Modeling and prediction of surface roughness using multiple regressions: A noncontact approach

Dhiren R. Patel1✉ | Mysore B. Kiran2 | Vinay Vakharia1

1Department of Mechanical Engineering, Pandit Deendayal Petroleum University, Gujarat, India
2Department of Industrial Engineering, Pandit Deendayal Petroleum University, Gujarat, India

Correspondence
Dhiren R. Patel, Department of Mechanical Engineering, Pandit Deendayal Petroleum University, Gujarat, India.
Email: dhirenpatel85@gmail.com

Abstract
In the present work, a machine vision system is introduced, which captures images and extracts surface texture features of machined surfaces. The texture feature parameters are extracted using the gray-level co-occurrence matrix and correlated with different surface roughness parameters recorded by a contact-type surface profilometer. The image acquisition carried out at different roughness levels in order to extract texture features. The variation between each texture features and surface roughness parameter is investigated. Multiple regression models are developed to predict the subjective estimation of surface roughness parameter (Ra) and qualitative detection of the degree of surface roughness. It is observed that the linear detection model shows better performance characteristics compared with a nonlinear detection model. The comparison between measured and predicted results shows that the linear detection model had a maximum relative error of 2.01%, drastically better than nonlinear detection model of −9.60% error parts, hence indicating better surface detection capability over the nonlinear detection model. The results demonstrate that the prediction of surface roughness using linear regression model is a reliable approach of noncontact measurement.

KEYWORDS
gray-level co-occurrence matrix, surface profilometer, surface roughness parameters, texture features

1 INTRODUCTION

Technological advancement in the heavy industry requires precise and quality machined surface, which directly or indirectly demands methods in terms of accuracy, precision, and quick measurement.1 Turning operation generates tiny valley and peak with microgeometric uniqueness known as surface roughness due to friction, fracture, or plastic deformation during chip separation. There are numerous parameters that influence surface roughness.2 In machining industries, surface roughness has a direct impact on the fatigue resistance, quality, and performance of the product.3 Average surface roughness, also known as arithmetical mean deviation, is a key parameter widely used to demonstrate the individuality of the machined surface.
Many researchers have proposed different approaches to predict surface roughness based on machining theory.4-9 Surface measurement is primarily divided into two categories: (a) contact measurement and (b) noncontact measurement.10-12 Contact-type measurements are currently used due to the compact design, high measurement accuracy, and the ability to deliver consistent output for surface inspection.13 However, the study did not provide universal testimony for the significance of these advantages for the accuracy of measurements.14 Extensive research is carried out on non-contact-type assessment of surface roughness parameters using machine vision system and artificial intelligence technology, which include methods such as laser speckle, light scattering, and optical interference.15-19 Pontes et al20 proposed the technique called multilayer perceptron (MLP) network architecture, which considerably reduces errors in predicting surface roughness parameters of machined components compared with currently used techniques. Huaian et al presented a new methodology to assess surface roughness that uses uniform texture direction without any primary necessities, which defeats the present issues such as limited range, complex calculations, and so on. This improves the accuracy of noncontact measurement up to a certain degree. However, the field of reference for relevancy still needs to be straightened out.21 Mia et al established a model based on an artificial neural network to predict surface roughness of turned components. The Bayesian regularization of network architecture provided the highest accuracy.22 Chen et al23 developed an optical path using the laser speckle method, which enhances the accuracy of measurement in inspection machinery, though the workability of the proposed method is very crucial to accomplish on a regular basis. Zhu et al24 proposed a surface roughness prediction model based on a multiwavelength fiber optic sensor to minimize the error difference (less than 3%), which is better than characteristic curves between surface roughness and scattering intensity ratio.

The objective of the present work is to examine the correlation between surface roughness parameters and image texture features of computer numerical control (CNC) turned components with non-contact-type approach as it consists of points of interest such as high efficiency of measurement with accuracy, great adaptability, noncontact in nature, the ability to secure a large amount of information, and high performance-price ratio over contact-type measurement. It is aimed to extract the surface texture features by gray-level co-occurrence matrix (GLCM) and correlate it to surface roughness parameter measured by a surface profilometer. Linear and nonlinear regression models were established for arithmetical mean deviation (Ra) prediction, and the feasibility of detection models has been explored in the present work.

Subsequent sections of the article are organized as follows. Section 2 describes preparation of specimen and measurement of surface roughness using surface profilometer followed by image processing. Section 3 talks about linear and nonlinear regression model development for the comparison of the predicted roughness values with the measured values. Section 4 deals with concluding part where the researcher identifies that both the models are efficient; however, the linear regression model dominates in terms of precision.

2 MATERIALS AND METHODS

The average surface roughness (Ra) is generally used as a dimensional index to determine the surface finish of a machined surface.25 Assessment of roughness parameters plays a vital role to distinguish problems such as friction, contact deformation, and tightness of contact joint accuracy in industrial sectors.26

2.1 Measurement of surface roughness parameters using surface profilometer

The machining process of 12 low carbons steel workpieces having a diameter of 30 mm and a height of 18 mm was carried out on a CNC turning machine. The experiments were conducted by varying operating parameters such as spindle speed, feed rate, and depth of cut using Taguchi method. Table 1 shows the value of CNC turning cutting parameters.

Stylus instrument, also known as surface profilometer, is used as a contact-type surface roughness measurement of the machined component. It consists of a diamond stylus probe that is moved perpendicularly to the direction of roughness, and a characteristic of surface roughness is recorded at the other ends.13 It is most widely used technique because of its advantages and generating a profile of an object along a well-defined direction.13 Surface roughness measurement of 12 CNC turned components has been carried out on contact-type stylus instrument called surface profilometer as shown in Figure. 1. The measuring conditions for measurement are given in Table 2.
| Specimen number | Speed (rpm) | Feed (mm/min) | Depth of cut (mm) |
|-----------------|-------------|---------------|------------------|
| 1               | 400         | 150           | 0.05             |
| 2               | 400         | 750           | 0.15             |
| 3               | 400         | 1250          | 0.25             |
| 4               | 400         | 2000          | 0.45             |
| 5               | 800         | 150           | 0.05             |
| 6               | 800         | 750           | 0.15             |
| 7               | 800         | 1250          | 0.25             |
| 8               | 800         | 2000          | 0.45             |
| 9               | 1200        | 150           | 0.05             |
| 10              | 1200        | 750           | 0.15             |
| 11              | 1200        | 1250          | 0.25             |
| 12              | 1200        | 2000          | 0.45             |

**Table 1** Cutting parameters of computer numerical control turning

**Figure 1** Surface profilometer (Handysurf 35B)

### 2.2 Image processing of CNC turned surfaces

In order to achieve precise information from captured images of the machined surface, uneven illumination, geometric image distortion, and noise should be eliminated. The digital image contains noise generated from photosensitive electron microscope elements. A filtering algorithm is used to eliminate unwanted noise from digital images as it is difficult to remove dead pixels and other pollutants directly through a charge-coupled device (CCD) camera. The algorithm retains the important details of the image texture.

The machine vision system has been taken into account for direct measurement because of its advantages in many sectors. It is connected with CCD camera PULNIX; captures the image of a machined surface, illuminated by ordinary lighting as shown in Figure 2.

The machine vision system has been kept in such a manner that the camera can focus on the machined surface and store corresponding images. It takes advantage of high speed, higher spatial resolution, and easiest method to measure the roughness of the workpiece more precisely. It can be very useful to predict surface roughness offline, online, and in-process. In order to collect rich information from captured raw images as shown in Figure 3, it needs to be preprocessed to make free from all artifacts and noise. The image processing tool of MATLAB was used to enhance the captured images to get precise result.
### Table 2: Measuring Condition

| Parameter               | Value  |
|-------------------------|--------|
| Evaluation length       | 8 mm   |
| Measuring speed         | 0.6 mm/s |
| Cutoff value            | 0.8 mm |
| Type of filter          | Gaussian |
| Form remove             | Straight |
| Material of stylus      | Diamond |
| Radius of stylus        | 5 μm   |
| Number of line scans    | Single |

**Figure 2** Setup of a machine vision system

**Figure 3** Raw images of turned components
The preprocessing of the captured image was executed before the stage of image feature extraction to enhance the image by adjusting the contrast. The actual image of the machined component was subdivided into 15 equal parts to take advantage of the nonoverlapping loop of images that help to create a strong database, and ultimately developed model will be more robust compared with overlapping. Furthermore, subimages were preprocessed by continuous two-dimensional (2D) wavelet transform in which images are being converted into grayscale by extracting coefficient from discrete wavelet transform. It provides better result for nonstationary signals. “Wavelet image processing” toolbox of MATLAB has been utilized to remove the noise. Haar wavelet has been chosen as it gives the least coefficient from discrete wavelet transform. It provides better result for nonstationary signals.

Generally in the captured image of a machined component, GLCM works on the probability of two pixels occurrences in a certain positional manner. The relative position between the two pixels and the gray value distribution in the texture image space is accessible by GLCM. As an advantage of discrimination of textures, texture analysis was done for image classification for different datasets.

As shown in Table 4, various image texture features were extracted using the gray-level co-occurrence matrix. Segmenting the preprocessed image into 32 × 32 pixels of subimages, assists to prepare the image dataset. This dataset of images has been loaded to extract the various texture features listed in Table 4. The extraction process has been carried out by varying orientation at 0°, 45°, 90°, and 135° at constant displacement of d = 1.

### Table 3: Denoise process parameters in 2D wavelet

| Wavelet     | Haar          |
|-------------|---------------|
| Level       | 2             |
| Thresholding method | Soft, fixed from the threshold |
| Noise structure | Unscaled white noise, horizontal details coefficient |
| Threshold value at level 1 | 3.33 |
| Threshold value at level 2 | 2.884 |

### Table 4: Texture features extracted using gray-level cooccurrence matrix

| Texture feature | Equation | Texture feature | Equation |
|-----------------|----------|-----------------|----------|
| Contrast        | $G - 1 \sum_{n=0}^{G-1} \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \right\}_n$ | Homogeneity | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \left( \frac{1}{1 + x} \right)$ |
| Correlation     | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left( \frac{P(i,j)}{x(x+1)} \right) \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \log(P(i,j))$ | Sum entropy | $\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \log(P(i,j))$ |
| Cluster prominence | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left( i + j - \mu_x - \mu_y \right)^4 X P(i,j)$ | Difference variance | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 P(i,j)$ |
| Dissimilarity   | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) | i - j |$ | Difference entropy | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \log(P(i,j))$ |
| Energy          | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left( P(P(i,j)) \right)$ | Inverse difference moment normalized | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left( \frac{1}{1 + x(j-j)} \right) P(i,j)$ |
| Entropy         | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) X \log(P(i,j))$ | Homogeneity | $G - 1 \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j)$ |
3 | RESULTS AND DISCUSSION

In this section, the results of surface roughness measurement using surface profilometer and multiple regressions are compared and discussed.

3.1 | Texture feature extraction and analysis

The image acquisition of machined components has been carried out for several times at roughness levels of 2.20, 2.60, 2.80, 2.90, 3.43, 3.50, 3.80, 5.06, 5.36, 6.50, 7.30, and 8.10 μm. The GLCM was established at an angle of 0°, 45°, 90°, and 135°. As a result of this, numerous texture feature parameters such as contrast, correlation, cluster prominence, dissimilarity, energy, entropy, homogeneity, maximum probability, sum entropy, difference variance, difference entropy, inverse difference normalized (INN), and inverse difference moment normalized were extracted. Correlation values of all texture features are listed in Table 5.

From the extracted data, the average value of each texture features was computed at every stage. The relevancy of texture features and Ra can be visualized graphically as shown in Figures 4 to 16.

From the diagrams of texture features and roughness parameter, it can be seen that correlation (F2), homogeneity (F7), maximum probability (F8), INN (F12), and inverse difference moment normalized (F13) showed a proportional trend with change in the value of arithmetic mean deviation, whereas contrast F1), cluster prominence (F3), dissimilarity (F4), entropy (F6), sum entropy (F9), difference variance (F10), and difference entropy (F11) showed inversely proportional behavior as texture feature decreases with an increase in arithmetic mean deviation.

3.2 | Development and analysis of multiple linear detection models

The relationship between two or more variables can be estimated by regression analysis. Multiple regression equations were developed for surface roughness detection of the workpiece as stated in texture feature and roughness variation

| Texture feature       | Correlation with Ra (%) | Texture feature       | Correlation value (%) |
|-----------------------|-------------------------|-----------------------|-----------------------|
| Contrast (F1)         | −82.59                  | Maximum probability (F8)| 99.60                 |
| Correlation (F2)      | 89.05                   | Sum entropy (F9)      | −98.64                |
| Cluster Prominence (F3)| −90.89                 | Difference variance (F10)| −82.59                |
| Dissimilarity (F4)    | −95.67                  | Difference entropy (F11)| −98.33                |
| Energy (F5)           | 98.86                   | Inverse difference normalized (F12)| 85.00                |
| Entropy (F6)          | −99.04                  | Inverse difference moment| 83.58                 |
| Homogeneity (F7)      | 87.33                   | Normalized (F13)      |                       |

**TABLE 5** Correlation values between arithmetical mean deviation and texture features

[FIGURE 4] Correlation trend between gray-level co-occurrence matrix texture feature contrast (F1) and average surface roughness Ra (μm)
FIGURE 5  Correlation trend between gray-level co-occurrence matrix texture feature correlation (F2) and average surface roughness Ra (µm)

FIGURE 6  Correlation trend between gray-level co-occurrence matrix texture feature cluster prominence (F3) and average surface roughness Ra (µm)

FIGURE 7  Correlation trend between gray-level cooccurrence matrix texture feature dissimilarity (F4) and average surface roughness Ra (µm)

FIGURE 8  Correlation trend between gray-level cooccurrence matrix texture feature energy (F5) and average surface roughness Ra (µm)
FIGURE 9  Correlation trend between gray-level cooccurrence matrix texture feature entropy (F6) and average surface roughness Ra (µm)

FIGURE 10  Correlation trend between gray-level cooccurrence matrix texture feature homogeneity (F7) and average surface roughness Ra (µm)

FIGURE 11  Correlation trend between gray-level cooccurrence matrix texture feature maximum probability (F8) and average surface roughness Ra (µm)

FIGURE 12  Correlation trend between gray-level cooccurrence matrix texture feature sum entropy (F9) and average surface roughness Ra (µm)
**FIGURE 13** Correlation trend between gray-level cooccurrence matrix texture feature difference variance (F10) and average surface roughness Ra (µm)

**FIGURE 14** Correlation trend between gray-level cooccurrence matrix texture feature difference entropy (F11) and average surface roughness Ra (µm)

**FIGURE 15** Correlation trend between gray-level cooccurrence matrix texture feature inverse difference normalized (F12) and average surface roughness Ra (µm)

**FIGURE 16** Correlation trend between gray-level cooccurrence matrix texture feature inverse difference moment normalized (F13) and average surface roughness Ra (µm)
rule. Results obtained by surface profilometer and image texture features extraction using GLCM shows that dissimilar-
ity, energy, entropy, homogeneity, maximum probability, sum entropy, difference variance, difference entropy, INN have
strong relationships with average surface roughness (Ra). The mathematical model for linear regression can be obtained
as the following Equation (1). The statistical analysis results are listed in Table 6.

\[
Ra = -17.46 - 1.883 \times F4 + 7.009 \times F5 - 3.220 \times F6 - 7.032 \times F7 + 22.406 \times F8 + 4.610 \times F9 + 0.1686 \times F10 + 0.979 \times F11 + 29.63 \times F12.
\] (1)

Regression Equation (1) can be justified from Table 6, as the coefficient of determination \( R^2 (0.9989) \) approaches to 1. \( F \)-statistics and associated probability demonstrate that regression model showed an outstanding linear relationship.
The above parameters conclude that linear detection model generated for finding relationship behavior was suitable.32

### 3.3 Development and analysis of multivariate nonlinear detection model

In regression analysis, it is quite difficult to conclude the behavior of detection model for evaluation of sample data.
Various curve models have been taken into account to overcome this difficulty. Palanikumar33 selected several functional
forms such as exponential, power, inverse, logarithmic, two times and three times functions for the nonlinear fitting
of image texture feature, and surface roughness parameters. The results showed that there was a linear, quadratic, and
cubic relationship between Ra and dissimilarity (F4), homogeneity (F7), and entropy (F9), respectively. The nonlinear
regression Equation (2) constructed with image texture features and average surface roughness (Ra) is shown below.

\[
Ra = 61.5 + X1 \times F4 + X2 \times F7 + X3 \times F9 + X4 \times F4^2 + X5 \times F7^2 + X6 \times F9^2 + X7 \times F4^3 + X8 \times F7^3 + X9 \times F9^3.
\] (2)

In Equation (2), X1 to X9 represents the regression coefficients. The coefficient values obtained for nonlinear mul-
tiple regression model are shown in Table 7. By substituting the values of regression coefficients in Equation (2), the
mathematical model of the nonlinear detection model can be obtained as follows.

\[
Ra = 61.5 - 128.3 \times F4 + 120.1 \times F7 + 69.97 \times F9 + 51.9 \times F4^2 - 319.6 \times F7^2 - 43.72 \times F9^2 - 7.09 \times F4^3 + 287.3 \times F7^3 + 8.63 \times F9^3.
\] (3)

One cannot judge the reliability of nonlinear function relation between the roughness parameter and texture features
directly. To judge it, a fitting degree of Equation (3) should be determined first in order to check the performance of the
established model. The \( R^2 \) and \( F \) tests were performed on the model to evaluate the fitting effect on multiple regression
models. The test results of the nonlinear detection model are shown in Table 8.

| Test factor | \( R^2 \) | \( F \) | \( P \) | Error variance |
|-------------|----------|--------|--------|---------------|
| Calculating value | 99.98% | 23602.26 | .002 | 0.0008 |

**TABLE 6** Statistical result of linear regression model

| Regression coefficient | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 |
|-------------------------|----|----|----|----|----|----|----|----|----|
| Calculating result      | -128.3 | 120.1 | 69.97 | 51.9 | -319.6 | -43.72 | -7.09 | 287.3 | 8.63 |

**TABLE 7** Nonlinear multiple regression coefficients

| Test factor | \( R^2 \) | \( F \) | \( P \) | Error variance |
|-------------|----------|--------|--------|---------------|
| Calculating value | 99.64% | 1170.45 | .007 | 0.0162 |

**TABLE 8** Statistical results of nonlinear regression model
TABLE 9 Analysis of the relative error between actual and predicted roughness value

| Test samples of image texture features | Linear regression detection model | Nonlinear regression detection model |
|---------------------------------------|---------------------------------|---------------------------------|
|                                       | Actual value Ra (µm) | Detection value Ra (µm) | Absolute error | Relative error (%) | Actual value Ra (µm) | Detection value Ra (µm) | Absolute error | Relative error (%) |
|                                       | 2.200              | 2.219                  | −0.019       | −0.85             | 2.200              | 2.208                  | −0.008       | −0.37             |
|                                       | 2.600              | 2.548                  | 0.052        | 2.01              | 2.600              | 2.628                  | −0.028       | −1.07             |
|                                       | 2.800              | 2.798                  | 0.002        | 0.08              | 2.800              | 3.038                  | −0.238       | −8.51             |
|                                       | 2.900              | 2.921                  | −0.021       | −0.74             | 2.900              | 3.178                  | −0.278       | −9.60             |
|                                       | 3.430              | 3.425                  | 0.005        | 0.14              | 3.430              | 3.352                  | 0.078        | 2.28              |
|                                       | 3.500              | 3.514                  | −0.014       | −0.39             | 3.500              | 3.563                  | −0.063       | −1.81             |
|                                       | 3.800              | 3.755                  | 0.045        | 1.19              | 3.800              | 3.978                  | −0.178       | −4.68             |
|                                       | 5.060              | 5.069                  | −0.009       | −0.18             | 5.060              | 5.036                  | 0.024        | 0.48              |
|                                       | 5.360              | 5.366                  | −0.006       | −0.11             | 5.360              | 5.623                  | −0.263       | −4.91             |
|                                       | 6.500              | 6.514                  | −0.014       | −0.21             | 6.500              | 6.674                  | −0.174       | −2.68             |
|                                       | 7.300              | 7.314                  | −0.014       | −0.19             | 7.300              | 7.369                  | −0.069       | −0.95             |
|                                       | 8.100              | 8.064                  | 0.036        | 0.45              | 8.100              | 8.289                  | −0.189       | −2.34             |

From Table 8, as the coefficient of determination $R^2$ (0.9964) approaches toward unity, it signifies that the nonlinear regression Equation (3) fits well. The existence of the remarkable nonlinear relationship was noticed between dependent and independent variables, hereby confirming the successful demonstration of nonlinear detection model for the evaluation of sample data.$^{34}$

### 3.4 Performance analysis of multivariate regression detection model

Multiple regression analysis is a statistical method that assists to find a correlation between a continuous dependent and at least two discrete independent variables. It is considered to estimate surface roughness parameters due to the broad area of tasks such as analyzing categorical, ordinal, or experimental data.$^{35}$ Multiple models have been utilized to expose the surface roughness of the test sample. By doing so, one can identify the reliability and performance of the regression
model. Substituting the values of texture feature parameters into Equations (1) and (3), the detected values and error values can be obtained as presented in Table 9.

The comparison graph of testing results and measured results for linear and nonlinear detection model is shown in Figure 17A,B, respectively. The maximum relative error in the linear detection model is 2.01%, which justifies the good detection capability of the linear detection model developed for the turned workpiece. The maximum relative error observed in the nonlinear detection model is \(-9.60%\) as shown in Table 9.

From the test results, it is found that detection capability for linear detection model is better compared with nonlinear detection model for turned workpiece surface roughness. Compared with nonlinear detection model, the maximum detection error was decreased by 80% using the linear detection model, which demonstrates the better execution attributes over nonlinear detection model.

4 | CONCLUSION

The researcher has used the CNC turning workpiece as an outcome of the study to detect surface roughness by image texture feature analysis, which proposes a detection method via a noncontact approach based on the machine vision system. The mathematical relationship was developed using multiple regression modeling between image texture features of machined surfaces and arithmetic mean deviation (Ra) measured by a surface profilometer. Multiple linear and nonlinear regression models were used to judge the behavior of the detection model and analyze the experimental data. Statistical analysis showed that both linear and nonlinear detection models fit well into the multivariant regression model. In the present work, researcher found that performance of maximum detection error for linear detection model was 2.01% over nonlinear detection model of \(-9.60\%\), which showed better performance characteristics of linear detection model over nonlinear detection model to predict various statistical roughness parameters of flat rough surfaces. From the results, one can conclude to the point of predicting surface roughness effectively via a noncontact approach. Experiments show the minimal relative error in prediction of Ra and hence the obtained results provide motivation for extending proposed prediction model for amplitude parameters, namely, root mean square roughness (Rq); maximum height of peaks (Rp); maximum height of the profile (Rt), and 10-point height (Rz).

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.
AUTHOR CONTRIBUTIONS
Dhiren R. Patel contributed to the conceptualization, data curation, formal analysis, methodology, resources, software, validation, and writing original draft. M. B. Kiran and Vinay Vakharia supported supervision, writing, review, and editing.

NOMENCLATURE

| Symbol | Description |
|--------|-------------|
| μm     | micrometer  |
| μx     | mean value of Px |
| μy     | mean value of Py |
| 2D     | two dimensional |
| ANN    | artificial neural network |
| CCD    | charge-coupled device |
| CNC    | computer numerical control |
| d      | pixel distance |
| DWT    | discrete wavelet transform |
| Fi     | texture feature number |
| G      | number of gray levels utilized |
| GLCM   | gray-level co-occurrence matrix |
| i      | gray value |
| INN    | inverse difference normalized |
| j      | gray value |
| min    | minute |
| mm     | millimeter |
| R²     | coefficient of determination |
| Ra     | arithmetic mean deviation of profile |
| RPM    | revolutions per minute |
| σx     | SD of Px |
| σy     | SD of Py |
| Θ      | orientation |
| μ      | mean value of P |

ORCID

Dhiren R. Patel https://orcid.org/0000-0002-0249-6842

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