Texture Classification of Machined Surfaces Using Image Processing and Machine Learning Techniques

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The identification of surface texture images from machining surfaces using image processing techniques has been a prominent research area in the recent decades. The aim of this paper is to identify various machined surface texture images using machine learning techniques. Charge coupled device is used to capture images of machined components. Based on captured images, twelve statistical features are extracted and feature vector is formed. Grey Level Co-occurrence Matrix is used to extract statistical features from the machined surface images. Four Machine learning algorithms such as Random Forest, Support Vector Machine, Artificial Neural Network and J48 were utilized to characterize machined surfaces. Training and Ten-fold cross validation process is utilized for identification of machined component images. It is found that Artificial Neural Network and Random forest give100 % training accuracy and 99% cross validation accuracy. Results obtained demonstrate the efficiency of proposed methodology, which is useful for identifying texture images.

Keywords: *Surface texture,Grey level co-occurrence matrix,Feature extraction,Classification,Ten-fold cross validation.*

1. INTRODUCTION

Texture of an object can be defined as an appearance of an object based on shape, size, density and surface characteristics. Investigation on surface texture is an intriguing topic in the image processing and machine learning domain and has applications in remote sensing, object tracking, object recognition, segmentation of images etc. [1].

Haralick et al. [2] proposed to utilize Co-occurence matrix to extract texture features. Classification of the variety of textures enables us to extract information about the structural arrangement of the surfaces. Texture classification techniques are categorized as structural [3], statistical [4], signal processing [5], stochastic based on model [6], and techniques based on morphology [7].

Signal processing techniques are used to extract useful information from the signals and images.GLCM is a type of statistical technique which is used to compute first-order,second-order and higher-order statistical features and to form feature vector which is used for training and testing by machine learning algorithms for identification of images [8].

Non contact technique for texture characterization is considered to be a reliabile method for analyzing machined surfaces in manufacturing industries and is emerging as a prominent area of research [9].

Image processing techniques are consider as a non contact technique for capturing images which will be useful for determination of surface roughness, to accurately measure dimensions and to detect geometries of difficult to machined components. For developing image processing based surface texture identification techniques various authors proposed intensity histograms [10], Gray-level co-occurrence matrix (GLCM) [11], fractal analysis methods [12] etc. For capturing images from machined surfaces,digital images obtained by charge coupled device (CCD) cameras are used for surface characterization [13].

Tool condition monitoring is an area where several authors used signal processing,image processing and machine learning algorithms to identify the condition of tool as well severity of damage.

There have been a significant experimental study conducted on various machining processes like turning, milling, boring etc. to distinguish the tool conditions,prediction of tool wear with the aid of machine learning, since conventional tool detection system does not have the capacity of self-learning.

To correctly identify texture images,machine learning is considered to be a prominent techique. It is used for classification and regression and is used by many authors in the variety of applications such as EEG signal classification [14],

Fault diagnosis [15,16], Manufacturing [17,18] etc. Support Vector Machine (SVM) [19], Artificial Neural Network (ANN) [20],

Naive Bayes (NB) are widely used machine learning algorithms and is used by many authors for classification purpose. Feature vector is an important parameter through which condition of any tool,specimen can be determined accurately. To form a feature vector, statistical parameters need to be extracted from the images. It is believed that feature vector if

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extracted properly contains all relevant information. This feature vector is then used for training,testing and cross validation using machine learning algorithms. For determination of tool flank wear, Sun et al. [19] applied SVM for multi classification of tool wear and the experimental results revealed,that the proposed method is useful for tool wear identification.

Gupta and Raman [20] calculated the surface roughness of cylindrical bar based on the images obtained through laser scatter pattern. Images are captured when rotation of cylindrical bar varied from 140 to 185 rpm.

Kassim et al. [21] used Hidden Markov Model to differentiate the various conditions of wear in tool. Thirteen element feature vector obtained from the captured images from end milled and turning process was used for analysis. The Grey Level Co-occurrence Matrix is utilized to separate the features of the end milled surface texture images by Nathan et al. [22].

Authors established relationship between roughness and surface texture of milled components.

In an another study, Suarez et al. [23] classified surface roughness utilizing the texture features extracted from GLCM.

Based on the available literature. it is observed that the combination of image processing techniques and machine learning is advantageous in manufacturing domain due to the following reasons:

1) no force or load is applied to the specimen during examination.

2) to examine the conditions of manufacturing process, sensors or their combination are required, which is expensive.

3) Quick decision can be made about the condition of specimen; once images obtained from CCD are combined with machine learning algorithms. Based on available literature,it is envisaged that the combination of image processing and machine learning methods have tremendous applications which are unexplored specifically in manufacturing applications.

In this paper, authors investigate, the effects of twelve texture features extracted from GLCM for classification of textured surfaces obtained from EDM, Shaping,

Milling and Sand Blasting. Support Vector Machine, Random Forest, Artificial Neural Network, and J48 classifier are used for texture identification using training and ten-fold cross validation. The experimental result obtained suggests that the proposed methodology will be useful for texture feature identification from various machining processes. Figure 1 shows the procedure used for texture classification.

2. GREY LEVEL CO-OCCURRENCE MATRIX

Haralick et al. [2] have proposed Grey Level Co-occurrence Matrix (GLCM) which is a popular technique for feature extraction and is used for images. Gray level co-occurrence matrix has been ended up being an intense tool for texture image segmentation [24].

GLCM which is a statistical technique,finds the association between the images and pairs of pixels.GLCM converts the image in to a matrix in which the the number of rows and columns is equal to the pixel value in the images of surface.

The matrix acquired from GLCM depicts the recurrence of one gray level showing up in a predefined spatial linear relationship with another gray level inside the area of investigation.

Figure-2 indicates the process of computing a few values in the GLCM of 4-by-5 image by grey co-matrix. In the GLCM, component (1, 1) holds the esteem 1 because there is one and just case in the image where two, on a level plane bordering pixels have the qualities 1 and 1. Component (1, 2) in the GLCM hold the esteem 2 since there are two cases in the image where two, equitably nearby pixels have the qualities 1 and 2. Component (1, 3) in the GLCM has the esteem 0 because there are no events of two on a level plane neighboring pixels with the qualities 1 and 3. Grey co framework keeps preparing the info image, checking the image for other pixel sets (i, j) and recording the total in the relating component of the GLCM.GLCM tabulates the frequency of appearance of combination of gray levels in images.

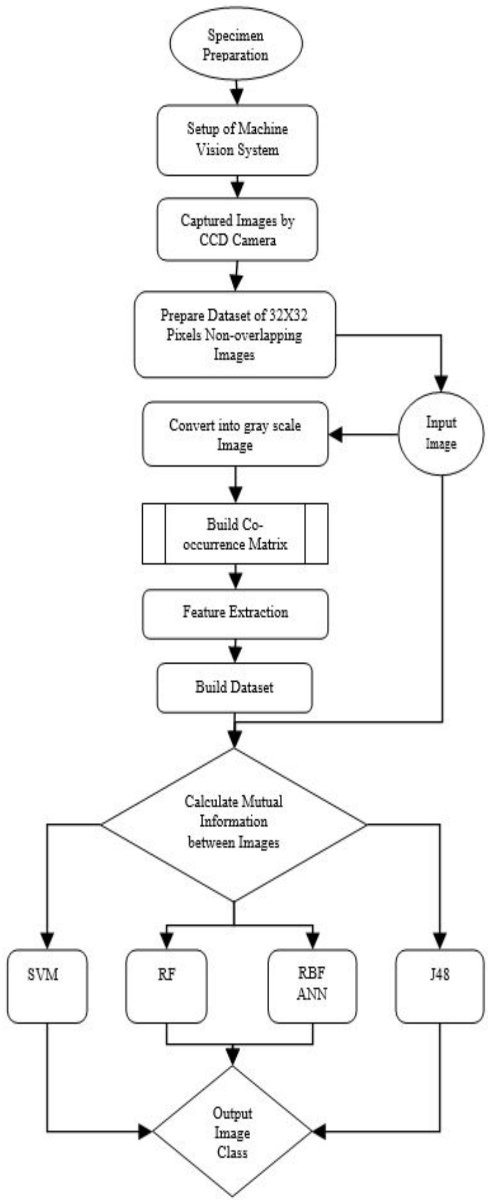

Fig. 1. Methodology for Texture Classification

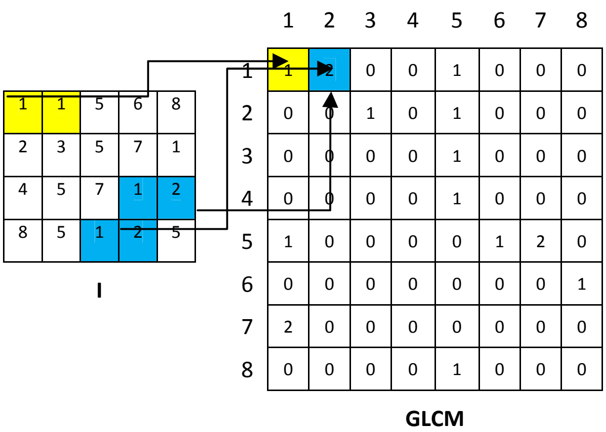

Fig. 2. Conversion of Image into GLCM

3. TEXTURE CLASSIFICATION TECHNIQUES

Machine learning is emerged as a methodology which is used for classification and regression. Supervised and Unsupervised are widely used machine learning techniques. In supervised machine learning, labels are required for classification. On the other hand, labels are not required in unsupervised learning and emphaisis is given to identify patterns after forming clusters.

3.1 Support Vector Machine

Support vector machine (SVM) is a machine learning method which is based on learning theory and the structural risk minimization principle. It is a type of supervised learning algorithm principally used for classification and regression analysis [25].

To get better accuracy from a given data set by classifying into different groups, SVM uses support vectors. This support vector lies on the largest margin to find on optimal hyper plane. Optimal hyper plane separates data of one class from another class and classification result is obtained [26].

For multi-class classification problems SVM model work as follows: Let C represents the total number of classes and initially C1 is trained considering it as a new class and the rest of the class with another class. In the second stage C1 is removed and C2 is considered as new class and the remaining classes as second classes. The process will continue for the rest of the class and average result will give final result for multiclass data sets.

3.2 Random Forest

Random forest is a classifier algorithm introduced by Breiman L [27]. It is considered as an ensemble method which uses tree as a predictor.

A large number of decision trees are built in RF from dataset based on bagging to improve classification. The purpose of bagging is to reduce variance in dataset and simultaneously avoid over-fitting.

The training set in the initial phase divided into in-bag and out-bags set. The decision tree is built for each in-bag data set and out-of-bag set is used for evaluating the classification accuracy [28]. Final results are obtained from the trees constructed from out-bag set from the entire training dataset.

3.3 Artificial *Neural Network*

Artificial Neural Network (ANN) is a technique used for classification with the help of feature vector after converting input feature vector in to training and testing data sets. ANN is deployed to solve problems related to pattern recognition, manufacturing, forecasting, robotics etc.

A Neural network consists of various layers of interconnected nodes. The feature vector serves as an input to the algorithm via input layer which consists of at least one hidden layers where the real preparing of data is completed [26].

The input vector consists of n dimensional vectors where n represents the total number of attributes i.e.features. In present paper, Radial basis function (RBF) kernel function is used in ANN, which formulates individual layer of RBF with output layer with corresponding node for retaining every information of a specific class. The hidden layer consits of neurons which may vary and the count of hidden neurons in RBF is proportionate to the aggregate number of data in training. The set of nodes connected with output layer reflects the classification results. Classification decision is made based on the weightage gain by each instances based on given attributes.

3.4 J 48

J48 algorithm is a supervised algorithm used for classification of data sets. J48 is considered as a modified version of C4.5 and ID3 algorithm which are generally used for construction of decision trees [29].

Decision trees utilized graph based branching method for analysis of datasets provided by user. The internal node represents test on an attribute, branch characterize the outcomes of test and leaf node represents class labels. For identifying a class, instance is splitted by internal node in to subspaces based on discrete function of attribute values. Instances are classified by guiding them from root of the tree to a leaf, where each leaf is assigned to one class which represents the most appropriate target value. The process is repeated till the outcome of final decision about class identification will be obtained.

4. EXPERIMENTAL SETUP

The schematic diagram of experimental set-up is shown in Figure 3. Specimens are machined with manufacturing processes like EDM, Shaping, Milling and sand-blasting for the purpose of classification i.e. identification of images.Four images are further divided in to 15 subsets of each images. Therefor the input feature vector contains 60 non-overlapping sub images of 32 x 32 pixels. Charge Coupled Device (CCD) Camera from PULNIX was used to capture machined surface images which is illuminated by lighting for proper illumination of surfaces.

The captured images stored in a computer which is connected to an advance image processing software and hardware. The captured images are further processed for noise cancellation. Figure-4 shows sample images obtained from various machining processes.

Fig. 3. Experimental setup to capture texture images through CCD

5. TEXTURE FEATURES EXTRACTION FROM GLCM

Texture features generally refers to the surface characteristics and object appearance which is further defined by geometric properties, shape, size etc. When features are extracted considering above mentioned parameters from the images of machined components then it is known as texture feature extraction.

Texture analysis is broadly classified into classification, segmentation, synthesis and shape from texture. In texture classification, the images are identified when a set of input known as feature vector is fed in to machine learning algorithms.

Algorithm maps the input information with the output label during training and then identified images during testing. Statistical features are classified as first order, second order and higher order. In the current study twelve texture features are calculated from the GLCM which are mentioned below:

Homogeneity, Angular Second Moment (ASM):

$$\sum_{\boldsymbol{i}=0}^{\boldsymbol{G}-1}\sum_{\boldsymbol{J}=0}^{\boldsymbol{G}-1}\{\boldsymbol{P}(\boldsymbol{i},\boldsymbol{j})\}^2 \tag{1}$$

Contrast [2]***:***

$$\sum_{\mathrm{n}=0}^{\mathrm{G}-1}\mathrm{n}^2\left\{\sum_{\mathrm{i}=1}^{\mathrm{G}}\sum_{\mathrm{j}=1}^{\mathrm{G}}\mathrm{P}(\mathrm{i},\ \mathrm{j})\right\},\ |\mathrm{i}-\mathrm{j}|=\mathrm{n} \tag{2}$$

Local Homogeneity, Inverse Difference Moment (IDM) [1,2]**:**

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{1}{1+(i-j)^2}P(i,j) \tag{3}$$

Entropy [1,2]***:***

$$-\sum_{i=0}^{G-1}\sum_{J=0}^{G-1}P(i,j)\,Xlog(P(i,j)) \tag{4}$$

Correlation:

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{\{i\ X\ j\}\ X\ P(i,j)-\{\mu_x\ X\ \mu_y\}}{\sigma_x\ X\ \sigma_y} \tag{5}$$

Sum of Squares, Variance:

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-\mu)^2\ P(i,j) \tag{6}$$

Sum Average:

$$\sum_{i=0}^{2G-2} i\,P_{x+y}(i) \tag{7}$$

Sum Entropy [13]***:***

$$-\sum_{i=0}^{2G-2} P_{x+y}(i)\log\left(P_{x+y}(i)\right) \tag{8}$$

Difference Entropy:

$$-\sum_{i=0}^{G-1} P_{x+y}(i)\log\left(P_{x+y}(i)\right) \tag{9}$$

Table 1 Sample texture features obtained from EDM machined surface

Feature No.	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
F1	0.75	0.74	0.68	0.63	0.64	0.68	0.62	0.78	0.67	0.70	0.64	0.79	0.79	0.69	0.68
F2	0.70	0.76	1.09	1.40	1.20	1.15	1.57	0.57	1.19	1.04	1.38	0.54	0.54	1.07	1.12
F3	0.75	0.74	0.68	0.63	0.64	0.68	0.62	0.78	0.67	0.70	0.64	0.79	0.79	0.69	0.68
F4	2.10	2.13	2.28	2.48	2.46	2.39	2.54	2.02	2.47	2.33	2.47	1.88	1.88	2.26	2.34
F5	0.50	0.49	0.40	0.29	0.36	0.48	0.29	0.63	0.48	0.51	0.36	0.57	0.57	0.40	0.44
F6	17	17	18	20	20	19	20	17	20	19	19	15	15	17	19
F7	5.52	5.52	5.61	5.88	5.95	5.74	5.91	5.47	5.93	5.67	5.78	5.14	5.14	5.50	5.68
F8	1.62	1.64	1.67	1.75	1.76	1.76	1.79	1.63	1.82	1.74	1.77	1.50	1.50	1.66	1.72
F9	0.91	0.93	1.05	1.15	1.08	1.08	1.20	0.84	1.10	1.05	1.15	0.82	0.82	1.06	1.07
F10	3.35	3.81	5.93	4.49	4.43	7.86	4.70	6.24	8.07	8.05	5.97	4.34	4.34	5.22	6.82
F11	18	21	35	28	28	49	30	38	52	51	36	23	23	30	43
F12	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.99	0.98	0.98	0.98	0.99	0.99	0.98	0.98

Table 2 Sample texture features obtained from Shaping machined surface

Feature No.	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
F1	0.72	0.72	0.72	0.70	0.73	0.72	0.71	0.75	0.75	0.73	0.67	0.78	0.72	0.72	0.75
F2	0.86	1.02	1.08	0.84	0.84	1.01	1.21	0.75	0.77	1.03	1.30	0.64	0.86	1.15	0.85
F3	0.72	0.72	0.72	0.70	0.73	0.72	0.71	0.75	0.75	0.73	0.67	0.78	0.72	0.72	0.75
F4	2.76	2.53	2.46	2.68	2.70	2.57	2.62	2.45	2.58	2.50	2.74	2.29	2.77	2.46	2.26
F5	0.80	0.68	0.67	0.75	0.78	0.73	0.69	0.77	0.80	0.74	0.70	0.78	0.78	0.69	0.67
F6	57	47	44	52	54	48	48	46	51	47	53	43	56	45	40
F7	9.21	8.40	8.11	8.90	9.03	8.42	8.44	8.33	8.81	8.28	8.82	8.02	9.21	8.12	7.76
F8	2.22	1.94	1.89	2.14	2.17	2.00	2.01	1.99	2.12	1.96	2.09	1.88	2.21	1.91	1.77
F9	0.98	1.05	1.06	0.96	0.97	1.04	1.10	0.93	0.94	1.04	1.14	0.88	0.98	1.08	0.97
F10	15	7	12	10	11	15	15	14	15	20	12	15	12	18	11
F11	157	65	85	98	120	118	119	108	138	157	124	107	132	131	73
F12	0.99	0.99	0.98	0.99	0.99	0.99	0.98	0.99	0.99	0.98	0.98	0.99	0.99	0.98	0.99

Inertia:

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{i-j\}^2\ X\,P(i,j) \tag{10}$$

Cluster Shade:

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left\{i+j-\mu_x-\mu_y\right\}^3\ X\,P(i,j) \tag{11}$$

Cluster Prominence:

$$\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left\{i+j-\mu_x-\mu_y\right\}^4\ X\,P(i,j) \tag{12}$$

In the methodology adopted in present paper,authors capture the texture images from the four specimen which were machined by EDM, Shaping, Milling and Sandblasting.

The captured images are filtered using GLCM and all the four images are further divided in to 15 subimages. In total, 60 images are used for extracting the tweleve statistical parameters.

A matrix of 60 X 12 forms a feature vector which is used for identification of specimen, manufactured from the machining process.A sample feature vector obtained from EDM and Shaping textured images is shown in Table 1 and Table 2 respectively.

Table 3. Confusion Matrix for SVM

E	S	M	SB	Prediction	E	S	M	SB	Prediction
13	0	0	2	E	13	0	0	2	E
0	15	0	0	S	0	15	0	0	S
0	0	15	0	M	0	0	15	0	M
0	0	0	15	SB	0	1	0	14	SB

Table 4. Confusion Matrix for Random Forest

E	S	M	SB	Prediction	E	S	M	SB	Prediction
15	0	0	0	E	14	0	1	0	E
0	15	0	0	S	0	15	0	0	S
0	0	15	0	M	0	0	15	0	M
0	0	0	15	SB	0	0	0	15	SB

Table 5. Confusion Matrix for ANN (RBF)

E	S	M	SB	Prediction	E	S	M	SB	Prediction
15	0	0	0	E	15	0	0	0	E
0	15	0	0	S	0	15	0	0	S
0	0	15	0	M	1	0	14	0	M
0	0	0	15	SB	0	0	0	15	SB

Table 6. Confusion Matrix for J48

E	S	M	SB	Prediction	E	S	M	SB	Prediction
15	0	0	0	E	14	1	0	0	E
0	15	0	0	S	0	15	0	0	S
0	0	15	0	M	0	0	15	0	M
0	0	0	15	SB	0	2	0	13	SB

Table 7. Showing average texture characterization accuracy of machining process

Classifier	SVM	RF	ANN (RBF)	J48
Training accuracy	96	100	100	100
Cross Validation (10fold)	95	99	99	96

6. RESULTS AND DISCUSSION

In the experiment conducted authors used 4 different texture images obtained from machining processes as shown in Fig. 4. Nonoverlapping images of 32×32 sizes were constructed, which form a database of 60 images. For decomposition authors have used GLCM technique and extracted twelve different texture features. Table 3-Table 6 shows the confusion matrix showing the classwise prediction accuracy. In confusion, matrix diagonal elements represent correctly classified instances, whereas nondiagonal element represents incorrectly classified instances.

Table 3 shows the confusion matrix obtained when SVM is used as a classifier for Training and ten-fold cross validation purpose. When training is done for the texture features with SVM as a classifier then SVM is able to predict correctly Shaping (S), Milling (M), Sand blasting (SB), classes, whereas for EDM (E) class 13 out of 15 instances is predicted accurately.

For cross validation SVM is able to identify Shaping and Milling classes accurately and 13 out of 15 instances are predicted accurately for E class and 14 out of 15 are instances predicted accurately for Sand blasting class. It is clear that E class is anticipated less both for training and cross validation while SVM is utilized as a classifier. Table 4 shows confusion matrix formed when Random forest is used as a classifier.

Random forest predicts all the instances correctly for all the classes when training of texture feature is carried out. While performing cross validation only EDM class is misidentified, whereas other classes are predicted accurately. Similar observation is obtained when ANN and J48 were used as a classifier for training and cross validation of texture features shown in Table 5 and Table 6. For cross validation, 14 out of 15 instances were predicted for milling when ANN is used as a classifier and the other classes are identified accurately.

All 15 classes are identified correctly for EDM,Shaping and Milling, whereas 13 out of 15 instances were predicted accurately for sand blasting, when J48 is used as a classifier.

Table 7 shows the average texture classification accuracy with classifiers. It is observed that 100 % training accuracy is achieved using RF, ANN and J48 classifier and 96 % training accuracy is achieved utilizing SVM as a classifier.

For ten-fold cross validation RF and ANN gives maximum texture characterization accuracy of 99 % where as J48 gives 96 % and SVM gives 95 % cross validation texture characterization accuracy.

For predicting texture characterization of machined images RF and ANN gives highest accuracy based on the proposed methodology. The texture classification results obtained from the images of machining process is shown in Table 5 Training and ten- fold cross validation of feature sets are carried out with twelve texture features using SVM, RF, ANN and J48 classifiers.

7. CONCLUSIONS

In this paper,the application of image processing techniques and machine learning algorithms for identification of texture images of machined surface is examined. For automated inspection, the image processing techniques emerge as a potential tool for decision making.

The advantage of texture analysis is that it is non contact type inspection methodology which can be useful for tool condition monitoring, roughness assessment, detection of defects etc. Authors have used GLCM matrix which represents the texture images, to extract texture features obtained from machined specimens.

Grey Level Co-occurrence Matrix is used to extract twelve statistical features from the images of various machined surfaces.

A feature vector is formed which consist of features extracted from texture images from EDM, Shaping, Milling, and Sand Blasting and feature vector is fed in to classifier as SVM, RF, ANN and J48.

Training and ten-fold cross validation is performed on the feature set. Result reveals that RF and ANN gives 99 % cross validation accuracy for identifying texture images from machined surfaces.

From the experimental results it is observed that methodology used for extracting features from GLCM and machine learning algorithms suggest the potential application in industry for the advancement of real time characterization of images from various manufacturing processes and applications.

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NOMENCLATURE

G	Number of gray level utilized
μ	Mean value of P
μ_x	Mean value of P_x
μ_y	Mean value of P_y
σ_x	Standard deviation of P_x
σ_y	Standard deviation of P_y
F_n	Texture Feature Number

КЛАСИФИКАЦИЈА ТЕКСТУРЕ ОБРАЂЕНИХ ПОВРШИНА КОРИШЋЕЊЕМ ОБРАДЕ СНИМАКА И ТЕХНИКАМА МАШИНСКОГ УЧЕЊА

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Одређивање површинске текстуре на основу снимака обрађених површина коришћењем техника обраде снимака добија на значају последњих деценија. Циљ рада је одређивање различите текстуре обрађених површина на основу снимака применом техника машинског учења. Помоћу ЦЦД сензора прикупљани су снимци обрађених компонената. На основу снимака издвојено је дванаест статистичких карактеристика и формиран је вектор атрибута. Статистичке карактеристике су издвојене помоћу Грејове матрице. Алгоритми за машинско учење (РФ, СВМ, АНН и Ј48) су коришћени за карактеризацију обрађених површина. Одређивање текстуре обрађених површина на основу снимака је

извршено помоћу тренинга и десетоструком унакрсном валидацијом. Утврђено је да се коришћењем АНН и РФ постиже прецизност тренинга од 100% и прецизност валидације од 99%. Добијени резултати потврђују ефикасност предложене методологије одређивања текстуре помоћу снимака.