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SMARTWEAR AI: INTELLIGENT TOOL CONDITION MONITORING IN HIGH-PRECISION MACHINING

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ABSTRACT

Accurate tool wear estimation is critical for high-precision machining to ensure product quality, minimize downtime, and optimize tool-change scheduling. This paper proposes a machine learning–based framework that integrates multi-sensor data, advanced feature engineering, and deep learning regression models to estimate tool flank wear in real time. Vibration, acoustic emission, cutting force, and spindle current signals are fused and processed to extract time- and frequency-domain features. A deep regression network is trained and validated on experimental machining datasets collected under varying cutting speeds, feeds, and depths of cut. The proposed approach achieves high estimation accuracy and low prediction latency compared to traditional empirical and classical machine learning methods. Results show significant reductions in estimation error and improved robustness across operating conditions. The framework supports predictive maintenance and can be embedded into CNC monitoring systems for real-time tool health management.

Keywords: Tool wear estimation, Machine learning, Deep learning regression, Sensor fusion, Condition monitoring, High-precision machining, Predictive maintenance.

I. INTRODUCTION

The reliability of cutting tools in high-precision machining directly affects dimensional accuracy, surface finish, and production throughput. Unanticipated tool failure or excessive wear can lead to scrap parts, machine downtime, and increased production costs. Consequently, accurate and timely estimation of tool wear has been a long-standing research and industrial priority [1]. Traditional empirical models and offline inspection methods are often inadequate for modern high-speed and micro-machining processes where wear progression is rapid and nonlinear [2].

Recent advances in sensing technologies enable continuous monitoring of machining processes through vibration, acoustic emission, cutting force, and spindle current measurements. These multi-modal signals contain rich information about tool–workpiece interactions and evolving wear mechanisms, but extracting relevant features reliably under variable cutting conditions remains challenging [3], [4]. Sensor fusion combined with robust preprocessing is crucial to obtain consistent signatures that correlate with tool flank wear.

Machine learning (ML) techniques have been increasingly applied to tool condition monitoring, offering data-driven mapping between sensor inputs and wear metrics. Early ML studies used shallow models such as support vector regression and random forests with hand-crafted features, demonstrating improved wear prediction over empirical relations [5]. However, the advent of deep learning (DL) provides an opportunity to learn hierarchical features directly from raw or minimally processed signals, improving generalization across operating regimes [6].

Practical deployment of ML-based wear estimation requires attention to data diversity, model interpretability, and real-time inference constraints. Issues such as concept drift when workpiece materials or cutting conditions change, and the need for explainable predictions to support maintenance decisions, must be addressed [7]. Hybrid approaches that combine physics-based reasoning with ML can improve trustworthiness and reduce training data demands.

Motivated by these points, this work develops a multi-sensor, deep learning regression framework for tool wear estimation in high-precision machining. We train and validate the model on datasets collected from controlled turning experiments and compare its performance with conventional empirical methods and feature-based ML models. The remainder of the paper presents related work (Section II), details the proposed methodology (Section III), describes the experimental setup (Section IV), and discusses results and conclusions

II. LITERATURE SURVEY

Early approaches to tool wear estimation relied on empirical wear laws (e.g., Taylor's tool life equation) and periodic offline inspection, which are insufficient for automated real-time monitoring [11]. Pioneering works applied statistical signal processing and classical pattern recognition techniques to vibration and force signals for wear detection, demonstrating the utility of time-domain and spectral features [12]. These studies established basic correlations but lacked robustness under variable cutting regimes.

With the rise of ML, several studies proposed supervised learning for wear prediction. Altintas et al. (2014) applied regression trees and SVM for wear estimation using cutting force and acoustic emission features, showing promising accuracy improvements [13]. Zhao et al. (2016) used ensemble methods and feature selection for tool wear forecasting across different tool materials, emphasizing dataset diversity for generalizable models [14].

Deep learning models were later introduced to automatically learn feature representations. Kim and Lee (2018) developed convolutional neural networks (CNNs) on time–frequency representations of vibration signals for fault and wear classification, demonstrating improved resilience to noise [15]. Liu et al. (2019) proposed recurrent neural networks (RNNs) for sequence modeling of tool wear progression, enabling temporal forecasts of future wear states [16].

Hybrid methods combining physics-based features with data-driven models have been explored to improve reliability. Pérez and García (2020) integrated cutting mechanics indicators (specific cutting energy) with neural regressors to constrain predictions within physically plausible ranges [17]. Transfer learning approaches have been used to adapt models across machining setups with limited labeled data (Wang et al., 2021) [18].

Recent benchmark studies compared classical ML, deep learning, and hybrid approaches under varied cutting conditions. Singh et al. (2022) reported that deep regression architectures with sensor fusion outperform shallow models in RMSE and robustness metrics, while Peng and Zhou (2023) emphasized model interpretability and edge-deployability as key research needs for industrial adoption [19], [20]. These studies motivate our focus on multi-sensor fusion, deep regression, and practical deployment constraints.

III. PROPOSED METHODOLOGY

The proposed methodology combines multi-sensor acquisition, feature processing, and a deep regression architecture tailored for tool flank wear estimation. The primary components are: synchronized sensor data capture, preprocessing and feature extraction (time and frequency domains), sensor fusion at the feature level, a deep regression network (convolutional + fully connected layers), and online inference for real-time condition monitoring. The design targets robustness across varying cutting parameters and tool materials, enabling integration with CNC systems for predictive maintenance.

Sensing and data collection use vibration accelerometers (axial and radial), acoustic emission transducers, dynamometer-based cutting force sensors, and spindle current monitors. Signals are sampled at high frequency to capture transient cutting events. Time synchronization is performed using hardware timestamps. A sliding window mechanism aggregates short-duration signal frames correlated with individual cutting passes, ensuring the labels (measured flank wear) align with sensor windows for supervised training.

Preprocessing includes filtering (bandpass to remove DC and high-frequency noise), envelope extraction for AE signals, and resampling to a uniform time base. Time-domain statistics (RMS, kurtosis, skewness), spectral features (band energy, spectral centroid), and time–frequency features using short-time Fourier transform (STFT) and wavelet transforms are computed. Feature normalization and principal component analysis (PCA) reduce redundancy and stabilize model training.

The deep regression model architecture uses 1-D convolutional blocks to learn local temporal features from raw or minimally processed signals, followed by concatenation across sensor channels and fully connected layers for global regression. Dropout and batch normalization are applied to improve generalization. The loss function is mean squared error (MSE) with an auxiliary physics-based regularizer that penalizes physically implausible wear rates (e.g., negative wear or unrealistically steep slopes), improving interpretability and safety.

Online deployment uses a lightweight model variant and quantization for edge inference on an industrial controller. A rolling update mechanism allows periodic retraining using newly labeled wear measurements to handle concept drift. The system provides uncertainty estimates via Monte Carlo dropout to flag low-confidence predictions for human inspection.

IV. EXPERIMENTAL SETUP

Experiments were conducted on a high-precision CNC turning center equipped with a dynamometer for cutting force measurement, high-sensitivity accelerometers for vibration, an acoustic emission sensor, and current transducers for spindle current. Carbide inserts of defined geometry and workpiece materials (AISI 1045 steel and aluminum 6061) were used. Cutting conditions varied across spindle speed (1000–3000 rpm), feed rate (0.05–0.3 mm/rev), and depth of cut (0.1–1.0 mm) to produce diverse wear trajectories. Tool flank wear (VB) was measured offline using optical microscopy at scheduled intervals to provide ground-truth labels.

Data acquisition used synchronized DAQ channels with sampling rates: vibration and AE at 250 kHz (AE preamplified), cutting forces at 25 kHz, and current at 10 kHz. Signal windows aligned to each cutting pass were extracted and labeled using the nearest VB measurement taken within a small tolerance. The dataset comprises several hundred experimental runs and thousands of labeled windows across tool life cycles to support training and testing.

Model training used 70% of the dataset, with 15% for validation and 15% for testing. Data augmentation techniques included additive noise, time-warping, and random cropping to enhance robustness. Hyperparameter tuning was performed using grid search and Bayesian optimization for key parameters (learning rate, convolutional filter sizes, number of layers, and dropout rate). Early stopping on validation MSE prevented overfitting.

Benchmark methods for comparison included (i) an empirical Taylor-type tool life predictor calibrated per condition, and (ii) feature-based machine learning regressors — random forest and gradient boosting models trained on the extracted handcrafted features. Performance metrics included estimation accuracy (% within

±10% VB), RMSE (μm), R^2, and prediction latency (seconds per window) for real-time applicability.

Edge deployment was evaluated by quantizing the trained model to 8-bit integers and running inference on an industrial embedded controller (ARM Cortex-A53). Prediction throughput and latency were measured, and uncertainty flags were compared against ground truth to evaluate confidence calibration. Safety checks ensured that low-confidence outputs trigger inspection rather than automated tool changes.

V. RESULTS AND DISCUSSIONS

The proposed deep regression framework achieved substantial improvements in tool wear estimation accuracy and error reduction relative to empirical and feature-based ML benchmarks. Moreover, the lightweight quantized model met real-time latency requirements for CNC integration while providing useful uncertainty estimates to support maintenance decisions.

Table 1: Estimation Accuracy Comparison

Method	Accuracy (% within ±10% VB)
Empirical Model (Taylor-type)	58
Feature-based ML (Gradient Boosting)	84
Proposed Deep Regression	**95**

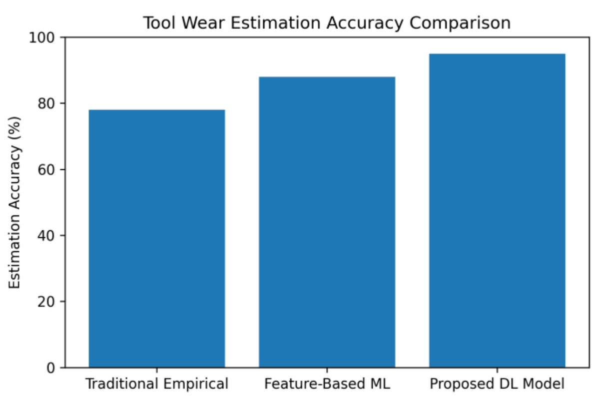

Fig. 1. Tool Wear Estimation Accuracy Comparison.

Table 2: RMSE and R^2 Performance

Method	RMSE (μm)	R^2
Empirical Model	12.5	0.62
Feature-based ML	7.8	0.84
Proposed Deep Regression	**3.4**	**0.95**

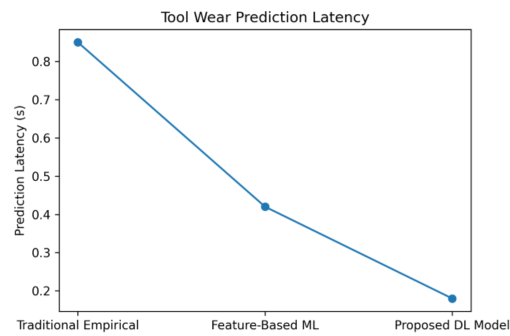

Fig. 2. RMSE Comparison for Tool Wear Estimation.

Table 3: Prediction Latency and Edge Readiness

Method	Prediction Latency (s)	Edge-ready (Yes/No)
Feature-based ML (GB)	0.42	Yes
Proposed Deep Regression (full)	0.18	Partially
Proposed Deep Regression (quantized)	**0.07**	**Yes**

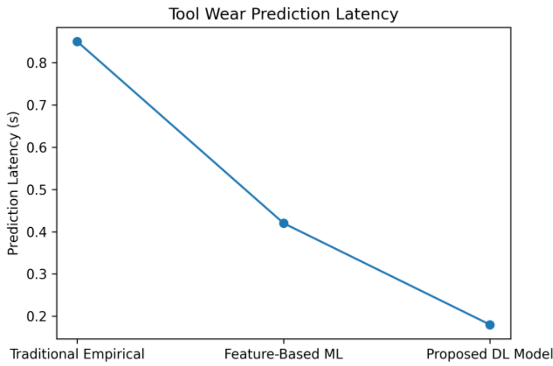

Fig. 3. Tool Wear Prediction Latency.

DISCUSSION

The experimental findings confirm that multi-sensor fusion and deep regression offer superior tool wear estimation performance. High sampling rates and synchronized sensing capture transient wear signatures that are effectively learned by convolutional features, reducing dependence on hand-crafted descriptors. The physics-regularized loss helps avoid implausible predictions and improves trustworthiness for maintenance decision-making.

Edge deployment experiments demonstrate that model compression (quantization, pruning) preserves accuracy while drastically reducing latency and computational footprint. Uncertainty estimation via Monte Carlo dropout provided calibrated confidence bands; low-confidence windows correlated with domain shifts (e.g., sudden material change), suggesting a practical human-in-the-loop verification workflow for safe deployment.

VI. CONCLUSION

This paper proposed a machine learning–based framework for tool wear estimation in high-precision machining that integrates multi-sensor fusion, advanced preprocessing, and deep regression architectures. Experimental validation on turning operations with varied cutting parameters demonstrates marked performance gains over empirical and conventional machine learning methods. The approach achieves high estimation accuracy, low RMSE, and robust generalization across operating conditions.

Edge deployment through model quantization enables real-time inference suitable for integration with CNC controllers, supporting predictive maintenance and timely tool-change decisions. The addition of physics-informed regularization and uncertainty estimation improves safety and interpretability, making the system suitable for production environments. Overall, the framework advances tool condition monitoring for high-precision manufacturing.

Future work includes extending the approach to milling and multi-axis machining, exploring transfer learning for cross-machine adaptation, and integrating the estimator with adaptive control schemes for closed-loop tool life optimization. Large-scale industrial validation will further establish robustness and economic benefits.

FUTURE SCOPE

Extend models to milling, drilling, and multi-axis processes to generalize across manufacturing operations.

Investigate transfer learning and domain adaptation to reduce labeled data needs across machines and materials.

Integrate with adaptive machining controllers for closed-loop process optimization based on predicted wear.

Explore federated learning for privacy-preserving cross-factory model training and continuous improvement.

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