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OPTICAL METHODS

Detection and Segmentation of Cracks in Weld Images Using ANFIS Classification Method

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Abstract—This paper proposes the detection and classifications of weld images for crack detection using image processing techniques. The proposed method consists of preprocessing stage, feature extraction stage, classification stage and crack region segmentation regions. The image enhancement method is used as preprocessing stage and texture and statistical features are extracted from the enhanced weld images. These computed features are then classified into "Excess weld", "Good weld", "No weld" and "Undercut weld", using Adaptive Neuro Fuzzy Inference System (ANFIS) classification method. This proposed method is analyzed in terms of sensitivity, specificity, accuracy, positive predictive value, negative predictive value and precision. The simulation results of the proposed method are compared with other state of the art methods.

Keywords: Detection, cracks, regions, classifications, features

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1. INTRODUCTION

The usages of welded materials are high in construction of flyover bridges, ship construction areas and find many applications in machinery manufacturing and industrial areas. Hence, there is a need for proper welded materials for these kinds of applications for assuring quality and safety as stated in Jinping et al. (2015), Yue et al. (2010), Ahn et al. (2018). Though the manufactured welded materials are quality products, sometimes there may be occurring of cracks on the welded materials due to high temperature and improper molding on these materials (Xu et al., 2014). Hence, the detection of cracked weld is important and it is some more difficult task due to similar structure on the welded surface. In conventional crack detection methods used magnetic particle approach and infrared (IR) thermography methods (Zhang Yiyang (2014), Salman et al. (2013), Pingrang Wang et al. (2010)). The main limitations of these conventional methods are that they produced low level of improper weld detection accuracy for low resolution acquired weld images. Also, the lighting conditions affect the detection accuracy. This paper overcomes these limitations of the conventional method by proposing soft computing approaches in order to improve the level of improper weld region detection and segmentation accuracy.

Figure 1 shows the method for detecting the defects in welded materials. This method uses IR camera (which passes the IR rays over the welded materials) for the acquisition of weld regions and then the proposed crack detection method is applied on the welded images for detecting the cracks or defects. The general crack or defect detection system consists of processing, acquisition, synchronization and all these stages are computed and processed through the computer. The acquisition is the related with IR camera as a hardware unit which access the image through IR camera. This image is synchronized with computer and then image processing algorithms have been applied on the captured image to detect or identify the cracked regions. The IR camera captures the image through the inductive coil which is externally power supplying device in order to eliminate the field losses during the image acquisition process. During the image acquisition, the welded materials which are going to be tested should be placed over the media through which the eddy current is passed.

The main contribution and originality of this paper is to develop an efficient and fully automated method for detecting defects in welded materials using soft computing approach. The proposed method stated in this paper uses ANFIS classifier to detect and classify the defects in welded materials which requires minimum number of training images when compared with other classification approaches.

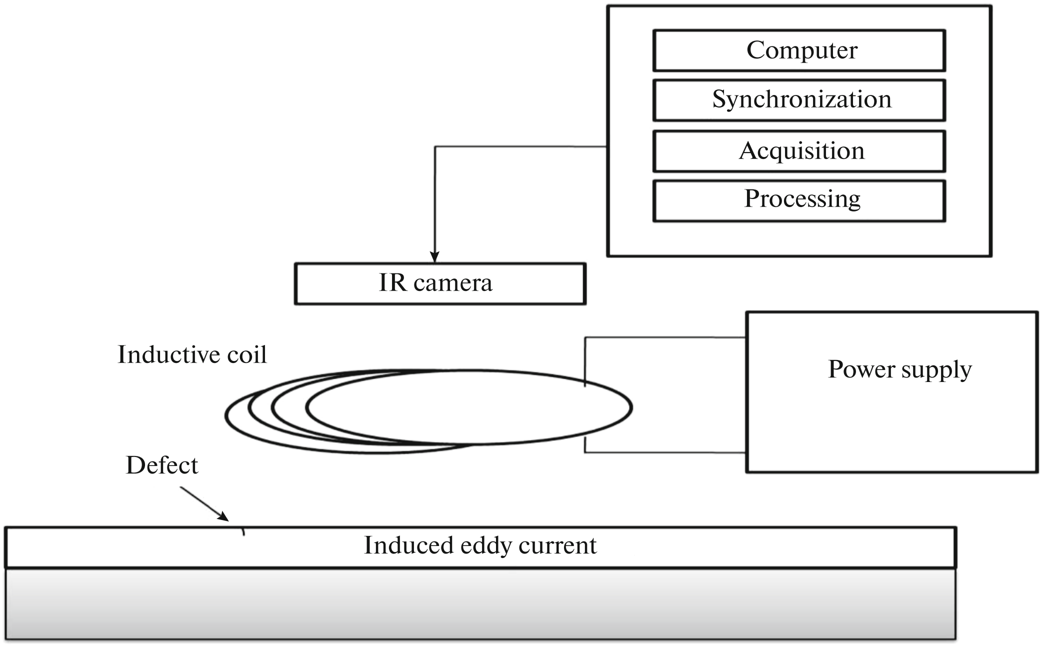

Fig. 1. Method for detecting the defects in welded materials.

This paper is organized as, the conventional crack or defects detection methods are illustrated in section 2, the proposed methods for crack detection and classification is given in section 3, the simulation results and their discussion are given in section 4, the conclusion is depicted in chapter 5.

2. LITERATURE SURVEY

This section discusses various conventional methodologies for crack or defect detections in welded images based on the classification approaches and feature extraction process.

Wu et al. (2019) used thermal processing techniques for region cracks detection in weld materials. The authors analyzed that the classifier methods suitable for different kind of weld samples. Roman Sizyakin et al. (2019) proposed a Convolutional neural network classification approach for detecting or identifying the cracks in welded images. This method used max-pooling algorithm for reducing the feature set in each Convolutional layers. Then, Support Vector Machine (SVM) approach was used on the classified weld image for locating the boundary of the crack regions in improper welded images. Zhu et al. (2019) and Deotale et al. (2019) used GLCM feature extraction models for the identification of defect patterns for various non-uniform regression model based applications. ArunMohana et al. (2018) discussed various methods for detecting the cracks in welded materials with respect to various classification structures along with various performance analysis parameters. Zhao et al. (2017) developed linear methods for detecting the cracks regions using circle-ferrite induction thermography. The thermal detection methods applied thermal grapy analysis of weld methods. Gaochao Wang et al. (2018) used triple-threshold Canny edge detector on the captured weld images in order to locate and segment the cracked regions. This edge detector detects the accurate improper weld regions on both excess weld case and undercut weld case. The authors then applied linear classification algorithm for classifying the located cracked regions in segmented weld images. Liu et al. (2017) applied eddy current thermal image processing approaches on the welded images for locating the cracks in improper welded regions. The authors detected fatigue cracks in welded images and they obtained 89.5% of improper weld region detection and segmentation accuracy. This method tested the proposed approach on large weld image dataset.

Yang et al. (2015) used x-rays methods on weld materials and the scanned regions were applied into proposed crack detection process. The authors used low frequency components for detecting the cracks in weld regions. Broberg, Patrik. (2013) used thermal image processing techniques to identify the defects in welded images. This method identified and classified the welded images into Excess weld and undercut weld. The classification rate of this crack detected method was about 78% of Excess weld and 81% for undercut weld. The main limitation of this method was that the classification accuracy level was reduced when the low resolution weld images used. Salman et al. (2013) used Gabor transforming approach for locating the crack regions in welded materials. This multi oriented filtering approach was designed by its multi level and multi phase kernels. The various directional regions of pixel in welded materials were detected through the convolving functionalities of the welded image with its kernel function. The crack detected images were inspected with respect to variety of pixel patterns. This method for crack pattern detection achieved 95% of precision rate.

Patricia Melín et al. (2014) developed a chaotic time series using type 1 and type 2 fuzzy integrators with the linear prediction model. This developed methodology used various fuzzy integrators for constructing the time series model for the features. Further, this proposed linear model was improved by adopting the Genetic Algorithm (GA) optimization algorithm for optimizing the simulation results. The performance evaluation parameter root mean square error was reduced using this proposed fuzzy model along with optimization technique. Soto et al. (2013) proposed a methodology for time series prediction using ensemble classification based ANFIS model. This model used different types of fuzzy integrators for improving the prediction model. Many standard statistical techniques were tested on this proposed model to improve the developed model accuracy rate. Leocundo Aguilar et al. (2003) constructed a working model for controlling the stepping motor operation for the applications of robotics. The authors developed closed loop controlling algorithm using neuro-fuzzy hybrid approach which was entirely based on ANFIS model with respect to sugeno fuzzy rules. Oscar Castillo et al. (2003) developed a robotic identification and control system using intelligent adaptive models. The author constructed their own fuzzy model system for optimizing the controlling efficiency of the robotic model. Patricia Melin et al. (2003) proposed an efficient framework for developing adaptive intelligent control theory for controlling the aircraft systems using the integration of soft computing techniques such as fuzzy rules and neural networks. This developed non-linear model system was tested on different environments to validate the testing results.

The following limitations were found in literature survey.

— No machine-vision classification method available for detecting the cracks in welded materials;

— The classification rate of the conventional methods was low;

— The conventional methods for crack detection produced superior results for high resolution constrained environment weld images.

3. PROPOSED METHODOLOGY

This paper proposes the detection and classifications of weld images for crack detection using image processing techniques. The proposed method consists of preprocessing stage, feature extraction stage, classification stage and crack region segmentation regions. The image enhancement method is used as preprocessing stage and texture and statistical features are extracted from the enhanced weld images. These computed features are then classified into "Excess weld", "Good weld", "No weld" and "Undercut weld", using ANFIS classification method. The proposed flow for weld image classifications is illustrated in Fig. 2.

Preprocessing

This technique enhances the image pixel regions for further feature extraction process. The crack regions are very minute defects which cannot be determined by normal methods and also they are having very low resolution boundary pixels in these cracked regions as illustrated in Campos et al. (2019). Hence, there is a need for enhancing the low resolution boundary pixels to high resolution boundary pixels using enhancement process. Many conventional enhancement methods such as histogram equalization and threshold processing are available, which enhanced the entire regions. This paper uses local histogram equalization method which divides the entire image region into 3 × 3 non-overlapping sub modules. This method is mainly enhances the pixels belonging to the cracked regions in welded images. The enhancement of the center pixel in each 3 × 3 sub module is done using the following equation 1.

$$\text{Enhanced(center\_pixel)} = wh\left[\frac{\text{CDF}(p) - \text{Min}\,(\text{CDF}(p))}{wh - \text{Min}\,(\text{CDF}(p))}(N-1)\right], \tag{1}$$

where CDF is the Cumulative Distribution Function and p is the center pixel in wh window with the maximum pixel intensity is denoted by N.

Figure 3a shows the source weld image which has low intensity pixels and the boundary pixels are enhanced and depicted in Fig. 3b, respectively.

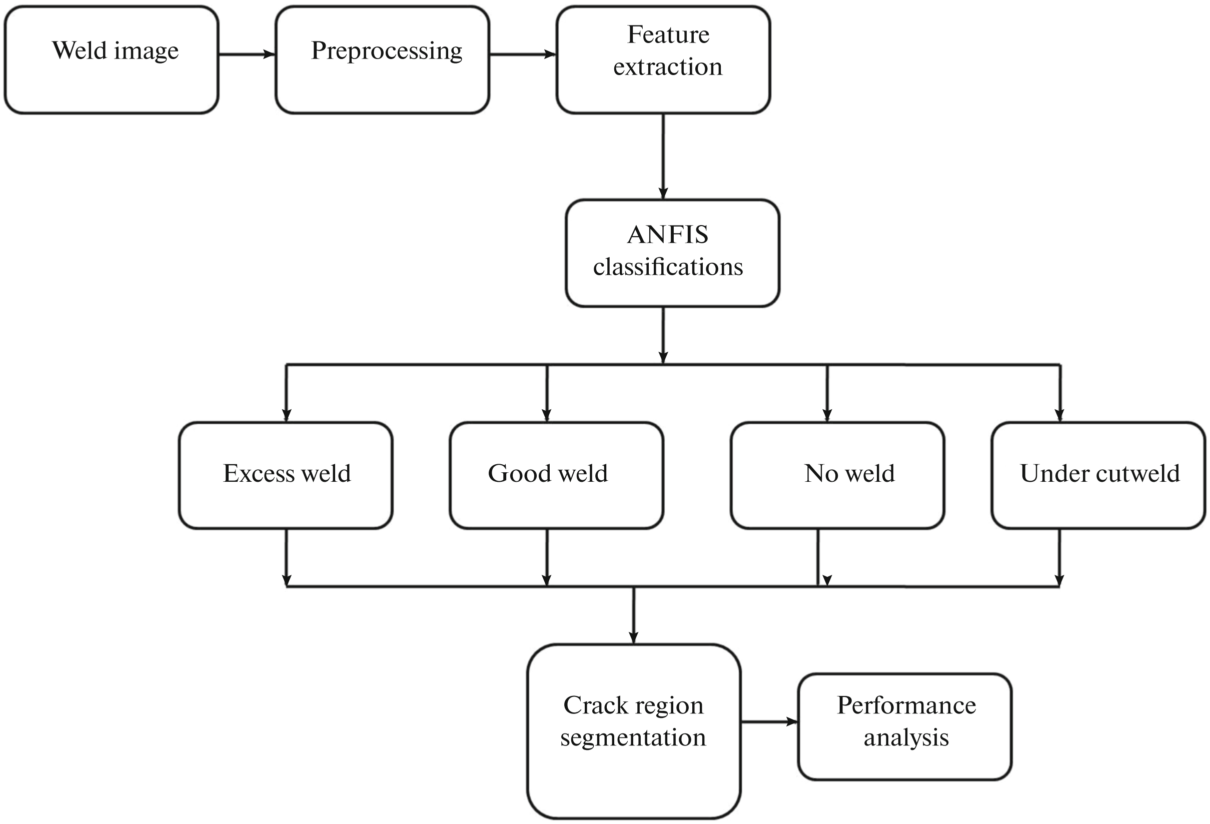

Fig. 2. Proposed weld image classifications and detection of cracks.

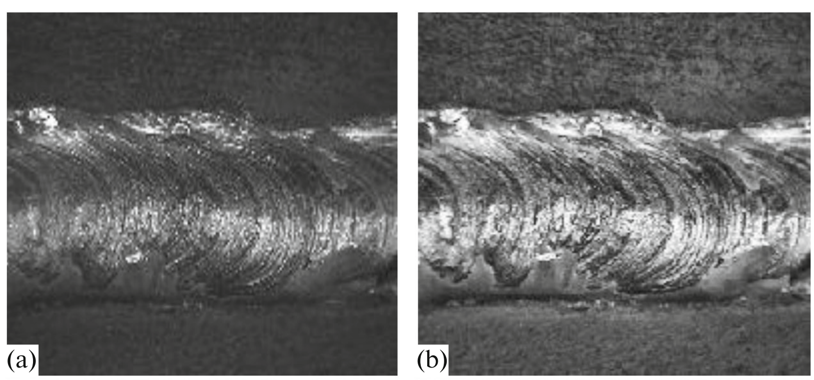

Fig. 3. (a) Source weld image (b) Enhanced weld image.

GLCM Features

Features are derived from the enhanced weld image for identifying the defects on it. In order to differentiate the Good weld images from other cases of weld images, there is a need for extracting the features index from the source weld images (Pandiselvi et al. 2019 and Sainudiin et al. 2019). This paper uses Grey Level Co-occurrence Matrix (GLCM) features, which can be obtained at the orientation of 45 degree for obtaining the detailed index feature values from the enhance image. The GLCM matrix is constructed and the following features are extracted from this matrix using the mathematical equations (2)–(5).

$$\text{Contrast} = \sum \left(|i - j|^2 \, p(i, j) \right), \tag{2}$$

$$\text{Energy} = \sum p(i, j)^2, \tag{3}$$

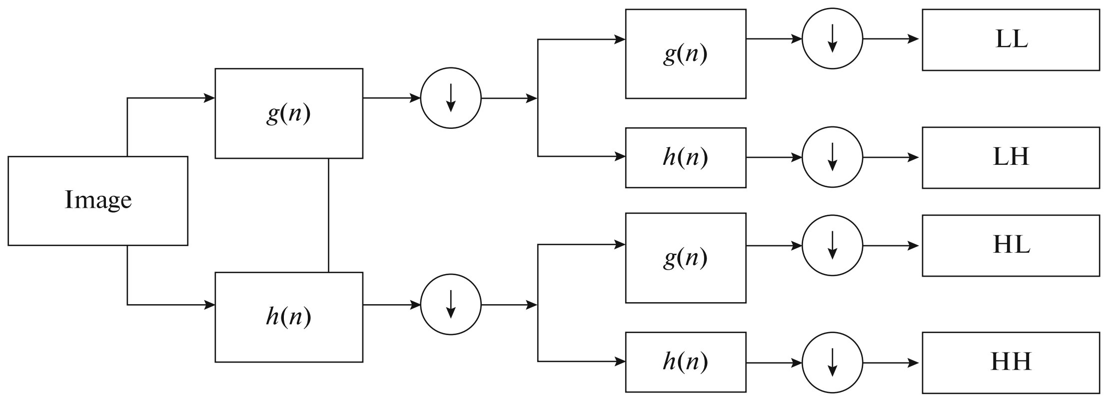

Fig. 4. DWT structure for obtaining features.

$$\text{Entropy} = -\sum p(i, j)[\log_2 p(i, j)], \tag{4}$$

$$\text{Correlation} = \sum (i - \mu i)(j - \mu j)\frac{p(i, j)}{[\sigma i \sigma j]}, \tag{5}$$

where each element in this constructed matrix is denoted by $p(i, j)$ and "σ" is the standard deviation.

DWT

The 2-dimensional Discrete Wavelet Transform (DWT) is applied on the preprocessed weld image, which decomposes the images into "Approximate", "Horizontal", "Vertical" and "Diagonal" sub bands, respectively. Among these four sub bands, the 'Approximate' sub band is low resolution or frequency sub band and others are belonging to high frequency sub bands. Figure 4 shows the DWT structure for obtaining features at scale 3 stage. The enhanced image is passed through the three stage of filters as the low pass filter $g(n)$ and high pass filter $h(n)$. These filters decomposed the image into low and high frequency sub bands. These frequency sub bands are further down sampled by down sampler with decimation factor 2 in order to reduce the frequency rate. The same procedure is applied for other two stages, which produces the final sub bands at the end of stage 3.

Statistical Features

In this paper, the following statistical features such as mean, variance, kurtosis and skewness are computed from the preprocessed weld image. The statistical features are explained in the equations (6)–(9).

$$\text{Mean} = \overline{x} = \frac{\sum_{i=1}^{N} x_i}{N}, \tag{6}$$

where N is the number of pixels in preprocessed image and x_i is the pixels in the preprocessed enhanced weld image.

$$\text{Variance} = \sigma^2 = \frac{\sum_{i=1}^{N} (x_i - \overline{x})^2}{N}, \tag{7}$$

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{(x_i - \overline{x})^3}{N}\right], \tag{8}$$

$$\text{Variance} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{(x_i - \overline{x})^4}{N}\right]. \tag{9}$$

Table 1. Resolution analysis of proposed method with conventional methods

Image sequences	Total number of cracked pixels	Methodologies		
		Proposed method	Roman Sizyakin et al. (2019)	
1	1000	980	863	816
2	990	979	868	737
3	995	986	827	793
4	999	985	875	718
5	1000	991	817	743
6	1012	979	891	719
7	1010	984	828	758
8	998	985	857	817
9	1028	968	868	847
10	1005	949	847	848

ANFIS Classification

Classification is used to classify the source weld image into either cracked image or non-cracked image (Krizhevsky et al. (2017) and Liao et al. (2019)). The conventional classification approach such as fuzzy system, SVM and Neural Networks (NN) have certain limitations as they requires large number of training samples for training phase of the classifier, which makes high computational time for defect detection and classification process. In order to overcome such limitations in conventional methods, ANFIS classifier with incorporated unsupervised fuzzy rules, is used in this paper.

Hence, ANFIS classifier is adopted for the weld image classifications. This classification module has two phases as learning and classification. In learning phase of the ANFIS classification, the features from cracked and non-cracked weld images are trained in order to produce the trained patterns. In classification phase of the ANFIS classifier, the features which are extracted from source test weld image are classified with respect to trained patterns. The classification phase of this classifier produces either low or high binary value. The low binary value corresponds to the non-cracked cervical image and high binary value corresponds to the cracked image.

Then, morphological operations (consist of erosion function followed by dilation function), are used to detect the cracked regions in the classified weld image. The threshold value is computed using the average mean function in the morphologically processed weld image. Then, the morphologically processed image is converted into threshold image using connected component analysis, where the nearby similar pixels are connected into same type of pixel. The final morphological processed image is the crack detected image.

Table 1 shows the resolution analysis of proposed method with conventional methods in terms of cracked pixels in welded regions with the conventional methods Roman Sizyakin et al. (2019) and Darcis et al. (2008), respectively.

4. RESULTS AND DISCUSSION

In this paper, the weld images are obtained from WDXI an open access dataset (Guo et al., 2018). The IR camera is placed over the welded materials and produces grey scale images. The image resolution is about 256 × 256 as width and height. This paper uses 55 number of "Excess weld" images, 34 number of 'Good weld' images, 78 number of "No weld" images and 75 number of "Undercut weld" images. The total number of weld images used in this paper is 242. The proposed method correctly classifies 54 over 55 Excess weld images, 33 over 34 "Good weld" images, 77 over 78 "No weld" images and 75 over 75 "Undercut weld" images. Hence, the classification accuracy of Excess weld case is about 98%, 97% for "Good weld" case, 98% for "No weld" case and 100% for "Undercut weld" case. Hence, the overall classification accuracy is about 98%, as illustrated in Table 2.

Table 3 shows the impact of extracted features on analysis of proposed crack detection method. The classification accuracy with respect to different features is clearly illustrated in Table 3. The proposed system with GLCM, DWT and statistical features achieves high classification accuracy when compared with other combination of extracted feature set.

Table 2. Classification accuracy of proposed method

Weld case	Number of images	Number of correctly classified weld images	Classification accuracy, %
Excess weld	55	54	98
Good weld	34	33	97
No weld	78	77	98
Undercut weld	75	75	100
	242	239	98

Table 3. Impact of features on analysis of proposed crack detection method

Evaluation parameters	Classification accuracy, %
GLCM features alone	67
DWT features alone	71
Statistical features	70
GLCM + DWT	84
GLCM + Statistical	87
DWT + Statistical	90
GLCM + DWT + Statistical	98

In this paper, the proposed crack detection methodology using ANFIS classification approach is applied on the weld image detaset and its performance is analyzed with respect to the following evaluation parameters as described in the mathematical equations (10)–(15).

$$\text{Sensitivity(Se)} = \frac{\text{Tr\_Po}}{\text{Tr\_Po} + \text{Fa\_Ne}}, \tag{10}$$

$$\text{Sensitivity(Sp)} = \frac{\text{Tr\_Ne}}{\text{Tr\_Ne} + \text{Fa\_Po}}, \tag{11}$$

$$\text{SegmentationAccuracy(SA)} = \frac{\text{Tr\_Po} + \text{Tr\_Ne}}{\text{Tr\_Po} + \text{Fa\_Ne} + \text{Tr\_Ne} + \text{Fa\_Po}}, \tag{12}$$

$$\text{Precision(Pr)} = \frac{\text{Tr\_Po}}{\text{Tr\_Po} + \text{Fa\_Po}}, \tag{13}$$

$$\text{FalsePositiveRate(FPR)} = \frac{\text{Fa\_Po}}{\text{Fa\_Po} + \text{Tr\_Ne}}, \tag{14}$$

$$\text{FalseNegativeRate(FNR)} = \frac{\text{Fa\_Ne}}{\text{Tr\_Po} + \text{Fa\_Ne}}, \tag{15}$$

where Tr_Po, Tr_Ne is the number of correctly identified cracked and Non-cracked pixels, Fa_Po, Fa_Ne is the number of non-correctly identified cracked and Non-cracked pixels, respectively.

Table 4 shows the simulation results of the proposed crack detection in weld images with respect to sensitivity, specificity and segmentation accuracy. The proposed ANFIS based crack detection methodology in weld images achieves 96% of sensitivity, 97% of specificity and 98% of segmentation accuracy.

Table 5 shows the performance analysis of proposed crack detection method with respect to sensitivity, specificity and segmentation accuracy.

The enhancement process improves the contrast of the cracked regions in welded images. Hence, the performance of the proposed crack detection system is analyzed with respect to enhancement technique. Table 6 shows the performance analysis of proposed crack detection method with and without enhancement technique. From Table 6, it is very clear that the proposed system with enhancement technique provides high performance metrics than the proposed method without enhancement technique.

Table 7 shows the performance comparisons of proposed crack detection method with respect to other conventional classification approaches as SVM and NN. The conventional SVM classification approach obtained 92% of sensitivity, 93% of specificity, 93% of accuracy, 92% of precision, 91% of false positive rate

Table 4. Simulation results of the proposed crack detection in weld images

Image sequences	Sensitivity (Se), %	Specificity (Sp), %	Segmentation accuracy (SA), %	Pr, %	FPR, %	FNR, %
1	96	97	98	98	96	97
2	95	97	98	97	97	98
3	97	96	98	98	98	98
4	97	96	98	98	98	96
5	98	98	97	97	96	97
6	96	97	97	97	97	97
7	97	98	98	98	97	98
8	96	97	98	98	98	96
9	96	96	98	98	98	95
10	97	97	98	97	98	98
Average	**96**	**97**	**98**	**98**	**97**	**97**

Table 5. Performance analysis of proposed crack detection method

Evaluation parameters	Experimental results, %
Sensitivity	96
Specificity	97
Accuracy	98
Precision	98
False Positive Rate	97
False Negative Rate	97

Table 6. Performance analysis of proposed crack detection method

	Experimental Results, %	
Evaluation parameters	with enhancement technique	without enhancement technique
Sensitivity	96	90
Specificity	97	91
Accuracy	98	91
Precision	98	92
False Positive Rate	97	93
False Negative Rate	97	91

Table 7. Performance comparisons of proposed crack detection method

Evaluation parameters	Experimental Results, %		
	ANFIS (in this paper) classifier	SVM classifier	NN classifier
Sensitivity	96	92	90
Specificity	97	93	91
Accuracy	98	93	91
Precision	98	92	87
False Positive Rate	97	91	85
False Negative Rate	97	90	87

Table 8. Comparisons of proposed crack detection methods with conventional methods

Methodology	Sensitivity (Se), %	Specificity (Sp), %	Segmentation accuracy (SA), %	Classification accuracy, %
Proposed work (in this paper)	**96**	**97**	**98**	**98**
Roman Sizyakin et al. (2019)	95	95	96	92
Darcis et al. (2008)	94	94	95	91

and 90% of false negative rate. The conventional NN classification approach obtained 90% of sensitivity, 91% of specificity, 91% of accuracy, 87% of precision, 85% of false positive rate and 87% of false negative rate.

Table 8 shows the comparisons of proposed crack detection methods with conventional methods Roman Sizyakin et al. (2019) and Darcis et al. (2008).

5. CONCLUSIONS

In this paper, the cracks in welded images are detected and classified using machine learning algorithm. This proposed work consists of crack image classification stage and crack region detection or segmentation stage. The proposed method consists of preprocessing stage, feature extraction stage, classification stage and crack region segmentation stage. The image enhancement method is used as preprocessing stage which enhances the low resolution regions in welded image into high resolution image using local histogram equalization technique and texture feature GLCM along with DWT features and statistical features are extracted from the enhanced weld images. These computed features are then classified into four different cases as "Excess weld", "Good weld", "No weld" and "Undercut weld", using ANFIS classification method.

The proposed method correctly classifies 54 over 55 Excess weld images, 33 over 34 "Good weld" images, 77 over 78 "No weld" images and 75 over 75 "Undercut weld" images. Hence, the classification accuracy of Excess weld case is about 98%, 97% for "Good weld" case, 98% for "No weld" case and 100% for "Undercut weld" case. Hence, the overall classification accuracy is about 98%. The feature extraction method also plays an important role in weld image classification. The proposed system with integrated all extracted features provides high classification rate. The proposed ANFIS based crack detection methodology in weld images achieves 96% of sensitivity, 97% of specificity and 98% of segmentation accuracy. The simulation results of the proposed system are well compared with other state of art methods to validate the effectiveness of the proposed system. In future, linear optimization algorithm will be applied on the extracted feature set in order to optimize the classification accuracy along with other performance evaluation parameters. Also, deep learning architecture based classification algorithm will be developed in future for the classification of weld images.

ABBREVIATIONS

ANFIS	adaptive neuro fuzzy inference system
SVM	support vector machine
GLCM	grey level co-occurrence matrix
CDF	cumulative distribution function
DWT	discrete wavelet transform
NN	neural networks
Se	sensitivity
Sp	specificity
SA	segmentation accuracy
Pr	precision
FPR	false positive rate
FNR	false negative rate

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