Use of Deep Learning for Classification of Machined Surfaces

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The process of taking an input and converting it into a class or a likelihood that it belongs to that class is termed as image classification. For use in image processing applications, traditional machine learning models necessitate formal image processing, de-noising, feature extraction, and dimensionality reduction. Deep learning eliminates the requirement for it. It is a subset of machine learning that has grown in popularity as processing units have improved, data sizes have grown larger, and research in the field has increased. In this paper, CNN is used to classify images of various machined surfaces. This study shows how to identify and classify machined surfaces such as turned, shaped, and ground surfaces using a 2D-CNN, deep learning-based machine vision inspection method. The goal of utilizing this model is for the surfaces to be detected properly the majority of the time, and for the model to run efficiently even for limited datasets. This model employs ReLU, sigmoid, softmax activation functions, max pooling layers, and optimizers to learn unusual, unique patterns and determine what should be fed to the adjacent neuron. The proposed method is used to improve performance with a large image dataset, which comprises of various machined surfaces. When small datasets are supplied to the 2D-CNN, the model is more likely to over fit. To prevent this from happening, data augmentation can be used to produce higher, near-accurate outcomes with a smaller dataset fed to the suggested model. The proposed model produces the best results and demonstrates that without the usage of external computational resources such as a GPU, CNN can perform efficiently and produce improved and near-accurate results. In addition, when comparing the model proposed in this work to traditional machine learning approaches like ANN, it can be inferred that CNN provides better outcomes and accuracy using the same datasets as inputs to the models presented.

Keywords: Image classification, feature classification, 2D-CNN, machined surfaces, data augmentation, sigmoid.

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1. Introduction

Machining is the removal of material from a workpiece using a power-driven machine tool in order to shape it into the desired shape. During the production process, almost all components are subjected to some sort of machining. Advanced machining techniques such as precision CNC machining, water jet cutting, laser cutting, electrical discharge machining and electro-chemical machining have been popular in recent years as a way to get faster and more accurate dimensions in components with less mistake. Turning, drilling, and milling are the three most common machining techniques. Following the process of machining, several elements of the machined surface obtained, such as surface roughness, must be considered. During machining processes, cutting speed, feed rate and depth of cut are the characteristics that must be considered.

Feed rate refers to how fast the workpiece moves across its axis towards the cutting tool while depth of cut refers to how deep the tool moves against the workpiece [8]. Good surface finish is desired for enhancing the fatigue strength, aesthetic appeal, tribological properties, and corrosion resistance of the product [11].

Grzesik et al. [12] in their work have discussed that surface roughness is a factor that prominently influences the fabricating expenses. It narrates the geometry of the machined surface. The attainment of a desirable value of surface roughness is a monotonous process that can be time consuming.

There exist different kinds of approaches to arrive at the surface roughness by knowing certain input parameters, of which few are discussed further. Computer-Aided Design (CAD) techniques are made use of so as to attain a model which enables us to mimic the formation of the machined surface profile, hence measuring the surface roughness and envisioning the surface topography [13].

The geometric model development acts as the basis of the approach using meticulous mathematical equations. This model is implemented using a computer algorithm so as to control composite calculations. There exist a few theoretical models that associate the cutting conditions and surface roughness, for example, feed rate [14].

The most ‘obvious’ method being experimental approach: experiments with the factors that are considered to be of utmost important are performed and the obtained results are used to look into the effect of each factor and also the governing mechanism on the observed quality characteristic. The experimental approach is mainly embraced where analytical formulation of the cause-and-effect relationships between the different factors cannot be done [13].

Some of the modelling and prediction techniques that have gained enough popularity of which few of them are, Response Surface Methodology (RSM), Fuzzy Logic, Random Forest Regression (RFR), Quantile Regression, Artificial Neural Networks, and Support Vector Machines (SVM), [2]. Techniques like Fuzzy Logic, Artificial Neural Network (ANN) [6] is being developed and used for classification.When it comes to predicting the surface roughness of a machined surface AI models like Adaptive Neuro Fuzzy Inference System (ANFIS) Artificial Neural Network (ANN), and many others can be used [1].

Dhiren R. Patel et al. [4] carried out an empirical study on different machining processes such as, milling, reaming, turning etc. to determine tool conditions, predict tool wear, when using the machine learning, because conventional tool detection systems are not capable of self-learning.
Upadhyay R. et al. [9] proposed that for accurate identification of texture images, machine learning is an important technique. It is used for regression and classification, used in various applications such as classification of Electroencephalogram (EEG) signals.

Computer vision is an interdisciplinary field of science that deals with how computers can gain high-level understanding from digital images or videos. From a technical perspective, it tries to understand and automate tasks performed by the human vision system. Computer vision tasks include collecting, analysing, extracting large-scale data from the real world, processing and understanding digital images, and to produce digital information or representations.

Ganesh B & Kumar C [7] in their work state that the application areas of deep learning and image processing are diverse and include areas such as medicine, robotics, security, and surveillance. In deep learning, neural networks are used to learn useful features directly from data. Image processing using deep learning is used to pre-process and enhance images for different applications with better results.

Muriel Mazzetto et al. [3] use deep learning to facilitate visual inspection tasks without interfering with the production environment and explore it as an end-to-end tool for creating favourable conditions for configuring Computer Vision Systems. The approach proposed is illustrated by four proofs of concept in a real automotive assembly line based on anomaly detection, semantic segmentation and object detection models.

As a result, the output obtained after training and testing the various models will closely match the experimental data. However, even though the parameters provided to the models were the same, the sensitivity analysis of the results revealed that different AI-based models behaved differently. Various models, their parameters, and the input provided will yield different outcomes. As a result, the findings obtained with AI-based models did not differ significantly from the experimental results, indicating that AI may be employed effectively in surface roughness modelling and prediction.

This paper discusses about developing a deep neural network model, to automatically-extract the features from the input images and the output provided will be prediction of accurately classified operation based on the type of surface image fed as inputs. If the dataset used to train the model is smaller, then processes of data augmentation is performed on the existing dataset before it is used to train the model.

2. Experimental setup

The experimental set-up consists of a vision system, an appropriate lighting arrangement and PC for image processing as shown in Figure 1. A source of white light arranged at a certain incident angle was used for illumination. The photos of the machined surfaces were captured with a camera and converted to grey scale to make image processing easier by making all of the pixels of the image captured to black and white. Operations such as turning, grinding, and shaping operations were performed on mild steel specimens. Taylor Hobson, FORMTALLYSURF-50 using 5 mm sampling length, was used to measure surface roughness of the machined surface [10].

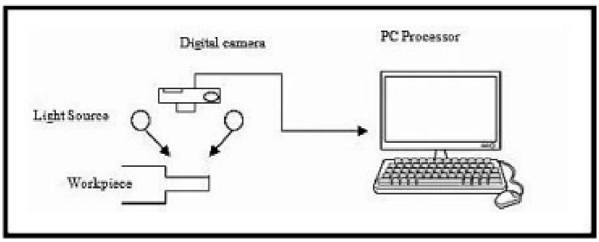

Fig. 1: Schematic Diagram of the Computer vision system

3. Convolutional neural network (CNN)

Convolutional Neural Network is a form of feed-forward network consisting of many different layers and deeply connected architecture. A modified form of the back-propagation algorithm was used to train the CNN model. They are widely used for this purpose because of their ability to recognize patterns with a lot of variations [7].

Convolutional Layer forms the first layer of every CNN model. It acts as a feature extractor and extracts features automatically without human intervention. Consider a Convolutional Layer l, having an input M with a kernel of size N, the output will be of the size (M – N +1), if k kernels are used the output will be of the size (M – N +1) * k. The different layers that contribute majorly towards the model performing in an effective manner and their mathematical relations established to strike relation between the input and output respectively is stated below accordingly [5].
The output of a Convolutional layer is given as follows:

$$Y_i^{(l)} = B_i^{(l)} + \sum_{a=1}^{M} W_i^{(l)} \times Y_i^{(l-1)} \qquad (1)$$

Where *Bi(l)* is a bias matrix and *(l)* is the filter of size N.
Then the convolutional layer applies its activation function, here ReLU is computed as:

$$x = max\,(0,x) \qquad (2)$$

where x is the input to the neuron.
Softmax function is used in the last layer to normalize the output of a network to a probability distribution over the predicted output classes. After the application of softmax function, each component will be in the interval (0, 1) and the component will add up to 1, so that it can be considered as a probability.

$$\sigma(\vec{z})i = \frac{e^{z(i)}}{\sum_{j=1}^{K} e^{z(i)}} \qquad (3)$$

σ – Softmax function,
$\vec{z}$ – Input vector,
$e^{z(i)}$ - Standard exponential function for input vector,
K – Number of classes in the multi-class classifier,
Adam Optimizer updates weights and biases so as to minimize the loss function of the model by taking small steps in the direction of the negative gradient. It is based on adaptive estimates of momentum of the parameters, as described in equations below:

$$v_{dp}^{i+1} = \beta_1 v_{dp}^{i} + (1-\beta_1)\nabla E(P_i) \qquad (4)$$

$$s_{dp}^{i+1} = \beta_2 s_{dp}^{i} + (1-\beta_2)(\nabla E(P_i))^2 \qquad (5)$$

$$P^{i+1} = P^{i} - \alpha \frac{v_{dp}^{i+1}}{\sqrt{s_{dp}^{i+1}} + \varepsilon} \qquad (6)$$

Where i refers to the iteration number, α is the learning rate, P refers to the parameter vector and $E(P_i)$ is the loss function, $\nabla E(P_i)$ refers to the gradient descent of the loss function v and s refers to the moment vector and β refers to the exponential decay rate for the moment estimates [5].

4. Methodology

Dataset Description: Machined Surface images dataset (Dataset1), consists of 3 Classes namely turned, shaped, ground with 18 images in each class. It is evident that Deep Learning works

effectively on a larger dataset. Data Augmentation can be performed on the machined surface dataset available to increase the count to 360 images per class (Dataset2).
The experiment and related computation were performed with Dataset1, using data augmentation process on the dataset, resulting in a dataset consisting of 360 images per class i.e. Dataset2. During computation, the dataset was split into testing and training datasets, with the former containing 15% of the data set. These datasets were used to train and test the model. Figure 2 demonstrate the methodology used for data generation and modelling.

Fig. 2: Methodology for generating Dataset2.

A general Convolutional Neural Network (CNN) model consists of 3 types of layers, input, hidden and output layers. All the layers that exist in between the input and the output layer is considered as hidden layer. The hidden layers of a Convolutional Neural Network typically consist of convolutional layers, pooling layers, flatten, dropout and fully connected layers/dense layers. The deep-learning model proposed here uses a convolutional 2D layer with 32 nodes in the input layer. Hidden Layer in this model consists of max pooling layer with 32 nodes followed by convolutional layer having 32 nodes. This acts as an input to the next max pooling layer with 32 nodes. This layer is followed by a convolutional layer consisting of 64 nodes which acts as an input to the next max pooling layer with 64 nodes. This is then fed to the dropout layer having 64 nodes. Dropout layer prevents the model from overfitting. The output from dropout layer is fed to a flatten layer, which acts as an input to dense layer of 128 nodes. Output from dense layer s then fed to a fully connected dense layer having 3 nodes. The working model is proposed as shown in Figure 3.

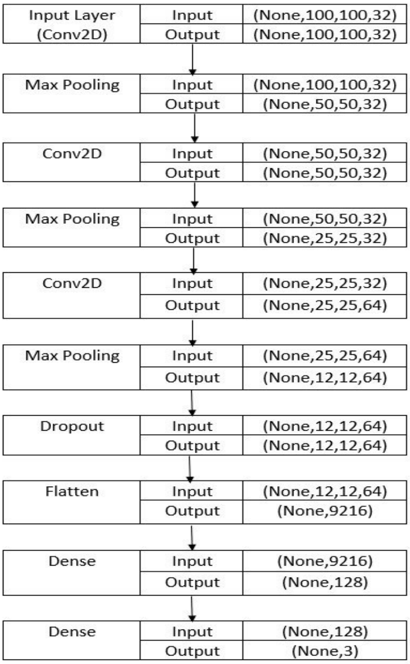

Fig. 3: Proposed CNN Model for Machined Surface Dataset (both Dataset 1 and 2)

5.Simulation parameters

The proposed model represented in Figure 3 is used to perform the image classification. The output of the model is a dense layer having softmax as its activation function, rest of the layers uses ReLU as its activation function. The model is trained using Adam optimizer and Sparse Categorical Cross entropy to calculate the loss function and is trained using 500 epochs and a batch size of 2 with a learning rate of 1×10^{-6} and 1,208,803 parameters. For Dataset1, the model took 300 seconds to train, whereas for Dataset2 the model took 3500 seconds to train. These models were built, trained and tested using 9th gen Intel i7 processor (6 core, 12 thread, 2.6GHz Base Frequency, Processor Graphics: Intel UHD Graphics 630, 8GB DDR4 (2666 MHz) RAM. The code editor used was Atom and anaconda terminal was used for execution of the code using Python 3.8.3.

6. Results and discussion

The accuracy and loss values are as shown in Figure 4 and Figure 5 respectively and the confusion matrix obtained is shown in Figure 6.
Table 1 compares the performance of the proposed CNN model for the two datasets, one with dataset2, and the other with dataset1. The table shows the training and test accuracy obtained for the two datasets along with the time taken to train each model.
From Table 1, it is evident that the deep learning model works better when the size of the dataset used to train is large. When the dataset available is small, the performance of the model is reduced. In such cases, the data augmentation process can be used to obtain significant improvement in the performance of the model.

Table 1. Results.

Content	Training data Accuracy	Test data Accuracy	Computation Time (s)
Machined surface dataset with Data-Augmentation (Dataset2)	97.6%	95.56%	3500
Machined surface dataset without Data Augmentation (Dataset1)	40.56%	33.3%	300

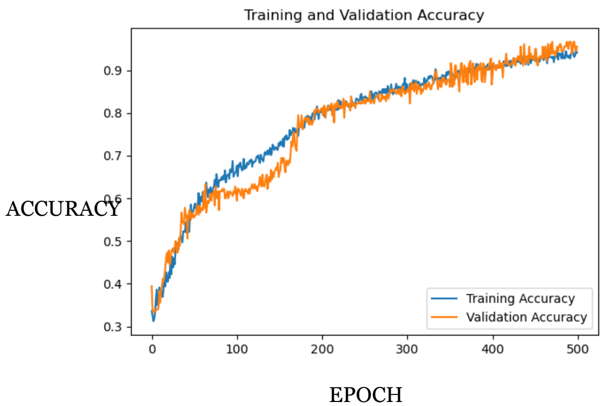

Fig. 4: Training and validation accuracy for model with dataset2

Figure 4 shows the relationship between the training and testing accuracy vs. epochs for dataset2. The accuracy as observed in Figure 4, increases with increase in epoch and will not provide a constant value for accuracy.

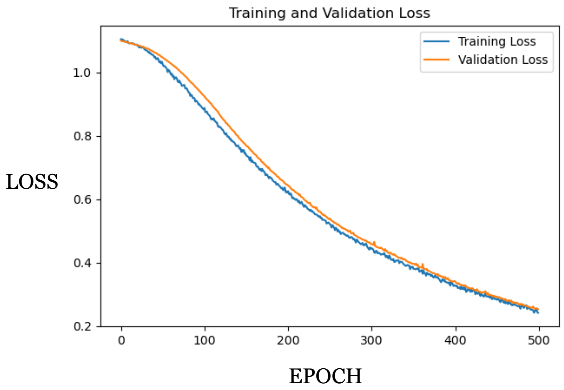

Fig 5: Training and validation loss for model with dataset2

Figure 5 shows the relationship between training and testing loss vs. epoch. The loss is seen to be decreasing as training progresses towards higher epochs. The nature of the graph observed in Figure 5 resembles the ideal nature of a loss vs. epoch graph.

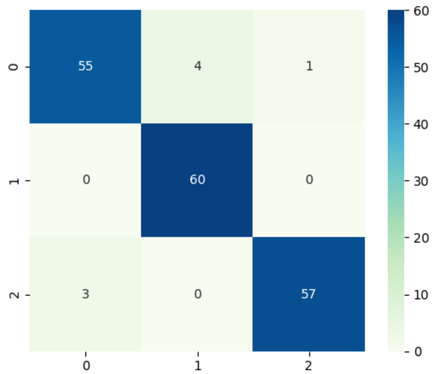

Fig. 6: Confusion matrix for model with dataset2

Figure 6 shows the confusion matrix obtained for dataset2. The non-diagonal values are either equal to 0, or is close to 0, when compared to diagonal elements. Hence predictions made by the model is accurate. Here class 0, class 1, class 2 represents ground, shaped and turned images respectively. 4 ground images were misclassified as shaped and 1 image as turned. All shaped images were classified correctly but 3 turned images were misclassified as ground image.

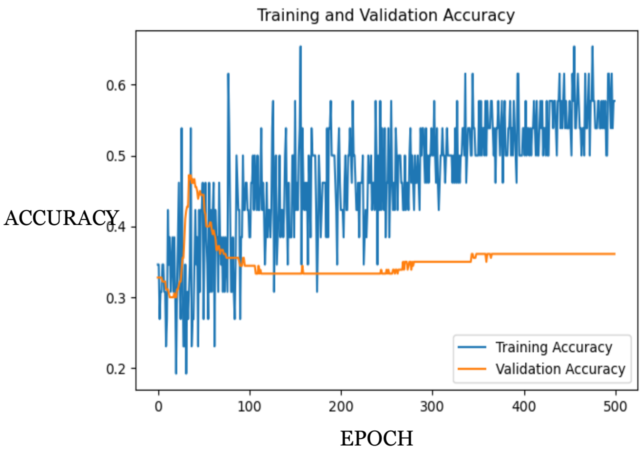

Fig. 7: Training and Validation accuracy vs. Epoch for model with dataset 1

Figure 7 shows the relationship between the training and testing accuracy vs. epochs for dataset1, which is the dataset of machined surface images without data augmentation. The testing accuracy value can be seen to peak at around 50% and then decreases to a value close to 40%. Ideally the curve for accuracy vs. epoch must increase with increasing epochs. The model is said to be over fitting if the accuracy stays constant with increasing epochs, hence the performance of the model as shown is Figure 7 is not desirable.

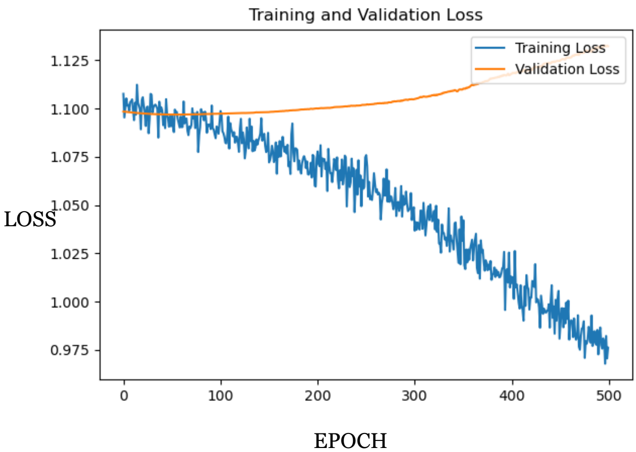

Fig. 8: Training and validation loss vs. Epoch for model with dataset1

Figure 8 shows the relationship between training and testing loss vs. epochs for dataset1. Ideally, the loss value for the model must decrease with epoch. Loss is a representation of the error in output of the neural network. Hence the loss is expected to decrease as the training progresses.

Figure 8 shows that the loss during validation increases with increase in epoch, which is not desirable, hence resulting in misclassifications.

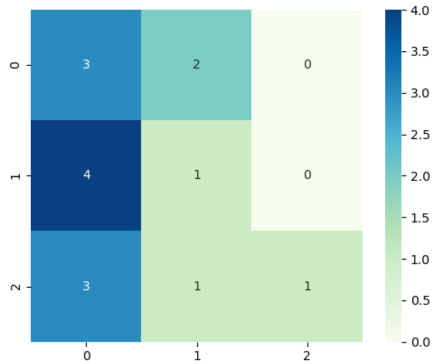

Fig. 9: Confusion matrix for CNN model with dataset1

Figure 9 shows the confusion matrix obtained for the model when applied to dataset1 which is the dataset of machined surface images without data augmentation. The non-diagonal elements represent the number of misclassifications obtained in the output. Here class 0, class 1, class 2 represents ground, shaped and turned images respectively. Figure 9 shows that 2 ground images were misclassified as shaped, 4 shaped images were classified as ground and 3 turned images as ground and 1 image as shaped.

7. Discussions

- For the model proposed in this work, it can be said that the data augmentation process performed on the machined surface images dataset (dataset2) yields 95.56% testing accuracy, when compared to the previously developed model for dataset without data augmentation (dataset1). This is considerably higher than the conventional machine learning model proposed in [6], which gave a prediction accuracy of 88.89 % on test data.
- Dataset with data augmentation was achieved by applying different data augmentation procedures on Dataset on which data augmentation was not performed and this dataset was fed to the model which yielded higher results of 95.56 %.
- Comparing results for the two different datasets, it can be concluded that the model works best with large datasets. Thus, in case of smaller dataset, data augmentation process can be used to obtain better results.
- Developing a model which achieves similar results with lesser training time will be the scope for future work using deep learning.
- There is a need to optimize the model to train faster and obtain better results.

8. Conclusions

- Deep Learning is effective on large datasets, 2-D CNN model built on the dataset on which data augmentation procedures were not performed and consisted of 54 images available for training and testing resulted in overfitting and gave lower results.
- Deep learning model working on data set generated using augmentation resulted in a training accuracy of 97.6 % and testing accuracy of 95.56% on test data.
- CNN can work effectively and yield better and near accurate results without the usage of external computing power such as a GPU, as all the reported work was carried out using a conventional CPU of specifications already given.

- CNN gives better results and higher accuracy, when compared to common machine learning techniques like Multi-Layer Perceptron (MLP), which is an ANN technique.

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