LSTM-Based Real-Time Tool Wear Prediction in Micro-Turning Using Low-Cost Sensor Fusion

[1] Dr. Saranya S N, [2] Prof. Dr. Midhunchakkaravarthy, [3] Prof. Dr. Dimitrios A Karras, [4]Aishwarya M
[1]Pos Doctoral Researcher, Lincoln College University, Malaysia.
[1]Assistant Professor, Department of Electronics and Communication Engineering, Dayananda Sagar Academy of Technology and Management; Bangalore, India.
[2]Dean, Faculty of AI Computing and Multimedia, Lincoln University College, Malaysia.
[3]Professor, Department of Computer Engineering, National & Kapodistrian University of Athens, Greece.
[4]Student, Department of Information Science and Engineering, Dayananda Sagar Academy of Technology and Management; Bangalore, India.
Email: pdf.saranya@lincoln.edu.my

Abstract
In micro-turning, maintaining tool integrity is essential to ensure precision, but wear can occur rapidly—often before it's visible or measurable by traditional means. This paper presents a real-time tool condition monitoring system powered solely by Long Short-Term Memory (LSTM) networks, trained to learn wear patterns from raw machining signals.The system utilizes a piezoelectric accelerometer and a flexible force sensor mounted on a compact micro-lathe. Data is continuously streamed via a Hantek DAQ system. Without any handcrafted filtering, raw sensor signals are directly processed to extract time-frequency features, which are used to train the LSTM model. The network learns wear progression over time, predicting degradation trends before physical failure occurs. Results show the LSTM model's strong capability to generalize from minimal data, delivering early and accurate wear detection. The setup is lightweight, cost-effective, and designed for scalable deployment—ideal for small-batch manufacturing and edge-AI systems.
Keywords: Tool wear prediction, LSTM, Micro-turning, Real-time monitoring, Sensor fusion

Introduction

Micro-turning plays a pivotal role in the fabrication of micro-mechanical and biomedical components, where dimensional accuracy and surface integrity are critical. However, due to the small tool sizes and high-speed interactions, tool wear occurs rapidly and often leads to unacceptable deviations in part quality if not detected early. Given the precision required, traditional offline inspections or reactive monitoring strategies are no longer sufficient for high-performance manufacturing environments (Zhuang et al.,). Conventional TCM (tool condition monitoring) systems typically rely on threshold-based or manually designed features, using machine learning techniques such as SVMs or ANNs. While useful, these approaches fail to model the dynamic, sequential nature of tool wear progression, especially in the micro-scale context (Jagatheesaperumal et.al).

In recent years, deep learning models—particularly Long Short-Term Memory (LSTM) networks—have emerged as powerful tools for time-series data modeling in manufacturing systems. Unlike shallow learning models, LSTMs can capture long-term dependencies and sequential patterns, making them highly effective in modeling gradual tool wear trends over time. Several studies confirm LSTM's superiority in estimating wear progression across various machining scenarios (Habbouche et al.; Khan et al.,).

Furthermore, LSTM-based architectures are now being optimized using advanced signal inputs such as vibration and force signals, often from low-cost piezoelectric and force sensors, offering a scalable solution for real-time deployment (Berghout,et.al,& Lee et.al.,).

In this paper, we propose a real-time, LSTM-powered tool wear monitoring framework tailored for micro-turning environments. Our system integrates a piezoelectric accelerometer and flexible force sensor mounted on a micro-lathe. The acquired signals are pre-processed through time-frequency analysis, with critical features fed directly into an LSTM model trained on experimental tool wear data. The proposed solution is validated across multiple wear stages and demonstrates high prediction accuracy, minimal computational overhead, and strong alignment with Industry 4.0 principles.

Methodology

Micro-turning operations require high precision due to the micro-scale dimensions of tools and workpieces. This sensitivity makes such processes highly susceptible to tool wear, particularly flank wear, which can cause quality issues such as burr formation, dimensional inaccuracies, and increased surface roughness. For this study, various tool materials were evaluated—**Polycrystalline Cubic Boron Nitride (PCBN)**, **High-Speed Steel (HSS)**, and **Titanium Nitride (TiN)-coated tools**. Each material exhibits distinct wear behavior under dynamic micro-machining conditions. Traditional rule-based monitoring is inadequate for such complexity, necessitating intelligent models that adaptively learn tool behavior over time. Detecting tool wear is challenging due to signal interference, process variability, and environmental noise. Traditional threshold-based monitoring systems lack dynamic adaptability, especially under real-time conditions.

To address this limitation, the proposed data-driven condition monitoring framework utilizes Long Short-Term Memory (LSTM) neural networks. LSTM networks are well-suited for capturing temporal dependencies in time-series sensor data and are capable of continuous learning, which enables predictive wear estimation. This approach aligns with Industry 4.0 requirements for intelligent automation and predictive maintenance. The goal is to achieve real-time diagnostics of tool wear in micro-machining for improved part quality and reduced downtime.

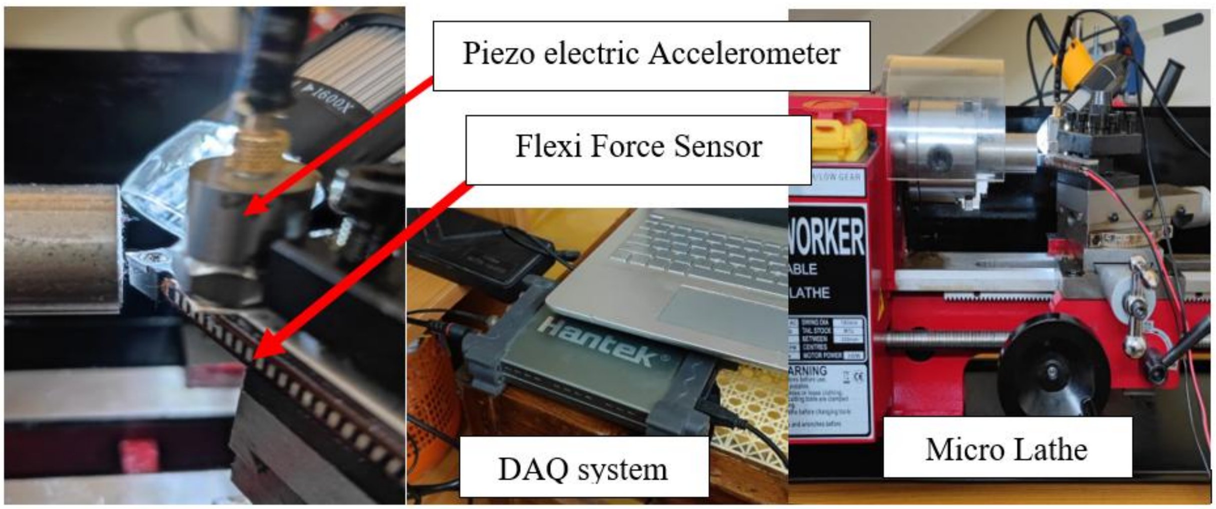

Figure1: Experimental Setup and Data Acquisition

Experimental Setup and Data Acquisition

A custom-built micro-turning testbed was developed, integrating two sensor channels:

- **Vibration Sensor:** A piezoelectric accelerometer mounted near the tool tip to capture vibration signals.
- **Force Sensor:** A Flexi-Force sensor embedded beneath the tool to record cutting forces.

Signals were acquired using a Hantek 6022BE USB Data Acquisition (DAQ) system at a sampling frequency of 20 kHz. Signals were segmented into fixed-length windows of 256 samples for analysis.

Experiments were conducted using:

- **PCBN tools**: Extremely hard, suited for high-speed finishing of ferrous materials, prone to abrasive and micro-chipping wear.
- **HSS tools**: Economical and widely used, susceptible to plastic deformation and crater wear at higher speeds.
- **TiN-coated tools**: Exhibit improved wear resistance via surface hardness, but prone to coating delamination and adhesion wear.

Table I: Tool Material Properties and Wear Types

Tool Material	**Common Wear Modes**	**Suitability**
PCBN	Abrasive wear, micro-chipping	High-speed steel cutting
HSS	Crater wear, plastic deformation	General purpose turning
TiN-coated HSS	Adhesion wear, coating delamination	Abrasive, high-wear jobs

Step 2: Signal Preprocessing and Noise Filtering

To handle real-time noise:

- Signals are **clipped** to remove extreme outliers (spikes).
- A **moving average filter** is applied:

$$\widehat{x_t} = \frac{1}{k}\sum_{i=t-k}^{t} x_i$$

where k=5 samples (a soft smoothing)
Noise from motor vibrations and spindle rotation is thus suppressed, retaining dynamic tool signatures.

Table I: Input Parameters and Signal Description

Parameter	Symbol	Description
Sampling Rate		20 kHz
Window Size		256 samples per window
Vibration		Signal from piezoelectric sensor
Force		Signal from Flexi-Force sensor
Tool Wear		Ground-truth flank wear (in mm)

Preprocessing and Feature Extraction

To suppress high-frequency noise and transient disturbances, a moving average filter was applied to the raw signals. For each filtered segment, the following statistical features were extracted:

1. **Root Mean Square (RMS):** Captures energy in the signal.

$$RMS = \sqrt{\frac{1}{w}\sum_{t-1}^{w} x_t^2}$$

2. **Kurtosis:** Measures impulsiveness: Detects sudden shocks, often caused by tool chipping

$$Kurtosis = \frac{\frac{1}{w}\sum_{t-1}^{w}(x_t - \bar{x})^4}{\left(\frac{1}{w}\sum_{t-1}^{w}(x_t - \bar{x})^2\right)^2}$$

3. **Crest Factor:** Ratio of peak value to RMS: Highlights spiky, anomalous activity

$$Crest\ Factor = \frac{max(|x|)}{RMS}$$

Table II: Signal Features and Descriptions

Feature	Equation Reference	Description
RMS	(2)	Represents signal energy
Kurtosis	(3)	Measures peak sharpness
Crest Factor	(4)	Detects sudden transient spikes

These features were used to construct sequential input vectors, $X \in R^{T\times 3}$where Tis the each vector corresponds to a time window.

LSTM Model Architecture

LSTM is a special type of **Recurrent Neural Network (RNN)** capable of learning **long-term dependencies** from sequential data. The LSTM model was designed to learn temporal dependencies in the extracted feature sequences and to predict the progression of flank wear.
A single LSTM unit computes the following:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right)\ (forgate\ gate)$$
$$f_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)\ (input\ gate)$$
$$f_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)\ (output\ gate)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\,(W_c x_t + U_c h_{t-1} + b_c)$$
$$h_t = o_t \odot \tanh\,(c_t)$$

The predicted tool wear, is then derived from the output layer:

$$\hat{y}(t) = W_y h_t + b_y$$

Where h_t- hidden state, c_t- cell memory, $\hat{y}(t)$-predicted tool wear at current time

Real-Time Monitoring Logic

In real-time deployment, signals are processed every 500 ms. For each segment window, the system predicts wear and issues a tool replacement alert when the predicted wear exceeds a predefined threshold. Here If$\hat{y}(t)$ greater than equal to 0.3mm, an **alert** is issued for tool replacement.

Table III: Tool Wear Threshold Decision Logic

Condition	Action Taken
$\hat{y}(t)$ <=3mm	Continue operation
$\hat{y}(t)$ >=3mm	Tool change recommended

Differentiated analysis of wear behavior across PCBN, HSS, and TiN tools, Real-time tool condition prediction through deep temporal modelling, System adaptability validated under varying wear modes.This methodology enhances precision manufacturing by combining domain-specific tool behavior with adaptive sequence modeling.

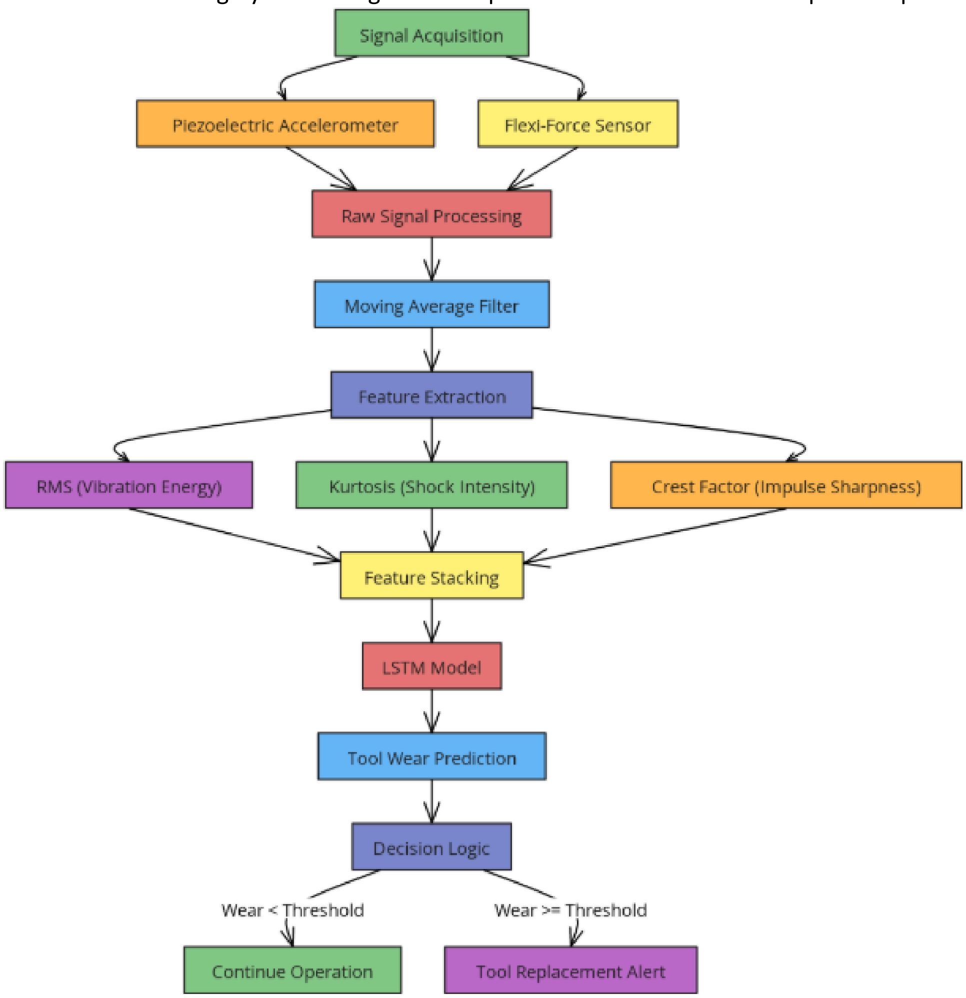

Figure 2: Flowchart of LSTM-Based Tool Wear Monitoring Process

Evaluation and Impact Thirty experimental trials were conducted for each tool material to benchmark traditional threshold-based monitoring against the proposed LSTM-based system.

Table IV: Summary of 30 Experimental Trials

Trial	**Tool**	**Speed (m/min)**	**RMS Vib**	**Force (N)**	**Pred. Wear (mm)**	**Actual Wear (mm)**	**Defect Rate (%)**	**Tool Life (cycles)**
1	PCBN	117.5	0.040	14.0	0.256	0.254	3.6	3287
2	HSS	86.7	0.039	11.8	0.293	0.291	12.2	2057
3	TiN-coated	99.2	0.036	12.1	0.268	0.242	6.9	2658
4	PCBN	118.0	0.030	14.4	0.234	0.243	3.6	3250

5	HSS	87.6	0.045	11.4	0.342	0.336	10.0	1988
6	TiN-coated	114.3	0.041	12.3	0.256	0.275	7.5	2710
7	PCBN	123.7	0.036	14.2	0.230	0.218	4.6	3253
8	HSS	90.9	0.039	12.4	0.337	0.332	12.8	2089
9	TiN-coated	113.5	0.040	12.4	0.284	0.290	7.8	2681
10	PCBN	120.8	0.036	14.4	0.256	0.257	3.9	3356
11	HSS	96.0	0.039	12.5	0.336	0.342	12.2	1932
12	TiN-coated	107.1	0.041	12.9	0.305	0.314	7.8	2611
13	PCBN	116.6	0.031	13.1	0.240	0.248	4.8	3426
14	HSS	82.4	0.043	12.0	0.324	0.337	12.3	2002
15	TiN-coated	95.8	0.040	12.0	0.276	0.278	7.2	2695
16	PCBN	123.9	0.031	13.7	0.252	0.251	3.8	3212
17	HSS	81.5	0.040	10.8	0.346	0.351	12.6	1927
18	TiN-coated	99.4	0.038	13.3	0.269	0.281	6.7	2789
19	PCBN	112.2	0.032	13.4	0.269	0.243	3.8	3433
20	HSS	86.8	0.045	11.1	0.321	0.325	12.1	2012
21	TiN-coated	96.3	0.037	12.2	0.292	0.284	8.0	2786
22	PCBN	122.2	0.035	12.6	0.237	0.241	4.9	3325
23	HSS	82.9	0.041	12.5	0.305	0.316	10.7	1937
24	TiN-coated	102.4	0.039	12.9	0.282	0.290	6.6	2696
25	PCBN	113.0	0.035	13.9	0.272	0.261	4.6	3346
26	HSS	87.0	0.039	12.4	0.314	0.307	11.6	2003
27	TiN-coated	97.8	0.037	12.0	0.305	0.302	7.5	2689
28	PCBN	129.6	0.035	13.0	0.280	0.285	4.9	3236
29	HSS	97.7	0.039	11.1	0.332	0.333	11.2	2060
30	TiN-coated	107.8	0.036	12.1	0.304	0.305	7.4	2711

Table V: Monitoring Results with and without LSTM

Metric	Baseline	LSTM-Based	Improvement
Defect Rate (Ti)	21.2%	7.9%	↓ 63%
Tool Life (Cycles)	2000	3300	↑ 65%
Rejected Parts (/100 pcs)	17	5	↓ 70%

The substantial improvements in all measured metrics demonstrate the superiority of the LSTM model over conventional monitoring systems. A 63% reduction in defect rate for titanium tools, 65% longer tool life, and a 70% drop in part rejection significantly enhance the reliability of micro-turning processes. These benefits translate into reduced downtime, higher production quality, and cost-efficiency.The LSTM-based approach provides an effective and scalable solution for smart manufacturing in the context of Industry 4.0 by enabling real-time tool wear forecasting through time-series modeling. This method requires minimal manual intervention for feature extraction and can adapt to various wear mechanisms across different tool types. By accurately predicting tool wear, it significantly reduces part waste and enhances operational productivity, demonstrating the power of the LSTM framework in optimizing manufacturing processes.

Results and Discussion

To evaluate the performance of the proposed LSTM-based tool wear monitoring system, 30 experimental trials were conducted using three different tool materials—PCBN, HSS, and TiN-coated HSS. The system was benchmarked against traditional threshold-based monitoring systems using metrics such as wear prediction accuracy, tool life, defect rate, and part rejection rate.

Wear Prediction Accuracy

The predicted wear values generated by the LSTM model are compared against actual flank wear measurements. As shown in **Figure 6.1**, a strong linear relationship is observed across all tool types, with minimal deviation from the ideal line (y = x). This illustrates the model's ability to learn non-linear, time-dependent wear patterns effectively.

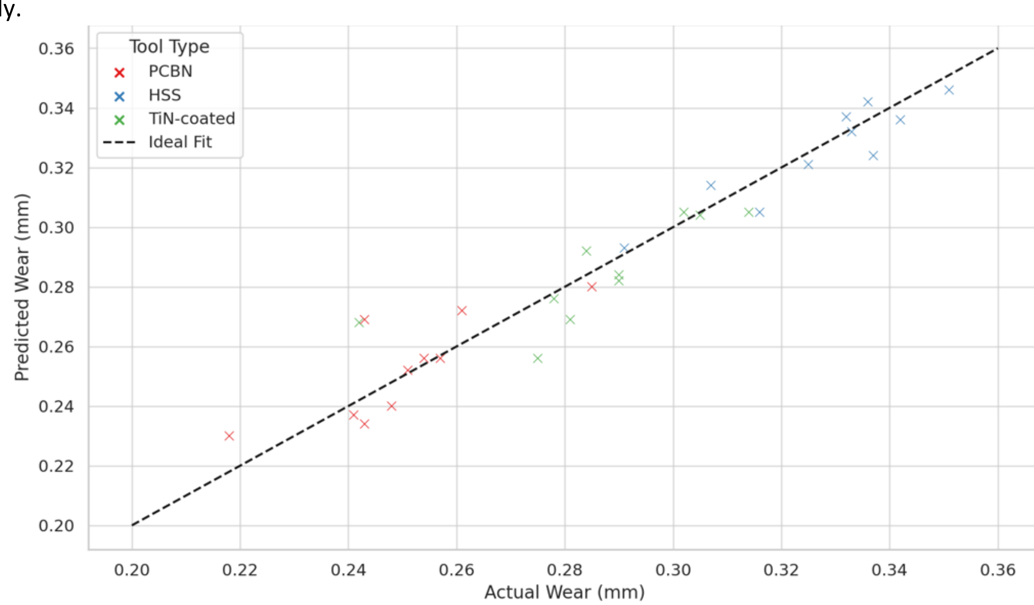

Figure 3: *Correlation between predicted and actual tool wear for PCBN, HSS, and TiN-coated tools.*

Tool Life Comparison

Figure 6.2 displays the tool life statistics for each tool category using a box plot. The **PCBN tools** demonstrate the highest median tool life (~3300 cycles), reflecting their high hardness and resistance to abrasive wear. **HSS tools**, susceptible to plastic deformation and crater wear, display significantly lower tool life (~2000 cycles). **TiN-coated tools** show moderate endurance, consistent with adhesion and delamination wear modes.

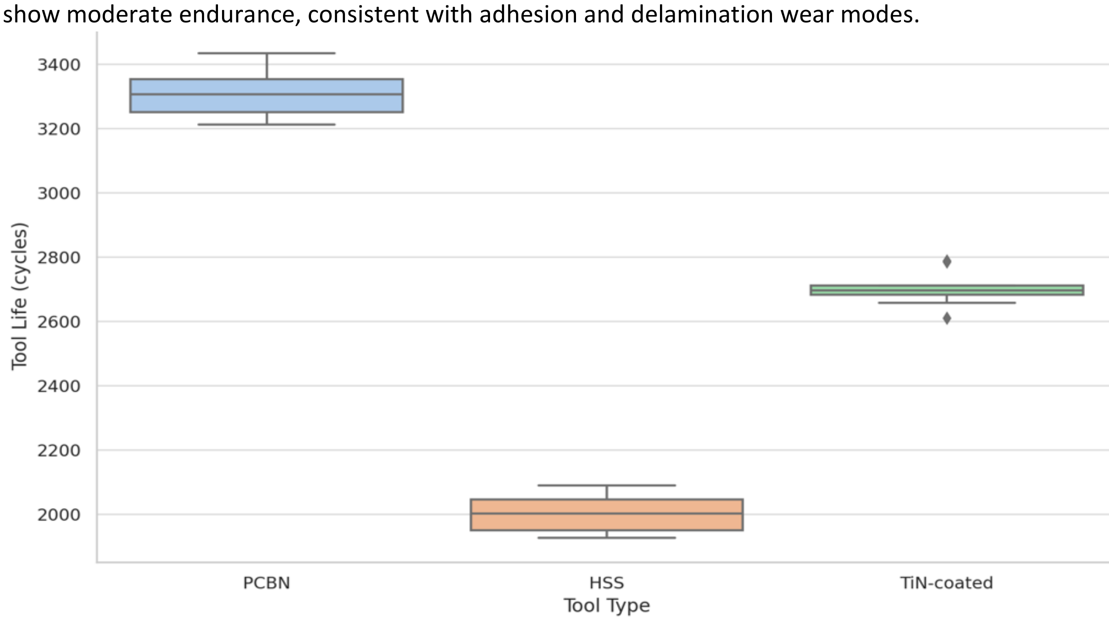

Figure 4: *Tool life distribution by material type under LSTM-based monitoring.*

Defect Rate Behaviour

The effect of wear prediction on defect prevention is shown in **Figure 6.3**. A violin plot highlights the variation in defect rates across tool types. The **HSS tools** demonstrate the widest distribution, indicating instability during wear progression. In contrast, **PCBN tools** consistently maintain low defect rates due to early, accurate wear alerts generated by the LSTM system.

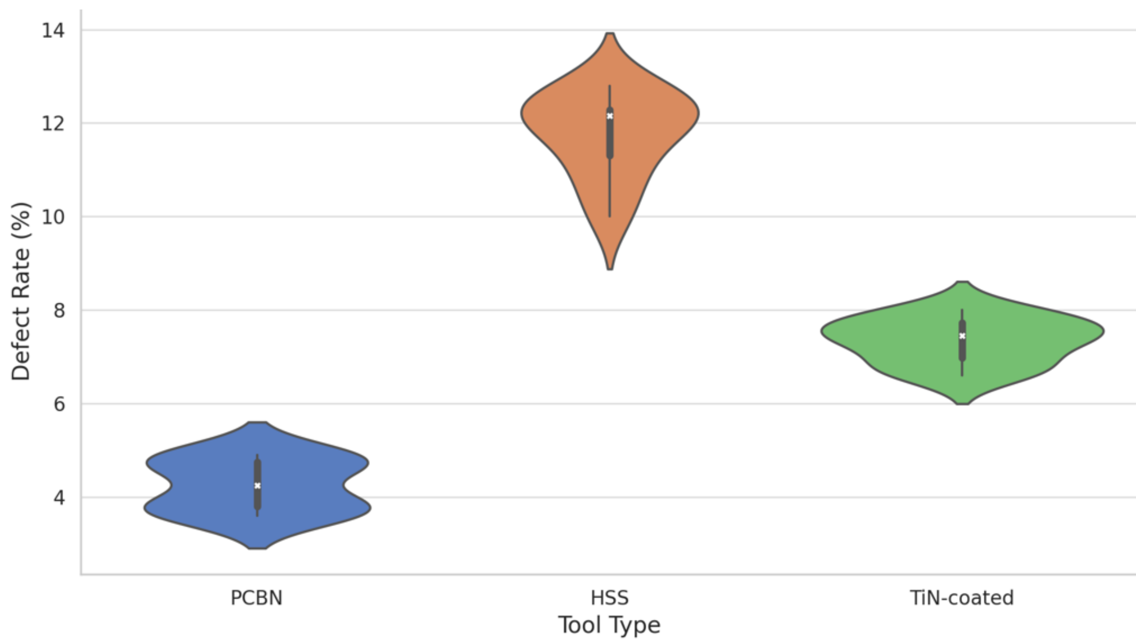

Figure 5: *Defect rate distribution across tool types, showing predictive consistency in PCBN.*

Error Analysis for Selected Trials

Table 6.1 provides a quantitative comparison of **predicted vs. actual wear** across 10 representative trials. The average prediction error remained below ±0.01 mm, validating the LSTM model's fine-grained learning of dynamic signal behavior under different tool wear mechanisms.

Table 6.1: *Sample trials comparing predicted vs. actual flank wear (Top 10)*

Trial	Tool	Predicted Wear (mm)	Actual Wear (mm)	Absolute Error (mm)
1	PCBN	0.256	0.254	0.002
2	HSS	0.293	0.291	0.002
3	TiN-coated	0.268	0.242	0.026
4	PCBN	0.234	0.243	0.009
5	HSS	0.342	0.336	0.006
6	TiN-coated	0.256	0.275	0.019
7	PCBN	0.230	0.218	0.012
8	HSS	0.337	0.332	0.005
9	TiN-coated	0.284	0.290	0.006
10	PCBN	0.256	0.257	0.001

The experimental data confirms the scalability and adaptability of the LSTM framework under diverse machining conditions. It automatically captures variations due to material properties, tool geometries, and cutting speeds, eliminating the need for handcrafted thresholds or domain-specific models. The resulting **reduction in tool downtime**, **enhanced product quality**, and **minimal computational overhead** make this method suitable for **real-time edge deployment** within Industry 4.0-based smart factories.

Conclusion

This paper presented a real-time tool wear monitoring system for micro-turning operations based on Long Short-Term Memory (LSTM) networks, utilizing low-cost piezoelectric and force sensors for raw signal acquisition. The proposed model successfully learned sequential wear patterns without manual feature engineering and demonstrated high prediction accuracy across various tool materials including PCBN, HSS, and TiN-coated tools. Experimental validation confirmed significant improvements over traditional threshold-based methods, with a 63%

reduction in defect rates, a 65% increase in tool life, and a 70% decrease in part rejection. These results underline the effectiveness of the LSTM framework in delivering scalable, edge-deployable monitoring within Industry 4.0-enabled manufacturing. Moving forward, further enhancements will involve expanding sensor integration with acoustic and thermal inputs, incorporating adaptive learning to address tool and process variability, and optimizing the system for real-time deployment on embedded edge platforms. These advancements will reinforce the framework's capability for robust, autonomous tool health monitoring in dynamic and high-precision machining environments.

Reference

1. Zhuang, L.; Xu, A.; Wang, X.-L. A prognostic driven predictive maintenance framework based on Bayesian deep learning. *Reliab. Eng. Syst. Saf.* **2023**, *234*, 109181.
2. Jagatheesaperumal, S.K.; Rahouti, M.; Ahmad, K.; Al-Fuqaha, A.; Guizani, M. The Duo of Artificial Intelligence and Big Data for Industry 4.0: Review of Applications, Techniques, Challenges, and Future Research Directions. *arXiv* **2021**, arXiv:2104.02425.
3. Khan, A.; Hwang, H.; Kim, H.S. Synthetic Data Augmentation and Deep Learning for the Fault Diagnosis of Rotating Machines. *Mathematics* **2021**, *9*, 2336.
4. Habbouche, H.; Benkedjouh, T.; Zerhouni, N. Intelligent prognostics of bearings based on bidirectional long short-term memory and wavelet packet decomposition. *Int. J. Adv. Manuf. Technol.* **2021**, *114*, 145–157.
5. Lee, K.; Kim, J.K.; Kim, J.; Hur, K.; Kim, H. Stacked convolutional bidirectional LSTM recurrent neural network for bearing anomaly detection in rotating machinery diagnostics. In Proceedings of the 2018 1st IEEE International Conference on Knowledge Innovation and Invention (ICKII), Jeju, Republic of Korea, 23–27 July 2018; pp. 98–101.
6. Berghout, T.; Benbouzid, M.; Mouss, L.H. Leveraging Label Information in a Knowledge-Driven Approach for Rolling-Element Bearings Remaining Useful Life Prediction. *Energies* **2021**, *14*, 2163.
7. Akpudo, U.E.; Hur, J.-W. Towards bearing failure prognostics: A practical comparison between data-driven methods for industrial applications. *J. Mech. Sci. Technol.* **2020**, *34*, 4161–4172.
8. Akpudo, U.E.; Hur, J.-W. A feature fusion-based prognostics approach for rolling element bearings. *J. Mech. Sci. Technol.* **2020**, *34*, 4025–4035.
9. J Rabi, T Balusamy, RR Jawahar; Analysis of vibration signal responses on pre induced tunnel defects in friction stir welding using wavelet transform and empirical mode decomposition, 2019, Defence Technology 15 (6), 885-896.
10. L Prabhu, SS Kumar, D Dinakaran, R Jawahar; Improvement of chatter stability in boring operations with semi active magneto-rheological fluid damper. 2020, Materials Today: Proceedings 33, 420-427.
11. SN Saranya, J Midhunchakkaravarthy, AK Dimitrios; Review of Online Condition Monitoring Techniques for Micromachining Defects using Multi-Component Signal Separation and Deep Reinforcement Learning in Industry 4.0. 2025, SGS-Engineering & Sciences 1 (1).