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Comparison of Fracture Delineation Methods in Anteroposterior Pelvic Radiographs

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Abstract: Pelvic fractures are very difficult to detect due to the visual complexity of the pelvic bone. Pelvic fracture occurs less frequently, only when there is a high energy event such as fall from a height or vehicle collision. In elder people and in osteoporosis patients even a low energy incident may cause fracture. The paper includes the comparison of three different fracture detection methods – GLCM and ANN based, Statistical curve fitting and classifier based and finally statistical curve fitting and ANN based method.

Keywords: Image segmentation, RMSE, GOF, GLCM, SSE

1. Introduction

The pelvis is the basin like bone structure supporting the major parts of human body. The pelvic bone forms the site of load transfer between the skelton and the upper limb of the body The pelvis consists of the coccyx, the paired hipbones and the sacrum. Any disruption in the continuity of the pelvic bone is known as the fracture. Approximately 50 percent of pelvic fractures result from motor vehicle collision, 30 percent from pedestrian versus motor vehicle collision, 10 percent due to fall from height, 4 percent from motor bike collision and others due to sports injury and low energy falls. The type of fracture depends on the injury impact, strength of the bones and energy involved.

One of the most frequently used methods of imaging for fracture detection is X-ray imaging. X-ray imaging technology was used for medical imaging immediately after X-ray was discovered by Rontegen. Picture of body's internal structure can be produced using radiography. A vacuum tube which consists of a cathode and an anode is used to generate x rays for medical imaging.

Rebecca Smith and Kevin Ward proposed a method for the detection of fracture and the measurement of displacement in x ray images of pelvic bone. Initially, the pelvic ring boundary is located utilizing combined Spline/ASM. A. S. Chowdhury suggested a coarse to fine strategy for automatic detection of fracture in CT pelvic images. Using curvature and intensity information, the potential area with fracture is identified. Precise fracture detection is done by using two different methods-spatially consistent valleys and 3D graph cut method. Jie Wu and Yang Tang proposed a hierarchical process for automatically detecting the pelvic bone fracture and measuring the displacement between the fractured pelvic bones [3].

Nitish Premanand Wadker, Prof. Amita Dessa iproposes a method of Distance Regularized Level Set Evolution for the fracture detection [6]. Segmentation is done using DRLSE and fracture detection is done using canny edge detector. GLCM is used for examining the displacement of the pubic bone. Simina Vasilache and Kayvan Najarian proposed an unsupervised, hierarchical and automated method for the pelvic bone segmentation [7]. The algorithm consists of automated seed growing, wavelet processing, histogram equalization and ACM.

2. The GLCM and ANN Based Fracture Detection Method

The proposed algorithm consists of a number of steps which include preprocessing, segmentation, feature extraction and fracture classification. The image is first converted in to gray level. Then preprocessing involves cropping, resizing and the applying Gaussian filter for noise removal. The preprocessed image is then segmented using canny edge detector and thresholding.

Parameter	Value	Parameter	Value
Contrast	0.17961	Maximum probability	0.20351
Correlation	0.96472	Difference variance	0.17961
Dissimilarity	0.16623	Difference entropy	0.45192
Energy	0.12235	Inverse difference normalized	0.98164
Homogeneity	0.91790	Information measure of correlation	0.96382

Figure 1: a)An example for anteroposterior pelvic radiograph b) GLCM parameter values obtained for the given pelvic radiograph

From the segmented image the features are extracted. Here in the first method ten different parameters or features are calculated using the Grey Level Co-occurance Matrix. These features are then used for fracture classification. The classification is done by training the Back

Propagation Neural Network using the GLCM parameters. The Neural Network is trained with 10 GLCM parameters calculated from the data base. The 10 parameters are Contrast, Correlation, Dissimilarity, Energy, Homogeneity, Maximum probability, Difference variance, Difference entropy, Information measure of correlation 2, Inverse Difference Normalized.

An example for anteroposterior pelvic radiograph is given in figure 1.a and the GLCM parameters calculated for the given image is shown in figure 1.b. The neural network tool box for the network trained with GLCM arameters is given in figure 2. The error histogram for the method is given in figure 3. The performance plot of the GLCM based fracture detection method is given in figure 4. From the performance plot it is clear that the best validation occurs at epoch 67 and the value of MSE is $1.533e^{-17}$. Figure 5 gives the training state plot of the network.

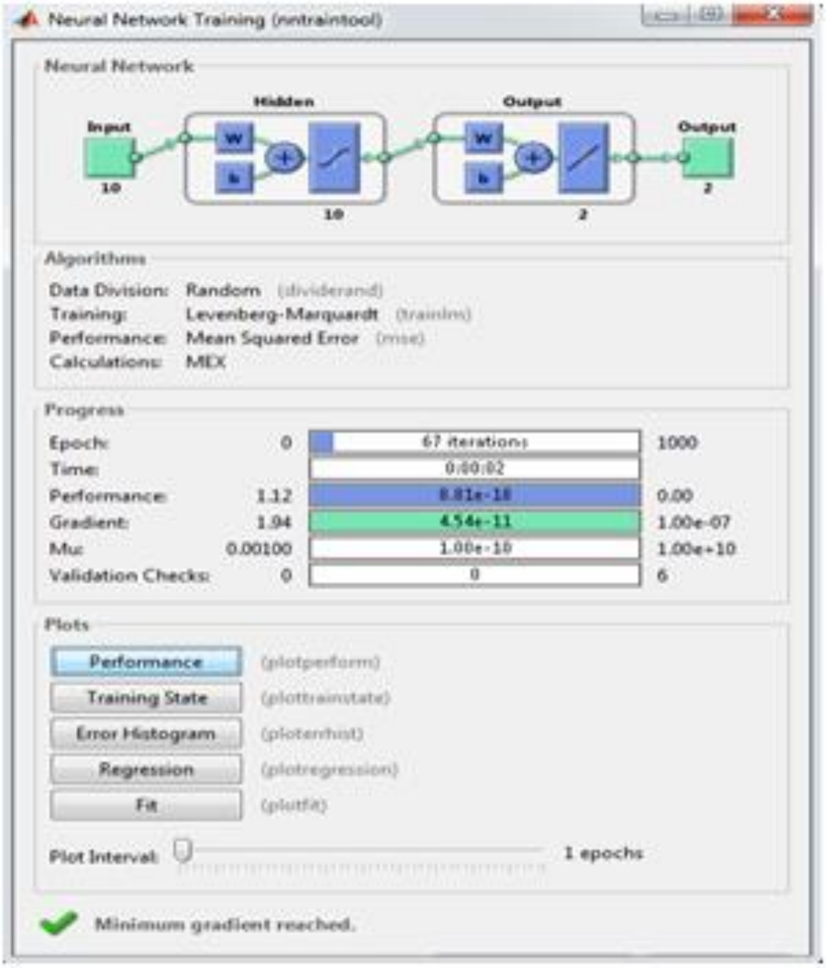

Figure 2. Neural Network tool box for the network trained with GLCM values

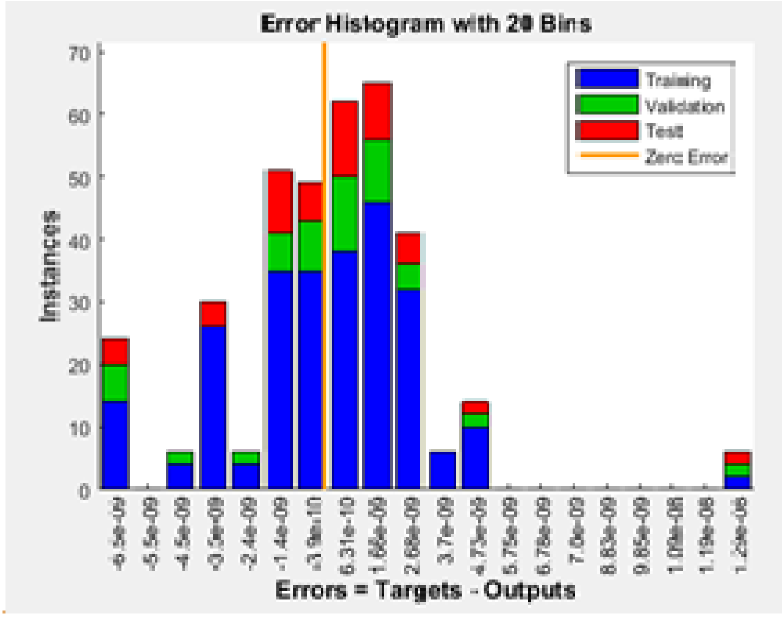

Figure 3.Error histogram for the GLCM and ANN based fracture detection method

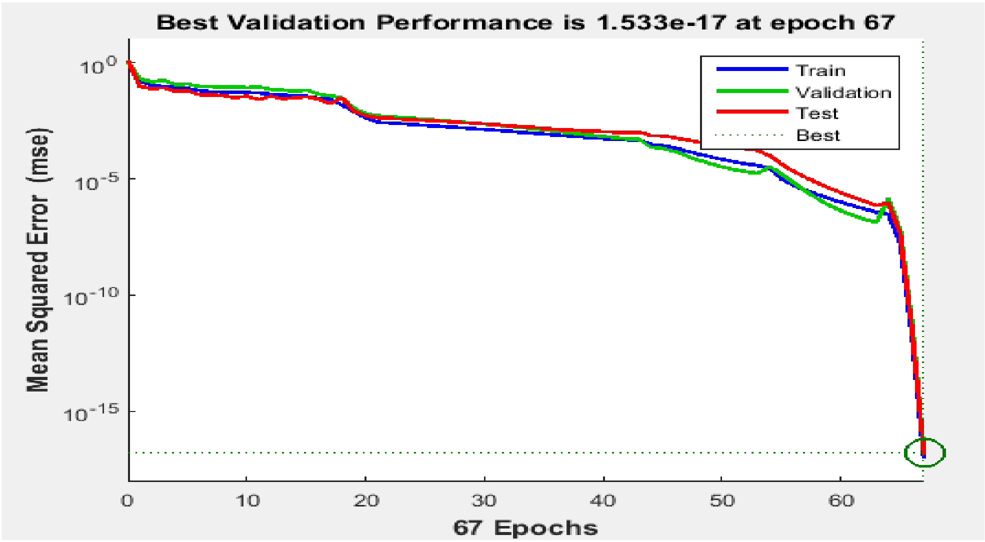

Figure 4.Performance plot for GLCM based fracture detection

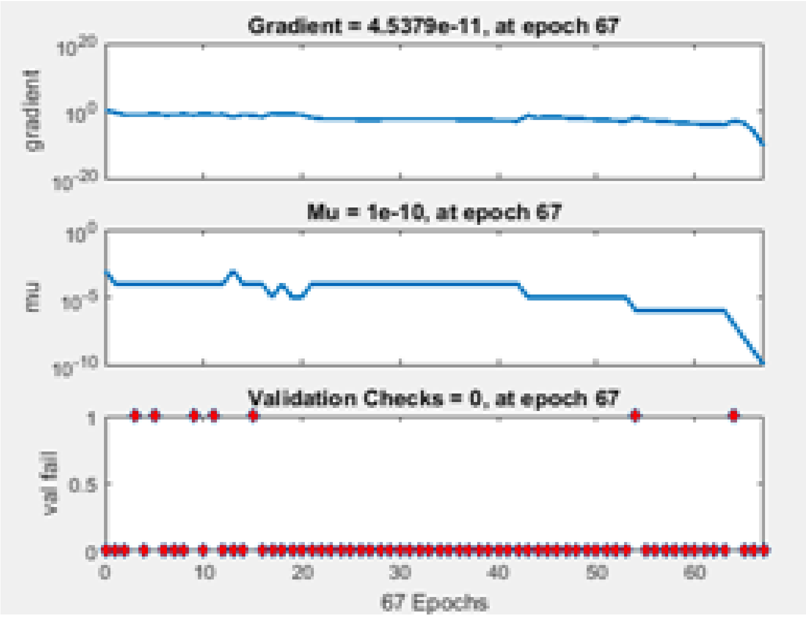

Figure 5.Training state plot for the GLCM and ANN based detection method

3. The Statistical Curve Fitting and Classifier based Fracture Detection Method

Here fracture classification is done using three different classification learners – Linear SVM, Fine KNN and Bagged trees. The classification learners are trained with statistical features of 198 different images. R square value is taken as the response and Root Mean Squared Error, the adjusted R square and Sum of squares due to error are taken as the predictors. Statistical curve fitting parameter values for the radiograph in figure 1a is given in figure 6. The features obtained for the given image were applied to three different classification learners and the performance is evaluated.

GOF left		GOF right	
SSE	1.46E+04	SSE	1.66E+05
RMSE	7.2138	RMSE	22.8386
Adjusted R square	0.9673	Adjusted R square	0.9044
R square	0.9676	R square	0.905

Figure 6.Statistical curve fitting parameter values for the given pelvic radiograph

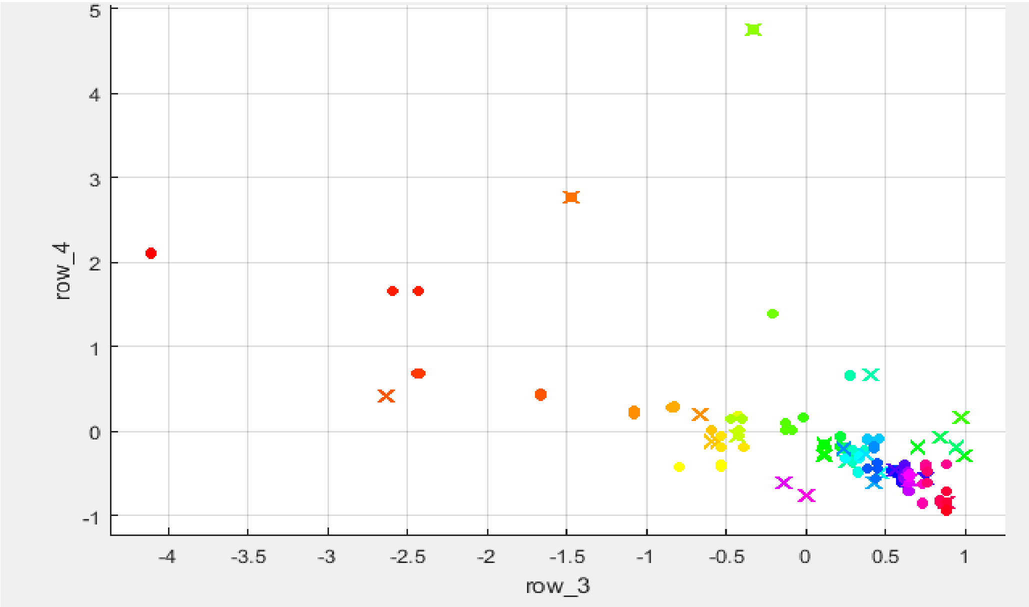

Figure 7. Scatter plot for the statistical curve fiying and SVM based classification

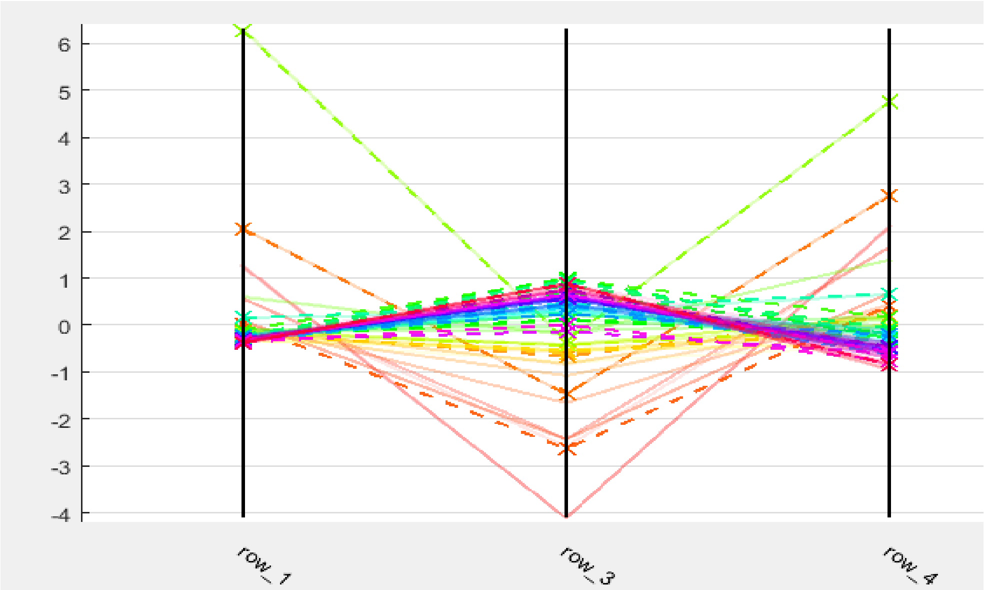

Figure 8.Parallel co-ordinate plot for the statistical curve fiying and SVM based classification

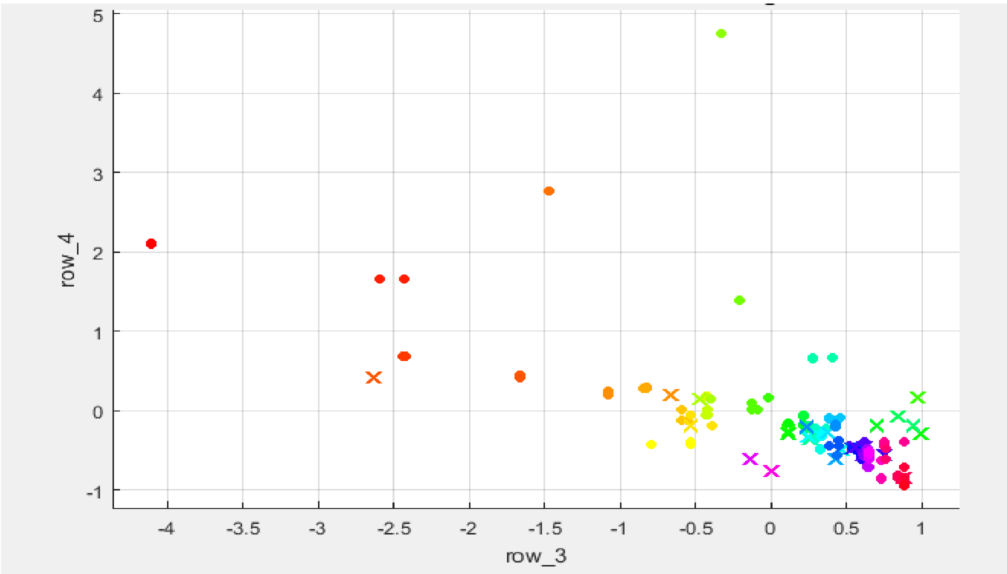

Figure 9. Scatter plot for the statistical curve fiying and Fine KNN based classification

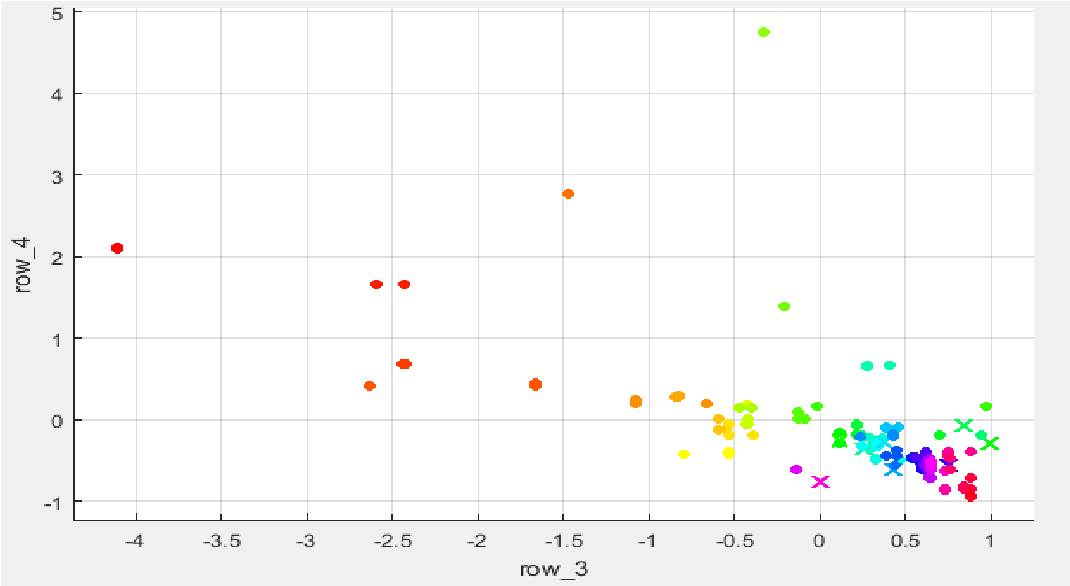

Figure 10.Scatter plot for the statistical curve fiying and bagged tree based classification

The scatter plot for the statistical curve fitting and SVM classifier based fracture detection method is given in figure 7. The parallel co-ordinate plot for the same is given in figure 8. Figure 9 gives the scatter plot for the statistical curve fitting and Fine KNN classifier based fracture detection where as figure 10 gives the scatter plot for the statistical curve fitting and Bagged tree based fracture detection. From the comparison of the scatter plot it is clear that bagged tree based method is more accurate than the other two methods.

4. The Statistical Curve Fitting and ANN Based Fracture Detection Method

Root Mean Square Error is the most distinguishing statistical curve fitting feature. So, the Neural Network was first initially trained with the RMSE value of 332 images and the performance analysis was done. Out of the 332 images, 232 were used for training, 50 were used for testing and 50 were used for validation, by the network. After completing the performance analysis for the single input ANN, the network was trained with all the four statistical curve fitting parameters. A Neural Network was created in which the input parameters are SSE, RMSE, r square, adjusted r square. The network consists of 4 input nodes and two output nodes.

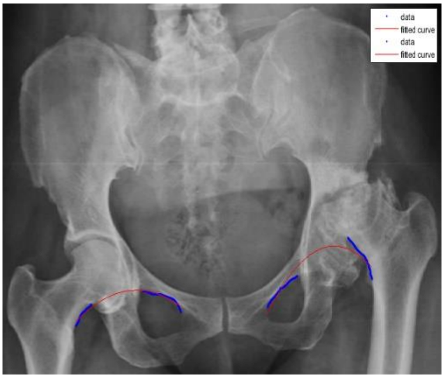

Figure 11.Trace of the shenton line and detection of NOF

Image	GOF left				GOF right				Detection
	SSE	R square	Adj. R square	RMSE	SSE	R square	Adj. R square	RMSE	Detection
Image 1	$1.05e^5$	.9726	.9723	6.2672	$2.83e^4$	.952	.9519	10.1316	Normal
Image 2	$1.52e^5$	.3587	.3541	23.322	$1.10e^4$	.941	.9401	7.591	NOF left
Image 3	$1.46e^4$	.9676	.9673	7.2138	$1.66e^5$	.905	.9044	22.8379	NOF right

Figure 12. Comparison of statistical parameters of images with and without NOF

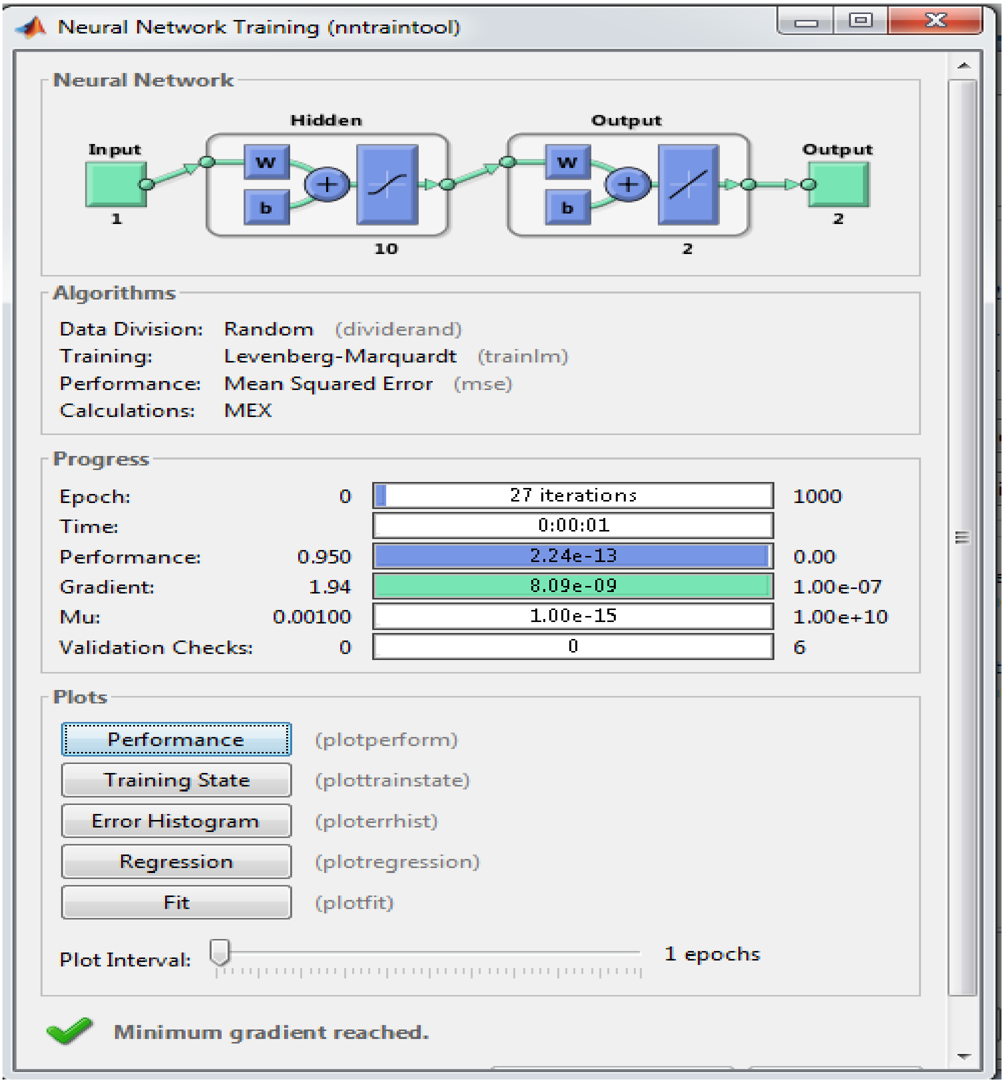

Figure 13.Neural Network tool box for the network trained with statistical curve fitting parameters

Figure 11 gives the detection of NOF by tracing the shenton line in the radiograph. Figure 13 gives the Neural Network tool box for the network trained with statistical curve fitting parameters. Figure 12 gives the goodness of fit parameters for three different images. From the table, it is noticed that the SSE and RMSE values are comparatively higher and r square and adj. r square values are comparatively lower for the fractured cases. Image 1 is normal. As compared to image 1, the goodness of fit parameters on the left side of image 2 is very high. Similarly, the goodness of fit parameters on right side of image 3 also has the same variations in value. So, image 2 is having NOF at the left side and image 3 is having NOF at the right side. Figure 14 gives the Training state plot for the ANN trained with the Root Mean Square Error Values. And figure 15 gives the performance plot for the method.

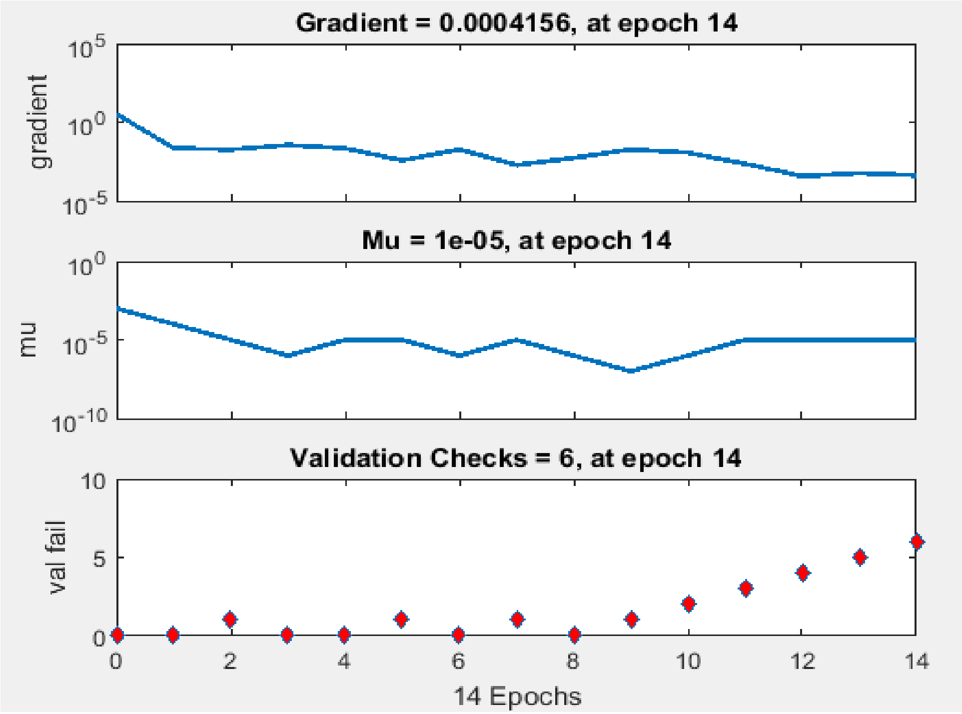

Figure 14. Training state plot for the ANN trained with the Root Mean Square Error Values

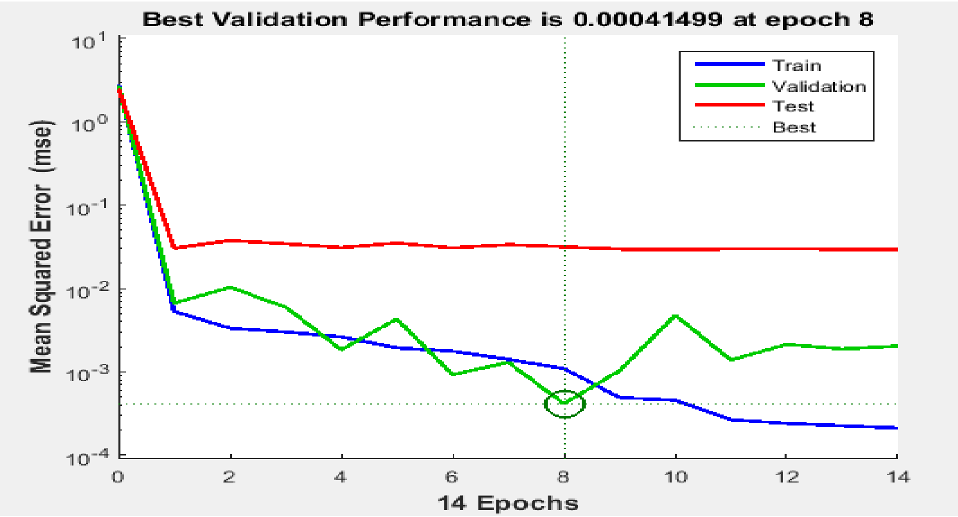

Figure 15.Performance plot for the ANN trained with the Root Mean Square Error values

5. Result and Discussion

Figure 16 gives the comparison of accuracy for the different methods of fracture detection. Accuracy of the GLCM and ANN based fracture detection system is 80 %. Statistical curve fitting based fracture detection system have better accuracy than the GLCM based method. Among the classification learners the bagged decision tree has maximum efficiency as compared to that of SVM and KNN classifiers. Above all, the accuracy obtained using the combination of statistical curve fitting and ANN is maximum as compared to all other detection methods. The maximum accuracy obtained is 96.6 %.

SI No.	Method	Accuracy
1.	GLCM and Artificial Neural Network	80%
2.	Statistical curve fitting and Support Vector Machine Classifier	85.4%
3.	Statistical curve fitting and Fine KNN classifier	86.9%
4.	Statistical curve fitting and Bagged tree classifier	96%
5.	Statistical curve fitting and Artificial Neural Network	96.6%

Figure 16.**Comparison of accuracy for different methods used for fracture detection**

6. Conclusion and Future Scope

The proposed algorithms provide good results over the conventional algorithms. Moreover, the algorithm can be modified by incorporating the treatment plan also along with the identification of fracture. In hospitals detailed diagnosis is performed by taking CT scans if there is a suspicion of fracture in the X-ray image. This can be avoided by the implementation of the proposed algorithm in hospitals. Moreover, deep learning algorithms can be utilized to further increase the accuracy of the proposed algorithm.

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