EPH–International Journal of Science & Engineering
Published by: E-Pub Solutions Private Limited
ISSN (Online): **2454-2016**
Volume 12 Issue 03 August 2026
DOI:10.67772/xhavkr56

INTELLIGENT RECOGNITION OF CNC PRODUCTION STATES FOR IMPROVED MANUFACTURING EFFICIENCY

Dr.siddharth sonwane

[1]Professor, Dept of orthodontics, Ranjeet Deshmukh Dental College and Research Centre, Nagpur/ MAHARASHTRA STATE UNIVERSITY OF HEALTH SCIENCE NASHIK. 440027, https://orcid.org/0000-0003-4766-7876, siddharth5678@gmail.com

Article History:
Article Type: Research
Received Date: **13/07/2026**
Revised Date: **12/08/2026**
Accepted Date: **19/08/2026**
Published Date:**29/08/2026**

Keywords: CNC machining, production-state recognition, machine learning, manufacturing efficiency, process monitoring

ABSTRACT

Intelligent identification of CNC production states can be used to assist real-time monitoring, and it can distinguish production and preparation, auxiliary operations, etc., and identify whether the production is in the normal state. In this study, a machine-learning-based framework to identify nine different milling states of CNC milling and determine their significance for manufacturing efficiency was created. The 25,286 observations of time-series data in 18 experiments were analysed with 45 motion, electrical, spindle and feed-rate data predictors. The classifiers under study were Gaussian Naives Bayes, Decision Tree, Random Forest and Extra Trees classifiers and evaluated using 80:20 split of data in the stratified fashion and experiment-grouped validation as a robustness check. Extra Trees had the highest on holdout (74.36%), balanced (73.73%) and macro-F1 (74.11%) scores. The best class-specific F1 score was achieved by Layer 3 Down and the best recall was achieved by Repositioning. A mean productive-time percentage was calculated for active cutting and these values were higher than for interrupted experiments (69.29%). Nevertheless, the performance of grouped validation was not as high, suggesting that the results were not easily transferable to new experiments. The framework illustrates the importance of multivariate CNC signals for state-aware monitoring, and emphasizes the need for more industrial data and more temporal structured models.

Introduction

Computer numerical control machining has become a central technology in modern production because it combines programmable precision, repeatability, and flexibility across complex manufacturing tasks. Current CNC systems are moving beyond automated motion execution toward intelligent platforms capable of sensing, interpreting, and responding to changing process conditions. Intelligent machining now integrates data acquisition, machine learning, optimization, and adaptive control to improve production reliability and resource use (Yoon et al., 2025). In the broader realm of artificial intelligence, the rise of automated diagnosis, prediction, and decision support (Rahman et al., 2023) has bolstered additive and subtractive manufacturing, enhancing their capabilities.More of the general development of AI has strengthened AMM capabilities through automated diagnosis, prediction, and decision support (Rahman et al., 2023). This has led to the recognition of production becoming an important base for autonomous manufacturing rather than being secondary monitoring.

There are multiple states in a CNC production cycle such as preparation, active cutting, transition between layers, reposition of the tool, and completion. The resulting patterns of axis position, velocity, acceleration, motor current, voltage, spindle behaviour, feed rate and power are characteristic of each state. The patterns can be reliably recognised so that a monitoring system can recognise what the machine is doing without relying only on manual observation. It has been proven that intelligent status recognition has been useful in distinguishing between multivariate industrial signals and machine and working condition (Jia et al., 2022). It has also been observed that pattern-recognition mechanisms have been used to promote autonomous recovery from milling disturbances, as an example, showing the potential for state awareness for resilient machining operations (Taha et al., 2023).

State recognition is more than just classification accuracy. Production efficiency is based on the compromise between value adding cutting time and supporting activities that include preparation and repositioning. If too much time is spent in non-cutting states, it can be a sign of workflow inefficiency, slower transitions between states, settings that are not appropriate for the process or interruptions in the process. AI can reveal these trends, and targeted manufacturing improvement can be provided using signal-based AI (Singla, 2025). In-process efficiency improvement has also been facilitated by spindle-power information, and machine signal is found to be correlated with the operational recognition and performance improvement (Jiang et al., 2024). Another practical approach is to use energy states to identify state as the energy demand of machines varies significantly between idle, transitional, and cutting operations (Xu et al., 2024).

Intelligent monitoring of modern CNC machines to create opportunity and challenges due to generating heterogeneous signals at high temporal resolution. Motion variables describe commanded and actual machine behaviour, while electrical variables reflect the loads imposed on individual axes and the spindle. Multi-source information fusion has improved the sensing of spindle-related thermal behaviour by combining complementary measurements (Yang et al., 2024). Vibration-monitoring frameworks have also shown that data quality and signal validation are essential for trustworthy CNC quality control (Apostolou et al., 2024). Intelligent operation monitoring based on energy data further demonstrates that internally available machine measurements can support status identification without extensive external instrumentation (Selvaraj et al., 2023).

Machine-learning models are well suited to this task because relationships between production states and machine measurements are nonlinear, interactive, and temporally dependent. Tree ensembles can capture complex feature interactions, while probabilistic and deep-learning methods provide alternative representations of state boundaries. Image-based machine learning has also been applied to predict milling-cutter material loss, reflecting the growing diversity of intelligent condition-recognition approaches (Li, 2024). Although reviews of intelligent machining highlight the importance of model accuracy, they also note that algorithms must be interpretable, transferable, and be compatible with the actual manufacturing constraints (Imad et al., 2022).

The digital-twin and edge-intelligence architectures provide paths for bringing the recognition model near the CNC machine. The digital twin that is enabled by edge computing can be used to link real-time signals from machines to virtual models, allowing for quick analysis and feedback on the operations of machines (Yu et al., 2023). This can be supplemented with feature recognition and optimized trajectory planning for CNC machines, which can convert process information into more efficient tool paths (Li et al., 2024). Intelligent CNC technology can thus be used not only to monitor processes but also to plan, control, and optimise production processes in an intelligent manner throughout the production cycle (Du, 2023). The recent advancements in achieving autonomous and sustainable CNC systems further underscore the necessity of monitoring systems that not only meet recognition accuracy but also achieve meaningful operational results (Lim et al., 2025).

Research has focused heavily on tool wear, fault diagnosis, thermal error, energy monitoring or overall working-status classification. The temporal composition of detailed production steps in a full milling trajectory and the conversion of this composition into efficiency indicators have received less attention. A lot of studies also are based on special sensors or are carried out for a narrow range of binary conditions, making them limited in their applicability for multiclass production monitoring. The data available for the CNC milling machine will be able to measure the X, Y and Z motors and the spindle in tandem during preparation, during the six state of milling layers, repositioning and when the parts are finished. This structure enables comparison of intelligent classifiers while quantifying productive and supporting activity durations. The study consequently aims to develop a data-driven framework for recognizing CNC production states and evaluating their relevance to manufacturing efficiency. Its objectives are:

1. To characterize CNC production states using multivariate motion, electrical, spindle, and feed-rate measurements
2. To compare machine-learning models for accurate and reliable recognition of distinct CNC machining states
3. To quantify productive and supporting machining durations as efficiency-oriented indicators across CNC experiments

2. Methodology

2.1 Research Design

A quantitative secondary-data design was adopted to build an intelligent classifier of CNC production states and links to operational efficiency (Sun, 2018). Each 100-millisecond machine observation during the 18 milling experiments was analyzed. Multiclass supervised learning found preparation, six active layer cutting states, repositioning and process completion. Descriptive analysis captured state prevalence and duration, while comparative modeling evaluated recognition accuracy. Efficiency was evaluated in terms of effective cutting time, auxiliary-state time, completion status and percentage of recorded time in active machining.

2.2 Data Source and Dataset Characteristics

The data was taken from University of Michigan SMART Laboratory CNC milling dataset. Eighteen experiments were conducted to machine S-shaped paths in wax blocks at different feed rates, clamping pressures and tool conditions. The archive contained 18 time series files and one file at the experiment level. After concatenation, there were 25,286 observations and 48 original columns. The measurements included commanded and actual position, velocity, acceleration, current, voltage, power, spindle behavior and feed rate . Categorical Machining_Process field and experiment identifiers were used to test robustness in the production-state outcome.

2.3 Data Preprocessing and Feature Engineering

The experimental files were combined and numbered 1–18. End records in lowercase were normalized to End. The single Starting record was merged with Prep. This resulted in nine classes. No missing cells detected. Machining_Process and experiment ID were excluded from predictors. M1_CURRENT_PROGRAM_NUMBER and M1_sequence_number were also deleted, as they may directly indicate programd stages. The remaining 45 numerical predictors were kept. Standardized scaling was used for Gaussian Naive Bayes and tree models used values in their original measurement scales.

2.4 Machine-Learning Development and Validation

We compared Gaussian Naive Bayes, class weighted decision tree, Random Forest and Extra Trees. Data were split into stratified training and testing sets with 80% and 20% of observations, respectively, using a random seed of 42. The Random Forest and Extra Trees models used 150 estimators and the decision tree had a minimum of two observations per terminal leaf. A complementary five-fold stratified group validation ensured that complete experiments remained together to test transferability to unseen machining runs and quantify sensitivity to experiment-specific signal patterns.

2.5 Model Evaluation and Efficiency Analysis

The performance of the recognition was assessed through accuracy, balanced accuracy, macro-precision, macro-recall, macro-F1 score and class-specific metrics. Macro measures treated all nine production states equally important despite unequal frequencies. To analyze efficiency, the number of observations was converted to minutes using the sampling interval of 0.1 seconds. The six layer-cutting classes were classified as productive states, while Prep, Repositioning, and End were treated as supporting states. The productive-time percentage was calculated for each experiment and summarized by tool condition and machining-completion status, without interpreting these descriptive relationships as causal effects.

3. Results

3.1 Analytical Dataset Profile

The consolidated data set had no missing data and 18 experiments and 25,286 observations. After harmonizing the labels, the number of production states was reduced to nine; and the production number and sequence number were removed, leaving 45 predictors for modelling. A stratified split resulted in 20,228 observations for training and 5,058 observations for testing. The number of active cutting records was 17,520 while supporting-state records were 7,766. The final analytical architecture and the indication on the number of experiments performed were provided in Table 1, so that the number of independent experiments was still limited, but the dataset provided adequate coverage of the rows to support multiclass recognition (Figure 1).

Table 1. Numerical characteristics of the analytical dataset

Characteristic	Value
Total observations	25,286
Independent experiments	18
Original variables	48
Retained predictors	45
Production-state classes	9
Missing cells	0
Training observations	20,228
Testing observations	5,058
Active-cutting observations	17,520
Supporting-state observations	7,766

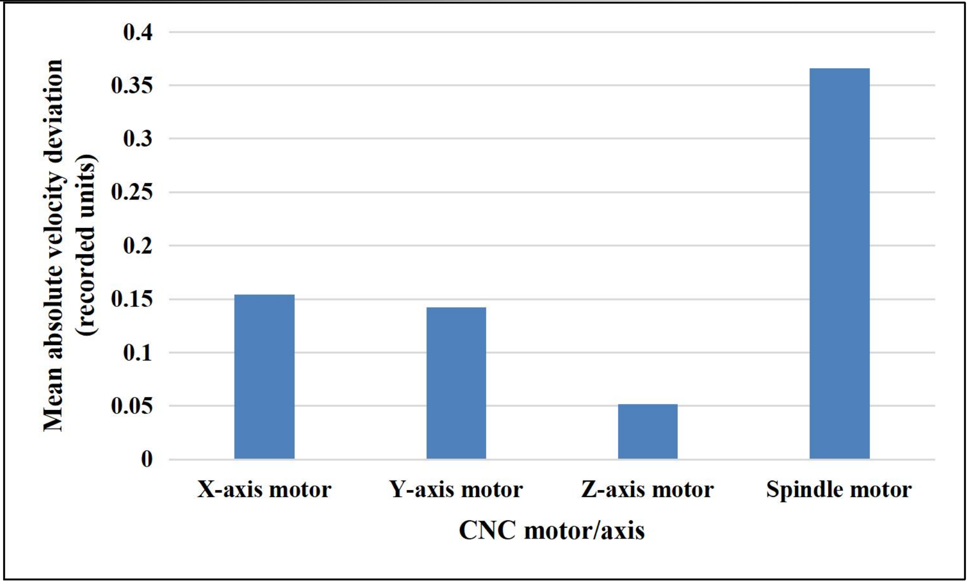

Figure 1. Mean Velocity-Tracking Deviation Across CNC Motors

3.2 Distribution of CNC Production States

There was some degree of production-state unevenness (Table 2). The largest number of observations (4,085) or 16.16% of the data was in the class titled Layer 1 Up, while the smallest class (1,796) accounted for 7.10% of the data. The 6 active cutting classes accounted for 69.29% of the total time recorded. The mean times were repositioning (5.63 minutes) and End (4.32 minutes) for all experiments. This distribution provided good coverage of all the states retained, but also revealed that approximately one-third of monitored time was spent on preparation, repositioning or completion activities (Figure 2).

Table 2. Distribution and recorded duration of CNC production states

Production state	Observations (n)	Percentage (%)	Duration (minutes)
Prep	1,796	7.10	2.99
Layer 1 Up	4,085	16.16	6.81
Layer 1 Down	2,655	10.50	4.43
Layer 2 Up	3,104	12.28	5.17
Layer 2 Down	2,528	10.00	4.21
Layer 3 Up	2,794	11.05	4.66
Layer 3 Down	2,354	9.31	3.92
Repositioning	3,377	13.36	5.63
End	2,593	10.25	4.32
Total	25,286	100.00	42.14

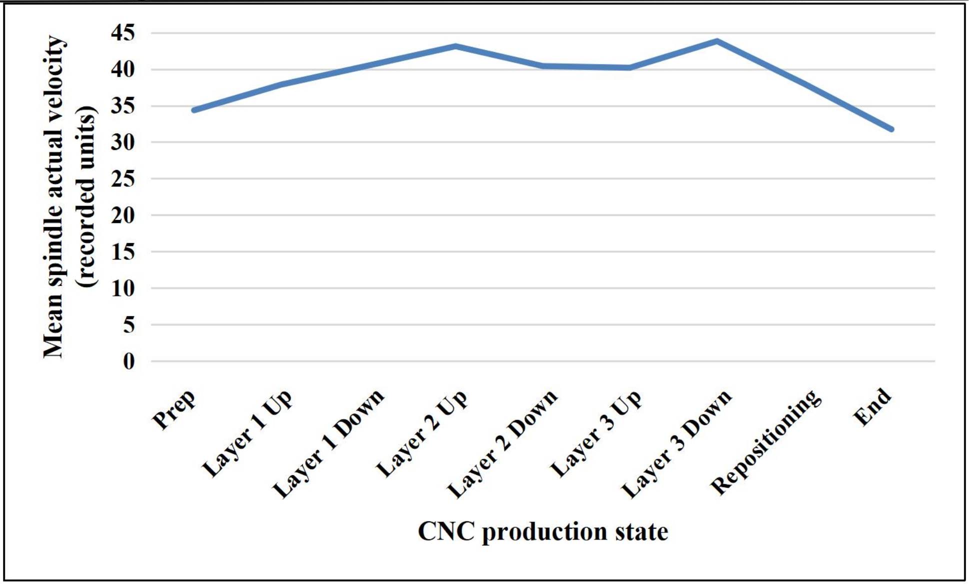

Figure 2. Mean Spindle Velocity Across CNC Production States

3.3 Comparative Model Performance

Extra Trees showed the best results on holdout data with an accuracy of 74.36%, a balanced accuracy of 73.73% and a macro-F1 score of 74.11%, as shown in Table 3. Random Forest achieved second best accuracy of 71.41% and macro-F1 of 71.11%. The performance of the decision tree was moderate, while Gaussian Naive Bayes was poor, suggesting nonlinear and interacting patterns in the signal. Every model was significantly reduced in experiment grouped validation, with the best grouped macro F1 only 11.55% for Random Forest, lack of transferability to completely unseen experimental runs for the present feature representation (Figure 3).

Table 3. Comparative performance of CNC production-state classifiers

Model	Accuracy (%)	Balanced accuracy (%)	Macro-precision (%)	Macro-recall (%)	Macro-F1 (%)	Grouped macro-F1 (%)
Gaussian Naive Bayes	14.69	14.52	15.04	14.52	9.75	6.42
Decision Tree	60.46	60.47	59.81	60.47	60.00	10.50
Random Forest	71.41	70.40	72.36	70.40	71.11	11.55
Extra Trees	74.36	73.73	74.72	73.73	74.11	11.46

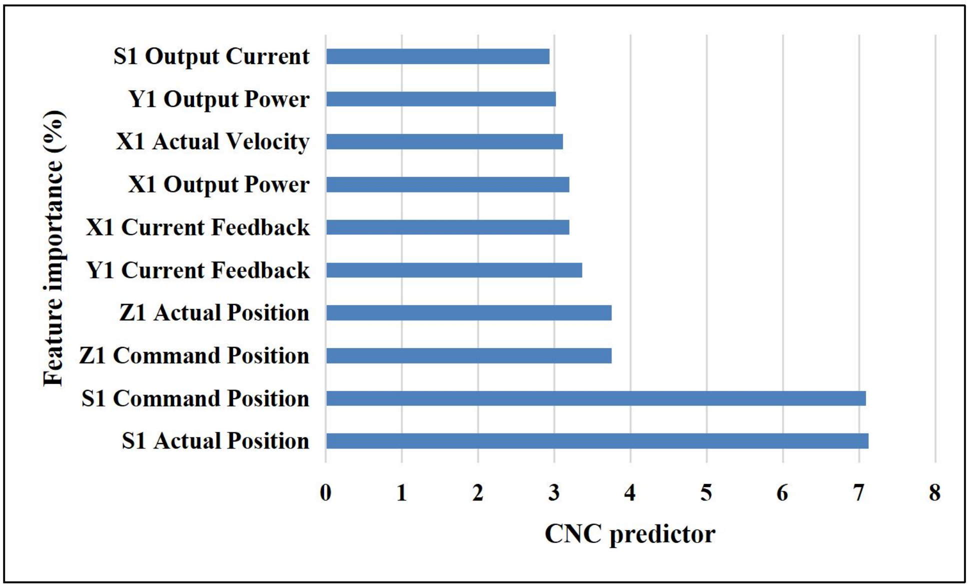

Figure 3. Feature Importance for CNC Production-State Recognition

3.4 State-Specific Recognition Performance

Table 4 presents state-specific results for the Extra Trees classifier. F1 scores ranged from 70.43% for Prep to 76.63% for Layer 3 Down, indicating relatively consistent recognition across production stages. Layer 3 Down obtained the highest F1 score, followed by Layer 2 Up and Repositioning. Prep showed the lowest recall at 64.35%, suggesting confusion with nearby supporting or transition activities. Repositioning achieved the highest recall at 79.85%, demonstrating that its multivariate machine signature was comparatively distinguishable within the stratified holdout sample.

Table 4. State-specific performance of the Extra Trees classifier

Production state	Test observations (n)	Precision (%)	Recall (%)	F1 score (%)
Prep	359	77.78	64.35	70.43
Layer 1 Up	817	73.39	76.62	74.97
Layer 1 Down	531	74.40	75.52	74.95
Layer 2 Up	621	76.58	74.24	75.39
Layer 2 Down	506	76.03	72.73	74.34
Layer 3 Up	559	74.26	72.27	73.25
Layer 3 Down	471	75.99	77.28	76.63
Repositioning	675	71.39	79.85	75.38
End	519	72.67	70.71	71.68

3.5 Manufacturing-Efficiency Patterns

The monitored experiments contained 42.14 minutes of combined machine activity, of which 29.20 minutes represented active cutting. Table 5 shows that completed experiments had a mean productive-time percentage of 72.52%, compared with 45.40% for interrupted experiments. Completed runs also lasted longer and contained more active cutting and repositioning time. Worn-tool experiments recorded a slightly higher mean productive share than unworn-tool experiments, despite shorter average duration. These findings describe operational composition rather than proving that tool wear improved efficiency or caused completion differences (Figure 4).

Table 5. Numerical efficiency indicators by experimental group

Experimental group	Experiments (n)	Mean total time (min)	Mean active time (min)	Mean preparation time (min)	Mean repositioning time (min)	Mean productive time (%)
All experiments	18	2.341	1.622	0.166	0.313	66.49
Completed	14	2.753	1.967	0.180	0.382	72.52
Interrupted	4	0.900	0.416	0.120	0.070	45.40
Unworn tool	8	2.495	1.675	0.156	0.386	64.33
Worn tool	10	2.218	1.580	0.174	0.254	68.21

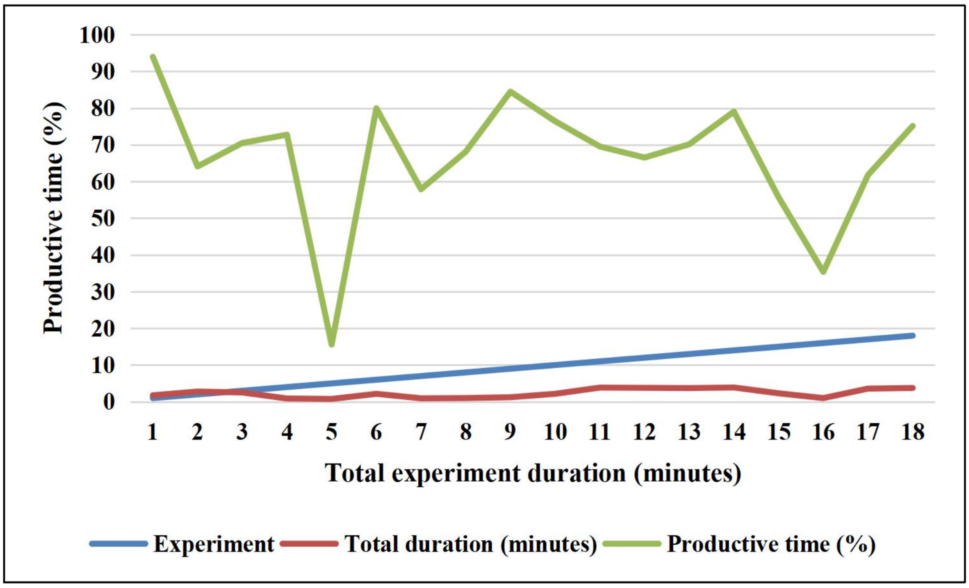

Figure 4. Relationship Between Experiment Duration and Productive-Time Percentage

4. Discussion

A qualified level of predictive performance was achieved with recognition of nine CNC production states from multivariate machine signals. Extra Trees yielded the best performance on the stratified holdout sample with 74.36% accuracy, 73.73% balanced accuracy and 74.11% macro-F1. This is its advantage over Random Forest and the single decision tree since the randomized ensembles were better able to represent nonlinear interactions among motion, electrical, spindle and feed-rate variables. The poor performance of the Gaussian Naive Bayes was due to its distributional and conditional-independence assumptions being inappropriate for strongly related CNC measurements. The similarity of accuracy and balanced accuracy also indicates that the chosen model could not have merely been the better model for the biggest production state.

The results were consistent across the nine stages of the classification, with relatively few variations by state. The highest F1 score was obtained by Layer 3 Down (76.63%) and the highest recall was achieved by Repositioning (79.85%). These results suggest that cutting and non-cutting spindle motion can be identified by multiple signatures. The lowest F1 score and recall were observed in Prep, indicating that there was an overlap between preparatory and transition/completion behaviour. The width of the F1 range was good, as it showed that the classifier was able to recognize both cutting and supporting activities and not just the more dominant one in the data. Thus production-

state recognition gave an overview of the operations other than simple binary normal vs fault classification.
The ensemble advantage is in accordance with the studies indicating that intelligent technologies can optimize manufacturing by uncovering the knowledge of the process while operating it, using complex process data (Li, 2024). The present multiclass method is an extension of this concept, which looks at the stages of the machining process within one machining trajectory in detail, in addition to forecasting final quality or equipment condition. The reuse of CNC processes has been studied and some important points for intelligent manufacturing such as, structured machining knowledge for intelligent manufacturing, converting recognized states to reusable operational information, have been pointed out. The use of continuously collected machine signals as a basis for performance monitoring is also supported by the evidence that the use of IoT and machine learning can increase the productivity of CNC-shops (Tiwari et al., 2025).
The efficiency results align with a study which correlates advanced CAM strategies and more controlled and shorter CNC processes (Satrazanis, 2025). The mean productive-time percentage was 72.52% for completed experiments and 45.40% for interrupted experiments showing that state composition can differentiate between efficient completion patterns and interrupted runs. Machine data and process interpretable production decisions are also essential to integrate process planning, digital twins, and smart manufacturing (Afif & Sarhan, 2025). The results provide an additional layer of state recognition that can be used as input for such integrated systems. The current results indicate that operational classification is also possible by internal controller measurements and have shown that surface-roughness prediction can improve precision with vibration-assisted artificial intelligence.
The results also support arguments that the artificial intelligence can support CNC optimization by adaptive analysis of machining behaviour (Bai, 2025). The real-time condition monitoring and self-adaptive control have been identified as relevant deployment pathways for multi-sensor digital-twin research, which is a relevant deployment pathway for the identified state patterns (Zhang et al., 2025). The ability to recognize preparation, cutting, repositioning and completion may provide the digital twin with timely contextual information prior to the selection of control actions. The same understanding also aligns with the growing use of robotics automation in CNC machine tools, where it is essential to coordinate machines, material handling, and automated responses (Soori et al., 2024).
The operational analysis revealed that 69.29% of the total sequence recorded was active cutting, while 30.71% was spent on preparation, repositioning and completion. Re-positioning took 5.63 minutes, which is a target for trajectory/scheduling improvement. The higher productive share from the worn-tool experiments should not be taken as a positive wear effect as there was a variation in both the feed rate, clamping pressure, completion status and experiment duration. The best use of the framework is as a diagnostic tool to help identify time allocations and also flag time periods of unusual durations. The outputs generated by the managers can be used to compare cycles, explore long supporting activities and prioritize process changes.
There are some caveats that should be borne in mind when interpreting the results. There were only 18 independent experiments performed, which used the same configuration of the CNC machine and wax workpieces in one laboratory. The drastic decrease of the macro-F1 score from 30.64% to 11.55% shows that models based on row-level observations were not readily transferrable to totally unseen experiments. Time allocation and completion-related efficiency factors were used to represent manufacturing efficiency rather than direct throughput, cost or energy efficiency. Research into future work should focus on more independent runs, machines, tools, and workpiece materials, build window-based temporal features, and run sequence models with grouped validation. Recognized states can achieve measurable productivity gains and significantly shorten repositioning time and enhance cycle completion, as determined by real-time industrial testing.

5. Conclusion

Intelligent recognition of CNC production states was demonstrated using 25,286 time-series observations of nine preparation, cutting, repositioning, and completion states were successfully used to demonstrate intelligent recognition of CNC production states. The findings indicated that multivariate motion, electrical, spindle and feed-rate measurements have enough information to differentiate the production activities, but this was not the case for all validation settings. The model with the highest accuracy, balanced accuracy and macro-F1 on the stratified test set was Extra Trees with 74.36%, 73.73% and 74.11%, respectively. The results were relatively similar at the state level with Layer 3 Down achieving the highest F1 score and Repositioning achieving the highest recall. The framework can be used to make the controller signals received reliably into understandable information about the activity of the machine and the development of the process and thus contributes to intelligent CNC monitoring. Active cutting comprised 69.29% of all monitored time and preparation, repositioning and completion made up the other 30.71% of the monitored time, highlighting the potential for opportunities for improvements in productive time allocation and resource utilization through state recognition. No need to move towards fully autonomous control; deployment should begin with decision support and operational diagnostics. Further studies are needed to validate the framework with additional experiments that are independent of each other, industrial CNC machines, different tools and workpiece materials, and temporal structured models. But real time trials should also prove if known states can really decrease the need for unnecessary repositioning, increase completion rates, decrease the amount of energy needed, and provide measurable productivity gains.

References

1. Afif, M. F., & Sarhan, A. A. D. (2025). Computer-aided process planning, digital twin, and smart manufacturing: interconnections and integration in CNC machining processes. International Journal of Production Research, 63(24), 9593-9632.
2. Apostolou, G., Ntemi, M., Paraschos, S., Gialampoukidis, I., Rizzi, A., Vrochidis, S., & Kompatsiaris, I. (2024). Novel framework for quality control in vibration monitoring of CNC machining. Sensors, 24(1), 307.
3. Bai, Z. (2025). Enhancing Mechanical Design, Manufacturing, and Automation through AI-Based Computer Numerical Control (CNC) Optimization. Revista Gestão & Tecnologia, 25(2), 74-89.
4. Du, S. (2023, November). Analysis of the application of intelligent CNC technology in machinery manufacturing. In Journal of Physics: Conference Series (Vol. 2649, No. 1, p. 012010). IOP Publishing.
5. Imad, M., Hopkins, C., Hosseini, A., Yussefian, N. Z., & Kishawy, H. A. (2022). Intelligent machining: a review of trends, achievements and current progress. International Journal of Computer Integrated Manufacturing, 35(4-5), 359-387.
6. Jia, F., Jebelli, A., Ma, Y., & Ahmad, R. (2022). An intelligent manufacturing approach based on a novel deep learning method for automatic machine and working status recognition. Applied Sciences, 12(11), 5697.
7. Jiang, Y., Liu, K., Huang, J., Zhao, D., Yang, W., & Wang, Y. (2024). Intelligent in-process enhancement technique for machining efficiency in CNC machine tools based on spindle power. Mechanical Systems and Signal Processing, 216, 111495.
8. Li, P., Chen, M., Ji, C., Zhou, Z., Lin, X., & Yu, D. (2024). An agent-based method for feature recognition and path optimization of computer numerical control machining trajectories. Sensors, 24(17), 5720.
9. Li, Z. (2024). Transforming manufacturing with intelligent technologies: Process optimization and industry applications. In Matec web of conferences (Vol. 404, p. 02006). EDP Sciences.
10. Lim, J. M., Song, W., Lee, J. S., Park, J. M., Shin, H. M., Oh, I. W., ... & Min, B. K. (2025). Recent advances in CNC technology: Toward autonomous and sustainable manufacturing. International Journal of Precision Engineering and Manufacturing, 26(9), 2311-2344.
11. Rahman, M. A., Saleh, T., Jahan, M. P., McGarry, C., Chaudhari, A., Huang, R., ... & Shakur, M. S. (2023). Review of intelligence for additive and subtractive manufacturing: current status and future prospects. Micromachines, 14(3), 508.
12. Satrazanis, C. (2025). A Strategic Approach to Enhancing Manufacturing Efficiency Using

Advanced CAM Software for CNC Machining Processes (Doctoral dissertation, School of Science and Technology).
13. Selvaraj, V., Xu, Z., & Min, S. (2023). Intelligent operation monitoring of an ultra-precision CNC machine tool using energy data. International Journal of Precision Engineering and Manufacturing-Green Technology, 10(1), 59-69.
14. Singla, U. (2025). Optimizing Manufacturing Processes With AI: A Signal-Based CNC Machining Case Study In The Automotive Industry. INTERNATIONAL JOURNAL OF ADVANCES IN SIGNAL AND IMAGE SCIENCES, 1687-1704.
15. Soori, M., Jough, F. K. G., Dastres, R., & Arezoo, B. (2024). Robotical automation in CNC machine tools: a review. acta mechanica et automatica, 18(3), 434-450.
16. Sun, S. (2018). CNC mill tool wear (Version 4) [Data set]. Kaggle. https://www.kaggle.com/datasets/shasun/tool-wear-detection-in-cnc-mill
17. Taha, H. A., Yacout, S., & Shaban, Y. (2023). Autonomous self-healing mechanism for a CNC milling machine based on pattern recognition. Journal of Intelligent Manufacturing, 34(5), 2185-2205.
18. Tiwari, N., Jaju, S., & Untawale, S. (2025, August). Integrating IoT and Machine Learning for Productivity Improvement in CNC Machine Shop. In 2025 12th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP) (pp. 1-6). IEEE.
19. Xu, Z., Selvaraj, V., & Min, S. (2024). State identification of a 5-axis ultra-precision CNC machine tool using energy consumption data assisted by multi-output densely connected 1D-CNN model. Journal of Intelligent Manufacturing, 35(1), 147-160.
20. Yang, Z., Liu, B., Zhang, Y., Chen, Y., Zhao, H., Zhang, G., ... & Zhang, Z. (2024). Intelligent sensing of thermal error of CNC machine tool spindle based on multi-source information fusion. Sensors, 24(11), 3614.
21. Yoon, J. S., Park, I. H., & Lee, D. Y. (2025). A Review of Intelligent Machining Process in CNC Machine Tool Systems. International Journal of Precision Engineering and Manufacturing, 26(9), 2243-2268.
22. Yu, H., Yu, D., Wang, C., Hu, Y., & Li, Y. (2023). Edge intelligence-driven digital twin of CNC system: Architecture and deployment. Robotics and Computer-Integrated Manufacturing, 79, 102418.
23. Zhang, J., Li, C., Deng, C., Luo, T., Deng, R., Luo, D., ... & Cao, H. (2025). Toward digital twins for intelligence manufacturing: Self-adaptive control in assisted equipment through multi-sensor fusion smart tool real-time machine condition monitoring. Journal of Manufacturing Systems, 82, 301-318.