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A Review on Prediction of Surface Roughness by Using Image Processing Techniques with Machine Learning

Ankur N Tank[1], Jignasa P. Mehta[2]
M.Tech Student, Mechanical Engineering Department, Darshan University, Rajkot, India [1]
Head of Department, Mechanical Engineering Department, Darshan University, Rajkot, India[2]

Abstract: *Surface roughness is one of the most important quality characteristics in machining and manufacturing industries because it directly affects functional performance, wear resistance, fatigue strength, friction, lubrication, and dimensional accuracy of machined components [1], [2]. Conventional contact-type measurement methods such as stylus profilometers are widely used for roughness evaluation; however, these techniques are time-consuming, unsuitable for real-time monitoring, and may damage delicate surfaces. To overcome these limitations, researchers have increasingly focused on non-contact measurement methods using image processing, machine learning, and deep learning techniques. This review paper provides a broad study of surface roughness prediction methods used in machining processes such as milling, grinding, turning, EDM, and additive manufacturing by using recent advancements in artificial intelligence. Various machine learning and deep learning models including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Random Forest (RF), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and hybrid models are discussed. The review also gives outline about preprocessing methods, feature extraction techniques, prediction accuracy, limitations, and research directions for future. The study shows that computer vision and deep learning-based approaches provide highly accurate, fast, and reliable non-contact surface roughness prediction and this is also suitable for Industry 4.0 modern manufacturing systems.*

Keywords: Surface Roughness (Ra), Machine Learning, Deep Learning, Computer Vision, CNN, ANN, Non-Contact Measurement, Industry 4.0

I. INTRODUCTION

In manufacturing and machining operations surface finish is most crucial quality characteristics. Surface roughness shows the irregularities and texture present on a machined surface generated during manufacturing processes. The quality of a machined surface significantly influences the performance, durability, wear resistance, fatigue strength, friction, lubrication, and corrosion resistance of engineering components [1], [2]. Therefore, maintaining proper surface finish is essential for achieving better product quality and dimensional accuracy.

Surface finish mainly consists of roughness, waviness, and lay [1], [2]. Among these elements, surface roughness is the most commonly used parameter for evaluating surface quality. Surface roughness is generally represented using parameters such as arithmetic average roughness (Ra) and root mean square roughness (Rq). In manufacturing industries, smoother surfaces are generally obtained using finishing operations, whereas rough surfaces are generated during machining processes such as planning and rough cutting operations.

Conventionally, surface roughness is measured using contact-type methods such as stylus profilometers [1], [14]. These techniques provide accurate and standardized measurements but suffer from several limitations including slow measurement speed, possibility of surface damage, inability to inspect delicate surfaces, and difficulty in real-time

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monitoring applications. Due to these limitations, researchers have shifted their attention toward non-contact measurement methods based on optical systems, image processing, signal processing, and artificial intelligence.

In recent years, machine learning and deep learning techniques have become highly popular for surface roughness prediction because of their ability to automatically learn complex surface characteristics from images and sensor signals [3]–[13]. Advanced computer vision systems combined with Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Random Forest (RF), and Gaussian Process Regression (GPR) have shown promising prediction accuracy in different machining environments. These intelligent systems are highly suitable for Industry 4.0 applications because they support automated inspection, real-time monitoring, and smart manufacturing.This review paper presents a detailed analysis of recent research work related to machine learning and computer vision-based surface roughness prediction techniques used in machining operations.

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II. IMPORTANCE OF SURFACE ROUGHNESS

Surface roughness is one of the most significant parameters used to evaluate the quality of machined surfaces. It directly influences the operational performance and reliability of engineering products. A poor surface finish can result in higher friction, wear, heat generation, lubrication failure, corrosion, and reduced fatigue life of components. Therefore, accurate control and prediction of surface roughness are essential in machining industries.

The major factors affecting surface roughness include cutting speed, feed rate, depth of cut, tool geometry, machine vibration, and workpiece material properties [1], [8], [10]. Generally, surface roughness decreases with increasing cutting speed, whereas it increases with higher feed rate and depth of cut. Improper machining parameters can lead to poor surface quality and excessive tool wear.

Modern manufacturing industries demand fast, reliable, and automated surface inspection systems [3]–[13]. Therefore, researchers are developing intelligent non-contact surface roughness prediction systems using image processing, computer vision, and machine learning techniques

III. SURFACE ROUGHNESS MEASUREMENT METHODS

Contact Type Measurement

Contact-type measurement methods use direct physical contact between the measuring probe and workpiece surface [1], [14]. Stylus profilometers are the most widely used instruments for measuring surface roughness. In these systems, a diamond stylus moves across the machined surface and converts surface irregularities into electrical signals for roughness evaluation.

The contact type measurement methods have advantages like high measurement accuracy, Standardized and reliable technique, Suitable for most machined metallic components, easy data collection.

The contact type measurement methods have disadvantages too like surface damage possibility for delicate components, very slow process, difficulties in measuring for complex surface and softer one, real time data collection not possible.

Non-Contact Type Measurement

Non-contact measurement techniques determine surface roughness without physically touching the workpiece surface [15]. These methods use optical systems, laser scanners, interferometry, image processing, and computer vision techniques.

The non-contact type measurement methods have advantages like no any kind of surface damage, fast measurement, suitable for soft and delicate components, real time inspection availability, large area surface measurement can possible.

The non-contact type measurement methods have disadvantages like equipment cost is high, data analysis may complex, sensitive for environment condition, skilled operator required.

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IV. LITERATURE REVIEW

CNN-Based Surface Roughness Prediction Using SEM Images

Kang et al. proposed a deep learning-based CNN model for predicting surface roughness using scanning electron microscopy (SEM) images of nanofiber membranes [3]. The study used preprocessing techniques such as CLAHE and Fourier transforms to improve image quality and feature extraction. The proposed model achieved a Mean Absolute Percentage Error (MAPE) of approximately 4.8%, demonstrating high prediction capability.

Deep Learning-Based Surface Roughness Classification

Nguyen and Tran developed a non-contact surface roughness classification system using image processing and AlexNet CNN architecture for turning and milling operations [4]. The system classified roughness grades according to ISO standards and achieved prediction accuracy close to 99.88% under controlled image acquisition conditions.

Surface Roughness Prediction Using Acoustic Emission Signals

Zangane et al. combined acoustic emission signals with deep learning models such as CNN-LSTM, ResNet18, and ShuffleNet for surface roughness prediction in milling operations [5]. The study showed that deep learning techniques provided significantly better accuracy compared to conventional machine learning models and achieved prediction accuracy between 96% and 99%.

Grinding Surface Roughness Measurement Using DB-VGG

Yi et al. proposed a visual measurement method for grinding surface roughness using a double-branch convolution neural network called DB-VGG [6]. Gaussian filtering and feature fusion methods improved recognition performance, resulting in approximately 97% prediction accuracy.

Regression-Based Roughness Estimation in Additive Manufacturing

Jáñez-Martino et al. developed a machine learning-based computer vision system for roughness estimation in stainless steel specimens manufactured using additive manufacturing [7]. Texture descriptors such as Local Binary Patterns (LBP) and Support Vector Regression (SVR) were applied, resulting in a Mean Absolute Error of approximately 0.65.

ANN-Based Computer Vision System

Karthikeyan et al. developed an Artificial Neural Network model for predicting surface roughness in CNC-machined Al7075 shafts using grayscale image features and machining parameters [8]. The proposed ANN model achieved prediction accuracy close to 96%.

CNN-Based Surface Roughness Measurement in EDM

Amit Kumar et al. proposed a CNN model for roughness prediction in EDM surfaces using mobile camera images [9]. Image preprocessing techniques including histogram equalization and Laplacian filtering were used to improve prediction performance. The study demonstrated the feasibility of low-cost non-contact roughness prediction systems.

Machine Learning Models for Machining Operations

Motta et al. applied Random Forest and Gaussian Process Regression models for surface roughness monitoring in turning operations using cutting force, vibration, and temperature sensor data [10]. The Gaussian Process Regression model achieved an RMSE value of approximately 0.3 µm and R^2 value near 0.92.

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Image Processing and RBF Neural Network-Based Prediction

Vishwanatha et al. proposed a hybrid prediction system combining Dual-Tree Complex Wavelet Transform, Principal Component Analysis, Particle Swarm Optimization, and Radial Basis Function Neural Networks for titanium alloy surface roughness prediction [11]. The model achieved prediction accuracy greater than 99%.

Machine Learning-Based Roughness Mapping

Giusti et al. developed a machine vision-based roughness prediction system using CNNs and industrial camera images for EDM machining applications [12]. The system achieved less than 10% prediction error and supported real-time roughness mapping.

Microscopic Vision and Deep Learning-Based Prediction

Shang et al. presented a deep learning-based grinding surface roughness prediction method using microscopic imaging systems and lightweight CNN architectures such as MobileNet and ShuffleNet [13]. The system achieved prediction accuracy greater than 99% and demonstrated the capability of intelligent microscopic vision systems for industrial roughness evaluation.

Transfer Learning Enhanced Gaussian Process Model

Recent studies introduced transfer learning-based surface roughness prediction systems for improving prediction performance using small datasets. Researchers combined Gaussian Process Regression with transfer learning frameworks to improve prediction stability and generalization capability across multiple machining environments. The study demonstrated that transfer learning approaches significantly reduce the dependency on large datasets and improve prediction robustness in practical industrial applications [16].

Deep Transfer Learning-Based Online Monitoring System

Advanced Industry 4.0 manufacturing systems require real-time online monitoring capability for intelligent machining operations. Researchers proposed deep transfer learning models for continuous online surface roughness monitoring using sensor fusion and computer vision systems. The proposed model improved prediction efficiency and enabled real-time industrial implementation with high prediction reliability [17].

Domain Incremental Learning-Based Roughness Prediction

Domain incremental learning approaches have recently gained attention for adaptive surface roughness prediction under changing machining conditions. The proposed incremental learning framework continuously updates the prediction model using new machining data without complete retraining. This approach improves model adaptability and long-term industrial usability [18].

Ensemble Learning-Based Surface Roughness Prediction

Ensemble learning methods combine multiple machine learning algorithms to improve prediction accuracy and stability. Researchers applied ensemble regression techniques for machining parameter optimization and roughness prediction in turning and milling operations. The study reported improved prediction performance compared to conventional single-model approaches [19].

V. SUMMARY OF OBSERVATION FROM LITERATURE REVIEW

The literature survey shows that a major shift from traditional contact-type surface roughness measurement methods toward intelligent non-contact techniques. Most recent studies and experiments focus on machine learning and deep learning-based systems capable of automatically predicting surface roughness using surface images, vibration signals, acoustic emission signals, and optical data.

In experiment the researchers widely used Convolutional Neural Networks because of their capability to automatically extract texture features from surface images without manual intervention. Advanced CNN architectures such as AlexNet, ResNet, ShuffleNet, MobileNet, VGG, and ConvNeXt demonstrated high prediction performance in various machining operations including grinding, milling, EDM, and turning.

The review also shows that preprocessing techniques play a critical role in prediction performance. Methods such as CLAHE, wavelet transform, Gaussian filtering, histogram equalization, Fourier transform, and image patch extraction improved feature visibility and reduced noise.

Several studies also used hybrid approaches combining machine learning with optimization algorithms such as Particle Swarm Optimization, Principal Component Analysis, and signal processing methods. These systems improved prediction accuracy while reducing computational complexity.

Most studies achieved prediction accuracy greater than 90%, proving the effectiveness of intelligent surface roughness prediction systems for modern Industry 4.0 applications [4], [5], [6], [11], [13].

VI. MAJOR CHALLENGES

Although machine learning and deep learning-based approaches provide excellent prediction performance, several practical challenges still exist in real-world implementation.

- Surface images are highly sensitive to illumination conditions and environmental variations.
- Different machining processes generate different surface textures, making generalized model development difficult.
- Most deep learning models require large datasets for proper training.
- Real-time industrial implementation demands high-speed image acquisition and processing capability.
- Sensor noise and machine vibration can affect prediction accuracy.
- Surface roughness prediction in complex geometries and micro-scale components still remains challenging.
- Most studies are limited to laboratory conditions and controlled environments.

VII. RESEARCH GAPS

Despite significant advancements in machine learning-based surface roughness prediction systems, several research gaps still exist.

- Most studies are limited to specific machining processes and materials.
- Standardized and publicly available datasets are not widely available.
- Many systems are sensitive to illumination and environmental variations.
- Most studies focus only on Ra values and ignore other surface characteristics.
- Real-time industrial implementation remains limited.
- Large datasets are required for training deep learning models.
- Generalization capability across different machining operations is still challenging.

VIII. CONCLUSION

This review paper presented a comprehensive study of machine learning and computer vision-based surface roughness prediction techniques used in modern machining industries [3]–[13]. Conventional contact-type methods provide accurate measurement but suffer from limitations such as slow operation, surface damage, and lack of real-time capability. Recent advancements in image processing, deep learning, and machine learning techniques have enabled highly accurate and automated non-contact surface roughness prediction systems.

Among the reviewed methods, Convolutional Neural Networks and hybrid AI models demonstrated excellent prediction performance with accuracy often exceeding 95%. The integration of intelligent prediction systems into modern manufacturing environments supports improved machining quality, reduced inspection time, enhanced productivity, and Industry 4.0 implementation. However, challenges related to dataset standardization, model generalization, and industrial implementation still require further research.

IX. FUTURE SCOPE

Future research can focus on developing generalized AI models capable of predicting surface roughness across multiple machining processes and materials [5], [10], [13]. Hybrid deep learning architectures combined with optimization algorithms can further improve prediction accuracy. Integration of intelligent surface roughness monitoring systems into Industry 4.0 environments will support fully automated smart manufacturing systems.
Future studies may also focus on:

- Real-time industrial deployment
- Multi-parameter surface characterization
- Hybrid AI optimization models
- Transfer learning for small datasets
- Edge AI and embedded systems for online monitoring

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