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# Identification and classification of materials using machine vision and machine learning in the context of industry 4.0

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## Abstract

Manufacturing has experienced tremendous changes from industry 1.0 to industry 4.0 with the advancement of technology in fast-developing areas such as computing, image processing, automation, machine vision, machine learning along with big data and Internet of things. Machine tools in industry 4.0 shall have the ability to identify materials which they handle so that they can make and implement certain decisions on their own as needed. This paper aims to present a generalized methodology for automated material identification using machine vision and machine learning technologies to contribute to the cognitive abilities of machine tools as wells as material handling devices such as robots deployed in industry 4.0. A dataset of the surfaces of four materials (Aluminium, Copper, Medium density fibre board, and Mild steel) that need to be identified and classified is prepared and processed to extract red, green and blue color components of RGB color model. These color components are used as features while training the machine learning algorithm. Support vector machine is used as a classifier and other classification algorithms such as Decision trees, Random forests, Logistic regression, and k-Nearest Neighbor are also applied to the prepared data set. The capability of the proposed methodology to identify the different group of materials is verified with the images available in an open source database. The methodology presented has been validated by conducting four experiments for checking the classification accuracies of the classifier. Its robustness has also been checked for various camera orientations, illumination levels, and focal length of the lens. The results presented show that the proposed scheme can be implemented in an existing manufacturing setup without major modifications.

**Keywords** Industry 4.0 · Image processing · Machine vision · Machine learning · Material classification · Support vector machine

## Introduction

Industry 4.0 is a newly emerging concept which is multidisciplinary and complex in nature (Moeuf et al. 2018). Context awareness, fully automatic, autonomy, flexibility, reliability, accuracy, modularity, digital presence, scalability, agility, resilience are some of the characteristics of industry 4.0 (Mittal et al. 2019). These are being realized through many evolving technologies such as machine learning, big data, and analytics, cyber-physical systems, internet of things, virtual reality, and augmented reality. Characteristics such as context awareness, fully automatic and autonomy can be achieved through machine learning algorithms. Depending on a particular application, various machine learning algorithms like regression, decision trees, support vector machines (SVM), k-Nearest Neighbor, clustering and neural networks have already been explored. The cognitive behavior of machine tools and associated material handling devices such as robots can be enhanced with the help of machine learning. The importance of cognitive abilities of machine tools was emphasized by Zhao and Xu (2010) and Woods (1985). Shea et al. (2010) have proposed a cognitive machine shop. There had been plenty of work done on the application of machine learning techniques in manufacturing to solve a plethora of problems. For instance, Vejdannik and Sadr (2018) used probabilistic neural networks to automatically

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carry out microstructural characterization and classification. Strese et al. (2017) used Naive Bayes and classification tree for classifying meshes, stones, glossy surfaces, wooden surfaces, rubbers, fibers, textiles, papers, and foams.

Demir (2018) used SVM for classifying textured images based on a histogram of oriented gradients. Denkena et al. (2018) implemented machine learning algorithms like k-Nearest Neighbor, neural networks, SVM and decision tree for material identification during machining of cylindrical workpieces. Kwon et al. (2018) have applied deep neural work for classifying the melt pool images in laser melting, while Kucukoglu et al. (2018) combined neural networks with wearable technology to identify defective assembly processes. Pimenov et al. (2018) have employed artificial intelligence methods to predict the roughness of surfaces by monitoring wear on the face mill teeth. Various machine learning techniques and their applications for several manufacturing related applications are described in deatail by Pham and Afify (2005). Still, many narrow areas of manufacturing are left unexplored, which would offer exciting solutions to many problems related to manufacturing. This would be leading to the realization of industry 4.0 along with other technologies mentioned earlier. Machine learning by itself shall not be the only tool available for the realization of industry 4.0, but machine vision combined with machine learning could address a wide variety of problems.

Machine vision, also known as computer vision in general, is the technology that enables machines to visually understand their surroundings with the aid of one or more vision sensors along with an application specific software. For obtaining the desired results, the required intensity of illumination of an object or scene may also vary from application to application and in some cases from manufacturer to manufacturer of machine vision systems. However, the amount of illumination has to be of a constant value for a given application. Machine vision has replaced human vision in many areas of manufacturing and other fields as well. For instance, Tarlak et al. (2016) have developed a method for measuring the color of food materials using machine vision. Whereas, Kita et al. (2017) presented the applications of machine vision in manufacturing. Though machine vision by itself is sufficient enough to deal with the majority of the problems in many fields of engineering, it is being applied along with machine learning methods to unleash the possibilities of introducing cognition in manufacturing. Experiments of this type were already carried out by many researchers. Silvén et al. (2003) employed nonsupervised clustering methods for inspection of wood from colored images. Lin et al. (2018) automated the defect inspection process of LED bulb chips using convolutional neural networks along with machine vision. Joshi et al. (2018) developed a machine vision system for inspecting small parts employing machine learning methods.

Color models are mathematical descriptions of color distribution in an image. There are many color models available, some among them are RGB, CMY, HSI, YIQ and L*a*b (Wen et al. 2004). This paper makes use of the RGB color model for extracting the features as input to a machine learning model. RGB color model is an additive model in the sense that different proportions of red, green and blue when added will give different colors. All colored images are made up of different proportions of RGB colors.

Meshes, stones, glossy surfaces, wooden surfaces, rubbers, fibers, textiles, papers, and foams were classified using machine learning methods as presented by Strese et al. (2017). Fabric, metal and tree surfaces textures are also classified using a histogram of oriented gradients (HOG) by Demir (2018). This technique cannot classify the materials either metallic or nonmetallic with same texture and different colors. HOG can detect textures only because of the patterns present in the textures irrespective of the visual appearance. Hence, colors of the surfaces which possess same texture cannot be differentiated using HOG. So, there is a need for another methodology. An effort to identify cylindrical workpieces during machining using machine learning methods is demonstrated in Denkena et al. (2018). Textures of some materials can be found in a database as well (Fritz et al. 2004). Based on the RGB values of an image, printed fabric pattern color differentiation is carried out by Kuo et al. (2008). A clearly defined visible research gap could be found here on the classification of flat material surfaces of metallic or nonmetallic materials with same or different texture which would differ visually during machining. For materials such as Aluminium, Copper, and Wood, there is no generalized methodology available for their classification and no such published data set is available, to the best of our knowledge. Hence, the aim and objective of this work are to identify and classify any flat materials at macroscopic level during machining so that machine tools are aware of the type of material they are machining, which is critical for taking certain decisions so as to adjust feed rate, depth of cut and switching of coolant, etc. The materials considered for classification in the present work are Aluminium, Copper, Wood, and Mild steel.

## Novelty

The features mentioned in the literature for classification of the surfaces are textures of the surfaces, acceleration, and force signals. Collecting these features is expensive and they are also not suitable for classifying the materials during machining. Hence, the mean values of red, green, and blue are proposed as novel features for the classification work reported in the paper. The implementation of SVM for classifying the engineering materials particularly during machining has not yet been reported in literature. Hence, a novel methodology of using SVM is proposed for the first time in this work to classify the materials during machining.

With this introduction, the rest of the paper is constructed as follows. The methodology proposed is presented in the next section followed by details on the experimental setup used in the collection of images. The mathematical formulation related to image processing towards feature extraction, histograms, correlation plot and a box plot of features along with a description of dataset are presented subsequently. A section on "Training the machine learning model" is allocated to explain the details of the training of SVM. The results and discussions are presented thereafter followed by conclusion and future research.

## Proposed methodology

Based on the research gap identified, a generalized methodology is proposed which is shown in Fig. 1. This scheme combines machine vision, machine learning, and a data set of surface images of Aluminium, Copper, Medium density fiberboard (MDF) and Mild steel-rusted for demonstrating the methodology. All images have been acquired with the ambient light of intensity of 37 lx and without any special light effects. Features are extracted by processing the entire data set and the machine learning model has been trained for classification. To get rid of the effect of ambient light disturbance over the material, a strict lighting provision needs to be adopted, which is not standardized as different manufacturers supply diverse lighting provisions to meet versatile requirements. However, the proposed methodology remains the same and can be applied under any kind of illumination provided all such images are collected with the same amount of illumination.

To summarize, the contributions of this research work are,

- Development of a generalized methodology for identification of materials using machine vision and machine learning algorithms.
- Means to impart perception and decision making abilities of machine tools to mimic human cognition as mentioned by Dowe and Hern (2012) and Hien et al. (2017) to facilitate selection of suitable machining parameters based on the material identified.
- Development of Technology for the machine tool manufacturers for manufacturing intelligent machine tools.

## Experimental setup for image collection

The machining operations applicable for flat material surfaces include drilling, milling, grinding, polishing as needed. In all these operations, the flat surface of the material will be kept perpendicular to the tool. Similarly, it is better to mount

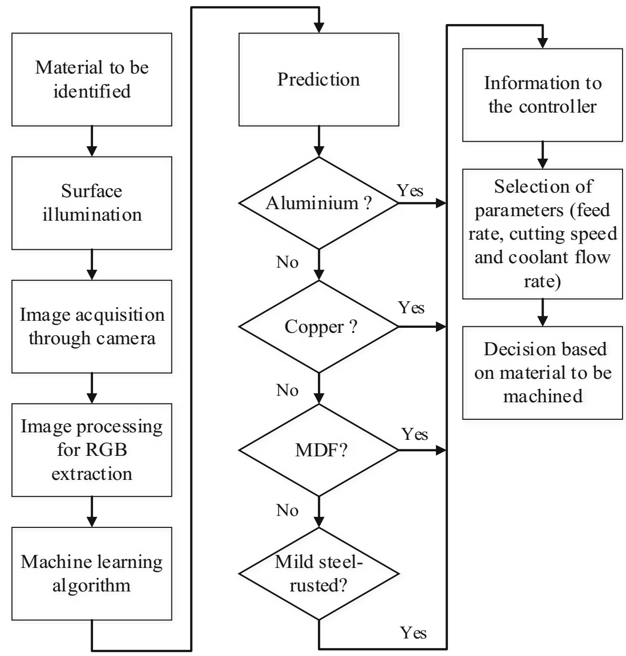


**Fig. 1** Proposed methodology

**Fig. 2** Experimental set up used for the generation of data set

the camera perpendicular to the surface so that high-quality images of the material surfaces could be obtained. Further in machine vision applications, frames are extracted from a video acquired by the camera and the same is also mimicked in gathering the data set of surfaces of flat materials towards feature extraction. A DSLR camera is used with the settings that can be found on a typical industrial smart camera. It is worth mentioning here that the settings of any industrial smart camera will always vary from application to application. The experimental set up used for the generation of data set is shown in Fig. 2. It consists of a Nikon D5300 DSLR camera with AF-P DX NIKKOR 18–55 mm lens mounted at the end of an ABB robot attached with a fixture for holding the camera. The camera is connected to a Laptop through HDMI cable to preview the surfaces of materials before scanning them. The robot arm is brought to the horizontal position so that it holds the camera normal to the material surface under it. The lens is zoomed to 55 mm to increase the field of view so that only surface under the camera could be captured in the frame which would eliminate further image processing to remove the unnecessary regions of the frame. The distance between the material and the lens is kept as 26 cm. The process is carried out at the light intensity of 37 lx. This intensity of light has a direct effect on the quality of the image captured and hence, in the present work, no special light was used. Video settings were adjusted to 1080 × 920 pixels and frame rate to 30 fps, as most of the industrial cameras are capable of providing these settings.

Automatic exposure on the camera is used initially for scanning the surfaces of materials but it did not give satisfactory quality for all material surfaces and hence manual exposure is adapted for scanning. The scanning process was initiated by ensuring that there is no reflection of any light from the surface of the material being scanned. The material is manually moved under the camera as it could scan the surface that passes under it automatically. The surfaces of Aluminium, Mild steel-rusted, MDF and Copper are scanned with the above-mentioned settings and procedure. Care is also taken to scan the entire area of the materials in all cases.

## Image processing and feature extraction

After scanning, the files are downloaded to a PC and the videos are further separated into individual frames, which is how it is being done in machine vision applications. The frames of different material surfaces are stored separately and all folders are manually inspected to remove the frames that contain geometric discontinuities and wear scars. The size of each frame is 1080 × 920 and frame format considered is "jpg".

## Feature extraction

The images have been processed using "Open cv", an open source library for machine vision. The result of this processing is the average values of RGB for each frame of each category of material. Thus, the average values of three components of the RGB color space of each frame are arranged with a total of 3559 rows and number of rows is kept equal to the number of samples in the data set. Hence, the size of the data set now becomes 3559 × 4. The four columns here are blue, green, red and class label respectively. Let $f(x,y)$ corresponds to the pixel $(x,y)$, then the digital gray level image can be represented by (Wen et al. 2004),

$$f(x, y) = \sum_{i=1}^{M} \sum_{j=1}^{N} g(i, j)\delta(x - i, y - j) \tag{1}$$

here M × N is the size of the image, $g(i, j)$ is original continuous image and $\delta(i, j)$ is a delta function. For a color image, $f(x, y)$ can be represented as,

$$f(x, y) = \left[ f_r(x, y), f_g(x, y), f_b(x, y) \right] \tag{2}$$

where

$$f_k(x, y) = \sum_{i=1}^{M} \sum_{j=1}^{N} g_k(i, j)\delta(x - i, y - j)$$

and $k = r, g, b$, are red, green and blue components of the RGB color model respectively.

Equation (2) can be used for the extraction of total values of RGB colors of an image.

The histograms that show the distribution of pixel intensities in a digital image for all surfaces of the materials considered in this work are plotted and shown in Fig. 3. The right side of the histogram corresponds to the brighter pixel intensities and the left side corresponds to the darker image. For an image of normal exposure, the histogram colors should be distributed between left and right extremes of the histogram.

It is clear that the images are neither brighter nor darker and hence processed for obtaining RGB color components. These components for all images of the four materials are extracted and accordingly, a data set is prepared. Aluminium has 883 instances, Copper has1075 instances, MDF has 812 instances and Mild steel-rusted has 789 instances. The final data set for classification is obtained by combining the four data sets that comprise of all instances of the materials considered. The description of this data set along with individual data set descriptions of four classes is presented in Table 1. A close look at the description of each data set reveals that the standard deviations of red, green and blue within each class are not the same and means are also different. A well-conditioned data for machine learning problems does not look like this. Hence, the data is conditioned before feeding it to the machine learning classifier as described in Pedregosa et al. (2011). The mean and standard deviations of the red, green and blue colors of the RGB model of final data set also have different values and hence, the final data set also need to be normalized before training the machine learning classifier.

Figure 4 gives the split-up red, green and blue planes of Aluminium along with three planes combined. All images of surfaces of four materials in the data set are made up of three such planes which when combined represent the image in RGB color model. All the pixels in three planes are represented by values from 0 to 255 according to the intensity of color. The values will be closer to 255 for brighter intensities and closer to 0 for darker intensities. When all the pixel values of a plane are added together, the average value of the color distribution of that plane is obtained. These

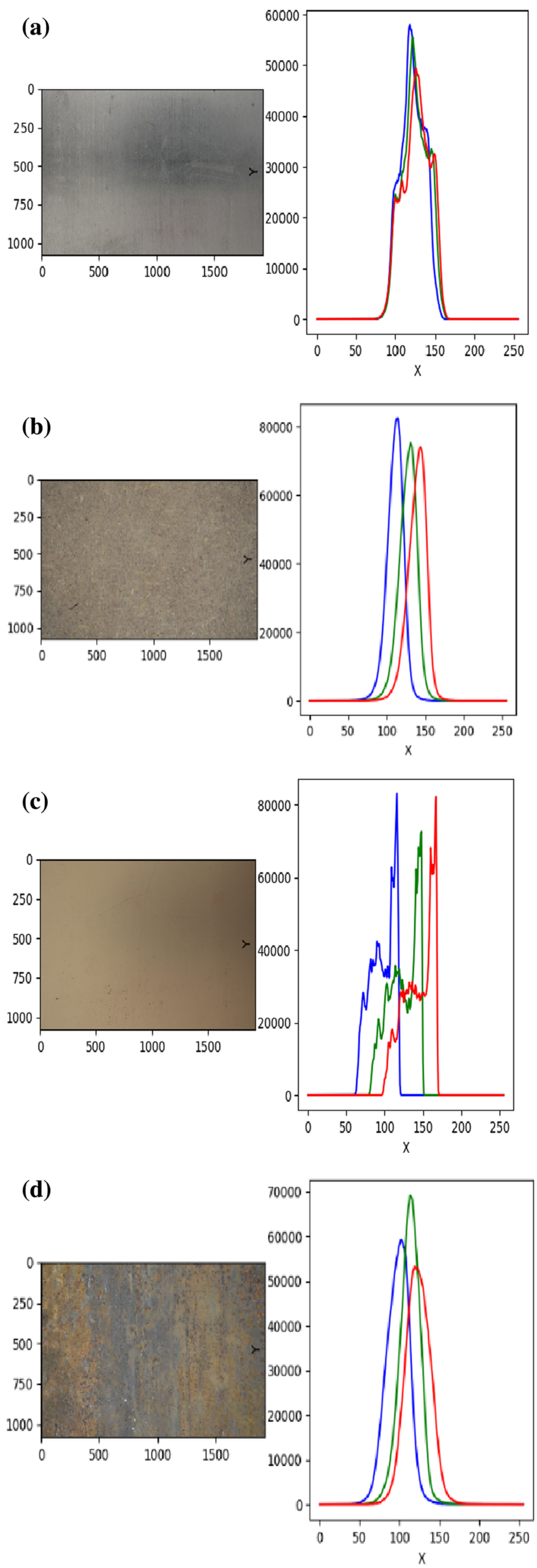


**Fig. 3** Surface images along with their histograms: **a** aluminium, **b** medium density fibre board, **c** copper, and **d** mild steel-rusted

**Table 1** Data set descriptions of the material surfaces

| | Blue | Green | Red |
|---|---|---|---|
| *Aluminium data set description* | | | |
| Count | 883 | 883 | 883 |
| Mean | 123.107480 | 126.156857 | 127.406257 |
| σ | 10.281995 | 9.748596 | 8.672441 |
| Min | 111.611409 | 114.806231 | 116.343236 |
| 25% | 117.406774 | 120.536919 | 122.126947 |
| 50% | 121.410352 | 124.671336 | 126.387364 |
| 75% | 124.857405 | 128.200845 | 129.822057 |
| Max | 188.406082 | 188.261246 | 183.817523 |
| *Copper data set description* | | | |
| Count | 1075 | 1075 | 1075 |
| Mean | 97.431928 | 124.263844 | 143.776428 |
| σ | 2.260549 | 2.602631 | 2.781498 |
| Min | 92.233418 | 118.714769 | 138.512082 |
| 25% | 95.764794 | 122.359241 | 141.671372 |
| 50% | 97.110008 | 123.709813 | 142.865523 |
| 75% | 99.449474 | 126.871722 | 146.450147 |
| Max | 102.682103 | 129.762743 | 149.716393 |
| *Medium density fibre board data set description* | | | |
| Count | 812 | 812 | 812 |
| Mean | 123.475938 | 138.035393 | 147.847038 |
| σ | 4.374849 | 4.559062 | 3.957009 |
| Min | 110.365963 | 127.084963 | 138.991082 |
| 25% | 121.581304 | 135.237657 | 145.109948 |
| 50% | 124.074886 | 138.137221 | 147.797543 |
| 75% | 126.400773 | 141.528720 | 150.585891 |
| Max | 131.589578 | 147.199079 | 156.593704 |
| *Mild steel-rusted data set description* | | | |
| Count | 789 | 789 | 789 |
| Mean | 94.147082 | 107.788622 | 117.305564 |
| σ | 3.591528 | 4.719103 | 5.735289 |
| Min | 86.576721 | 96.979002 | 104.895604 |
| 25% | 90.887907 | 105.097553 | 112.905828 |
| 50% | 94.148713 | 108.635486 | 119.102255 |
| 75% | 97.647802 | 111.408794 | 121.065658 |
| Max | 100.180730 | 114.752816 | 126.131978 |
| *Final data set description* | | | |
| Count | 3559 | 3559 | 3559 |
| Mean | 109.015942 | 124.223124 | 134.775294 |
| σ | 14.884114 | 11.816716 | 13.283917 |
| Min | 86.576721 | 96.979002 | 104.895604 |
| 25% | 96.339057 | 117.986286 | 123.058197 |
| 50% | 100.591029 | 123.920144 | 140.410541 |
| 75% | 122.412190 | 130.775500 | 146.276710 |
| Max | 188.406082 | 188.261246 | 183.817523 |

σ = standard deviation of the features

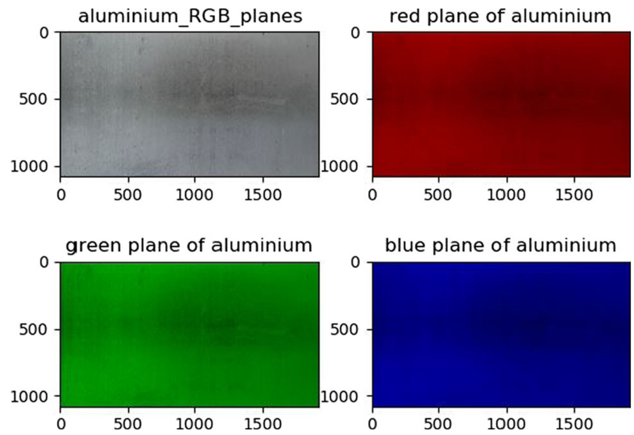


**Fig. 4** Split up RGB planes of aluminium

average values of the three components of RGB are different for different surfaces of materials considered in the present work.

Figure 5 helps to visualize the distribution of surface images of flat materials considered based on the pairwise combination of values of the three features. The four classes of materials have a clear space separating them, which can be seen in Fig. 5. It can also be understood that given two features, one class can be easily distinguished from the other class. Figure 6 shows the distribution of blue, green and red features in the entire data set.

## Training the machine learning model

This is a multi-class classification problem with four class labels that are the four materials and three features for each class. The three features of each class are the blue, green and red color components of the RGB color model. The Support Vector Machine is considered in this work to solve this multi-class classification problem.

## Support vector machine (SVM)

It is considered to be an extension of perceptron. In these algorithms, the margin, which is the distance measured between the separating hyperplanes, also called decision boundaries, is to be maximized for classification. The training samples which are very near to the decision boundary are called support vectors. It is a practice to have decision boundaries with a large margin to avoid overfitting. For a binary classification problem, the positive and negative hyperplanes which are parallel to the decision boundary are represented by a mathematical expression as follows (Raschka and Mirjalili 2007).

Let, $w_0$ = bias vector, $w^T$ = weights vector, and $x_{pos}$ and $\mathbf{x}_{neg}$ are the features on right and left side of the separating plane respectively, then

$$w_0 + w^T x_{pos} = 1 \tag{3}$$

$$w_0 + w^T x_{neg} = -1 \tag{4}$$

If Eq. (4) is subtracted from Eq. (3), the resulting equation will be,

$$w^T(x_{pos} - x_{neg}) = 2 \tag{5}$$

Equation (5) is normalized by using a vector '$w$' as follows.

$$\frac{w^T(x_{pos} - x_{neg})}{\|w\|} = \frac{2}{\|w\|} \tag{6}$$

$$\|w\| = \sqrt{\sum_{j=1}^{n} w_j^2} \tag{7}$$

here $\|w\|$ is the norm of the vector to the hyperplane. The left-hand side of Eq. (6) can be interpreted as the distance between positive and negative hyperplanes which is called as the margin and it needs to be maximized. This margin of the SVM can be maximized with the constraint that the samples should be correctly classified which can be represented as follows,

$$\left.\begin{array}{l} w_0 + w^T x^{(i)} \geq 1, \quad \text{if } y^{(i)} = 1 \\ w_0 + w^T x^{(i)} \leq -1, \text{ if } y^{(i)} = -1 \end{array}\right\} \tag{8}$$

where, $i$ = 1…n. and n = number of training samples in the dataset.

The right-hand side of Eq. (6) is minimized by using quadratic programming, in order to optimize the margin between the hyperplanes. The linearly inseparable data is used for creating nonlinear combinations of the original features to project them on to a high dimensional space through a mapping function $\phi$ so that the problem under consideration becomes linearly separable. For linearly inseparable classification problems, kernel SVM could be used as presented below.

Let $(x^{(i)}, y^{(j)})$ be a pair of samples or features, then the kernel function for this can be defined as follows,

$$K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)}) \tag{9}$$

The most used kernel is the Radial Basis Kernel (RBF), also known as Gaussian kernel, and is expressed by,

$$K(x^{(i)}, x^{(j)}) = \exp\left[-\left(\frac{\|x^{(i)} - x^{(j)}\|}{2\sigma^2}\right)^2\right] \tag{10}$$

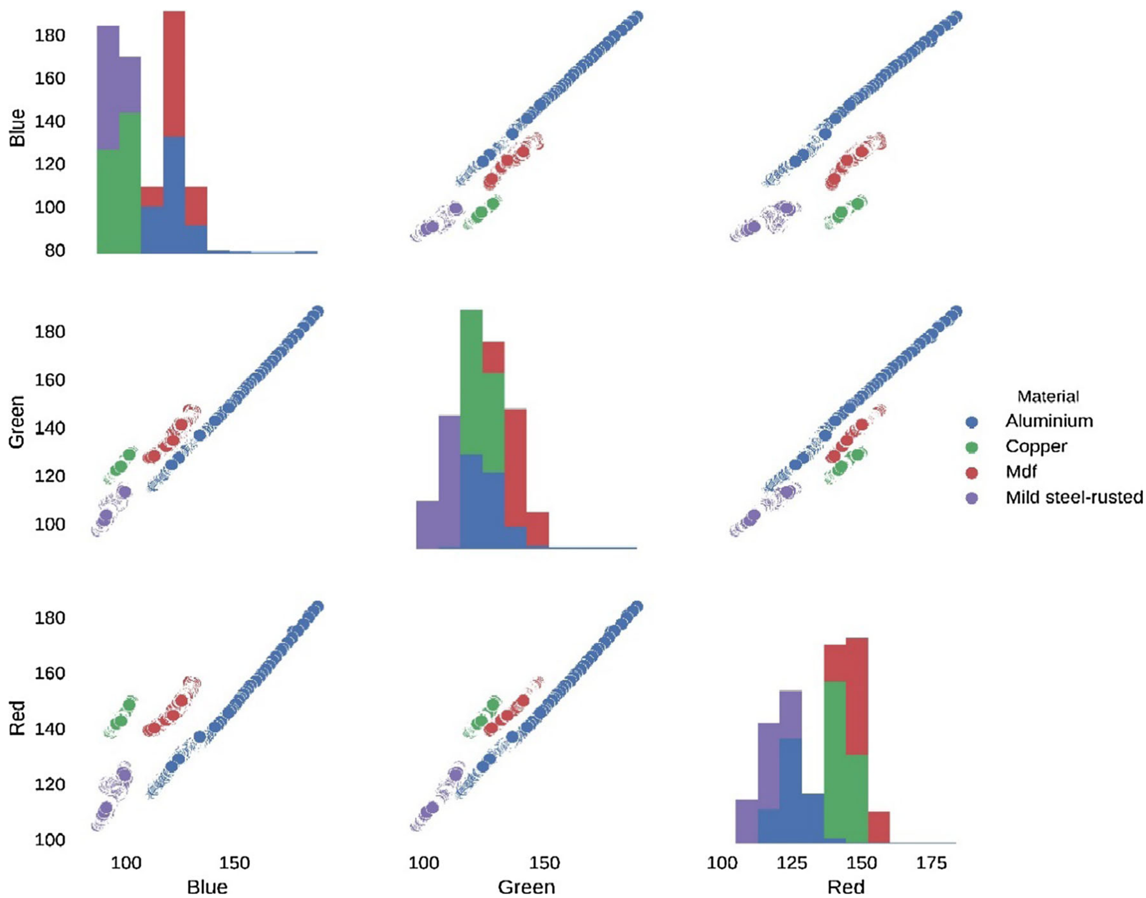


**Fig. 5** The pairwise plot of features

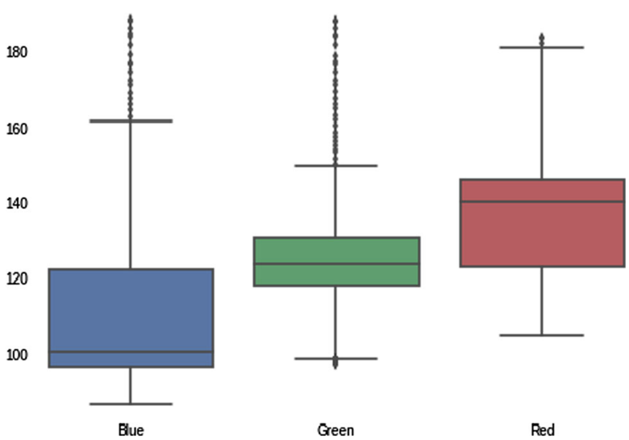


**Fig. 6** Box plot of features

here, $\sigma$ is the standard deviation of the features. Now Eq. (10) can be rearranged as,

$$K(x^{(i)}, x^{(j)}) = \exp\left(-\gamma \left\| x^{(i)} - x^{(j)} \right\|^2\right) \tag{11}$$

where $\gamma = 1/2\sigma^2$ which is the free parameter that needs to be optimized. Kernel function measures the similarity between a pair of samples and the result will be 1 if they are similar otherwise zero if they are dissimilar. The classifier is trained till it gets converged as per condition set which is shown in Fig. 7. The convergence parameters $\alpha$ and $\beta$ represent the functions of a feasible solution of quadratic programming to maximize the margin between hyperplanes and $\varepsilon = 0.001$ as mentioned by Chang et al. (2011).

Though the methodology proposed in the work is used in the context of manufacturing the same can also be considered as a generalized methodology for classifying any other materials based on feature extraction and training.

Some of the images of KTH-TIPS database (Fritz et al. 2004), which have been used initially for checking the capability of the proposed methodology to identify the different group of materials are shown in Fig. 8.

For multi-class classification under study, SVM is implemented using Scikit-learn using the "one-against-one" approach as presented by Pedregosa et al. (2011). The data set is split into training and testing dataset in the ratio of 70 and 30 respectively. As mentioned earlier, there are 3559 samples in the dataset and hence, the training set consists of

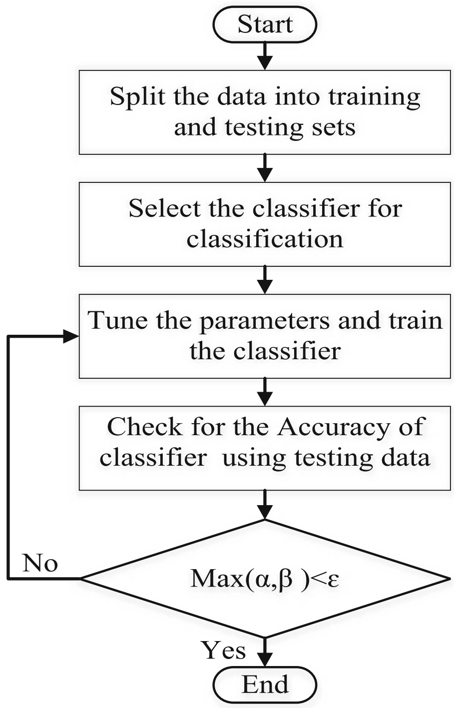


**Fig. 7** Flow chart for the classifier implementation

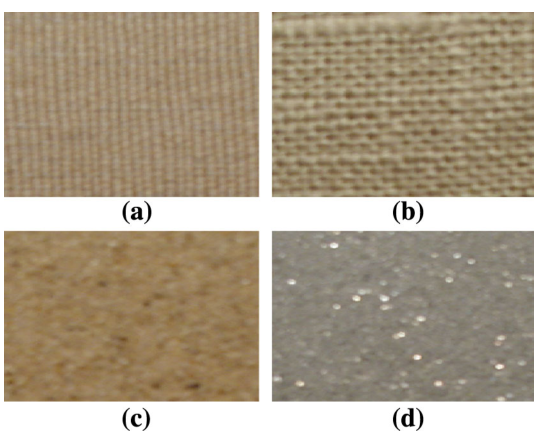


**Fig. 8** KTH-TIPS database: **a** cotton, **b** linen, **c** sandpaper, **d** styrofoam

2491 samples and the testing set comprises 1068 of samples. It is to be noted that due to effective training, SVM achieved the testing accuracy of 100%. This maximum accuracy is also validated using tenfold cross-validation. The ability of the classifier to learn to classify from the data set is measured by the classification accuracy achieved. The more the accuracy, the better is the classifier ability to correctly classify the data. Classification accuracy is given by,

**Table 2** Classification accuracies on images

| Sl. no. | Classification algorithm | Training accuracy (%) | Testing accuracy (%) |
|---|---|---|---|
| 1 | SVM | 100 | 100 |
| 2 | Decision trees | 100 | 92 |
| 3 | Random forest | 100 | 89 |
| 4 | Logistic regression | 100 | 100 |
| 5 | k-nearest neighbor | 94 | 94 |

$$\text{Accuracy} = \frac{\text{Samples predicted correctly}}{\text{Total samples in testing set}} \times 100\% \tag{12}$$

The proposed methodology is first implemented for classifying the four classes of textures of images namely, Sandpaper, Styrofoam, Cotton, and Linen, which are shown in Fig. 8. Each class consists of 81 samples so the final dataset has 324 samples. The details related to the classification accuracies are presented in the next section.

## Results and discussion

The proposed SVM has been trained with four classes of materials from the database, with 194 training samples and 130 testing samples. Along with SVM, other classification algorithms are also trained and the results obtained are presented in Table 2.

Though the data set size is very small, SVM is able to learn perfectly and exhibited 100% accuracy. On the other hand, other algorithms did not learn accurately. The reason for this is that the data set contains images with slight variations in visual appearance such as different colored images within the class. SVM is able to learn perfectly due to its generalization to real-world problems as mentioned earlier. However, if large samples of variations are included in the data set, then all algorithms will learn accurately.

The support vectors for the four classes of the database have been found and presented in Table 3. It is clear that the linear kernel is best suited as the number of support vectors for each class is less than half the number of samples.

The SVM presented is able to successfully achieve 100% classification accuracy which is also validated by tenfold cross-validation. The number of support vectors for the four classes of materials is found which are presented in Table 4. From the table, it is clear that the number of support vectors for class 0 is 10 when the linear kernel is applied and 30 when RBF kernel is applied. In both the cases, the number of support vectors is very much less than the number of the samples of class 0 which is 883 and this is the proof that the

**Table 3** Support vectors for the four classes of images

| Label/class | Material | Number of samples in the data set | Number of support vectors | |
|---|---|---|---|---|
| | | | Linear kernel | RBF kernel |
| 0 | Cotton | 81 | 31 | 46 |
| 1 | Linen | 81 | 32 | 41 |
| 2 | Sandpaper | 81 | 6 | 46 |
| 3 | Styrofoam | 81 | 3 | 49 |

**Table 4** Support vectors for the classes

| Label/class | Material | Number of samples in the data set | Number of support vectors | |
|---|---|---|---|---|
| | | | Linear kernel | RBF kernel |
| 0 | Aluminium | 883 | 10 | 30 |
| 1 | Copper | 1075 | 7 | 22 |
| 2 | MDF | 812 | 6 | 26 |
| 3 | Mild steel-rusted | 789 | 5 | 22 |

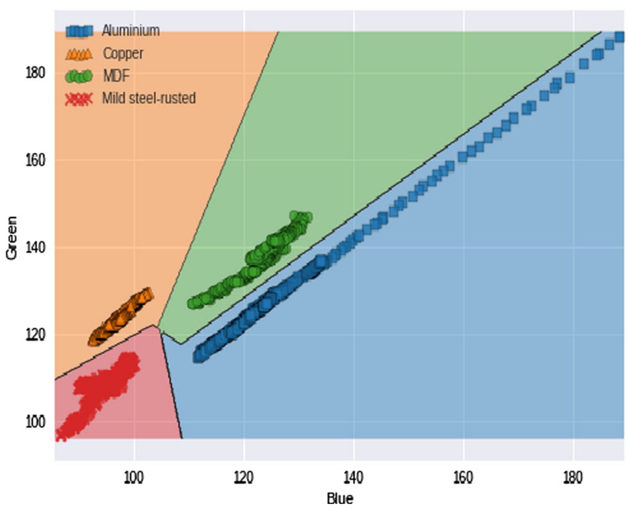


**Fig. 9** Decision boundaries for four classes

SVM is not overfitted and can be generalized. The support vectors of the remaining classes are also very much less than the number of samples they contain and this is a proof for accurate training of classifier without overfitting.

The decision boundaries for the four classes considered are plotted with the package developed by Raschka (2018) with two out of the three features, red and green and are shown in Fig. 9. It can be seen that for the features considered for plotting, the classes have clearly defined decision boundaries.

A grid search is performed for tuning the hyperparameters of the SVM and it is found that penalty parameter C = .1 in C ∈ [0.0001, 0.001, 0.01, 0.1, 10, 100, 1000] and the free parameter $\gamma$ of Eq. 11 become 0.01, and kernel, the linear kernel in Kernel ∈ [linear, RBF] are the best hyperparameters for SVM. The accuracies of SVM for tenfold cross validation are found as,

{100, 100, 100, 100, 100, 100, 100, 100, 100, 100}

Hence, the classification accuracy of the SVM is thus validated using tenfold cross-validation technique. Different classification algorithms such as decision trees, random forest, logistic regression, and k-Nearest Neighbor, VGG-16 deep Convolutional Neural Network (CNN) (Karen and Zisserman 2015) with transfer learning were trained on the same dataset and their classification accuracies are presented in Table 5. For logistic regression, the classification accuracies in both training and testing are achieved 100% for a C value of 3 and l1 penalty, where C is a regularization parameter. It is clear from the training accuracy and testing accuracy columns that other classification algorithms are able to achieve a classification accuracy of 100%. For real-world applications, SVM would perform better than other machine learning algorithms as mentioned by Scholkopf et al. (1997). Hence, SVM can be adapted for the classification purpose in the proposed methodology. Further, as other classification algorithms, except deep CNN, are also able to accurately classify the flat materials considered. It is clear from Table 5 that it is absolutely possible to identify the flat materials including metallic and non-metallic provided a machine learning algorithm is trained with their features. This can be extended to include any number of materials. Also observed that, CNN training consumed 150 min which is very expensive.

The confusion matrix is a tabular layout that visualizes the performance of the classifiers in the field of machine learning. Confusion matrix gives the total number of false positives, true positives, false negatives and true negatives of the classifier. A well-trained classifier has to have only true positives. The confusion matrix of the trained SVM with the testing data of 1068 samples is shown in Fig. 10 with True labels

**Table 5** Classification accuracies with other algorithms

| Sl. no | Classification algorithm | Training accuracy (%) | Testing accuracy (%) |
|---|---|---|---|
| 1 | Decision trees | 100 | 100 |
| 2 | Random forest | 100 | 100 |
| 3 | Logistic regression | 100 | 100 |
| 4 | k-nearest neighbor | 100 | 100 |
| 5 | Convolutional neural net | 91 | 75 |

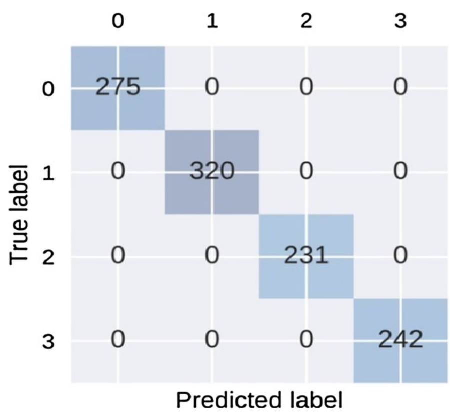


**Fig. 10** Confusion matrix of the trained SVM

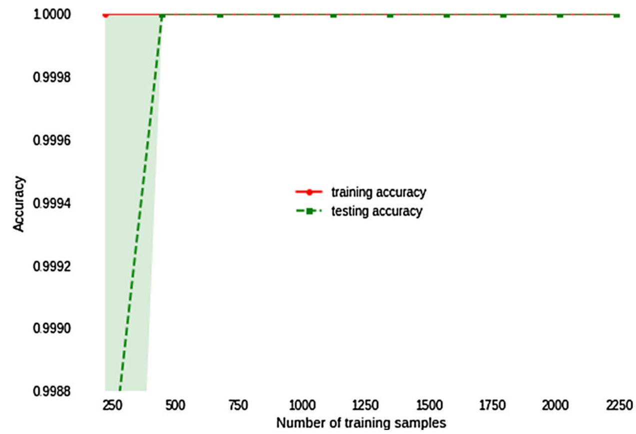


**Fig. 11** Accuracy versus number of training samples

versus Predicted labels. The true labels are Aluminium, Copper, MDF and Mild steel-rusted respectively and this order applies to predicted labels as well. The confusion matrix contains only true positives, which is an indication of the fact that the model can classify correctly and is also accurate enough.

The number of training samples considered in the training data set is 2491. The training and testing accuracies of the SVM classifier are checked with the size of the data set, which is graphically presented in Fig. 11. It is clear that the training accuracy remains at 100% irrespective of the size of training data set whereas the testing accuracy is raised from 99 to 100% in between the sample size of 250 to 500 and remained there throughout the entire sample size. In machine learning problems, it is desirable always to have large amount of data, as the classifiers learn from the data. So, the data set is prepared while keeping this in mind with total samples of 3559 which includes training and testing samples.

## Checking for robustness

Four real-time experiments have been performed to check the robustness of the methodology and the results are presented in Table 6. One is based on the data collected in the similar conditions where data for training the classifier is collected and three others are on the data collected in different conditions. The same materials were used for data collection in all the experiments. The camera is moved over the surfaces manually under two different illuminations at 25 lx and 265 lx respectively and using a robotic arm at 77 lx. 25 lx and 77 lx are the light intensities due to ambient light and 265 lx is due to ambient and ceiling light in the lab. The ceiling light is introduced to induce some illumination difference over the surfaces.

The images of the surfaces under these intensities are presented in Fig. 12. When the intensity of light falling on any metallic/non-metallic surface changes, the light reflected from the surface also changes. This reflecting light impacts the surface visually which is also verified by extracting the mean values of red, green and blue. These values will remain the same for a particular material under a particular intensity of illumination and will get changed along with the intensity of illumination. For shining surfaces such as metals, the reflected light will create bright spots on the surfaces. These bright spots will significantly change the mean values of the red, green, and blue. To avoid the formation of these bright spots, it is important to maintain a controlled intensity of lighting over the surfaces of the materials. This will ensure that the features extracted for classification will be able to differentiate the surfaces. As long as there are no differences in the visual appearance of the surfaces, they can be classified accurately using machine learning and machine vision techniques.

The SVM classifier is able to perform very well with an accuracy of 100% on all the materials based on the data collected at similar conditions. But the performance is not good on the data collected in other conditions. This is due to the different levels of illuminations of the surfaces of the materials. When the intensity of light is 265 lx, there are even some reflections from the Aluminium surface. From Table 6, it is clear that the SVM is able to maintain the classification accuracy very well, as the experiment is conducted at similar

**Table 6** Experimental evaluation of proposed methodology at different illumination levels

| Sl. no. | Class | Experiment at similar conditions | | Experiment at 25 lx | | Experiment at 77 lx | | Experiment at 265 lx | |
|---|---|---|---|---|---|---|---|---|---|
| | | Supplied | Predicted | Supplied | Predicted | Supplied | Predicted | Supplied | Predicted |
| 1 | 0 | 301 | 301 | 204 | 204 | 444 | 420 | 747 | 281 |
| 2 | 1 | 1212 | 1212 | 261 | 0 | 681 | 681 | 519 | 0 |
| 3 | 2 | 975 | 975 | 246 | 0 | 597 | 68 | 456 | 0 |
| 4 | 3 | 789 | 789 | 434 | 119 | 855 | 855 | 564 | 0 |

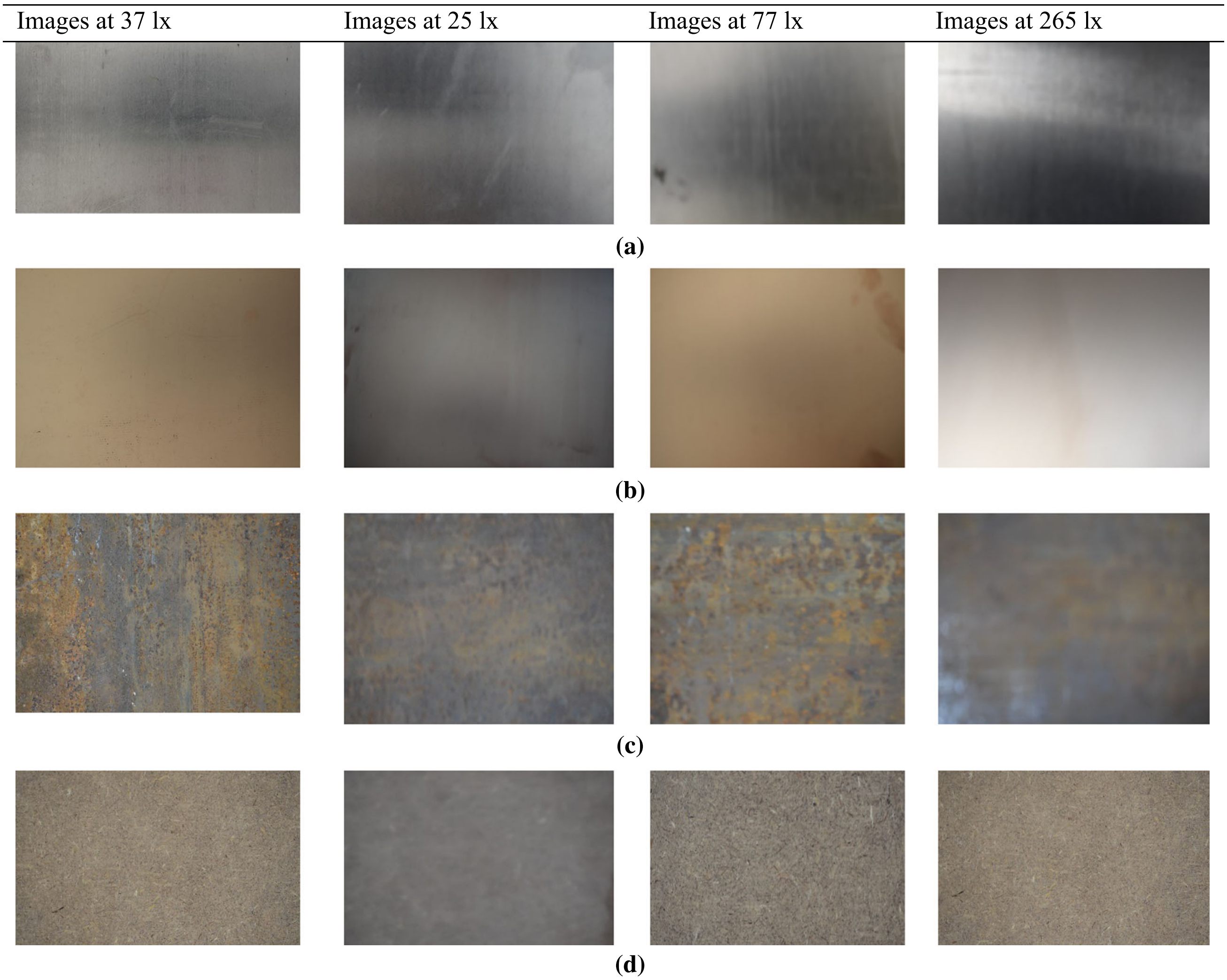


**Fig. 12** Surface images under different lighting conditions: **a** aluminium, **b** copper, **c** mild steel-rusted, **d** MDF

illumination levels where the data is obtained for training the SVM.

In the remaining experiments, the SVM is not able to maintain the classification accuracy due to differences in the illumination levels during the experiments for image collection. As the intensity of light increases, as seen in the fourth experiment, the performance of SVM becomes deteriorated. Hence, this validates the proposed generalized methodology for the identification and classification of materials using machine vision and machine learning.

The constraint on the proposed generalized methodology is that the same intensity of illumination at which the data is collected should be maintained while carrying out the identification of the materials and this is the common prerequisite of machine vision applications. To support this statement, two more experiments have been conducted with different

**Table 7** Experimental evaluation of proposed methodology with camera orientations and scale

| Sl. no. | Class | Camera orientation with the vertical axis (in deg.) | | | | | | Camera lens at 35 mm focal length | |
|---|---|---|---|---|---|---|---|---|---|
| | | 15 | | 30 | | 45 | | | |
| | | Supplied | Predicted | Supplied | Predicted | Supplied | Predicted | Supplied | Predicted |
| 1 | 0 | 130 | 3 | 147 | 05 | 143 | 03 | 121 | 0 |
| 2 | 1 | 132 | 104 | 139 | 94 | 152 | 105 | 138 | 92 |
| 3 | 2 | 132 | 15 | 132 | 19 | 154 | 19 | 132 | 0 |
| 4 | 3 | 132 | 19 | 126 | 54 | 132 | 31 | 143 | 36 |

camera orientations and scale of the lens and the results are presented in Table 7. From these results, it is observed that the orientation of the camera and scale of the lens have an adverse effect on the performance of the classifier. To address this challenge, a lot of data corresponding to these conditions have to be supplied to the classifier during training.

## Conclusion

A novel generalized methodology based on Support Vector Machine had been developed to accurately identify and classify flat materials being machined in a typical manufacturing environment. This was accomplished using machine vision and machine learning techniques. A data set consisting of 3559 samples was prepared. The machine learning classifier, SVM, was trained with 2491 samples and tested against 1068 samples for checking the classifying accuracy. The accuracy achieved is 100% which was validated by ten-fold cross-validation technique and the accuracies of 10 cases agreed with the previously achieved values. The classification accuracy of other cases is also determined and presented. The deep CNN VGG-16 is also trained based on the data sets. These results are not as satisfactory as those obtained from SVM. The training time needed for CNN is 150 min, which is computationally expensive. Though deep CNN can learn features automatically, they are not suited well for the classification of the materials considered in the present task.

An insight was presented graphically on training and testing accuracies of the classifier with the size of 2491 data set and concluded that a minimum of 500 samples is required for achieving the 100% classification accuracy in training as well as in the testing of the classifier. This 100% accuracy is subjected to the limitation that same lighting condition need to be maintained for all images, which has practical limitations as well. The robustness of the proposed methodology was also checked for multiple camera orientations, illumination, and focal lengths. The generalized methodology proposed can be applied in a factory equipped with conventional machine tools with minor modifications. This scheme can also be recommended in a factory equipped with state-of-the-art modern machine tools without any major modifications. In fact, this technology can be integrated with the machine tools being produced today based on their nature of machining to make them more intelligent than ever and enable them to be Industry 4.0 compliant by incorporating the perception and decision-making cognitive abilities. The proposed methodology will be applied to machine tools and robots commissioned in smart manufacturing set up. These results will be made available in future communications.

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