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Acoustic signature based weld quality monitoring for SMAW Process using Data Mining Algorithms

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Abstract

The quality of weld depends upon welding parameters and exposed environment conditions. Improper selection of welding process parameter is one of the important reasons for the occurrence of weld defect. In this work, arc sound signals are captured during the welding of carbon steel plates. Statistical features of the sound signals are extracted during the welding process. Data mining algorithms such as Naive Bayes, Support Vector Machines and Neural Network were used to classify the weld conditions according to the features of the sound signal. Two weld conditions namely good weld and weld with defects namely lack of fusion, and burn through were considered in this study. Classification efficiencies of machine learning algorithms were compared. Neural network is found to be producing better classification efficiency comparing with other algorithms considered in this study.

Introduction

Shielded Metal Arc Welding (SMAW) is a manual arc welding process which joins materials using consumable electrode covered with flux. A power supply, either alternating current or direct current struck the arc between joining materials and electrode which in turn melts the metal and electrode. SMAW is most commonly used process for structural welding applications. Welding defects are unacceptable discontinuities that seize usefulness of weldment. Distortion, Hot cracking, Gas inclusion, Undercut, Cold cracking, Hydrogen Embrittlement, Lack of fusion, Burn through and Porosity are few common defects occur during SMAW process. Welding defects incurs damage leads to cost and time loss. For identifying the weld defects Non Destructive Testing (NDT) methods are commonly used. NDT is a offline, post weld checking process and also time consuming.

Many researchers have investigated and proposed techniques considering Arc sound signal, Electronic temperature, Non-contact acoustic signal, Spectral signal of arc light, thermal image, Arc current and voltage as a parameters to detect defects online and off-line. Many researchers are also implemented advanced machine learning algorithms for classifying good weld and weld with defects. Kamal et al. [1] used the arc sound signal and analyzed the sound signal in time domain and frequency domain to correlate with process parameters. Sadek [2] measured Iron and Manganese

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temperatures within welding arc column and correlated weld defect with the temperature. Abrupt change in average and standard deviation of temperatures provides indication of presence of defects. Zhiyong et al. [3] conducted spectroscopy of GTA weld to determine weld quality with spectral signal of arc light. Mirapeix et al. [4] detected defects using CCD-spectrometer and photo diode based setup. Infrared thermography was proposed by Sreedhar et al. [5] showed good result compared to offline nondestructive radiography. Wei et al. [6] employed linear discriminate analysis of arc current spectral density and discriminated porous weld from nonporous weld. Hong et al. [7] analyzed audible sound signals during laser welding and classified weld defects using Artificial Neural Network was constructed to diagnose welding faults. Ranganathan et al.[8] predicted the machining parameters correlated with roughness from detailed experimentation and anova findings using ANN and RSM.
Praveenkumar et.al [9] used the SVM Algorithm for fault diagnosis of automobile gearbox. Saimurugan et.al[10] used the machine learning approaches like decision tree an SVM for the fault diagnosis in rotating Machinery. Suresh et al [11] made a model for surface roughness that utilizes the computational techniques like ANN and RSM. Model found to concur with experimental and predicted results. Sumesh et. al [14] studied the classification of sound data using decision tree algorithms.

From the literatures it's found that the usability of various algorithms like SVM, Naive Bayes and Neural network was very less explored in the case of welding. This work aims at correlating the weld quality as Good and Bad with SVM, Naive Bayes and Neural network using sound as the signature.

Experimental Design

The experimental setup comprises of power source, electrode holder, electrode, torch, microphone and mild steel plates. Mild steel plates of 6mm thickness were clamped on to a 100 mm channel using four hooks and provided root gap of 1.5mm. A 150 × 150 × 6 mm size specimen was considered for all welding trials. Root face thickness and groove angle adopted was 1.5mm and 30 ° respectively. The standard electrode, AWS A 5.1, E6013 with 3.15mm diameter was used for welding. For capturing the arc sound, a good quality highly sensitive microphone was placed in the proximity of the weld region. Based on the central composite design, experimental trials were carried out. Twenty experiments comprise of 15 unique experiments and 5 repetitive experiments were carried out. These 5 repetitive experiments ensure stability of the experiments. The weld input parameters play a significant role in deciding the weld quality. The input variables considered in this study are Weld current, Voltage and Weld speed. Their rage of operation was carefully studied by conducting preliminary experiments. The sound signals were captured for all the trials during welding of these specimens. The experimental setup is shown in Figure 1 and the details of the weld groove and the photograph of the welding setup is shown in Figure 2(a) and 2(b) respectively.

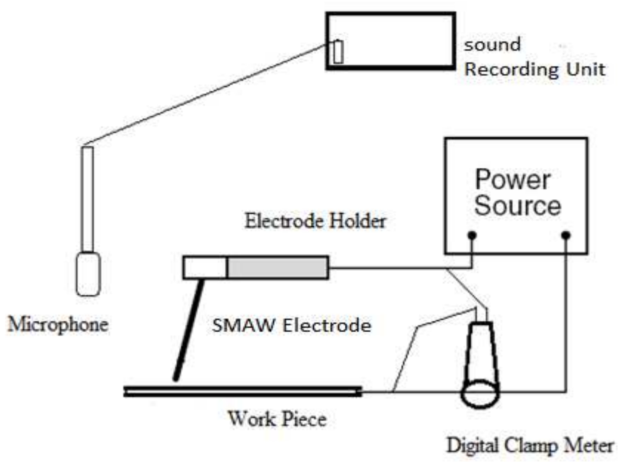
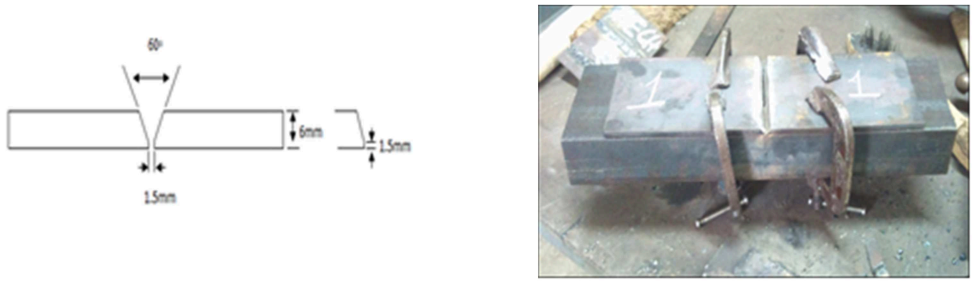


Fig. 1. Experimental setup



(a) (b)

Fig.2. Weld Details: (a) Weld groove details, (b) Photograph of the Weld setup

Methodology

The methodology adopted in this study is shown in the Figure 3. The input parameters and output responses are shown in the Table 1. The output response is the quality of weld. Weld quality was inspected using the visual and NDT technique.

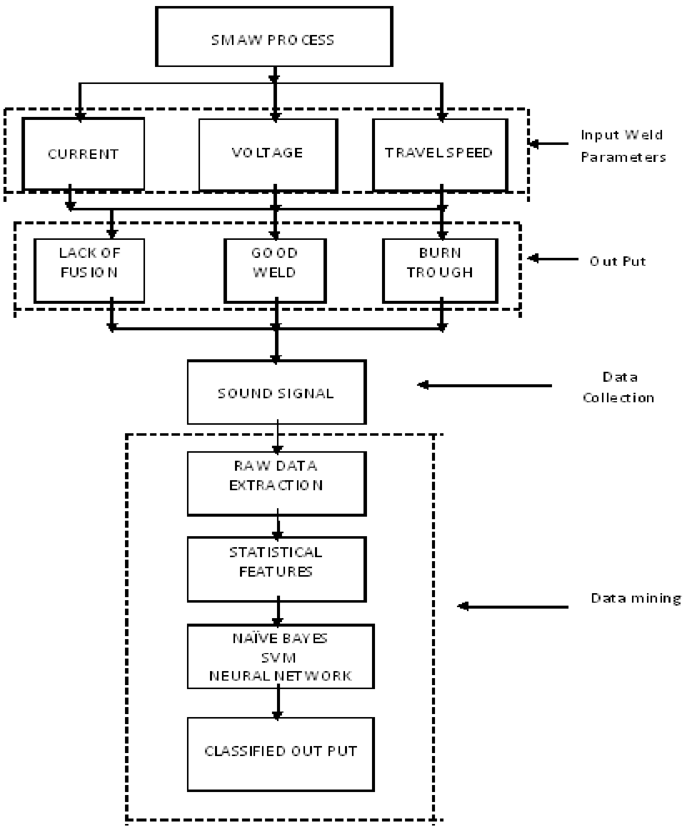


Fig.3 Methodology

Table 1. Welding Parameters

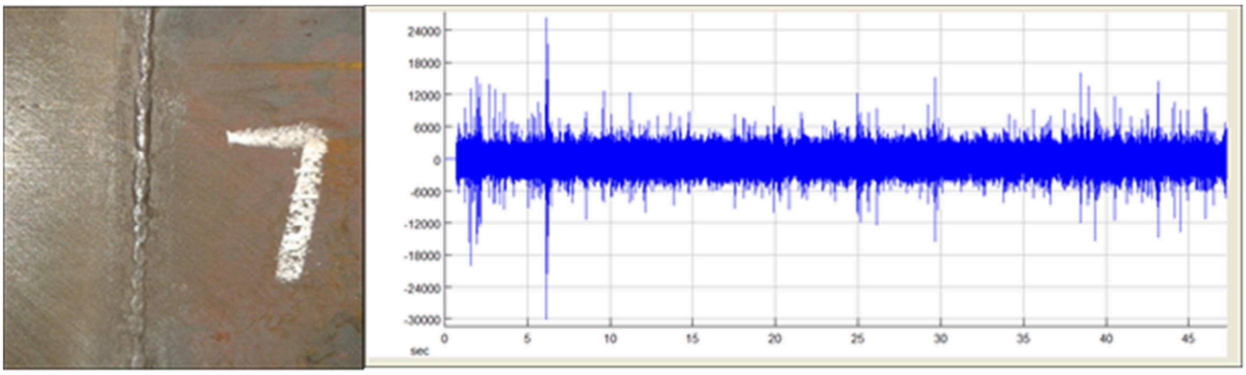
Sample No	Amps	Volts	Speed (mm/s)	Result
1	80	28	2.13	LF (Bad)
2	105	28	2.63	Good
3	80	18	2.13	LF (Bad)
4	105	30	3.03	Good
5	105	16	1.85	LF (Bad)
6	80	28	2.04	Good
7	105	23	2.13	Good
8	105	23	2.00	Good
9	68	23	1.35	LF (Bad)
10	105	23	2.50	Good
11	82	24	2.00	LF (Bad)
12	138	36	1.61	BT (Bad)
13	130	28	1.39	BT (Bad)
14	130	28	1.79	BT (Bad)
15	130	28	1.45	BT (Bad)
16	105	23	2.17	Good
17	154	26	2.27	BT (Bad)
18	80	18	1.90	LF (Bad)
19	105	23	2.50	Good
20	105	23	2.27	Good

The captured raw sound signals were digitized and statistical features were extracted. The statistical features extracted are mean, standard error, median, mode, standard deviation, sample variance, kurtosis, skewness, range, minimum, maximum and sum. Statistical features are fed to the machine learning algorithms for data classification. An association is established corresponding to the weld quality with the input sound signal.

Results and discussions.

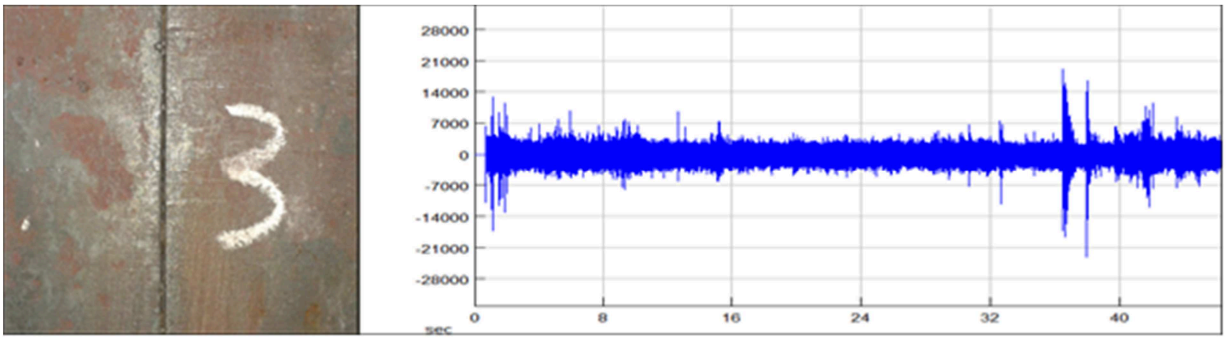
Comparison of Weld quality with Sound Signals

Two weld conditions (classes) were studied in this research work namely, Good Weld (Good) and, Defective Weld (Bad) with defective weld condition being either Lack of Fusion (LF) or Burn-Through (BT). The characteristic sound signals vary for each condition. Statistical features were extracted from the weld signals to identify the corresponding weld conditions. Sample welds for various conditions considered in the present study and their sound signals are shown in Fig.4, Fig.5 and Fig.6.



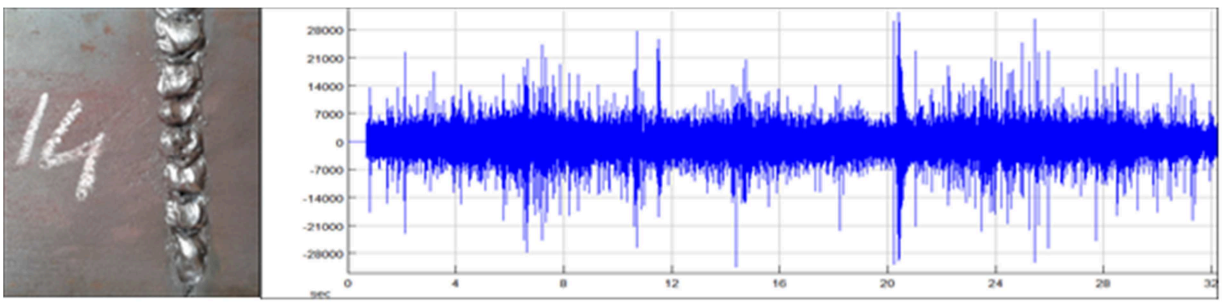
(a) (b)

Fig.4 Good Weld: (a) Specimen Photograph (b) Sound signal for Good Weld



(a) (b)

Fig.5 Lack of Fusion (LF): (a) Specimen Photograph (b) Sound signal for LF



(a) (b)

Fig.6 Burn-Through (BT): (a) Specimen Photograph (b) Sound signal for BT

As shown in the Fig. 4(b) the amplitude of the signal is almost constant. A very few spikes are seen in the sound signal. In the cases of bad weld, as shown in the Fig. 5(b) and 6(b), the spikes are very common and irregular amplitude variations are observed. But differentiating good and bad weld from amplitude plot is difficult. Classification Algorithms were used for this purpose.

Comparison of Weld quality with Classification algorithms

Three different classifiers were considered in the present study. The classifiers considered are naïve Bayes, Support Vector Machine (SVM) and Artificial Neural Networks (ANNs). For all the classifiers considered in the present study, the dataset was partitioned into randomly selected training and testing sets with 80% points used for training and remaining 20% for testing. A brief description of each of the classifiers is given below:

Naïve Bayes

Naive Bayes is a conditional probability model which classifies instances based on Bayes theorem assuming strong independence between the features. Considering a k- class classification problem. Given an n-dimensional input feature vector, say $X = \{x_1, x_2, \dots, x_n\}$, where x_1 , x_2 , …, x_n are the feature values, Naive Bayes classifier calculates the posterior probability $p(C_i|X)$ where i = 1,2,.., k based on the relation:

$$p(C_i|X) = \frac{p(X|C_i)p(C_i)}{p(X)} \quad \dots \qquad \text{(Eq. 1)}$$

Here,

$p(C_i)$ is the prior probability of class C_i ; $p(X|C_i)$ is the likelihood; $p(X)$ is the data evidence, and $p(C_i|X)$ is the posterior probability, i.e. the probability that the sample X belongs to class C_i Assuming independence among the features, in Eq. (1), we use:

$$p(C_i|X) = p(x_1|C_i).p(x_2|C_i) \dots .p(x_n|C_i) \dots \qquad \text{(Eq. 2)}$$

The sample X is assigned to the class C_j if $p(C_j|X) > p(C_i|X)\ \forall\ i = 1,2, \dots, k$ and $i \neq j$

In the present study, two classes are considered: C_1 = Good Weld (Good) and C_2 = weld with defects (Bad). Table 2 shows the confusion matrix of Naïve Bayes algorithm.

Table 2. Confusion Matrix of training and testing data for Naïve Bayes

Actual Training Class		
Good	Bad	Classified as
282	589	Good
130	535	Bad

Actual Testing Class		
Good	Bad	Classified as
71	114	Good
30	169	Bad

Support Vector Machine

A Support Vector Machines (SVMs) are statistical classifiers. An SVM uses optimization to identify the support vectors s_i , weights α_i and bias b such that the sample x gets classified to class C based on:

$$C = \sum_i \alpha_i . k(s_i , x) + b \quad \dots \qquad \text{(Eq. 3)}$$

SVM used in the present study is a binary classifier and hence if $C \geq 0$, the sample belongs to class C_1 = Bad Weld (Bad) else to class C_2 = Good Weld (Good). In equation (3), k (.) represents the kernel function employed. In the present study, a linear kernel is used. The optimization technique used in this study is Sequential Minimal Optimization (SMO) [10]. Table 3, shows the confusion matrix for SVM classifier used in the present study.

Table 3. Confusion matrix of training and testing data for SVM classifier.

Actual Training Class		
Good	Bad	Classified as
418	434	Good
189	495	Bad

Actual Testing Class		
Good	Bad	Classified as
118	86	Good
37	143	Bad

The classification accuracy of the algorithms Naïve Bayes and SVMs vary during training and testing in every iteration (due to the random selection of training and testing samples). Classification efficiency of SVM and Naïve Bayes are shown in Fig. 7.

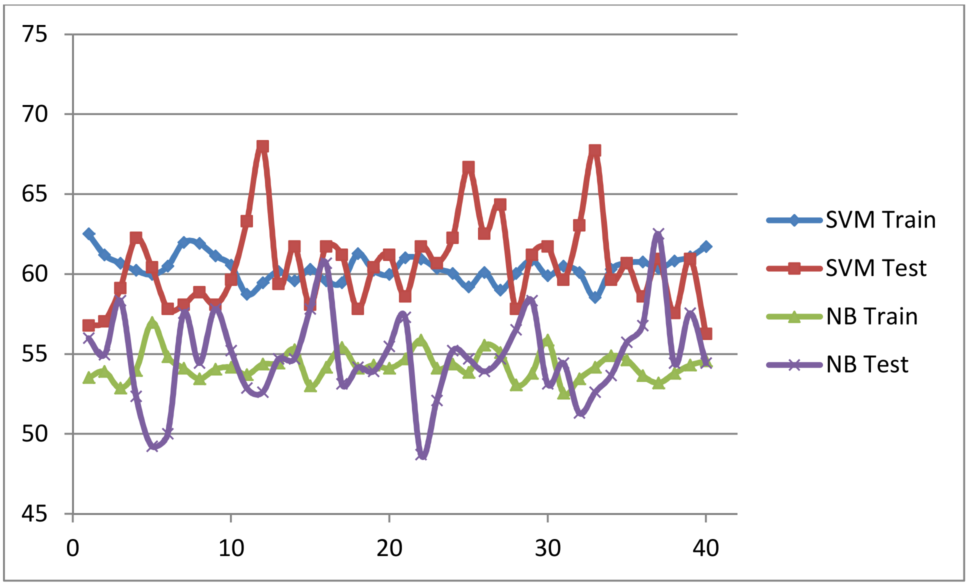


Fig.7. Comparison of SVM and Naïve Bayes Classifiers in Weld classification

Artificial Neural Network (ANN)

The third category of classifiers considered in the present study is ANNs. A feed-forward neural network was used in the present study for classification of welds into good or bad. The objective function considered was the mean squared error (E), where:

$$E = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \ldots \qquad \text{(Eq. 4)}$$

Here

N = Total number of samples in the dataset; t_i = target value for the i-th sample ; y_i = ANN output value for the i-th sample

The network was trained using Levenberg Marquardt (LM) algorithm, since it has been found to generate better results compared to other learning algorithms [11]. Minimum performance gradient was set at 10^{-7} and a sigmoidal activation function was used in the hidden layers. Input and output layers employed linear activation function. The damping term used in the LM algorithm had the range 0.001 - 10^{10}. ANN performance for different number of hidden layer neurons is also presented in the study. Results are shown in Fig. 8, 9. Table 4 shows the confusion matrix of Neural Network Algorithm.

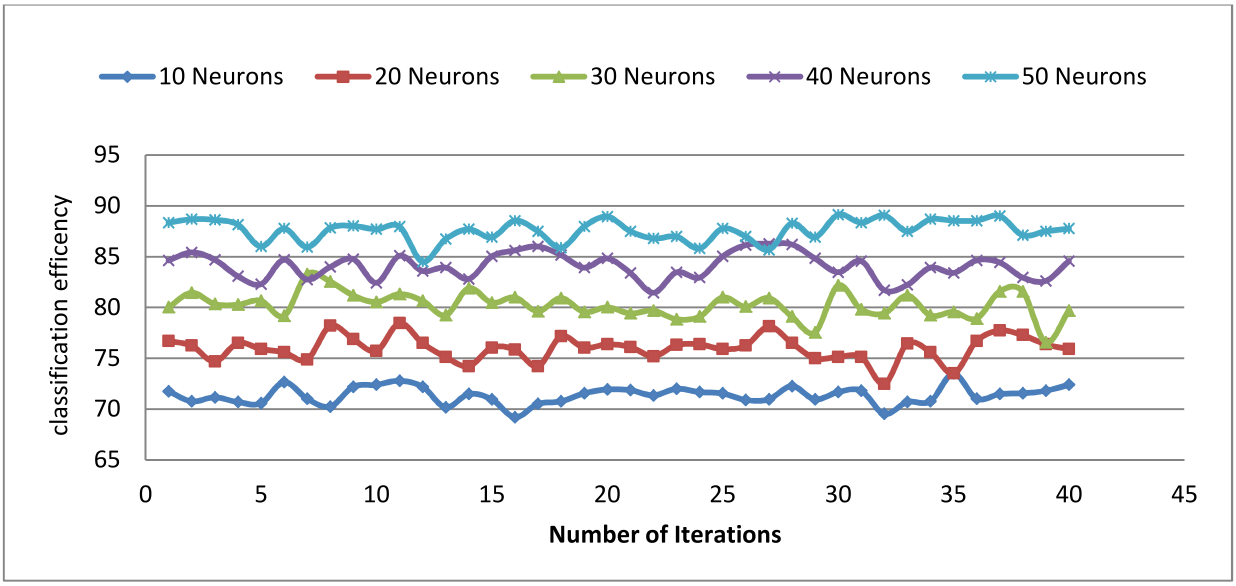


Fig.8. Training accuracy of ANN based weld classification system for different hidden neurons

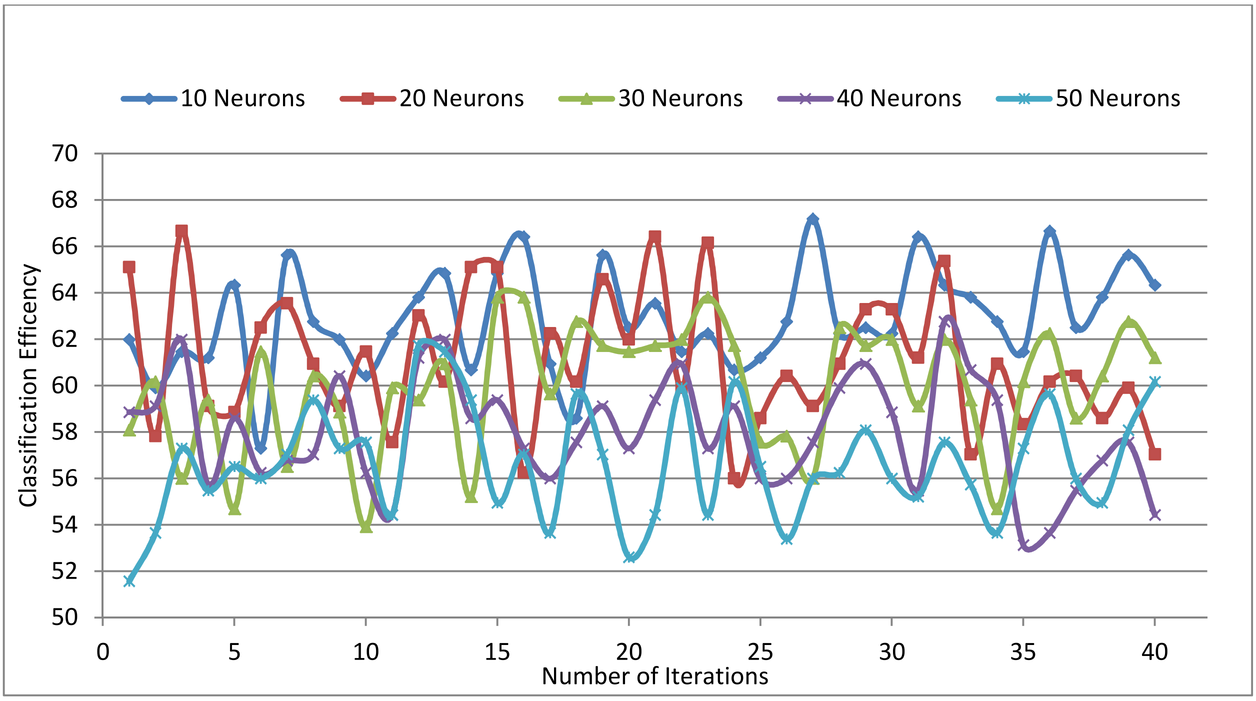


Fig.9. Testing accuracy of ANN based weld classification system for different hidden neurons

Table 4. Confusion matrix of actual Class and Predicted Class for Neural Network

Actual Training Class		
Good	Bad	Classified as
768	79	Good
89	600	Bad

Actual Testing Class		
Good	Bad	Classified as
118	91	Good
72	103	Bad

Classification accuracies of Naïve Bayes, Support Vector Machines and Neural Network were found to be 62.50%, 67.96% and 82.76% respectively. The Classification efficiencies are also shown in Fig.11.

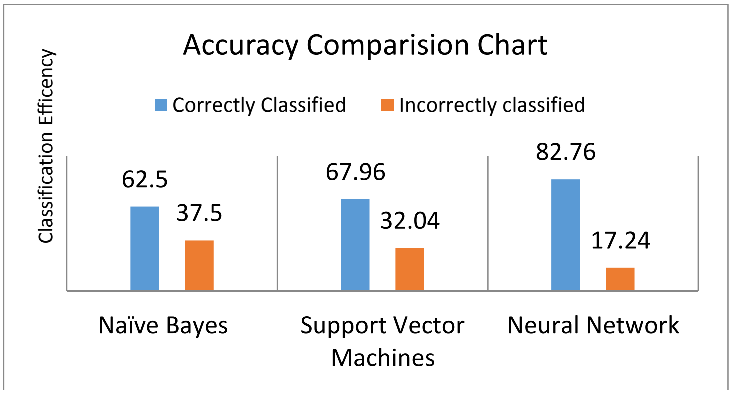


Fig.11. Accuracy Comparison Chart

From the analysis it is found that Neural Network algorithm yielded better accuracy compared to Naïve Bayes and Support Vector Machine for classifying SMAW defects.

Conclusion

Present work is carried out to train and classify the SMAW conditions such as good weld and weld with lack of fusion and burn through. Based on the Central Composite Design, experimental trials were carried out. Arc sound signals are captured during the welding of carbon steel plates. Statistical features of the sound signals are extracted during the welding process. Data mining algorithms such as Naive Bayes, Support Vector Machines and Neural Network were used to classify the weld conditions according to the features of the sound signal. Classification efficiencies of Naïve Bayes, Support Vector Machines and Neural Network were found to be 62.50%, 67.96% and 82.76% respectively. The efficiency of the algorithms may be improved by filtering the unwanted the noises during the welding process.

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