

# Evaluating the Thermal Condition of Mechanical Equipment via IRT Image Analysis by TWSVM and Boosting TWSVM

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**Abstract-** Infrared thermography technology is one of the most effective non-destructive testing techniques for predictive faults diagnosis of mechanical components. Faults in mechanical system show overheating of components which is a common indicator of poor connection or any defect. Thermographic inspection is employed for finding such heat related problems before eventual failure of the system. Their accurate detection is a key issue in computer aided detection scheme. To improve the performance of detection, we propose a Boosting TWSVM and TWSVM to detect the faults in mechanical equipment. The algorithm is composed of five modules: taking a picture, normalizing, segmentation, feature extraction component, and the boosting TWSVM, TWSVM and SVM modules, then tested it on 160 thermal images of mechanical installations. Based on the results of the study shows that the automatic recognition system based on algorithm Boosting TWSVM has Accuracy 94.7 %, Sensitivity 95.2 %, Precision 96.7 %, specificity 93.7 % compared with the SVM & TWSVM classification have best result.

**Keywords-** Boosting TWSVM, TWSVM, thermography, mechanical equipment, image processing

## I. INTRODUCTION

Infrared thermography is one of the popular non-destructive testing (NDT) and condition monitoring tools which is generally used to investigate the invisible thermal abnormalities on the surface of the materials in various applications such as military, industrial, electrical, structure and medical fields [3-12]. In mechanical thermography, infrared radiation emitting by the surface of equipment is collected as temperature distribution profile by infrared camera.

Thermal image of equipment shows a range of temperatures represented as color variations and allows observers to find hot spots (or cold spots). Both quantitative and qualitative methods are adopted to measure the temperature of material. In quantitative measurement, the exact temperature value of material is taken. But due to the influence of environmental factors (such as ambient temperature, humidity and emissivity etc.), the accuracy of this technique is problematic. On the other hand, qualitative method accounts

the relative temperature of a hotspot with respect to other normal spot (reference) of the component with the similar conditions [1].

Under the equal loading condition, the overheated area is detected by determining the temperature value of the area which shows higher temperature than the similar reference component temperature value. In addition, from the visual inspection the overheated area contains red (brighter) color. Then, temperature difference between the reference and overheated component is determined. The temperature difference value is generally referred as Delta T ( $\Delta T$ ) criteria. Several standards for  $\Delta T$  value are found such as National Fire Protection Association (NFPA) – NFPA70-B [2], International Electrical Testing Association (NETA) [3] and American Society for Testing & Materials (ASTM) – E [4] etc. Sometimes thermographers prefer to classify thermal conditions of components based on their inspection experiences instead of following available standards. Finally, the thermal conditions of components are classified for diagnosing and the components are followed, tested and repaired on the basis of thermal condition. However, manual heat detection and thermal condition classification technique do not produce good performance due to slow process, technical and human errors. Some experiments on automated or semi-automated thermographic screening using computer aided visualization and intelligent diagnosis have already been developed to increase the mechanical systems diagnostic performance [5].

The process of capturing thermal images was in reach and useful, and has been taken by infrared cameras with resolution. The word thermography means writing with high heat which is only referring to capturing pictures (writing with light). Infrared thermography is a strong tool for engineers and architects to use for testing building [6].

Using image processing on thermal images will provide this possibility to automatically recognize the place of failure, which this technical has a lot of application in medicine. The available classifying methods have a low speed in diagnosing the faults for solving this problem and improving speed, precision, accuracy, sensitivity and specificity the TWSVM algorithm is recommended for this kind of work which is a newer method for automatic diagnosis of fault in thermal images.

TWSVM solves a pair of quadratic programming problems (QPPs). The two QPPs have a smaller size than the one larger QPP [7].

In this study, first order statistical feature and second order statistical feature (GLCM) has been used to feature extraction as well as TWSVM classification utilized for separation Thermal mechanical parts conditions (faulty / normal). The prop algorithm same as SVM is unstable because it has high sensitivity to the educational there for another algorithm is proposed to solve this problem.

In second method Boosting TWSVM which is one kind of TWSVM is applied. This method has more performance, reliability and less sensitivity to the educational instances. The result of second proposed method has more accuracy, precision, sensitivity and specification compare been better than other algorithms.

The rest of the paper is organized as follows, in part 2 the benefits of using thermography, in part 3 the literature, section 4 the proposed method, section 5 debate on the empirical results and conclusions and suggested is given in section 6.

## II. ADVANTAGES OF INFRARED THERMOGRAPHIC INSPECTION

Infrared thermography is a well-known diagnosis technology due to several advantages. Some of them are described as follows:

(i) Thermographic inspection can see the actual area of defects in equipment. Thus, it reduces disassembling, rebuilding, repairing or unnecessary replacement of good components which are pointless, expensive and time consuming issues. By using infrared thermographic inspection, we can recognize the defect and repair quickly only what and where requires repairing. Thus maintenance costs are reduced and the revenues are increased [8].

(ii) Thermography is a non-contact remote sensing diagnosing system and does not have any risk to be injured of living body or damaged of target equipment. Since infrared rays are harmless to living body [2].

(iii) The system can diagnosis the faults without interruption or shutdown of the service which results an increase of production [5].

(iv) The diagnosis system allows early avoidance of equipment failure which significantly decreases unscheduled outage and connected equipment damage. The cost of an emergency outage is more than the planned maintenance. Additionally, failure of electrical components could be catastrophic and cause serious bodily injury or even death of employees, maintenance personnel or the public [5].

### A. literature

In this section, the history of the work in the field of applications for prediction and detect diagnosis using image processing techniques based on the type of classification:

Mohd Shawal Jadin et al. (2012) to detect and diagnose automatic situation electricity equipment by analyzing the infrared image. First thermal image segmentation to find the target. Well - known areas, which have the same properties in the region, to remove unwanted areas are grouped together and ultimately the statistical properties of each region, mining and known by the SVM classification. Experimental results show that the proposed system thermal state electrical equipment to identify and classifies [9]. Rajesh et al. (2014) detect breast cancer and classifying cancer cells and natural cells from various techniques of artificial intelligence including LS - SVM , KNN, ANN , SVM. Results show that the LS - SVM with both radius based classification and RBF kernel line the highest rate of classification. So the LS -SVM classification can be natural cells and unnatural using cell image features, in a short time against other methods have been reported so far to separate [10]. Bartosz Krawczyk et al.( 2014) combined to set up a committee classification for breast of submitted that this model is a useful alternative to identify with tumors smaller size compared with mammography that standard method is that this could lead to early detection [11]. Cruz – Ramirez Nicandro et al. a relatively new technique, presented based on the temperature tumor. They through the classification Bayesian on thermal images to the dignity of suspected patients with cancer. Results show that this technique as a supplement diagnosis tool is effective [12]. Marina Milosevic et al. (2014) a system based on techniques for feature extraction and technical image segmentation to identify and unnatural patterns in the breast thermal images provided that the proposed system consists of three stages: feature extraction , classification based on natural pattern and unnatural and division of the abnormal pattern. Properties Based on the gray level (GLCM) and calculated to be part of the fabric of information gathered by the areas. a total of 20 feature of the GLMC by thermography extracted. The attributes the SVM classification, Bayesian and KNN were used. The results indicate that the best classification closely related to the KNN 92.5 % [13].

Gang-Min Lim et al (2014) proposed a system based Fault diagnosis of rotating machine by thermography method on support vector machine. Feature-based classification techniques consist of data acquisition, preprocessing, feature representation, feature calculation, feature selection, and classifiers. They are useful for online, real-time condition monitoring and fault diagnosis / features, which are now available with the development of information technologies and various measurement techniques. In this paper, an intelligent feature-based fault diagnosis is suggested, developed, and compared with vibration signals and thermal images. Fault diagnosis is performed using thermal imaging along with support vector machine (SVM) classification to simulate machinery faults, resulting in an accuracy level comparable to vibration signals. The observed results show that fault diagnosis using thermal images for rotating machines can be applied to industrial areas as a novel intelligent fault diagnostic method with plausible accuracy. It can be also proposed as a unique non-contact method to analyze rotating systems in mass production lines within a short time [14]. A.S.N.Huda et al (2014) a new thermography NDT for condition monitoring of electrical components using ANN with

confidence level analysis proposed. Infrared thermography technology is one of the most effective non-destructive testing techniques for predictive faults diagnosis of electrical components. Faults in electrical system show overheating of components which is a common indicator of poor connection, overloading, load imbalance or any defect. Thermography inspection is employed for finding such heat related problems before eventual failure of the system. However, an automatic diagnostic system based on artificial neural network reduces operating time, human efforts and also increases the reliability of system. In the present study, statistical features and artificial neural network (ANN) with confidence level analysis are utilized for inspection of electrical components and their thermal conditions are classified into two classes namely normal and overheated. All the features extracted from images do not produce good performance. Features having low performance reduce the diagnostic performance. After selecting the suitable features, the study introduces the intelligent diagnosis system using suitable features as inputs of neural network. Finally, confidence percentage and confidence level were used to find out the strength of the network outputs for condition monitoring. The experimental result shows that multilayered perceptron network produced 79.4% of testing accuracy with 43.60%, 12.60%, 21.40, 9.20% and 13.40% highest, high, moderate, low and lowest confidence level respectively [5]. Dr.S.RAVI et al (2014) Breast Cancer Detection on Thermogram at preliminary stage by using fuzzy inferences system proposed. Thermogram is considered as one of the most effective methods for early detection of breast cancers. However, it is difficult for radiologists to detect Micro calcification clusters. Therefore a computerized scheme for detecting early-stage Micro calcification clusters in mammograms is proposed. Optimal set of features are selected by Genetic algorithm which are fed as input to Adaptive neuro fuzzy inference system for classifying image into normal, suspect and abnormal categories. This method has been evaluated on 322 images comprising normal and abnormal images. The performance of the proposed technique is analyzed in terms convergence time. The results shows that the features used are clinically significant for the accurate detection of breast tumor [15].

**B. The proposed method**

In this section of the proposed method is that a new strategy on the issue of diagnosis in mechanical equipment is shown in Figure 1:

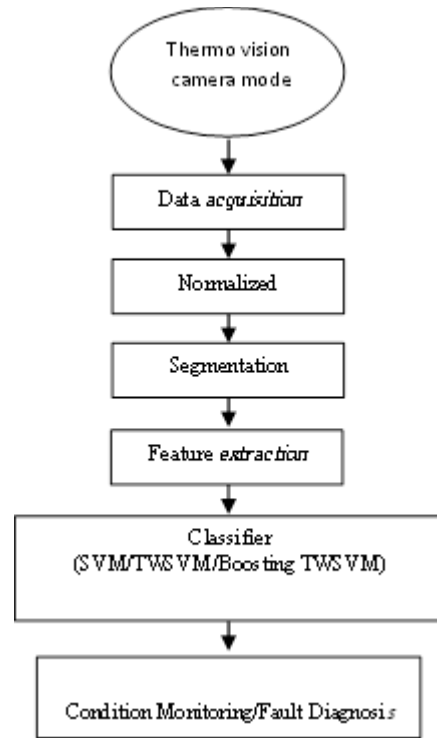


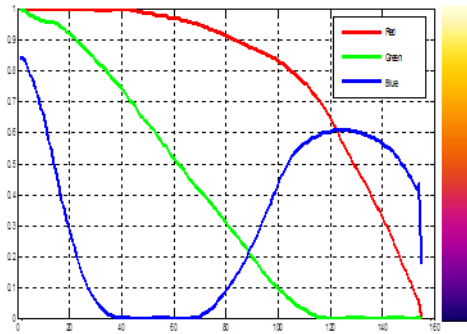
Figure 1. proposed methodology

**1) Acquisition thermal images**

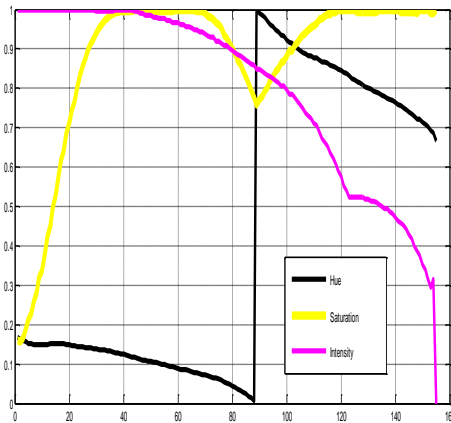
A data set of 160 thermal images was captured from mechanical facility using infrared thermal camera LT3. The detector type of this camera is focal plane array (FPA) of 160 × 120 pixels, spectral range of 4–8 μm and thermal sensitivity of 0.1 c at 30c. Additionally, each image of equipment has one or more hot components and similar reference or normal component. The distance between the target mechanical equipment and the infrared camera was in the range of 0.5–1.0 m. The emissivity value was set at 0.95 as recommended generally for mechanical equipment. The ambient temperature around the equipment was about 30–33 °C during the inspection.

**2) Normalization**

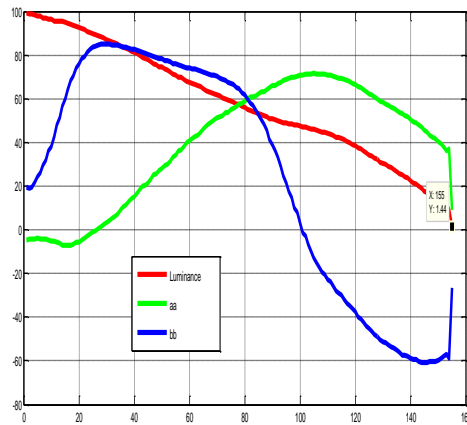
Given that bar color imaging machine, color spectrum to every picture shows. For the adaptation of the actual temperature with each pixel image, the need to images normalized with respect to the minimum and maximum values in the whole images. In the same context in search of a linear relationship between the color bar with the range of color outlet temperatures are Bar, therefore, to describe different colored space.



(a)



(b)



(c)

Figure 2. a) changes graph RGB space in the Color bar b) changes graph HSI space in Color bar c) changes graph L \* a \* b space in standard Color bar imaging device

Research conducted in the work on a different color spaces in all channels showed that the channel ( Luminance ) linear relationship with range of the temperature shown in the color bar. So the image of the Luminance Channel gray in color space L \* a \* b \* to normalize images will be used.

The relation between the grayscale intensity and the actual temperature,  $T_r$  for each image pixel can be represented as:

$$T_r = T_{min} + \frac{T_{Luminance}}{T_{max\_Luminance}} * (T_{max} - T_{min}) \quad (1)$$

TABLE I. THE INTRODUCTION OF THE LIST OF PARAMETERS THAT HAVE BEEN USED IN THE ACTUAL TEMPERATURE

$T_{ri}$ the number of pixels of the gray level with the level of i	$T_r$ Actual temperature for each pixel.
$T_{max}$ each maximum temperature of the image.	N the total number of pixels of the area.
$T_{Luminance}$ the amount of the illumination in particular point of pixels in the image of the gray color space L * a * b *.	$T_{min}$ image shows the minimum temperature.
$\Delta T$ The temperature difference between the target and the region shows the reference. $\Delta T = T_{rmax} - T_{other\_region}$	$T_{avg}$ shows the average temperature in the region. $T_{avg} = \frac{1}{N} \sum_{i=1}^N T_{ir}$

One of the common methods uses of inspection equipment, the criteria depends on  $\Delta T$ . When comparing as appropriate technique and good for the differences between the two (or more), often used to represent their status. Table 2 shows the maintenance testing specifications for electrical equipment published by the International Electrical Testing Association (NETA). NETA provides guidelines for thermal inspections of electrical equipment. These guidelines are based on differences in temperature from one phase conductor or component to another. Recommended action is dependent on the difference in the temperatures [16].

At first, the thermal conditions were manually classified into four groups based on priorities (priority levels 1, 2, 3 and 4). From these four conditions can be divided further into two categories, overheated (priorities 1 and 2) and normal (priorities 3, 4) conditions. The  $\Delta T$  values and necessary steps regarding the conditions have been described in Table 2.

TABLE II. MAINTENANCE TESTING SPECIFICATIONS FOR ELECTRICAL EQUIPMENT [16]

Priority	$\Delta T$ between similar components under similar load (°C)	$\Delta T$ over ambient temperature (°C)	Recommended Action
4	1-3	1-10	Possible deficiency warrants investigation
3	4-15	11-20	Indicates probable deficiency repair as time permits
2	----	21-40	Monitor until corrective measures can be accomplished
1	>15	>40	Major discrepancy; repair immediately

So with regard to the  $\Delta T$  obtained and based on the standard of NETA will be decided that the mainland is safe, or faulty (fault major / probabilistic defect in normal circumstances, but a specific temperature should not exceed the maximum allowable.

### III. SEGMENTATION

#### A. Methods based on clustering

One of the fuzzy clustering segmentation methods. This approach is based on fuzzy set theory is a way to express introduces uncertainty. Unlike the usual set, which are members of the characteristics of the precise, fuzzy sets to functions are concerned that the degree of the characteristics of (defined as imprecise) among the members of the measure sets [17]. For separation from the targeted areas of clustering is used. This method can be used to reduce the search space.

#### B. Thresholding

One of the simplest ways in which to segment of images used, thresholding. Thresholding techniques segment scalar images with binary division intensities of brightness.

To use the brightness of the image thresholding techniques using image histogram, conventional and appropriate. The basic idea is very simple histogram threshold. If an area to be considered for segmentation, to n-1 values {v1, v2, ..., vn} in the range histogram that best define these areas. In this case, the intensity of the new image is (2) is:

$$T(x, y) = \begin{cases} l(0) & f(x, y) < v_1 \\ l(1) & v_1 < f(x, y) < v_2 \\ \cdot & \cdot \\ \cdot & \cdot \\ l(n-1) & v_{n-1} < f(x, y) \end{cases}$$

1 (i) intensity is attributed to each group [18]. Because of the priorities here are 4 classes, so n = 4 and the values {v1 = 10, v2 = 20, v3 = 40} according to the thresholding prioritized (Table NETA) is determined.

#### C. Feature Extraction

A process in which an operation on the data, and determine its prominent features is determined. When the image data we do not have the required number of features are extracted from the image.

For feature extraction of thermal images to analyze the fault of the statistics based first order (according to the illumination histogram pixels), the statistical properties, the second - order or the same GLCM will be used [19].

First order features [18]

##### 1. Mean

$$m = \sum_{i=0}^{l-1} z_i p(z_i)$$

##### 2. Standard deviation

$$\sigma = \sqrt{\mu_2(z)} = \sqrt{\sigma^2}$$

##### 3. Max Intensity

Max ( z<sub>i</sub> )

Second – order features (GLCM) [13]

##### 1. Angular second Moment

$$f1 = \sum_{i=0} \sum_{j=0} P_{ij}^2$$

##### 2. Contrast

$$f2 = \sum_i \sum_j |i - j|^2 p(i, j)$$

##### 3. Correlation

$$f3 = \sum_i \sum_j \frac{(i - m_r)(j - m_c)p(i, j)}{\sigma_r \sigma_c}$$

$$\sigma_r \neq 0, \sigma_c \neq 0$$

##### 4. Variance

$$f4 = \sum_{i=0}^{l-1} \sum_{j=0}^{l-1} (i - \mu)^2 p(i, j)$$

##### 5. Homogeneity

$$f5 = \sum_i \sum_j \left( \frac{p(i, j)}{1 + (i - j)^2} \right)$$

##### 6. Sum average

$$f6 = \sum_{i=2}^{2Ng} i p_{x+y}(i)$$

##### 7. Sum Variance

$$f7 = \sum_{i=2}^{2Ng} (i - f_8)^2 P_{x+y}(i)$$

##### 8. Sum entropy

$$f8 = \sum_{i=2}^{2Ng} P_{x+y}(i) \log(P_{x+y}(i))$$

##### 9. Entropy

$$f9 = - \sum_{i=0} p(i, j) \log p(i, j)$$

##### 10. Difference Variance

$$f10 = \sum_{i=0}^{Ng-1} i^2 p_{x-y}(i)$$

##### 11. Difference entropy

$$f11 = \sum_{i=0}^{Ng-1} P_{x-y}(i) \log(p_{x-y}(i))$$

12. Information Measure of Correlation 1

$$f_{12} = \frac{HXY - HXY1}{\max\{HX, HY\}}$$

13. Information Measure of Correlation 2

$$f_{13} = (1 - \exp[-2.0(HXY2 - HXY)])^{\frac{1}{2}}$$

Where

$$HXY = -\sum_i \sum_j P(i, j) \log(p(i, j))$$

$$HXY1 = -\sum_i \sum_j P(i, j) \log\{p_x(i)p_y(j)\}$$

$$HXY2 = -\sum_i \sum_j p_x(i)p_y(j) \log\{p_x(i)p_y(j)\}$$

14. Autocorrelation

$$f_{14} = \sum_i \sum_j (i, j)p(i, j)$$

15. Dissimilarity

$$f_{15} = \sum_i \sum_j |i - j|p(i, j)$$

16. Cluster shade

$$P(i, j) * f_{16} = \sum_{i=0} \sum_{j=0} \{i + j - \mu_x - \mu_y\}^3$$

17. Cluster prominence

$$\sum_{i=0} \sum_{j=0} \{i + j - \mu_x - \mu_y\}^4 * P(i, j)$$

18. Maximum Probability

$$f_{18} = \text{MAX}_{i,j} P(i, j)$$

19. Inverse Difference Normalized

$$f_{19} = \sum_i \sum_j \frac{p(i, j)}{1 + |i - j| / Ng^2}$$

20. Inverse Difference Moment Normalized

$$f_{20} = \sum_i \sum_j \frac{p(i, j)}{1 + (i - j)^2 / Ng^2}$$

Following notations are used to describe the various GLCM features: P(i,j) - (i,j)th entry in a normalized gray-tone spatial dependence matrix. Ng - number of distinct gray levels in the quantized image.

$$\sum_i x_i = \sum_{i=0}^{Ng} x_i \quad \text{and} \quad \sum_j x_j = \sum_{j=0}^{Ng} x_j$$

$P_x(i)$  -  $i$ th entry in the marginal - probability matrix obtained by summing the rows of P(i,j),

$$P_x(i) = \sum_{j=1}^{Ng} p(i, j)$$

$$P_y(j) = \sum_{i=1}^{Ng} p(i, j)$$

$$P_{x+y}(k) = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i, j) \quad , \quad i+j=k, \quad k=2,3,\dots,2Ng$$

$$P_{x-y}(k) = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} p(i, j) \quad , \quad |i - j| = k, \quad k=0,1,\dots, Ng - 1$$

$$\mu_x = \sum_i \sum_j iP(i, j), \quad \mu_y = \sum_i \sum_j jP(i, j)$$

$$\mu = \sum_{i,j} iP(i, j)$$

$$\sigma_x = \sum_i \sum_j (i - \mu_x)^2 P(i, j)$$

$$\sigma_y = \sum_i \sum_j (i - \mu_y)^2 P(i, j)$$

Thermography of these attributes as their relations is evident, a number that are suitable for producing feature vector. For each image a feature vector that in the corresponding the image. Program in every time, an image processing and work on it, and it will feature vector. Thus, for every image, a feature vector.

D. Classification

- REVIEWS OF SUPPORT VECTOR MACHINES

The idea of SVM was first proposed by Vapnik of Lucent Technology's Bell Laboratories in 1995. The SVM learns a separating hyperplane to maximize the boundary margin and produce good generalization ability. In standard linear classification problem, suppose we have l given observations, each consisting of a pair of data: a data vector  $X_i \in R^n$ ,  $i = 1, \dots, N$  and a class label  $y_i \in \{+1, -1\}$  for each vector. The binary classification problem can be posed as follows:

$$\text{Minimizing } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \varepsilon_i \quad (3)$$

Subject to the constraints

$$y_i (w \cdot X_i + b) \geq 1 - \varepsilon_i, \quad \varepsilon_i \geq 0, \quad i = 1, \dots, m \quad (4)$$

Where  $y_i [w \cdot \varphi(X_i) + b] \geq 1$  comprises first the given constraints  $w \cdot \varphi(X_i) + b \geq +1$  if  $y_i = +1$ ,  $w \cdot \varphi(X_i) + b \leq -1$  if  $y_i = -1$ , and C is used to weight the penalizing relaxation variables  $\varepsilon_i$  and  $(\cdot)$  denotes the inner product of W and X vectors. The following parameters need to be determined: the bias b, the number of support vectors m, the support vector  $X_i$  and associated  $y_i$  values,  $i=1,2,\dots,l$ , as well as the Lagrangian multipliers  $\alpha_i$ .

$$y = \text{sign}(f(x)) = \text{sign}\left(\sum_{s.v.}^m \alpha_i y_i K(X_i, X_j) + b^*\right) \quad (5)$$

A detailed discussion on these approaches can be found in [20].

E. Boosting-Based Twin Support Vector Machine

In this paper, we defined  $X_i \in R^n$  as a pattern to be classified, and y as its class label (i.e.,  $y \in \{\pm 1\}$ ). In addition, let  $\{(X_i, y_i), i=1,2,\dots,m\}$  denote a given set of m training examples. And mean while we define m row vectors  $A_i (i = 1,2, \dots, m)$  in the n dimensional real space  $R^n$ , where  $A_i = (A_{i1}, A_{i2}, \dots, A_{in})$  and then  $A_i = X_i^T$ . Here, data points

belonging to classes 1 and -1 are represented by matrices A and B. Let the number of patterns in class 1 and -1 be given by  $m_1$  and  $m_2$ , and then  $m = m_1 + m_2$ . Therefore, the sizes of matrices A and B are  $(m_1 \times n)$  and  $(m_2 \times n)$ , respectively.

#### F. Reviews of Twin Support Vector Machine

Twin support vector machine (TWSVM) is a recently developed and very effective binary classification algorithm which obtains nonparallel planes around which the data points of the corresponding class get clustered. Each of the two quadratic programming problems in a TWSVM pair has the formulation of a typical SVM, except that not all patterns appear with constraints of either problem at the same time.

The TWSVM classifier is obtained by solving the following pair of quadratic programming problems:

$$TWSVM_1: \text{Min} \left\{ \frac{1}{2} (AW^1 + e_1 b^1)^T (AW^1 + e_1 b^1) + c_1 e_2^T q \right\} \quad (6)$$

s.t.:  $-(BW^{(1)} + e_2 b^{(1)}) + q \geq e_2, q \geq 0$

$$TWSVM_2: \text{Min} \left\{ \frac{1}{2} (BW^2 + e_2 b^2)^T (BW^2 + e_2 b^2) + c_2 e_1^T q \right\} \quad (7)$$

s.t.:  $-(AW^{(2)} + e_1 b^{(2)}) + q \geq e_1, q \geq 0$

Where  $C_2, C_1 > 0$  are parameters and  $e_1$  and  $e_2$  are vectors of ones of appropriate dimensions.

This approach aims to find two optimal hyperplanes, one for each class, and classifiers points according to which hyperplane a given point is closest to. The first term in the objective function of (6) or (7) is the sum of squared distances from the hyperplane to points of one class. Therefore minimizing it tends to keep the hyperplane close to points of one class (i.e., class 1). The constraints require the hyperplane to be at a distance of at least 1 from points of the other class (i.e., class -1); a set of error variables is used to measure the error wherever the hyperplane is closer than this minimum distance of 1. The second term of the objective function minimizes the sum of error variables, thus attempting to minimize misclassification due to points belonging to class -1 [7].

#### G. Boosting TWSVM

Boosting TWSVM is proposed by Freund et al. in which sample distributions are used to generate new training dataset. The base classifier is trained by using original dataset where each sample is assigned with equal weight. Depending on the sample classification, the weight is either increased or decreased. If the data sample is classified correctly, the corresponding weight is decreased while for inaccurate classification the weight assigned to sample is increased. At last, a weighing voted method is used so that a large weight is assigned to more accurate classifier as compared to a less accurate classifier. Generally, there are two types of learners, one is weak and another one is strong learner. As the name indicates strong learner easily learns from the training sample and constructs a classifier which mostly gives an accurate result while classifier constructed by weak learner is not good but may be considered better than the random guessing. The construction of a classifier using strong learner is difficult as compared to the construction of a classifier using weak learner. So, the main concept behind boosting is to learn from weak learner and then

boost them into strong learner by learning from earlier mistakes. Construction of a weak classifier by using weak learner starts with uniform weighing and then the data samples are assigned with new weight according to the performance of the classifier. So the main focus of the boosting is to enhance the capability of weak learner by using suitable weights. This subsequently generates a strong learner and provides better results. The stability of TWSVM depends upon the type of training samples [21].

Experimental and theoretical results have shown that Boosting can improve a good but unstable classifier significantly. This is exactly the problem of TWSVM. However, directly using Boosting in TWSVM is not appropriate since we have only a very small number of samples. To overcome this problem, we develop a novel Bagging strategy. The bootstrapping is executed only on the negative samples since there are far more negative samples than the positive samples. This way each generated classifier will be trained on a balanced number of positive and negative samples [7]. The Boosting TWSVM algorithm is described in Table II.

**Input:** positive training set  $S^+$ , negative training set  $S^-$ , weak classifier I (TWSVM), integer T (number of generated classifiers)

And the test sample  $X_i (i = 1, \dots, N)$ .

Distribution D over the N examples

Integer T specifying number of iterations

For  $i=1, \dots, N$ . **Initialize** the weight vector :  $w_i^1 = D(i)$

**Do for**  $t=1, 2, \dots, T$

1. Set

$$p^t = \frac{w^t}{\sum_{i=1}^N W_i^t}$$

2. Call Weak classifier, providing it with the distribution

$X \rightarrow [0, 1]$ . Get back a hypothesis  $h_t$ :  $P^t$ ;

3. Calculate the error of

$$h_t: \epsilon_t = \sum_{i=1}^N P_i^t |h_t(x_i) - y_i|$$

4. Set  $\beta_t = \epsilon_t / (1 - \epsilon_t)$ .

5. Set the new weights vector to be

$$w_i^{t+1} = w_i^t \beta_t^{1 - |h_t(x_i) - y_i|}$$

**Output** the hypothesis

$$h_f(x) = \begin{cases} 1 & \text{if } \sum_{t=1}^T \left( \frac{\log 1}{\beta_t} \right) h_t(x) \geq \frac{1}{2} \sum_{t=1}^T \log \frac{1}{\beta_t} \\ 0 & \text{otherwise.} \end{cases}$$

Boosting TWSVM has better performance, greater stability and less sensitive to the sample training than TWSVM. [21] Boosting me.

H. Empirical results

For identifying the energy dissipation in mechanical equipment with classified Boosting TWSVM, the following steps are :

1. Camera pictures of thermo vision with LT3 model.
2. Because of pictures have best quality, doesn't need preprocessing stage .
3. Normalized to equalize suffering color temperatures in the bar.
4. To split the image of the field and separation of temperature ranks, according to NETA standard of fuzzy clustering and Astana ordinary bombing.
5. For feature extraction of thermal images to analyze the violation of 3 - statistic for the first order and 20 demographic characteristics to second - order (GLCM) is used. Apply feature extraction methods to get the feature vector x.
6. Samples that  $\Delta T > 20$  are suspected samples and samples that  $\Delta T < 20$  are considered normal.
7. Suspected and normal samples in order considered class (+1) and (-1).
8. We consider 160 pictures from 60 pictures for training samples and 95 pictures for testing samples.

Use the trained SVM, TWSVM, Boosting TWSVM classifiers to make decision whether x belongs to class (+1) or not (-1). For base model selection, the SVM, TWSVM classifiers is first trained by using the 10-fold cross-validation procedure with different model and parametric settings. In our training stage, we used generalization error, which was defined as the total number of incorrectly classified examples divided by the total number of samples classified, as a metric to measure the trained classifier Generalization error was computed using only the samples used during training. For the sake of convenient, the parametric values of  $C_1$  and  $C_2$  in our experiment are set to equal (i.e.  $C_1 = C_2 = 0.1$ ).

The classification performances can be evaluated in several ways. The most commonly used methods of classification quality are built from a confusion matrix which records correctly and incorrectly recognition.

In our case, we define true positive (TP) and true negative (TN) as correctly predicted abnormal (fault) and normal (no fault) equipment respectively. In contrast, false positive (FP) and false negative (FN) are defined as false predicted abnormal and false predicted normal equipment correspondingly. The classification performances are judged based on percentage of specificity, sensitivity, precision and accuracy, which given as [22].

$$\text{Specificity} = \frac{TN}{TN+FP} * 100\% \tag{8}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} * 100\% \tag{9}$$

$$\text{Precision} = \frac{TP}{TP+FP} * 100\% \tag{10}$$

$$\text{Accuracy} = \frac{TP+TN}{TN+TP+FN+FP} * 100\% \tag{11}$$

Sensitivity relates to the measure of the system's ability to identify the thermal fault correctly. Specificity is the rate of correct detection of normal equipment. Precision is a function of true positives and examples misclassified as positives (false positives). Accuracy is the total percentage of correct classification of normal and abnormal equipment over the entire tested samples [22].

TABLE III. MEASURE OF THE SYSTEM 'S ABILITY

Classification method	TP	TN	FP	FN
BoostingTWSVM	60	33	1	1
TWSVM	60	30	3	2
SVM	50	35	5	5

To evaluate the performance of the algorithm proposed, we compare the results of Boosting TWSVM and TWSVM algorithms with SVM. The results are shown in Table 4 is shown.

TABLE IV. ACCURACY, THE SENSITIVITY OF THE PROPOSED ALGORITHM IS CALCULATED

Classification method	Accuracy	Precision	Sensitivity	specificity
BoostingTWSVM	97.89%	98.3%	98.3%	97.05%
TWSVM	94.7%	95.2%	96.7%	93.7%
SVM	89.4%	90.9%	90.9%	87.5%

The results shows that classification by selecting 23 features, Boosting TWSVM algorithm , Precision Accuracy, specificity and Sensitivity better than other compared algorithms.

IV. CONCLUSIONS

In this paper, we present Boosting TWSVM and TWSVM algorithms that new strategies in the development of thermal smart monitor the situation in mechanical components to identify defects in the thermal images is introduced. In this method, combined image features are extracted from each image block of positive and negative samples, and Boosting-TWSVM is trained through supervised learning with the 23 dimensional feature to test at( every location whether detect that mechanical equipment is impact or not). The decision function of the trained SVM, TWSVM and Boosting-TWSVM is determined in terms of ensemble classifier model that are modeled from the positive and negative samples during training stage.

The results showed that Boosting TWSVM Accuracy Precision with 97.89 % and 98.3 % in comparison to the TWSVM and SVM is better because of the algorithm iterative method uses the right and the accuracy of its performance improved with more and better because TWSVM, SVM is that



of cloud non - page two parallel to split into two classes of quadratic programming problems, two smaller size instead of solving a large size unit planning comes second is used so that each page to one of the classrooms, and close to the other class and Boosting with Sensitivity 98 TWSVM 3% and specificity 97. 05% in comparison to the TWSVM and SVM is better because the weight of the samples, at any stage and tries to reduce the error classification.

Compared to TWSVM classifier, Boosting-TWSVM can solve the unstable problem of TWSVM.

## V. SUGGESTIONS

1 - According to choose TWSVM parameters that it is difficult to use evolutionary optimization algorithms proposed.

2 - Selecting a number of features extracted containing the most useful information are minimizing public error is classified. Feature selection after feature extraction, have been proposed.

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