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Investigation of deep neural network with drop out for ultrasonic flaw classification in weldments †

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Abstract

Ultrasonic signal classification of defects in weldment, in automatic fashion, is an active area of research and many pattern recognition approaches have been developed to classify ultrasonic signals correctly. However, most of the developed algorithms depend on some statistical or signal processing techniques to extract the suitable features for them. In this work, data driven approaches are used to train the neural network for defect classification without extracting any feature from ultrasonic signals. Firstly, the performance of single hidden layer neural network was evaluated as almost all the prior works have applied it for classification then its performance was compared with deep neural network with drop out regularization. The results demonstrate that given deep neural network architecture is more robust and the network can classify defects with high accuracy without extracting any feature from ultrasonic signals.

Keywords: Deep neural network; Drop out; Ultrasonic testing; Weldment flaws classification

1. Introduction

Ultrasonic methodologies are one of major methods for inspection and characterization of defects in weldments in the non-destructive testing and evaluation. These techniques have been used very extensively in industries for the evaluation of structural integrity and quality of welds. The most common ultrasonic testing technique employed for flaw classification depends on the shape and time-of-flight (TOF) information of reflected ultrasonic waves from defects. Although the method is effective for defect classification but the interpretation of reflection signals is error prone and it depends on the skills and experience of the operators. So, it is strongly needed in industries to develop automatic ultrasonic flaw classification system to reduce interpretation burden from operators, who can then focus their efforts for flaw evaluation.

During the last three decades, several automatic flaw classification techniques have been developed. These include artificial intelligence algorithms, ultrasonic pattern recognition procedures and neural networks. Flaw classification with neural networks has been very popular in the past. Several authors have used neural networks to classify weldment defects. Song et al. [1] applied probabilistic neural network (PNN) to classify flaws in Weldment by extracting time domain features from ultrasonic waves. A combination of Fisher discriminate analysis and the neural network was exercised to classify cracks, slag inclusions and porosity defects from ultrasonic signatures [2]. Margrave et al. [3] evaluated different configurations of neural networks on 5 MHz A – Scans, for accurate flaw detection in steel pipes. Drai et al. [4] compared the performance of artificial neural network (ANN) on time & frequency domain features and wavelet features to classify planer and volumetric defects from ultrasonic signals. An intelligent ultrasonic evaluation system (IUES) was developed by Song et al. [5] for ultrasonic flaw classification in Weldment. An integration of feed forward neural network and wavelet e blind separation methods was employed to classify guided ultrasonic waves corresponding to the position, width and depth of defects in not accessible pipes [6]. Sambath et al. [7] applied wavelet transform with the artificial neural network on ultrasonic signatures to improve automatic flaw detection and classification in ultrasonic testing. An embedded electronic system was developed to classify delamination and fractures in composites from A – Scan measurements [8]. A comparison of different features extraction techniques along with dimensionality reduction approaches was debated in Ref. [9] to efficiently categorize ultrasonic signatures of lack of penetration, porosity and slag inclusion defects by the neural network.

In spite of the fact, most of the above-mentioned approaches had good performance for automatic defect classification, however, complex and not very practical for industrial

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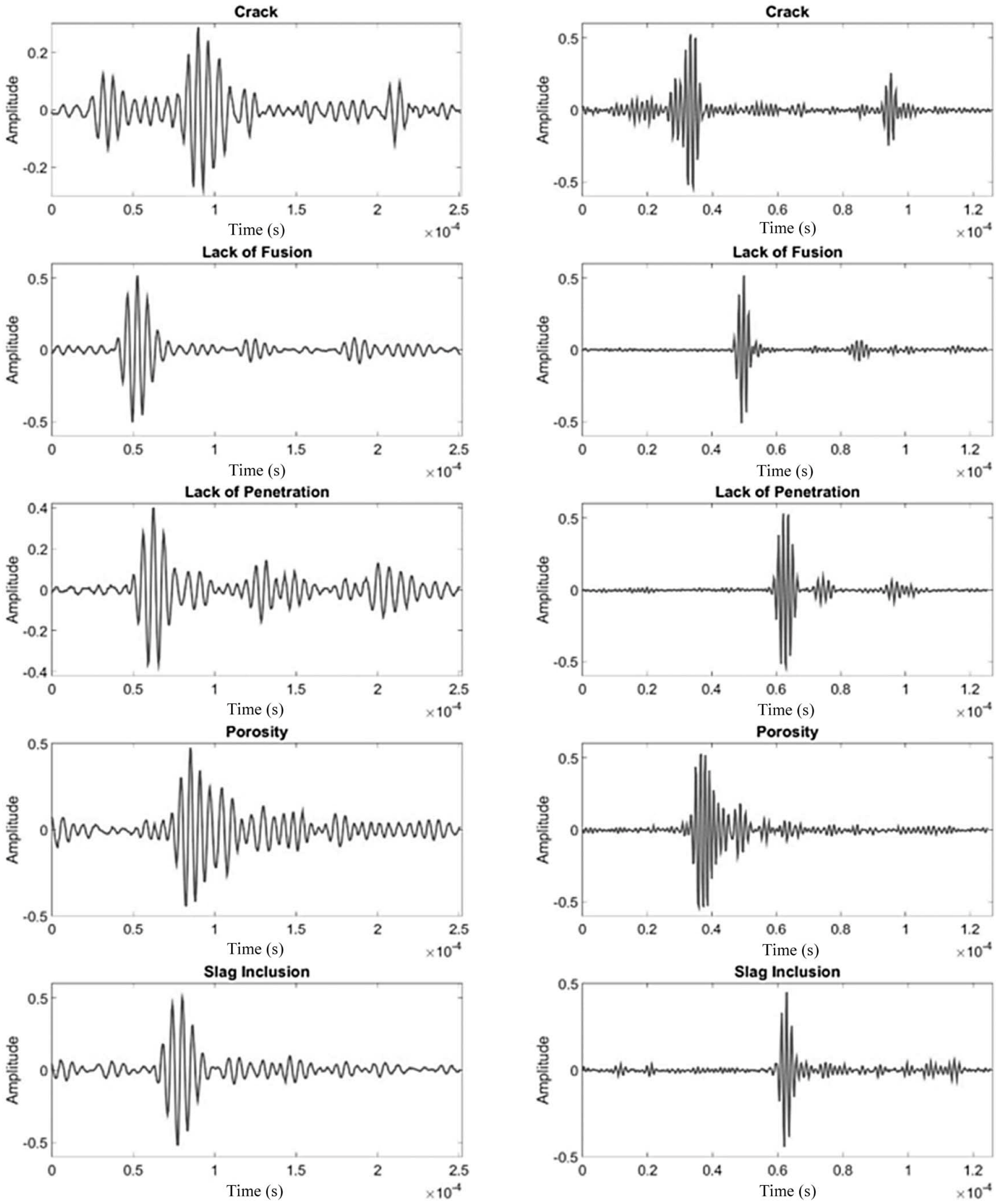

(a) (b)

Fig. 1. Ultrasonic flaw signals with (a) 2 MHz; (b) 4 MHz transducers.

application. The main barrier that increases their complexity, involve features extraction from ultrasonic signals to train neural network. Although, the feature extraction is very helpful for dimensionality reduction but require careful selection of features that remain insensitive to the operating conditions. So, an automatic defect classification system is required that remain independent of features.

In fact, almost all the works studied and cited before, have applied feature extraction approaches except an effort made by Margrave et al. [3]. They applied single hidden layer feed forward neural network to classify flaws without extracting any feature. However, the efficiency of the network was discussed for 5 MHz ultrasonic signatures only and it is very common practice in industries to use more than one central frequency transducers to evaluate flaws, so their results may not be generalized for industrial big database having mixed frequencies signals.

Nowadays, due to a tremendous increase in computing

Table 1. Ultrasonic signals database.

Defects	No of signals		
	2 MHz	4 MHz	Total
Cracks	121	120	241
Lack of fusion	115	115	230
Lack of penetration	34	35	69
Porosity	35	35	70
Slag inclusion	55	55	110
Total	360	360	720

power and the state of the art performance of deep neural networks for computer vision and artificial intelligence problems [10, 11], this article focuses to apply deep neural network for supervised learning, on mixed frequencies ultrasonic signals database of the weldment defects. The results demonstrate that the adopted deep architecture is itself robust and does not require feature extraction procedures.

As almost all the researches to date have adopted single hidden layer neural network for Weldment defect classification, so this article first compares the testing performance of single hidden layer feed forward neural network (NN) on single frequency database (database set I) and mixed frequencies database (database set II) of ultrasonic signals. Then it will analyze the testing performance index achieved by the deep neural network (DNN) on database set II and compare its results with single hidden layer NN. The performance comparison indicates that DNN with drop out regularization is more effective on database set II than single hidden layer NN and does not require features to achieve high testing performance.

2. Ultrasonic flaw database

Current research used the ultrasonic signal database generated in the previous research [5]. The work pieces evaluated for data collection were the Flawtech weldment specimens and had deliberate defects i.e. 1) Cracks, 2) lack of fusion (LOF), 3) lack of penetration (LOP), 4) porosity, 5) slag inclusions.

To collect ultrasonic signatures of defects, 2 different central frequency transducers were selected (2 MHz and 4 MHz) and a database of 720 ultrasonic signatures was collected by varying their sizes and incidence angle. Each ultrasonic acquired signal, windowed for defect information only and has 502 sampling points as shown in Fig. 1. The database included 360 waves using a 2 MHz transducer and 360 waves using a 4 MHz transducer. The summary of signals for each defect category is in Table 1. The database of 720 ultrasonic signals was then arranged into two database sets. 1) Database set I (360 signals of 2 MHz transducer), 2) database set II (720 signals of 2 MHz and 4 MHz transducer).

The signatures in each database set were then further divided randomly into two sets named as training set and testing set. In the database set I, training set contained 323 signals and testing set contained 37 signals while in database set II training set contained 646 signals and 74 signals for the testing set. The complete representation of each defect in each database set along with training and testing sets is in Tables 2 and 3.

Table 2. Database set I with training and testing sets.

Defects	Database set I	
	Training set	Testing set
	2 MHz	2 MHz
Cracks	109	12
Lack of fusion	103	12
Lack of penetration	30	4
Porosity	31	4
Slag inclusion	50	5
Total	323	37
Grand total	360	

Table 3. Database set II with training and testing sets.

Defects	Database set II					
	Training set			Testing set		
	2 MHz	4 MHz	Total	2 MHz	4 MHz	Total
Cracks	109	108	217	12	12	24
Lack of fusion	103	103	206	12	12	24
Lack of penetration	30	31	61	4	4	8
Porosity	31	31	62	4	4	8
Slag inclusion	50	50	100	5	5	10
Total	323	323	646	37	37	74
Grand total	720					

3. Artificial neural network

NN are the mathematical models to simulate the biological neurons and to perform parallel information processing in a simple and objective way. Single hidden layer feed forward NN typically contains one input layer, hidden layer and output layer while DNN has more than one hidden layer.

3.1 Regularization of neural network

DNN with the large number of hidden layers and millions of learnable parameters are very useful models but usually suffer from over fitting without regularization. It means that the network performs well on training dataset but its performance degrades on the testing dataset. There are several regularization techniques to avoid this problem that include early stopping, l_1 and l_2 regularization and max norm etc., but drop out is the most popular one [12].

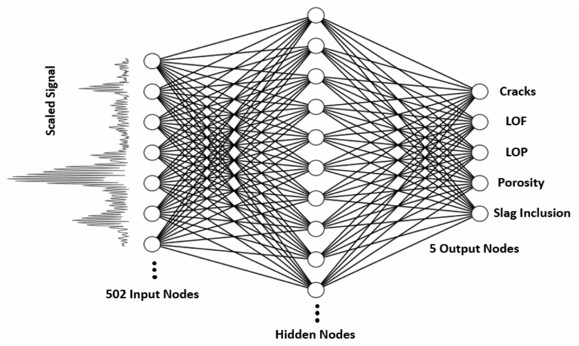

Fig. 2. Architecture of single hidden layer neural network.

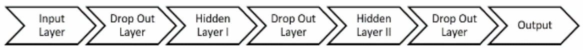

Fig. 3. Layout of deep neural network with drop out.

3.2 Drop out method

Drop out regularization method prevents the over fitting by avoiding co–adaptation among hidden nodes of deep feed forward NN on each training case [13, 14]. This is done by dropping some of the nodes in NN layers during training phase. The choice of, which nodes to drop, is random and nodes are usually dropped with the probability of 0.5. When the NN trained with drop out, nodes are present in layers only with a given probability but are always present during testing [14].

3.3 Adopted single hidden layer NN architecture

In this study, the adopted single hidden layer NN had 502 nodes in the input layer because there were 502 sampling points in each ultrasonic signal. To select the number of nodes in the hidden layer, several trails were run and chose the number of nodes that gave the best results. And, there were 5 output nodes in the adopted network because there were five defect classes to classify. The nonlinear activation function used was sigmoid function, $\left[\frac{1}{1+e^{-x}}\right]$. The choice for activation function and loss function was made to keep the algorithm consistent with the approach discussed in Ref. [3]. The architecture of single hidden layer NN is shown in Fig. 2.

3.4 Adopted deep neural network architecture

The adopted DNN with drop out was designed in Tensorflow (*Google open source software for deep learning*). It contained 2 hidden, 3 drop out layers with probability of 0.5 and one output layer as shown in Fig. 3.

The number of nodes in the input layer and the output layer were 502 and 5, respectively, but several trials were run for the number of nodes in hidden layers and chose the number of nodes that gave good performance. The activation function of the hidden layers was rectified linear unit (Relu) $Relu(x) = \max(0,x)$, because of its state of the art performance for DNN [15-17]. Error was calculated with sparse softmax cross entropy loss which is equal to applying softmax activation function $\left[\sigma(y)_i = \frac{e^{y_i}}{\sum_{k=1}^{K} e^{y_k}}\right]$ (where y is a vector of the inputs to the output layer and i indexes the output units, so $i = 1,2,\ldots\ldots K$) and then computing the cross entropy [12]. This loss function was used due its improved classification accuracy for multiclass problems. Mathematical form of cross entropy loss is defined by Eq. (1).

$$H_{y'}(y) = -\sum_i y_i' \log(y_i) \tag{1}$$

where y_i represents the predicted labels and y_i' represent the true labels.

3.5 Scaling of datasets

Before feeding, both the networks with ultrasonic signals, all the signals were scaled with the Eq. (2) [18]. This scaling was applied to get all the signals on the same scale and to avoid saturation of activation functions.

$$\text{Scale} = \left(\frac{|\text{Signal}|}{\max|\text{Signal}|} \times 0.99\right) + 0.01\,. \tag{2}$$

4. Classification results

4.1 Performance of single hidden layer NN

To compare the performance of single hidden layer NN on the database sets I and II, the network was trained with training set for 3000 epochs with a different number of hidden nodes (10 – 1010) and its performance was evaluated on testing set (testing performance) after each training epoch. In this manner, the number of nodes that gave favorable performance were selected. For database sets I and II, the best testing performance was acquired at 980 and 270 hidden nodes respectively. Despite of the fact, single hidden layer NN may have potential to improve its accuracy if it ran for more training epochs but due to lack of improved results, the training process is terminated at 3000 epochs. For the given number of nodes and training epochs, the maximum testing performance achieved for the database set I was 86 % while for database set II was only 78 %. The learning curves of NN for the database set I and the database set II for 3000 epochs are shown in Fig. 4.

It is quite clear from curves in Fig. 4 that single hidden layer NN starts slowly with approximately 15 % of testing accuracy but by training it repeatedly with training set, it gradually improves its testing performance. NN learning rate is swift for the database set I than database set II due to its simplicity (2 MHz signals only). For database set I, single hidden layer NN testing performance become stable after 312th epoch and then

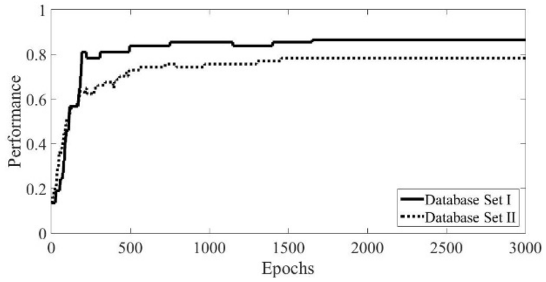

Fig. 4. Comparison of performance on single hidden layer NN for database sets I and II.

slowly achieve testing performance of 86 % at 1652nd epoch, the highest performance achieve so far. Then, in order to ensure that 86 % of testing performance has the global minimum cost associated, the NN was kept on training for more epochs to see any further improvements. But due to lack of improved results the process was terminated after 3000 epochs. For database set II, single hidden layer NN again starts slowly, become stable at 564th epoch and finally gets its maximum performance of 78 % at 1456th epoch. Here network again ran for more epochs to see any possible improvements but due to lack of improved results, the process was terminated after 3000 epochs.

It is evident from Table 4 and Fig. 5 that the flaw classification accuracy of single hidden layer NN for the database set I is also better than database set II. For database set I, it correctly classifies more than 90 % of the LOF and porosity signals, it also accurately classifies 83.33 % of the crack signals, but for lack of penetration and slag inclusion, the accuracy remains 75 % and 80 %, respectively. However, for database set II, single hidden layer NN classifies more than 90 % of the LOF signals, 75 % correct classification of the cracks, LOP and porosity signals, however, only 60 % correct detection of slag inclusions signals. The exact values of correctly accepted (proportion of samples from a certain class classified correctly) and false rejected (proportion of samples from the other classes misclassified into certain class) defect's signals are given in Table 4 where Eqs. (3) and (4) describe the correctly accepted and false rejection terms [6].

$$\left(\text{Correct accept}\right)_i = \frac{m_i}{n_i} \tag{3}$$

m_i : No of testing examples from class i classified correctly
n_i : Total no of testing examples from class i

$$\left(\text{False rejects}\right)_i = \frac{\sum_j m_{ji}}{\sum_j n_j} \qquad \left(j \neq i\right) \tag{4}$$

m_{ji} : Number of testing examples from class j classified into class i
n_j : Total no of testing examples from class

Table 4. Classification accuracy of single hidden layer neural network for database sets I and II.

Defects	Database set I		Database set II	
	Correct accepted	False rejected	Correct accepted	False rejected
Cracks	83.33 %	16.6 %	75 %	39.16 %
Lack of fusion	91.67 %	8.3 %	91.67 %	14.16 %
Lack of penetration	75 %	8.3 %	75 %	8.3 %
Porosity	100 %	0 %	75 %	8.3 %
Slag inclusions	80 %	8.3 %	60 %	16.67 %

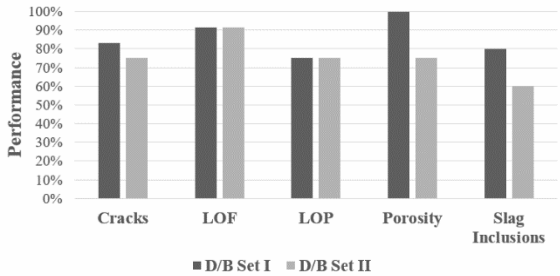

Fig. 5. Defect classification accuracy comparison of single hidden layer NN for database sets I and II.

From above discussion, it is evident that single hidden layer NN performs well on single frequency database but for mixed frequencies database, its testing performance was 8 % less. Furthermore, as it is common practice in industries to evaluate flaws with different frequency transducers, so it can be concluded that for larger databases having mixed frequencies ultrasonic signatures, the single hidden layer NN is not robust and needs modifications.

4.2 Performance comparison of DNN with single hidden layer NN on database set II

In order to address the weaknesses of single hidden layer NN, a DNN with drop out regularization method was adopted and its testing performance was evaluated on both database sets I and II. Single hidden layer NN was also regularized with drop out method to see any improvements in the results.

The testing performance of regularized DNN was first compared with single hidden layer NN and then with regularized single hidden layer NN. However, due to lack of considerably improved results against single hidden layer NN and its regularized version, database I results were omitted in favor of database set II where DNN gave significantly better results.

To evaluate DNN testing performance on dataset set II, various combinations of the number of hidden nodes were tried and then finally 500 and 50 nodes in hidden layer 1 and

Table 5. Performance comparison of DNN with drop out, single hidden layer NN with drop out and single hidden layer NN.

Defects	DNN with drop out		Single hidden layer NN with drop out		Single hidden layer NN	
	Correct accepted	False rejected	Correct accepted	False rejected	Correct accepted	False rejected
Cracks	91.67 %	14.16 %	83.33 %	16.60 %	75 %	39.16 %
Lack of fusion	95.83 %	4.16 %	91.67 %	14.16 %	91.67 %	14.16 %
Lack of penetration	87.5 %	4.16 %	87.50 %	4.16 %	75 %	8.30 %
Porosity	87.5 %	4.16 %	75 %	8.30 %	75 %	8.30 %
Slag inclusions	90 %	4.16 %	80 %	8.30 %	60 %	16.67 %

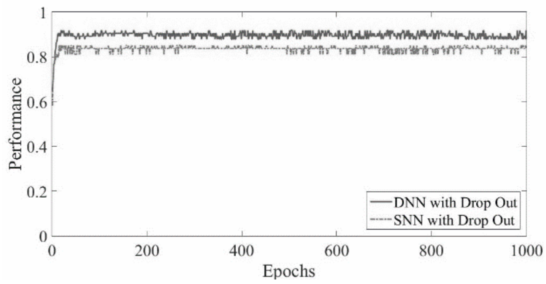

Fig. 6. Performance comparison of DNN with drop out and single hidden layer NN (SNN) with drop out.

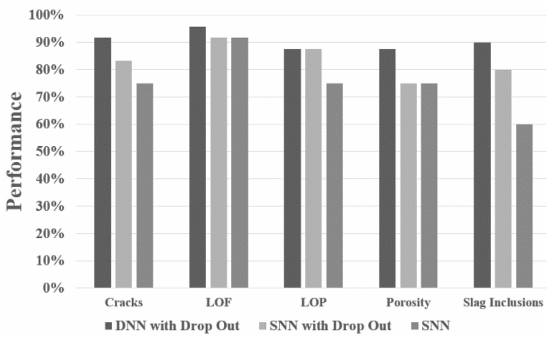

Fig. 7. Defect classification accuracy comparison of DNN with drop out, single hidden layer NN (SNN) with drop out and single hidden layer NN on database set II.

layer 2 were selected respectively. With this configuration, the overall average testing performance achieved was 90 %, while the maximum testing performance index was 91.89 %. However, for the regularized single hidden layer NN the overall average testing performance achieved was 84 % and the maximum testing performance index was 85.13 %. Their performance comparison is shown in Fig. 6. It is quite obvious that testing performance keeps on fluctuating around convergence point, this happens due to oscillation of gradient around global minimum loss. This effect can be minimized by reducing the network learning rate but at the cost of much longer training time.

It can be seen from Table 5 and Fig. 7 that DNN with drop out has the considerable higher testing performance against the single hidden layer NN and its regularized version for mixed frequency dataset (database set II). In the comparison of 75 % and 83.33 % accuracy for cracks given by single hidden layer NN and regularized single hidden layer NN respectively, DNN with drop out accuracy is 91.67 %. For LOF, DNN accuracy is 95.83 % rather than 91.67 % for single hidden layer NN and single hidden layer NN with drop out. For LOP, porosity and slag inclusions DNN accuracy is 87.5 %, 87.5 % and 90 % , in contrast to 75 %, 75 %, 60 % for single hidden layer NN and 87.5 %, 75 %, 80 % for single hidden layer NN with drop respectively. The complete details of correctly accepted and false rejected signals are present in Table 5.

It is quite evident from above mentioned testing accuracies that DNN is a more robust network than both single hidden layer NN and its regularized form. Regularization of single hidden layer NN improves the testing performance but still less than DNN with drop out. So, DNN can have more potential application for industrial big data of mixed frequencies ultrasonic signals without extracting features from them.

5. Summary

In this research, investigation of DNN is made to move a step further from traditional automatic ultrasonic flaw classification methods and to remove the barriers for their industrial implementation. Here more robust DNN architecture was adopted to make the classification system independent of feature extraction approaches.

Reliability of the proposed method is checked for a dataset containing mixed frequencies ultrasonic signatures, as it is common practice in industries to evaluate flaws with different frequency transducers.

This paper first compares the performance of single hidden layer NN on a single frequency dataset (database set I) and mixed frequencies data set (database set II). This comparison was made to check the robustness of single hidden layer neural network as all the prior works have applied single hidden layer NN for flaw classification. The DNN was then adopted for database sets I and II and its performance was collated with single hidden layer NN and regularized single hidden layer NN. Comparison results for database set I being less significant were then omitted in favor of database set II, where DNN gave more remarkable results.

In the light of above discussion, it can be seen that DNN with drop out performs well on the mixed frequency dataset (database set II) and achieved the highest accuracy of 91.89 %, whereas, the single hidden layer NN performs well on the database set I achieving testing accuracy of 86 % but its performance decreased to 78 % when applied to more realistic mixed frequency dataset (database set II). The performance accuracy of single hidden layer NN increased to 85.13 % when regularized by drop put but still less than DNN. So, it can be concluded that DNN with drop out, is feature independent and a more robust network for larger datasets containing mixed frequencies signals. Its performance is better than single hidden layer NN and has potential to use on industrial big data set that contains thousands of signals of different frequency transducers.

6. Future work

This article shows that the performance of DNN is satisfactory for mixed frequency datasets, however, as there are only two different frequency signals in mixed frequency dataset (i.e. 2 MHz and 4 MHz), the need of other frequency signals in mixed frequency dataset is inevitable. So, the future work will be to augment the mixed frequency dataset with more signals of different frequencies (e.g. 5 MHz, 2.25 MHz etc.) to make the technique more reliable. Moreover, as C – Scans are also very useful in the context of non-destructive evaluation, so gathering a mixed frequency database of both B – Scans and C – Scans of defects and their classification with DNN will also be considered as further work to address current industrial needs.

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Nomenclature

DNN : Deep neural network
LOF : Lack of fusion
LOP : Lack of penetration
NN : Neural network
SNN : Single hidden layer neural network
RELU : Rectified linear unit

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