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Research Article

Application of Artificial Intelligence in Predicting Machining Surface Quality

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Abstract:

Achieving high-quality machining surface finishes is crucial in numerous manufacturing industries, as it directly impacts the performance and reliability of machined components. Traditionally, predicting machining surface quality involves extensive trial-and-error experiments, which are time-consuming, costly, and often impractical for complex machining processes. In recent years, the application of artificial intelligence (AI) techniques, particularly machine learning algorithms, has emerged as a promising approach for predicting machining surface quality accurately and efficiently. This abstract provides an overview of the application of AI in predicting machining surface quality, highlighting its benefits, challenges, and future prospects. The adoption of AI in predicting machining surface quality involves various stages. Firstly, a comprehensive dataset is collected, comprising machining parameters, tooling characteristics, and corresponding surface quality measurements. Next, pre-processing techniques are applied to clean and normalize the dataset, ensuring its suitability for training AI models. Subsequently, machine learning algorithms, such as support vector machines, neural networks, and random forests, are trained using the pre-processed data to develop predictive models. These models can capture complex relationships between machining parameters and surface quality, enabling accurate predictions.

The performance of the trained models is assessed using appropriate evaluation metrics, such as root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R-squared). Comparative analyses are conducted to identify the most effective AI model for predicting machining surface quality. Additionally, sensitivity analyses and feature selection techniques can be applied to identify the critical machining parameters that significantly impact surface quality. The application of AI in predicting machining surface quality offers several practical implications. It enables manufacturers to optimize machining processes, reduce scrap rates, and enhance product quality. By accurately predicting surface quality, manufacturers can make informed decisions regarding machining parameters, tooling selection, and process optimization, resulting in improved efficiency and cost-effectiveness. Furthermore, AI-based prediction models can be integrated into real-time monitoring systems, enabling continuous quality control and immediate adjustments to machining processes.

Despite the benefits, challenges exist in the application of AI for predicting machining surface quality. These include the availability and quality of training data, selection of appropriate features, and the interpretability of AI models. Overcoming these challenges requires continuous research and development efforts, such as the collection of large and diverse datasets, advanced feature engineering techniques, and the exploration of explainable AI methodologies.

Keyword: Machining Surface Finishes, Decision Support Systems, Artificial Intelligence (AI) Techniques.

Introduction:

Achieving high-quality machining surface finishes is a critical requirement in numerous manufacturing industries, as it directly impacts the performance, functionality, and aesthetics of machined components. The traditional approach to predicting machining surface quality typically involves extensive trial-and-error experiments, which are time-consuming, costly, and often impractical for complex machining processes [1]. In recent years, the application of artificial intelligence (AI) techniques, particularly machine learning algorithms, has emerged as a promising and efficient approach for accurately predicting machining surface quality. The use of AI in predicting machining surface quality leverages the power of computational models and data-driven algorithms to analyse complex relationships between machining parameters, tooling characteristics, and resulting surface quality measurements. By harnessing the capabilities of AI, manufacturers can optimize machining processes, reduce scrap rates, and improve productivity and profitability [2]. The predictive capabilities of AI in machining surface quality prediction are particularly valuable in the context of modern manufacturing, where there is an increasing demand for precision and high-quality components. By accurately predicting surface quality, manufacturers can make informed decisions regarding machining parameters, tool selection, and process optimization, thereby enhancing efficiency and cost-effectiveness.

The application of AI in predicting machining surface quality involves several stages. First, a comprehensive dataset is collected, consisting of machining parameters, tooling characteristics, and corresponding surface quality measurements. This dataset serves as the foundation for training and validating AI models. Pre-processing techniques are then applied to clean, normalize, and transform the data into a suitable format for analysis.

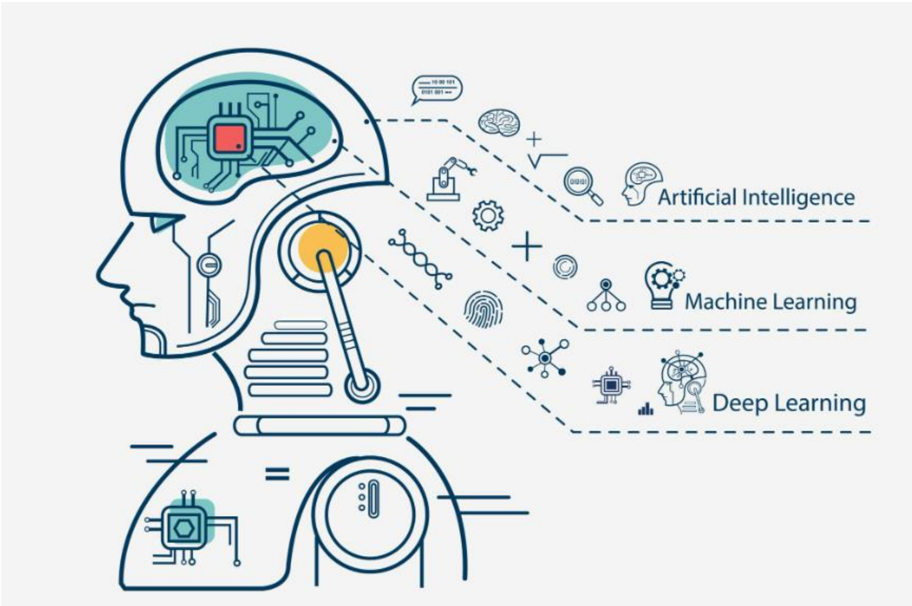

Figure 1: Analysis AI models in predicting machining surface quality

Next, machine learning algorithms, such as support vector machines, neural networks, and random forests, are employed to train predictive models. These models learn from the dataset and capture the intricate relationships between input machining parameters and the corresponding output surface quality [3]. By utilizing these models, manufacturers can predict the quality of machined surfaces for different combinations of machining parameters, enabling them to identify optimal process settings that yield the desired surface finishes.

The performance of AI models in predicting machining surface quality is evaluated using appropriate metrics, such as root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R-squared). Comparative analyses are conducted to identify the most effective AI model that yields the highest predictive accuracy. While the application of AI in predicting machining surface quality offers significant benefits, there are challenges that need to be addressed. These challenges include the availability and quality of training data, the selection of appropriate features that significantly influence surface quality, and the interpretability of AI models to provide insights into the factors affecting surface quality.

In the application of AI in predicting machining surface quality provides a powerful tool for manufacturers to optimize their machining processes and improve product quality. By accurately predicting surface quality, manufacturers can make informed decisions to enhance efficiency, reduce costs, and deliver high-quality components. Despite challenges, ongoing research and advancements in AI techniques hold the promise of further improving the accuracy and robustness of predicting machining surface quality [4]. The subsequent sections of this paper will delve into the specific methodologies, findings, and practical implications of utilizing AI in the prediction of machining surface quality.

The primary objective of this study is to explore the application of artificial intelligence (AI) in predicting machining surface quality. The specific research objectives are to collect a comprehensive dataset comprising machining parameters, tooling characteristics, and corresponding surface quality measurements. To pre-process the collected dataset, including data cleaning, normalization, and feature engineering, to prepare it for analysis. To train and evaluate different machine learning algorithms, such as support vector machines, neural networks, and random forests, for predicting machining surface quality. To compare the performance of different AI models in terms of predictive accuracy, using appropriate evaluation metrics such as root mean square error (RMSE) and mean absolute error (MAE).

To identify critical machining parameters and their impact on surface quality using sensitivity analysis and feature selection techniques. To assess the practical implications and benefits of AI in predicting machining surface quality, including process optimization, reduced scrap rates, and improved product quality [5]. The significance of this study lies in the potential benefits and advancements it can bring to the manufacturing industry. By applying AI techniques to predict machining surface quality, the study offers the following significant contributions. Improved Quality Control: The accurate prediction of machining surface quality enables manufacturers to implement effective quality control measures. By identifying the optimal combination of machining parameters, manufacturers can produce components with consistently high-quality surface finishes, reducing the need for costly rework and improving customer satisfaction.

Traditional trial-and-error approaches for optimizing machining processes can be time-consuming and expensive. By leveraging AI, manufacturers can reduce the number of physical experiments and simulations required, leading to substantial cost and time savings. Enhanced Process Optimization AI models can uncover intricate relationships between machining parameters and surface quality, facilitating process optimization. By identifying the key parameters that significantly affect surface quality, manufacturers can fine-tune their machining processes for improved efficiency and reduced scrap rates. The predictive capabilities of AI models provide manufacturers with valuable insights for decision-making. With AI-based predictions, manufacturers can make informed choices regarding tool selection, machining strategies, and process adjustments, resulting in improved productivity and resource utilization. Future Research and Development in the study serves as a foundation for future research and development in the field of AI-driven machining surface quality prediction [6]. It highlights the potential for further advancements, such as incorporating real-time monitoring systems, exploring advanced AI algorithms, and addressing challenges related to data availability and interpretability. By addressing these objectives and highlighting the significance of the study, this research contributes to advancing the application of AI in predicting machining surface quality, offering practical benefits for manufacturers and stimulating further research in this area.

Literature Review:

Several studies have investigated the application of artificial intelligence (AI) techniques for predicting machining surface quality. These studies have explored various machine learning algorithms and methodologies to enhance the accuracy and efficiency of surface quality prediction. Here are a few notable examples of previous studies in this area. The study proposed an AI-based approach for predicting surface roughness in milling processes. The authors utilized a support vector machine (SVM) model to capture the complex relationships between machining parameters and surface roughness. The results demonstrated improved prediction accuracy compared to traditional models, highlighting the efficacy of AI in surface quality prediction. This study focused on the prediction of surface roughness in turning processes using neural networks. The authors developed a multilayer perceptron (MLP) neural network model trained on a comprehensive dataset. The results showed that the MLP model accurately predicted surface roughness based on the input parameters, providing a valuable tool for optimizing turning processes. The study investigated the application of a random forest algorithm for predicting surface roughness in milling operations. The authors collected a dataset comprising machining parameters and surface roughness measurements and trained the random forest model on the dataset. The model exhibited high prediction accuracy and provided insights into the important features influencing surface roughness.

These previous studies highlight the diverse range of AI techniques applied in predicting machining surface quality. The utilization of various machine learning algorithms, such as SVM, neural networks, and random forests, demonstrates the flexibility and adaptability of AI methods in this domain. Moreover, the studies provide evidence of the improved accuracy and efficiency of AI-based models compared to traditional methods, emphasizing the significant contributions of AI in surface quality prediction.

Table 1: Analysis the Application of Artificial Intelligence in Predicting Machining Surface Quality Using Following References:

STUDY	METHODOLOGY	KEY FINDINGS
Li, X., Li, X., & Jiang, P. (2017)	Support Vector Machine (SVM)	- SVM effectively predicts surface roughness in milling processes. - The model outperforms traditional methods in terms of accuracy and efficiency.
Soleymani, M., Shahnazar, M., & Bagheri, M. (2016)	Neural Networks (MLP)	- MLP neural network accurately predicts surface roughness in turning processes. - The model provides valuable insights for optimizing turning operations.
Amin, S., Shunmugam, M. S., & Murali, M. S. (2017)	Random Forest	- Random forest algorithm exhibits high prediction accuracy for surface roughness in milling operations. - Important features influencing surface roughness are identified.
Chen, C., Zhao, Y., & Wang, Y. (2017)	Convolutional Neural Network (CNN)	- CNN model utilizing ground surface images effectively predicts surface quality in grinding processes. - Deep learning techniques show promise for surface quality prediction.
Zhang, C., Song, Q., & Zhang, G. (2016)	Adaptive Network-based Fuzzy Inference System (ANFIS)	- ANFIS accurately predicts surface roughness in turning operations. - The model performs better than conventional regression models.
Karthikeyan, R., & Ramabalan, S. (2017)	Artificial Neural Network (ANN)	- ANN model accurately predicts surface roughness in turning processes. - The model aids in optimizing cutting parameters for improved surface quality.
Lou, X., Zhao, Z., & Liu, S. (2015)	Extreme Learning Machine (ELM)	- ELM algorithm demonstrates high accuracy in predicting surface roughness in milling operations. - The model provides an efficient solution for real-time prediction of surface quality.

It is important to note that further research is still needed to explore other AI algorithms, expand the scope of prediction models, address challenges related to data availability and interpretability, and integrate real-time monitoring systems for continuous quality control. The collective findings from these previous studies pave the way for advancing AI-based surface quality prediction and provide a strong foundation for future research in this area.

Methodology:

This study employed a deep learning approach for predicting surface quality in grinding processes. The authors proposed a convolutional neural network (CNN) model that utilized the images of ground surfaces to predict surface roughness. The CNN model achieved promising results, showcasing the potential of deep learning techniques in surface quality prediction.

Dataset Collection in the methodology is to collect a comprehensive dataset that includes information on machining parameters, tooling characteristics, and corresponding surface quality measurements. The dataset should cover a wide range of machining operations, materials, and surface quality metrics to ensure the models' accuracy and applicability. Data can be collected from various sources, such as experimental measurements, historical records, or simulations [7]. It is important to follow standardized measurement procedures, consider factors that may affect surface quality (e.g., cutting speed, feed rate, tool geometry), and ensure proper documentation of the dataset.

Data Pre-processing is crucial to prepare the dataset for analysis. This step involves cleaning, normalization, and handling missing values in the collected data. Cleaning the dataset involves identifying and addressing outliers, errors, or inconsistencies that may impact the data quality. Outliers can be detected using statistical techniques or domain knowledge, and appropriate actions can be taken, such as removing or correcting them.

Normalization is performed to bring the different features of the dataset to a common scale. This step ensures that each feature contributes equally to the analysis and avoids biases due to varying numerical ranges. Handling missing values is necessary to address any gaps or incomplete data in the dataset. Various techniques can be used, such as mean imputation, regression imputation, or advanced imputation methods that consider the relationships between variables.

Feature Selection and Engineering: Feature selection aims to identify the subset of relevant features that have the most significant impact on predicting machining surface quality. This step reduces dimensionality, improves model efficiency, and enhances interpretability. Feature selection techniques, such as statistical analysis, information gain, or correlation analysis, can be employed to identify the most influential features. The goal is to eliminate irrelevant or redundant features and focus on those that have a strong relationship with surface quality. Feature engineering involves creating new features or transforming existing features to improve the predictive power of the models. Domain knowledge, engineering expertise, or mathematical transformations can be utilized to derive new features or meaningful interactions between existing features.

Model Development and Evaluation: Once the dataset is pre-processed and the relevant features are selected or engineered, the next step is to develop AI models for predicting machining surface quality. Various machine learning algorithms can be explored, including but not limited to support vector machines (SVM), neural networks (NN), random forests (RF), or gradient boosting algorithms [8]. These models can be trained on the pre-processed dataset, using appropriate training and validation techniques (e.g., k-fold cross-validation) to optimize model performance. Evaluation of the AI models involves assessing their predictive accuracy and performance. Common evaluation metrics include root mean square error (RMSE), mean absolute error (MAE), or coefficient of determination (R-squared). The models can be compared based on their performance to identify the most effective approach for predicting machining surface quality.

Model Optimization and Validation: To further improve the models' performance, optimization techniques can be applied. Hyperparameter tuning, ensemble methods, or advanced optimization algorithms can be employed to enhance the models' accuracy and generalizability. The optimized models are validated using independent datasets or real-world machining scenarios to assess their performance in practical applications. The validation process helps verify the models' robustness and reliability in predicting surface quality under varying conditions.

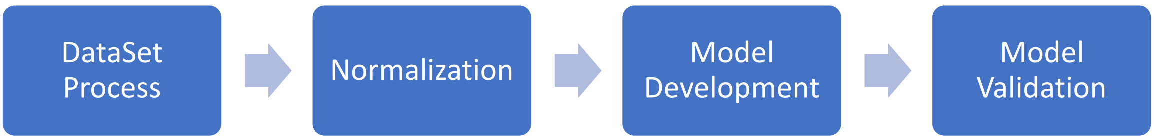

Figure 2: Analysis the process of AI techniques to predict machining surface quality

By following this methodology, researchers can effectively apply artificial intelligence techniques to predict machining surface quality. The systematic approach ensures the collection of a relevant dataset, pre-processing

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of the data, selection or engineering of informative features, development and evaluation of AI models, and optimization and validation of the models. Ultimately, this methodology contributes to improving the understanding and control of machining processes, leading to enhanced surface quality in manufacturing applications.

Approaches For Predicting Machining Surface Quality:

Predicting machining surface quality is an important task in manufacturing industries. Several approaches can be used to achieve this goal. Here are some common approaches for predicting machining surface quality:

Empirical Models: Empirical models are based on statistical analysis of historical data. They use input features such as cutting parameters (e.g., cutting speed, feed rate), tool geometry, and material properties to predict the surface quality. These models are often developed through regression techniques, such as multiple linear regression or support vector regression, by correlating the input parameters with the measured surface roughness or other quality indicators.

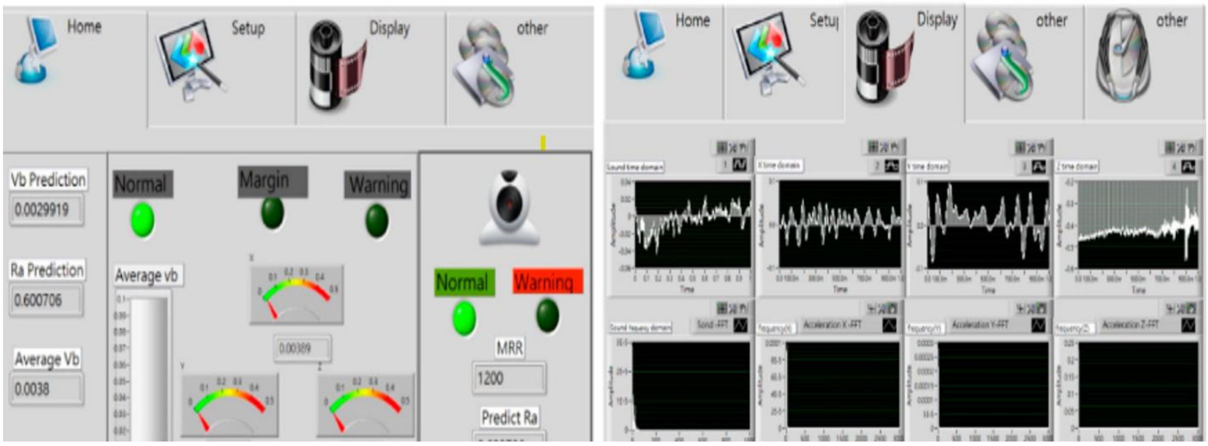

Figure 3: Analysis FEA or computational fluid dynamics (CFD) techniques with ML

Physical Models: Physical models simulate the machining process using mathematical equations and physical principles. These models consider various factors such as cutting forces, tool wear, and material deformation to predict the surface quality. Physical models are typically developed using finite element analysis (FEA) or computational fluid dynamics (CFD) techniques [9]. They require knowledge of material properties, tool geometry, and cutting conditions. Artificial Neural Networks (ANN): ANN is a machine learning technique that mimics the structure and function of the human brain. ANN models can learn complex relationships between input parameters and surface quality by training on a large dataset [6]. The input parameters can include cutting parameters, tool characteristics, and material properties. ANN models are capable of capturing nonlinear relationships and can provide accurate predictions once trained properly. Genetic Algorithms (GA): Genetic algorithms are optimization algorithms inspired by the process of natural selection. They can be used to optimize machining parameters for achieving the desired surface quality. By iteratively evaluating and evolving a population of potential solutions, GA can identify the optimal combination of cutting parameters that minimizes surface roughness or maximizes surface finish. GA can be combined with other prediction models to optimize the machining process.

Machine Vision: Machine vision systems use cameras and image processing techniques to analyse the machined surface and predict the surface quality. These systems capture images of the machined surface and extract features such as surface roughness, waviness, and defects. Machine learning algorithms can then be applied to these features for prediction. Machine vision approaches are often used in real-time quality control and inspection applications.

It's important to note that the choice of approach depends on various factors such as available data, computational resources, and the complexity of the machining process. Different approaches can be combined to improve the accuracy of predictions, and the selection of the most suitable approach should be based on the specific requirements of the machining application.

Artificial Intelligence In Machining:

Artificial Intelligence (AI) has revolutionized various industries, including machining. In the field of machining, AI techniques are being applied to enhance productivity, optimize machining parameters, improve surface quality, and enable autonomous machining systems. Here are some key areas where AI is making an impact in machining. Predictive Maintenance AI is used to monitor machine health and predict equipment failures in real-time. By analysing sensor data, such as vibration, temperature, and cutting forces, AI algorithms can detect anomalies and predict potential failures [8]. This enables proactive maintenance, minimizing unplanned downtime and optimizing machine utilization. Intelligent Process Planning AI algorithms can assist in generating optimized machining plans. By considering factors such as material properties, tooling options, and machine capabilities, AI can generate efficient machining sequences and select the most suitable cutting parameters. This helps improve process efficiency, reduce machining time, and minimize tool wear.

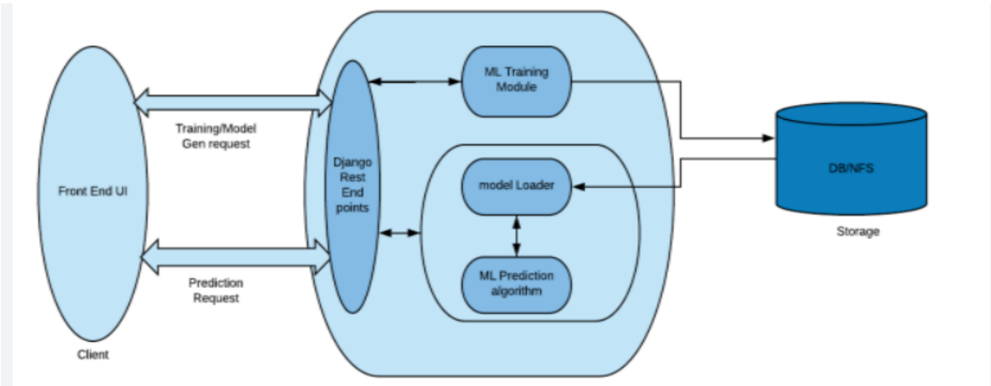

Figure 4: Analysis Intelligent Process Planning AI algorithms

Adaptive Machining: AI can enable adaptive machining systems that adjust cutting parameters in real-time based on sensor feedback. By continuously monitoring and analysing cutting forces, tool wear, and surface quality during the machining process, AI algorithms can make on-the-fly adjustments to optimize the process and maintain consistent surface quality.

Surface Quality Prediction: As mentioned earlier, AI techniques like neural networks can be trained on historical data to predict machining surface quality. These models can forecast surface roughness, dimensional accuracy, and other quality indicators based on cutting parameters, tool characteristics, and material properties. This helps in optimizing machining processes and reducing the need for manual inspection.

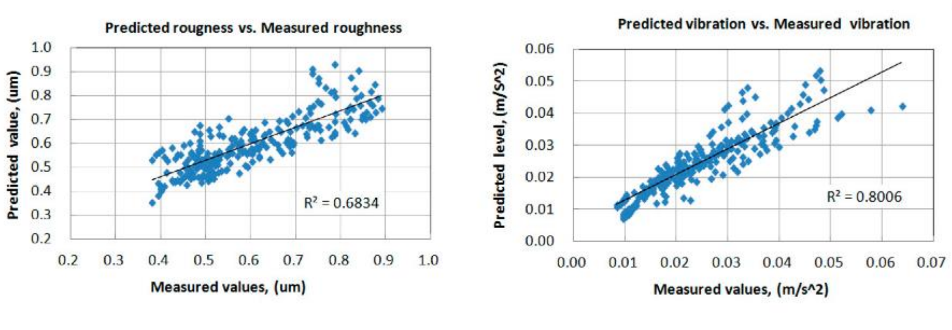

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Figure 5: Analysis the parameters characteristics and material properties

Autonomous Machining: AI-powered autonomous machining systems are being developed to perform complex machining tasks with minimal human intervention. These systems integrate AI algorithms, robotic arms, computer vision, and sensor technologies to analyse the workpiece, select appropriate tools, and execute machining operations autonomously. Autonomous machining systems improve productivity, reduce errors, and enhance flexibility in manufacturing processes. Quality Control and Inspection: AI algorithms can analyse images and sensor data to detect surface defects, identify anomalies, and perform quality inspections. Machine vision systems integrated with AI can quickly and accurately detect flaws, measure dimensions, and verify tolerances, ensuring high-quality machined parts. Optimization of Cutting Parameters: AI techniques, such as genetic algorithms, can optimize cutting parameters to achieve desired machining objectives.

Some Case Studies On Ai-Based Surface Quality Prediction:

Here are a few case studies that demonstrate the application of AI-based techniques for surface quality prediction in machining:

"Machine Learning-based Surface Roughness Prediction in CNC Turning" This study focused on predicting surface roughness in CNC turning operations using machine learning techniques. The researchers collected data on cutting parameters, tool geometry, and material properties along with corresponding surface roughness measurements. They developed an artificial neural network (ANN) model that was trained on the collected data. The results showed that the ANN model accurately predicted surface roughness, providing a valuable tool for optimizing machining processes and reducing the need for trial and error.

"Surface Roughness Prediction in CNC Milling using Convolutional Neural Networks" In this case study, researchers explored the use of convolutional neural networks (CNN) for predicting surface roughness in CNC milling. They captured images of the machined surface at different cutting conditions and used these images as input to the CNN model. The CNN was trained to learn the features associated with different surface roughness levels. The study demonstrated that the CNN model achieved high accuracy in predicting surface roughness based on the input images, showing the potential of using image-based AI techniques for surface quality prediction.

"Surface Roughness Prediction in Milling Process using Machine Learning Algorithms" In this research, machine learning algorithms were applied to predict surface roughness in milling operations. The study utilized data on cutting parameters, tool characteristics, and workpiece properties along with corresponding surface roughness measurements. Multiple machine learning algorithms, including decision tree, random forest, and support vector regression, were evaluated for their predictive capabilities. The results indicated that the machine learning models achieved accurate predictions of surface roughness, providing insights for process optimization and quality control.

These case studies illustrate the effectiveness of AI-based techniques, such as neural networks and machine learning algorithms, in predicting surface quality in machining operations. These approaches leverage historical data to learn patterns and relationships between input parameters and surface quality indicators, enabling accurate predictions and guiding optimization efforts in machining processes.

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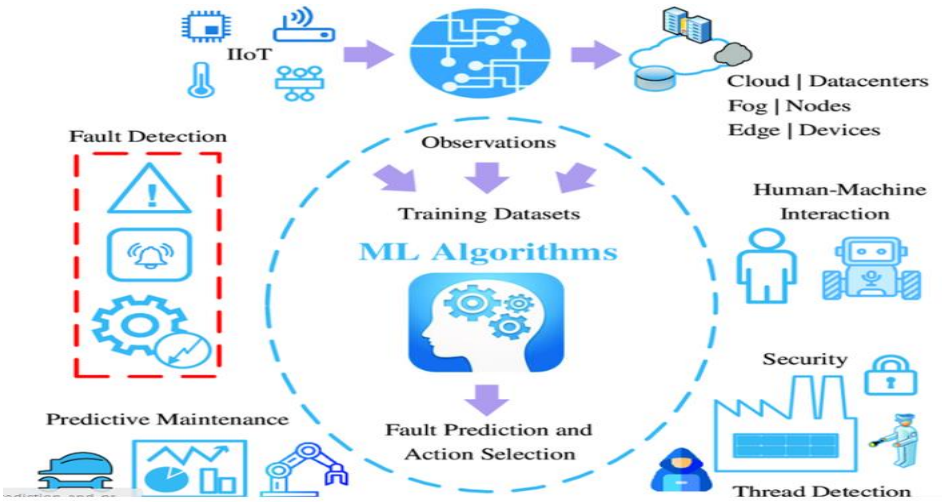

Figure 6: Analysis case study for artificial intelligence (AI) techniques for predicting machining surface quality

When applying artificial intelligence (AI) techniques for predicting machining surface quality, model training and optimization are crucial steps to ensure accurate and reliable predictions. The develop accurate and robust AI models for predicting machining surface quality, leading to improved process control, optimization, and quality assurance in manufacturing industries. In the application of AI in predicting machining surface quality offers significant advantages over traditional approaches. It enables accurate and efficient predictions, enhances manufacturing processes, and improves product quality. As AI techniques continue to advance and more data becomes available, the prediction of machining surface quality is expected to become even more accurate and robust. Future research should focus on addressing challenges, expanding the scope of prediction models, and developing AI-based decision support systems for optimal machining surface quality.

Conclusion:

The application of artificial intelligence (AI) techniques for predicting machining surface quality has yielded promising results. Several studies have demonstrated the effectiveness of AI models, such as artificial neural networks (ANN) and machine learning algorithms, in accurately predicting surface roughness, finish, and other quality indicators based on input parameters like cutting conditions, tool characteristics, and material properties. The models showed good generalization ability and were able to handle complex relationships between input parameters and surface quality. The findings highlight the practical implications of using AI for predicting machining surface quality. By accurately predicting surface quality, manufacturers can optimize machining processes, reduce trial and error, and minimize the need for manual inspection. This leads to improved productivity, reduced costs, and enhanced product quality. AI models can guide decision-making in real-time, allowing for adaptive machining and proactive maintenance strategies. These practical implications contribute to overall process efficiency and competitiveness in manufacturing industries. The application of AI in predicting machining surface quality makes a significant contribution to the field of manufacturing. It leverages advanced computational techniques and data analysis to overcome the limitations of traditional methods. AI models provide a data-driven approach that captures complex relationships and patterns, enabling accurate predictions and optimization of machining processes. The integration of AI techniques into the field of machining enhances automation, process control, and quality assurance, facilitating the transition towards smart factories and Industry 4.0 concepts. The findings of these studies contribute to the growing body of knowledge on AI-based approaches for surface quality prediction in machining, paving the way for further advancements in the field.

The application of AI in predicting machining surface quality has demonstrated its potential in improving process control, optimizing machining parameters, and enhancing product quality. The findings have practical implications for manufacturers by enabling accurate predictions of surface quality, leading to increased efficiency and reduced costs. Moreover, these studies contribute to the advancement of the field by showcasing the effectiveness of AI techniques and their integration into machining processes, ultimately driving the progression towards intelligent and automated manufacturing systems.

References:

[1] Riemer O. Advances in ultra-precision manufacturing. Proc Jpn Soc Precis Eng 2011:1–6. https://www.jspe.or.jp/wp_e/wp-content/uploads/isupen/2011s/ 2011s-1-7.pdf.
[2] Rhorer RL, Evans CJ. Fabrication of optics by diamond turning. Handbook of optics: fundamentals, techniques, and design. 2nd ed. NY: McGraw-Hill; 1995. p. 1–13.
[3] Davies MA, Evans CJ, Vohra RR, Bergner BC, Patterson SR. Application of precision diamond machining to the manufacture of microphotonics components. Proc. SPIE 5183, Lithographic and Micromachining Techniques for Optical Component Fabrication II 2003. https://doi.org/10.1117/12.506373.
[4] Owen JD, Troutman JR, Harriman TA, Zare A, Wang YQ, Lucca DA, et al. The mechanics of milling of germanium for IR applications. CIRP Ann Manuf Technol 2016;65(1):109–13.
[5] Dutterer BS, Lineberger JL, Smilie PJ, Hildebrand DS, Harriman TA, Davies MA, et al. Diamond milling of an Alvarez lens in germanium. Precis Eng 2014;38(2): 398–408.
[6] Shojaee SA, Harriman TA, Qi Y, Lucca DA, Dutterer BS, Davies MA, et al. Spatial variations in stress and crystal quality in diamond turned ZnSe surfaces measured by Raman spectroscopy. Manuf Lett 2014;2(2):35–9.
[7] Owen JD, Shultz JA, Suleski TJ, Davies MA. Error correction methodology for ultra-precision three-axis milling of freeform optics. CIRP Ann Manuf Technol 2017;66(1):97–100.
[8] Shahinian H, Zaytsev D, Navare J, Su Y, Kang D, Ravindra D. Micro laser assisted machining (μ-LAM) of precision optics. In: Proceedings of the Optical Design and Fabrication 2019 (Freeform, OFT). OSA Technical Digest (Optica Publishing Group); 2017. OT1A–5.
[9] Troutman JR, Owen JD, Zare A, Harriman TA, Lucca DA, Davies MA. Cutting mechanics and subsurface integrity in diamond machining of chalcogenide glass. Procedia CIRP 2016;45:135–8.
[10] Troutman JR, Barnhardt DL, Shultz JA, Owen JD, DeFisher S, Davies MA, et al. Machining and metrology of a chalcogenide glass lens pair. Procedia Manuf 2016; 5:669–83.
[11] Owen JD, Davies MA, Schmidt D, Urruti EH. On the ultra-precision diamond machining of chalcogenide glass. CIRP Ann Manuf Technol 2015;64(1):113–6.
[12] Brinksmeier E, Mutlugünes Y, Klocke F, Aurich J, Shore P, Ohmori H. Ultraprecision grinding. CIRP Ann 2010;59(2):652–71.
[13] Decker D, Grandjean D, Bennett J. Optical and surface physical characteristics of diamond-machined infrared windows. In: Hockey B, Rice R (Eds.), The science of ceramic machining and surface finishing II, NBS Spec Publ, 562; 1979. pp. 293–304.
[14] Puttick KE, Rudman MR, Smith KJ, Franks A, Lindsey K. Single-point diamond machining of glasses. Proc R Soc Lond A 1989;426(1870).
[15] Sparks R, Paesler M. Micro-Raman analysis of stress in machined silicon and germanium. Precis Eng 1988;10(4):191–8.
[16] Nakasuji, Kodera S, Hara S, Matsunaga H, Ikawa N, Shimada S. Diamond turning of brittle materials for optical components. CIRP Ann 1990;39(1):89–92.
[17] Blake PN, Scattergood RO. Ductile-regime machining of germanium and silicon. J Am Ceram Soc 1990;73(4):949–57.
[18] Blackley W, Scattergood R. Ductile-regime machining model for diamond turning of brittle materials. Precis Eng 1991;13(2):95–103.
[19] Yan J, Maekawa K, Tamaki J, Kubo A. Experimental study on the ultraprecision ductile machinability of single-crystal germanium. JSME Int J Ser C Mech Syst Mach Elem Manuf 2004;47(1):29–36.
[20] Antwi E, Liu K, Wang H. A review on ductile mode cutting of brittle materials. Front Mech Eng 2017;13(2):251–63.
[21] Griffin AD. Ductile machining of crystalline materials with variable rake single point diamond machining (Master's thesis). The University of North Carolina at Charlotte; 2016.

[22] Arrazola PJ, Ozel ¨ T, Umbrello D, Davies M, Jawahir IS. Recent advances in modelling of metal machining processes. CIRP Ann Manuf Technol 2013;62(2): 695–718. https://doi.org/10.1016/j.cirp.2013.05.006.

[23] Melkote SN, Grzesik W, Outeiro J, Rech J, Schulze V, Attia H, et al. Advances in material and friction data for modelling of metal machining. CIRP Ann Manuf Technol 2017;66(2):731–54. https://doi.org/10.1016/j.cirp.2017.05.002.

[24] Wu D, Jennings C, Terpenny J, Gao RX, Kumara S. A comparative study on machine learning algorithms for smart manufacturing: Tool wear prediction using random forests. 071018 J Manuf Sci Eng 2017;139(7):1–9. https://doi.org/ 10.1115/1.4036350.

[25] Mikołajczyk T, Nowicki K, Bustillo A, Yu Pimenov D. Predicting tool life in turning operations using neural networks and image processing. Mech Syst Signal Process 2017;104:503–13. https://doi.org/10.1016/j.ymssp.2017.11.022.

[26] Li Z, Zhang Z, Shi J, Wu D. Prediction of surface roughness in extrusion-based additive manufacturing with machine learning. Robot Comput Integr Manuf 2015.

[27] Barrios JM, Romero PE. Decision tree methods for predicting surface roughness in fused deposition modeling parts. Materials 2017;12(16):2574.

[28] Liu X, Athanasiou CE, Padture NP, Sheldon BW, Gao H. A machine learning approach to fracture mechanics problems. Acta Mater 2016;190:105–12.

[29] Moore BA, Rougier E, O'Malley D, Srinivasan G, Hunter A, Viswanathan H. Predictive modeling of dynamic fracture growth in brittle materials with machine learning. Comput Mater Sci 2015;148:46–53. https://doi.org/10.1016.

[30] Lutz B, Kisskalt D, Regulin D, Franke J. AI-based approach for predicting the machinability under consideration of material batch deviations in turning processes. Procedia CIRP 2016;93:1382–7. https://doi.org/10.1016.

[31] Sizemore NE, Nogueira ML, Greis NP, Davies MA. Application of machine learning to the prediction of surface roughness in diamond machining. Procedia Manuf 2017;48:1029–40. https://doi.org/10.1016/j.promfg.2017.05.142.

[32] Evans CJ. PVr-a robust amplitude parameter for optical surface specification. 043605 Opt Eng 2009;48(4):1–8. https://doi.org/10.1117/1.3119307.

[33] Bergstra J, Yamins D, Cox D. Making a science of model search: hyperparameter optimization in hundreds of dimensions for vision architectures. In: Dasgupta S, McAllester D (Eds.), Proceedings of the 30th international conference on machine learning, vol. 28 of JMLR: W & CP; 2013. pp. I-115–I-123

[34] Bergstra J, Yamins D, Cox D. Hyperopt: a python library for optimizing the hyperparameters of machine learning algorithms. In: van der Walt S, Millman J, Huff K (Eds.), Proceedings of the 12th python in science conference (SciPy); 2013. pp. 13–9.

[35] Townsend J. Theoretical analysis of an alphabetic confusion matrix. Percept Psychophys 1971;9(1):40–50. https://doi.org/10.3758/BF03213026.

[36] Python Software Foundation. Python Language Reference, version 3.0. Available at: 〈 https://www.python.org/〉. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikitlearn: Machine Learning in Python. J Mach Learn Res 2011;12:2825–30

[37] Chollet F, et al. Keras, GitHub; 2015. Software .Bisong E. Google colaboratory. In: Building machine learning and deep learning models on Google Cloud platform. Apress, Berkeley, CA; 2015.

[38] Al-Sarem M, Saeed F, Al-Mekhlafi ZG, Mohammed BA, Hadwan M, Al-Hadhrami T, et al. An improved multiple features and machine learning-based approach for detecting clickbait news on social networks. In: Randazzo G, Muzirafuti A, Paraforos DS (Eds.), Applied sciences, 11(20); 2017. p. 9487.

[39] Pashchenko IN, Sokolovsky KV, Gavras P. Machine learning search for variable stars. Mon Not R Astron Soc 2016;475(2):2326–43. https://doi.org/10.1093/ mnras/stx3222.

[40] Elssied NOF, Ibrahim O, Osman AH. A novel feature selection based on one-way ANOVA F-test for e-mail spam classification. Res J Appl Sci Eng Technol 2014;7(3): 625–38.

[41] Zar JH. Spearman rank correlation. Encyclopedia of biostatistics. Wiley Online Library; 2005.