

TWO DIMENSIONAL DEEP LEARNING NETWORK FOR WELD FLAW CHARACTERIZATION FROM ULTRASONIC SIGNALS

Submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in
Electronics and Communication.

By

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
SCHOOL OF ELECTRONICS AND
COMMUNICATION ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

Accredited with Grade "A" by NAAC I 12B Status by UGC I Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

APRIL - 2021



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DEPARTMENT OF ELECTRONICS AND COMMUNICATION

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of Aldrin Shaji Lukose (37130015), Sri Sai Prasanth (37130014).who carried out the project entitled "**TWO DIMENSIONAL DEEP LEARNING NETWORK FOR WELD FLAW CHARACTERIZATION FROM ULTRASONIC SIGNAL**" under my / our supervision from NOVEMBER2020 to MARCH2021.

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Submitted for Viva voce Examination held on

Internal Examiner

External Examiner

DECLARATION

I Aldrin Shaji Lukose (37130015) and Sri Sai Prasanth (37130014) hereby declare that the Project Report entitled "TWO DIMENSIONAL DEEP LEARNING NETWORK FOR WELD FLAW CHARACTERIZATION FROM ULTRASONIC SIGNAL "done by us under the guidance of Dr. N.M.Nandhitha, ME, PHD .is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics And Communication.

DATE:**PLACE: SIGNATURE OF THE CANDIDATE**

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I convey my thanks to Dr. N.M.Nandhitha, M.E, ph. D. Dean, School of Electrical And Electronics Engineering and Dr. T. RAVI, M.E, ph. D, Head of the Department, Dept. of Electronics And Communication Engineering for providing me necessary support and details at the right time during the progressive reviews.

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ABSTRACT

Computer maintained Interpretation of Ultrasonic signals portraying absconds in weld pieces is portrayed in this work. In this work, believability of Long Short Term Memory (LSTM) for imperfection portrayal is examined. Attributable to the benefit of LSTM, the fundamental framework fuses arranging LSTM unmistakably with the signals as information sources and testing its capacity to portray the imperfections from the data signals. Taking into account wide variety in the length of data groupings, which presented insufficiency in different strategies, by and large exactness is affected. As such in the subsequent system, LSTM are set up with highlights of the signals and it is tracked down that the general exactness for test information is 67.64%. These highlights are genuine cutoff points acquired from the measure co-equipped for the information signals. The information signals are decayed with a novel wavelet plan. Regardless the necessities in consolidate extraction again impacts the presentation of the proposed framework. Thus the proposed works targets making two dimensional convolutional neural relationship for the blemish portrayal from ultrasonic signals.

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CHAPTER 1

INTRODUCTION

Welding technology has advanced to the point that massive amounts of welds can be accumulated. As a result, quality inspection of weld pieces is required prior to delivering welded piece to purchasers. UT (Ultrasonic Testing) is used for detecting surface and subsurface defects. Ultrasonic testing is divided in two categories: resounding (reflected wave appraisal) and Time of Flight Diffraction, which involves plotting and isolating the sent wave. The high recurrent Ultrasonic sign is expressed from the imperfection when a distortion occurs in a weld object. The error representation of this sign is then plotted and evaluated.

The depiction of flaws entails observing the distortion, its parcel from the surface, the form, and the direction of the defect. In this piece, depiction proposes a simple check of a specific flaw. Around here, a broad assessment is carried out. Munira et al. (2018) suggested a metric for depicting distortions such as slag, entry non-attendance, And so on using neural affiliation, there is no presence of mix, split, or porosity. S Esther Florence et al suggested a flaw depiction based on a fictitious neural affiliation with bending top adequacy as a simple cutoff. BorMojskerc et al (2017) suggested an assessment technique for concrete joints. K. Sudheera et al. (2019) improved a mechanized PC-controlled apparatus for improving and isolating weld deformity from weld radiographs. Principal Component Analysis (PCA) is an overall structured contraption for knowledge game-plan, according to Varun Gupta et al., (2011). WangXiaokai et al., (2018) used a molecule swarm streamlining support vector machine to finish the get-together of the twists on 100 occasions of spot welding absconds. Highlights were killed and the get-together of the twists was completed (PSO-SVM). Achieving 90+ affectability and separation is currently a fundamental test, as inferred from the expectedness of the multifaceted configuration of the yield signal. Carried out of such approaches is inextricably linked to the procedures employed.

1.2 OVERVIEW OF DEFECTS

Lack of fusion occurs when the welded metal and the base plate's surfaces do not combine. The bend should be holding on the puddle's main edge once more. When this is completed, the weld puddle will not become ridiculously large and will not be able to pad the bend. Another point to clarify is the use of a broad weld joint. In the event that the round partition is used to reduce the joints intermingling area, The liquid weld metal will simply flow and cast against the base plate's side dividers without dissolving them. The base plate can be crumbled using the twist's shine. This is accomplished by making the joint less noticeable or by positioning the indirect bit against the base plate's side mass. When multi-pass welding thick material, a split spot structure should be used after the root passes wherever possible. Large weld contacts that span the entire opening should be avoided.

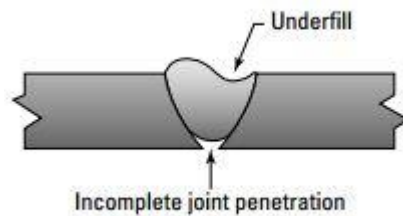


Figure 1.1 Lack of Fusion

When the weld fails to circuit to the side of the root, isolated root fusion occurs. When the various sides of the root carelessness occur, nonattendance of direction occurs. Subverting is a score that occurs near the weld root in the base metal. The joint and base metal surfaces must be well planned. Near proximity to the right materials and welding strategies will aid in preventing these turns, which can result in poor performing, weak welds, and possible breaking.

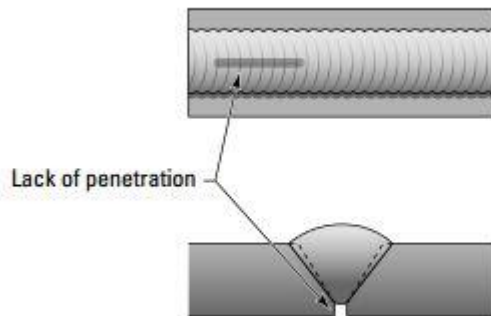


Figure 1.2 Lack of Penetration

The freezing in of gas passed on from the weld pool as it cements creates porosity. The acculturation of nitrogen, oxygen, and hydrogen which is in the liquid weld tank, which is then done hardening, results in porosity. Nitrogen and oxygen acculturation in the weld pool by and large beginnings from vulnerable gas protection. Porosity results from less than 1% air entrainment in the receiving gas, and more than 1.5 percent results in net surface breaking pores.

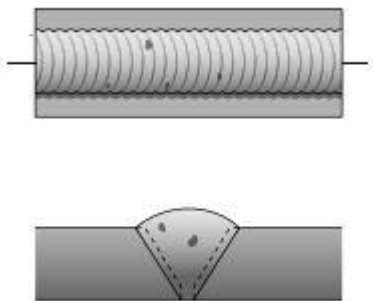


Figure 1.3 Porosity

Cracking can be caused by a variety of factors, ranging from rapid cooling to spoilage. In almost all situations, though, the clarification split occurs because the internal pressure outperforms either weld, base metal, or both. Both base metal and weld begin to sidestep as they cool after you weld. This makes inside burdens. If some way or another or another one has sabotaged the

strength of weld or base metal so it's more delicate than the pressure, it won't have the choice to hold itself together and begins breaking.

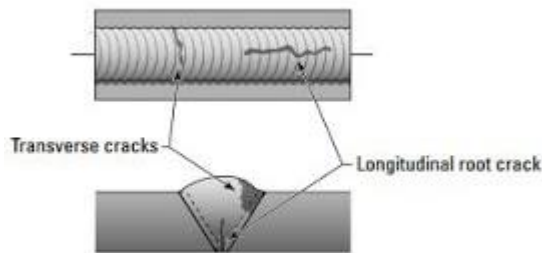


Figure 1.4 crack

Weld slag is shaped when flux, a strong protecting material utilized in the welding interaction, softens in or on top of the weld zone. Slag is the hardened excess flux that structures over the weld dab as the weld area cools.

Protected metal bend welding (SMAW or stick welding) and motion cored curve welding (FCAW) use flux materials to create slag that ensures or helps with securing the weld during weld puddle hardening. The gases delivered from the slag frameworks for either measure are equivalent to those commonly provided remotely in different strategies for welding. Generally both of these welding measures likewise produce more noteworthy measures of spatter.

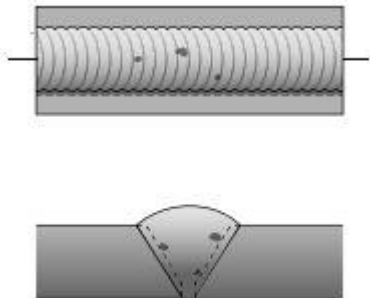


Figure 1.5-slag

Ultrasonic Testing uses a pulser receiver that sends the Ultrasonic signal and captures the signal with the receiver. The nature of the signal is an indicator of the defect. In the case of normal weld, only front wall and back wall echoes are present. On the other hand, when there is a defect, the signal is reflected form the top and bottom of the defect ad there is a burst in between the front and the back wall echo. Number of side lobes, harmonics, amplitude and the time period are the indicators of the defect. The pulsar Receiver used for acquiring the ultrasonic signals is shown in Figure 1.6.

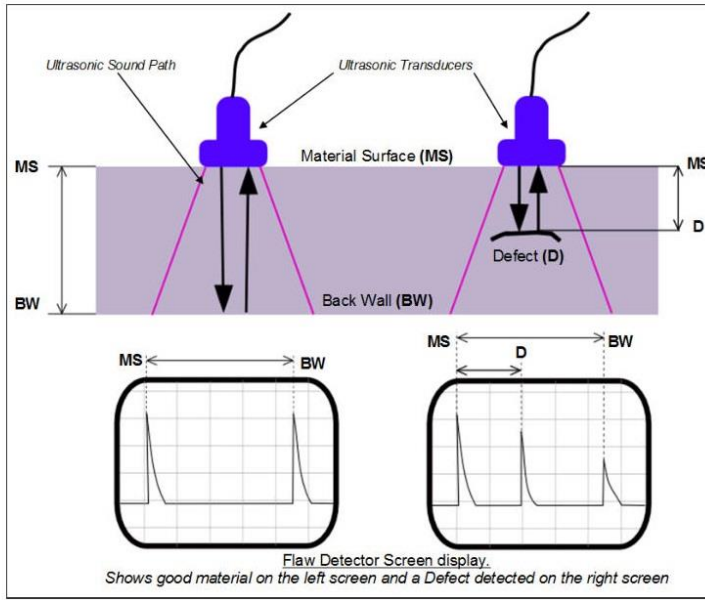


Figure 1.6 Pulser Receiver

As these Ultrasonic signals are One Dimensional in nature, one dimensional transforms are used for feature extraction. Features are then fed to classifiers for defect detection. However there is a scope of improvement and hence in this work, feasibility of Two Dimensional Convolutional Neural Networks for the classification of weld defects is studied.

1.3 PROBLEM DEFINITION

The proposed work aims at developing Convolutional Neural Networks for the classification of weld defects from Ultrasonic signals. Also a modified architecture is provided for better classification of defects than the conventional architectures.

1.4 OBJECTIVES

The objectives of the research work are as follows:

- To acquire Ultrasonic signals depicting weld flaws.
- To preprocess ultrasonic signals.
- To study the techniques for converting 1D signal into 2d matrix (periodogram, spectrogram etc.).
- To study the feasibility of 2 D CNN for weld flaw characterization.
- To modify CNN for better characterization of weld flaws.

1.5 ORGANIZATION OF THE REPORT

A detailed literature survey is dealt in Chapter 2. The Research database is provided in Chapter 3. Proposed methodology is described in Chapter 4. Results are also discussed. Chapter 5 concludes the research findings and provides the future directions.

CHAPTER-2

2.1 LITERATURE SURVEY

AUTHORS	TITLE OF THE PAPER	DETAILS	PROBLEM DEFINITION	METHODOLOGY	REMARKS
Gang Wang and T Warren Liao	Automatic identification of different type of welding defects in radiographic images	22 May 2002, https://doi.org/10.1016/S0963-8695(02)00025-7	Development of computer helped identification system to identify flaws	Using MLP neural network flaws are classified from x ray images	MLP neural network trained with defects achieved higher accuracy compared to fuzzy k-nn
Domingo Merry and Miguel	Automatic detection of welding defects using texture features	http://www.diiinf.usach.cl/~dmery	Detecting welding defects from films which are gotten from texture features	Texture features are used on x-rays to find the patterns in image	Features based on co - occurrence matrix provide much more accuracy than anticipated
Seiji Katayama , Yousuke Kawahito, Masami Mizuta	Elucidation of laser welding phenomena and factors affecting weld penetration and welding defects	@c 2010 Published by Elsevier B.V	Research on the effects of fiber laser welding on weld pieces	Characteristics of laser induced plume is studied.	It is observed that a high rate of defects can occur due to laser welding
Wenhui Hou, Ye Wei, Jie Guo, Yi Jin, Chang'an Zhu	Automatic Detection of Welding Defects using Deep Neural Network	IOP Conf. Series: Journal of Physics: Conf. Series 933 (2018) 012006	Automatic detection of defects by testing and training deep neural network	It uses unsupervised learning for intrinsic feature and softmax with	The defects can be found without the information on the specific type

				supervised learning is used	
Juan Zapata and Rafael Vilar	An adaptive-network-based fuzzy inference system for classification of welding defects	Universidad Politécnica de Cartagena, 1, 30202 Cartagena, Spain	Development of fuzzy systems to identify weld defects	Using fuzzy systems to obtain the maximum available accuracy	It shows the ways to analyze the radiographic images
Je-Kang Park and Woo-Hyun An	Convolutional Neural Network Based Surface Inspection System for Non-patterned Welding Defects	© Korean Society for Precision Engineering 2019	We use convolutional neural network to find the flaws on the surface of weld pieces	Identifying non patterned defects on welding pieces	Were able to get a desired accuracy
A. P. Vieira and E. P. de Maura	Characterization of welding defects by fractal analysis of ultrasonic signals	Department de Engenharia de Metalurgia e de Materiais, Universidade Federal do Rio de Janeiro, RJ, Brazil	Developing tools to study the properties of time to the problem classifying defects	Introducing ultrasonic waves and checking the scattering pattern to identify defects	Fractal techniques are definitely useful in weld classification

CHAPTER 3

3.1 RESEACH DATABASE

It is essential to build a database of ultrasonic signals in order to develop automated defect characterization techniques. Using the AM70-4L Pulse Receiver, a number of signals were obtained from the Indira Gandhi Center for Atomic Research (IGCAR) in Kalpakkam for this study. Welding is often done with carbon steel, and defects are purposefully introduced for signal acquisition. The term porosity refers to the gas pores contained in cemented weld globules. After the weld region cool, slag is the set leftover motion.

Carbon steel plates of length 145mm, width 143mm and thickness 20mm are used. To obtain the ultrasonic signs from the weld plates an Angle Beam Transducer AM4S – 8x9 – 45 have been utilized. This is a pulse/recipient transducer with 4 MHZ recurrence crystal creating a shear wave from the crystal size of 8x9mm. The angle of incidence of the wave got from this transducer is 45o. This transducer is utilized to gain the output signals from the weld plates. The speeds of longitudinal wave and shear wave are 5800m/s and 3100m/s separately. It is significant that speed of shear wave is half of the longitudinal wave. The critical angle is less than the angle of incidence.

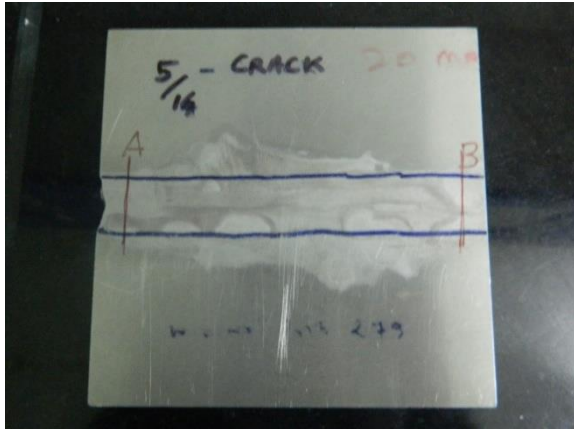


Figure 3.1 weld plate depicting crack

Prior to beginning of data acquisition the calibration of the setup is finished. The oscilloscope range is set for 150 with the assistance of common reference V1 block. The pulse mode must be in P/E mode, the beam must be perpendicular to the orientation of the defect to acquire the signal from the material. The signals are gained from welded plates, Carbon Steel specifically PL21800 (Carbon Steel), PL21798 (Carbon Steel), PL4445 (Carbon Steel), PL21797 (Carbon Steel).

Table 3.1 Flaw dimensions in Carbon Steel

Carbon Steel plate	Defect	Surface distance (cm)	Depth (cm)	Thickness (cm)
PL4445	ROOTCRACK	21.49	0.50	1.4
PL21798	PO	9.62	12.39	1
PL21800	LOF	21.85	0.44	1.5
PL21806	LOP	-	-	1
PL21799	SLAG, ROOT CRACK	-	-	1.5
PL21802		14.83	7.17	1.5
PL4441	LOP	-	-	1.4
PL4450		6.67	14.67	1.4
PL4442	LOF	-	-	1.4
17442	PO	-	-	1.5
PL4484	LOP	-	-	1.5
PL4460	LOF	-	-	1.5
17445	CRACK	-	-	1.5
2 SONASPECTION	ROOTCRACK	-	-	1.5
7SONASPECTION	SLAG	-	-	1.5

In any case, by presenting the above defects to Carbon Steel, a set of 74 signals was obtained. Later, the research data set is expanded by another set of 174 signals depicting the flaws in Carbon Steel mentioned above. Of which a set of 248 signals is utilized in this research work. To create computer aided results, it is first important to comprehend the effect of the defects on the Ultrasonic signals (Figures 3.2 to 3.7).

Table 3.2 Research database

S.No	Type of the flaw	Type of Steel	No. of signals
1	Lack of Fusion	Carbon Steel	30
2	Lack of Penetration	Carbon Steel	26
3	Porosity	Carbon Steel	32
4	Slag inclusion	Carbon Steel	24
5	Crack	Carbon Steel	23

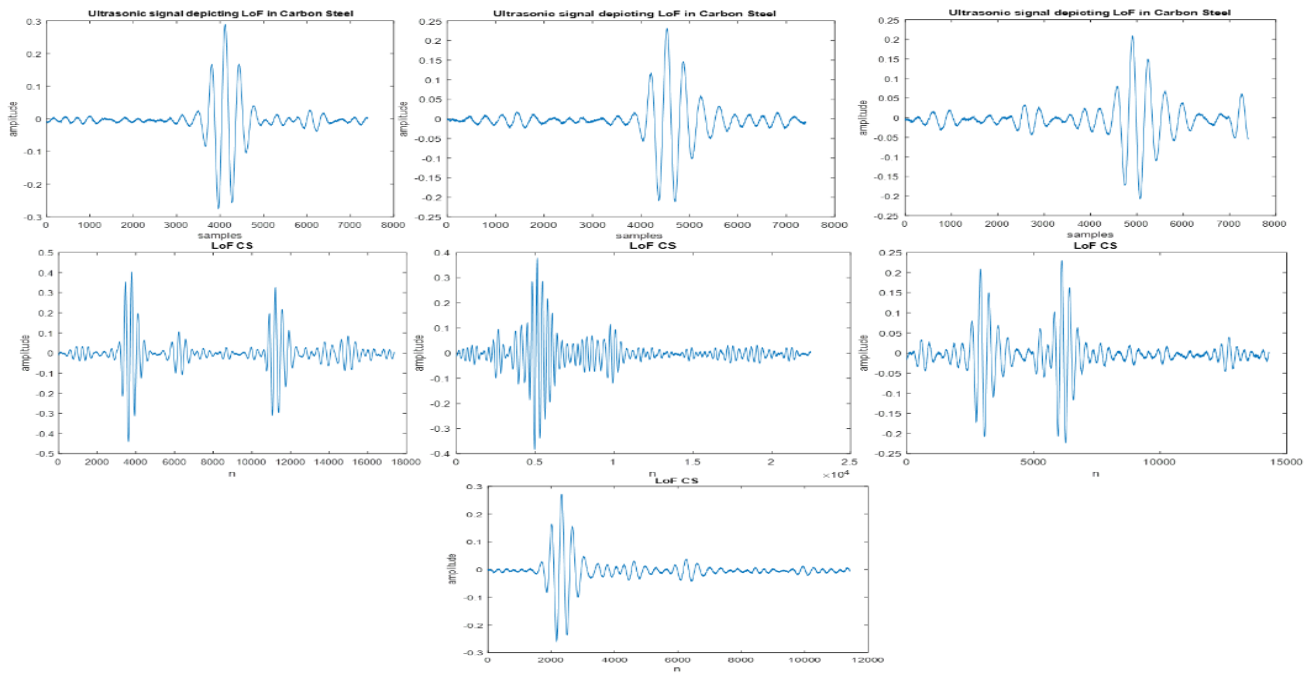


Figure 3.2 Lack of Fusion

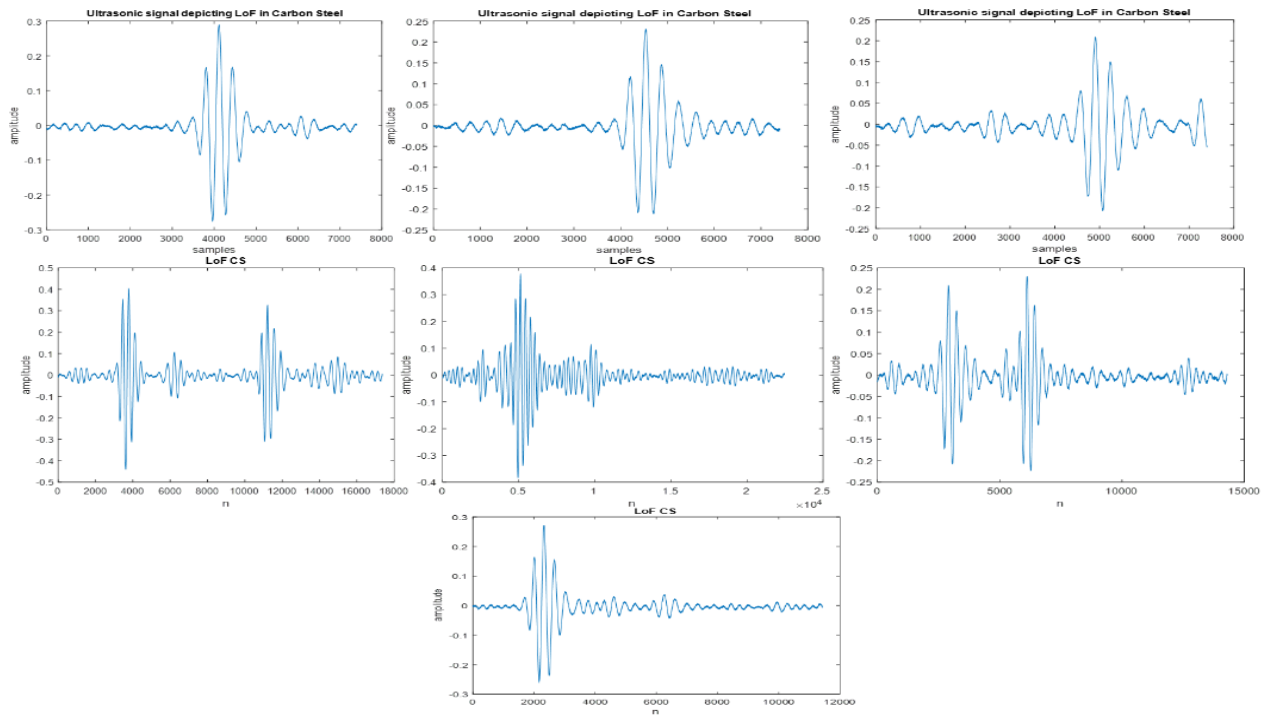


Figure 3.3 Lack of Penetration

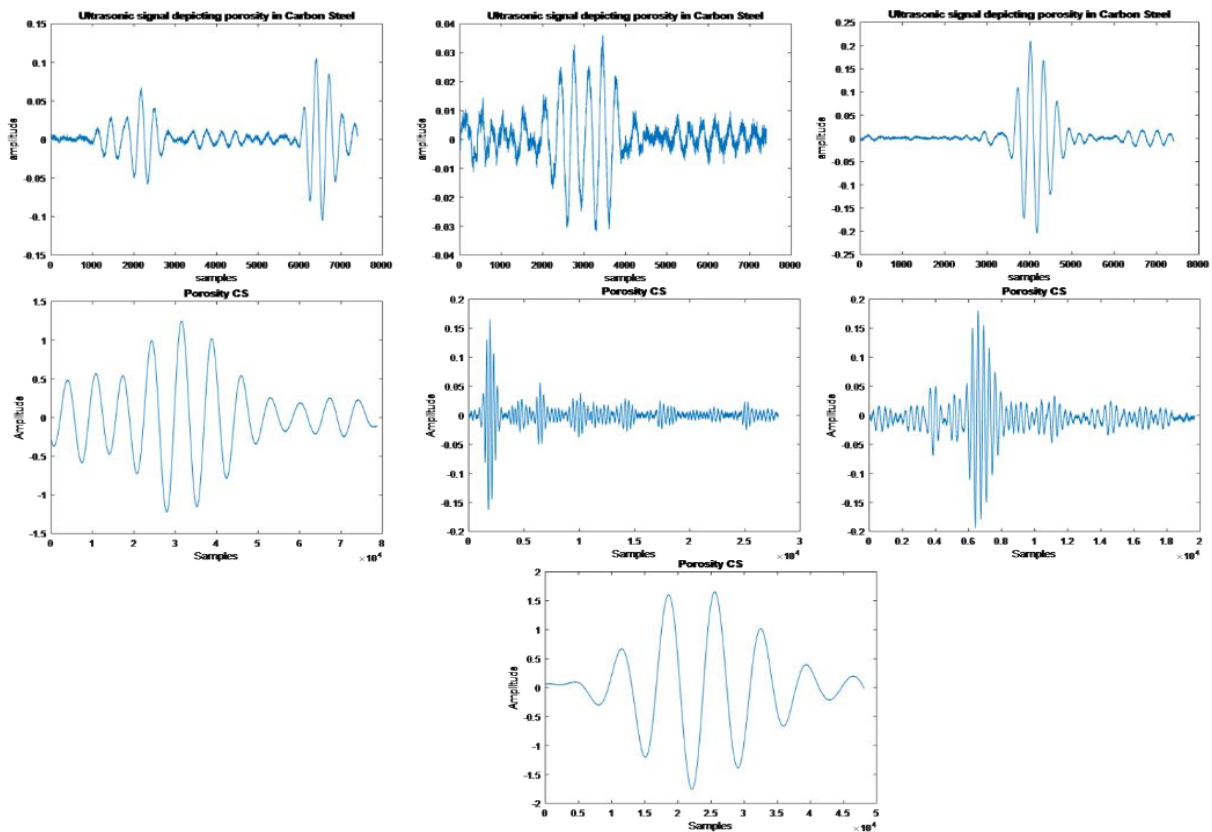


Figure 3.4 Porosity

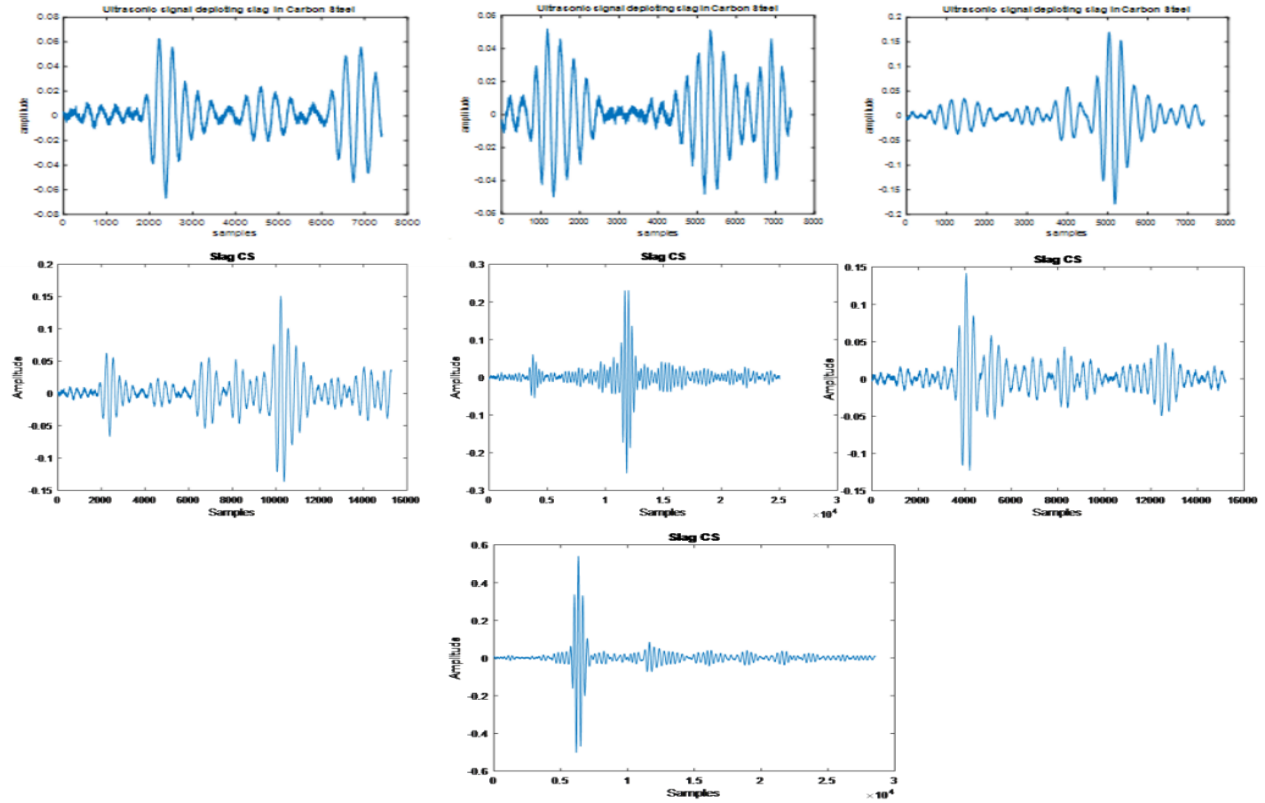


Figure 3.5 Slag

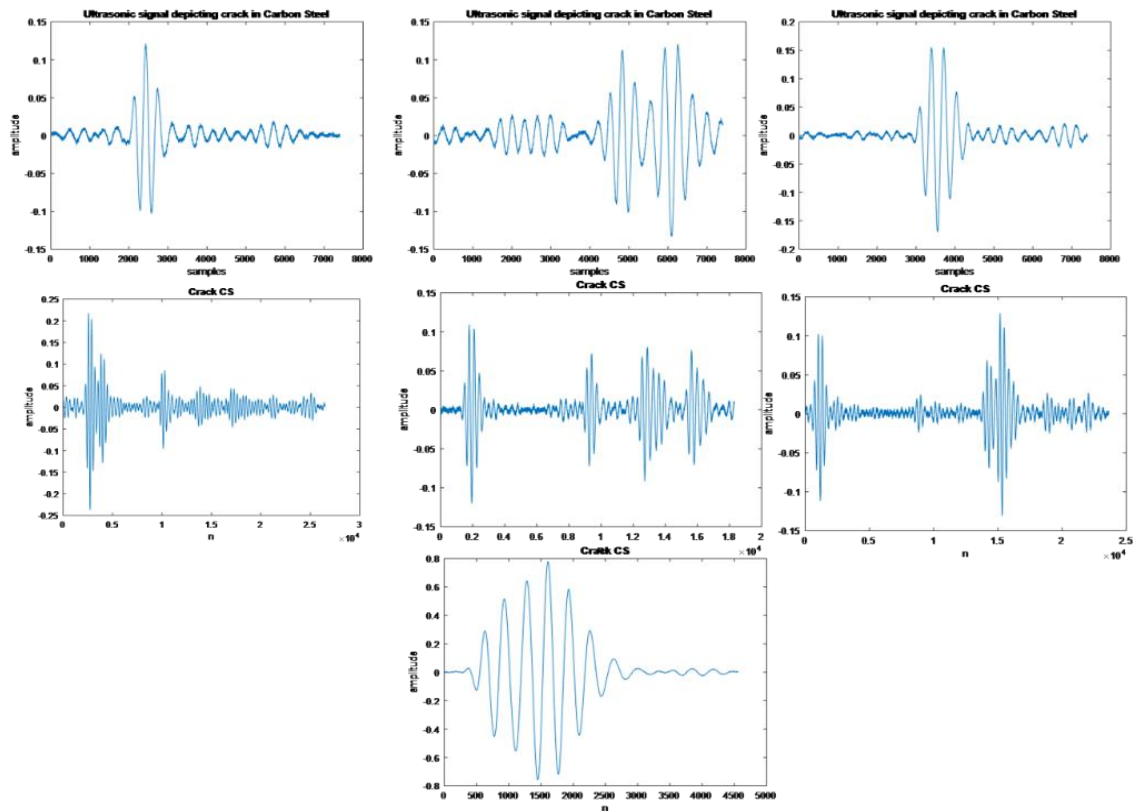


Figure 3.6 Crack

Altogether in these signals, front wall echo is eliminated and the defect locale alone is featured. Flaws show themselves as burst in the signal. Nonetheless, the frequency of the burst, greatest force of the main lobe, slope between the main lobe and the side lobe and number of burst are diverse for various defects. As the signals are real time signals, the above factors are shifting inside the group and are comparative between the groups. Significant test in creating computer aided methods for the intelligent grouping of flaws. Having acquired these signals, the next task is to convert the One Dimensional signals into Two Dimensional Spectrograms.

CHAPTER 4

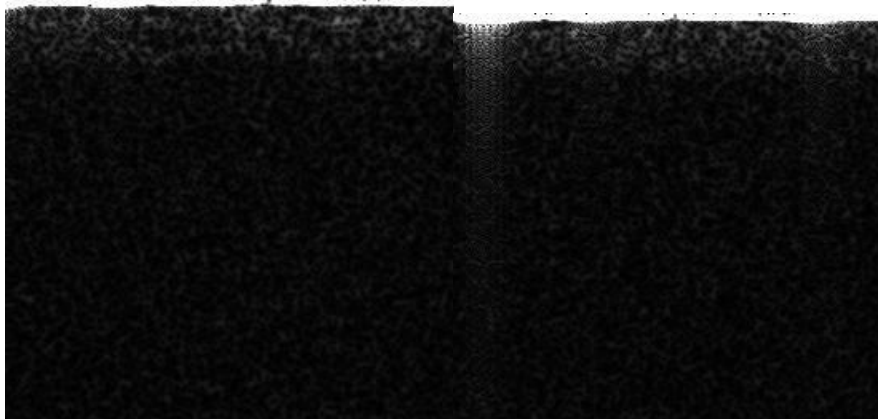
4.1 CONVOLUTIONAL NEURAL NETWORKS FOR WELD DEFECT CLASSIFICATION

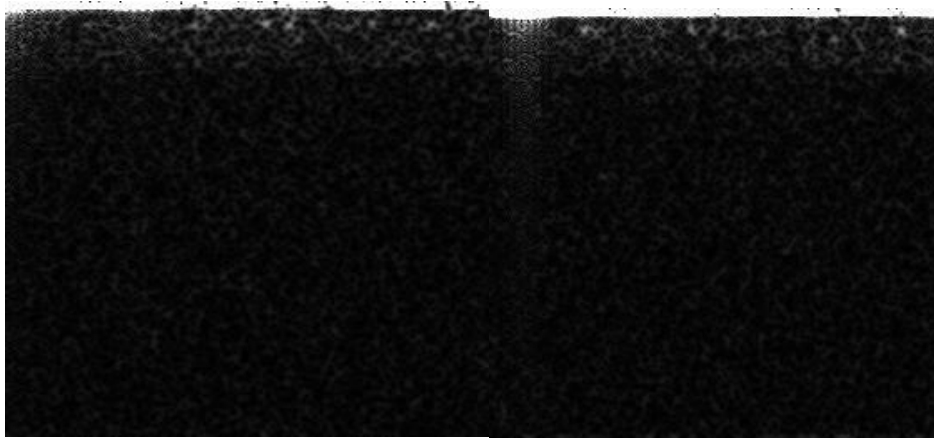
Steps involved in the work are as follows: Conversion of one Dimensional signal into Two Dimensional spectrograms; Choosing an appropriate CNN architecture, Performance evaluation of the proposed technique. Two dimensional spectrograms of Ultrasonic signals depicting Lack of Fusion, Lack of Penetration and porosity are determined using Kaiser Window. Spectrogram gives the relationship between the loudness of the signal with the different frequencies.

The spectrograms for trained and test data set are show in fig.4.1 to 4.2

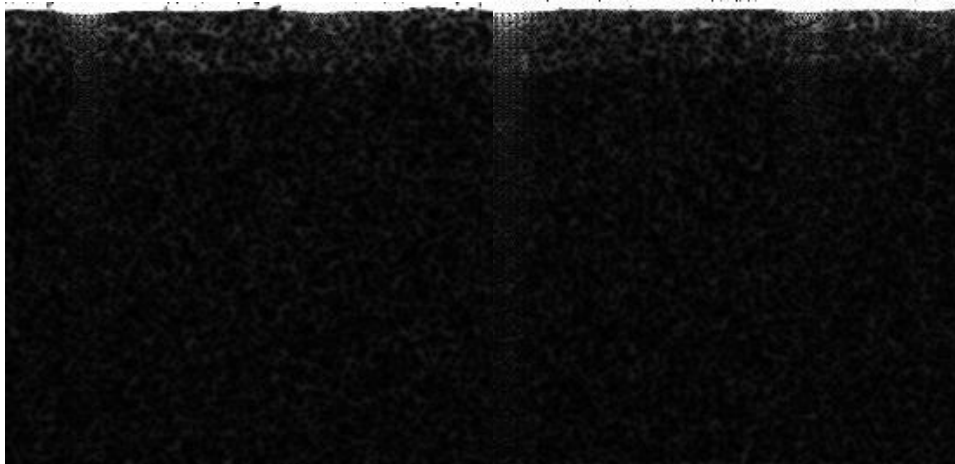
4.1 Train Ultrasonic Signals

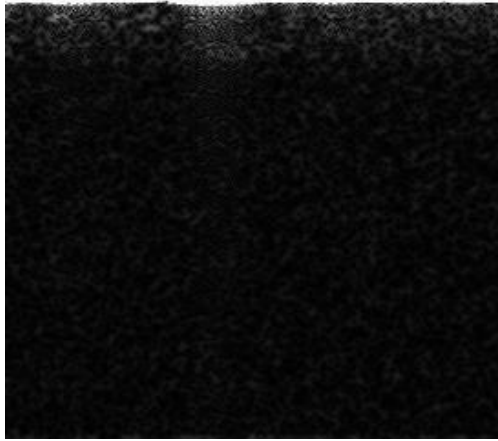
4.1a-Lack of Fusion



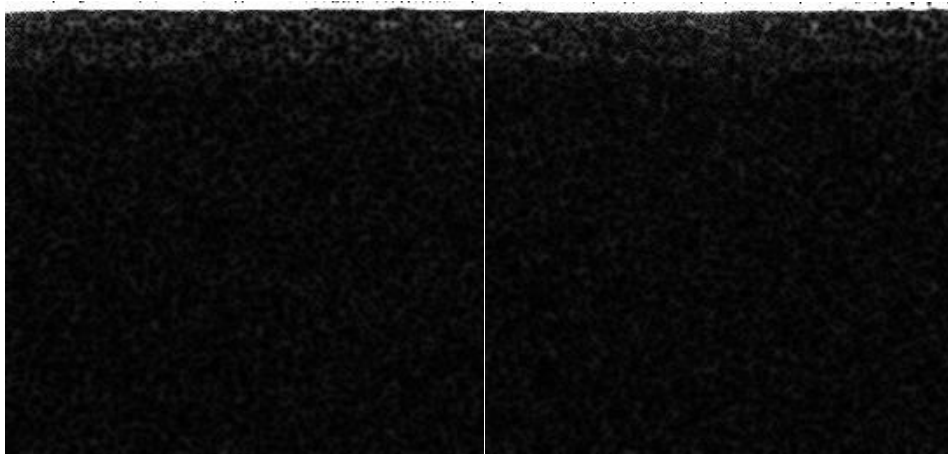


4.1b-Lack of Penetration



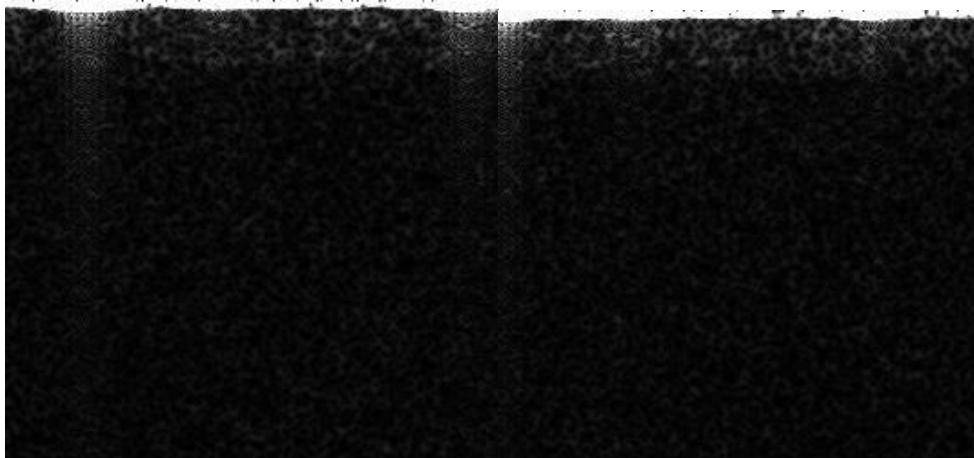
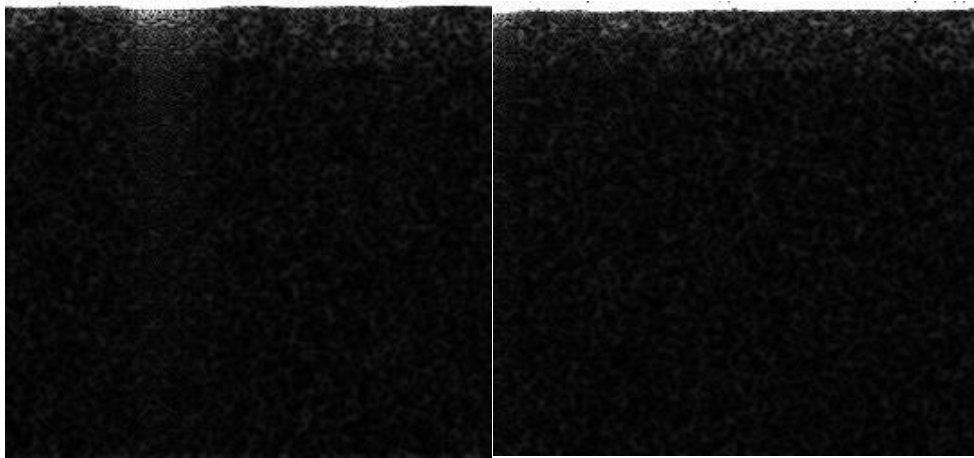


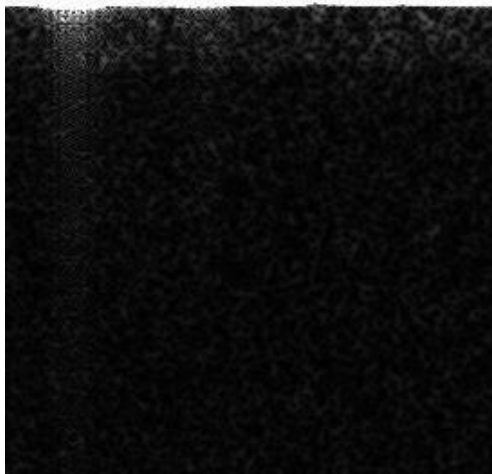
4.1c-Porosity



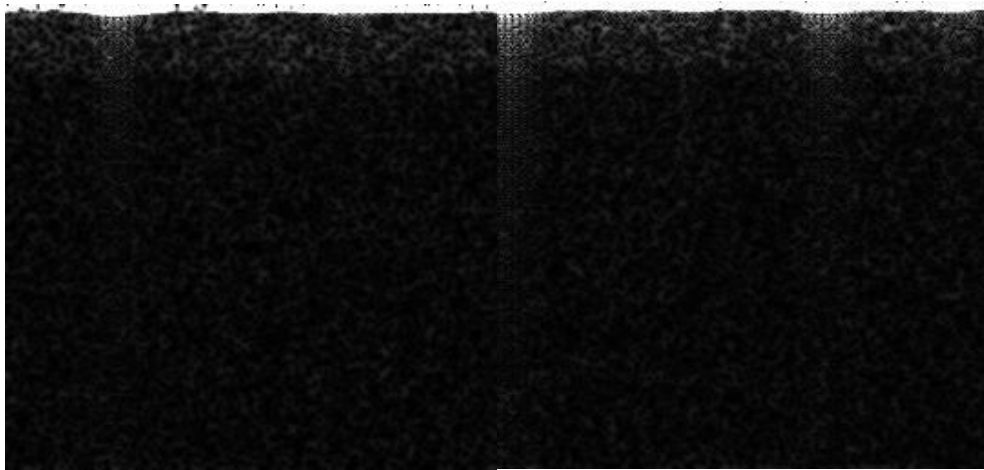
4.2 Test Ultrasonic Signals

4.2a-Lack of Fusion





4.2b-Lack of Penetration





4.2c-Porosity



4.2 Feasibility of CNN for weld defect classification:

Fifty percent of the signals are taken for training and the remaining 50% is taken for testing. In this work, conventional RESNET architectures are used for classification. RESNET18, RESNET50 and RESNET101 are used for weld flaw classification. Though RESNET architecture

are deep layered networks, the core idea lies in skipping the Convolutional layers and extracting the features. Extracted features are then fed to the classification layer which uses transfer learning to classify the defects. Performance is measured in terms of Probability of Detection.

Table 4.1 Probability of Detection (RESNET 18)

Defect	LF	LP	Porosity
LF	4	3	0
LP	3	2	0
Porosity	1	2	0

Table 4.2 Probability of Detection (RESNET50)

Defect	LF	LP	Porosity
LF	7	0	0
LP	5	0	0
Porosity	3	0	0

Table4. 3 Probability of Detection (RESNET101)

Defect	LF	LP	Porosity
LF	7	0	0
LP	3	2	0
Porosity	3	0	0

Table 4.4 Sensitivity of weld defect detection

Defect/ Performance Metrics	Sensitivity		
	RESNET18	RESNET50	RESNET101
Lack of Fusion	57.14%	100%	100%
Lack of Penetration	40%	0%	40%
Porosity	0%	0%	0%

Also the accuracy of RESNET18, RESNET50 and RESNET101 are 40%, 46.67% and 60% respectively. Of the three different architectures, RESNET101 provides better performance than the other two architectures. In order to improve the performance, Darket19 is used. From the conventional Darknet19 architecture, two Convolutional layers are removed. Removal of the Convolutional layers helps in removing the excess extraction of features and hence results in improved performance. Probability of Detection for Darknet19 and modified darknet19 are shown in Tables 5 and 6. Impact of various networks architecture on sensitivity and accuracy are shown in Figures 7 and 8.

Table4. 5 Probability of Detection (Darknet19)

Defect	LF	LP	Porosity
LF	2	2	3
LP	3	1	1

Porosity	0	0	3
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Table 4.6 Probability of Detection (Modified Darknet19)

Defect	LF	LP	Porosity
LF	4	2	1
LP	0	3	2
Porosity	0	0	3

Table 4.7 Sensitivity analysis for Darknet19 and Modified Darknet19

Defect/ Performance Metrics	Sensitivity	
	Darknet19	Modified Darknet19
Lack of Fusion	28.57%	57.14%
Lack of Penetration	20%	60%
Porosity	100%	100%

CHAPTER-5

5.1-Results&Limitations

The basic types of deformities on welded joints are presented in this project. Another deep learning-based strategy for identifying various types of deformities is also proposed. In comparison to current work, we use ultrasonic testing for blemish detection in metals and CNN to increase the exactness for imperfection assurance. The affectability of depicting a split and the absence of penetration is 85.71 percent and 83.33%, respectively. The sensitivity for the absence of mixture, porosity, and slag is half, and the precision is generally about 80%. It has been discovered that LSTMs prepared with highlights have higher affectability than LSTMs prepared with signals. The exploratory results were analysed, and the created technique was found to be extremely successful.

LIMITATIONS:

- Deep learning almost consistently requires a lot of explained information.
- Deep Nets perform well on benchmarked datasets, however can flop severely on true pictures outside the dataset.

5.2-Conclusion and Future Work

Computer interpretation of Ultrasonic signals mostly involves one dimensional analysis as these are signals. In this paper, feasibility of two dimensional transforms is studied. Ultrasonic signals are converted into spectrograms and these spectrograms are fed as inputs to the four different CNNs namely RESNET18, RESNET50 and RESNET101 and Darknet19. However these networks could not identify all the three classes of weld defects. Hence in this work, modified draknet19 architecture is proposed, pretrained and is used for weld defect classification. The proposed network has not only classified all the defects but also has sensitivity greater than the other networks. Accuracy of modified Darknet19 is 66.67%. Scalability of the proposed algorithm is yet to be verified for large dataset of Ultrasonic signals. Also the performance can be improved further by optimizing the inherent parameters of various layers in modified Darknet19.

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