Introduction

Chapter 1

This chapter focusses on basic definition of Welding and Non – Destructive Testing. It also gives a detailed report about the types of faults and the need for Non – Destructive Testing. It also give outline about the thesis work being carried out in the present report

1.1 GENERAL

Welding is the experienced way of joining metals together. It is an efficient and economy the process. It is an assembling process where materials are joined. It is achieved by adding some extra molten joining material on melting part of the materials to be joined. It forms strong bond when the molten material is cooled. It plays a major role in industries for the purpose of construction, joining and repairing of steel beams, reinforcing rods in buildings, bridges, spacecraft, pipe lines, nuclear containers etc. During the process of welding a number of different types of discontinuities can be produced, which may arise due to material inconsistencies of the material, error produced by the operator, or other factors that are beyond the operators control. Irrespective of the source of error, detection of discontinuities is critical. An unacceptable weld extremely reduces the bond between two materials and may cause failure. With the emphasis on using X-ray imaging modality for investigating structure-function relationships, many new challenges have come up, and to meet the same, the development of X-ray (radio graphical) imaging has to accelerate even faster. This would be further driven by the rapid advancement of digital computer technology, new methods of extracting in vivo functional and dimensional information, and the relentless efforts in establishing localized flaws and progression of defects in the weldment.

The manual interpretation of radiographic NDE weld images depends upon the level of expertise of the specialist and is usually a time consuming process as well as subjective. To remove the subjectivity in evaluation and expedite the inspection process, there is always a need for automation. Image processing plays a vital role to interpret these images with an aim to spot the flaws in weldments. A semi-automated system can be developed by employing the image processing techniques that would provide a consistent system when compared to the classical methods. It would also be helpful in taking decision with the help of a set of manipulating tools. The present work has been an effort in the direction of automating the inspection process [1-7].

1.2 DEFECTS IN WELDMENTS

Instead of smooth joint, sometimes, due to various reasons, during the process of welding, weldments are not joined properly. It results in producing different types of flaws in weldments. These flaws can be observed in the form of gaps, cracks and thin lines. Lack of fusion, lack of penetration or excess penetration, gas cavities, slag inclusion, cracks, undercuts, lamellar tearing, shrinking cavities are some of the defects in weld that are usually present in weldments [8].

Lack of fusion arises due to too little heat input and/ or too rapid traverse of the welding torch (gas or electric). Lack of penetration or excess penetration is the result of too high a heat input and/ or too slow speed of the welding torch (gas or electric). When gases are trapped in the solidifying weld metal, gas cavities can be observed. Porosity is the result of trapping of solidification gases in the welded zone. Different types of slag inclusion exists in welding. This defect can be of any shape and direction – slag lines (elongated cavities contain slag or other foreign matter), weaving faults, (faults from bad chipping, faults at electrode change, and faults at junction of seams). Sulphur and phosphorus are the major elements that cause cracks in weldments. It usually occurs in higher carbon steels. Longitudinal s and transverse cracks are the two types of cracks which exists. The cracks that usually appear in straight lines along the centerline of the weld bead is known as longitudinal crack, while the cracks that are straight lines perpendicular to centerline are transverse cracks. It appears occasionally. Due to the reduced thickness of one (or both) of the sheets at the toe of weld, arising because of imprecise settings/procedure, undercuts are observed. The lamellar tearing is a problematic defect that is shown in low quality steels. It occurs in plates which are having low ductility. The thermal shrinkage or a combination of steam accompanying phase change, shrinkage cavities exists. [9]. Fig 1.1 and Table 1.1 illustrates different types of the weld defects and types of weld flaws in cross-section (British Standard 1998) [10].

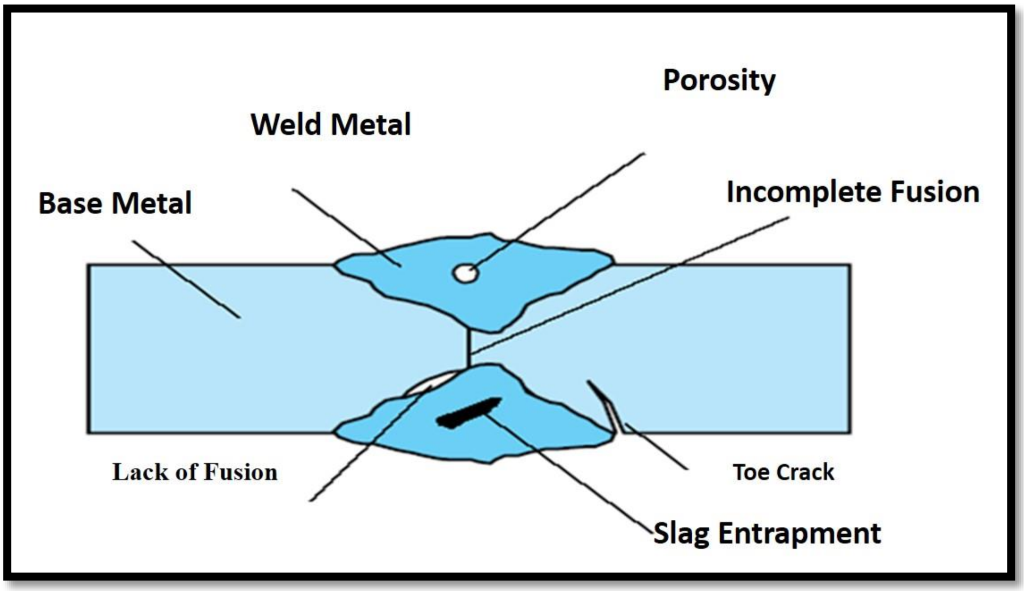


Fig. 1.1: Different Types of the Weld Defects

1.3 DETECTING FLAWS USING NDT

It is essential to inspect the manufactured components to detect the presence of any defects or degradation during production, post production or in-service. Non-destructive testing or evaluation (NDT or NDE) is done for safety, risk management and critical path management. It is usually achieved during the various phases of postproduction and in service. NDT examination has the advantages of improved speed during inspection and dependability, sensitivity to flaws of any orientation, suited to high operating temperatures. In the last two decades, NDT sciences have witnessed a revolutionary progress in radio graphical imaging and computerized ultrasonic image processing.

As per the definition, non - destructive tests should be non - damaging and non –invasive. Several methods and techniques have been established to substantial levels of complexity. They all require operation of equipment and interpretation of results by skilled, well-trained personnel.

It allows examination without interfering with the use of final product. Also, an outstanding balance between quality control and cost-effectiveness is established. The term "NDI" includes many methods that can be summarized as follows:-

1. Notice internal or external inadequacies
2. Structure, composition, or material properties can be determined
3. The Degree of geometric characteristics can be evaluated

4. Amount of the development of flaw can be measured
5. Severity of the flaws can be depicted

It can and should be used in any stage of design of the product's and manufacturing process that comprises of selection of materials, research and development, assembly, quality control and maintenance. All kind of difficulties and flaws can be observed in the development and use of mechanical devices, electrical equipment, hydraulic systems, transportation mechanisms etc. Several NDT methods are present to assist the engineer to inspect these different problems and various defects in an assortment of materials under varying circumstances [11 - 12].

Liquid penetrant (fluorescent inspection), magnetic particle inspection, eddy current testing, radiographic inspection and ultrasonic inspection are the various non-destructive inspection methods that exists.

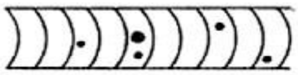
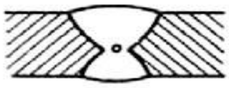
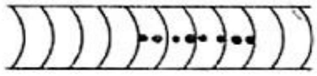
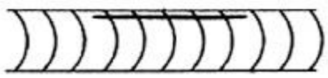
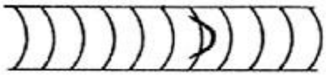
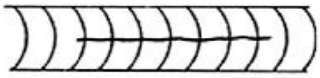
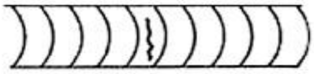
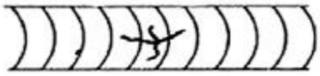
A brief discussion of these methods is presented below:

Expansions in digital image processing have broadly extended the application and utility of NDI methods in the industry [13].

- ***Penetrant Testing (PT)*** is also known as Dye Penetrant Inspection (DPI), Liquid Penetrant Inspection (LPI) or Fluorescent Penetrant Inspection (FPI). Surface breaking flaws can be disclosed by bleeding out a colored or fluorescent dye from the flaw in this method. The capability of a liquid to be drawn in to a ‘clean’ surface breaking flaw by capillary action is the adopted technique for this testing. After a period of penetration time, excessive surface infiltration is detached and a developer is applied. It results in the penetrant from the flaw to reveal its presence.

- ***Eddy Current Testing (ET)*** or ***Electromagnetic Technique*** can only be used on conductive materials. Crack detection to the rapid sorting of small components for flaws, size variations, or material variation can be evaluated by this method. Aerospace, automotive, marine and manufacturing industries are the various areas where its use can be found. Eddy currents are induced in to the specimen by an energized coil which is brought near the surface of a metal component that tends to oppose the original magnetic field by the currents setup magnetic field. The impedance of coil in close nearness to the specimen is affected by the presence of the induced eddy currents in the specimen. When the eddy currents in the specimen are distorted by the existence of the defects or due to variations in the materials, impedance the coil is changed. This change is measured and displayed in such a way that specifies the type of flaws or material condition.

Table 1.1 Real Images of Radiographs (Types of Weld Flaws in Cross-Section) British Standard 1998, [10].

Description	Cross-section of weld	Radiogram
Worm hole		
Linear Slag Inclusion -|		
Gas Pore		
Porosity (Linear)		
Lack of side-wall fusion - (lack of root fusion)		
Lack of inter-run fusion		
Longitudinal Crack		
Traverse Crack		
Radiating Cracks		

- ***Magnetic testing*** *also known as* ***MPI (Magnetic Particle Inspection):*** It is a method which is used to find surface and near surface flaws in steel and iron that belongs to ferromagnetic materials. The flaw is detected on the principal where magnetic lines of flux is distorted due to the existence of a flaw in such a way that reveals its presence. The ‘flux leakage’ is used to detect the flaw. It follows the application of fine iron particles for the area under examination. Magnetic particles inspection is mainly used to find surface breaking flaws. It can also be used to locate sub-surface flaws, but its quality reduces with the rise in depth of flaw.

- ***Ultrasonic testing*** **(UT):** helps in mapping the defects and characterizing the three dimensional co-ordinates of the defects this is essential to carry out analysis of defect dimensions and hence take decision for reject/rework/acceptance. UT is very reliable methodology to establish repeatability and reliability of defects being descaled.

- ***Radiography testing*** **(RT):** is the commonly used NDT method that notices the internal welding flaws. X-rays are made to pass through metal and other materials that are opaque to ordinary light, and thereby produce photographic records by the transmitted radiant energy [227]. Since, dissimilar materials absorb X-ray to different extent, penetrated rays indicate variations in intensity showing internal structure of a weld. It is based on recording the varying degree of absorption of the penetrating radiation by object on the conventional film radiography. This varying degree of absorption produces a latent image of the object that is inspected on a film that provides the internal details of the object (weldment, in this case). Amount of absorption depends on the thickness of material, the density of material and the atomic number of the absorber. Detectors such as radiography film or a fluorescent screen are used to record the variation in intensity of the emerging beam as visual images or signals.

Industrial Radiography is primarily concerned with recording images on film. Radiography consists of using the penetrations and differential absorption characteristics of radiation energy to examine materials for internet discontinuities. X-rays are produced by high voltage x-ray machines, whereas gamma rays are produced from radioactive isotopes such as Iridium 192 and Cobalt 60. The x-rays or gamma rays are located near to the material to be inspected and are made to pass through the material and are then taken on film. This film is then chemically processed and the image is obtained as a series of gray shades between black and white. This permanent shadow image of the internal and external condition of the object is called the radiograph.

1.4 OUTLINE AND CONTRIBUTIONS OF THESIS

Present chapter gives an introduction of Welding, defects in weldments and need of Non – Destructive Testing for identifying the flaws. Chapter 2 presents an extensive literature reviewed throughout this research work. During this the focus was on need of signal processing tools and artificial neural network for classification of weldments faults. Chapter 3 gives the detailed literature of signal processing tools used for feature extraction such as Wavelet Transform, the neural network employed for carrying out classification. Chapter 4 focuses on the algorithm developed by extracting the features of Wavelet Transform and classifying the weld images by Artificial Neural Network. Chapter 5 shows the intricacies to of the result obtained. Finally, in chapter 6 conclusions from this research work are derived and further directions for future work are also suggested.

Literature Survey

Chapter 2

This chapter discusses about the work carried out for Welding and Non – Destructive Testing. It also gives a detailed report about the author was motivated to carry out the present research work. It also give outline about the research gap and research objective carried out in the present report

2.1 GENERAL

As discussed in chapter1, Welding is the most versatile way of permanently joining two metal plates. It plays a major role in industries for many purposes. Welding, in its various process and methods, can produce different types of flaws, which can result, from material inconsistencies, operator error or from uncontrollable factors. These flaws are seen in the form of gaps, cracks or bubbles. Common weld defects include lack of fusion, lack of penetration, excess penetration, gas cavities, slag inclusion, cracks, undercut, lamellar tearing, shrinking cavity, porosity etc. To identify these flaws, nondestructive inspection or testing (NDI or NDT) is used. The NDI is the examination of an object or material with technology that retains its future usefulness without destroying or damaging the product. There are many NDT techniques but X-ray inspection is used most often. Ultrasonic Testing (UT) is also used for imaging of flaws in welding. The analysis of UT images may also be helpful in categorization of the weld defects.

The manual interpretation of ultrasonic and radiographic images depends upon the level of expertise of the specialist and is usually a time consuming process as well as subjective. To remove the subjectivity in evaluation and expedite the inspection process, there is always a need for automation. Most of the NDT techniques have been made automated these days but the interpretation of signals or images still is not fully standardized. Image processing plays an important role to interpret these images with an aim of detecting flaws in weldments. With the help of image processing, a semi-automated system can be developed which would be more reliable as compared to the classical methods and also helpful in taking decision with the help of a set of manipulating tools. The present proposed research plan is an effort in the direction of automating the inspection process.

Feature extraction is the operation to extract different image features (geometrical, textures and relational) for classification or interpretation of meaningful object from the images and is considered as one of the most important aspect. It can be defined as function of one or more measurements, each of which specify the quantifiable property of an object and are computed such that it quantifies some significant characteristics of objects.

The proposed research work consists of three major steps: image pre-processing, feature extraction, defect detection and classification. Digital image processing techniques are employed to lessen the noise effects and also to improve the contrast, so that the principal objects in the image can be more apparent than the background. Feature extraction is used to reduce the dimensionality of the matrix while keeping the basic nature intact and finally extracted features are used to classify the weld flaws accurately by use of artificial neural network (ANN).

2.2 MOTIVATION

A framework of classification is used to solve a multiclass problem. Information extraction from radiographic images is used for providing knowledge about it. It will generate features as classes from radiographic image, like length, breadth, dimension and so on. Information extraction results can be optimized well enough using multiple databases. The integration of spectral, spatial and structure parameters plays a very important role in extraction.

To get state of the art technological developments in the field, a chronological overview of radiographic weld inspection, segmentation and classification methods for information extraction is presented below:

The application of image processing in the field of radiographic images has started from 1990 and still it’s a challenging work for computer vision applications.

At the beginning, Gayer A. et al. [14] developed a two-step method for the automatic inspection of welding defects from real-time radiography. Here, first step is a fast search, which locates defective regions, and in the second step, defects are located with more details. This has been achieved by a sequential similarity detection algorithm or a thresholding algorithm. Murakami K. [15] offered a simple algorithm which can automatically detect internal defects and classify them accordingly. The author classified defect types with an expert system. Features used for classification include the shape, position and intensity level of the defect pattern. However, result obtained from this method strongly depends on the types of defects. The system detects wormholes easily, but detecting cracks is difficult. On the same time, machine vision has been first applied for automatic inspection by Ker J. et al. [16]. Nockeman C. et al. [17] studied reliability of radiographic weld inspection using relative operating characteristic and show that it successfully differentiate between the inspection performance of various equipment or physical detection methods. Kato Y. et al. [18] proposed computer-aided radiographic inspection expert system for identifying different types of welding defects. The identification rules were based on the interviews with expert inspectors. The knowledge used for defect identification is of two types: knowledge obtained directly from a film (in terms of ten features) and knowledge obtained from something other than radiographic films.

Wu Z. et al. [19] have exploited histogram shape, object attribute or clustering behavior, histogram entropy information, spatial context information and local adaptation for such purpose and developed a system using wavelet theory to detect multi scale edges. An interpretation system for automated visual inspection for quality evaluation of weldment was developed with the help of pixel intensity scan by Cook G. E. et al. [20].

Hyatt R. et al. [21] presented a multistage method for segmenting flaw regions from the background radiographic images. The method was designed to remove the overall background structure while preserving the defect details. The filtered images were then examined using a double-threshold method for defects signature segregation. On the same year, Liao and Ni [22] proposed a methodology for the extraction of welds from digitized radiographic images. The method was based on the observation that the intensities of pixels in the weld area distribute more as a Gaussian distribution than other areas in the image. This method has been proved to be effective only for segment linear welds. Later, in 1997, Liao and Tang [23] applied a multilayer perceptron (MLP) neural network based procedure for the detection of weld. This method was successfully applied to segment both linear and curved welds. Another welding flaw detection method was presented by Liao and Li [24]. This method was based on the observation that welding flaws usually result in distortions in the overall line profile of a weld. The whole process consist of four parts: preprocessing, curve fitting, profile-anomaly detection and post processing. Test results in this case indicate that their method has high successful detection rate and had an acceptable false alarm rate. Liao et al. [25] proposed another approach using fuzzy clustering methods. Twenty-five features were selected for each line of the radiographic image. The results showed that fuzzy *K*-NN outperformed fuzzy *c*-means.

Liao and Li [26] employed fuzzy classifiers, specifically fuzzy K-NN and fuzzy c-means, instead of neural networks as the pattern classifier. This method can also be applied to segment curved welds, and can handle varying number of welds in one radiographic image at the same time. On the same year Laggoune H. et al. [27] developed a system of image processing for the geometry characterization of fusion zone based on edge detection using wavelet transform for multistate edge detection which is based on an algorithm using generalized Canny having good signal to noise ratio.

Chan C. et al. [28] discovered in their study that human visual inspection can only catch around 60-75% of the signification defects. They have concluded that human inspection of gas pipe line is hard and difficult task when a great number of welds are to be counted and inspected. Therefore, in order to lower the cost of inspection process and to improve the inspection quality, it is necessary to automate the inspection process. Elewa I. M. et al. and Wang G. et al. [29 -30] assessed the welding defects in radiographs of gas pipeline using computer vision and developed an algorithm to identify different types of welding defects in radiographic images.

Mery D. et al. [31] used texture feature for automatic detection of welding defects. They segmented potential defects edges using Laplacian of Gaussian edge operator. The features of potential defects are extracted next. The features vectors provided by edge detection algorithm, in this case, were based on two features of texture i.e. occurrence matrix and 2D Gabor function.

Siqueira M. H. S. et al. [32] used radiographic test to estimate the accuracy of classification of the main types of weld defect such as, undercut, lack of penetration, porosity, slag inclusion, crack or lack of fusion. To carry out these work non-linear pattern classifiers were developed using neural networks. The results pointed to an estimated accuracy of around 80% for the classes of defects analyzed. Few filtering aspects were also used to improve the quality of radiographic image quality. Wang Xin et al. [33] compare adaptive wavelet thresholding with median filter and found that adaptive wavelet thresholding can enhance perception of defects better. Silva R. R. et al. used geometrical features for defect classification with nonlinear classifier and prove that the quality of the features is more important than the quantity [34].

Alaknanda, et al developed a flaw detection algorithm in radiographic weld images using morphological approach on the basis of pixel characteristics [35]. Valavanis I. et al. [36] proposed a method for weld defect detection and classification in radiography images. This method is based on texture measurements and the geometrical features as inputs to the SVM, ANN and k-NN classifier and found that the accuracy very much depends on number of feature extracted for classification. As reported, the accuracy is very low in the case of cracks, lack of fusion and non-defects. Here only six types of flaws were introduced. Nanditha N. M. et al. [37] proposed a comparative study on the suitability of feature extraction techniques for tungsten inclusion and hotspot detection from weld thermographs. Anouncia S. M. et al. [38] presented a knowledge based model for image interpretation but accuracy of classification is still unstable. Jebarani Sargunar P. N. J. et al. [39] developed Gaussian mixture model (GMM) classifier to classify the defects in input image. Vilar R. et al. [40] described an automatic system of classification of weld defects using adaptive-network-based fuzzy inference system.

Zapata J. et al. [41] described an automatic system to detect, recognize and classify welding defects in radiographic images and evaluate the performance for two neuro-classifiers based on an artificial neural network (ANN) and an adaptive-network-based fuzzy inference system (ANFIS). The accuracy was 78.9% for the ANN and 82.6% for the ANFIS. This methodology was tested on 86 radiograph images containing 375 defects having five types of flaws.

In the above context, the present work has contribute towards the application of image processing techniques for extracting information in radiographic images. To date, there are several works in progress for detection, feature extraction and classification of all the possible information. The proposed work aims to improve the process of automated information extraction system.

2.3 RESEARCH GAP

Based on the above survey, following research gaps have been identified.

1. Radiographic weld images are low contrast, dark and high noise images. It becomes difficult to detect the defects properly with the noise in images. So enhancement is a significant part of automated defects detection in weld images. As presented in state of art, the classical filters such as mean and median filters are mostly used to remove the noise in weld images. It removes the impulse noise effectively. However, it is less efficient to preserve the sharp transition of the defects and degrades the resolution. It is not effective to remove other types of noises also. A very less work have been reported on application of transform based thresholding approach for noise suppression in weld images but it may prove to be an efficient approach for removing the noise as much as possible while retaining more edges because of its inherent features.

2. Image features play key role in classification of weld flaws. Geometrical features are widely used for classification of weld flaws whereas texture feature are not much explored till now. There is a scope to extract features using 2nd order statistical texture features using gray level co-occurrence matrix (GLCM). Some of the important features which are extracted from GLCM are entropy, homogeneity, energy, contrast, correlation, variance, sum average, sum entropy, difference entropy.

3. There are less works reported in literature, concentrated on weld flaws classification using ANN, SVM and ANFIS. In recent published paper, the accuracy was 78.9% for ANN and 82.6% for ANFIS while only five types of defect were considered. The accuracy of weld flaws classification gets affected, especially between cracks and lack of fusion [28]. Apart from this limitation, all different nine flaws have not been considered for classification by using different classifier, as mentioned above. So, there is a scope to classify considering all possible flaws in available data set.

2.4 RESEARCH OBJECTIVE:

On the basis of research gaps, the following objectives are specified:

1. Authenticated Image database needs to be created with different types of flaws.
2. The Image is subjected to digital signal processing tool and feature is thus extracted.
3. This extracted feature will be used for input to the artificial intelligent based classifiers (ANN) to classify the weld flaws with an intention to improve the effectiveness and efficiency of the system.

Thermal Properties of Weld Images

Chapter 3

This chapter focusses on Thermal aspects of Weld Images

Welding is a thermal process in which heat and pressure are employed to join two metal pieces either of same material or of different material together. The heat (Q) used for the welding is provided by a number of methods like using electric current (I), electric voltage (V), gas or using laser beam. The heat is used for raising the temperature (T) of the material to be welded or that of the filler material. Pressure (P) is used in welding when materials are not heated up to their melting point and kept at a temperature slightly below that. In such types of material especially the ductile materials which cannot tolerate that high temperature pressure is used for joining the materials. It's a joining process which is function of temperature and pressure which can be further expressed in terms of electric current, electric voltage, electrode gap, gas composition, chemical composition (as in case of thermit welding , where mixture of aluminum powder and iron oxide is used for heat production). Any slight deviation from one of these parameters causes discrepancies to arise which are presented in the form of weld defects like porosity, slag, inclusion, lack of penetration, worm hole etc. , which here have been detected using radiographic image.

3.1 GAS CAVITY:

Gas cavities are present in the form of spherical bubbles which are spherical or of random shapes and are generally present parallel to the longitudinal axis of the weld. The gas cavities occur in the temperature range of 510^0C -610^0C. When the temperature in the molten metal reaches a value higher than the requisite value gases are evolved (due to impurities in the metal) and get trapped in the molten pool. These trapped gases causes defect to arise in joint.

3.2 LACK OF PENETRATION:

The presence of this welding defect occurs when the speed of moving of the welding torch is low or a large piece is welded in a single stroke. This defect is also caused due to use of low electrical voltage (V) for welding. As the voltage will be low, heat (Q) required for the smooth and perfect weld will also be low. Due to low heat production, temperature (T) of the weld piece will also not rise to the requisite range and defect will appear in the form of beads. The temperature is about 1927^0C.

3.3 POROSITY:

The presence of gases in the molten weld pool like nitrogen, hydrogen, or oxygen causes defect which is called porosity. The presence of these gases is caused due to a number of thermal effect like presence of moisture on the weld surface. It is also caused due to varying current. When the current (I) is varied, the heat (Q) is also varied which causes the variation in temperature (T) on the weld surface.

As,

$$Q = I^2 * R * t, \tag{3.1}$$

Where, R = Resistance

T= Time in seconds

The presence of moisture also causes the drop in temperature, and this derivative of temperature causes the gases to entrap in the molten metal at different temperature ranges.

Another cause of this defect is excessively high gas flow rate ($m^{\cdot}$) and turbulence in the weld pool which leaves some gap in the molten weld. As the temperature drops in the molten weld by giving away its heat to the surrounding and the temperature gradient between the molten weld and the surrounding metal, the gases remain trapped in the weld pool .These gases escape from the surface as the temperature further drops down leaving voids which results in porosity.

3.4 SLAG:

Slag is differentiated in the form of long elongated lines which can appear as continuous or discontinuous lines along the length of the weld and are easy to be identifiable radiographic image.

3.5 CRACK:

This is a defect which arises due to localize heating (Q). In such a case the heating cause the temperature to arise at that part whereas the temperature at its neighborhood is still low. This gives rise to stresses which results in cracks on the weld. These defects can be further classified as hot or cold. The hot cracks occur at higher temperature and form when the temperature of the molten weld starts coming down i.e during solidification of weld material. Cold cracks develop after solidification and are caused due to stresses.

3.6 LACK OF FUSION:

This defect arises when the weld does not fuse well with the parent metal. The temperature at which this error arises is 1000^0F.

3.7 WORM HOLE DEFECTS:

This defect gives indication of large amount of gases trapped in the solidified weld part. This defect arises to a large temperature gradient. During welding, because of the higher temperature gases evolve from the impurities present in the metal. The temperature gradient causes the gases to evolve from the metal leaving behind the hole.

3.8 UNDER CUT DEFECTS:

Under cut is a welding defect which is identified by unfilled groove s along the edge of the weld. One of the main reasons for defect is presence of excessive current (I) and higher travel speed. This type of defect is detected at a temperature range of greater than 1000 Fahrenheit (538^0C). Another reason which can be contributed to the presence of this defect is the use of high level voltage (V), which gives rise to higher heat generation (Q) and thus higher temperature.

$$V= IR \tag{3.2}$$

$$Q= I^2 * R* t \tag{3.3}$$

Where, R= electrical resistance

t = Time in seconds

The temperature range of various is shown in figure 3.1 consists of welding defects.

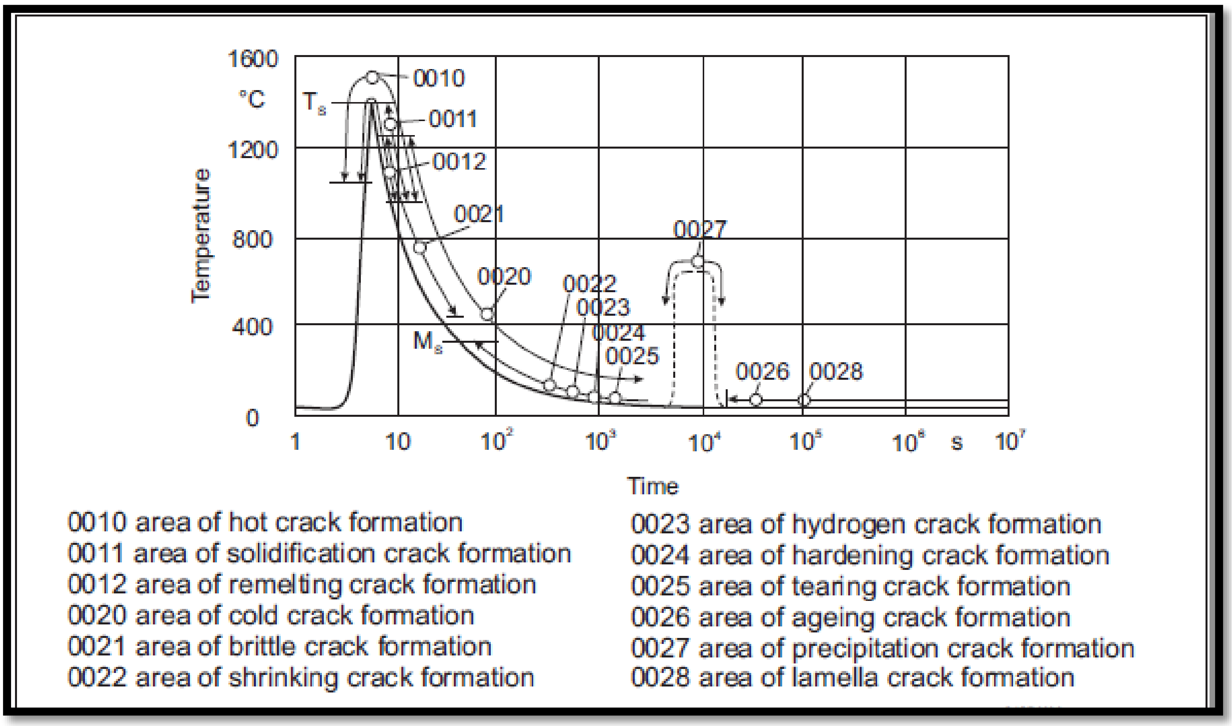


Fig 3.1: Temperature Distribution of Welding Defects

Modern Tools and Techniques for Feature Extraction and Classification

Chapter 4

This chapter discusses about the modern tools and techniques for feature extraction and classification. It also gives a detailed report about the author was motivated to carry out the present research work. It also give outline about the research gap and research objective carried out in the present report

Feature extraction is the basic need for development of protection algorithms using digital signal processing tools. It transforms data of high dimension to a lower dimension. But at the same time, the embedded information content is kept intact. Also the dimensionality of data is reduced. Further, the complexity for the purpose classification or regression is decreased. This chapter presents a brief concept of the tools used for feature extraction. It covers a brief overview of the signal processing tools involved in the development of algorithm i.e. Wavelet Transform. Also, it presents a brief overview of Artificial Neural Network meant for the classification.

4. 1. NEED FOR WAVELET TRANSFORM

The periodicity of the time functions is present in Fourier series transform [42] - [43]. The sinusoidal and cosine wave functions present in Fourier can be found in frequency as well as in time period. If the information about frequency present in a signal is evaluated using Fourier transform, the mean of the signal over the complete duration of time is obtained. It means that suppose, if a local transient is observed in a signal over a particular time period in the particular time frame of signal, then the Fourier transformation will be contributed by this signal. But it will lose its location on the time axis. Thus, one can conclude that the Fourier analysis does not take into account the frequencies that change with time. It is worth mentioning that in order to get detail on transient signal, a windowed-Fourier transformation approach should be used in such a manner that different sequences of windows of different widths are applied. Hence, a wide window fetches a proper frequency resolution but fails to give a proper resolution in time. Whereas, proper resolution of time is achieved with poor frequency resolution can be fetched by a narrow window.

Wavelet Transform conquers over the drawbacks of the Fourier methods since it is able to examine functions both present in time as well as frequency domain. It is highly appropriable to analyze non – periodic wideband signals. Sinusoidal and impulse components can be present in a transient signal. By use of the wavelet transform, small duration of high-frequency component of signal and large-time duration for low frequency components in the presence of fundamental and low-order harmonics can be analyzed. Hence, one can say that Wavelets have an adapting window in order to provide appropriate resolution.

4.2 WAVELET TRANSFORM

The waveforms which consists of electromagnetic transients' are found to be non-periodic. It contains oscillations of high-frequency and have impulses of very short-duration. Further, These signals superimposed on signals of low power frequency. Due to this Fourier transform fails to analyze the given signal. A very high sampling rate is required by the signal as periodicity is assumed for the signal. It means if the signal is of large duration, good resolution can be maintained in the range of small - frequency. Short - Term Fourier analysis found its way to overcome this difficulty but overall, Wavelet Transform finds edge over Fourier and Short Time Fourier Transform.

4. 2. 1 Continuous Wavelet Transform

The mother wavelet is a prototype function employed by the analysis of Wavelet. It has mean zero and decays suddenly in an oscillations. It suddenly gets down to zero on both side of its middle path. Mathematically, the Continuous Wavelet Transform (CWT) of a given signal s (t) with respect to a mother wavelet g (t) is defined as:

$$\text{CWT (c, d)} = \frac{1}{\sqrt{c}}\int_{-\infty}^{\infty} s(t)\,p\left(\frac{t-d}{c}\right)dt \,. \qquad (4.1)$$

Where (c,d) denotes the dilation or scale factor and *(d)* is known as the translation factor. It should be noticed that these variables are continuous in nature. It can be seen from equation

(3.1) that the original one-dimensional signal in time-domain *s (t)* is plotted to a new two-dimensional functional space across scale (c) and translation (d) by the use of wavelet transform (WT).

Coefficient of continuous wavelet transform (a,b) at particular scale and translation yields material about how the original signal s(t) are scaled and in that particular manner. It also provides information about its matching with the translated mother wavelet. Further, it can be concluded that the set of wavelet coefficients of Continuous Wavelet Transform of a particular signal are the wavelet representation of the original signal *s(t)* with respect to the mother wavelet *p(t).* The mother wavelet can be seen as a windowing function. It should be kept in mind that the scale factor (c) and the size of windowing function are interdependent. It means that smaller window represents a smaller scale. The features of a particular signal can be captured by either small-band frequency components present in the signal with a less scale factor. Also, wideband frequency components with a huge scale factor can too give information about the signal.

For the purpose of multi-resolution, WT includes an infinite set of wavelets. For instance, by changing the scale and translation factors one can generate different types of wavelets can be obtained. These are called as daughter wavelets and can be obtained from one mother wavelet. A daughter wavelet can be distinguished from the family of other wavelets on the basis of coefficients obtained and the number of iterations used. Several kinds of mother wavelets can be used for analyzing the signal. The characteristics of the mother wavelet need to be considered for selecting the appropriate mother wavelets which can be used for the analysis. Haar, Symmlet, Daubechies, Morlet are the examples of mother wavelet Haar and Morlet are orthogonal in nature. Symmlet and Daubechies are non-orthogonal. It has been found that Daubechies Wavelet is preferred for detecting low amplitude signals. It is also helpful in small duration, rapid decaying and fluctuating type of signals can also be detected by Daubechies Wavelet.

4. 2. 2 Discrete Wavelet Transform

Similar to Continuous Fourier Transform and Discrete Fourier Transform, the Discrete Wavelet Transform is the complement of Continuous Wavelet Transform. It is defined by the following equation:

$$\text{DWT}(l, q) = \frac{1}{\sqrt{c_0^l}} \sum_r g\left(\frac{v - rd_0 c_0^l}{c_0^l}\right) \tag{4.2}$$

Here, p (.) is the mother wavelet and the scaling and translation parameters (c) and (d) shown in equation (3. 2) are functions of an integer parameter m, i.e. c = c_0^l and d = $rd_0 c_0^l$ which results into daughter wavelets. q is an integer variable that refers to a specific sample number present in an input signal. The scaling parameter gives rise to geometric scaling, i.e. $1, \frac{1}{c_0}, \frac{1}{c_0^2}, \ldots\ldots\ldots$ The logarithmic frequency coverage of the discrete wavelet transform is given by the above scaling.

Rectangular time-bandwidths are observed to be small at larger frequencies are the product of Discrete Wavelet Transform. The bandwidth increases with the decrease in the frequency. It successful isolates exactly the highest frequency band. It takes less than the quarter cycle to distinguish the signal at the occurrence. It shows the multi-resolution qualities of the wavelet transform in the signal. Further, it analyzes a non-stationary transient signal that consists of high and low frequency component.

4. 2. 3 2 – D Discrete Wavelet Transform

The 1-D DWT decays a signal $f(t) = L^2(\mathbb{R})$ in terms of shifted and dilated mother wavelet $\psi(t)$ and scaling function $\varphi(t)$.

$$f(t) = \sum_{l \in Z} s_{j_o,l} \varphi_{j_o,l}(t) + \sum_{j \geq j_0} \sum_{l \in Z} w_{j,l} \psi_{j,l}(t) \tag{4.3}$$

where,

$$\varphi_{j_0,l}(t) = 2^{\frac{j_0}{2}} \varphi(2^{j_0} t - l) \tag{4.4}$$

$$\psi_{j,l}(t) = 2^{\frac{j}{2}} \psi(2^j t - l) \tag{4.5}$$

If $\left\{\varphi_{j_0,l}, \psi_{j,l} \quad j \geq j_0, l \in Z\right\}$ forms an orthonormal basis of $L^2(\mathbb{R})$, then the scaling coefficients $s_{j_o,l}$ and wavelet coefficient $w_{j,l}$ can be evaluated using the standard L^2 inner product: $s_{j_o,l} = < f, \varphi_{j_0,l} >$ and $w_{j,i} = < f, \psi_{j,i} >$.

A separable 2-D discrete wavelet transform is evaluated competently in discrete space by the application of the 1-D filter bank related with it to each column of the image and then the filter bank is applied to each row of the resultant coefficients thus obtained.

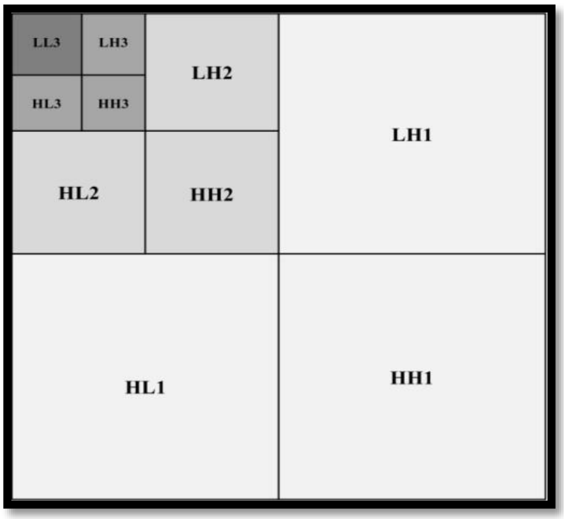


Fig. 4.1: 2-D DWT decomposition

Fig. 3.1 shows a three level pyramidal wavelet decomposition of an image $I = f(x, y)$. Three-stage decomposition will give rise to three low pass sub images and nine (three each in horizontal (0º), vertical (90º), and diagonal (±45º) direction) high pass directional sub images. The low pass sub images are low resolution versions of the original image at different scales. The horizontal, vertical and diagonal sub images gives necessary the data about the change in the brightness corresponding to the directions respectively.

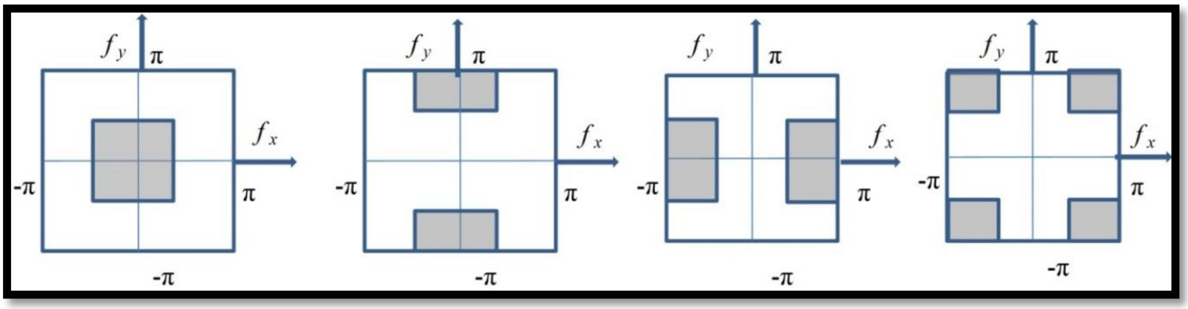


Fig. 4.2: The Frequency Domain Partition Resulting from the One Level DWT Decomposition

Fig. 2.2 illustrates the frequency domain partition resulting from the one level DWT decomposition.

4.3 ARTIFICIAL NEURAL NETWORK (ANN)

A neural network [43] is described as the set of organized elements better known as neurons. Every connection has weight linked with it. The neurons are usually organized in a series of layers. It can give the desired output based on the adjustment of weights and trial and error method. It basically contains of three or more layers [44]. The primary layer is the input layer which feds data into the network. The intermediate layer also knows as the hidden layer has weights associated with it. The neurons present in the hidden layer gather the weighted inputs and calculate the outputs by the given transfer function hidden layer is fed to the subsequent layer until the desired output is achieved. No rule defines the selection of hidden layer. It is basically selected on hit and trial method. Artificial Neural Network (ANN) is a powerful tool [45] which can effectively solve the existing protection problems such as identifying classifying and locating faults. Based on the training with the simulation/field data, the fault and no fault conditions can be differentiated.

Data can be classified in neural network. The technique of classification involves two main steps the first one is learning and other one is recall. In the procedure of learning, the network weights are adjusted in such a manner that the data become accustomed to the patterns obtained on the training data. Similarly, in the process of the recall, this trained network gives the responses of the test data. Several training algorithms can be used for feed-forward networks. The gradient of the performance function is used in order to optimize the performance. The gradient is computed back propagation technique. It performs calculations backwards through the network. Back propagation artificial neural networks (BP-ANN) are found to be highly operative for the purpose of pattern recognition. They find their effective use in detection, identification and location of faults in both distribution and transmission system.

4.4 LEARNING IN ARTIFICIAL NEURAL NETWORK

For the purpose of learning in neural network, the nature of data sets needs to be described. These data sets are input vectors, outputs vector and target vector. The neural network is always trained to get the desired output. The algorithms for learning in ANN can easily be classified into three categories.

4.4.1 Supervised Learning

During the training a neural network, input vectors are fed to network in order to get the output. The received output is now compared matched until the resulting output is achieved. Whenever there exists a difference between obtained output and preferred output an error signal is generated. This error modifies the network weights till the point when the actual output equals the desired output. Multi-Layer Perceptron (MLP) is based on the concept of supervised learning.

4.4.2 Unsupervised Learning

In the present learning method, the network receives inputs but does not obtain supervised target outputs. It refers to the difficulty of finding the hidden structure. During the training process, the network is fed with different input vectors. It randomly systematizes the input vectors into clusters. Now, when an input vector is fed during the course of testing the network matches the output with the input vector. The self-organizing map (SOM) and adaptive resonance theory (ART) are found to be under this category.

4.4.3. Self-Supervised Learning

In this process learning occurs by a knowledge component without having a training system providing feedback on correctness. The system generates the error signal is fed back. Several iterations are required to obtain the correct target.

4.5 MULTI-LAYER PERCEPTRON (MLP)

A Multi-Layer Perceptron (MLP) [46] - It is an example of feed forward artificial neural network. It contains of several layers. Each layer is linked to the next layer. Each node consists of a neuron with a nonlinear activation function. MLP works on the concept of a supervised learning. As usual it contains input, hidden and output layer. Hidden layer is the link between the inputs and the output. It extracts useful features from the input data so that the output values can be predicted. It is sometimes known as Back Propagation Network (BPN). Since, the training is done by error back propagation.

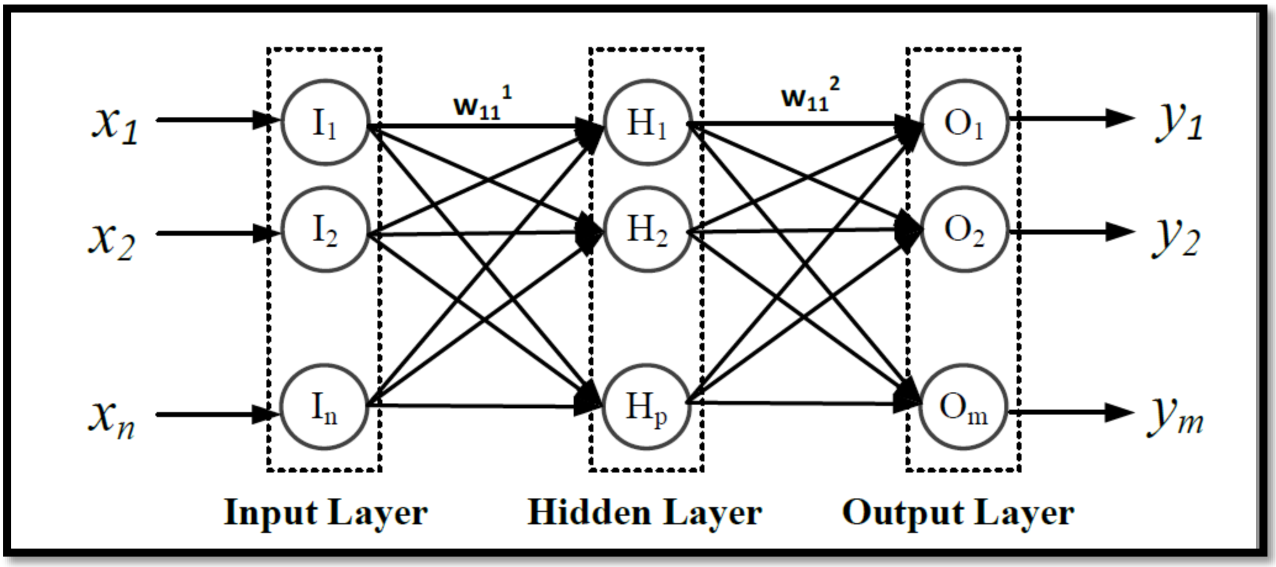


Figure 4.3: Multi -Layer Perceptron (MLP)

When an input pattern is applied to the input layer of network, it spreads through every next layer of the network until an output is generated. Now, the obtained output is matched with the desired target. An error signal is computed for each output. This error signal then spreads backward from the output layer to each node in the intermediate layer in order to get the desired output. The weights are updated by the error signal that is received. Back propagation algorithm is an iterative gradient search algorithm that reduces the cost function equal to the average of square error/mean squared error with regularization between the desired and actual output of MLP. Multi -Layer Perceptron can be seen in figure 3.3.

4.5.1 Performance Function

Selection of performance function plays a vital role while training a neural network. Usually, the performance function selected for training feed forward neural networks is the mean sum of squares of errors.

$$\text{Pf} = \text{mse} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{3.6}$$

Here, "t" and "a" represents the "N" dimensional vector of the input model. The performance function is altered by adding a term that consists of the mean of the sum of the squares of the network weights and biases.

$$\text{msereg} = \Upsilon\text{mse} + (1-\Upsilon)\ \text{msw} \tag{3.7}$$

Where Υ is the performance ratio and

$$msw = \frac{1}{n}\sum_{j=1}^{n} w_j^{\ 2} \tag{3.8}$$

It pushes the network to have less weights and biases. On the same hand, it asserts that the response of the network is smooth.

4.5.2 Activation Function

To add layers one need to do one more thing other than just connecting some new weights. By using a sigmoidal activation function, efficient output layer is obtained. It helps to get over of the mathematical values that are present in the middle. They may force values to become from low to even lower and high to be even higher. It should be observed it consists of two basic commonly used sigmoidal activation functions.

The Logistic Sigmoid which is also called as the *logsig*.

$$g(a) \equiv \frac{1}{1+e^{-a}} \tag{3.9}$$

The tangential sigmoid also called as the *tansig*, is resultant from the hyperbolic tangent. It is able to handle negative numbers.

$$g(a) \equiv \tanh(a) \equiv \frac{e^{a}-e^{-a}}{e^{a}+e^{-a}} \tag{3.10}$$

Algorithm

Chapter 5

This chapter discusses about the algorithm developed for the present work and also describes in detail about the image database.

5. 1. ALGORITHM

The algorithm used for feature extraction and classification of weld images is as follow in figure 4.1:

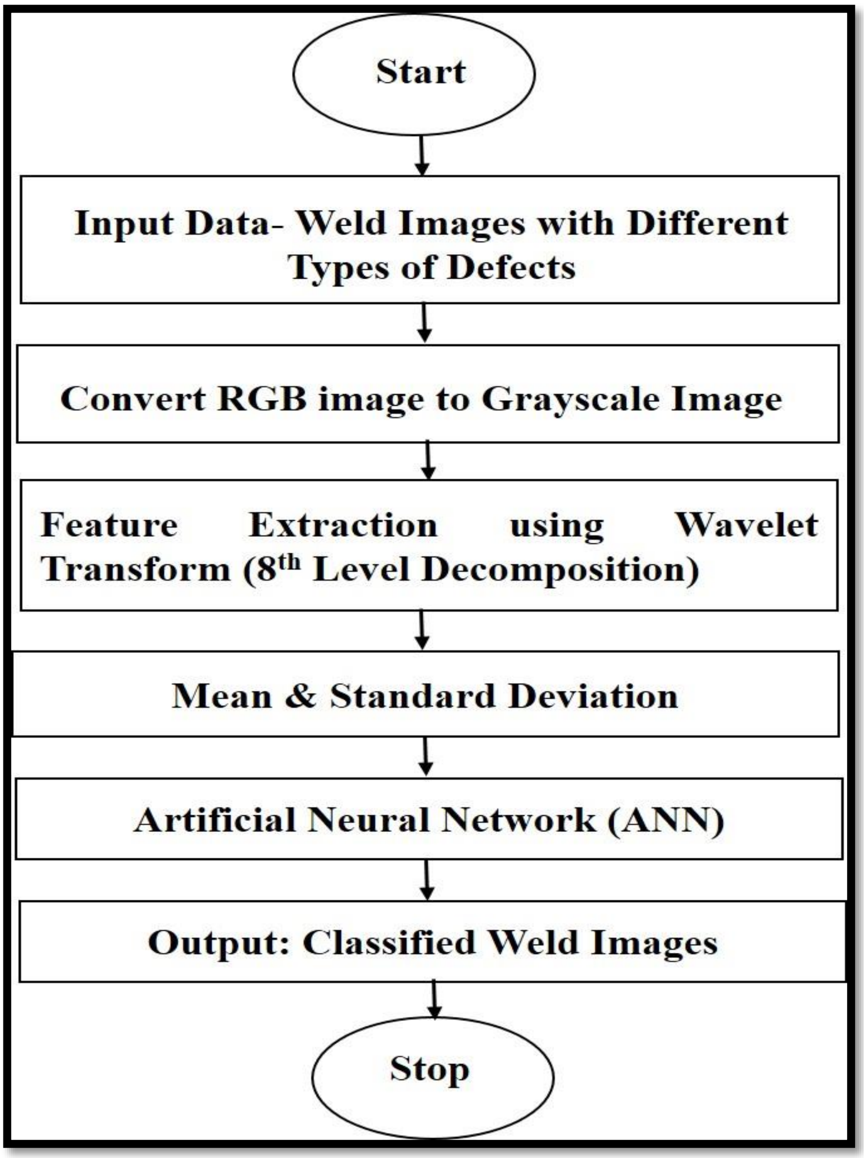
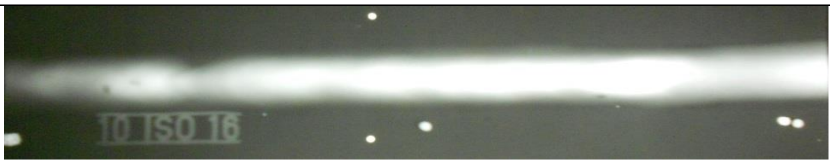
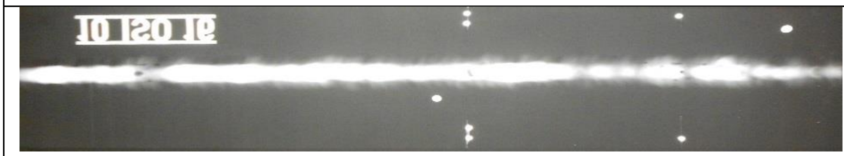
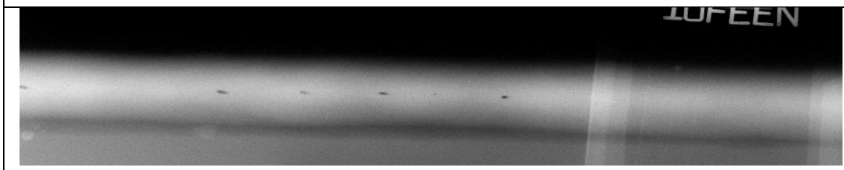
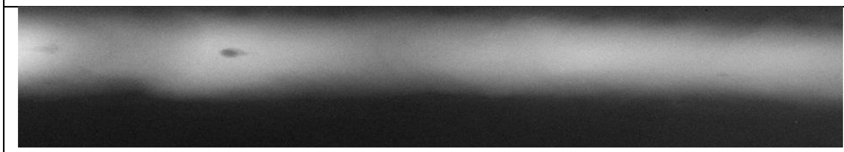


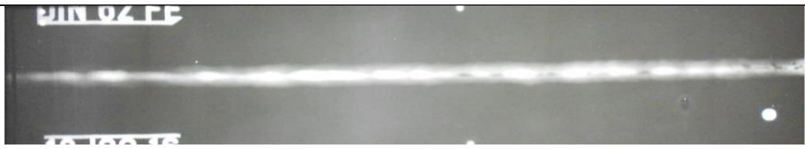
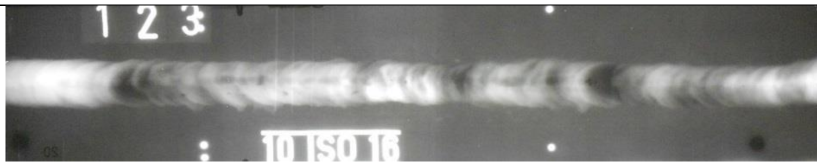
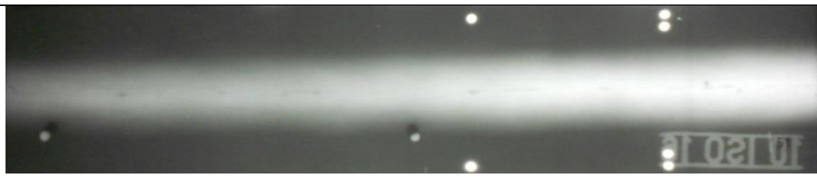
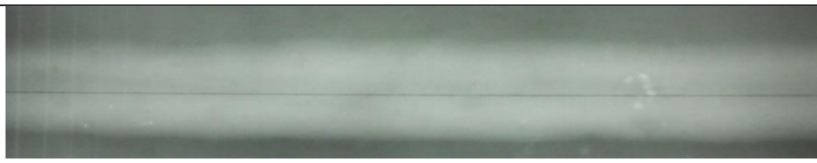
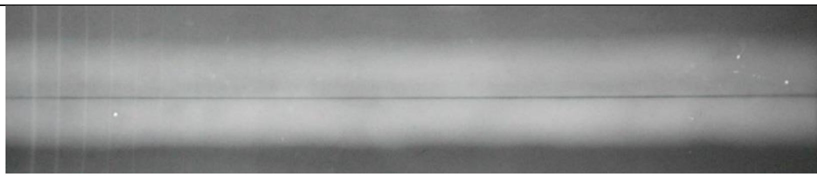
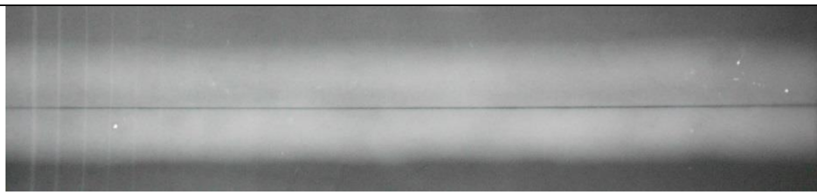
Figure 5.1: Algorithm

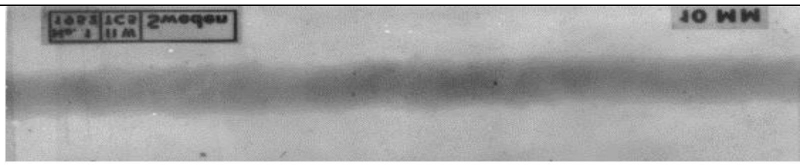
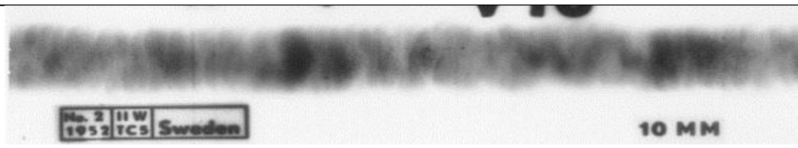
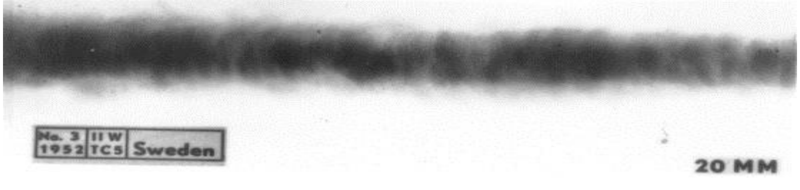
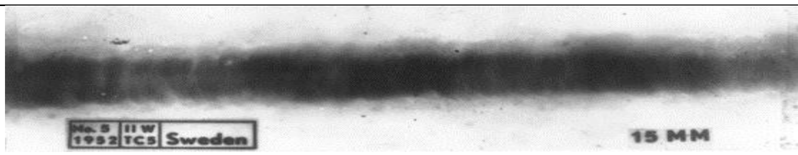
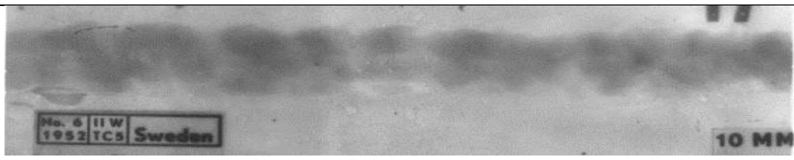
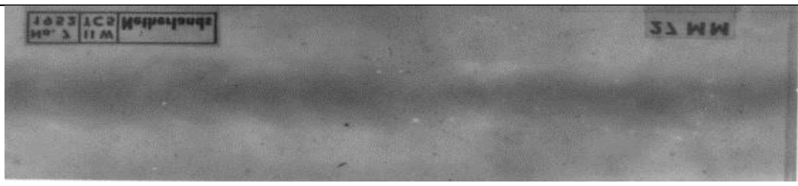
5. 2. IMAGE DATABASE

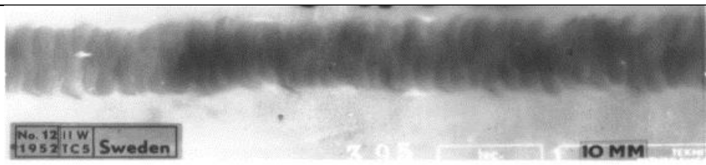
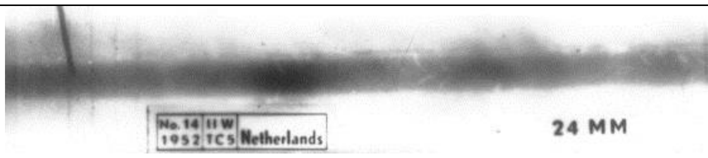
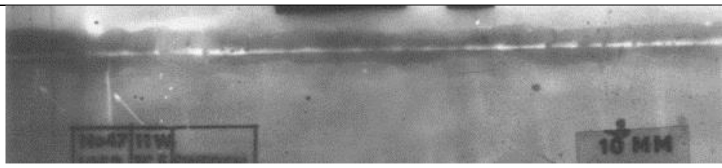
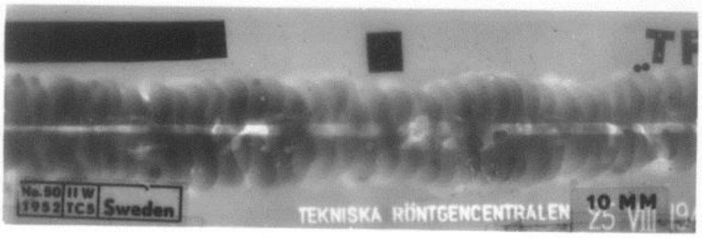
In total 79 images have been considered. The image has been collected from Bharat Heavy Electricals Limited (BHEL), Haridwar and Indian Institute of Technology Roorkee. This database consists of 08 types of flaws.

TABLE 5.1: IMAGE DATABASE

S. No	Type of Flaw	Image
1.	**Gas Cavity**	
2		
3		
4		
5		
6		
7		

S. No	Type of Flaw	Image
8	**Gas Cavity**	
9	**Lack of Penetration**	
10		
11		
12		
13		
14		
15		

S. No	Type of Flaw	Image
16	Lack of Penetration	
17		
18		
19		
20		
21		
22		

S. No	Type of Flaw	Image
23	Lack of Penetration	
24		
25		
26		
27		
28		
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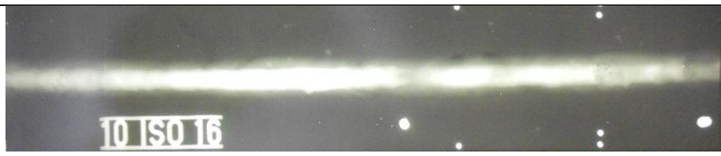
30		

S. No	Type of Flaw	Image
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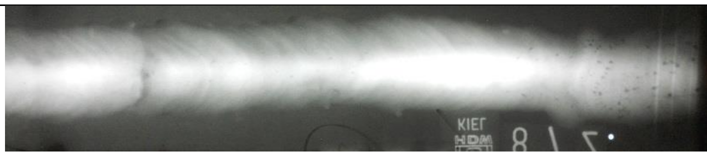
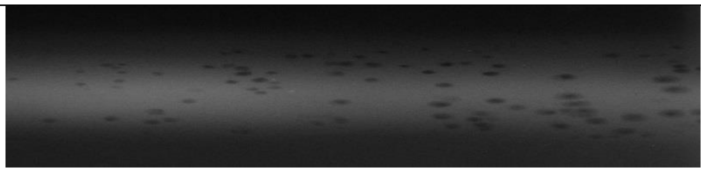
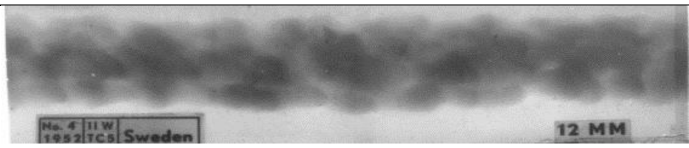
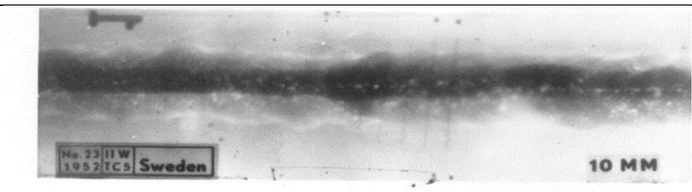
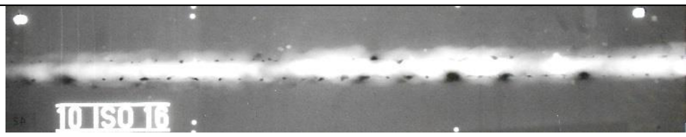
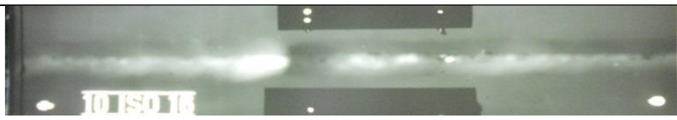
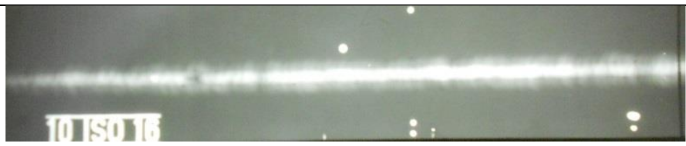
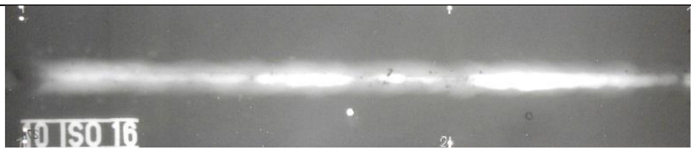
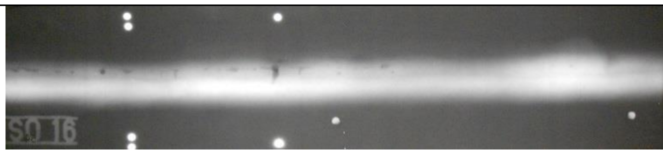
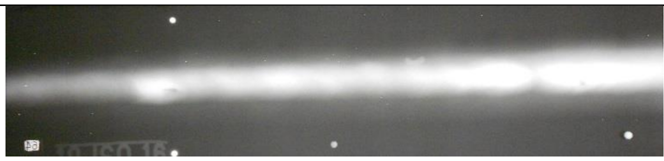
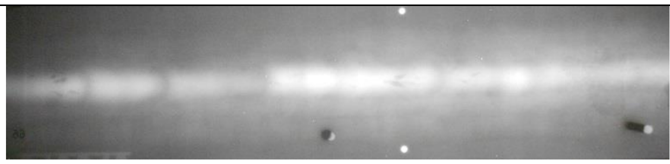
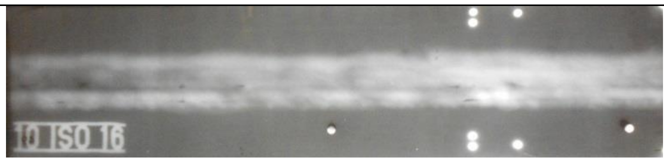
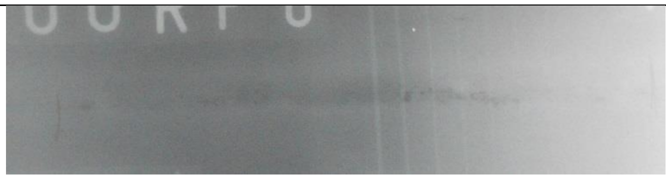
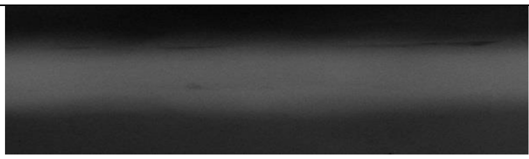
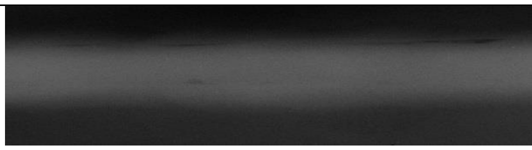
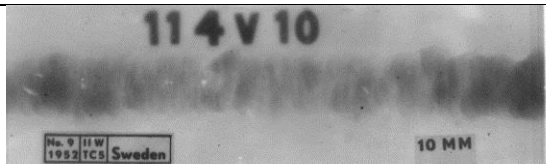
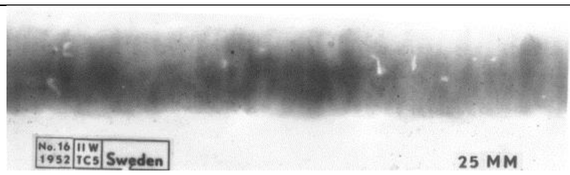
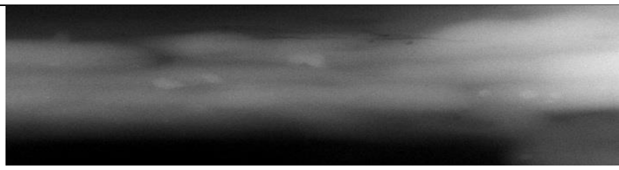
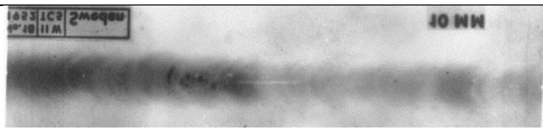
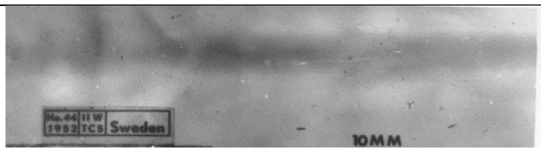
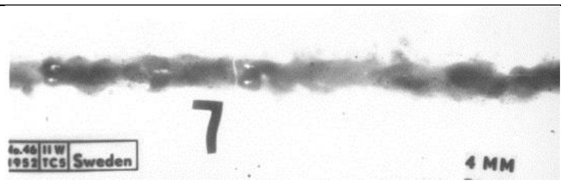
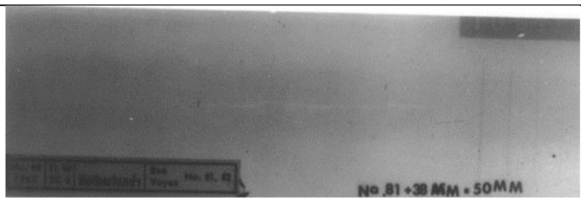
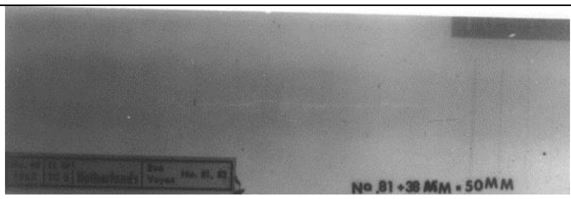
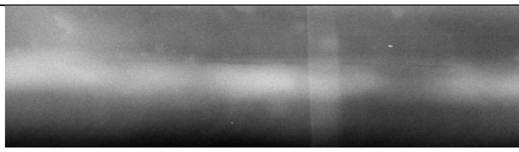
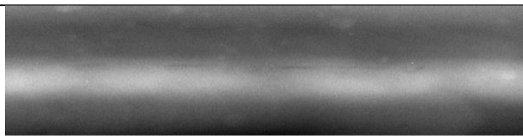
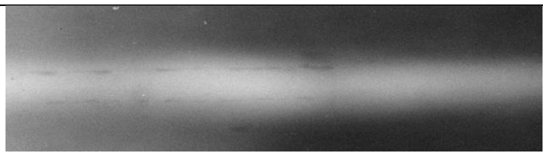
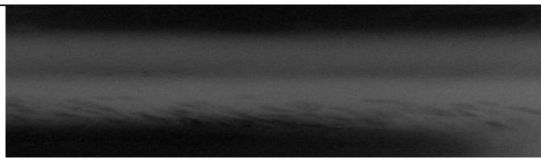
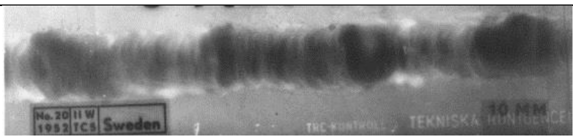
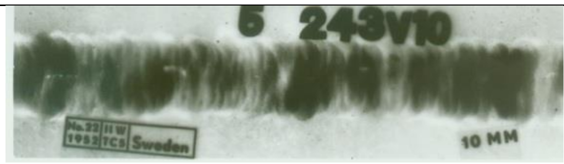
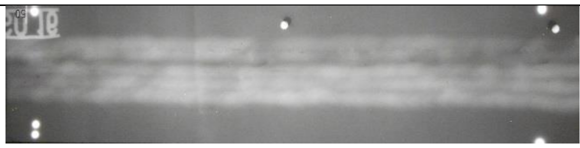
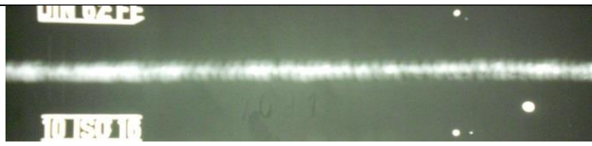
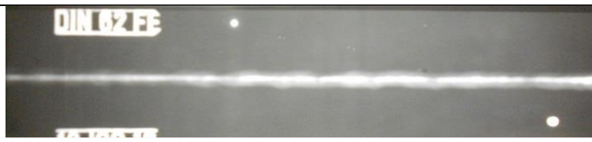
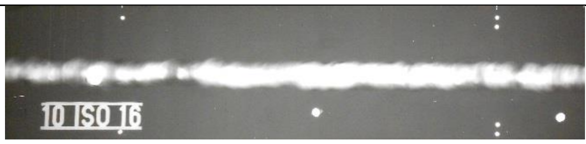
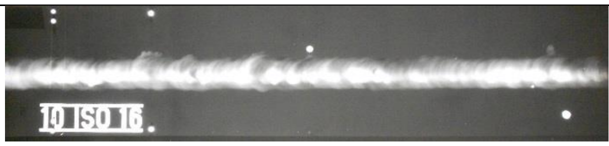
32		
33		
34		
35		
36	Slag	
37		
38		
39		

S. No	Type of Flaw	Image
40	Slag	
41		
42		
43		
44		
45		
46		
47		

S. No	Type of Flaw	Image
48		
49		
50	**Slag**	
51		
52		
53	**Crack**	
54		

S. No	Type of Flaw	Image
55	Crack	
56		
57		
58		
59		
60		
61		
62		

S. No	Type of Flaw	Image
63	**Lack of Fusion**	
64		
65		
66		
67		
68		
69		
70	**Worm Hole**	
71		

S. No	Type of Flaw	Image
72	Under Cut	
73		
74		
75	No Defect	
76		
77		
78		
79		

5. 3. STEPS INVOLVED IN ALGORITHM:

The steps involved in algorithm are explained below:

1. **Conversion of RGB Image to Grayscale:** By eliminating the hue and saturation information while retaining the illuminance the true color weld image in RGB is converted to Grayscale.
2. **Wavelet Transform Decomposition:** After converting the images into grayscale, the images are subjected to wavelet transform. 8 (Eight) level decomposition is obtained

for the grayscale images. In the present work, eight level decomposition was used as it yield better result.

3. **Mean:** It is applied twice to the matrix of grayscale image. The first time mean is applied to a matrix and it calculates the means of each column and returns these values as a vector. Applying mean again to this vector, gives a single mean value for the whole matrix.
4. **Standard Deviation:** It is the computation of deviation from its mean value. Mathematically, it is given as:

$$\gamma(t_1, t_2) = \left(\int_{t_1}^{t_2} (y(t) - \bar{y})^2 \, dt\right)^{\frac{1}{2}} \tag{4.2}$$

γ: Standard deviation. Standard deviation for a normal signal without fault is one. While, for a transient signal the value deviates from one. Figure 6.1 gives the method adopted to distinguish between load data and fault data

5. **Artificial Neural Network:** In the present work, Back Propagation neural network is utilized where; Levenberg–Marquardt algorithm is employed. The network performance parameters mean square error "mse" was used for the purpose of weld images classification.

In case of weld image classification, the features of current samples collected from wavelet transform are fed to the neural network. In the present work, target value is set to 0.00001 and the number of epochs taken for consideration are 1000. As the set value is reached in terms of the number of iterations or mse the network stops its learning. The purpose of training is to reduce mse to reasonably low value in few epochs. Another feature of the algorithm is that it only involves 70% of the samples for training and rest 15% for validation and testing respectively.

Results and Discussion

Chapter 6

This chapter discusses about the results obtained from the algorithm developed

6.1 RESULTS:

The radiographic weld images interpreted various welding defects. It was found that the welding defects arose due to a number of various discrepancies which were primarily linked to deviation in the required temperature range.

The welding defects have been classified. The weld images are collected at different range of temperature. It should be kept in mind that the gas cavity defect temperature ranges from 510 ºC – 610ºC. The lack of fusion is in range of 1927 ºC. The lack of fusion occurs at 1500 ºC. These are the original images of welding collected from BHEL Haridwar and Indian Institute of Technology Roorkee.

After obtaining the features from wavelet transform, they are fed to neural network in order to classify and obtain the images. Overall Classification accuracy obtained is. The results are compared with Jayendra et –al and are illustrated in figure 5.1

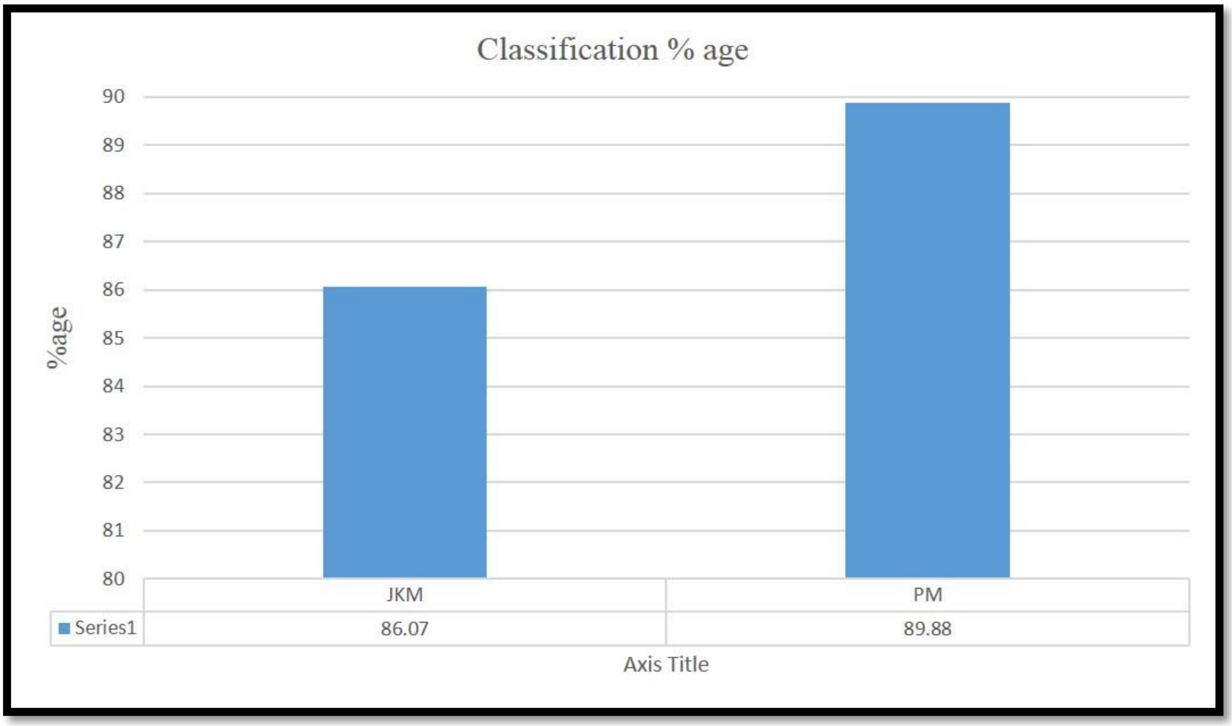


Figure 6.1: Classification Accuracy

In the above figure 6.1, classification methods of JKM and PM is depicted. JKM refers to paper no [48] from which the results are compared. The proposed method yields 89.88% age classification rate as compared to JKM which gives 86.07%. This proves that the proposed method outperforms the previous method. In the JKM method, 68 images were identified as compared to the proposed method PM were 71 images were classified.

The detail classification result of different types of faults are given in figure 6.2.

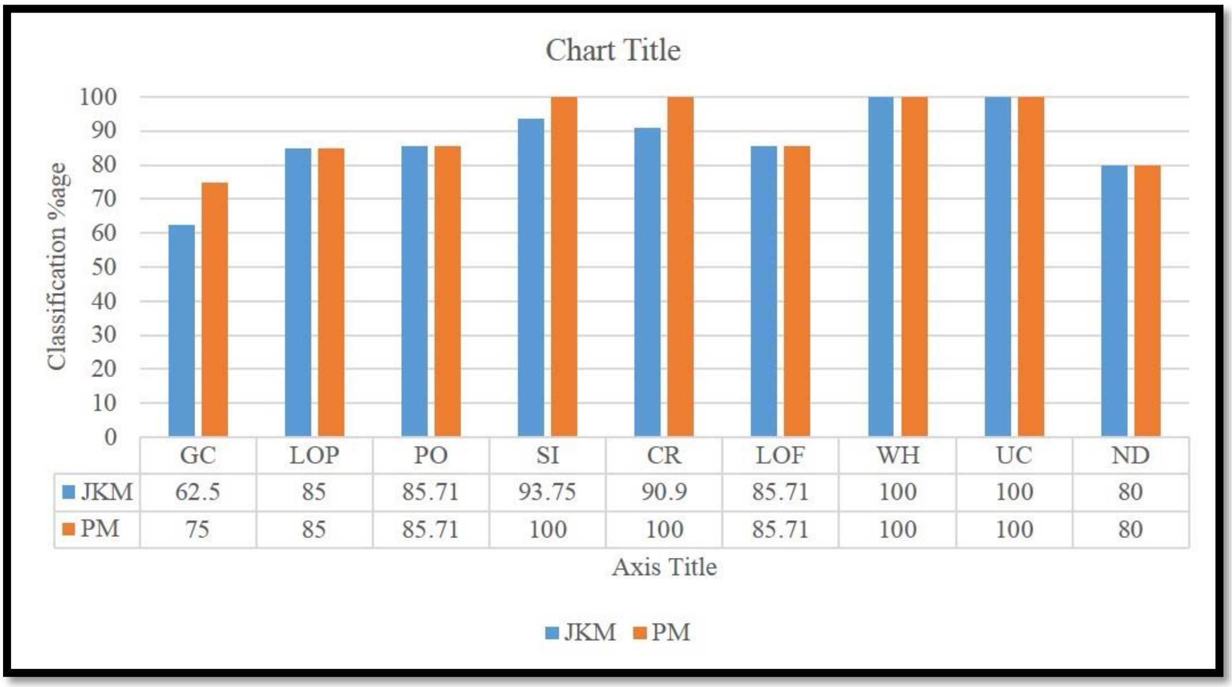


Figure 6.2: Classification% and Accuracy for Different Types of Flaw

The classification error of different types of faults are listed below. GC stands for gas cavity, LOP stands for Lack of Penetration, PO is for Porosity, SI stands for Slag, CR is for cracks, LOF is lack of fusion,. WH is Worm Hole, UC stands for Under Cut and ND stands for No defect images. As seen in figure bin all the cases the proposed method outperforms the JK method. For GC and SI images, the proposed method is able to recognize 75% and 100% images as compared to 62.5% and 93.75% respectively.

As discussed earlier, neural network has been employed for classification of faults in weld images. 16 epochs were required to fetch the result. Here, epochs refers to iterations. Thus, 16 iterations were required to achieve the result. Figure 5.3 shows the performance graph of neural network employed in the present work.

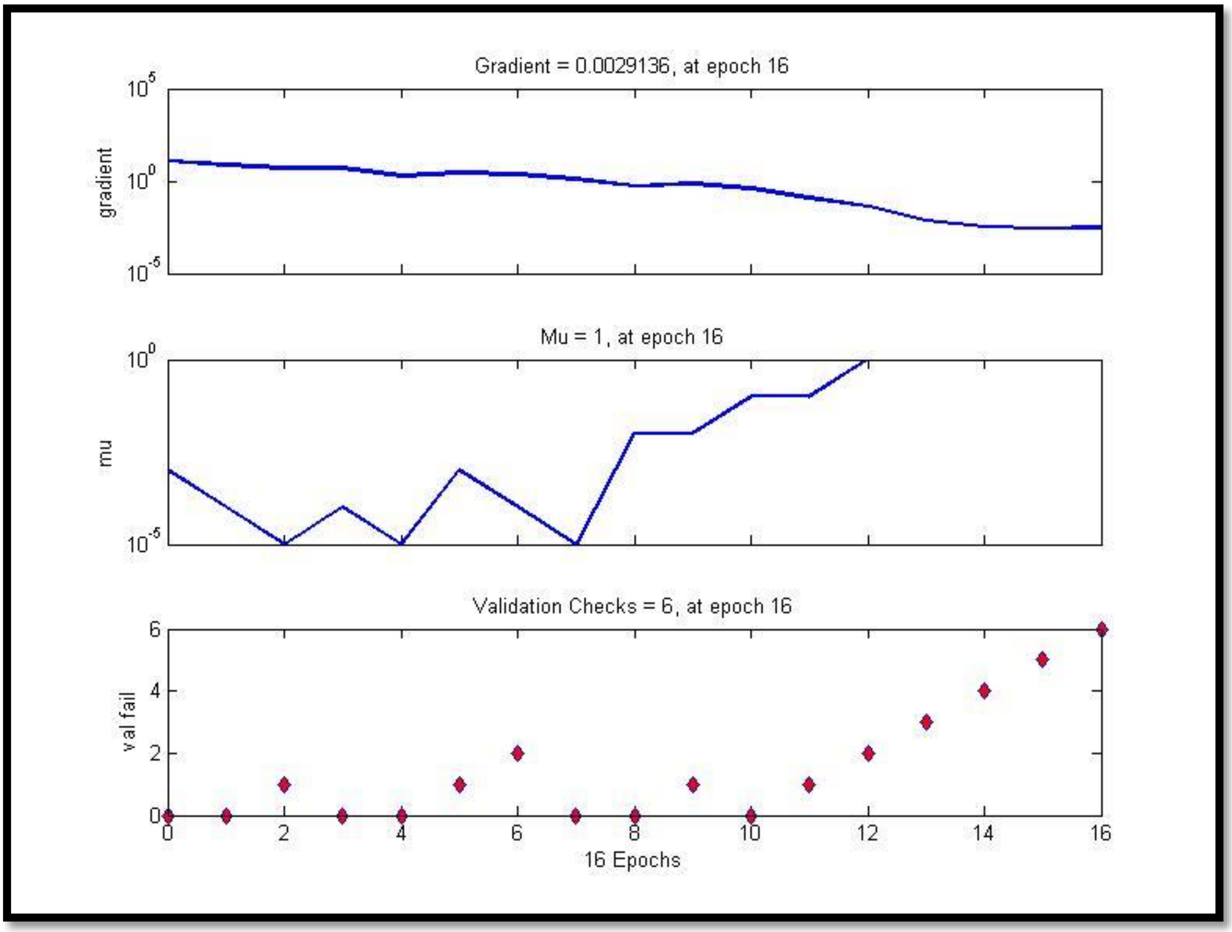


Figure 6.3: Neural Network Performance Graph at 16 Epochs

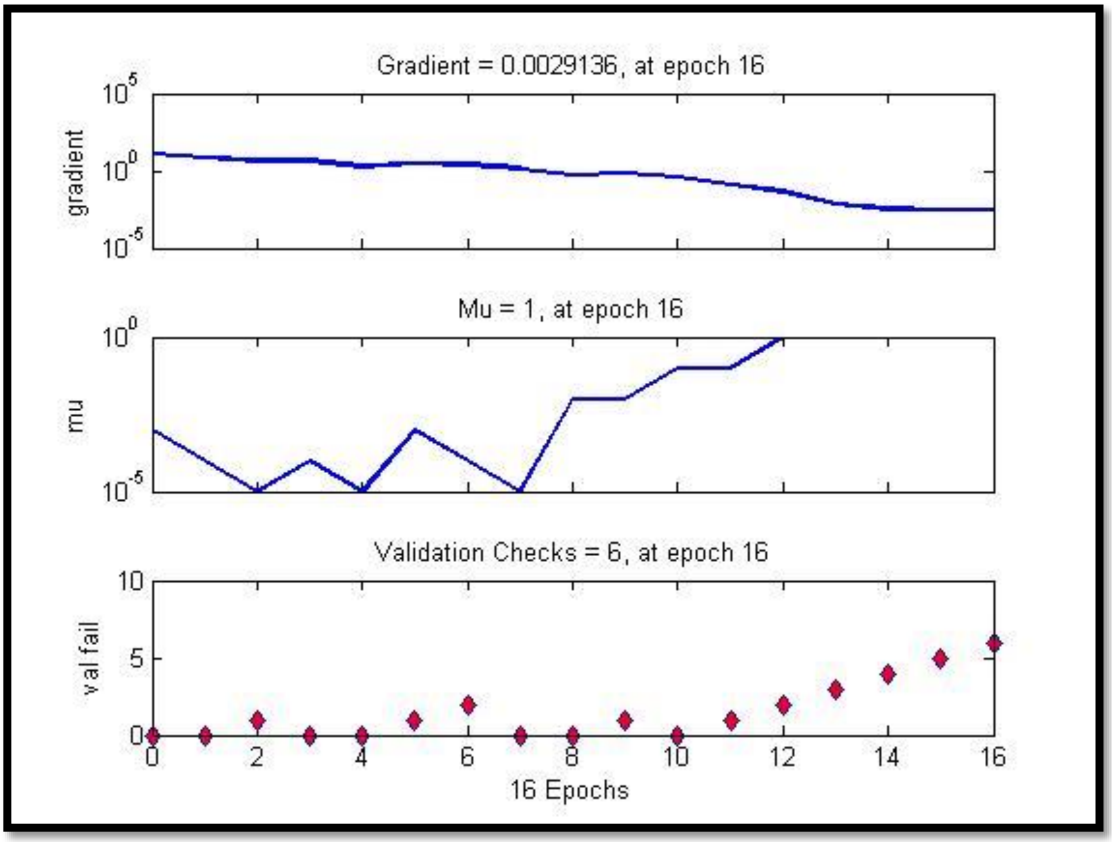


Figure 6.4: Neural Network Performance Graph at 16 Epochs

The regression plot for the neural network is presented below in fig 5.5

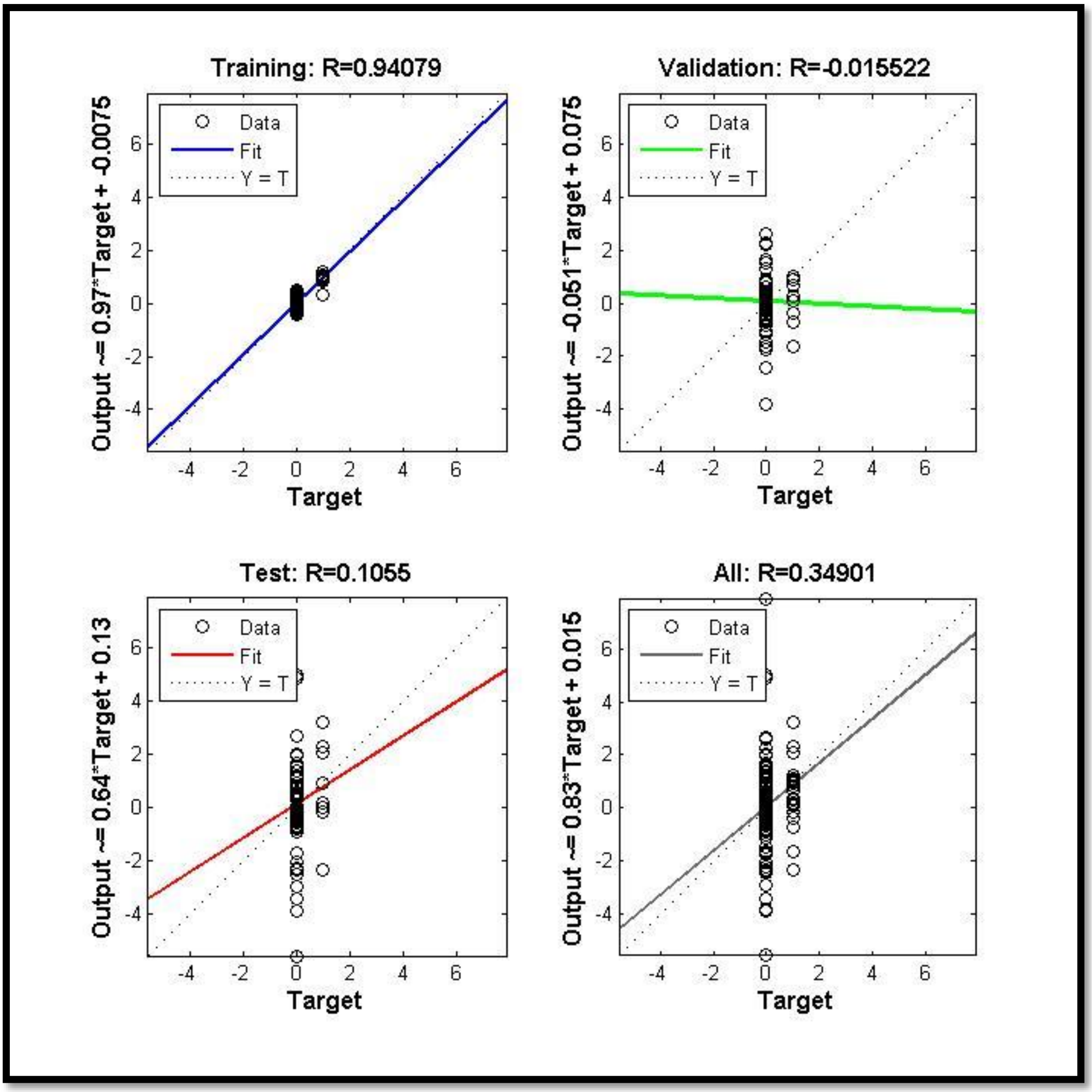


Figure 6.5: Neural Network Performance Graph at 16 Epochs

Hence, by observing the above graphs and result, it is concluded that the proposed method provides a better result as compared to the method proposed in [48]. Thereby, validating the effectiveness of the algorithm.

Conclusion and Future Perceptive

Chapter 7

This chapter draws the inference of the work carried for the present research. It also gives the future perspective of the work

As discussed, welding is the experienced way of joining metals together. It is an efficient and economy the process. It is an assembling process where materials are joined. It is achieved by adding some additional molten joining material on melting part of the materials to be joined It plays a major role in industries for the purpose of construction, joining and repairing of steel beams, reinforcing rods in buildings, bridges, spacecraft, pipe lines, nuclear containers etc. During the process of welding a number of different types of discontinuities can be produced, which may arise due to material inconsistencies of the material, error produced by the operator, or other factors that are beyond the operators control.

In total 79 images have been considered. The image has been collected from Bharat Heavy Electricals Limited (BHEL), Haridwar and Indian Institute of Technology Roorkee. This database consists of 08 types of flaws. The flaws are as follows :GC stands for gas cavity, LOP stands for Lack of Penetration, PO is for Porosity, SI stands for Slag, CR is for cracks, LOF is lack of fusion,. WH is Worm Hole, UC stands for Under Cut and ND stands for No defect images.

The proposed method yields 89.88% age classification rate as compared to JKM which gives 86.07%. This proves that the proposed method outperforms the previous method. In the JKM method, 68 images were identified as compared to the proposed method PM were 71 images were classified. Therefore, it proves that the feature extracted from wavelet transform are suitable for classification and gives good result.

7.1 FUTURE PERSPECTIVE

Based on the above experience, the work can be extended in the following directions:

- The present database considered for the work is 79. The effectiveness of the algorithm can be tested on higher database. It should be kept in mind that the database were taken from BHEL Haridwar, and Indian Institute of Technology Roorkee.
- In the present work, wavelet transforms were considered. But other high end transform such as Wavelet Packet transform and Gabor transform can be used to verify the effectiveness of the transform.
- In the present work, segmentation can be considered, which can give the exact location of fault in an image.
- Artificial Neural Network has been used to classify the results, other classifiers such as Support Vector Machine can also be used in order to improve the accuracy.

REFRENCES

1. B. Smith, "Making war on defects. Six-sigma Des," *IEEE Spectrum*, vol. 30, no. 9, pp. 43-47, 1993.
2. Debasish Basak "Non-destructive evaluation of drive ropes: a case study", Nondestructive Testing and Evaluation, vol. 20, no. 4, pp. 221 – 229, 2005.
3. D. J. Grieve, Welding Defects.www.tech.plym.ac.uk/sme/strc201/ wdefects.htm
4. Hartmut Baumbach, Dragos Cioclov, Siegfried Kraus, Volker Schmitz, "Non-destructive testing and quality management Technology", *Law and Insurance*, , vol. 3, no. 3, pp. 191 – 195, 1998.
5. Hayes C "ABC's of nondestructive weld examination" *weld journal*, vol.76, no.5, pp. 46-51, 1997.
6. Steve Dixon, "Weld inspection" EPSRC advanced research fellow, Department of Physics, University of Warwick, 1998.
7. T. Stepinski , "Advanced Non destructive methods for inspection of canisters for spent nuclear fuel", Uppsala University. Sweden. Jun 2002.
8. "Welding defects to avoid and correct : Solutions with effective, powerful advice", Welding-defects : Description, search and assessment, www.welding-advisers.com/welding-defects.
9. "Welding Defects : An Introduction", www.tech.plym.ac.uk/sme/strc201/wdefects.htm
10. Ioannis Valavanis , Dimitrios Kosmopoulos ,"Multiclass defect detection and classification in weld radiographic images using geometric and texture features" *Expert Systems with Applications vol. 37, no. 12*, pp. 7606-7614, Jul 2010.
11. A. Daaland, "Real time radiography for in service inspection of flexible pipeline system. Trends in NDE science and technology," *In Proc. 14th World Conf. Non-Destructive Testing*, New Delhi, vol. 3, pp. 1361-1364, 1996.
12. B. P. C. Rao, "Visual techniques in non-destructive testing, encyclopedia of materials," *Science and Technology*, pp. 6043-6046, 2001.
13. "NDT Techniques", www.ndt.cegelec.com/pages/en/activities/techniques/techniques.asp

14. A. Gayer, A. Saya, and A. Shiloh, “Automatic recognition of welding defects in real-time radiography”, NDT & E International, vol. 23, no.3, pp. 131-6, 1990.

15. K. Murakami, “Image processing for non-destructive testing”, Weld International, vol. 4, no. 2, pp. 144-149, 1990.

16. J. Ker and K. Kengshool, “An efficient method for inspecting machined part by a fixtureless machine vision system”, In Proc. SME Vision, Detroit, vol. 2, pp. 45-51, 1990.

17. C. Nockeman, H. Heidt and N. Tomsen, “Reliability in NDT: ROC study of radiographic weld inspection”, NDT & E International, vol. 24, no 5, pp 235-245, 1991.

18. Y. Kato, T. Okumura, S. Matsui, K. Itoga, T. Harada, K. Sugimoto, K. Michiba, S. Iuchi, and S. Kawano, “Development of an automatic weld defect identification system for radiographic testing”, Weld World, vol. 30, no.7/8, pp. 182-8, 1992.

19. Z. Wu, “Homogeneity testing for unable data: A performance evaluation”, CVGIP: Graph. Models Image Process, vol. 55, pp. 370-380, Sept 1993.

20. G. E. Cook, R. J. Barnett, K. Andersen, J. F. Springfield and A. M. Strauss, “Automated visual inspection and interpretation system for weld quality evaluation”, IEEE, pp. 1809-1816, 1995.

21. R. Hyatt, G. E. Kechter, and S. Nagashima, “A method for defect segmentation in digital radiographs of pipeline girth welds”, Mater Eval. pp. 925-928, Aug 1996.

22. T. W. Liao and J. Ni, “An automated radiographic NDT system for weld inspection. Part I. weld extraction”, NDT & E International, vol. 29, no. 3, pp. 157-162, 1996.

23. T. W. Liao and K. Tang, “Automated extraction of welds from digitized radiographic images based on MLP neural networks”, Appl. Artif. Intell., vol. 11, pp. 197-218, 1997.

24. T. W. Liao and Y. M. Li, “An automated radiographic NDT system for weld inspection. Part II. Flaw detection”, NDT & E International, vol. 31, no. 3, pp. 183-192, 1998.

25. T.W. Liao, D.M. Li, Y.M. Li, “Detection of welding flaws from radiographic images with fuzzy clustering methods”, Fuzzy Sets Syst, vol.108, pp. 145–158,1999.

26. T. W. Liao, D. M. Li and Y. M. Li, “Extraction of welds from radiographic images using fuzzy classifiers”, Inform. Science, vol. 126, pp. 21-42, 2000.

27. H. Laggoune and S. P. Gouton, “Dimensional analysis of the welding zone”, In Proc. 22nd International Conf. Information Technology Interface, pp. 451-456, 2000.

28. C. Chan, K. H. Grantham, “Fabric defect detection by fourier analysis”, IEEE Trans

Ind Appl., vol. 36, no. 5, pp. 1267-1275, 2000.

29. I. M. Elewa, A. A. Abdel-Shafy, E. S. Gadelmawla and H. I. Shafeek. "Assessments of welding defects for gas pipeline radiographs using computer vision", Proc. Third Assuit International Conf. Mech. Engg. Advanced Technol. for Industrial Production, Assiut, Egypt, pp. 216-223, 2002.

30. G. Wang and L. T. Warren, "Automatic identification of different types of welding defects in radiographic images", NDT & E International, vol. 35, no. 8, pp. 519-528, 2002.

31. D. Mery and M. A. Berti, "Automatic detection of welding defects using texture features", Insight, vol. 45, pp. 676-681, 2003 .

32. M. H. S. Siqueira R. Ra da Silva, M.P.V de Souza, J. M. A Rebello and L. P Caloba, D. Mery, "Estimated accuracy of classification of defects detected in welded joints by radiographic tests", In Proc. 16th WCNDT 2004 - World Conference on NDT CD-ROM, Internet Version of 600 Papers, Montreal, Canada, Aug - Sep 2004.

33. Wang, Xin, Brian Stephen Wong, and Tui Chen Guan. "Image enhancement for radiography inspection", In Proceedings of SPIE, vol. 5852, pp. 462-468. 2004.

34. R. R. Silva, L. P. Caloba, M. H. S. Siqueira, and J. M. A. Rebello, "Pattern recognition of weld defects detected by radiographic test", NDT & E International, vol. 37, pp. 461-470, 2004.

35. Alaknanda, Pradeep Kumar and R.S. Anand "Flaw detection in radiographic weld images using Morphological approach", NDT&E International, vol. 39, no. 1, pp. 29-33, Jan 2006.

36. Ioannis Valavanis , Dimitrios Kosmopoulos, "Multiclass defect detection and classification in weld radiographic images using geometric and texture features", Expert Systems with Applications vol. 37, no. 12, pp. 7606-7614, 2010.

37. N.M.Nanditha and N.Manoharan, "Comparative study on the suitability of feature extraction techniques for tungusten inclusion and hotspot detection from weld thermographs for online weld montoring", International Journal of Engineering and Material science, vol. 17 pp. 20-26, Feb 2010.

38. S. Margret Anouncia, R.Saravana, "A knowledge model for gray image interpretation with emphasis on welding defect classification", Computer in Industry, vol. 61, pp. 742-749, Oct 2010.

39. P.N.Jebarani Surgunar ,R.Sukanesh, "Automatic detection of weld defects in pressure vessels using fuzzy neural network", International Journal of Computer Applications, vol. 1, no. 21, pp. 119-125, 2010.

40. Rafael Vilar, JuanZapata, "An adaptive-network-based fuzzy inference system for classification of welding defects", NDT & E International, vol. 43, no. 3, pp. 191-199, Apr 2010.

41. Juan Zapata, Rafael Vilar, Ramon Ruiz, "Performance Evaluation of an automatic inspection system of weld defects in radiographic images based on neuro – classifiers", vol. 38, pp. 8812 -8824, 2011.

42. C. H. Kim, Raj Aggrawal, "Wavelet Transform in Power System", Power Engineering Journal, pp.81-87, April 2000.

43. K. R. Soman, K. I. Ramachandran, "Insight into wavelets", PHI Pvt. Ltd., 2nd Edition, October 2006.

44. Pratul Arvind, Rudra Prakash Maheshwari, "Comparison between wavelet and wavelet packet transform features for classification of faults in distribution system", Proceedings of the Sixth Global Conference on Power Control and Optimization. AIP Conference Proceedings, Volume 1499. AIP Conference Proceedings, Volume 1499, Issue 1, pp.25-30.

45. O. P. Malik, " Application of Neural Networks in Transmission Line Protection, Power Engineering Society General Meeting, pp. 1-6, 2007.

46. R. N. Mahanty, P. B. Dutta Gupta, "ANN based fault classifier with wavelet MRA generated inputs", International Journal of Engineering Intelligent Systems, Vol. 16, No. 2, pp. 75-85, June 2008.

47. Fan Chunju , K.K. Li , W.L. Chan , Yu Weiyong , Zhang Zhaoning , "Application of wavelet fuzzy neural network in locating single line to ground fault (SLG) in distribution lines," International Journal of Electric Power Systems Research, vol.29, pp.497-503, 2007.

48. Jayendra Kumar, R. S. Anand, S.P.Srivastava, laws Classification using ANN for Radiographics Weld Images IEEE Conference on Signal Processing and Integrated networks, 2014.