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EFFECT OF MACHINING PARAMETERS ON SURFACE ROUGHNESS IN MILD-STEEL TURNING AND COMPUTER-VISION-BASED TOOL WEAR PREDICTION

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Abstract

In this paper, we present a combined experimental and data-driven study of surface integrity and tool condition in mild-steel turning. Controlled experiments were conducted on a semi-automatic lathe to analyze the effects of spindle speed, feed rate, depth of cut, and coolant use on surface roughness (Ra), with surface finish measured using a Mitutoyo SJ-210 profilometer and high-resolution images of machined surfaces and cutting tools acquired with a Nikon D-3000 imaging setup. Experimental findings showed that coolant application reduced Ra by an average of 22.69%, with the improvement more pronounced at higher spindle speeds due to enhanced thermal control, lubrication, and chip evacuation. To complement these results, a computer vision–based framework was developed for tool health monitoring using semi-supervised anomaly detection, wherein a PaDiM-based model trained exclusively on healthy tool images successfully identified worn-tool states and Grad-CAM heatmaps localized wear regions on tool edges, thereby enhancing explainability. The trained model was further optimized with OpenVINO for edge deployment, enabling real-time inference on CPU-based industrial devices with minimal latency. The contributions of this work are threefold: (i) systematic analysis of machining parameters on surface roughness, (ii) development of a computer-vision–driven framework for tool wear classification and prediction under limited labeled data, and (iii) demonstration of edge-optimized deployment for real-time shop-floor feasibility. This integrated approach addresses critical gaps in machining research by jointly considering machining parameters, measured roughness, and visual tool/surface features, paving the way for intelligent, explainable, and deployable monitoring systems in smart manufacturing.

Keywords. *Machining parameters; surface roughness; tool wear; computer vision; semi-supervised learning; Open VINO; mild steel; turning.*

1. Introduction

Turning remains one of the most widely used machining operations across manufacturing industries. Among the critical quality metrics, surface roughness (Ra) directly affects fatigue life, dimensional accuracy, tribological properties, and overall product performance [1]. Simultaneously, tool wear governs machining stability and productivity, with excessive wear leading to poor surface integrity, dimensional deviations, and unscheduled downtime [2]. Conventional maintenance strategies are often reactive, relying on fixed replacement schedules or post-process inspections. These approaches increase operational costs and fail to exploit opportunities for predictive maintenance and adaptive machining. The emergence of Industry 4.0 has motivated the integration of data-driven techniques, machine learning (ML), and computer vision (CV) into manufacturing. Several studies have demonstrated the effectiveness of process parameter optimization and sensor-based monitoring in predicting surface finish and tool wear [3] – [6]. However, three key challenges remain. First, while designed experiments and statistical models, such as ANOVA and Taguchi methods, provide valuable insights into the effects of machining parameters on Ra [7], these works typically restrict themselves to profilometer measurements and regression modeling. Second, sensor-based monitoring approaches using vibration, acoustic, and current signals, combined with ML or deep learning, achieve high prediction accuracy [8], [9], but they require multiple dedicated sensors and do not exploit directly observable visual features from machined surfaces and tools. Third, existing ML studies on roughness or tool wear often assume access to abundant labeled datasets, whereas industrial environments typically provide limited annotated images. Semi-supervised and anomaly-detection methods suitable for such conditions remain underutilized, and their deployment on resource-constrained edge devices has been rarely explored [10], [11].

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This work addresses these gaps. We conduct controlled turning experiments on mild steel, measure Ra under varying machining parameters and coolant conditions, and collect paired tool and surface images. A hybrid ML pipeline is developed that combines statistical analysis (process parameters → Ra) with CV-based modeling (images → tool wear prediction). To handle limited labeled data, semi-supervised anomaly detection (Anomalib) is employed, and the models are optimized for real-time inference using OpenVINO. The contributions of this work are:

i. A reproducible experimental dataset linking process parameters, profilometer-measured Ra, and high-resolution images of machined surfaces and tools.
ii. A hybrid CV + ML pipeline for tool wear prediction that leverages semi-supervised learning under limited labeled conditions.

2. Literature Review

Numerous studies have analyzed the effect of process parameters on surface finish in turning operations. Siddique et al. [7] investigated the influence of cutting speed, feed rate, and depth of cut on surface roughness and tool wear in Inconel 718 turning using Taguchi design and ANOVA. They reported that feed rate had the most significant effect on Ra, while coolant application improved both surface finish and tool life. Similar approaches demonstrate that statistical DOE methods provide robust insights into parameter contributions, but they often stop short of incorporating data-driven predictive models.

Recent advances have integrated sensor fusion with ML and deep learning for tool wear estimation. Huang and Lee [8] proposed a 1D convolutional neural network (CNN) for tool wear prediction using fused vibration, sound, and spindle current signals. Their system achieved low root mean square error (RMSE ≈ 0.029 mm) in flank wear estimation and demonstrated an online alarm application. Tabaszewski et al. [9] applied vibration signal analysis with machine learning classifiers (CART, fuzzy rules, ANN) to classify tool wear in grey cast-iron turning, showing that classical models can achieve effective decision-making when supported by well-selected features. While sensor-based approaches are effective, they require hardware integration and may be cost-prohibitive in small and medium-scale industries. Machine learning has also been applied to predict surface roughness from machining parameters. A recent study [10] employed least-squares support vector machines (LSSVM) and multi-gene genetic programming (MGGP) for Rz prediction, enhanced by Gaussian data augmentation of a Taguchi dataset. These models achieved high predictive accuracy ($R^2 > 0.95$) and demonstrated that ML can extend the utility of small datasets. However, such parameter-based models do not incorporate visual features of surfaces or tools, limiting interpretability.

Visual imaging of machined surfaces and tools offers an intuitive, non-intrusive method for wear monitoring, but it is less explored compared to sensor-based techniques. Existing CV work often relies on large labeled datasets, which are difficult to obtain in industrial environments. Semi-supervised and anomaly-detection methods have recently gained traction in defect detection, but their use for tool wear monitoring remains limited [11]. Moreover, deployment challenges such as inference latency and hardware constraints are rarely addressed, leaving a gap in translating CV models to practical shop-floor settings. A review of prior studies highlights several limitations that motivate the present work. Existing research has predominantly emphasized sensor-centric approaches, relying on vibration, acoustic emission, or spindle current signals for tool condition monitoring. While effective, such methods often overlook the potential of high-resolution visual imagery of machined surfaces and tool faces as a primary diagnostic input for machine learning (ML) models. Another limitation lies in the restricted dataset sizes employed in many investigations. Experimental studies frequently use small sample sets, such as Taguchi arrays (e.g., L27 designs), supplemented with data augmentation or accelerated-wear protocols. Although this enables controlled analysis, it may limit the generalizability of models under diverse shop-floor conditions. From a deployment perspective, the literature provides limited detail on industrial implementation and edge optimization. While several works prototype online monitoring systems, few extend to lightweight deployment pipelines optimized for resource-constrained environments, such as microcontrollers or edge devices. Approaches such as model quantization, pruning, or inference acceleration (e.g., via OpenVINO) are rarely documented, thereby reducing industrial applicability.

In summary, the field remains constrained by the underutilization of visual features, the absence of integrated modeling of parameters, profilometer data, and imagery, and the limited adoption of semi-supervised learning and edge-optimized frameworks for real-time, resource-efficient monitoring. The present study aims to address these gaps by conducting a joint experimental and computer vision–based investigation of mild steel turning, leveraging semi-supervised ML models for tool wear prediction and exploring pathways for efficient edge deployment.

3. Materials and Methods

The experiments were conducted on commercially available mild steel (AISI 1018 equivalent) cylindrical specimens of dimensions. The mechanical properties of the

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workpiece material are listed in Table 1. The machining trials were carried out on a manual lathe. A high-speed steel (HSS) pointed cutting tool was employed. The cutting parameters were varied systematically: Spindle speed (n): Varied in steps of 90, 180 & 270 rpm, Feed rate (f): Auto Feed of 0.4 mm/rev, Depth of cut (d): 0.2 mm, Coolant condition: dry machining and coolant application.

Table 1. Material Properties

Property	Value	Unit
Hardness	83.16	HRB
Yield Strength	525.446	MPa
Elongation	2.8	%

Surface roughness (Ra) of machined samples was measured using a Mitutoyo SJ-210 contact profilometer (Fig. 1). For each workpiece, measurements were taken at equidistant locations along the turned surface, and the mean Ra value was recorded.

Fig. 1. Experimental Setup for Surface Roughness Measurement

Tool wear progression was monitored through high-resolution imaging. A Nikon D-3000 DSLR camera equipped with a 55-200mm lens was fixed at a distance from the tool tip. Illumination was ensured accordingly to minimize shadows. Images were captured and stored as JPEGs. Each tool was photographed after every machining run, and corresponding surface images were recorded to build a dataset linking cutting conditions, surface roughness, and tool wear.

For tool wear detection, the PaDiM (Patch Distribution Modeling) algorithm from the Anomalib framework was employed. PaDiM is an image-based anomaly detection method that models the distribution of feature embeddings extracted from a pretrained convolutional neural network (CNN).

Fig. 2. Cameras for image acquisition

In this study, ResNet-18 was used as the backbone network, and features were extracted from three intermediate layers (layer1, layer2, and layer3). This hierarchical feature selection enabled the model to capture both low-level texture information and higher-level semantic representations relevant to wear patterns.

During training, the model was provided exclusively with images of healthy tools, allowing it to establish the statistical distribution of normal conditions. Anomalous samples (i.e., worn tools) were never presented during training. At inference, PaDiM computed the Mahalanobis distance between incoming image features and the learned multivariate Gaussian distribution of normal embeddings. High deviation scores were interpreted as anomalies indicative of worn-tool conditions.

The training procedure was orchestrated using the Anomalib Engine, configured for image classification with min–max normalization of anomaly scores and adaptive thresholding based on the F1 score criterion. The AUROC metric was used to assess detection performance. The model was trained for one epoch on a CPU with a batch size of 32 and an image resolution of 256 × 256 pixels.

For deployment, the trained PaDiM model was exported to the OpenVINO Intermediate Representation (IR) format, ensuring compatibility with edge devices. This enabled real-time inference on CPU-based systems without requiring GPU acceleration.

4. Results and Discussion

The measured surface roughness (Ra) values under different machining conditions are summarized in Table 2. Coolant usage consistently reduced Ra across all trials, with an average improvement of 22.69% compared to dry cutting.

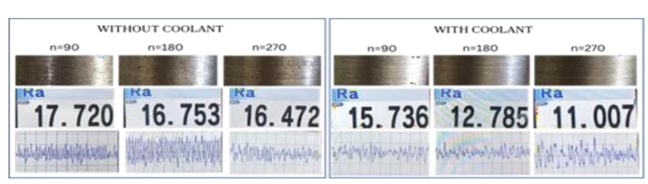

Fig. 3. Profilometry Results

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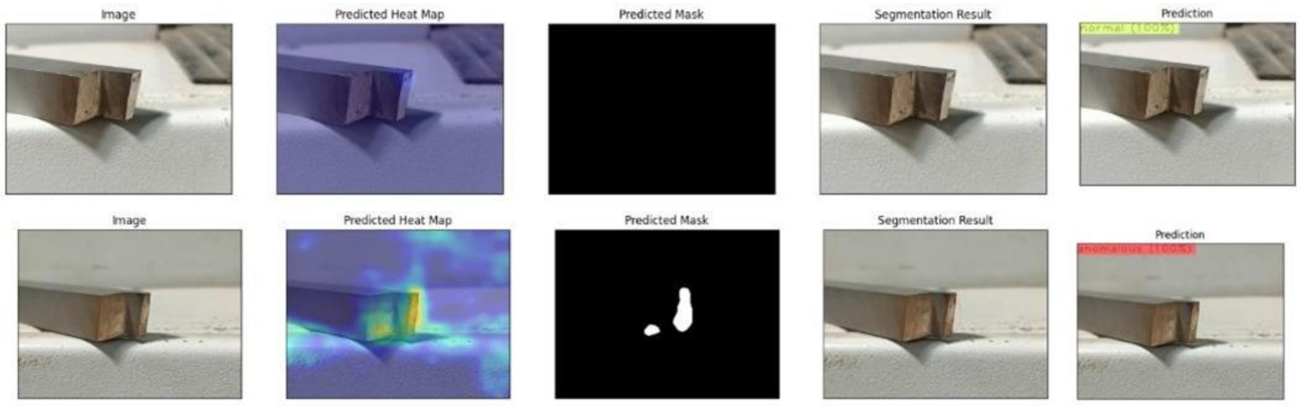

Fig. 4. Tool Wear Prediction by ML Model.

The comparative analysis of surface roughness across varying spindle speeds demonstrates a clear and consistent trend in which the application of coolant significantly improves surface integrity. This improvement can be attributed to three primary mechanisms: thermal control, lubrication, and chip evacuation. By mitigating heat buildup at the tool–workpiece interface, coolant minimizes thermal distortion and tool wear. Its lubricating action reduces friction, enabling stable cutting and preventing surface tearing, while effective chip evacuation prevents re-cutting of debris and associated surface damage. The beneficial effect of the coolant becomes more pronounced at higher spindle speeds. For instance, at n=270 rpm, surface roughness decreases by 33.20%, emphasizing that coolant plays a critical role in high-speed machining where both thermal and mechanical stresses are intensified. Beyond improving the aesthetic and functional quality of the machined surface, coolant use also extends tool life, reduces the need for post-processing, and enhances dimensional accuracy—factors essential to achieving high standards in precision manufacturing.

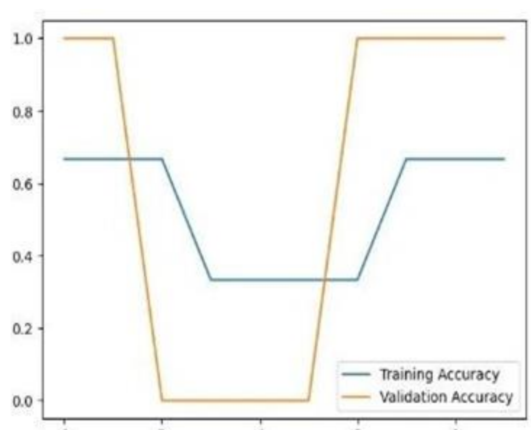

Fig. 5. Training accuracy stable at ~0.5, validation accuracy dips to 0 then recovers → indicates instability and under-training due to small dataset.

Table 2. Surface Roughness Comparison

Spindle Speed (n)	Ra Without Coolant	Ra With Coolant	% Improvement
90	17.720	15.736	11.20%
180	16.753	12.785	23.66%
270	16.472	11.007	33.20%

The anomaly-detection model trained on healthy tool images effectively detected worn-tool conditions. Grad-CAM heatmaps (Fig. 4) localized wear regions, providing explainability and validating that the model focused on tool edges rather than background regions. These findings demonstrate the feasibility of real-time tool condition monitoring in resource-constrained environments.

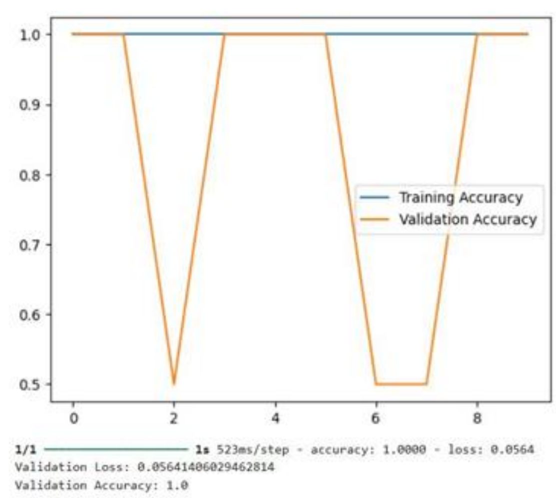

Fig. 6. Training accuracy at 1.0, validation oscillates 0 ↔ 1 → indicates overfitting with tiny validation split.

The training and validation accuracy curves are presented in Fig. 5 and Fig. 6. In Fig. 5, the training accuracy remained relatively stable (~0.5–0.6), whereas the validation accuracy dropped sharply to zero during intermediate epochs before recovering. This instability is attributed to the small dataset size and the short training schedule, in which a single misclassification can significantly affect the validation metric. In Fig. 6, the training accuracy converged to 100%, while the validation accuracy oscillated between 0 and 1 across epochs. This pattern indicates overfitting, as the model memorized the training data but failed to generalize consistently due to the limited validation set. Despite these fluctuations, the anomaly detection framework consistently flagged worn-tool images as anomalies in the test set.

Complementing the accuracy results, Grad-CAM visualizations (Fig. 4) localized activation regions along the tool cutting edges, confirming that the model's predictions were physically meaningful. Thus, even though dataset size and training duration introduced instability in quantitative metrics, the qualitative explainability outcomes demonstrate that the model learned relevant wear features. This combination highlights both the feasibility of the approach and the need for larger, more balanced datasets in future work to stabilize validation performance.

5. Conclusion and Future Work

This study presented an integrated framework for analyzing the effect of machining parameters on surface roughness in mild-steel turning and for predicting tool wear using computer vision and machine learning. Experimental analysis confirmed that coolant conditions are influential factors on Ra. The proposed ML pipeline successfully classified tool wear states and carried out semi-supervised anomaly detection. Optimization with OpenVINO further demonstrated the potential for deployment in edge devices, enabling real-time monitoring on the shop floor.

Future research will focus on extending the present work along several key directions. One critical avenue is to diversify datasets to encompass a wider range of tool geometries, workpiece materials, machining environments, and operating parameters, thereby enhancing the robustness and scalability of the framework. Another direction involves transitioning from static image analysis to real-time video-based monitoring, enabling continuous, dynamic tracking of tool wear progression across varying cutting conditions. The development of digital twin models represents an additional focus area, wherein virtual simulations of tool behavior can be leveraged for adaptive machining strategies and predictive maintenance planning. Furthermore, the deployment pipeline will be optimized through quantization, pruning, and lightweight model architectures to achieve efficient edge computing performance in industrial settings. To address the challenge of limited labeled datasets, advanced machine learning paradigms, including transfer learning, semi-supervised learning, and few-shot learning, will be employed to accelerate adoption in real-world scenarios.

In conclusion, this project establishes a strong foundation for the adoption of AI-driven predictive maintenance in smart manufacturing. By combining computer vision, anomaly detection, and edge-optimized deployment, the study addresses immediate challenges in tool wear monitoring while simultaneously paving the way for next-generation, autonomous, and sustainable machining systems.

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