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Performance Analysis of Surface Roughness modeling using Soft Computing Approaches

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Abstract: In this paper, classification algorithms are used to classify the test data samples for determining the error rate by comparing its classification response with actual response. In this paper, Random Forest (RF) and Adaptive Neuro Fuzzy Inference System (ANFIS) classification algorithms are used as soft computing techniques to determine the error rate for the prediction of surface roughness of the materials. The parameters feed, depth of cut, speed and mean are extracted from the test sample materials and they are given to classification mode of the ANFIS classifier which produces vision measurement value. The error rate is determined by subtracting the vision measurement values from the stylus instrument values. The performance is compared with other conventional methods.

Keywords: classification, soft computing, stylus instrument, error rate, random forest

1 Introduction

The measurement of stylus instruments plays an important role in measuring or predicting the surface roughness of the materials. This is complex methodology and has less flexibility for various numbers of parts in material surface. This methodology is entirely based on post processing technique and it is not suitable for automobile equipment materials [1]. Nowadays, prediction of surface roughness of the work piece materials is done by computer aided approaches, which reduces the complexity of the process and work time. The quality and accuracy of the surface roughness prediction are often affected by poor surface image quality and cutting parameters. In this way, obtaining good quality of surface image of the materials is required for predicting the surface roughness through computer-aided approaches. The probabilistic neural networks were proposed in [1] to predict the surface roughness with respect to different cutting operations on various test materials. The methodology proposed in this work was not supported by low resolution surface-captured digital images. The authors achieved 6.2% of error rate by implementing this proposed method. In order to improve the efficiency of the surface roughness prediction, the accurate measurement of cutting parameters as cutting speed, feed rate and depth of cutting of the work piece material. These cutting-edge parameters affect the functional behavior of the surface roughness prediction process [2].

A conventional classification methodology such as neural network [3] which adopts the concepts of fuzzy logic was developed in order to reduce the error rate of the surface prediction process. These conventional methods were suitable for only linear mapping operations and they are not suitable for non-linear operations [16].

Fig.1 shows the high resolution surface-captured image and Fig.2 shows the Low resolution surface captured image.

Maohua Xiao et al. [5] developed a methodology for predicting the surface roughness using response surface estimation method. In this method, the cutting speed, cutting rate with cutting depth was given as trained parameters for predicting the surface roughness. The regression model is used in this paper in order to improve the accuracy of the surface roughness prediction. Sarnobat et al. [7] designed a methodology for predicting the surface roughness through cutting tool vibration. The

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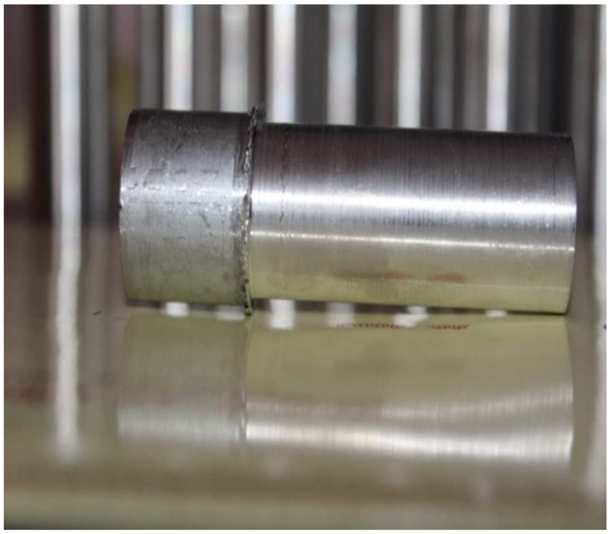

Fig. 1: High resolution surface captured image

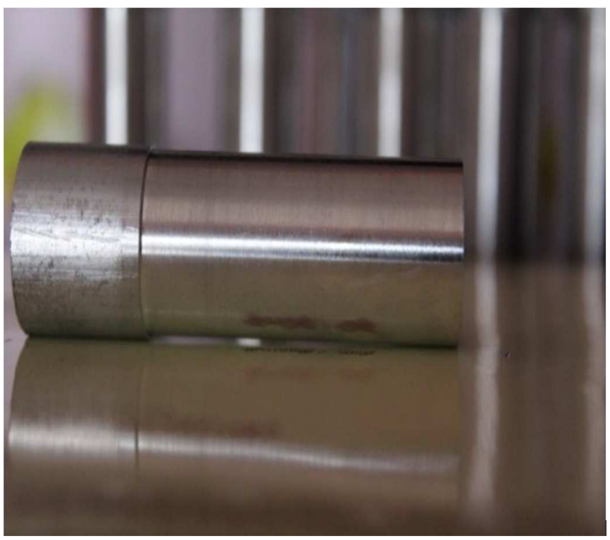

Fig. 2: Low resolution surface captured image

authors fed the depth of the cutting, speed of the cutting process with cutting rate and hardness of the materials into the soft computing algorithms. The authors used artificial neural network classification algorithm for predicting the surface roughness of the materials and regression model was used in this work for testing the proposed methodology. Hao et al. [6] proposed an efficient modeling scheme for predicting the surface roughness for thin walled products for various manufacturing devices. The authors used computer-aided approaches for predicting the surface roughness of the device.

Shinn-Ying Ho et al. [1] used ANFIS classification algorithm for the prediction of surface roughness using various cutting-edge parameters. The authors developed non-linear prediction models for surface roughness prediction and the accuracy of this method is degraded by low resolution surface-captured images. The authors applied their proposed methodology on 57 sample test surface captured image and obtained 0.41% of an average error rate. Muhammad Rizal et al. [2] developed a methodology for predicting the surface roughness using ANFIS classification algorithm. The authors constructed a rigid algorithm for online tool implementation for surface roughness prediction and modeling.

Kaye et al. [3] modified the speed of the spindle based on the prediction in an online mode. Bell type Watt transducer was used in this work in order to modify the power consumption of the three phases motor. The authors analyzed the power consumption of the proposed Watt transducer with other non-predictable type of transducers. Kopac and Sali [4] obtained speed of the cutting process and its feed rate and analyzed those measurements were determined under the frequency range of 22 KHz. The authors also analyzed the effect of noise on the machines under stable conditions. Choudhury and Kishore [9] determined flank wear with the aid of cutting force signal. The authors developed modeling methodology to analyze the cutting conditions with respect to flank wear model.

This paper implements non-linear classification algorithms as ANFIS and random forest for surface roughness prediction and modeling in order to overcome the limitations in conventional methods. The paper is organized as section 2 proposes an efficient methodology for surface roughness prediction, section 3 discusses the simulation results and section 4 concludes the paper.

2 Materials And Methods

2.1 Materials

In this paper, Aluminium Al6063 materials (3.5 cm diameter and 8 cm length) which are mainly used in many measurement equipments and automobile components as shaft and plate, are used as test piece sample materials. Canon EOS 1300D camera with 18 Mega pixels resolution camera is used to obtain the digital images of the work pieces. This produces 1024*1024 pixel digital images as image width and height. These obtained images are stored in 500 GB internal hard disk for further processing. In this paper, 50 digital images of work piece are used and they are categorized into training and testing set. The training set contains 30 images and testing set contains 20 images. The training and testing dataset are independent to each other.

2.2 Methods

The main application of this paper is to inspect the surface roughness of the materials which are available in conveyor of many automobile industries, using soft computing techniques as ANFIS and RF classification algorithms. The main contribution of this research work is to detect the error rate of the surface roughness of the materials in order to improve the production rate in automobile industries.

In this paper, ANFIS and random forest classification algorithms are used to predict the surface roughness with various cutting edge parameters.

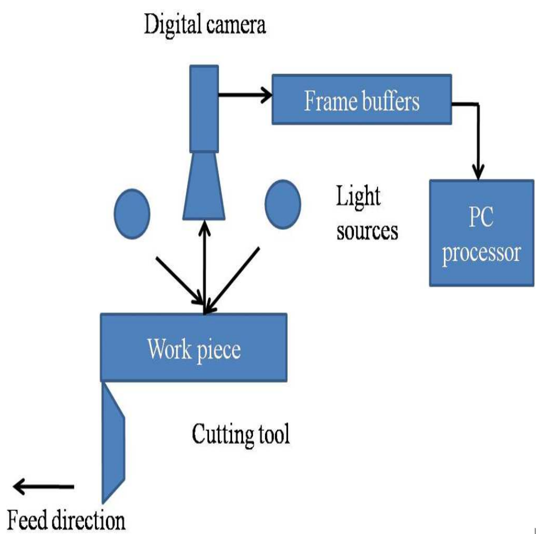

Fig. 3: Proposed flow of work

The work piece is placed over the cutting tool and the dual light sources are placed over the work piece at the inclination of 450. The high-resolution digital camera is placed over the work piece at 900. The light source emits the light over the surface of the work piece and the camera captures the digital image of the work piece. These digital images are stored in frame buffers and then they are transferred to PC for further processing, as depicted in Fig.3.

The digital images of work piece are obtained from PC and they are converted into grey-scale image. Each pixel in grey scale image consists of eight bits and they are resized into 128*128 pixels as image width and height. The mean features are now extracted from the resized digital image of the work piece and they are stored in vector array, as depicted in Fig.4.

The surface roughness of the test sample material is the average of the absolute value of the mean and it is depicted in the following equation.

$$R = \frac{1}{N}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} I(i,j) \quad (1)$$

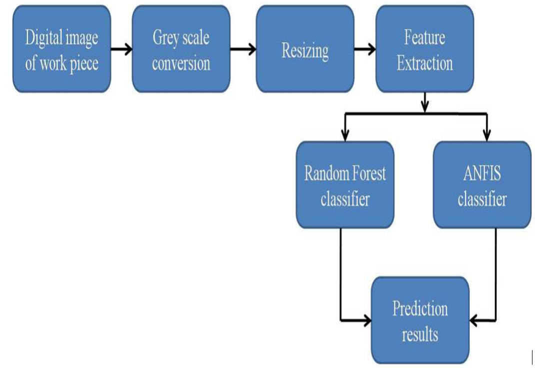

Fig. 4: Proposed surface prediction model

Whereas, N is the total number of test samples, P is number of rows, Q is number of columns and $I(i,j)$ is the digital image of the test sample.

3 Classifications

In this paper, classification algorithms are used to classify the test data samples for determining the error rate by comparing its classification response with actual response. In this paper, Random Forest (RF) and ANFIS classification algorithms are used as soft computing techniques to predict the error rate. These classification algorithms are explained in the following sections.

3.1 Random Forest Classifier

This classification methodology is used to obtain error rate by using predicted and actual values of the materials. It is ensemble classification processes which also have many decision tree paths for perfect classifications and prediction. RF consists of several trees in forest and each tree has its own cost for classification and prediction.

Fig. 5 shows the RF classification procedure in which all the test sample data are divided into different subset data with different length. From each subset of data, tree is constructed and then individual sub child leaf is formed from the parent node.

The algorithm for the prediction of the materials is illustrated in the following section.

Each tree in forest is considered as training data samples and they are contemporarily represented by,

$$X = x1, x2, x3, \ldots\ldots, xN \quad (2)$$

Whereas, N is the total number of trees in forest. In this paper, N is the total number of data samples.

Each tree in forest also has its individual labels and they are represented by,

$$Y = y1, y2, y3, \ldots.yN \quad (3)$$

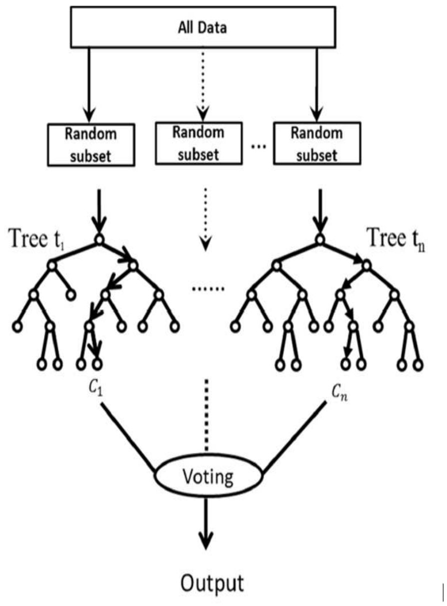

Fig. 5: Random Forest Classification Procedure

Each individual label in forest may have the value which ranges from -1 to +1.

RF classification procedure

Inputs: Training data samples;

Output: Classification result;

Start;

Step 1: Choose class of subset from the training samples with different length and store them in a ector array.

Step 2: Form classification tree for each class of sub sets in training samples.

Step 3: Choose threshold m randomly from training samples and divide each class of subset into two child leafs.

The threshold (t) can be determined using the following equation,

$$t = \frac{\sum_{i=1}^{N} X_{ij} \times \sum_{j=1}^{N} Y_{ij}}{Corr(X,Y)} \tag{4}$$

Where as, X is the odd number of samples and Y is the even number of samples in training dataset, respectively.

The correlation factor between samples is given as,

$$Corr(X,Y) = \sum_{i,j=1}^{N} X_{ij} - \sum_{i,j=1}^{N} Y_{ij} \tag{5}$$

Step 4: Apply same procedure for all class of subsets till the formation of N number of child leafs. ***Step 5:*** Determine vote of each class of subset by counting the number of child leafs. The voting can be computed as,

$$V = \frac{1}{N} \sum_{i,j=1}^{N} [Corr(X,Y) - max(X,Y)] \tag{6}$$

Step 6: Find the class of sub set which has highest-vote count and it is considered as classified output of RF.

End;

3.2 ANFIS classification

In this paper, ANFIS classification [11] is used to predict the error rate using actual and predicted value from the test data samples. It is the integration of Neural Networks (NN) and Fuzzy logic. In NN classification models, the value from test data samples are trained and classified by feedback, the error rate if occurs in output of this classifier. This error feedback forwarding mechanism is used to reduce the error rate significantly when compared with other conventional non-feedback classification algorithms [13]. In this NN classifier, the test data samples are trained and classified based on their predicted weight from the inputs, not by setting any logics behind this classification procedure. In order to overcome such limitation, fuzzy logic rules are adopted to set the classification rules. These two principles are integrated to form ANFIS classifier which has both feedback mechanism and fuzzy rules. In fuzzy integration, triangular membership functions with Mamdani fuzzy rules [14] are used in order to reduce the error rate.

The fuzzy rules used in this design are described in the following equation,

$$F = w1 * F1 + w2 * F2 \tag{7}$$

The fuzzy rules are given as,

$$F1 = q1 * x + r1 * y + s1 \tag{8}$$

$$F2 = q2 * x + r2 * y + s2 \tag{9}$$

Substitute the above equations in Eqn. (10),

$$F = w1 * A + w2 * B \tag{10}$$

$A = (q1 * x + r1 * y + s1)$

$B = (q2 * x + r2 * y + s2)$

$$F = C + D + E + F + G + H \tag{11}$$

$C = (w1 * x) * q1$
$D = (w1 * y) * r1$
$E = (w1) * s1$
$F = (w2 * x) * q2$
$G = (w2 * y) * r2$
$H = (w2) * s2$

The generic fuzzy equation for N number of samples used for training is described as,

$(w1*x)1*q1+(w1*y)1*r1+(w1)1*s1+(w2*x)2*q2+(w2*y)2*r2+(w2)2*s2=F1$

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$(w1*x)N*q1+(w1*y)N*r1+(w1)N*s1+(w2*x)N*q2+(w2*y)N*r2+(w2)N*s2=F2$

This ANFIS classifier has been operated by two modes as named as training and testing, which has different input data samples. The proposed ANFIS architecture stated in this paper have five layers and functional response of each layer is described in the following section.

Layer 1:

The proposed ANFIS classification architecture stated in this paper has single input layer with its own membership functions. In this paper, Gaussian membership function is used in order to obtain high classification accuracy. The design parameters used in this layer are called as premise. Each node in this layer has the following mean-based membership function which is described in the following equation.

$O_{i,j}=\mu_{A_i}(x); i=1,2$

$$O_{i,j}=\mu_{B_i}(x); i=3,4 \tag{12}$$

Whereas, a,b, and c are the membership parameters which can be described as the shape of the membership function. The extracted feature functions are represented by x and y.

Layer 2:

The nodes (depicted as π in Fig.6) in this layer are based on the output response from the previous layer and all the nodes are stable and they are not changing their behavior throughout the entire operations in this layer. The response of this layer is the multiplication of the mean functions from previous layer with respect to derived feature functions. This layer can be designed using the following equation,

$$O_{2,i}=\mu_{A_i}(x).\mu_{B_i}(y); i=1,2 \tag{13}$$

Layer 3: The functionality of the nodes in this layer is the ratio between firing strength of each node and the total accumulative firing strength of all nodes in this layer. All nodes (depicted as N in Fig.5) in this layer are stable and its behavior is not changing through the entire computation. This can be described in the following equation.

$$O_{3,i}=\frac{\omega_i}{\omega_1+\omega_2}; i=1,2 \tag{14}$$

Layer 4: All nodes in this layer are unstable and its behavior is changed with respect the functional response of the previous layer [15]. The design parameters in this layer are called as consequent parameters. The response of this layer is the multiplication of the weighting functions from the previous layer and the firing rule as stated in the following equation.

$$O_{4,i}=\overline{\omega_i}(p_i x+p_i y); i=1,2 \tag{15}$$

Layer 5: The response from this layer is the product accumulation of the weighting function and its firing strength. All nodes in this layer are stable and its behavior is not changing through the entire process and the response from this layer is stated below.

$$O_{5,i}=\frac{\sum_i \overline{\omega_i} f_i}{\sum_i \omega_i} \tag{16}$$

Fig.6 shows the various internal layers in ANFIS classifier.

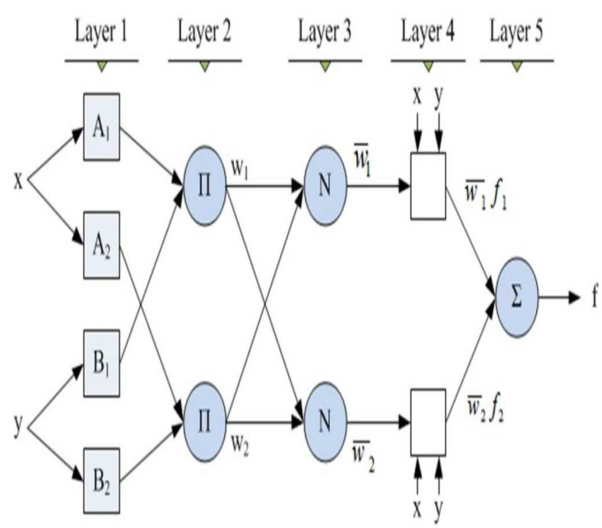

Fig. 6: ANFIS Architecture

4 Results and Discussion

In this paper, MATLAB R2014b is used as simulating tool which has inbuilt ANFIS classification modules. The simulation process is carried out in Intel Pentium Core 2 Duo processor with 2 GB internal memory as hardware accessories.

Table 1 shows the experimental turning parameters and surface roughness for training modes of RF and ANFIS classifiers. The training mode of these classifiers receives the parameters F, DC and speed as input and produce certain trained patterns which is used by classifiers in testing mode in order to produce the

Table 1: Experimental turning parameters and surface roughness for training Modes of RF and ANFIS classifiers

Image sequneces	Feed Rate	Depth of Cut	Speed	Actual Values
1	0.05	0.5	1200	0.43
2	0.1	0.6	1200	0.38
3	0.15	0.7	1200	0.47
4	0.05	0.8	1300	0.45
5	0.1	0.9	1300	0.46
6	0.15	1	1300	0.59
7	0.05	0.5	1400	0.38
8	0.1	0.7	1400	0.41
9	0.15	0.9	1400	0.70
10	0.05	1	1500	0.53

predicted values. In this paper, 75 sample materials are trained.

Table 2 shows the experimental turning parameters and surface roughness for verification tests in ANFIS classifier. The parameters F, DC, speed and mean are extracted from the test sample materials and they are given to classification mode of the ANFIS classifier which produces stylus instrument value. The error rate is determined by subtracting the vision measurement values from the stylus instrument values as depicted in Table 2. This ANFIS classifier obtains 0.01% of error rate as low and 0.44% of error rate as high.

Table 3 shows the experimental turning parameters and surface roughness for verification tests in random forest classifier. The parameters F, DC, speed and mean are extracted from the test sample materials and they are given to classification mode of the random forest classifier which produces stylus instrument value. The error rate is determined by subtracting the vision measurement values from the stylus instrument values as depicted in Table 3. This random forest classifier obtains 0.012% of error rate as low and 0.181% of error rate as high.

Table 4 shows the performance comparisons of surface roughness in both RF and ANFIS classifiers in terms of error rate. The random forest classifier produces 0.058% of error rate as an average value and ANFIS classifier produces 0.22% of error rate as an average value.

Table 5 shows the comparisons of proposed surface prediction methods with other conventional methods as Shinn-Ying Ho et al. [1] and Maohua Xiao et al. [5] in terms of error rate. The conventional method Shinn-Ying Ho et al. [1] achieves 0.41% of error rate, Maohua Xiao et al. [5] achieves 0.38% of error rate.

Fig. 7 shows the comparisons of proposed methods with conventional methods in terms of error rate. It is very clear from Fig.6, the proposed methodology for surface roughness prediction using Random Forest classifier obtains low error rate when compared with other conventional methods.

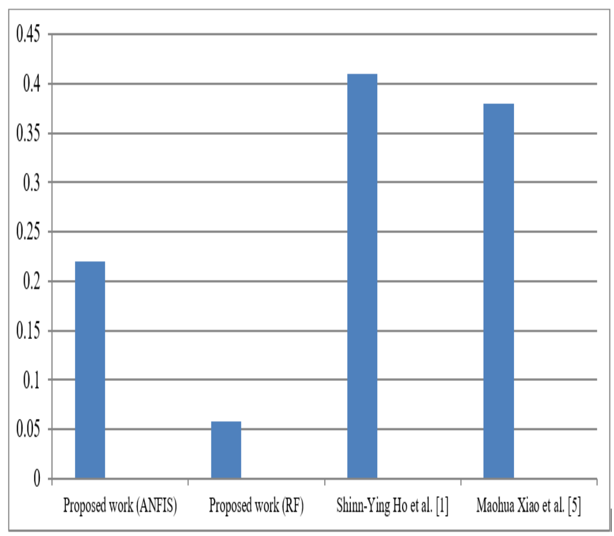

Fig. 7: Comparisons of proposed methods with conventional methods in terms of error rate

In this paper, k-fold cross validation method (Wong et al. [8]) is used to verify the methodology stated in this paper for predicting the surface roughness of the materials. This k-fold cross validation method splits the material images into k-number of equal frames. The first frame in these k-fold frames is used for developing validation work flow and the remaining frames are used for training the developed models. In this research work for predicting the surface roughness of the materials, three fold cross validation is used in order to evaluate or

Table 2: Experimental turning parameters and surface roughness for verification tests in ANFIS classifier

Image Sequences	F	D.C	Speed	Mean	Stylus instrument (μm)	Vision measurement (μm)	Error (%)
1	0.1	0.5	1500	103.81	0.42	0.455278	0.035278
2	0.15	0.7	1500	109.11	0.58	0.595016	0.015016
3	0.05	0.9	1200	112.60	0.42	0.071392	0.348608
4	0.05	1	1200	116.12	0.49	0.122507	0.367493
5	0.15	1	1200	119.92	0.7	0.446120	0.253880
6	0.15	0.5	1300	113.16	0.45	0.061826	0.388174
7	0.1	1	1300	111.17	0.54	0.292361	0.247639
8	0.05	0.5	1300	112.04	0.41	0.034777	0.444777
9	0.1	0.6	1400	108.50	0.44	0.335197	0.104803
10	0.05	0.5	1500	110.02	0.46	0.401139	0.058861

Table 3: Experimental turning parameters and surface roughness for verification tests in RF classifier

Image Sequences	F	D.C	Speed	Mean	Stylus instrument (μm)	Vision measurement (μm)	Error (%)
1	0.1	0.5	1500	103.816433	0.42	0.483333	0.063333
2	0.15	0.7	1500	109.118114	0.58	0.497933	0.082067
3	0.05	0.9	1200	112.604547	0.42	0.500133	0.080133
4	0.05	1	1200	116.123013	0.49	0.502533	0.012533
5	0.15	1	1200	119.926489	0.70	0.518800	0.181200
6	0.15	0.5	1300	113.166345	0.45	0.493867	0.043867
7	0.1	1	1300	111.175631	0.54	0.511467	0.028533
8	0.05	0.5	1300	112.045448	0.41	0.474400	0.064400
9	0.1	0.6	1400	108.507414	0.44	0.483333	0.043333
10	0.05	0.5	1500	110.022908	0.460000	0.474400	0.014400

Table 4: Performance comparisons of surface roughness in both RF and ANFIS classifiers

Image Sequences	Stylus instrument (μm)	RF (μm)	ANFIS (μm)	Error RF	Error Random ANFIS
1	0.420000	0.483333	0.455278	0.06	0.03
2	0.580000	0.497933	0.595016	0.08	0.01
3	0.420000	0.500133	0.071392	0.08	0.34
4	0.490000	0.502533	0.122507	0.01	0.36
5	0.700000	0.518800	0.446120	0.18	0.25
6	0.450000	0.493867	0.061826	0.04	0.38
7	0.540000	0.511467	0.292361	0.02	0.24
8	0.410000	0.474400	-0.034777	0.06	0.44
9	0.440000	0.483333	0.335197	0.04	0.10
10	0.460000	0.474400	0.401139	0.01	0.05

Table 5: Performance comparisons of surface roughness in both RF and ANFIS classifiers

Authors	Classification Algorithms	Error rate (%)
Proposed (In this work)	ANFIS	0.22
Proposed (In this work)	Random Forest	0.058
Shinn-Ying Ho et al. [1]	ANFIS	0.41
Maohua Xiao et al. [5]	Neural Networks	0.38

test the proposed methodology stated in this paper. This validation model determines the validation error (σ) using the following equation between the number of frames.

$$\sigma = \frac{1}{k}\sum_{k=1}^{K} S(k) \tag{17}$$

Where, k is set to 2 in this paper in order to reduce the cross validation error between samples after several trails. The cross validation error lies between 0 and 1. The low cross validation error shows that the method proposed in this paper is optimum for testing. The high cross validation error shows that the method proposed in this paper is not optimum for testing. In this way, the proposed methodology for predicting the surface prediction is validated for optimizing the results.

5 Conclusions

In this paper, classification algorithms ANFIS and random forest are used to classify the test data samples for determining the error rate by comparing its classification response with its corresponding actual response. The ANFIS classifier obtains 0.01% of error rate as low and 0.44% of error rate as high for the set of test sample work pieces. The parameters feed, depth of cut, speed and mean are extracted from the test sample materials and they are given to classification mode of the ANFIS and Random Forest classifier which produces Vision instrument value. The error rate is determined by subtracting the vision measurement values from the stylus instrument values. The Random Forest classifier obtains 0.012% of error rate as low and 0.181% of error rate as high. The Random Forest classifier produces 0.058% of error rate as an average value and ANFIS classifier produces 0.22% of error rate as an average value. The proposed methodology for surface roughness prediction using Random Forest classifier obtains low error rate when compared with other conventional methods.

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References

[1] Shinn-Ying Ho, Kuang-Chyi Lee, Shih-Shin Chen, and Shinn-Jang Ho. Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro fuzzy inference system. International Journal of Machine Tools & Manufacture, Vol. 42, pp. 1441-1446 (2002).

[2] Muhammad Rizal, Jaharah A. Ghania, Mohd Zaki Nuawia, and Che Hassan Che Harona. Online tool wear prediction system in the turning process using an adaptive neuro-fuzzy inference system. Applied Soft Computing, Vol. 13, pp. 1960-1968 (2013).

[3] J.E. Kaye, D.-H. Yan, N. Popplewell, S. Balakrishnan. Predicting tool flank wear using spindle speed change. International Journal of Machine Tools and Manufacture, Vol. 35, pp. 1309-1320 (1995).

[4] J. Kopac, and S. Sali. Tool wear monitoring during the turning process. Journal of Materials Processing Technology, Vol. 113, pp. 312-316 (2001).

[5] Maohua Xiao, Xiaojie Shen, and You Ma. Prediction of Surface Roughness and Optimization of Cutting Parameters of Stainless Steel Turning Based on RSM. Mathematical Problems in Engineering, pp. 1-15 (2018).

[6] Y. Hao and Y. Liu. Analysis of milling surface roughness prediction for thin-walled parts with curved surface. The International Journal of Advanced Manufacturing Technology, Vol. 93, pp. 2289-2297 (2017).

[7] Sarnobat SS, and Raval HK. Prediction of Surface Roughness from Cutting Tool Vibrations in Hard Turning of AISI D2 Steel of Different Hardness with Conventional and Wiper Geometry CBN Inserts. Journal of Applied Mechanical Engineering, Vol. 7, pp. 1-7 (2018).

[8] T. Wong and N. Yang. Dependency Analysis of Accuracy Estimates in k-Fold Cross Validation. IEEE Transactions on Knowledge and Data Engineering, Vol. 29, pp. 2417 - 2427 (2017).

[9] S.K. Choudhury, and K.K. Kishore. Tool wear measurement in turning using force ratio. International Journal of Machine Tools and Manufacture, Vol. 40, pp. 899-909 (2000).

[10] N.I.I. Mansor, M.J. Ghazali, M.Z. Nuawi, and S.E.M. Kamal. Monitoring bearing condition using airborne sound. International Journal of Mechanical and Materials Engineering, Vol. 4, pp. 152-155 (2009).

[11] M. Buragohain, and C. Mahanta. A novel approach for ANFIS modeling based on full factorial design. Applied Soft Computing, Vol. 8, pp. 609-625 (2008).

[12] B.Y. Lee, and Y.S. Tarng. Surface roughness inspection by computer vision in turning operations. International Journal

of Machine Tools and Manufacture, Vol. 41, pp. 1251-1263 (2001).

[13] Lo, Ship-Peng. An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling. Journal of Materials Processing Technology, Vol. 142, pp. 665-675 (2003).

[14] Benardos, P. G., and G-C. Vosniakos. Predicting surface roughness in machining: a review. International journal of machine tools and manufacture, Vol. 43, pp. 833-844 (2003).

[15] Reddy, B. Sidda, J. Suresh Kumar, and K. Vijaya Kumar Reddy. Prediction of surface roughness in turning using adaptive neuro-fuzzy inference system. Jordan Journal of Mechanical and Industrial Engineering, Vol. 3, pp. 252-259 (2009).

[16] T. Sathish. Heat Transfer Analysis Of Nano-fluid Flow In A Converging Nozzle With Different Aspect Ratios. Journal of New Materials for Electrochemical Systems, Vol. 20, pp. 151-237 (2017).

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