Journal of Manufacturing Engineering, September, 2013, Vol. 8, Issue. 3, pp 156-168

# AUTOMATIC INSPECTION FOR MIG WELDING JOINTS USING MACHINE VISION

**Senthil Kumar G[1], Natarajan U[2], Athijayamani A[3] and *Srinivasagan M[4]**

[1]Dept. of Mech. Velammal College of Engg & Tech. Madurai, Tamil Nadu, India
[2, 3, 4] Asst.Professor, Dept. of Mech. A. C College of Engg & Tech., Karaikudi, Tamil Nadu, India

## ABSTRACT

In this study, we use machine vision to inspection of welding surfaces produced by the MIG welding Process. Machine vision allows for the inspection of welded surfaces without touching or scratching the surface, and provides the flexibility for inspection parts. In this experimental work, inspection system has been developed for identifying and classifying the surface defects of fillet joint as per standard EN25817 in Metal Inert Gas (MIG) welding. In this proposed vision system, images of welding surfaces are captured through CCD camera. From these images, the regions of interest are segmented and the average gray levels of the characteristic features of these images are calculated.. Finally, welded joints can be classified into one of the four pre-defined ones based on the back propagation neural network. This proposed system, 80 welded samples are analysed with two different feature extraction methods.

**Keywords:** *Machine Vision, Weld Classification, MIG Welding and Vision Inspection Back Propagation Neuralnetwork (BPN).*

## 1. Introduction

With the development of surface mounting technology, the needs for automatic inspection are ever increasing. The current trends towards miniaturization of components, denser packing of boards, surface mounting technology, and highly automated assembly equipment make the task of detecting these defects more critical and more difficult. Machine vision may effectively replace human inspection in such demanding cases. Non-destructive testing (NDT) is a branch of engineering concerned with methods of detecting defects in objects without altering the object in any way. The reliable detection of weld defects is one of the most important tasks in non-destructive testing. Improvements in these methods are necessary, because the human factor still has great influences on the evaluation.

A feature is a value describing an object in a numerical form and the selection of good features is critical to the success of any classification algorithm. Generally 2D features are computationally simpler than 3Dfeatures [1]. Efficient techniques for solder joint inspection have been described using three layers of ring-shaped LED's with different illumination angles, three frames of images were sequentially obtained and segmented the regions and then classified the solder joints using a fuzzy membership function and neural network classifier [1]. S.Jagannathan,et al[2] developed a new system for the intelligent machine vision inspection of wave-solder joints. A modified Intelligent Histogram Regarding (IHR) technique was used that divides the gray level histogram of the captured images from a joint in to different modes and the neural networks was employed to identify and classify the defective solder joints. The back-propagation algorithm was employed to train the neural networks. After training, the neural network was employed to successfully identify and classify the defects of welded joints. They used images captured with light sources of ring shaped LEDs with different illumination angles in solder joints. In ring shaped LEDs illuminations are focused in centre of the image. In welding images, sizes of beads are not in circular shape and some information's about welding beads are missed. Poor quality radiographic images have led to the development of various automatic defect detection algorithms that focus on extracting defects using various image segmentation methods [2, 3, and 9]. Neural networks are used to improve the computational speed of the system for such activities as feature extraction and interpretation [3]. Two-dimensional images taken under controlled conditions of good lighting and low noise is the simplified strategy of industrial vision applications [4]. NDT testing is particularly important for critical applications where weld failure can be catastrophic, such as in pressure vessels, load-bearing structural members, and power plants [5]. Lashkia [8] proposed on a fuzzy reasoning to detect low-contrast defects using local image characteristics, such as special contrast,

*Corresponding Author - E- mail: srinivasagan_aue@yahoo.com

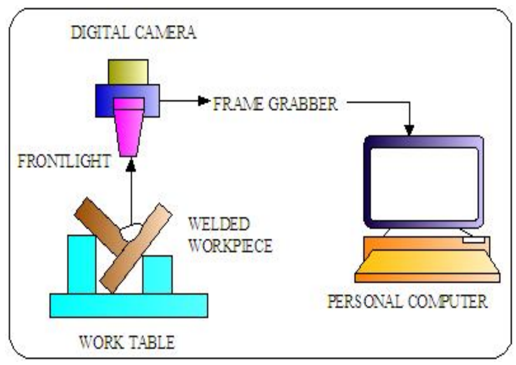
special variance and distance between two contrast regions. As the measurement system is Optical, only the surface of the weld was mapped. A digitized radiographic image is often corrupted by non-uniform illumination, noise and poor contrast [8]. The applied inspection criteria specified in the standards include measurement of the height and cross sectional area of the weld, together with detection of porosity density and undercuts [9]. The inspection welds is important not only to ensure the integrity of the welded engineering artifacts but also to improve the fabrication process [10]. Silva et al [11] also concluded that the lack of high number of samples to increase the reliability of the classification is a common problem in the automatic interpretation of weld radiographs. Radiographic films usually have noise and deficient contrast due to intrinsic factors involved in the inspection technique, such as non-uniform illumination and the limited range of intensities of the images capture device [12]. Liao and Li developed welding flaw detection based on the fitted line profiles of a weld image and successfully detected 93.33% of various defects from linear welds [16].

The information capture from different viewpoints can reinforce the diagnosis when a single image is insufficient [15]. In tune with the trend, four zones of LEDs with different illumination angles used to capture the weld joints. This new introduced vision system, 2D feature average gray values are extracted from the MIG welding joints and are classified by using back propagation neural network as good weld, excess weld, insufficient weld and no weld. In general, the calibration process is difficult to carry out in industrial environment due to vibrations and random movements that vary with time [15]. Therefore, any calibration process is not followed in this method. This paper is organized as follows: section 2 represents the overview of the system. The experimentation functions are discussed in section 3. Preprocessing of digitized image and feature extraction are discussed in section 4 and 5. Neural classifier is discussed in section 6. Test results are presented in section 7, followed by the conclusions.

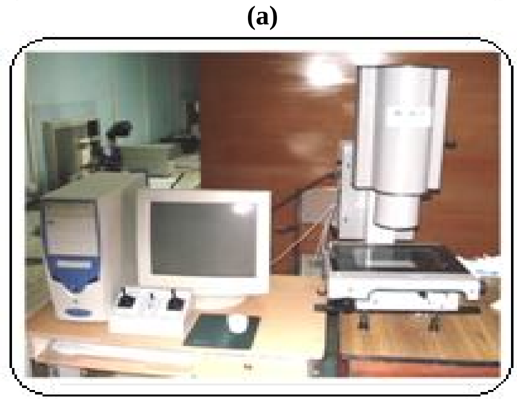
## 2. System Overview

The overall inspection system is shown in Fig.1 RAPID 1 V3.4 machine vision system is used to capture the images. Vision based inspection systems are set of new technologies for non- contact inspections and measurements. The instruments integrate multitude of technologies including digital imaging, electronics, embedded systems and software. The Rapid-1 V3.4, a vision based metrology instrument utilizes these cutting edges technologies to enable to do precise inspections. Further innovative design and creative developments have led to a wide range of hardware and software capabilities that will enhance our ability not only inspect manufactured parts but also in our design and development. Rapid-1 is a capable of carrying out diverse measurement task including all basic 2D measurements, depth and even threads parameters. Its primary advantage lies in its high resolution optics combined with precision work stage and power software.

The quality of imaging cannot be changed, if the hardware is not suitably designed [10].




**(a)**



**(b)**

**Fig. 1 (a) Schematic diagram of Machine Vision System for MIG Welding Inspection**

**(b) RAPID 1 Machine Vision System for Acquiring the Images**

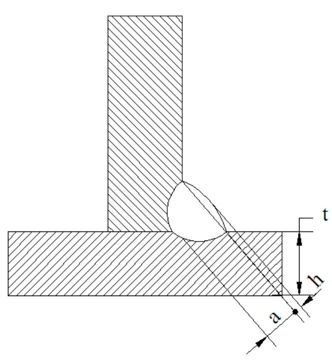
## 3. Experimentation

The main three functions are carried out in this experimentation. First of all different type of joints like acceptable and unacceptable joints in the fillet welding joint in MIG welding process has been prepared as per Standard EN 25817. Carbon steel plate size 80 x 20 x 4 mm is used as a parent material in this work. The voltage and current maintain during welding is 27V and 260 Amps. ER 70S6 with 1.2 mm diameter electrode is used in this experiment. Carbon dioxide is supplied during the welding process and standoff distance is maintained in15mm.

Second one is based on the values obtained for the various measurements acceptance or non acceptance of the weld will be decided in conformity with EN 25817 acceptance levels for intermediate service conditions. Fig.3 depicts the different types of acceptable and unacceptable groove weld profile in fillet joint. Fig.2 (a) shows the image of good weld, h, a and t denoted reinforcement height, nominal fillet weld throat thickness and thickness of the work piece respectively. Good weld refers, when the reinforcement height (h) has not been come $h \leq 1mm+0.3a$, maximum of 5mm and also under groove height has not been come $h1 \leq 0.1t$, maximum of 1mm. Fig.2 (b) shows the excessive weld, $h \leq 2mm + 0.2a$. When the reinforcement height (h) of the weld lies between 2 to 3mm, then it is called as excessive weld. Fig.2 (c) refers insufficient weld,s denote the prescribed depth of penetration. When the under groove height (h) lies between $h \leq 0.1s$, then it is called as insufficient weld. Fig.2 (d) illustrates No weld. When the groove surface is not filled, then it is called No weld.

The type of welding defects to be inspected includes defect free welded joint (good weld), excess weld, insufficient weld and no weld. Fig.3 shows the image of defect free welded joint. Fig.4 shows the image of excess weld. Fig.5 shows the image of insufficient weld. Fig.6 shows the image of no weld.

**Acceptable groove weld profile in Fillet joint**




**2(a) Good weld**

$h \leq 1mm+0.3a$ ,max 5 mm

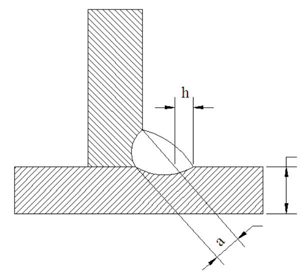
where a = nominal fillet weld throat thickness

s = prescribed depth of penetration

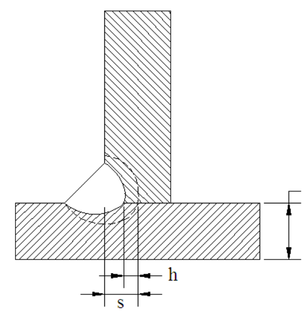
h = size (height or width) of imperfection in mm

t = work piece thickness

**Unacceptable groove weld profile in Fillet joint**

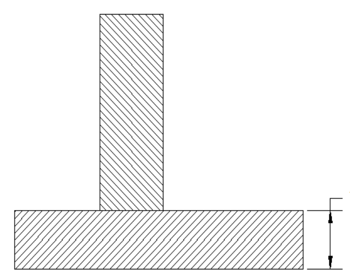



**2(b) Excessive weld** $h \leq 2mm+0.2a$




**2(c) Insufficient weld**

$h \leq 0.1s$ ,max 1.5 mm




**2(d) No weld**

**Fig.2 Different types of Acceptable and Unacceptable Groove Weld Profile in Fillet Joint as per EN 25817: (a) Good weld (b) Excessive weld (c) Insufficient weld (d) No weld**

**Fig.3 Image of Good Weld**

**Fig.4 Image of Excess Weld**

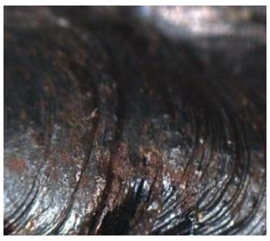


**Fig. 5 Image of Insufficient Weld**

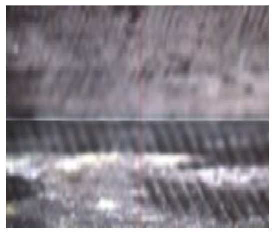


**Fig.6 Image of No Weld**

## 4. Pre Processing

Image processing seeks to Four frames of images are sequentially captured as four zones of LEDs are turned on, one after the other. Image processing seeks to modify and prepare the pixel values of a digitized image to produce more suitable form for subsequent operations. In this stage, the weld region must be isolated from the rest of the parent metals. Noise on images usually appears as randomly dispersed pixels having different values of intensity in relation to their nearest pixels. Low-pass filters are usually employed to remove the noise and extending the technique of Fuzzy k means clustering followed cropping mechanism, The ROI has been identified.

## 5. Feature Extraction

A feature is a value describing an object in a numerical form and the selection of good features is critical to the success of any classification algorithm. Rather than directly using the raw data, some measures or descriptors are often selected upon which, the classes of the observed objects are determined by classifier. These measures, commonly called features, form the feature space that is generally of a much lower dimension than the data space. The process of searching for internal structure in data items, that is, for features or properties of the data is called feature extraction. The process of choosing desirable features from the initial set of candidates is called feature selection. The relevancy of extracted features is determined either by trial and error or based on an automatic feature selection procedure [7].

Extraction of desirable features is an extremely difficult task and very much problem dependent [5]. In order to distinguish welds from non welds, features with discriminating capability must be identified [6]. In this process, 2D features are the average gray levels and the percentage of highlights of $I_1$, $I_2$, $I_3$, $I_4$ are extracted from the digitized images of samples. The Bitmap Images are read and stored it into an array variable. Then true color images are converted into a gray scale images. After this selection, a region of interest is cropped for further processing. Finally average values of pixels in the cropped images are computed and two types of feature extractions (2D feature vector and Gaussian distribution based features) as follows [1].

1) 2D feature vector

$$x=(x_1, x_2, x_3, x_4) \quad (1.1)$$

$$x_1 = \frac{1}{N}\sum_{(x,y)\in R} I_1\ (x,y) \quad (1.2)$$

$$x_2 = \frac{1}{N}\sum_{(x,y)\in R} I_2\ (x,y) \quad (1.3)$$

$$x_3 = \frac{1}{N}\sum_{(x,y)\in R} I_3\ (x,y) \quad (1.4)$$

$$x_4 = \frac{1}{N}\sum_{(x,y)\in R} I_4\ (x,y) \quad (1.5)$$

Where, x is the 2D feature vector

$x_1$ is the average gray scale value of zone 1 cropped image

$x_2$ is the average gray scale value of zone 2 cropped image

$x_3$ is the average gray scale value of zone 3 cropped image

$x_4$ is the average gray scale value of zone 4 cropped image

$I_i(x,y)$ is the image of ith layer,

R is the welded region, and N is the number of pixels in the welded region.

2) Gaussian distribution based features

(F1)Mean $\mu = A + \frac{1}{N}\sum_{i=1}^{n} f_i d_i$

where, $d_i = \frac{x_i - A}{C}$

(F2)Standard deviation

$$\sigma = \sqrt{c^2\left\{\frac{1}{N}\sum_{i=1}^{n} f_i {d_i}^2 - \left(\frac{1}{N}\sum_{i=1}^{n} f_i d_i\right)^2\right\}}$$

(F3)Co-eff of variation $C.V = 100 * \frac{\sigma}{\bar{x}}$

(F4)Median $M = l + \frac{h}{f}\left(\frac{N}{2} - c\right)$

(F5)Mode $Mo = l + \frac{h(f_1 - f_0)}{2f_1 - f_0 - f_2}$

(F6)Pearson's co-eff of skewness $S_k = \frac{3(M-M_o)}{\sigma}$

where σ is the standard deviation of the distribution

(F7)Bowley's co-eff of skewness $S_k = \frac{Q_3+Q_1-2M_d}{Q_3-Q_1}$

where, $Q_1 = l + \frac{c}{f}\left(\frac{N}{4} - m\right)$e,

$Q_3 = l + \frac{c}{f}\left(\frac{3N}{4} - m\right)$

(F8)Co-eff of kurtosis $\beta_4 = \frac{\mu_4}{\mu_2^2}$

where l is the lower limit of the median class,
f is the frequency of the median class,
h is the magnitude of the median class,
'c'is the c.f of the class preceding the median class, and N=∑f.
$f_1$ is the frequency of the modal class,

$f_o$ and $f_2$ are the frequencies of the classes preceding and succeeding the modal class respectively.
σ is the standard deviation of the distribution.
$Q_1$ is the first Quartile of the Distribution $Q_3$ is the first Quartile of the Distribution

The average gray values of pixels in the cropped images are calculated and tabulated. In this work, 80 welded image samples are taken into account for classification process. Table 1 shows the average gray values of 80 samples.

## 6. BPN Classifier

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the biological nervous systems, such as the brain process information. ANN has been successfully employed in similar applications to perform the classification. After feature selection, a back propagation neural network (BPN) is employed to perform the classification [14]. Block diagram of the back propagation neural net work is shown in Fig .7

**Table 1.1: The Average Gray Values of 80 Samples of Single zone Image (2D Feature Vector)**

| Sample No | Single zone | Type of weld | Sample No | Single zone | Type of weld |
|---|---|---|---|---|---|
| 1 | 128.1032 | No weld | 41 | 68.25344 | Excess weld |
| 2 | 127.89 | | 42 | 67.12 | |
| 3 | 126.89 | | 43 | 67.21 | |
| 4 | 127.45 | | 44 | 66.13 | |
| 5 | 126.45 | | 45 | 68.64 | |
| 6 | 127.59 | | 46 | 68.78 | |
| 7 | 126.59 | | 47 | 68.87 | |
| 8 | 127.48 | | 48 | 69.12 | |
| 9 | 126.48 | | 49 | 69.21 | |
| 10 | 125.89 | | 50 | 68.46 | |
| 11 | 129.56 | | 51 | 66.31 | |
| 12 | 128.29 | | 52 | 67.49 | |
| 13 | 128.489 | | 53 | 67.94 | |
| 14 | 127.489 | | 54 | 67.28 | |
| 15 | 126.47 | | 55 | 66.54 | |
| 16 | 127.69 | | 56 | 67.82 | |
| 17 | 128.95 | | 57 | 66.45 | |
| 18 | 129.12 | | 58 | 66.51 | |
| 19 | 128.7 | | 59 | 66.15 | |
| 20 | 128.12 | | 60 | 67.19 | |
| 21 | 51.74025 | Insufficient weld | 61 | 45.92654 | Good weld |
| 22 | 50.72 | | 62 | 44.12 | |
| 23 | 50.85 | | 63 | 44.21 | |
| 24 | 50.236 | | 64 | 44.89 | |
| 25 | 51.236 | | 65 | 45.21 | |
| 26 | 50.458 | | 66 | 45.12 | |
| 27 | 51.79 | | 67 | 44.98 | |
| 28 | 51.47 | | 68 | 45.56 | |
| 29 | 51.23 | | 69 | 45.65 | |
| 30 | 51.36 | | 70 | 46.28 | |
| 31 | 50.13 | | 71 | 46.27 | |
| 32 | 51.456 | | 72 | 46.76 | |
| 33 | 51.789 | | 73 | 46.67 | |
| 34 | 51.897 | | 74 | 46.94 | |
| 35 | 51.426 | | 75 | 46.49 | |
| 36 | 51.624 | | 76 | 46.82 | |
| 37 | 51.67 | | 77 | 46.35 | |
| 38 | 50.92 | | 78 | 46.53 | |
| 39 | 51.76 | | 79 | 47.94 | |
| 40 | 50.29 | | 80 | 47.58 | |

**Table 1.2: The Average Gray Values of 80 Samples of Single Zone Image (Gaussian distribution based features)**

| Sample No | Single zone | | | | | | | | Type of weld |
|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | |
| 1 | 91.80 | 52.78 | 57.50 | 90.00 | 79.58 | 0.03 | 0.05 | 2.51 | No weld |
| 2 | 91.50 | 52.71 | 56.50 | 89.00 | 79.48 | 0.03 | 0.04 | 2.52 | |
| 3 | 91.40 | 52.76 | 56.76 | 89.50 | 79.68 | 0.025 | 0.03 | 2.53 | |
| 4 | 91.26 | 52.58 | 56.98 | 88.45 | 78.99 | 0.027 | 0.06 | 2.51 | |
| 5 | 91.75 | 53.78 | 56.76 | 89.63 | 79.14 | 0.028 | 0.07 | 2.56 | |
| 6 | 92.00 | 54.78 | 56.50 | 89.47 | 78.36 | 0.027 | 0.04 | 2.54 | |
| 7 | 92.50 | 51.78 | 56.78 | 88.94 | 79.86 | 0.024 | 0.07 | 2.51 | |
| 8 | 92.23 | 52.30 | 57.24 | 91.00 | 79.24 | 0.023 | 0.06 | 2.53 | |
| 9 | 92.45 | 52.75 | 57.80 | 91.25 | 79.77 | 0.024 | 0.04 | 2.45 | |
| 10 | 92.78 | 52.46 | 57.23 | 91.50 | 79.79 | 0.023 | 0.05 | 2.47 | |
| 11 | 91.80 | 52.78 | 57.50 | 90.00 | 79.89 | 0.026 | 0.06 | 2.48 | |
| 12 | 91.50 | 52.71 | 56.50 | 89.00 | 77.98 | 0.028 | 0.07 | 2.49 | |
| 13 | 91.40 | 52.78 | 56.76 | 89.50 | 79.48 | 0.029 | 0.05 | 2.46 | |
| 14 | 91.26 | 52.58 | 56.78 | 88.45 | 79.35 | 0.026 | 0.06 | 2.41 | |
| 15 | 91.75 | 53.78 | 56.76 | 89.63 | 79.87 | 0.022 | 0.05 | 2.55 | |
| 16 | 92.00 | 54.78 | 56.50 | 89.47 | 79.68 | 0.021 | 0.06 | 2.65 | |
| 17 | 92.50 | 51.78 | 56.78 | 88.94 | 78.98 | 0.027 | 0.07 | 2.66 | |
| 18 | 92.50 | 52.30 | 57.24 | 91.00 | 79.31 | 0.028 | 0.05 | 2.68 | |
| 19 | 92.45 | 52.75 | 57.80 | 91.25 | 79.11 | 0.024 | 0.06 | 2.56 | |
| 20 | 92.78 | 52.46 | 57.23 | 91.50 | 78.37 | 0.028 | 0.07 | 2.45 | |
| Sample No | | | | | | | | | Type of weld |
| 21 | 94.14 | 47.11 | 50.04 | 91.50 | 98.18 | 0.06 | 0.13 | 2.27 | Insufficient weld |
| 22 | 95.14 | 46.11 | 51.14 | 92.50 | 98.82 | 0.05 | 0.32 | 2.77 | |
| 23 | 94.24 | 46.21 | 50.23 | 90.50 | 98.38 | 0.06 | 0.14 | 2.48 | |
| 24 | 94.34 | 47.21 | 50.07 | 93.50 | 99.18 | 0.05 | 0.14 | 2.38 | |
| 25 | 94.44 | 46.31 | 50.98 | 91.20 | 97.18 | 0.06 | 0.15 | 2.47 | |
| 26 | 95.14 | 47.41 | 49.98 | 91.80 | 97.82 | 0.05 | 0.15 | 2.57 | |
| 27 | 93.14 | 47.81 | 51.02 | 91.80 | 97.92 | 0.06 | 0.19 | 2.29 | |
| 28 | 95.00 | 46.11 | 48.99 | 91.90 | 98.82 | 0.06 | 0.20 | 2.30 | |
| 29 | 94.15 | 45.91 | 50.54 | 91.70 | 99.48 | 0.09 | 0.12 | 2.37 | |
| 30 | 94.90 | 47.11 | 50.23 | 90.40 | 98.23 | 0.05 | 0.12 | 2.48 | |
| 31 | 94.14 | 47.11 | 50.07 | 91.50 | 98.18 | 0.06 | 0.13 | 2.38 | |
| 32 | 95.14 | 46.11 | 50.98 | 92.50 | 98.82 | 0.06 | 0.32 | 2.47 | |
| 33 | 94.24 | 46.21 | 49.98 | 90.50 | 98.38 | 0.05 | 0.15 | 2.57 | |
| 34 | 95.00 | 47.21 | 51.02 | 93.50 | 99.18 | 0.09 | 0.15 | 2.29 | |
| 35 | 94.44 | 46.31 | 48.99 | 91.20 | 97.82 | 0.06 | 0.19 | 2.30 | |
| 36 | 95.14 | 47.41 | 50.54 | 91.60 | 97.82 | 0.05 | 0.20 | 2.37 | |
| 37 | 93.14 | 47.81 | 51.25 | 91.80 | 97.92 | 0.06 | 0.12 | 2.29 | |
| 38 | 95.00 | 46.11 | 51.30 | 91.90 | 98.82 | 0.06 | 0.12 | 2.30 | |
| 39 | 93.14 | 45.91 | 51.32 | 91.70 | 99.48 | 0.09 | 0.13 | 2.37 | |
| 40 | 94.44 | 47.81 | 51.02 | 90.40 | 98.23 | 0.09 | 0.32 | 2.47 | |
| Sample No | Single zone | | | | | | | | Type of weld |
| 41 | 103.14 | 47.58 | 46.13 | 109.20 | 117.00 | -0.13 | -0.11 | 4.63 | Excess |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 42 | 102.14 | 46.58 | 46.35 | 110.20 | 116.00 | -0.17 | -0.17 | 4.31 | weld |
| 43 | 102.24 | 46.68 | 46.46 | 111.00 | 115.00 | -0.13 | -0.11 | 4.83 | |
| 44 | 103.64 | 46.88 | 45.13 | 109.00 | 118.00 | -0.12 | -0.10 | 4.66 | |
| 45 | 103.44 | 45.58 | 45.43 | 109.70 | 119.00 | -0.16 | -0.07 | 4.53 | |
| 46 | 102.54 | 45.83 | 45.93 | 109.70 | 118.00 | -0.16 | -0.20 | 4.73 | |
| 47 | 103.54 | 45.58 | 45.85 | 108.80 | 118.00 | -0.14 | -0.19 | 4.66 | |
| 48 | 103.64 | 46.33 | 47.13 | 108.50 | 114.00 | -0.16 | -0.17 | 5.13 | |
| 49 | 104.14 | 47.78 | 46.15 | 109.50 | 119.00 | -0.20 | -0.11 | 5.23 | |
| 50 | 103.74 | 47.93 | 47.35 | 110.00 | 117.50 | -0.19 | -0.14 | 5.43 | |
| 51 | 103.14 | 47.58 | 46.13 | 109.20 | 117.00 | -0.13 | -0.11 | 4.63 | |
| 52 | 102.14 | 46.68 | 46.35 | 110.20 | 116.00 | -0.17 | -0.17 | 4.31 | |
| 53 | 102.24 | 46.68 | 46.46 | 111.00 | 115.00 | -0.13 | -0.11 | 4.83 | |
| 54 | 104.14 | 46.88 | 45.13 | 109.00 | 118.00 | -0.12 | -0.10 | 4.66 | |
| 55 | 103.44 | 45.58 | 45.43 | 109.80 | 119.00 | -0.16 | -0.07 | 4.53 | |
| 56 | 102.54 | 45.83 | 45.93 | 109.70 | 116.00 | -0.16 | -0.20 | 4.73 | |
| 57 | 103.54 | 46.53 | 47.13 | 108.80 | 118.00 | -0.14 | -0.19 | 4.68 | |
| 58 | 103.64 | 46.33 | 47.13 | 108.50 | 114.00 | -0.16 | -0.17 | 5.13 | |
| 59 | 104.14 | 47.78 | 47.35 | 110.00 | 119.00 | -0.20 | -0.11 | 5.23 | |
| 60 | 103.74 | 47.93 | 47.35 | 110.00 | 117.50 | -0.19 | -0.14 | 5.43 | |
| Sample No | | | | | | | | | Type of weld |
| 61 | 92.34 | 51.32 | 55.58 | 104.40 | 100.80 | -0.23 | -0.32 | 2.48 | |
| 62 | 91.30 | 50.32 | 54.58 | 103.57 | 100.50 | -0.29 | -0.38 | 2.78 | |
| 63 | 94.20 | 51.42 | 55.68 | 104.11 | 100.90 | -0.22 | -0.31 | 2.82 | |
| 64 | 93.40 | 50.56 | 55.98 | 104.42 | 99.65 | -0.30 | -0.33 | 2.62 | |
| 65 | 92.60 | 51.12 | 53.98 | 104.17 | 100.01 | -0.23 | -0.34 | 2.47 | |
| 66 | 91.70 | 51.25 | 52.98 | 103.94 | 100.90 | -0.25 | -0.34 | 2.48 | |
| 67 | 91.80 | 50.58 | 54.76 | 104.14 | 100.30 | -0.30 | -0.30 | 2.18 | |
| 68 | 92.42 | 51.33 | 55.58 | 103.40 | 100.50 | -0.28 | -0.35 | 2.28 | |
| 69 | 92.56 | 50.63 | 55.58 | 104.97 | 100.19 | -0.25 | -0.38 | 2.38 | |
| 70 | 92.54 | 51.62 | 55.56 | 103.12 | 99.97 | -0.24 | -0.37 | 2.46 | |
| 71 | 92.34 | 51.32 | 55.58 | 104.40 | 100.21 | -0.23 | -0.32 | 2.48 | |
| 72 | 92.54 | 50.32 | 54.58 | 103.57 | 100.90 | -0.29 | -0.38 | 2.78 | |
| 73 | 94.20 | 51.42 | 55.68 | 104.11 | 100.30 | -0.22 | -0.31 | 2.82 | Good weld |
| 74 | 93.40 | 50.56 | 55.98 | 104.42 | 100.30 | -0.30 | -0.33 | 2.82 | |
| 75 | 92.60 | 51.12 | 55.56 | 104.17 | 100.50 | -0.23 | -0.30 | 2.47 | |
| 76 | 91.70 | 51.25 | 52.98 | 103.94 | 100.19 | -0.25 | -0.34 | 2.48 | |
| 77 | 91.80 | 50.58 | 54.76 | 104.14 | 99.97 | -0.30 | -0.30 | 2.18 | |
| 78 | 92.42 | 51.33 | 55.58 | 103.40 | 100.21 | -0.28 | -0.35 | 2.28 | |
| 79 | 92.56 | 50.63 | 55.58 | 104.42 | 100.90 | -0.25 | -0.38 | 2.38 | |
| 80 | 92.54 | 51.62 | 55.56 | 103.12 | 100.30 | -0.24 | -0.37 | 2.46 | |

**Table 2.1: Inputs and Outputs of the Training Samples (2D feature vector)**

| Sample No | Input | Output | Type of weld | Sample No | Input | Output | Type of weld |
|---|---|---|---|---|---|---|---|
| 1 | 0.988756 | 1 | | 41 | 0.986179 | 0.5 | |
| 2 | 0.98711 | 1 | | 42 | 0.969802 | 0.5 | |
| 3 | 0.979392 | 1 | | 43 | 0.971102 | 0.5 | |
| 4 | 0.983714 | 1 | | 44 | 0.955498 | 0.5 | |
| 5 | 0.975996 | 1 | | 45 | 0.991764 | 0.5 | |
| 6 | 0.984795 | 1 | | 46 | 0.993787 | 0.5 | |
| 7 | 0.977076 | 1 | | 47 | 0.995087 | 0.5 | |
| 8 | 0.983946 | 1 | | 48 | 0.9987 | 0.5 | |
| 9 | 0.976227 | 1 | | 49 | 1 | 0.5 | |
| 10 | 0.971673 | 1 | | 50 | 0.989163 | 0.5 | Excess weld |
| 11 | 1 | 1 | No weld | 51 | 0.958099 | 0.5 | |
| 12 | 0.990198 | 1 | | 52 | 0.975148 | 0.5 | |
| 13 | 0.991734 | 1 | | 53 | 0.98165 | 0.5 | |
| 14 | 0.984015 | 1 | | 54 | 0.972114 | 0.5 | |
| 15 | 0.97615 | 1 | | 55 | 0.961422 | 0.5 | |
| 16 | 0.985567 | 1 | | 56 | 0.979916 | 0.5 | |
| 17 | 0.995292 | 1 | | 57 | 0.960121 | 0.5 | |
| 18 | 0.996604 | 1 | | 58 | 0.960988 | 0.5 | |
| 19 | 0.993362 | 1 | | 59 | 0.955787 | 0.5 | |
| 20 | 0.988885 | 0.75 | | 60 | 0.970813 | 0.5 | |
| **Sample No** | **Input** | **Output** | **Type of weld** | **Sample No** | **Input** | **Output** | **Type of weld** |
| 21 | 0.99698 | 0.75 | | 61 | 0.958 | 0.25 | |
| 22 | 0.97732 | 0.75 | | 62 | 0.920317 | 0.25 | |
| 23 | 0.979825 | 0.75 | | 63 | 0.922194 | 0.25 | |
| 24 | 0.967994 | 0.75 | | 64 | 0.936379 | 0.25 | |
| 25 | 0.987263 | 0.75 | | 65 | 0.943054 | 0.25 | |
| 26 | 0.972272 | 0.75 | | 66 | 0.941176 | 0.25 | |
| 27 | 0.997938 | 0.75 | | 67 | 0.938256 | 0.25 | |
| 28 | 0.991772 | 0.75 | | 68 | 0.950355 | 0.25 | |
| 29 | 0.987148 | 0.75 | | 69 | 0.952232 | 0.25 | |
| 30 | 0.989653 | 0.75 | Insufficient weld | 70 | 0.965373 | 0.25 | Good weld |
| 31 | 0.965952 | 0.75 | | 71 | 0.965165 | 0.25 | |
| 32 | 0.991502 | 0.75 | | 72 | 0.975386 | 0.25 | |
| 33 | 0.997919 | 0.75 | | 73 | 0.973509 | 0.25 | |
| 34 | 1 | 0.75 | | 74 | 0.979141 | 0.25 | |
| 35 | 0.990924 | 0.75 | | 75 | 0.969754 | 0.25 | |
| 36 | 0.99474 | 0.75 | | 76 | 0.976637 | 0.25 | |
| 37 | 0.995626 | 0.75 | | 77 | 0.966834 | 0.25 | |
| 38 | 0.981174 | 0.75 | | 78 | 0.970588 | 0.25 | |
| 39 | 0.99736 | 0.75 | | 79 | 1 | 0.25 | |
| 40 | 0.969035 | 0.75 | | 80 | 0.992491 | 0.25 | |

**Table 2.2: Inputs and Outputs of the Training Samples (Gaussian Distribution Based Features)**

| Sample No | Single zone | | | | | | | | Output | Type of weld |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.9894374 | 0.96349032 | 0.994809689 | 0.98360656 | 0.996119665 | 0.03 | 0.05 | 0.93656716 | 1 | |
| 2 | 0.9862039 | 0.96221249 | 0.977508651 | 0.9726776 | 0.994867943 | 0.03 | 0.04 | 0.94029851 | 1 | |
| 3 | 0.9851261 | 0.96312523 | 0.98200692 | 0.97814208 | 0.997371386 | 0.025 | 0.03 | 0.94402985 | 1 | |
| 4 | 0.9836172 | 0.95983936 | 0.985813149 | 0.96666667 | 0.98873451 | 0.027 | 0.06 | 0.93656716 | 1 | |
| 5 | 0.9888985 | 0.98174516 | 0.98200692 | 0.97956284 | 0.990612092 | 0.028 | 0.07 | 0.95522388 | 1 | |
| 6 | 0.991593 | 1 | 0.977508651 | 0.97781421 | 0.980848667 | 0.027 | 0.04 | 0.94776119 | 1 | |
| 7 | 0.9969821 | 0.94523549 | 0.982352941 | 0.97202186 | 0.999624484 | 0.024 | 0.07 | 0.93656716 | 1 | No weld |
| 8 | 0.994072 | 0.954728 | 0.990311419 | 0.99453552 | 0.991863813 | 0.023 | 0.06 | 0.94402985 | 1 | |
| 9 | 0.9964432 | 0.96294268 | 1 | 0.99726776 | 0.998497935 | 0.024 | 0.04 | 0.9141791 | 1 | |
| 10 | 1 | 0.95764878 | 0.990138408 | 1 | 0.998748279 | 0.023 | 0.05 | 0.92164179 | 1 | |
| 11 | 0.9894374 | 0.96349032 | 0.994809689 | 0.98360656 | 1 | 0.026 | 0.06 | 0.92537313 | 1 | |
| 12 | 0.9862039 | 0.96221249 | 0.977508651 | 0.9726776 | 0.976092127 | 0.028 | 0.07 | 0.92910448 | 1 | |
| 13 | 0.9851261 | 0.96349032 | 0.98200692 | 0.97814208 | 0.994867943 | 0.029 | 0.05 | 0.91791045 | 1 | |
| 14 | 0.9836172 | 0.95983936 | 0.982352941 | 0.96666667 | 0.993240706 | 0.026 | 0.06 | 0.89925373 | 1 | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 15 | 0.9888985 | 0.98174516 | 0.98200692 | 0.97956284 | 0.999749656 | 0.022 | 0.05 | 0.95149254 | 1 | |
| 16 | 0.991593 | 1 | 0.977508651 | 0.97781421 | 0.997371386 | 0.021 | 0.06 | 0.98880597 | 1 | |
| 17 | 0.9969821 | 0.94523549 | 0.982352941 | 0.97202186 | 0.988609338 | 0.027 | 0.07 | 0.99253731 | 1 | |
| 18 | 0.9969821 | 0.954728 | 0.990311419 | 0.99453552 | 0.992740018 | 0.028 | 0.05 | 1 | 1 | |
| 19 | 0.9964432 | 0.96294268 | 1 | 0.99726776 | 0.990236575 | 0.024 | 0.06 | 0.95522388 | 1 | |
| 20 | 1 | 0.95764878 | 0.990138408 | 1 | 0.980973839 | 0.028 | 0.07 | 0.9141791 | 1 | |
| 21 | 91.169077 | 0.9894892 | 0.98535871 | 0.975058457 | 0.97860963 | 1.070665213 | 0.06 | 0.13 | 0.75 | |
| 22 | 90.928026 | 1 | 0.96444259 | 0.996492595 | 0.98930481 | 1.077644493 | 0.05 | 0.32 | 0.75 | |
| 23 | 82.542881 | 0.9905403 | 0.9665342 | 0.978760717 | 0.96791444 | 1.072846238 | 0.06 | 0.14 | 0.75 | |
| 24 | 82.077996 | 0.9915913 | 0.98745032 | 0.975643024 | 1 | 1.081570338 | 0.05 | 0.14 | 0.75 | |
| 25 | 80.924393 | 0.9926424 | 0.96862581 | 0.993374903 | 0.97540107 | 1.059760087 | 0.06 | 0.15 | 0.75 | |
| 26 | 77.859597 | 1 | 0.99163355 | 0.973889322 | 0.98181818 | 1.066739368 | 0.05 | 0.15 | 0.75 | |
| 27 | 80.61447 | 0.9789783 | 1 | 0.994154326 | 0.98181818 | 1.06782988 | 0.06 | 0.19 | 0.75 | |
| 28 | 76.120583 | 0.9985285 | 0.96444259 | 0.954598597 | 0.9828877 | 1.077644493 | 0.06 | 0.2 | 0.75 | |
| 29 | 78.841021 | 0.9895943 | 0.96025936 | 0.984801247 | 0.98074866 | 1.084841876 | 0.09 | 0.12 | 0.75 | Insufficient weld |
| 30 | 101.36211 | 0.9974774 | 0.98535871 | 0.978760717 | 0.96684492 | 1.071210469 | 0.05 | 0.12 | 0.75 | |
| 31 | 100.65617 | 0.9894892 | 0.98535871 | 0.975643024 | 0.97860963 | 1.070665213 | 0.06 | 0.13 | 0.75 | |
| 32 | 100.65617 | 1 | 0.96444259 | 0.993374903 | 0.98930481 | 1.077644493 | 0.06 | 0.32 | 0.75 | |
| 33 | 109.90221 | 0.9905403 | 0.9665342 | 0.973889322 | 0.96791444 | 1.072846238 | 0.05 | 0.15 | 0.75 | |
| 34 | 107.23343 | 0.9985285 | 0.98745032 | 0.994154326 | 1 | 1.081570338 | 0.09 | 0.15 | 0.75 | |
| 35 | 105.52885 | 0.9926424 | 0.96862581 | 0.954598597 | 0.97540107 | 1.066739368 | 0.06 | 0.19 | 0.75 | |
| 36 | 100.05354 | 1 | 0.99163355 | 0.984801247 | 0.97967914 | 1.066739368 | 0.05 | 0.2 | 0.75 | |
| 37 | 99.089337 | 0.9789783 | 1 | 0.998636009 | 0.98181818 | 1.06782988 | 0.06 | 0.12 | 0.75 | |
| 38 | 99.244298 | 0.9985285 | 0.96444259 | 0.999610288 | 0.9828877 | 1.077644493 | 0.06 | 0.12 | 0.75 | |
| 39 | 93.855078 | 0.9789783 | 0.96025936 | 1 | 0.98074866 | 1.084841876 | 0.09 | 0.13 | 0.75 | |
| 40 | 94.474925 | 0.9926424 | 1 | 0.994154326 | 0.96684492 | 1.071210469 | 0.09 | 0.32 | 0.75 | |
| Sample No | | | | Single zone | | | | | Output | Type of weld |
| 41 | 0.9903975 | 0.99269768 | 0.974234424 | 0.98378378 | 0.983193277 | -0.13 | -0.11 | 0.85267035 | 0.5 | |
| 42 | 0.9807951 | 0.97183392 | 0.978880676 | 0.99279279 | 0.974789916 | -0.17 | -0.17 | 0.79373849 | 0.5 | |
| 43 | 0.9817553 | 0.9739203 | 0.981203801 | 1 | 0.966386555 | -0.13 | -0.11 | 0.88950276 | 0.5 | |
| 44 | 0.9951988 | 0.97809305 | 0.9531151 | 0.98198198 | 0.991596639 | -0.12 | -0.1 | 0.85819521 | 0.5 | |
| 45 | 0.9932783 | 0.95097016 | 0.959450898 | 0.98828829 | 1 | -0.16 | -0.07 | 0.83425414 | 0.5 | |
| 46 | 0.9846361 | 0.9561861 | 0.97001056 | 0.98828829 | 0.991596639 | -0.16 | -0.2 | 0.87108656 | 0.5 | |
| 47 | 0.9942385 | 0.95097016 | 0.968321014 | 0.98018018 | 0.991596639 | -0.14 | -0.19 | 0.85819521 | 0.5 | |
| 48 | 0.9951988 | 0.96661798 | 0.995353749 | 0.97747748 | 0.957983193 | -0.16 | -0.17 | 0.94475138 | 0.5 | |
| 49 | 1 | 0.99687044 | 0.974656811 | 0.98648649 | 1 | -0.2 | -0.11 | 0.96316759 | 0.5 | |
| 50 | 0.996159 | 1 | 1 | 0.99099099 | 0.987394958 | -0.19 | -0.14 | 1 | 0.5 | |
| 51 | 0.9903975 | 0.99269768 | 0.974234424 | 0.98378378 | 0.983193277 | -0.13 | -0.11 | 0.85267035 | 0.5 | |
| 52 | 0.9807951 | 0.9739203 | 0.978880676 | 0.99279279 | 0.974789916 | -0.17 | -0.17 | 0.79373849 | 0.5 | Excess weld |
| 53 | 0.9817553 | 0.9739203 | 0.981203801 | 1 | 0.966386555 | -0.13 | -0.11 | 0.88950276 | 0.5 | |
| 54 | 1 | 0.97809305 | 0.9531151 | 0.98198198 | 0.991596639 | -0.12 | -0.1 | 0.85819521 | 0.5 | |
| 55 | 0.9932783 | 0.95097016 | 0.959450898 | 0.98918919 | 1 | -0.16 | -0.07 | 0.83425414 | 0.5 | |
| 56 | 0.9846361 | 0.9561861 | 0.97001056 | 0.98828829 | 0.974789916 | -0.16 | -0.2 | 0.87108656 | 0.5 | |
| 57 | 0.9942385 | 0.97079074 | 0.995353749 | 0.98018018 | 0.991596639 | -0.14 | -0.19 | 0.86187845 | 0.5 | |
| 58 | 0.9951988 | 0.96661798 | 0.995353749 | 0.97747748 | 0.957983193 | -0.16 | -0.17 | 0.94475138 | 0.5 | |
| 59 | 1 | 0.99687044 | 1 | 0.99099099 | 1 | -0.2 | -0.11 | 0.96316759 | 0.5 | |
| 60 | 0.996159 | 1 | 1 | 0.99099099 | 0.987394958 | -0.19 | -0.14 | 1 | 0.5 | |
| 61 | 0.9802548 | 0.9941883 | 0.992854591 | 0.96027436 | 0.99900892 | -0.23 | -0.32 | 0.87943262 | 0.25 | |
| 62 | 0.9692144 | 0.97481596 | 0.974991068 | 0.9574164 | 0.996035679 | -0.29 | -0.38 | 0.9858156 | 0.25 | |
| 63 | 1 | 0.99612553 | 0.994640943 | 0.96122702 | 1 | -0.22 | -0.31 | 1 | 0.25 | |
| 64 | 0.9915074 | 0.97946532 | 1 | 0.94931885 | 0.987611497 | -0.3 | -0.33 | 0.92907801 | 0.25 | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 65 | 0.9830149 | 0.99031383 | 0.964272955 | 0.9527484 | 0.991179386 | -0.23 | -0.34 | 0.87588652 | 0.25 | |
| 66 | 0.9734607 | 0.99283224 | 0.946409432 | 0.96122702 | 1 | -0.25 | -0.34 | 0.87943262 | 0.25 | |
| 67 | 0.9745223 | 0.97985277 | 0.978206502 | 0.9555111 | 0.994053518 | -0.3 | -0.3 | 0.77304965 | 0.25 | Good weld |
| 68 | 0.981104 | 0.99438202 | 0.992854591 | 0.9574164 | 0.996035679 | -0.28 | -0.35 | 0.80851064 | 0.25 | |
| 69 | 0.9825902 | 0.98082139 | 0.992854591 | 0.95446318 | 0.99296333 | -0.25 | -0.38 | 0.84397163 | 0.25 | |
| 70 | 0.9823779 | 1 | 0.99249732 | 0.95236734 | 0.990782953 | -0.24 | -0.37 | 0.87234043 | 0.25 | |
| 71 | 0.9802548 | 0.9941883 | 0.992854591 | 0.95465371 | 0.993161546 | -0.23 | -0.32 | 0.87943262 | 0.25 | |
| 72 | 0.9823779 | 0.97481596 | 0.974991068 | 0.96122702 | 1 | -0.29 | -0.38 | 0.9858156 | 0.25 | |
| 73 | 1 | 0.99612553 | 0.994640943 | 0.9555111 | 0.994053518 | -0.22 | -0.31 | 1 | 0.25 | |
| 74 | 0.9915074 | 0.97946532 | 1 | 0.9555111 | 0.994053518 | -0.3 | -0.33 | 1 | 0.25 | |
| 75 | 0.9830149 | 0.99031383 | 0.99249732 | 0.9574164 | 0.996035679 | -0.23 | -0.3 | 0.87588652 | 0.25 | |
| 76 | 0.9734607 | 0.99283224 | 0.946409432 | 0.95446318 | 0.99296333 | -0.25 | -0.34 | 0.87943262 | 0.25 | |
| 77 | 0.9745223 | 0.97985277 | 0.978206502 | 0.95236734 | 0.990782953 | -0.3 | -0.3 | 0.77304965 | 0.25 | |
| 78 | 0.981104 | 0.99438202 | 0.992854591 | 0.95465371 | 0.993161546 | -0.28 | -0.35 | 0.80851064 | 0.25 | |
| 79 | 0.9825902 | 0.98082139 | 0.992854591 | 0.96122702 | 1 | -0.25 | -0.38 | 0.84397163 | 0.25 | |
| 80 | 0.9823779 | 1 | 0.99249732 | 0.9555111 | 0.994053518 | -0.24 | -0.37 | 0.87234043 | 0.25 | |

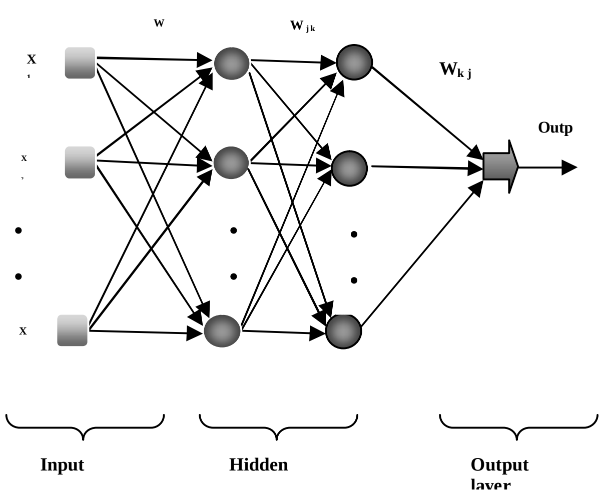



**Fig. 7 Block Diagram of Back Propagation Neural Network**

The back propagation algorithm minimizes the squares of the differences between actual output and desired output unit for all training pairs. The error obtained when training pair consisting of both input and output given to the input layer of the network, is given by equation

$$E_p=\frac{1}{2}\sum_i (T_{pi}-O_{pi})2 \quad (2.1)$$

Where,

Tpi is the i th component of the desired output.

Oi is the calculated output of i th neuron in the output layer.

The overall error of all the patterns is given by,

$$E = \sum Ep \quad (2.2)$$

To obtain a gradient descent in E, the weight W has to be updated

$$W_{ij} = \eta \partial pj O pj \quad (2.3)$$

Where,

$\eta$ is a constant real number called learning rate, which determines the influence of error over weight change.

$\partial$pj is the error due to the P th pattern connected to J th neuron.

Opj is the i th neuron output, when P th is processed by the network.

In the gradient descent equation (2.3), the error value pj can be computed as follows

$$\partial \partial_{pj}=o_{pj}(1-O_{pj})\,(T_{pj}-O_{pj}) \quad (2.4)$$

For hidden layers,

$$\partial_{pj}=O_{pj}(1-O_{pj})\sum O_{pj} W_{jk} \quad (2.5)$$

In this work, BPN classifier is used to classify the weld joints. The back propagation algorithm was used to train the network. The network was trained by using average gray values for four zones of images as input variables and types of weld joint as output variable.

In order to improve the performance of the system, normalizing the data is important. It can make the neural network training more efficient due to a significant reduction of the dimensionality of the input data.Normalization is done as follows.

$$x_1 = \frac{x_1}{x_{max}} \quad (2.6)$$

Where $x_1$ - average gray scale value of zone1 image.

$x_{max}$ – Maximum gray scale value of all zone images.

Table.2 shows the inputs and outputs of the training samples

- The features like average gray values of four zones for four types of weld joints are the inputs given to the input layer of ANN.
- The weights between input layer & hidden layer and weights between hidden layer and output layer are generated randomly for the selected topology 4-5-5-1 of the network.
- The number of training patterns used for training is 80.
- The patterns were normalized.
- The training was done off-line using the computer.

The training function TRAINLM is used in this network. The application of Leven berg-Marquardt to neural network training is the fastest method for training moderate – sized feed forward neural network. In many cases, Trainlm is able to obtain lower mean square errors than any of the other algorithms tested. Number of iterations in this work is 5000, learning rate is 0.0001, hyperbolic tangent function is an activation function and three layered feed forward BPN is used.

## 7. Results and discussions

In this work, the 80 weld joint samples are used for training and testing respectively. In each set, 20 images are used for each type, giving a total of 80 images for one good and three defect types training. For testing of sample, 80 images are used in the BPN network. The training data fed into the neural network are average gray values of four images for four zones as input variables and type of weld joint as output variable. Table.3 shows the training and test data of the four types of weld like Good, Excess insufficient and no weld.

**Table.3. Training and test data of the four types of weld**

| S.No | Type of weld | Training data | Test data |
|---|---|---|---|
| 1 | Good | 20 | 20 |
| 2 | Excess weld | 20 | 20 |
| 3 | Insufficient weld | 20 | 20 |
| 4 | No-Weld | 20 | 20 |
| | Total | 80 | 80 |

Network with different topologies have been tried. It is found that 4-5-5-1 architecture offers the accurate prediction than any other network structure. The average training error depends upon the iteration number. The performance of the trained BPN can be reiterated by using set of unseen pattern is known as testing or validation. The second group of data obtained is used for validation. Accuracy of the BPN is determined by means of recognition rate. The recognition rate is mostly depending on the number of hidden neurons and learning rate used in the network. The recognition rate is defined as follows.

$$\text{Recognition rate} = \frac{\text{Number of unseen patterns correctly classified}}{\text{Total number of unseen patterns}} \times 100$$

The network was trained at 0.0001 allowable errors, it can be seen that the error coverage was 7.8222e-005. The performance of the proposed classifier has been evaluated in terms of recognition rate and execution time. The classification performance of individual defect type is shown in Table 4.

**Table 4.1: Classification Performance of Different Types of Welding Images (2D feature vector)**

| S.No | Class | Number | Result | | | |
|---|---|---|---|---|---|---|
| | | | Correct | Incorrect | Correct (%) | Incorrect (%) |
| 1 | Good weld | 20 | 19 | 1 | 95 | 5 |
| 2 | Excess weld | 20 | 18 | 2 | 90 | 10 |
| 3 | Insufficient weld | 20 | 18 | 2 | 90 | 10 |
| 4 | No-weld | 20 | 18 | 2 | 90 | 10 |
| | Total | 80 | 73 | 7 | 91.25 | 8.75 |

**Table 4.2: Classification Performance of Different Types of Welding Images (Gaussian Distribution based Features)**

| S.No | Class | Number | Result | | | |
|---|---|---|---|---|---|---|
| | | | Correct | Incorrect | Correct (%) | Incorrect (%) |
| 1 | Good weld | 20 | 19 | 1 | 95 | 5 |
| 2 | Excess weld | 20 | 19 | 1 | 95 | 5 |
| 3 | Insufficient weld | 20 | 18 | 2 | 90 | 10 |
| 4 | No-weld | 20 | 18 | 2 | 90 | 10 |
| | Total | 80 | 74 | 6 | 92.5 | 7.5 |

For individual comparison, it was found that the accuracy varies with the type of defect. The highest accuracy is 95% for Good,Excess weld and the lowest is for Insufficient, No-weld (90%). The overall accuracy is 92.5%. As a matter of fact, 2D feature shows a significant difference in comparison test. Performance of BPN network using 80 samples is shown in Fig.8.

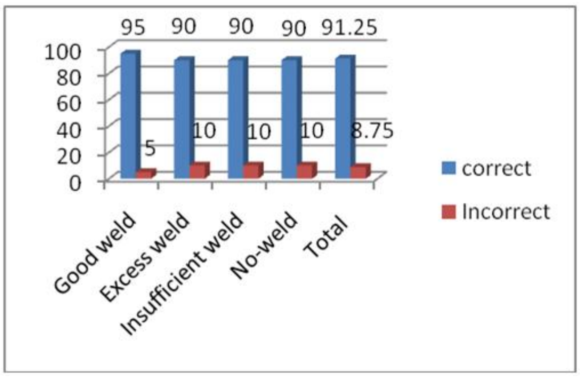



**Fig.8.1 Classification Performance of BPN Network using 80 Samples(2D feature vector)**

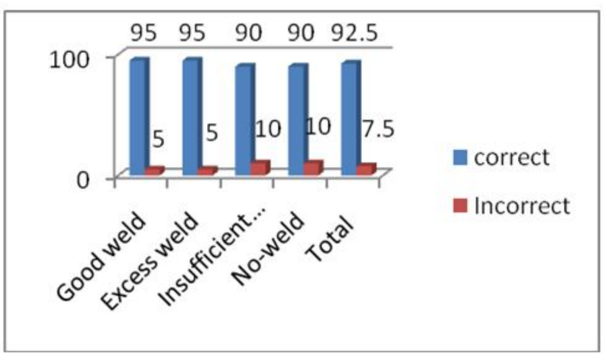



**Fig. 8.2 Classification performance of BPN Network using 80 Samples (Gaussian Distribution based Features)**

## 8. Conclusion

This paper has described a method for automatic inspection for welded joints using 2D feature extraction and Gaussian based feature . Performance of vision system using 2D feature extraction is 91.25 %. But in the performance using Gaussian based feature is 92.5 %. Table 5 & Fig.9 show the comparison of performance level of vision system using these two types of feature extractions. It can be used in computer aided inspection of welding defects in manufacturing systems. This vision based inspection system could be further used for classification of images with different joints in welding process.

**Table 5: Comparison of Different Types of Feature Extraction**

| S.No | Feature extraction | over all accuracy |
|---|---|---|
| 1. | 2D Feature vector | 91.25% |
| 2. | Gaussian Feature | 92.5% |

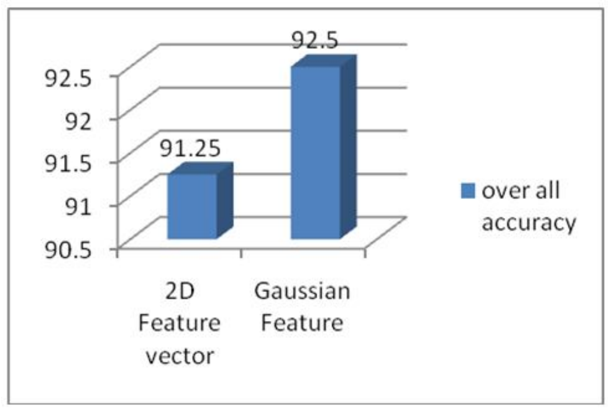



**Fig. 9 Comparison Chart for Different Types of Feature Extraction with Overall Accuracy**

## 9. References

1. *Tae-Hyeon Kim, Tai-Hoon Cho, Young Shik Moon and Sung Han Park (1999), "Visual Inspection System for the Classification of Solder Joints", Pattern Recognition, Vol. 32, 565-575.*

2. *S. Jagannathan (1997), "Automatic Inspection of Wave Soldered Joints using Neural Networks", Journal of Manufacturing Systems, Vol. 16.*

3. *Jagannathan S (1990), "Intelligent Inspection of Wave Soldered Joints - Technical Report", Journal of Manufacturing Systems, Vol. 11.*

4. *Elias N, Malamas, Euripides G M, Petrakis, Michalis Zervakis, Laurent Petit (2003), "A Survey on Industrial Vision Systems, Applications and Tools Image and computing", Vol. 21, 171-188.*

5. *Liao T W, Li D M and Li Y M (1999), "Detection of Welding Flaws from Radiographic Images with Fuzzy Clustering Methods", Fuzzy Sets and Systems, Vol. 108, 145-158.*

6. *Waren Liao T and Tang K (1997), "Automated Extraction of Welds from Digitized Radiographic Images based on MLP Neural Networks", Applied Artificial Intelligence, Vol. 11, 197-218.*

7. *Waren Liao T, Damin Li and Yueming Li (2000), "Extraction of Welds from Radiographic Images using Fuzzy Classifiers", Information Sciences, Vol. 126, 21-40.*

8. *Lashkia V (2001), "Defect Detection in X-ray Images using fuzzy reasoning", Image and Vision Computing, Vol. 19, 261-269.*

9. *Gauss M, Buerkle A, Laengle T, Woern H, Stelter J, Ruhmkorf S and Middelmann R (2003), "Adaptive Robot based Visual Inspection of Complex Parts", ISR2003.*

10. *Liao T W (2003), "Classification of Welding Flaw types with Fuzzy Expert Systems", Expert Systems with Application, Vol. 25, 101-111.*

11. *Romeu R, Da Silva, Luiz P, Caloba, Marcio H S, Siqueira, Joao M A and Rebello (2004), "Pattern Recognition of Weld Defects Detected by Radiographic Test", NDT&E International Vol. 37, 461-470.*

12. *Rafael Vilar, Juan Zapata and Ramon Ruiz (2009), "An Automatic System of Classification of Weld Defects in Radiographic Images", NDT&E International, Vol. 42, 467-476.*

13. *Yan Wang, Yi Sun, Peng L V and Hao Wang (2008), "Detection of Line Weld Defects based on Multiple Thresholds and Support Vector Machine", NDT&E International, Vol. 41, 517-524.*

14. *Garcia-Allende P B, Mirapeix J, Conde O M, Cobo A and Lopez-Higuera J M (2009), "Spectral Processing Technique based on Feature Selection and Artificial Neural Networks for Arc-Welding Quality Monitoring", NDT&E International, Vol. 42, 56-63.*

15. *Miguel Carrasco and Domingo Merry (2010), "Automatic Multiple View Inspection using Geometrical Tracking and Feature Analysis in Aluminum Wheels", Machine Vision and Applications.*

16. *Liao T W and Li Y M (2000), "An Automated Radiographic NDT System for Weld Inspection: part II- Flaw Detection", NDT &E International, Vol. 31, 183-192.*

17. *Senthilkumar G, Natarajan U and Ananthan S S (2011), "Vision Inspection System for the Identification and Classification of Defects in MIG Welding Joints", The International Journal of Advanced Manufacturing Technology.*

18. *Senthilkumar G, Natarajan U and Sankaranarayanan G (2011), "Performace Evaluation of Vision Inspection System for MIG Welding Defects", DOI:AA042011002.*