Rapid Material Characterization using Smart Skin with functional Data Analysis

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ABSTRACT

Non-Destructive Evaluation (NDE) is popular for component testing in the automobile industry because they do not cause any permanent alteration to components. Large-scale manufacturing in automotive industries are demanding for a rapid and reliable inspection to maintain the overall structural integrity. Some NDE techniques require sensors (Piezo Electric transducers, PVDF films, Optical fiber, etc.) that need to be bonded to the structure for testing. Some of these sensors are expensive and cannot be reused once detached. This work aims at rapid inspection with the reusability of sensors. Further, the reusable sensors can be deployed in an array configuration for multi-purpose NDE. Smart skin shall be explained as a Multiple-Transmitter-Multiple-Receiver (MTMR) Piezo-ceramic based sensor array which is embedded to a conformable skin.

In this work, we have validated the ability of rapid material characterization using different grades of aluminum. Using experimental data collected by Smart skin, we have developed an automated material classification algorithm using various machine learning algorithms. Features extracted based on wavelets, zero crossing coefficients are feed into Support Vector Machine (SVM) for classification. However, feature extraction is time consuming as it needs manual intervention and the classifier accuracy depends on the type of extracted feature. Here 2D Convoluted Neural Network (2D CNN) is developed that works directly on the obtained experimental signal instead of extracting features. Manual intervention is not needed for feature extraction for these deep learning models. Different dimensionality reduction techniques, functional data analysis is used to reduce the dimension of the features. The efficacy of different models is thereby compared. Encouraging results are obtained that shows the deep learning methodology is efficient over the conventional feature extraction method as it improves the prediction performance on the classifier and result in an autonomous and cost-effective model.

1. INTRODUCTION

Application of GW in material characterization and damage detection has been successfully demonstrated in several studies (Vogt, Lowe, & Cawley, 2004) (Hosten, Castaings, Tretout, & Voillaume, 2001) (Vishnuvardhan, Krishnamurthy, & Balasubramaniam, 2007) (Keulen, Yildiz, & Suleman, 2014). Recent studies used GW to detect disbonds, cracks, perform quality control, and in-service fatigue monitoring (Siryabe, Renier, Meziane, & Castaings, 2015) (Castaings, 2014) (Dalton, Cawley, & Lowe, 2001) (Drinkwater, Castaings, & Hosten, 2003) (Banerjee, Karpenko, Udpa, Haq, & Deng, 2018) (Banerjee, Palanisamy, Haq, Udpa, & Deng, 2019) (Banerjee, Palanisamy, Udpa, Haq, & Deng, 2019). A MTMR configuration is generally used for material characterization. In most of the above-mentioned studies, piezo-ceramic sensors are permanently bonded to the surface of the substrate during inspection. In this study we have developed

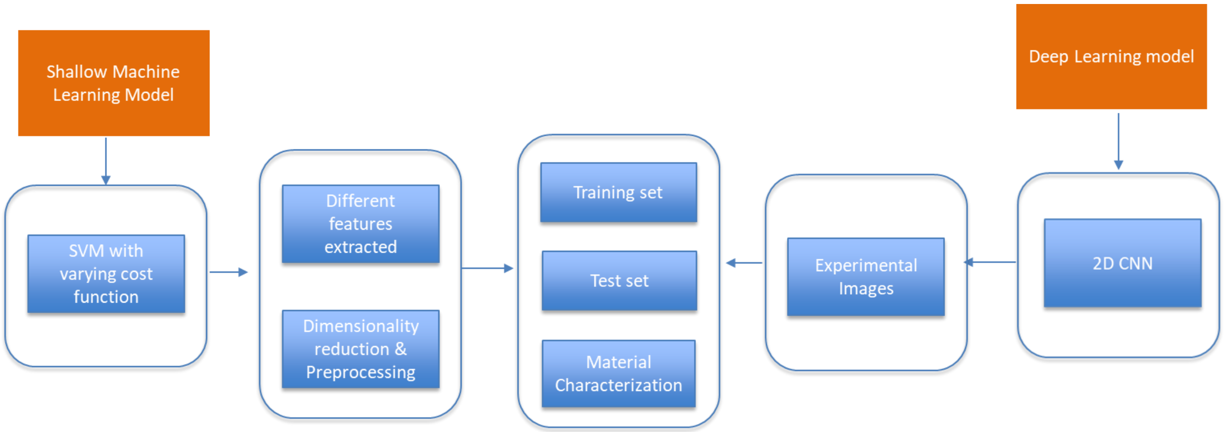

Figure 1. Schematic of the characterization methodology

a smart skin where the emended sensors can be reused. However, to enable rapid inspection machine learning models are used to process the data collected form smart skin. To demonstrate the ability of material characterization two grades of Aluminum having same thickness are chosen. Shallow machine learning models need efficient feature extraction for correct classification. Thus, the experimental signals are first preprocessed by clearing the offsets and by excluding the transmitted signal from the received ones. Then 21 features such as wavelet coefficients, zero crossing coefficients, mean, energy, standard deviation etc. are extracted. These obtained features are then feed into Support Vector Machine (SVM) classification algorithms (Rathod, Mukherjee, & Deng, 2020) for material characterization. However, extracting meaningful features are time consuming and need opinion of experts (Sultana, Chilamkurti, Peng, & Alhadad, 2019). Moreover, with massive amount of data these days there is possibility of erroneous classification and detection as the number of features become excessive which is called curse of dimensionality (Verleysen & François, 2005). Feature extractions and dimension reductions by Principal Component Analysis (PCA) though has great interpretability, but can leave out features with small contributions which can entail important information about material characterization. Deep learning involving Convoluted Neural Networks (CNN) show promising results as these networks reduce the manual design effort of feature extraction. Features are extracted directly from the raw data by these networks (Kwon, et al., 2019). Here the experimental images are directly feed into the developed 2D CNN network for binary classification. Figure 1 shows the schematic of the working methodology in this paper.

This paper is organized as follows. Section 2 and 3 describes the fabrication of smart skin and its application in Guided wave transmission and acquisition on aluminum plate. Section 4 illustrate the features extracted from experimental data and how they are used in SVM. Section 5 shows the development of 2D CNN technique. Results of material classification using SVM and 2D CNN are discussed in section 6. Summary, conclusion, and future work are presented in section 7.

2. Smart Skin

A Multiple-Transmitter-Multiple-Receiver (MTMR) Piezo-ceramic based sensor (PZT) array is embedded to a conformable skin. The bottom layer of the skin is coated with pressure-sensitive adhesive to be attached to most curved and non-curved structural surfaces (refer Figure **2**). Each PZT sensor nodes are individually controlled by a MATLAB code that actuates and receive the GW waves signals. The skin could actuate and receive GW waves in each direction of the material. Further, the reusable sensors can be deployed in an array configuration for multi-purpose NDE (Mahmoodul Haq, 2018). Figure **3** shows the application of “SMART SKIN” on an Aluminum plate for material characterization.

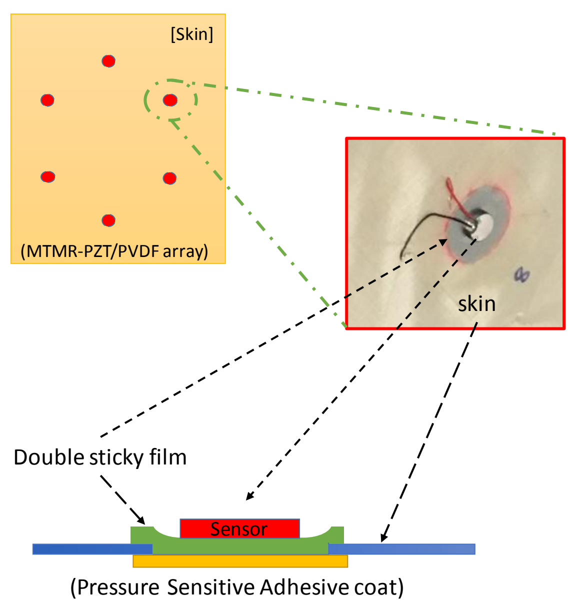

Figure 2 Schematic of smart skin

3. EXPERIMENTS

Two different grade of aluminum plates with same thickness as shown in Table **1** are chosen for classification

Table 1 Properties of selected Aluminum sample

Sample (name)	*Thickness (mm)*	*Elastic modulus, E (GPa)*
AL-6061 AL_1	1.6	68.9
AL-2024 AL_2	1.6	73.1

The block diagram in Figure 3 Smart skin attached to aluminum sample with GW DAQ setupshows the GW experimental setup. It consisted of 1) Smart skin deployed on the aluminum sample, 2) arbitrary waveform generator 33220A from Keysight Technologies, 3) Oscilloscope DSO 1004A from Keysight Technologies. Piezoelectric transduces embedded on smart skin were electrically connected to the output of the waveform generator. Excitation was done using a Morlet wavelet function with center frequency of 150 kHz. Guided waves transmitted through the aluminum plate were sensed using piezoelectric receivers, which were connected to the oscilloscope. Data was then transferred to a PC with MATLAB.

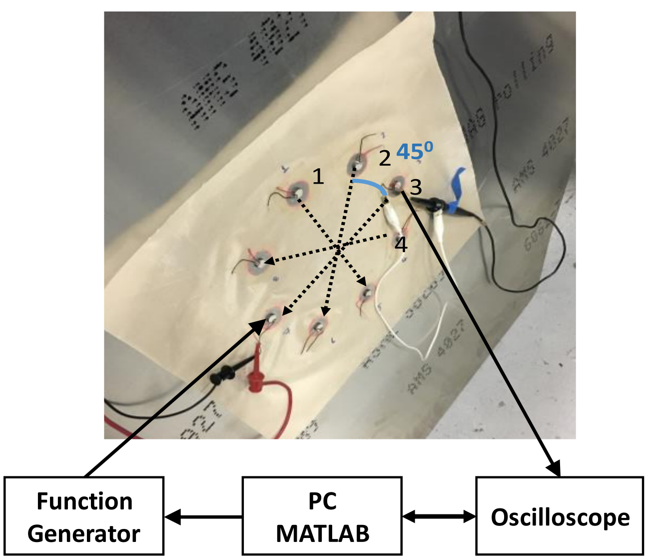

Figure 3 Smart skin attached to aluminum sample with GW DAQ setup

Based on the dispersion analysis for selected aluminum plates, excitation of 150 kHz would avoid any higher-modal excitation and lower dispersion of excited wave. Excited and received signal from one pair of transducers are shown in Figure **4**.

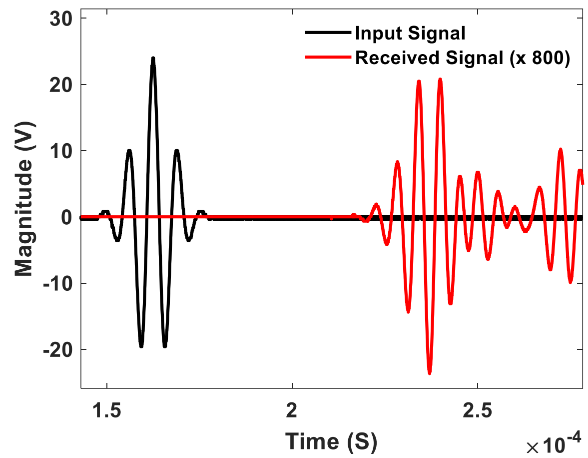

Figure 4 Excited and received guided wave signal form smart skin

4. NUMERICAL METHODS

Material Characterization of two grades of Aluminum is a binary classification problem. For each specimen type 40 signals are acquired. Thus, the entire data consists of 80 patterns where from each pattern 21 features are extracted. The data set is divided into 50 training data, 10 data for validation set and remaining 20 for test set. The extracted features are feed into shallow machine learning network (SVM) and the direct experimental images to deep learning network, 2D CNN.

4.1. Feature Extraction:

Here at first the signals have been normalized by considering the absolute of the maximum of the signals. Then from those normalized values different features like mean, variance, energy, zero crossing coefficients and discrete wavelet transform (DWT) are obtained. Wavelet transform constitutes an important feature as the guided wave based ultrasonic signals contain various stationary and non-stationary characteristics. Thus, signal analysis by wavelet decompositions provides an efficient method in NDE and SHM community compared to that with Fourier transforms (Bettayeb, Rachedi, & Benbartaoui, 2004; Mukherjee, Huang, Udpa, & Deng, 2019). From the experimental signals the offsets and transmitted signal is being eliminated. Now on this transformed signal Debauchies wavelet of level 4 based on Mallat's pyramidal algorithm (Mallat, 1999) has been used as an extracted feature. Zero crossing is the place where the sign of a mathematical function changes, thus providing another important feature (Higgins, 1980). At zero crossing, the time points where the amplitude of the experimental signal crosses zero has been considered. The insignificant segments at the beginning are ruled out by setting a minimum pass filter on standard deviation and maximum amplitude metrics at 10%. Different significant features as obtained from an experimental signal are shown in Figure **5**.

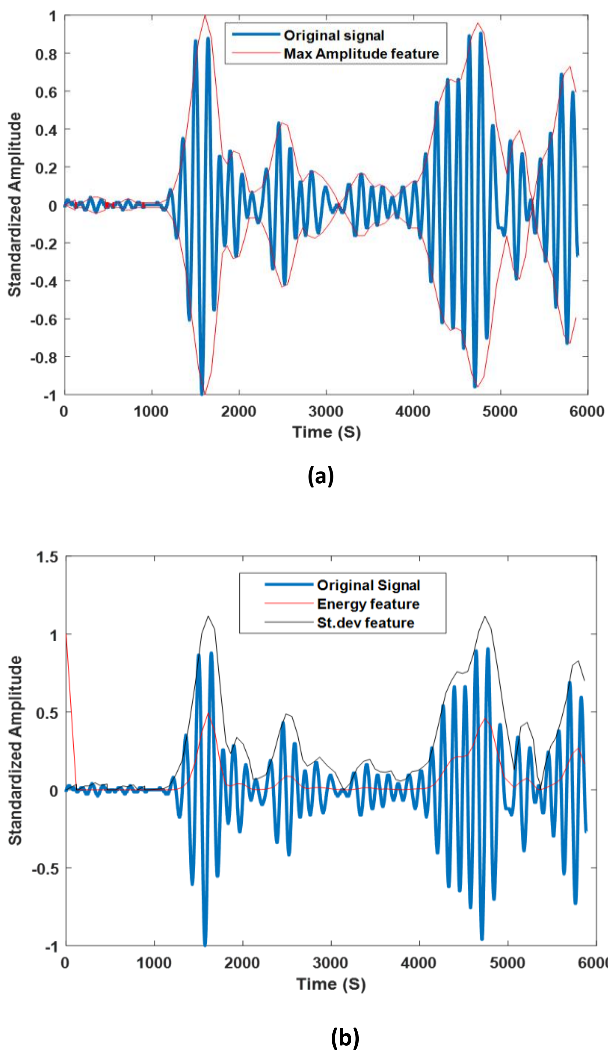

Figure 5 (a) maximum signal envelope of the signal, (b) standard deviation and energy feature of the signal

4.2. Description of the dataset:

The bar plot below shows the distribution of the features across the two classes. Color red (label 1) represents the class of AL_1 sample whereas light green (label2) represents the AL_2sample. As different features have different ranges, hence the features are normalized to the same scale in bar plot.

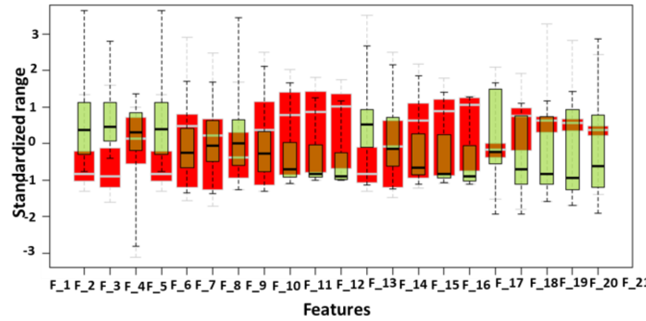

Figure 6 Feature distributions in bar plots representing A_1 in red and A_2 in light green. F_1 stands for Feature_1

4.3. Analysis Conducted

Dimension reduction is done by Principal Component Analysis (PCA) where 5 PC and 10 PC directions are used as extracted features forming two different datasets and the results are compared with that on original dataset. Table 2: Variability coverage based on Principal components (PC)shows the cumulative variability coverage by the PCA components. The table shows that the three few PCA components do not cover the entire variability of the data.

Table 2: Variability coverage based on Principal components (PC)

Variability Coverage by the Principal components				
1 PC	**2 PCs**	**3 PCs**	**4 PCs**	**5 PCs**
47.13%	68.26%	79.84%	84.96%	89.57%
6 PCs	**7 PCs**	**8 PCs**	**9 PCs**	**10 PCs**
93.73%	95.41%	96.59%	97.65%	98.52%
11 PCs	**12 PCs**	**13 PCs**	**14 PCs**	**15 PCs**
99.19%	99.47%	99.65%	99.78%	99.90%
16 PCs	**17 PCs**	**18 PCs**	**19 PCs**	**20 PCs**
99.96%	99.99%	99..99%	100%	100%

Figure **7** shows the variability in dataset based on first two principal components. From the below picture it is clear that it is hard to distinguish the two classes based on two PCs as there is overlap between the 2 classes

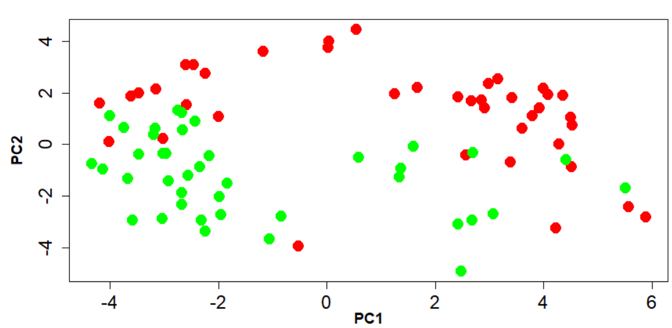

Figure 7 Data representation based on first two principal components

The AL_1 class is shown in red whereas AL_2 class is shown in dark green. Hence it is better to perform the classification analysis by taking into consideration more than 4 principal components or without dimension reduction.
Support Vector Machine (SVM) is applied where the cost parameter is varied from 1 to 10 on both the training and test sets. It is seen that cost parameter 8 produces the optimal result on the test set. Figure **8** shows the train and test errors when SVM is applied. Choosing the cost parameter as 8 gives the lowest misclassification rate on the test set.

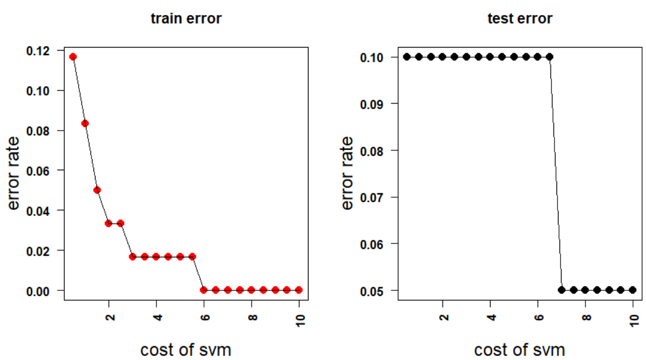

Figure 8 Error rate for different values of cost function

5. 2D CNN

Recently in the field of Nondestructive evaluation (NDE), studies involving defect classifications and material characterization using deep learning is gaining prominence (Liu, Bao, Wang, & Zhang, 2018) (Iyer & Sinha, 2005) (Mukherjee, Huang, Rathod, Udpa, & Deng, 2020). Here we have developed a 2D CNN network to perform the material characterization between two grades of Aluminum. The experimental data here are stored in the form of images of dimension $300\ X\ 30$. The deep learning models are developed in using keras and TensorFlow in Google Colab platform. A 2D CNN network uses convolution operation and deals with data in grid formats where it learns features in a hierarchical fashion by constructing deep neural architecture (Dahl, Sainath, & Hinton, 2013). The network comprised of 5 convolutional layers and 3 fully connected dense layers. Maximum pooling layers and dropout layers are also present on order to remove dimension and to introduce regularization respectively. The first convolutional layer contains 32 kernales each of size $3x3$ and stride as 1. After second convolution the output dimension reduces to $296x296x32$. Then maximum pooling of window size $2x2$ is applied which reduces the output dimension to $148x148x32$. Next dropout is introduced to reduce regularization. Then another layer of convolution, maxpooling and dropout layer is applied which further reduces the dimension to $73x73x32$. The fourth convolutional layer contains 64 kernels modifying the output dimension to $71x71x64$. as the non-linear activation function in the convolutional and dense layers. The optimizer used in the model is ADAM. Figure 9 shows the schematic of the described architecture of the 2D CNN.

6. Results and Discussions

In this section the performance of the shallow machine learning algorithms SVM on the extracted features and deep learning algorithm 2D CNN on the experimentally gathered data are compared. Out of total 80 data, 50 are used for training, 10 for validation and rest 20 are used for testing. Figure **10** shows the train and validation accuracies and losses as obtained from the 2D CNN. The accuracy obtained using 2D CNN on test dataset is 100%. Deep learning model is successful in material characterization.

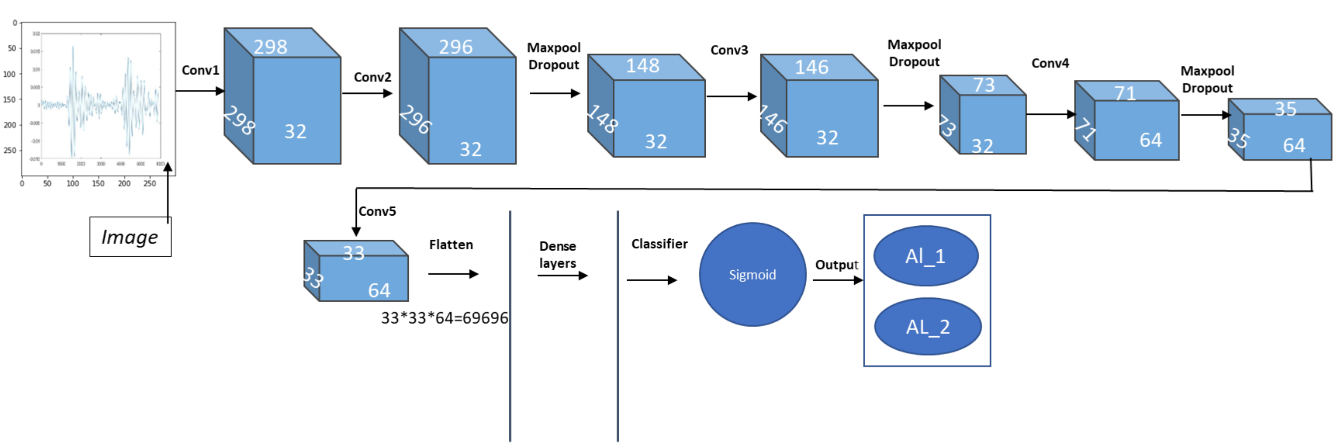

Figure 9 Schematic of the developed 2D CNN model

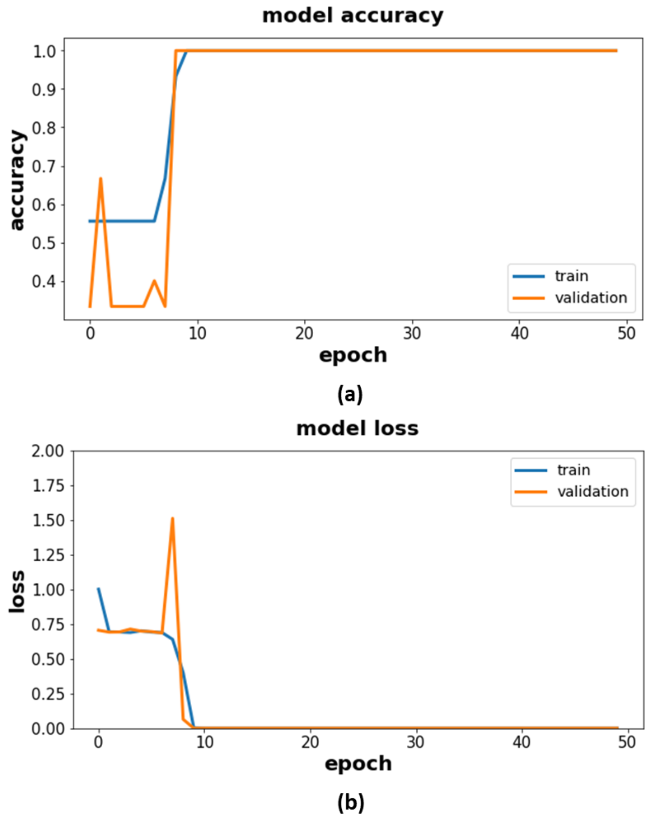

Figure 10 (a), (b) shows the 2D CNN accuracy and loss on the original dataset

The shallow machine learning models also produce accurate classification results as the dataset is small. we receive the accurate classification choosing cost parameter as 8 in SVM gives the accuracy of 95%. Thus, due to a smaller number of data almost all the classifiers give 100% accuracy. Figure **11** shows the confusion matrix for SVM and 2D CNN.

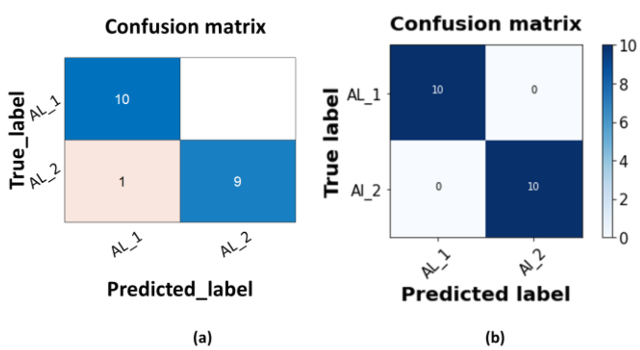

Figure 11 Confusion matrix of (a) SVM, (b) 2D CNN

7. Conclusion

This paper presents the development of smart skin for reusable and rapid NDE. Rapid Material characterization is one of the applications of smart skin. This application is achieved with various machine learning algorithms. SVM and 2D CNN is used successfully to classify two different grades of aluminum sheet. Classification results are promising and clearly indicates the ability to use smart skin for rapid material classification. In future, an improved algorithm for composite material property identification and classification is planned.

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Biographies

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Mr. Rajendra Prasath Palanisamy is a Graduate Research Assistant at Michigan State University. He is interested in developing novel sensors and algorithm for real-time structural health monitoring. Currently, he is working on ultrasound techniques for health monitoring of automotive composite structures.

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Subrata Mukherjee received his B.S. degree in electronics and communication engineering from the National Institute of Technology, Durgapur, India in 2015. He worked for three years in the telecommunication company Ericsson and is currently a third year Ph.D. candidate at NDEL at Michigan State University.

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