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MACHINE LEARNING BASED AUTOMATIC DEFECT DETECTION IN NON STATIONARY THERMAL WAVE IMAGING

A. Vijayalakshmi, V.S. Ghali, G.V.P. Chandrasekhar Yadav, V. Gopitilak and Muzammil Parvez M
Infrared Imaging Center, K L E F University, Vaddeswaram, India
E-Mail: vijayaavl6@gmail.com

ABSTRACT

Detection of subsurface non uniformity is crucial in deciding the strength of objects for various industrial applications. Non stationary thermal wave imaging is emerging as a reliable qualitative assessment procedure to detect anomalies in a wide range of materials. This paper proposes a supervised machine learning based classification modality to detect the subsurface defects using quadratic frequency modulated thermal wave imaging and experimentation has been carried over glass fibre reinforced polymer material (GFRP) with 10 Teflon patches having different depths and sizes and Carbon fibre reinforced polymer (CFRP) with 25 bottom holes having different sizes and depths. In this paper three well known supervised machine learning techniques, Decision tree (DT), Support vector machine (SVM) and k-nearest neighbour (KNN) classifiers are used for defect detection. Detection capability and reliability of defect detection have been assessed using signal to noise ratio and probability of detection respectively.

Keywords: infrared thermography, fibre reinforced polymers, classifiers and quadratic frequency modulated thermal wave imaging.

1. INTRODUCTION

Glass fibre reinforced polymer (GFRP) and Carbon fibre reinforced polymer (CFRP) are widely used in various applications due to their outstanding properties such as high stiffness, light weight, high resistance to corrosion. Defects such as delimitations, voids and cracks may occur during manufacturing of materials. These defects will spoil the peculiar properties of these materials and create chaos during in-service applications of whose pretesting and quality assessment is highly required. Non-destructive testing and evaluation (NDTE) plays vital role to provide defect free materials in cost effective manner in all aspects of materials and its applications, because NDE (non destructive evaluation) is a non-contact, non-invasive imaging method and is able to inspect large area within few seconds. This non-destructive testing enables to control the quality in manufacturing of materials. The main application areas of non-destructive testing are aerospace industry, chemical industry. Among various non-destructive methods infrared thermography is an attractive method to provide efficient inspection.

Infrared non-destructive testing (IRNDT) has a whole field, non-destructive and non-contact imaging method for testing integrity of the test sample without impairing its future utilization [1]. The infrared thermography is used to provide surface temperature contrast of test sample using infrared camera. This temperature map is used for further analysis. Infrared thermography further classified as passive thermography and active thermography.

In passive thermography, without any external known source a natural thermal response on test sample surface is used to identify subsurface defects. In active thermography, an external heat source is stimulates over the test sample and corresponding thermal response is collected using infrared camera. Further subsurface defect detection can be done by various processing methods. Depending on the external stimulus the active thermography can be divided into Pulsed thermography (PT), Pulse phased thermography (PPT), Lock in thermography (LT), and other modulated non stationary thermal wave imaging methods like Frequency Modulated Thermal Wave Imaging (FMTWI) and Quadratic frequency modulated thermal wave imaging (QFMTWI).

In Pulsed thermography (PT) [2-3], a high peak power source is energized within a short duration of time over surface of the test sample and the corresponding thermal response is collected from surface of test sample. Because of high peak Power and short duration of time, total test sample cannot absorb heat uniformly and enters two problems non-uniform emissivity and non-uniform radiation. In lock in thermography (LT) [4-6], instead of high peak power a mono-frequency continuous wave is used as external stimulus and the corresponding thermal response is captured by infrared camera. The thermal response collected from the infrared camera is analyzed using phase based analysis, because phase based analysis is less sensitive to non uniform radiation and non uniform emissivity. Because of mono frequency repetition of experiment is needed to detect the defects at various depths.

In pulse phased thermography (PPT) [7-9], it is the combination of pulse thermography and lock in thermography like pulse energy for stimulation and phase based analysis for defect detection. In this experimentation is like a pulse thermography but analysis is carried by Fourier Transform applied over thermal response to extract the phase delay. To overcome the above problems Frequency modulated thermal wave imaging (FMTWI) [10-14] is introduced by Mulaveesala *et al*. In this method, a suitable band of frequencies imposed over the test sample within a single experimentation. Quadratic frequency modulated thermal wave imaging (QFMTWI) [15] which can provide more energy to low frequency thermal waves and provides a deeper depth analysis along with all the advantages of FMTWI.

Machine learning is a branch of artificial intelligence which is used to evaluate the solution to a

problem with efficiently and accurately. Machine learning techniques are widely applicable in pattern recognition, signal processing, speech recognition, image processing etc. In the present work we consider machine learning for classification. The classification algorithm is used to make a boundary between two clusters. Classification is a supervised machine learning algorithms of predicting similar information from the categorical class variable. In this work, various supervised techniques are described. In supervised learning entire data can be dividing into testing and training datasets. Once prepare these data sets, we can use it for test the new data for feature information.

In this paper, supervised machine learning based defect detection is proposed with classification algorithms for carbon fibre and glass fibre reinforced polymers with different sizes and depths using quadratic frequency modulated thermal wave imaging.

In this paper, section II provides theory for quadratic frequency modulated thermal wave imaging, the methodology used in this paper were described in section III and section IV illustrates the experimental results and its analysis.

2. THEORY

2.1 Theory of thermal waves in QFMTWI:

In this section a theoretical development for surface evaluation corresponding to Quadratic frequency modulated thermal wave imaging as stimulation by solving one-dimensional heat equation. A quadratic chirped stimulus is provided to surface of test sample and is represented by [15]:

$$H(t)=H_0 \sin(a\,t + b\,t^3) \tag{1}$$

Where 'a' is initial frequency, 'b' as bandwidth of chirped excitation with peak value of stimulation 'H_0'. With this stimulation thermal perturbation creates on the surface of the sample and propagates deeper into test object. Depending on thermal properties of the surface temperature contributes over the surface of test sample. The surface temperature evolution of thermal wave can be obtained by solving one dimensional heat equation to homogeneous, isotropic and semi-infinite media, in the absence of heat sink or source and is represented by:

$$\frac{\partial^2 T\ (x,t)}{\partial T^2} = \frac{1}{\alpha}\frac{\partial T(x,t)}{\partial t} \tag{2}$$

Where 'α' is the thermal diffusivity of the material and 'L' is finite thickness of the sample. By solving equation 2 under boundary conditions is represented as:

$$-k\frac{\partial T}{\partial Z}\Big|_{x=L} = 0 \tag{3}$$

In Quadratic frequency modulated thermal wave imaging, at initial temperature the incident energy is attenuated in a thin layer over the surface of the sample and provides heat flux over the top of the surface of the sample represented by:

$$-k\frac{\partial T}{\partial Z}\Big|_{x=0} = Q_0 e^{j2\pi\left(a+bt^2\right)t} \tag{4}$$

Where 'k' is thermal conductivity of the material and 'Q_0' is amplitude of heat flux. By using boundary conditions, equation 2 is solved in Laplace domain and is represented by:

$$T(x,s) = \frac{Q(s)}{k\sigma(1-e^{-2\sigma L})}[e^{-\sigma x} + e^{\sigma(x-2L)}] - \frac{T_0}{s} \tag{5}$$

Where $\sigma = \frac{\sqrt{s}}{\alpha}$ and results are diffusion lengths are represented by:

$$\delta \propto \sqrt{\frac{\alpha}{1.77(a+bt^2)}} \tag{6}$$

By the equation 6, it is clear that Quadratic frequency modulated stimulation provides depth resolution with time-varying frequency.

3. METHODOLOGY

Some of standard classification techniques Decision tree (DT), Support vector machine (SVM) and K-Nearest Neighbors (KNN) were applied to evaluate classification of independent variables. In order to evaluate independent variables, these nonparametric classification techniques are used based on supervised machine learning.

3.1 Decision Tree classifier

Decision tree is one of nonparametric machine learning tool used for classification task. Generally it is like a tree structure. It is working based on CART (Classification and Regression Trees) [16, 17] algorithm. CART is a binary tree that means each node has two children nodes at the output. Tree consists of intermediate nodes and terminal nodes. The intermediate node perform test on input variables and terminal nodes indicating the labels of class. Here the input is thermal response of each pixel and output as class variable defect or non defect. The node is pure then it becomes a leaf node. If the tree is deeper with many leaves on the training data then it represents over fitting. The main purpose of decision tree is easy to use, robust even in the presence of missing values and free of ambiguity.

Decision tree classification stage enables defect detection. In the first stage data acquisition takes place from sequence of thermo grams from surface of test

sample using IR camera, then detection of each pixel is determined and gives pixel belongs to defected area or not. The main concept of decision tree **classifier** is pattern being recognized. The decision tree classifier assigns two classes the pixel belongs to defect or non defect area.

3.2 Support Vector Machine (SVM)

Support vector machines are supervised machine algorithm used for classification task. It is very effective in high dimensional spaces. SVM have capability to solving multi-class classification problems. This is used to classify defect and non defect regions.

SVM was developed by Vapnik in 90's. The main purpose of SVM is to minimize the empirical classifiers and maximize the geometric margin. If we consider maximal planes, SVM maps the input vector to higher dimensional spaces. In case of SVM we have two cases classification with linearly separable and non linear separable. Assume some data points as $\{(x_1, y_1), (x_2, y_2), (x_3, y_3),\ldots\ldots\ldots, (x_n, y_n)\}$. Here n is number of samples, 'x_n' as a real vectors. The training data can be divided using hyper plane represented as w.x + b = 0. Here w is p-dimensional vector and is perpendicular to hyper plane. But 'b' is offset parameter used to increase the margin. If 'b' is not in the hyper plane passed through origin. The training data is separable linearly with parallel hyper planes on both sides with maximum margin. Some problems are not a linearly separable then we need to apply nonlinear kernel for solving classification problems [18, 19]. Using different types of kernels data can be mapped in higher dimensional space and separate with their hyper plane.

The general form of kernel function is, $K(x, y) = \Phi(x)^T \Phi(y)$. Different kernels are available linear, RBF, polynomial and sigmoid. Among these RBF provides better classification. The representation of RBF kernel function represented as:

$$K(x,y) = e^{-\frac{\|x-y\|^2}{z\sigma^2}} \quad (7)$$

RBF kernel has less hyper parameters then other kernels, also has less numerical difficulties.

3.3 K-Nearest Neighbor Classifier (KNN)

The k-Nearest Neighbor is introduced by Fix and Hodges. The KNN is one of the most important non-parametric supervised learning algorithms [20, 21]. The KNN classifier assigns K closest neighbors to test sample of majority class. KNN classifier predicts the category of test sample according to k- nearest neighbors of the test sample. KNN is most popular algorithm for pattern recognition. The basic idea behind this as an object is classified according to majority vote of its neighbors. The algorithm for KNN to classify the sample is represented as, initially apply a training set and calculate the distance between sample y and training set. And find the k closest training sample. The k training sample can be determined by following expression.

$$C^k = \min_1^k(D(y, c_{ij})) \quad (8)$$

Where $(D(y, c_{ij}))$ is distance between y and c_{ij}, i as number of classes and j as number of samples in the training set. KNN mainly utilized in pattern recognition. KNN algorithm used for classifying the object based on closest training set. If the classification sample is unknown, it can be predicted by classification of its nearest neighbor of the samples. By considering the unknown sample and the training set, we compute the distances between unknown sample and all samples of training set, the smallest distance training set is closest to the unknown sample. So the classification of unknown sample is based on classification of nearest neighbors. The performance of KNN classifier is determined by value of K. If K value is small, the local estimate is very poor owing to mislabelled points. For further smooth, the K value should increases. If the value of K is very large over smoothing takes place and classification performance degrades. The selection of K value largely affects the classification performance of KNN.

4. RESULTS AND DISCUSSIONS

In order to extract the detectability of a material using proposed modality, experimentation is carried on 2 mm thick GFRP sample containing ten Teflon patches with different depths and various diameters and its layout is shown in Figure-1. The thermal properties of GFRP materials are, thermal diffusivity is about 0.13 $m^2\ s^{-1}$, thermal conductivity is about 0.3 $W\ m^{-1}\ {}^oC^{-1}$, specific heat is about 1,200 $J\ kg^{-1}\ {}^oC^{-1}$ and density is about 1,900 $kg\ m^{-3}$.

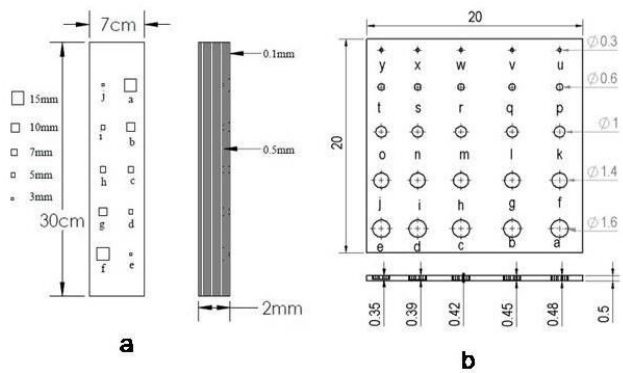

Figure-1. a. Layout of GFRP specimen b. Layout of CFRP specimen (All dimensions are in cm for CFRP).

During the experimentation the surface of the sample is energized by a Quadratic frequency modulated optical stimulus generated by a pair of 1 KW halogen lamps with a frequency sweep of 0.01-0.1 Hz in 100 s is shown in Figure-2. A cooled infrared camera is placed 1m opposite to the surface of test sample and capture temporal thermal response with a frame rate of 25Hz. And thermal response on the specimen captured with 2500 samples within 100 s.

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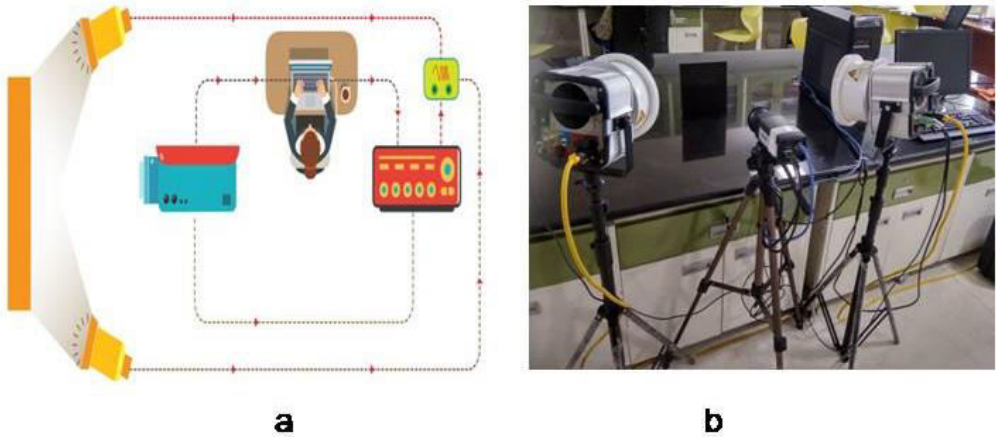

Figure-2. a. Schematic view b. experimental setup of active thermal wave imaging system.

In this work, first record the temporal sequence of thermograms from IR camera then form a training vector. The testing data is equal to number of thermograms in the sequence; here the input to each classifier is 2500 thermograms with 235x70 pixels each for GFRP sample and 616 thermograms with 439x445 pixels for CFRP sample. Then form a training vector by considering fifty percent of testing data with non defective pixels. Decision tree classifier uses training and testing data for detection of subsurface features. During training period hundreds of mean removed thermal profiles are used for training purpose with duration of approximately 180 sec with intel7, 16GBRAM and 512GB SSD laptop. The classifier provides outputs with defective and non defective area.

In order to extract the subsurface details of the test sample, with the mean removed thermal profiles the dynamic response of each pixel can be extracted. Further different machine learning supervised classification methods like decision tree (DT), support vector machine (SVM) and k-nearest neighbors (KNN) are employed over the mean removed profiles to extract the subsurface details. Figure-3 and Figure-4 illustrates the classification images collected from various machine learning approaches for GFRP test specimen with Teflon patches having different depths and sizes and CFRP sample with flat bottom holes respectively. Figure-3(c) is obtained from decision tree classifier and exhibiting every defect with deepest depths also with good contrast. Figure-3(b) collected from support vector machine classifier and acts as good classifier and Figure-3(a) Represents the k-nearest neighbor classifier exhibiting all defects expect the deepest ones having less contrast. Decision tree classifier provides best classification for all defects with deeper depths and also provides best defect detection similarly for CFRP sample represents in Figure-4.

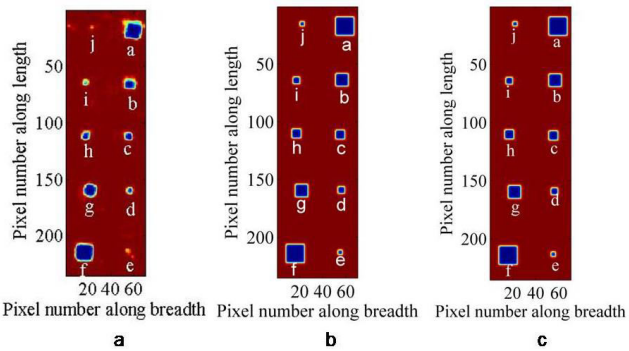

Figure-3. a. KNN classifier b. SVM classifier c. Decision tree classifier for GFRP sample.

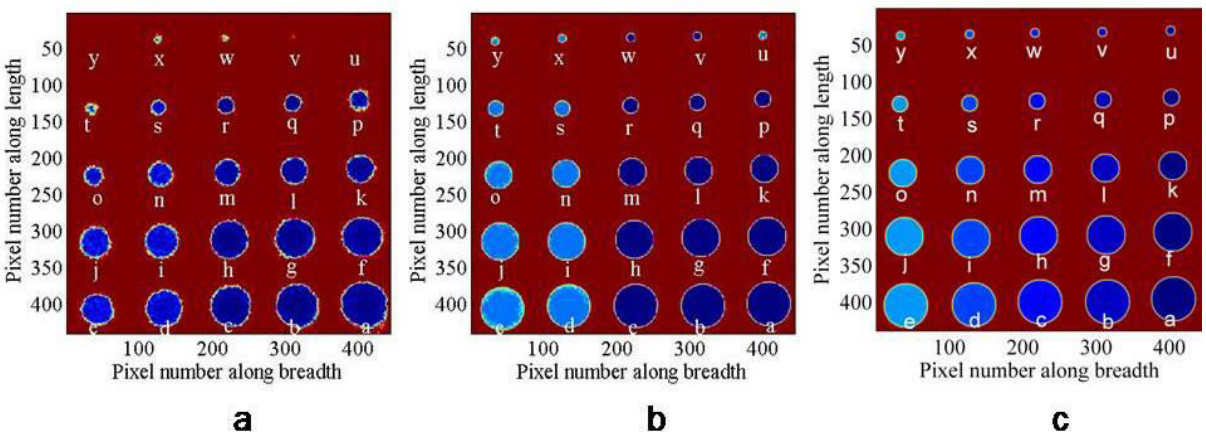

Figure-4. A. KNN classifier b. SVM classifier c. Decision tree classifier for CFRP sample.

In order to quantify the detectability of the test sample, the standard deviation of non defective region, mean of defective and non defective regions are calculated. Then calculate the signal to noise ratio of each defect of test sample using following equation.

$$\mathrm{SNR} = 20\log\left(\frac{\text{mean of defective area - mean of non defective area}}{\text{standard diviation of non defective area}}\right) \quad (9)$$

The Figures 5 and 6 illustrates the detectability of defects on the basis of SNR for GFRP sample and CFRP sample respectively. The proposed method decision tree classifier provides better detectability compared to all other classification methods. The detectability depends on size of defect and depth of defect.

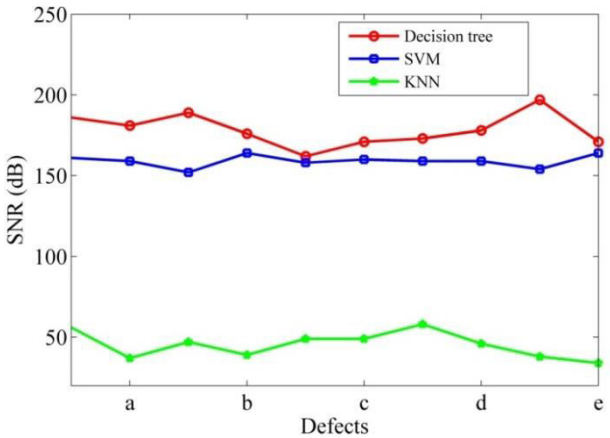

Figure-5. SNR of defects.

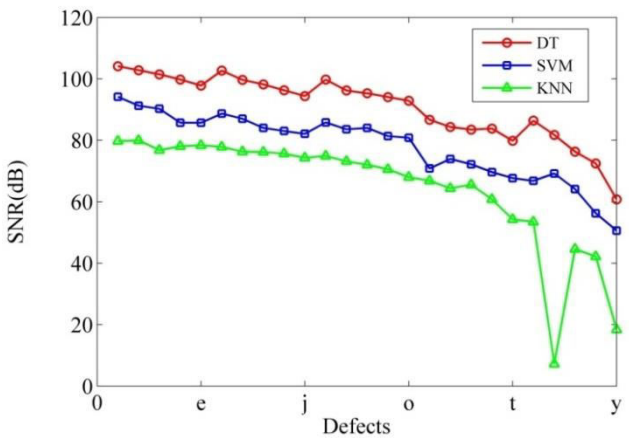

Figure-6. SNR of defects.

4.1 Defect sizing

The detectability also depends upon the depth and size of the defects. The size of the defects estimated using Full width at half maxima of the test specimen mentioned in Table-1 and Table-2, illustrates the decision tree based classifier provides the closest size of the defect compared to other classification methods mentioned in this paper. This is obtained by taking phase profiles passing through centres of defects a, b, c, d and e for GFRP sample and defects a, f, k, p and u for CFRP sample.

Table-1. Full width at half maxima of defects from centre line passing through defects for GFRP sample.

Defect	Actual Size (mm)	Estimated Size (mm)		
		DT	SVM	KNN
a	15	15.62	15.66	13.86
b	10	10.48	10.51	8.21
c	7	7.81	7.8	6.08
d	5	5.64	5.42	3.91
e	3	3.67	3.62	1.64

Table-2. Full width at half maxima of defects from centre line passing through defects for CFRP sample.

Defect	Actual Size (cm)	Estimated Size (cm)		
		DT	SVM	KNN
a	1.6	1.63	1.64	1.68
f	1.4	1.44	1.46	1.43
k	1	1.16	1.16	1.18
p	0.6	0.66	0.65	0.67
u	0.3	0.32	0.33	0.11

4.2 Probability of detection (POD)

For quantitative non distractive technique, the reliability of detection is one of the important aspects. The probability of detection (POD) is a process is used for estimation of defect detection capability of materials [22]. In this work the probability of detection ware calculated for Glass fibre reinforced polymer (GFRP) sample with Teflon patches and plotted the effect of probability of estimation with respect to accept ratio (size/depth) for different processing methods like Decision tree (DT), Support vector machine (SVM), and k-nearest neighbors (KNN). The probability of detection has been successfully used for detection capability of materials. Here the data deal with continuous signal response to characterize the defect. In this study, a GFRP sample with Teflon patches were inspected with Quadratic frequency modulated thermal wave imaging and using continuous phase contrast calculate the probability of detection to estimate the detection capability of GFRP sample. The corresponding POD with respect to aspect ratio for different processing methods is shown in Figure-7.

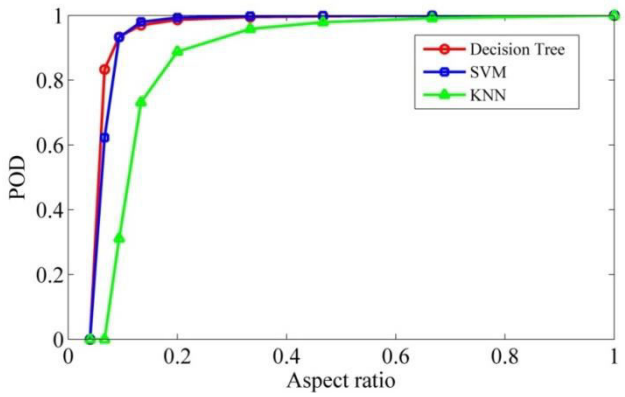

Figure-7. Probability of distribution curve of different processing methods for GFRP sample.

5. CONCLUSIONS

The defects identification with proper resolution has presented here using supervised learning methods on GFRP and CFRP samples and experimentally verified with Quadratic frequency modulated thermal wave imaging. The defect detection, probability of detection and size of defects has been studied. Among various supervised learning methods Decision tree classifier provides better detection capability compared to remaining processing methods.

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