



NDE2002 predict. assure. improve.  
National Seminar of ISNT  
Chennai, 5. - 7. 12. 2002  
[www.nde2002.org](http://www.nde2002.org)

## Weld Classification In Radiographic Images: Data Mining Approach

**S. V. Barai\***

Assistant Professor, Department of Civil Engineering,  
Indian Institute of Technology, Kharagpur 721 302 India  
e-mail : [skbarai@civil.iitkgp.ernet.in](mailto:skbarai@civil.iitkgp.ernet.in)

**Yoram Reich**

Associate Professor  
Department of Solid Mechanics, Materials and Systems  
Faculty of Engineering,  
Tel Aviv University, Ramat Aviv 69978 Israel  
e-mail: [yoram@or.eng.tau.ac.il](mailto:yoram@or.eng.tau.ac.il)

### **ABSTRACT**

*The need for non-destructive evaluation (NDE) technologies for maintenance of complex welded structures such as pressure vessels, load bearing structural members and power plants has long been recognized. This paper presents an application of data mining approach for weld data extracted from reported radiographic images. Data mining is the extraction of implicit, previously unknown and potentially useful information from data. In recent times, machine-learning models such, as neural networks are becoming standard tools for data mining of scientific data. This paper addresses various issues related to data mining and demonstrates their application. The study highlights the two major aspects of insight of data and prediction of the model for the problem domain.*

### **INTRODUCTION**

The assessment of the safety and reliability of existing welded structures such as pressure vessels, load bearing structural members and power plants, has been the focus of much investigation in recent years. An assessment of welded structural system requires knowledge of their strength, response characteristics, quantitative and qualitative data concerning the current state of the structure, and a methodology to integrate various types of information into decision-making process of evaluating the safety of entire structure. Perhaps the most challenging aspect of weld evaluation is need for developing a rational methodology to synthesize the diverse information related to the structural welds condition and their behavior.

In practice, non-destructive evaluation (NDE) technologies have been used very often for weld evaluation (Berger, 1977, Bray and Stanley, 1989). In a broad sense, NDE can be viewed as the methodology used to assess the integrity of the structure without compromising its performance. Recently, many studies have reported results where signal processing and neural networks (NN)

---

\* Conference Speaker

were used in characterizing defects of weld based on NDE (Rao et al., 2002, Liao and Tang, 1997, Nafaa et al, 2000, Stepinski and Lingvall, 2000).

Radiographic testing is one of the most popular NDE techniques adopted in inspecting welded joints. Usually real-time radiographic weld images are produced during radiographic testing of welded component (Bray and Stanley, 1989). These images are digitized without losing important information. Application of feature extraction methods to such digitized images helps in identifying features (Liao and Ni, 1996, Liao and Li, 1998). Further, Liao and his research group has proposed detection of welding flaws from radiographic images using soft-computing tools such as fuzzy clustering method and fuzzy K-nearest neighbor algorithms (Liao et al., 1999, Liao and Li, 1997).

Advancement in the field of data mining (Fayyad et al. 1996) can help researchers to handle complex problems like classification where many features extracted from digitized radiographic images play an important role. Recent publication by Liao et al. (2001) has attempted to explore data mining approach for weld quality models constructed using multilayer perceptron networks. They concluded that data mining based on sampled data leads to efficient and effective when proper sample size is used. And they found that there was no correlation between the representative data with similar statistical characteristics and model performance on testing data.

The main objectives of the paper are as follows: to introduce briefly about the data mining and to demonstrate systematic study on data mining for weld classification problem. The remainder of this paper discusses background on data mining, the dataset for the neural networks study, and the data mining process. The results, discussion, and conclusion close the paper.

## **DATA MINING: BACKGROUND**

Data mining is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in dataset. This process helps in extracting and refining useful knowledge from large datasets (Figure 1). The extracted information can be used to form a prediction or classification model, identify trends and associations, refine an existing model, or provide a summary of the datasets being mined. Numerous data mining techniques of various types such as rule induction, neural networks, and conceptual clustering, have been developed and used individually in domains ranging from space data analysis to financial analysis (Fayyad et al., 1996, Hand, 1998).

A recent review by Kohavi (2001) states that data mining serves two goals namely *Insight* and *Prediction*. Insight leads to identifying patterns and trends that are useful. Prediction leads to identifying a model that gives reliable prediction based on input data.

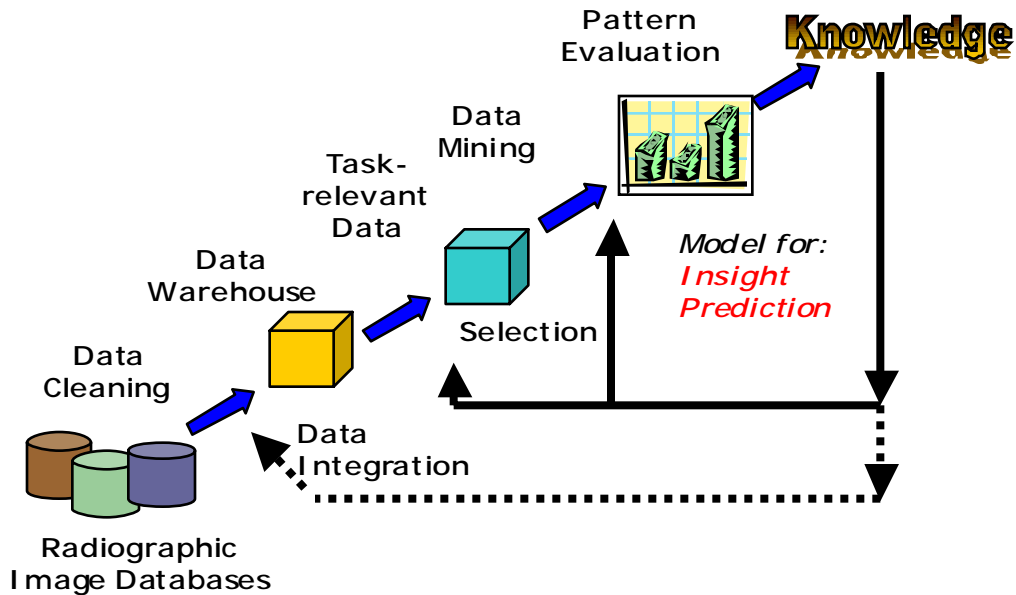


Figure 1 : Data mining and knowledge discovery process.

Obviously, the nature of data is critical to the success of data mining application. The nature of the data is related to its *source, utility, behavior* and *description*. Source of data can be online or off-line from static or dynamic systems. Data utility can be for analysis, design or diagnosis. Behaviour of data can be discrete or continuous. Data description can be in quantitative or qualitative form. A quantitative nature of the data depends on number of data points available for an application. A qualitative nature of the data demands answers to many questions such as, Are they sparse or dense? Are they in raw or clean form? Are they representative of the application domain? Are they noisy? Do they contain missing values? Researchers working in the field of scientific data mining have addressed an issue of *insight* such as novelty detection, anomalies and faults in experimental data for classification and regression problems. They are commonly addressed for pattern recognition, image analysis, process monitoring and control, and fault diagnostics. Dasgupta and Forrest (1999) demonstrated negative-selection mechanism of an immune system based novelty detection algorithm for the time series data sets. The data set was for simulated cutting dynamics in a milling operation and synthetic signal. Hickinbotham and Austin (2000a, 2000b, 2000c, 2000d) carried out a study in the field of novelty detection in strain-gauge failures during structural health monitoring of airframes. Brotherton et al (1998) showed the potential of class-dependent-elliptical basis function neural network for finding novelty in classification of collected electromagnetic signals. Marsland et al. (2001) demonstrated novelty filter, which can learn online from the robot's sonar sensor data. Ypma and Duin (1997) presented the results for self-organizing map based novelty detection in mechanical fault problem and pipeline leak detection problem.

The above papers studied regression and classification tasks of data and have used neural network as a machine learning *predictive* model. This brief review shows that data mining using neural networks is becoming a commonly used tool for such experimental datasets. Artificial

Neural Networks (ANN) can be applied to real world problems of considerable complexity. The most important advantage is in their ability to process data that are too complex for conventional technologies – problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. Because of their abstraction capability, ANNs are well suited to solve problems such as classification, pattern recognition and forecasting and/or recognizing trends in experimental data. ANNs have been applied successfully to hundreds of applications (Bishop, 1995).

The present paper revolves around data mining goals of *insight* and *prediction* for 'experimental data' of *extraction of welds from radiographic images* domain. There are many research issues associated with this experimental dataset such as: developing effective ways of managing and visualizing data; checking data quality; summarizing them into convenient and relevant forms for analysis; sampling them with minimum amount of bias; intelligent search for potentially useful structures; detecting anomalous and peculiar patterns; and avoiding missing interesting ones. Some of these issues will be addressed in the following sections.

## **DATA ACQUISITION AND NEURAL NETWORKS MODEL FOR DATA MINING**

The issues are classified in view of *insight* into data and neural networks as *predictive model*. The experimental data sets were studied with respect to their source, use, type and characteristics, their pre-processing nature, and the necessity to clean them, if required. Neural networks model study included ease of network construction, their capability of handling real data instead of simulated well behaved data, understanding their behavior, discovering unexpected information from their outputs and assessing their accuracy. For the present study, the data were collected from reference of Liao and Tang (1997).

### **Neural Networks Model and Prediction Evaluation**

Various kinds of neural networks models are available in the literature along with their performance evaluation approaches. The following paragraph briefly reviews them for the completeness of the paper.

#### *Neural Networks Models*

Neural networks are tools for creating models from data and hence, the data becomes an integral part of the model. Data needs to be subject to the same control as other model parameters. Fundamentally, the data needs to be of good quality and representative of the problem.

In the literature, varieties of neural network models, such as Hopfield net, Hamming net, Carpenter/Grossberg net, single-layer perceptron, multilayer network etc., are available. The single-layer Hopfield and Hamming nets are normally used with binary input and output under supervised learning. The Carpenter/Grossberg net, however, implements unsupervised learning. The single-layer perceptron can be used with multi-value input and output in addition to binary data. A serious disadvantage of the single-layer network is that complex decision may not be possible. The decision regions of a single-layer network is bounded by hyperplanes whereas those of two-layer networks may have open or closed convex decision regions (Haykin 1994,

Lippman, 1987). One can select the model depending upon the application domain. The multilayer network is very popular artificial neural network architecture and has performed well in a variety of applications in several domains including classification from radiographic testing (Liao and Tang, 1997, Stepinski and Lingvall 2000).

In the present study Kohonen rule based Linear Vector Quantization algorithm is used. Learning vector quantization (LVQ) is a method for training competitive layers in a supervised mode. A competitive layer will automatically learn to classify input vectors. However, the classes that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer probably will put them into the same class.

### *Neural Network Prediction Evaluation*

Various issues related to network performance evaluation are discussed elsewhere (Reich and Barai, 1999), however brief explanation is given below. Typical NN model evaluation methods are: (1) Resubstitution (2) Split Sample Validation (3) Cross-Validation such as k-fold cross validation, Leave-one-out method (Reich, 1997).

#### *Resubstitution:*

In this method the complete data set is used to train the network and later it is tested for the same data set. The estimation of generalization error for this network gives optimistic results, i.e., its error estimation is bias downward. Assuming that the data set is sampled from a large population of feature-extracted data, the performance of resubstitution is highly dependent on this sampling, i.e., it has high variability.

#### *Split-sample Validation or Hold-out Test:*

This is the most commonly used method for estimating generalization error in NN. The sample set is repeatedly and randomly divided into disjoint training *and* testing data sets. It is common to select 2/3 of the data set as the training set and remaining 1/3 as the test set. After training, the network is run on the test set and the error on the test set gives an unbiased estimate of the generalization error. In order to produce results with a confidence interval of about 95%, the testing set should include more than 1000 examples; otherwise, this method may produce poor results. In smaller data sets, this method is often repeated several tens of times, but the results have high variability that is dependent upon the initial random, in addition to the variability due to the sampling of the data set from the larger population. Note that these repetitions are not independent, having used the same data set. The results of this method may be pessimistic because not all available data is used for training.

#### *Cross-validation: k-fold Method or Leave-one-out:*

In k-fold cross-validation, one divides the data into k subsets of equal size. The NN is trained k times; each time leaving out one of the subsets from training, but using only the omitted subset to computer whatever error criterion is of interest. If k equals the sample size, this is called leave-one-out. A more elaborate and expensive version of cross-validation involves leaving out all

possible subsets of a given size. If  $k$  gets too small, the error estimate of a full sample analysis is pessimistically biased because fewer data points are used for training. A value of 10 for  $k$  is popular.

## **CASE STUDY OF DATA MINING: WELD CLASSIFICATION**

### **Problem Domain**

In this exercise the aim was to classify weld and non-welds category from digitized radiographic image features (Liao and Tang, 1997) and subsequently check the quality of the data after network performance evaluation.

### **Data Acquisition**

Non-destructive testing (NDT) of welded structure is used very often for failure analysis of important structures. Radiographic testing is one of the most popular NDT techniques adopted in inspecting welding joints. Usually real-time radiographic weld images are produced during the radiographic testing of welded component. Liao and Tang (1997) collected X-ray strips of about 3.5 inches wide by 17 inches long. They were digitized at 70  $\mu\text{m}$  resolution. These digitized images were produced using 5000 pixels by 6000 lines images. From these images down-sampled image of size 250 pixels by 300 lines were produced to find anomalies in weld. The down-sampled images were used for weld extraction. In order to formulate the classification problem of weld from non-welds, feature extraction was essential. Four features were defined for each object in line image and they are as follows.

- The peak position ( $x_1$ )
- The width ( $x_2$ )
- The mean square error between the object and its Gaussian intensity plot ( $x_3$ )
- The peak intensity ( $x_4$ )

A total of eighty-four samples were extracted that contain linear and non-linear welds. In present investigation, neural networks will be trained to identify whether the patterns are welds or non-welds.

This classification exercise is to identify welds ( $Y = 1$ ) or non-welds ( $Y = 0$ ) on the basis of input features,  $x_1$ ,  $x_2$ ,  $x_3$  and  $x_4$ . Three feature sets,  $f_1 = \{x_1, x_4\}$ ,  $f_2 = \{x_2, x_3, x_4\}$  and  $f_3 = \{x_1, x_2, x_3, x_4\}$  are considered to identify the best feature set. On these feature dataset, simple normalization was carried out on input and output parameters during pre-processing (Reich and Barai, 2000).

### **Model and Hypothesis Development**

There are many variants of the classification algorithm allowing for faster convergence and more accurate representation. In this study we used Kohonen Feature Map based Linear Vector Quantization (LVQ) supervised mode based neural networks (Demuth and Beale, 1994). The aim is to develop reliable predictive classification model and hence, the LVQ model was considered for data modeling

### *Selection of Neural Networks Model Parameters*

The Kohonen rule based LVQ network consisting of two layers was used: The first layer as a competitive layer to classify input feature sets and the second layer to transform competitive layer's classes into target classification of  $Y$ .

The program was implemented using MATLAB – Neural Networks Toolbox (Demuth and Beale, 1994). After several exercises, LVQ networks having 15 hidden units, the number of epochs as 5000 and learning rate as 0.05 were selected, maintaining a compromise between the accuracy and computational time. Note that there was no attempt to optimize the network architecture and training parameters (i.e., Epochs and learning rate) in the study but rather, to pick reasonable values.

### **Data Mining, Testing and Verification**

#### *Insight and Prediction:*

The neural networks study was carried out for the resubstitution, cross-validation and hold-out and results are summarized in Table 1.

Table 1: Classification accuracy in percentage

Exercise	$f_1 = \{x_1, x_4\}$	$f_2 = \{x_2, x_3, x_4\}$	$f_3 = \{x_1, x_2, x_3, x_4\}$
Resubstitution	97.62	94.05	95.24
Leave-one-out	95.24	92.86	95.24
Hold-Out	100	96.97	93.94

- The LVQ network did extremely well for feature set  $f_1$  relative to  $f_2$  and  $f_3$  in classifying welds or non-welds. The performance of network was evaluated using various testing methods as discussed in previous section. In general, for feature sets and above given testing methods, network classification accuracy was more than 92%.
- It is observed in previous paragraph that only two feature can represent the domain with low dimensionality and retaining sufficient information.
- In this problem domain, the quality of data was quite good. Hence, good quality models were developed in a single iteration compared to several iterations required when data quality is poor (Reich and Barai, 1999).
- In this study, we presented data mining methodology for a small dataset. The same approach can be easily extended for large size of dataset containing features of digitized radiographic weld images.

## Model Use

Good quality of feature extracted from radiographic image data leads to developing neural networks models that can be deployed to predict the weld defects.

## FUTURE PROSPECTS

- The neural network study can give a better *insight* about the data set and could trace down discrepancies in the data so that data entry errors could be corrected and better performance could be achieved (Barai and Reich, 2001).
- The integration of neural networks in decision support system is relatively easy. During this study it was observed that data of features extracted from digitized radiographic images is of good quality and hence, trained networks could be an integral part of Automated radiographic NDT system.
- Data quality and characterization is essential for successful experimental studies. Hence simultaneously cleaning the data and training the networks using the approach of *Cleaning* (Weigend et al., 1996) can help in getting better quality data.
- There is a scope to apply other machine learning models to acquire knowledge from the dataset of features.

## CONCLUSION

Advances in data mining have helped experimentalist in analyzing experimental data. In the present paper, we addressed two goals of data mining, namely *insight* and *prediction* in the context of features data extracted from digitized radiographic images of welds. At the “*insight*” stage of data mining, neural networks model could help us in identifying the features, which are important for proper neural networks modeling. Also, at the “*prediction*” stage, a neural networks model was evaluated using various testing methods and was found to perform very well due to better data quality. Finally, future work is discussed based on this study.

## ACKNOWLEDGMENT

Part of this work was done with the support of a VATAT fellowship to the first author at Tel Aviv University, Israel.

## REFERENCES

Barai S. V., and Reich, Y. (2001), "Data Mining of Experimental Data: Neural Networks Approach", *Proceedings of 2<sup>nd</sup> International Conference on Theoretical, Applied Computational and Experimental Mechanics ICTACEM 2001*, held during 27-30 December 2001, and organized by Department of Aerospace Engineering, Indian Institute of Technology, Kharagpur, (CD-ROM)

Berger, H. (1977), *Nondestructive Testing Standards - A Review*, STP 624, ASTM.

Bishop, C. M. (1995), *Neural networks for pattern recognition*, Clarendon Press, Oxford, Birmingham, UK.

Bray, D. E. and Stanley, R. K. (1989), *Nondestructive evaluation - A tool for Design, Manufacturing and Service*, McGraw-Hill Book Company

Brotherton, T., Johnson, T. and Chadderdon, G. (1998), "Classification and novelty detection using linear models and a class dependent - Elliptical basis function neural network", *Proceedings of the International Joint Conference on Neural Nets*. <http://www.iaconline.com/download.htm>.

Dasgupta, D. and Forrest, S. (1999), "Novelty detection in time series data using ideas from immunology", *Proceedings of The International Conference on Intelligent Systems*, [http://www.cs.unm.edu/~forrest/isa\\_papers.htm](http://www.cs.unm.edu/~forrest/isa_papers.htm)

Demuth, H. and Beale, M. (1994), *Neural networks toolbox - For use with MATLAB*, The Mathworks Inc., 24 Prima Park Way, Natick, MA, USA.

Fayyad, U. M., Piatetsky-Shapiro, G., Smyth, P. and Uthursamy, R. (1996), *Advances in knowledge discovery and data mining*, AAAI Press/The MIT Press, Cambridge, MA.

Hand, D. J. (1998), Data mining: Statistics and more?, *The American Statistician*, 52, 2, 112-118.

Haykin, S. (1994), *Neural networks - A comprehensive Foundation*, Macmillan College Publishing Company, New York, USA.

Hickinbotham, S. J., and Austin, J. (2000a), " Detecting strain-gauge failures in stress-cycle count matrices", <http://www.cs.york.ac.uk/arch/neural/publications/papers.html>

Hickinbotham, S. J., and Austin, J. (2000b), " Neural networks for novelty detection in airframe strain data", *International Joint Conference on Neural Networks*, <http://www.cs.york.ac.uk/arch/neural/publications/papers.html>

Hickinbotham, S. J., and Austin, J. (2000c), "Novelty detection in airframe strain data". *15<sup>th</sup> International Conference on Pattern Recognition*, <http://www.cs.york.ac.uk/arch/neural/publications/papers.html>

Hickinbotham, S. J., and Austin, J. (2000d), “Novelty detection for flight data from airframe strain data”. *European COST F3 Conference on System Identification and Structural Health Monitoring*, <http://www.cs.york.ac.uk/arch/neural/publications/papers.html>

Kohavi, R. (2001), “Data mining and visualization”, in *Sixth Annual Symposium on Frontiers of Engineering*, National Academy Press, D.C., 30-40.

Liao, T. W. and Li, D. (1997), “ Two manufacturing applications of the fuzzy k-NN algorithm”, *Fuzzy Sets and Systems*, Vol. 92, pp:289-303.

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, pp:145-158.

Liao, T. W. and Li, Y. (1998), “ An automated radiographic NDT system for weld inspection: Part II – Flow detection”, *NDT&E International*, Vol. 31, No. 3, pp: 183-192.

Liao, T. W. and Ni, J. (1996), “ An automated radiographic NDT system for weld inspection: Part I – Weld Extraction”, *NDT&E International*, Vol. 29, No. 3, pp: 157-162.

Liao, T. W. and Tang, K. (1997), “ Automated extraction of welds from digitized radiographic images based on MLP neural networks”, *Applied Artificial Intelligence*, Vol. 11, pp: 197-218.

Liao, T. W., Wang, G., Triantaphyllou, Chang, P. C. (2001), “A data mining study of weld quality models constructed with MLP neural networks from stratified samples data”, *Industrial Engineering Research Conference*, Dallas, TX, May 20-23, 2001  
[http://cda4.imse.lsu.edu/PROCEEDINGS\\_Papers/IERC2001paper.PDF](http://cda4.imse.lsu.edu/PROCEEDINGS_Papers/IERC2001paper.PDF)

Lippman, R. P. (1987), “An introduction to computing with neural nets”, *IEEE ASSP Magazine*, 4, 6-22.

Marsland, S. Nehmzow, U. and Shapiro, J. (2001), *Novelty detection in large environments*, Technical report series, Department of computer science, Manchester University, Report Number UMCS-01-4-1. <http://www.cs.man.ac.uk/cstechrep/titles01.html>.

Nafaa, N. Redouane, D. and Amar, B. (2000), “Weld defect extraction and classification in radiographic testing based artificial neural networks”, *15<sup>th</sup> WCNDT, Roma 2000*, <http://www.ndt.net/article/wcndt00/papers/idn575/idn575.htm>

Rao, B. P. C., Raj, B. and Kalyansundaram, P. (2002), “An artificial neural networks for eddy current testing of austenitic stainless steel welds”, *NDT & E International*, Vol. 35, pp: 393-398

Reich, Y. (1997), Machine learning techniques for civil engineering problems, *Microcomputers in Civil Engineering*, 12, 4, 307-322.

Reich, Y. and Barai, S. V. (1999), Evaluating machine learning models for engineering problems, *Artificial Intelligence in Engineering*, 13, 257-272.

Reich, Y. and Barai, S. V. (2000), A methodology for building neural networks model from empirical engineering data, *Engineering Applications of Artificial Intelligence*, 13, 685-694.

Stepinski, T. and Lingvall, F. (2000), “ Automatic defect characterization in ultrasonic NDT”, *15<sup>th</sup> WCNDT, Roma 2000*, <http://www.ndt.net/article/wcndt00/papers/idn393/idn393.htm>

Weigend, A. S., Zimmermann, H. G., and Neuneier, R. (1996), Clearning, In *Neural Networks in Financial Engineering*, World Scientific, Singapore, 511-522.

Ypma, A. and Duin, R. P. W. (1997), Novelty detection using self-organizing maps, *ICONIP 1997*, [http://www.ph.tn.tudelft.nl/~ypma/papers/list\\_of\\_papers.html](http://www.ph.tn.tudelft.nl/~ypma/papers/list_of_papers.html).