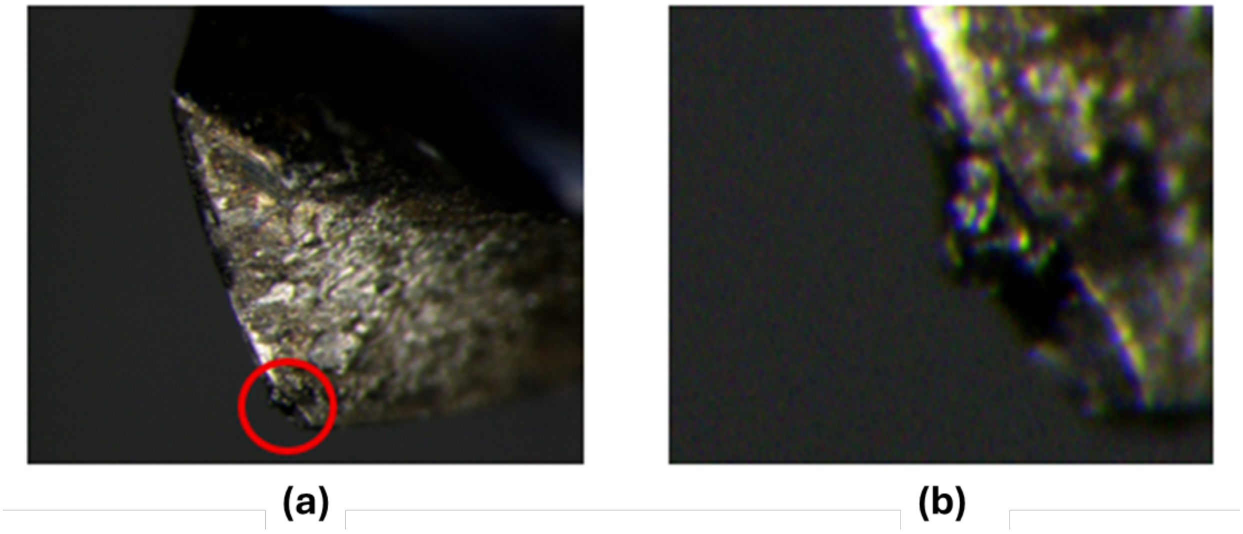


Fig. 1. Crop and Label Image; (a) Crop region [17] and (b) Image after Cropped [18]

2.1 Preprocessing

Preprocessing is a key feature in enhancing tool wear feature representation in image-based learning environments. In this research, we developed and evaluated four distinct preprocessing methods, each selected to target specific visual aspects of tool wear, as illustrated in Fig. 2. The rationale for these approaches is based on isolating geometric versus textural cues:

2.1.1 Geometric Feature Enhancement (Gray_Edge & Gray_MorphEdge)

Gray_Edge converts the image into grayscale, alters contrast, and applies Canny edge detection. This isolates boundary information, reducing sensitivity to complex, non-stationary background textures. Gray_MorphEdge builds upon this by applying morphological thickening to the detected edges, which helps in connecting broken contours and strengthening the representation of sharp wear features. These methods are conceptually designed to test whether the CNN can classify wear based solely on structural geometry.

2.1.2 Color and Texture Analysis (RGB_Enhanced)

This approach operates in the color and texture space through histogram equalization of each RGB channel. By enhancing visual hints in the form of burning and discoloration, this method aims to assist the CNN in identifying wear types that are characterized more by material degradation and surface staining than by geometric changes.

2.1.3 Human-Centric Feature Highlighting (ContourOnly

This method places red-colored edges on top of the grayscale image. It mimics human annotation practices, providing the model with both structural boundary information and original image context. This serves to bridge the gap between human visual inspection and machine-learned feature extraction. As a control, the original images were processed without any manipulation. This provided a raw input-based direct performance assessment of the CNN and served as a baseline for calculating the added value of the preprocessing steps.

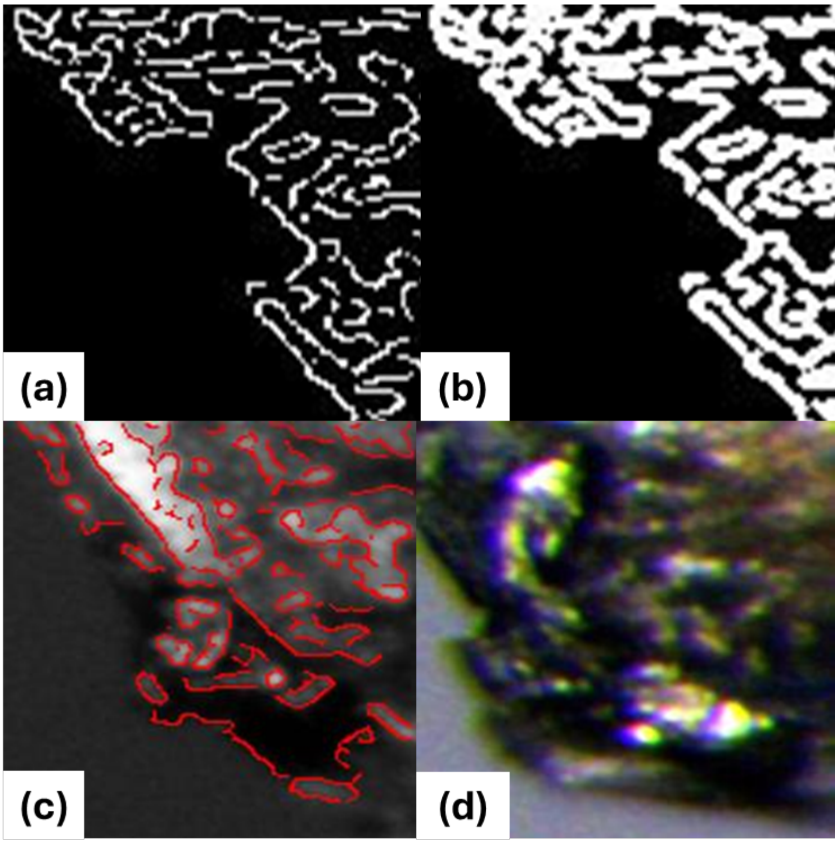


Fig. 2. Example of figures; (a) Gray_Edge Chipping [17]; (b) Gray_MorphEdge Chipping [18]; (c) ContourOnly BUE [18] and RGB_Enhanced BUE [17]

Following preprocessing, all images were resized to a uniform dimension to meet the input requirements of the pre-trained AlexNet architecture. Because AlexNet necessitates a fixed input size of 227×227 pixels, MATLAB's imresize function was utilized to standardize all datasets. This ensures that the model receives consistent spatial information, preventing errors and ensuring effective feature learning. As depicted in Fig. 3, the images were resized from their original 147×170 pixels to the required 227×227 pixels.

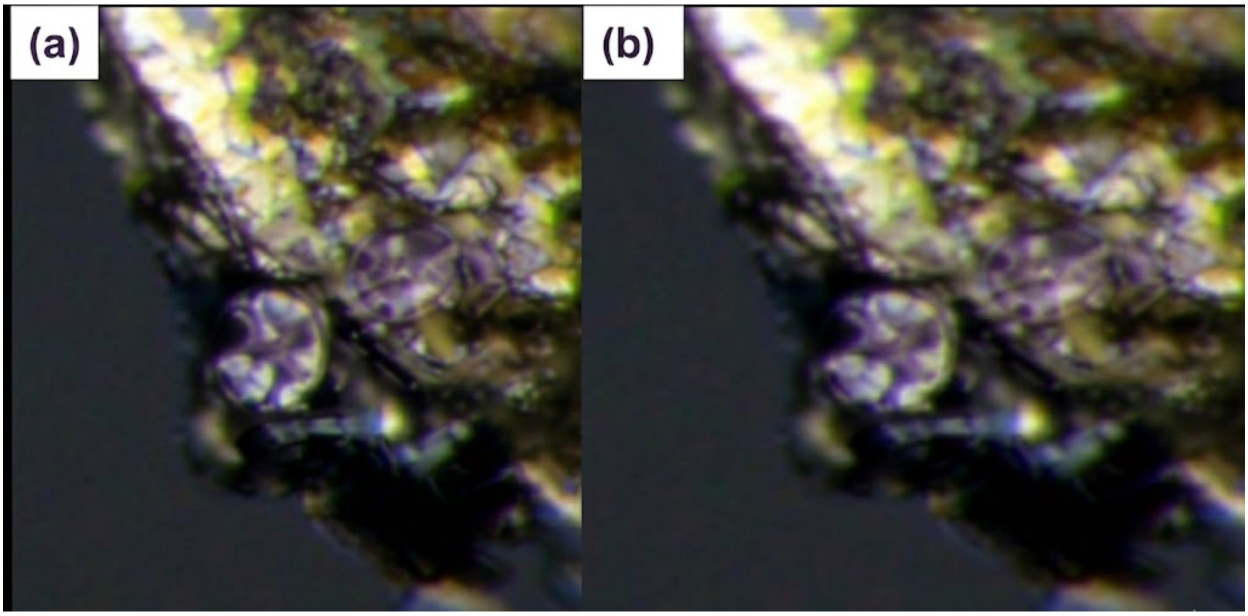


Fig. 3. Resizing Image; (a) 147×170 pixels [17] and 227×227 pixels [18]

Normalization was a preprocessing step that had been performed on all versions of an image such that pixel intensity values were always normalized. Normalization in this project implied converting images from 8-bit unsigned integer (uint8) format where intensity values were between [0, 255] to single-precision floating-point (single) format with intensity values between [0, 1]. This was done using MATLAB's im2single () function, applied after resizing and preprocessing. The process is based on the simple normalization formula in Eq. (1), which is a special case of the min-max normalization formula in Eq. (2) where x_i is the original pixel intensity value, given that the image's minimum and maximum pixel intensity values are 0 and 255, respectively.

$$x_{norm} = \frac{x_i}{255} \tag{1}$$

$$x_{norm} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{2}$$

2.3 CNN Model Training

The CNN model used in this study was built using MATLAB's Deep Learning Toolbox through leveraging the power of transfer learning using the AlexNet model and Adam optimization algorithm. This was because AlexNet possesses a strong image classification capability, especially when dealing with small to medium-sized datasets. Its two-layer design could effectively extract low to high-level features such as edges, contours and textures, which play important roles in distinguishing different tool wear types. Since it has been pre-trained on the large ImageNet database, AlexNet was already trained to extract universal and transferable visual features that did not need retraining from scratch and therefore facilitate faster convergence with less data.

Fig. 4 illustrated transfer learning with a pre-trained convolutional neural network (CNN). Transfer learning is three-step. First, a pre-trained network was initialized. The network was pre-trained on a large dataset, Alexnet which contained over a million images in thousands of categories. The initial layers of this network had already been trained to learn general low-level features like edges, textures and colors which could be applied to most image recognition tasks. In the second step, the last layers of the network, those initially used for classifying the dataset upon which the network was trained, were stripped out and new ones inserted. These new layers were optimized to learn user-specific characteristics of the user's data set, usually having fewer classes. The adapted network is retrained using the user's images. Since the early feature extraction layers were already well-trained, only the new layers need to be trained from scratch. Training time and performance were significantly saved using this method, even when training with a small data set. In conclusion, transfer learning facilitated effective adjustment of strong models to new, domain-related tasks even with little data and computer resources.

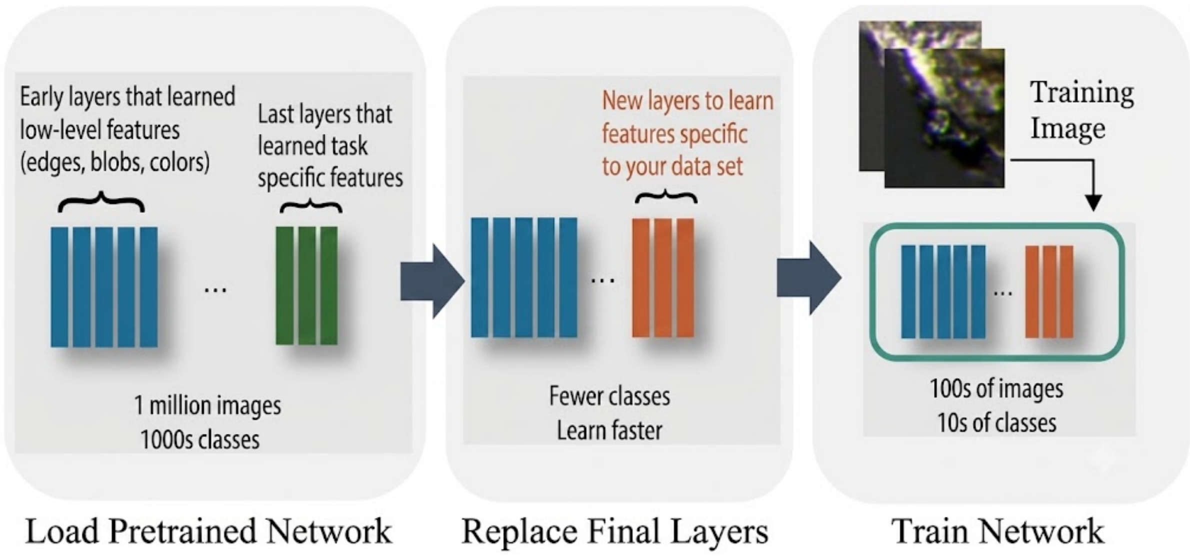


Fig. 4. Training Flow of AlexNet

2.4 Model performance evaluation

The CNN model was tested on a separate dataset for unseen tool images to assess its generalization capability after CNN model has been trained. The testing dataset covers images from different conditions of tool wear to ensure varied assessment of the model. Accuracy, precision, recall, F1-score and a confusion matrix were used to quantify the effectiveness of the model, which was calculated by using the Equation 3, 4, 5 and 6. These metrics would give further details on the ability of the model to classify wear patterns and identify any potential misclassifications. Besides that, classification performance was visualized using the *confusion chart* tool which already built in MATLAB, which helps in highlighting the areas for further optimization. Moreover, the robustness of the model was tested under various image conditions to ensure its reliability in industrial applications.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1 = \frac{2 \times precision \times recall}{precision+recall} \tag{5}$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{6}$$

2.5 Validation

In order to verify the performance of the CNN model, 5 reference images from a different dataset are selected for each wear class. These images were not manually labelled but they classify by the trained CNN model. The predicted results were then reviewed to determine whether the model can identify the correct wear types based on unseen data accurately. MATLAB was used to assist in enhancing and analysing the images during this verification process. This step was important to assess the generalization ability of the CNN and to confirm that it performed reliably when classifying new and unseen tool wear images.

3. Results and Discussion

3.1 Training Performance

The performance of four tested preprocessing techniques, Gray_Edge, Gray_MorphEdge, ContourOnly, and RGB_Enhanced was shown in Table 1, they had highly differential impacts on CNN classification performance per tool wear category. ContourOnly preprocessing performed the best with a best validation accuracy of 99.26%. It also performed balanced class classification with a recall of 0.99 for BUE and a perfect 1.00 recall for chipping. Even after removing internal textures, highlighting contour edges still produced discriminative structural detail sufficient for the detection of both kinds of wear. This supports the notion that well-defined boundary shapes alone can be very efficient especially when chipping wear has sharp or localized interruptions.

In contrast, Gray_MorphEdge generalised well with a validation accuracy of 95.56% and performed best at detection of BUE with recall of 0.99 recall and improving chipping recall to 0.74. Its partial texture preservation was able to segment complex patterns without overfitting. This method maintained good balance between edge sharpness and surface feature preservation and performed better than Gray_Edge and RGB_Enhanced specifically in classifying chipping.

The Gray_Edge model, while simple and efficient but lagged behind at a validation accuracy of 92.59%, tied with that of RGB_Enhanced but worse for chipping which was recall of 0.63 recall. While extremely accurate on BUE with strong edge contrast but it was not able to detect the subtle and irregular geometry of chipping due to its complete removal of surface detail. This demonstrated that edge information in isolation may not be adequate for all categories of wear.

For RGB_Enhanced, it despite having the highest visual resolution but did not outperform. Its accuracy in validation remained identical with Gray_Edge at 92.59%. While BUE detection remained perfect, recall of 1.00 but chipping recall dropped to 0.47. This indicates that excessive visual resolution so more color and texture may confuse or distract the CNN, particularly for weak or sparse features such as chipping. Therefore, the additional color might help in theory, but it creates noise in practice unless it has a model architecture that can accommodate it.

As a result, these findings clearly demonstrate that various wear types are sustained by various visual cues. Contour-only presentations worked very well, particularly when wear is visually distinguishable by geometry. Yet, texture or color-based categories such as BUE can still be aided by improved grayscale or RGB-based approaches under some conditions. This aligns with prior literature showing that preprocessing techniques must be matched carefully to wear type characteristics for optimal performance.

Table 1
Result of the CNN training with different preprocessing

Method	Class	Precision	Recall	F1-Score	Accuracy, %
Gray_Edge	BUE	0.94	0.97	0.96	92.59
	Chipping	0.80	0.63	0.71	
Gray_MorphEdge	BUE	0.96	0.99	0.97	95.56
	Chipping	0.93	0.74	0.82	
ContourOnly	BUE	1.00	0.99	1.00	99.26
	Chipping	0.95	1.00	0.97	
RGB_Enhanced	BUE	0.92	1.00	0.96	92.59
	Chipping	1.00	0.47	0.64	

3.2 Validation

For the validation of the generalization ability of the CNN models, a visual verification was conducted with a set of reference images, and the result is shown in Table 2. Ten reference images were selected, five each for chipping and built-up edge (BUE). These images served as visual guidelines for interpreting model predictions in addition to numerical metrics. It sought to determine whether the CNN models can effectively predict unseen, novel samples based on visual features exclusively learned and if human-observable wear features match predictions. Visual validation of such kind is recommended in tool wear research since it bridges the gap between statistical performance and real-world interpretability.

Verification was performed on models trained using each of the four preprocessing methods. Table 3 show some samples of the result by inputting the references image. The models trained on RGB_Enhanced and ContourOnly datasets comparatively agreed better with the reference images. The two models correctly classified 4 out of 5 chipping images, indicating the CNN's ability to localize edge breaks and abrupt damage which was the features that are visually prominent in chipping wear. These outcomes expressed that maintaining high surface detail and color resolution increases the ability to detect localized defects. Both models, however, only correctly classified 1 of 5 BUE images. The models were able to maintain surface information but struggled to detect BUE that lacks sharp visual boundaries and can resemble background glare or surface blemishes.

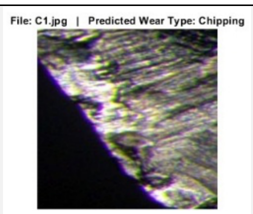
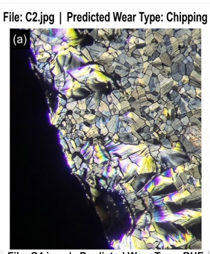
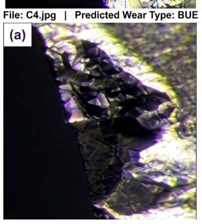
In contrast, the models trained on Gray_Edge and Gray_MorphEdge preprocessing performed considerably worse. In both cases, all ten reference images were misclassified and was predicted as BUE. This indicates a severe class bias that likely due to the removal of textural detail during preprocessing. Therefore, the edge-based methods are not sensitive to anything but geometric contours, which may not fully characterize chipping when edges are broken but not sharply delineated. Without texture or surface contrast, the models are unable to tell apart actual material build-up and edge chipping.

These results validate the earlier quantitative findings that in which Gray_Edge and Gray_MorphEdge models had poorer F1-scores and worse recall for the chipping class. The validation test confirms that preprocessing directly influences the performance of a model in terms of generalizability and adherence to human interpretation. In this case, RGB_Enhanced and ContourOnly were better at producing visually interpretable and consistent results, especially for chipping. Moreover, edge-only methods failed to capture salient visual cues and resulted in systematic misclassification. This reinforces the importance of selecting preprocessing strategies based on the visual characteristics of each wear type.

Table 2
Result of the CNN training with different preprocessing

Model	Chipping Correct (out of 5)	BUE Correct (out of 5)
Gray_Edge	0	0
Gray_MorphEdge	0	0
ContourOnly	4	1
RGB_Enhanced	4	1

Table 3
Result of the CNN training with different preprocessing

Image	Predicted Result	Actual
	Chipping	Chipping
	Chipping	Chipping
	BUE	Chipping

	BUE	BUE

The CNNs trained in this work showed encouraging results, but their classification accuracy and generalization were limited by several factors, including a small dataset size and a limited range of wear categories. Primarily, the performance was constrained by dataset imbalance; despite data augmentation being applied to increase training diversity, the original dataset had an unequal number of samples among wear types and severity levels. Light chipping samples were particularly underrepresented, and while techniques such as flipping, rotation, and brightness alteration helped, they could not successfully address this underlying imbalance. Thus, prediction bias was exhibited by certain models, especially towards the more dominant class (BUE).

Additionally, the system faced challenges regarding its microscope dependency and generalization across varying cutting conditions. Despite data augmentation efforts, the system could not fully replicate complex real-world environmental variations such as irregular illumination, fluctuating tool orientations, and surface reflections that are ubiquitous in industrial settings. These factors profoundly impact the visual representation of wear patterns, particularly under Built-Up Edge (BUE) conditions, where low contrast causes the defect to be obscured by background glare. Consequently, because the CNN models in this research were trained on images captured within controlled laboratory environments, their performance may be limited when implemented in uncontrolled settings with variations beyond the training set, resulting in sub-optimal generalization [19]. Addressing these hurdles is critical for future industrial adoption; therefore, this study highlights the necessity of developing low-cost, effective vision systems that can provide actionable, understandable solutions for smart manufacturing. By focusing on such systems, we aim to bridge the gap between high statistical performance in controlled tests and the robust, pragmatic requirements of real-world industrial feasibility.

A second significant limitation was the preprocessing methods. Despite their computational simplicity, Gray_Edge and Gray_MorphEdge aggressively reduce input information due to their removal of color and texture. Models trained on these datasets manifested severe class prediction bias and correctly classified no reference images. This finding serves to highlight that augmentation is less effectiveness if critical features have already been eliminated during preprocessing [20]. Therefore, the preprocessing must be well adapted to the visual character of the target features, or else even strong model architectures may act suboptimally due to loss of information at the input level [21, 22].

Finally, the validation method was constrained in scope and scale. Ten reference photos were used for a qualitative visual evaluation; however, this small sample size might not be representative of overall operating conditions. Furthermore, although manual inspection provided valuable feedback on interpretability, the study lacked broader quantitative tests on larger, unseen datasets. The failure to evaluate the system across diverse tool materials, coatings, and dynamic industrial environments further limits the current assessment.

Despite these limitations, the development of this low-cost vision system provides a vital, viable alternative to expensive, sensor-integrated machining centres. By leveraging accessible hardware and optimized CNN architectures, small-scale manufacturers can adopt smart monitoring practices, even while future research works to bridge the gap between laboratory results and industrial robustness. This approach directly supports the transition to Industry 4.0 by providing a feasible, scalable method for real-time tool health assessment that avoids the significant capital investment typically associated with high-end, proprietary diagnostic systems.

4. Conclusions

This study investigates the efficacy of Convolutional Neural Networks (CNNs) for the automated classification of tool wear, with a specific focus on built-up edge (BUE) and chipping. To evaluate the impact of input data quality, microscope-captured images were subjected to five preprocessing protocols: Gray_Edge, Gray_MorphEdge, RGB_Enhanced, ContourOnly, and Original (raw). These processed datasets were used to train a CNN model based on the AlexNet architecture, with parameters optimized via the Adam optimizer. Model performance was assessed using precision, recall, F1-scores, confusion matrices, and independent verification against a set of reference images. The results indicate that RGB_Enhanced and ContourOnly preprocessing yielded the highest classification accuracy, particularly for chipping detection, where both models correctly identified four out of five reference images. In contrast, the Gray_Edge and Gray_MorphEdge methods proved ineffective; their over-reliance on binary edge characteristics resulted in the misclassification of all reference samples as BUE. This systematic bias indicates that overly aggressive feature reduction leads to the loss of critical surface information, confirming that appropriate preprocessing is a prerequisite for robust feature extraction. Furthermore, none of the models achieved satisfactory BUE classification, a finding consistent with the inherent difficulty of identifying this specific wear type through visual inspection alone. Overall, this work demonstrates that when paired with targeted image enhancement, low-cost vision systems offer a viable approach for industrial tool condition monitoring. To overcome the limitation of this research, future work will focus on addressing the identified limitations and enhancing the robustness of the system. Research efforts will aim to expand dataset diversity by incorporating additional wear modes, such as flank and crater wear, while employing techniques to mitigate class imbalance. The investigation will also evaluate more sophisticated architectures such as ResNet, DenseNet, and MobileNet to determine if deeper hierarchical feature extraction can improve the identification of complex wear patterns like BUE. Given the inherent constraints of visual-only systems, such as sensitivity to glare and reflections, subsequent iterations will explore the integration of image data with multi-sensor signals, including acoustic and vibration measurements. Finally, the system will be validated across a wider range of tool materials, coatings, and industrial operating conditions to ensure its reliability and scalability for real-world deployment.

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