Thermal Wave Imaging for Detection of Osteoporosis

Prathipa R (prathipa.srini@gmail.com)
Research scholar, Sathyabama Institute of Science and Technology

Ramadevi R
Saveetha School of Engineering

Chinnammal V
Rajalakshmi Institute of Technology

Rajalakshmi S
Vellore Institute of Technology

Poonkuzhali I
Panimalar Institute of Technology

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Abstract

Osteoporosis is a clinical sickness wherein the bones end up brittle and volatile because of tissue loss, which is usually caused by hormonal changes or a calcium or vitamin D deficiency. Osteoporosis has neither clinical signs nor symptoms, until some fracture occur. The aim of our project is to predict bone brittleness in order to detect osteoporosis using Image processing techniques. The objective measurement of bone mineral density (BMD), is presently accepted as the best indicator of osteoporosis fractures. For measuring and assessing biomaterials, thermal wave imaging is a potential , non-invasive, non-contact and safe imaging method.. Thermal wave imaging has the unique ability to measure physiological changes. The thermal images of bone are taken and removal of noise is carried out and undergone stationary wavelets transform process to improve the resolution of edges. The result shows that Artificial Neural Network is capable of predicting the brittleness of the bone using Regression in Machine Learning.

I. Introduction

Osteoporosis (OP) is a bone disorder that influences both men and women. Smoking, Alcoholism and lifestyle is linked with increased cases of osteoporosis [12]. Millions of fractures occur due to osteoporosis which reduces bone strength and bone mass density [2]. In Latin osteoporosis means "porous bones”. The inside of a normal bone has small gaps like a honeycomb, and hence bone mass decreases [10]. Osteoporosis widens these holes, causing the bone's strength and density to degrade [4]. The exterior of the bone also weakens and thins. OP may strike anyone at any age, but it is more prevalent in older adults, especially women. People with osteoporosis are at risk of fractures or bone breaks when undertaking everyday tasks such as standing or walking. The most commonly afflicted bones are the elbows, ribs, and bones in the wrists and back. [3].

In this system, we proposed the method of detection of osteoporosis using thermal wave imaging technique. First step is to prepare the bone. We have used the bone of a goat instead of human bone as it is large enough to evaluate orthopedic implants [14]. The normal bone is converted into osteoporosis bone by bone sanding technique as it reduces the thickness of the bone. Then, the thermal RGB images are captured using Thermal Camera and software named SmartView is used to view the captured thermal images.

Denoising and generating smoothened images is the next step. The Butterworth Low Pass Filter is used in this case. Butterworth filter have a frequency response that is flat across the pass-band field. Low Pass Filter gives a constant response from DC up to cutoff frequency and attenuates all signals over cutoff frequency. The thermal RGB images are converted into Grayscale images to reduce the color complexity and magnitude and phase spectrum is obtained. The implementation of Non-decimated wavelet transform algorithm intended to improve the resolution of the edges by filtering the noise to make it better for further operations.

Finally, regression in machine learning is done. Regression is a supervised learning method for determining variable correlations and forecasting a continuous output variable utilizing single / more predictor variables. As a result, bone brittleness is expected.

Ii. Related Works

Methods for evaluating already obtained Computed Tomography (CT) images to determine a DXA-equivalent BMD at the hip and a finite element analysis-derived femoral strength are now available. [1, 9]. Osteoporosis causes a series of more complex bone changes, which affect the microstructure and composition of bones. Simple Radiographs or X-ray of bone can be used to find variation in bone density[11].An overview of the bone changes associated with osteoporosis, and the most common random imaging technique used to study this osteoporosis in clinics that specialize in micro-CT [5, 6]. This is because of its excellent image resolution and accuracy. The morphometric measurement and better highlight the changes in bone structure caused by osteoporosis. In addition, Micro-CT can use micro-finite element methods for optical density measurement and analysis, which can be used to predict fracture risk and future diagnosis of OP [6]. MRI is also used in detecting osteoporosis where changes in bone marrow due to increased fat content and reduced cellularity are used for diagnosis [7]. Unfortunately, advancements in technology are indeed required to decrease radiation exposure and scan duration., which currently limits the use of micro-CT in operating rooms [6]. The diagnosis has not yet been completed.

Iii. Proposed Methodology

The overall block diagram of the proposed method is shown in Fig. 1. Bone sanding technique is used to convert the normal bone into osteoporosis bone. To execute image denoising, the acquired RGB image is turned into grayscale image to minimize colour complexity. Butterworth low-pass filter is used to remove the unwanted signals and noise to produce smoothened image as it attenuates the high frequency and eliminates the low frequency. Regression in machine learning is used to compare the estimated value between the normal bone and osteoporosis bone. Thus the osteoporosis brittleness of the bone is predicted.

A. BONE SANDING

Sanding method is used to smoothed or polish the surface with sandpaper or mechanical sander. Here, we used this method to reduce the bone thickness thereby converting the normal bone into osteoporosis bone.

B. THERMAL RGB IMAGE

After bone sanding, thermal RGB images of normal bone and osteoporosis bone are captured using thermal camera and viewed using thermal Smart View software which is shown in Fig. 2 and Fig.

3Thermal imaging might potentially be used to improve visibility of things in low-light situations by detecting infrared and generating a picture based on that data.

C. BUTTERWORTH LOWPASS FILTERING

Butterworth low-pass filter is used to remove noise, as low-pass filter attenuates high frequency by eliminating low frequency to create the blurred or smoothened image. For image processing application, processing of colored image makes it complicated. So, RGB image is converted into Grayscale image to reduce color complexity and simplify mathematics. The magnitude spectrum shows variation in pixel values and tells you how powerful the harmonics are in an image. The phase spectrum depicts the location of this harmonic in space as well as variation in intensity.

In Fourier spectrum the transform's origin is shifted to the middle of the frequency rectangle.

NON-DECIMATED WAVELET TRANSFORM

Non decimated wavelet transform algorithm is used to improve the resolution of the edges to make it better for further operations. The wavelet transform permits extracting data of stationary and non-stationary signal variations in time and frequency [8] i.e., distinctive their frequency of occurrence, localization in time, and creating a reliable approximation of magnitude of this variation. It is possible to present an original grey image, a noisy image, a denoised image based on wavelet, and a denoised image based on stationary wavelet..

D. REGRESSION IN MACHINE LEARNING

Regression is the task of predicting continuous quantity. The analysis is carried out on the proposed Simulink supported ANN. For training the neural network we had Five hidden layers and one output layer. Various factors like gradient, Mu, epochs, time, performance and validation checks are used to proceed. Training state, Performance, error histogram, and regression are all included in the plot section.

The algorithms used are:

a. Random (Data division)

b. Levenberg-Marquardt (Training)
c. Mean Square Error (Performance)
d. MEX (Calculations)

A sample snapshot of neural network training displaying various parameters is shown in Fig. 4.

E. RESULT AND DISCUSSION

The best validation performance is 5.8971e-09 at epoch 350 as shown in Fig. 5 and 0.0086931 at epoch 82 is shown in Fig. 6 for normal & OP bones respectively. The performance is mse against number of

epochs. The graph depicts train, validation, and test trends.

The respective values of gradient, Mu and validation check at epoch 413 are 4.4649e-07, 1e-07 and 0 for normal bone shown in Fig. 7 and at epoch 88 are 0.00016411, 1e-08 and 6 for OP bone respectively is shown in Fig. 8. The plot is number of epochs against training state parameters.

The error histogram plot is errors against instances. The error is nothing but outputs subtracted from targets. Here, the error histogram is represented with 20 bins. Bin is the number of vertical bar observed in the graph. The plot shown in Fig. 9 and Fig. 10 shows trends of training, validation, test and zero error.

For normal bone, zero error is obtained at the 16th bin at -5.9e-05 and for OP bone, the zero error is obtained in the 12th bin at 0.01227.

The regression plots for training, validating and testing along with combination of their three plots (all) are shown in the Fig. 11 & 12. The plot displays the output with respect to targets of training, validating and testing. In normal bone regression plot, the data (pixels) is perfectly fitted along the dash line, where the output is equal to the target. The plots are plotted with value of R equal to 1 obtained by comparing the normal bone with normal bone. This case is same when OP bone is compared with OP bone. From this it is clear that the regression plot does not vary and fit perfectly in the dash line when same type of bone is trained.

But in OP bone, for perfect fit the data should fall along the dash line of 45 degree. The plots are plotted with value of R greater than 0.87027 i.e. <1 obtained by comparing normal bone with OP bone indicating that the bone is brittle. When the value of R obtained is less than 1, it means that the bone is bone is brittle and thus the disease osteoporosis can be detected.

Iv. Conclusion

In this, we demonstrated the use of linear frequency modulated thermal wave imaging technique that could detect osteoporosis. From the regression plot, it is clear that, when comparing the normal bone image with the OP bone the pixels are arranged in the form of curve and the value is R=0.87. When the value of R obtained is less than 1, it means that the bone is bone is brittle and thus the disease osteoporosis can be detected. Even though there are numerous methods for the detection of osteoporosis, this method helps to provide the accurate result of the bone brittleness prediction. This thermal wave imaging generation has created extra green and more secure technique of measurement.

Declarations

Ethics approval and consent to participate: Not applicable.

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Conflict of interests: The authors declare that they have no conflict of interests.

Informed Consent: Not applicable

Authors' contributions: All authors discussed the results and implications and commented on the manuscript at all stages. All authors read and approved the final manuscript for publication.

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Figures

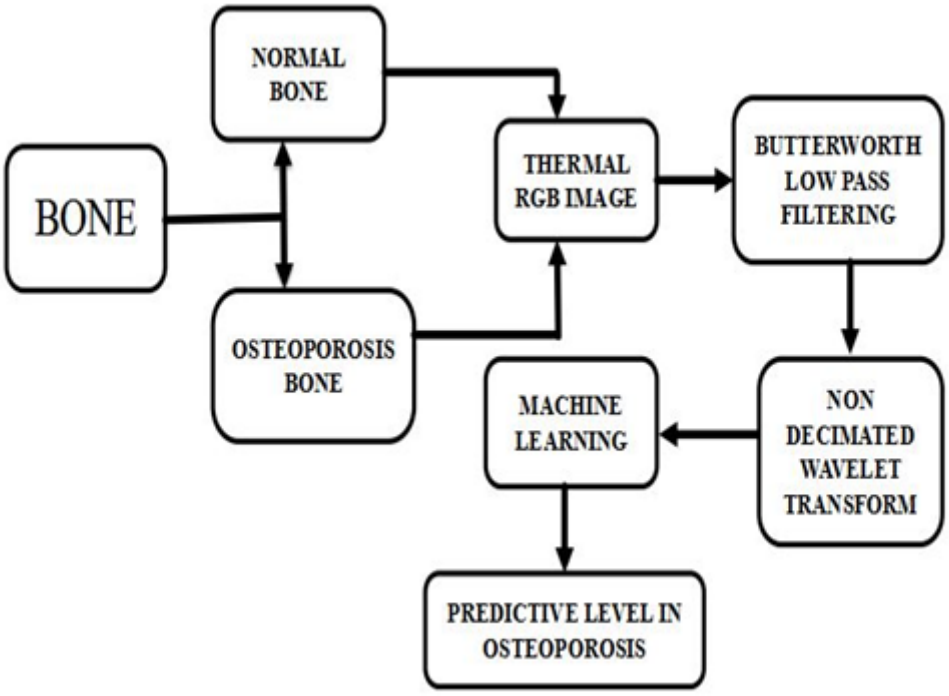


Figure 1

System Flow Diagram

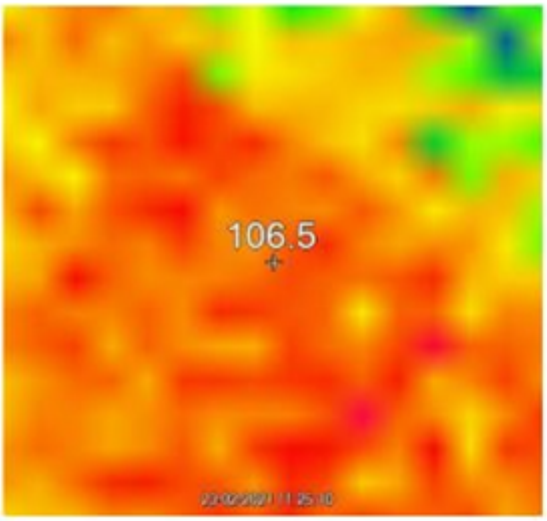


Figure 2

Thermal RGB image of normal bone

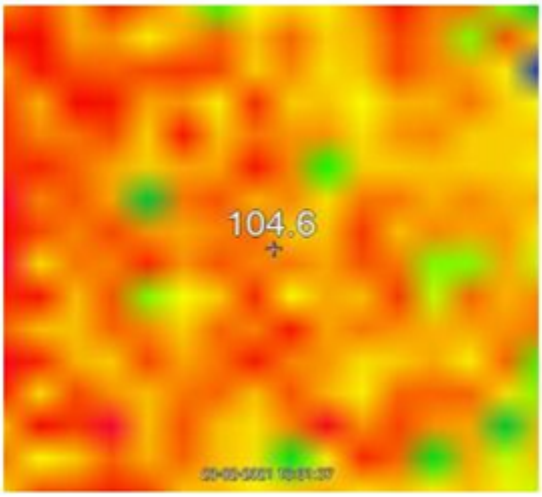


Figure 3

Thermal RGB image of osteoporosis bone

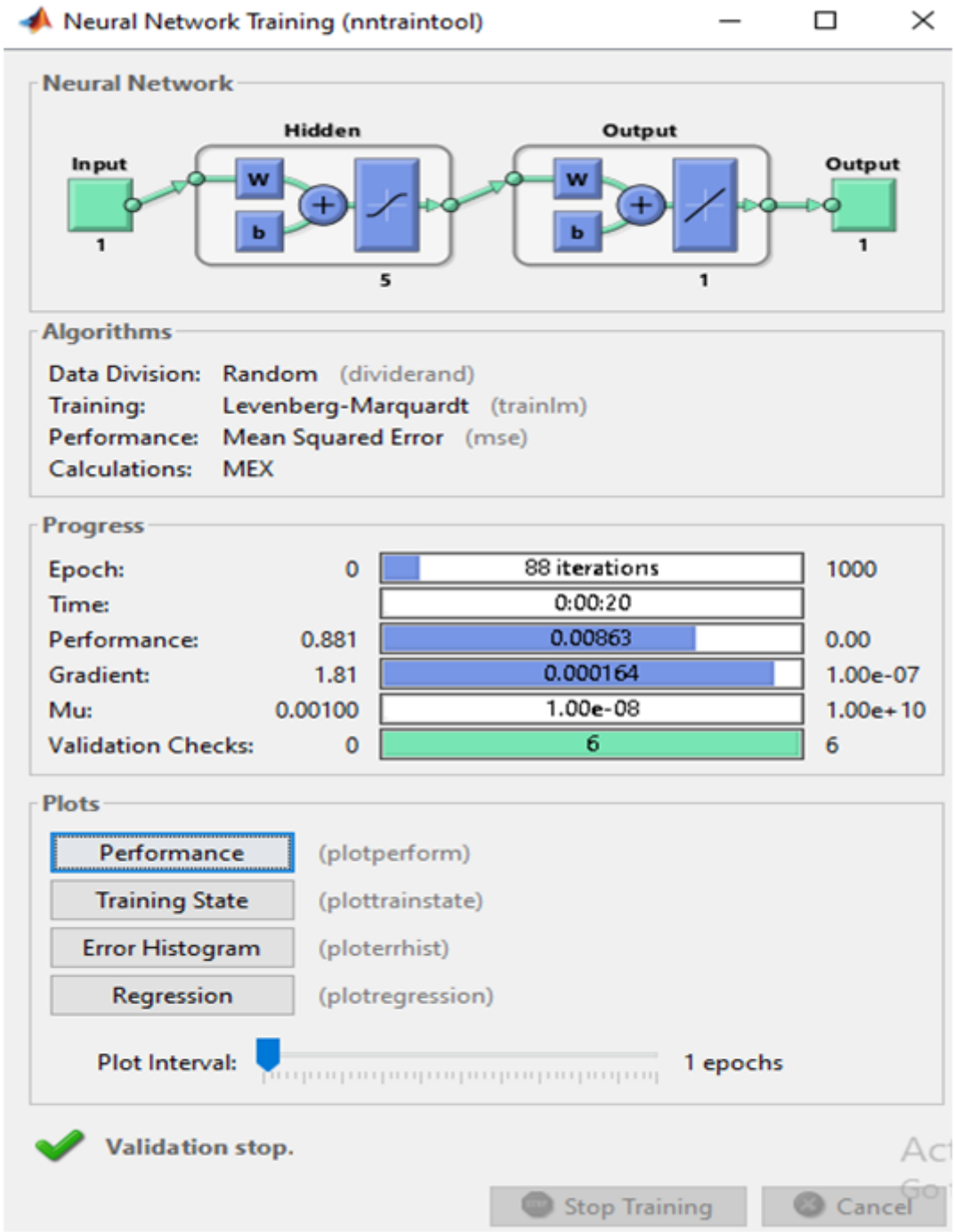


Figure 4

Neural network training tool showing various parameters

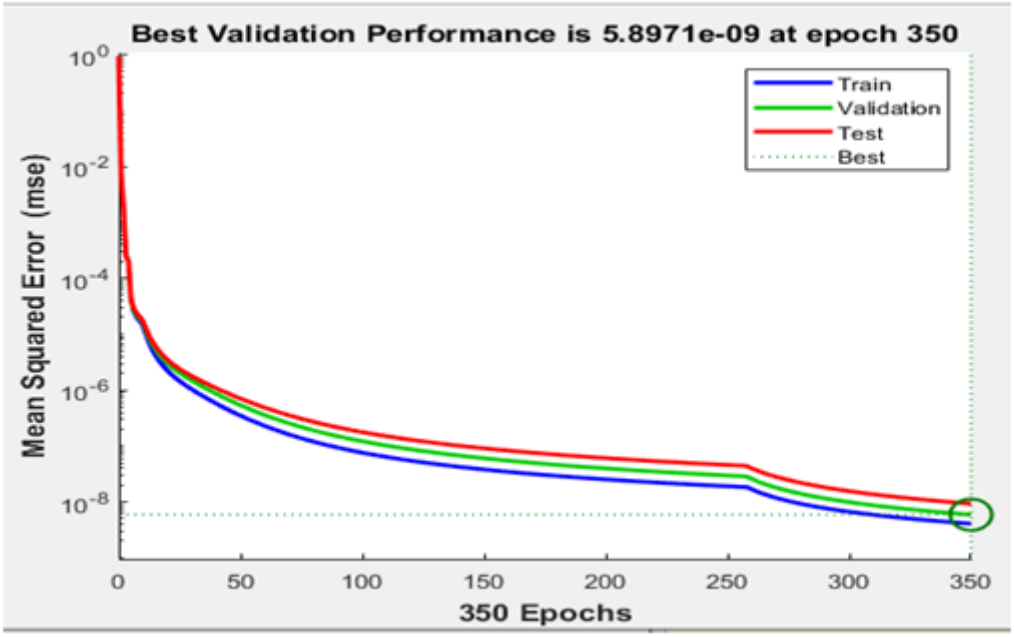


Figure 5

No.of epochs vs. mse for normal bone

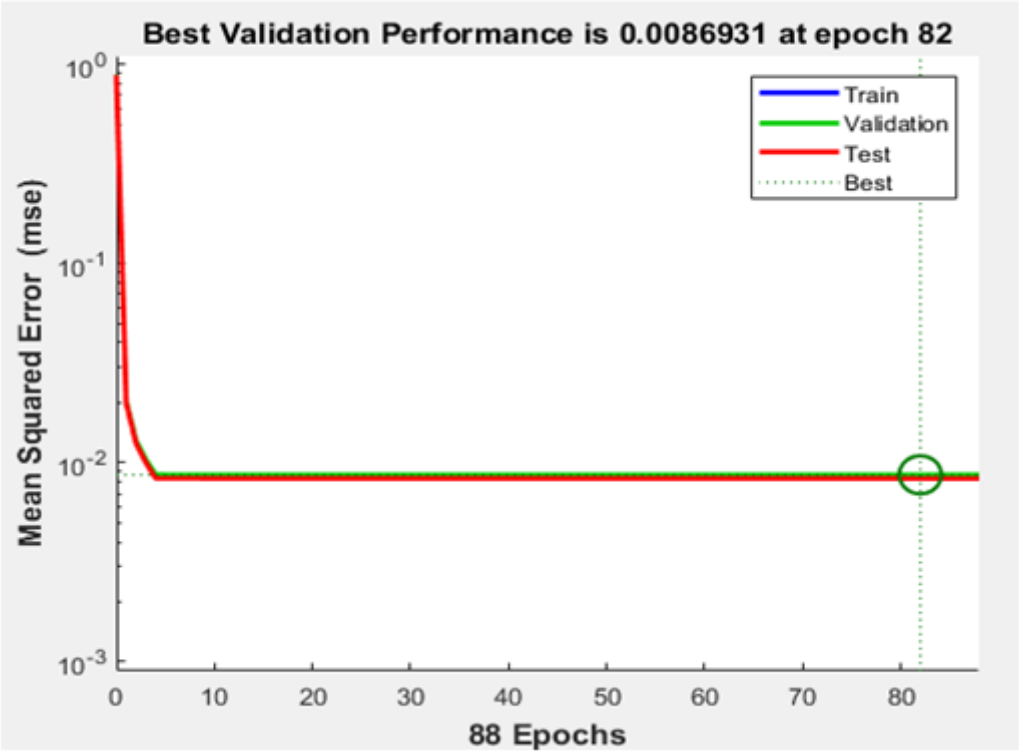


Figure 6

No. of epochs vs. mse for OP bone

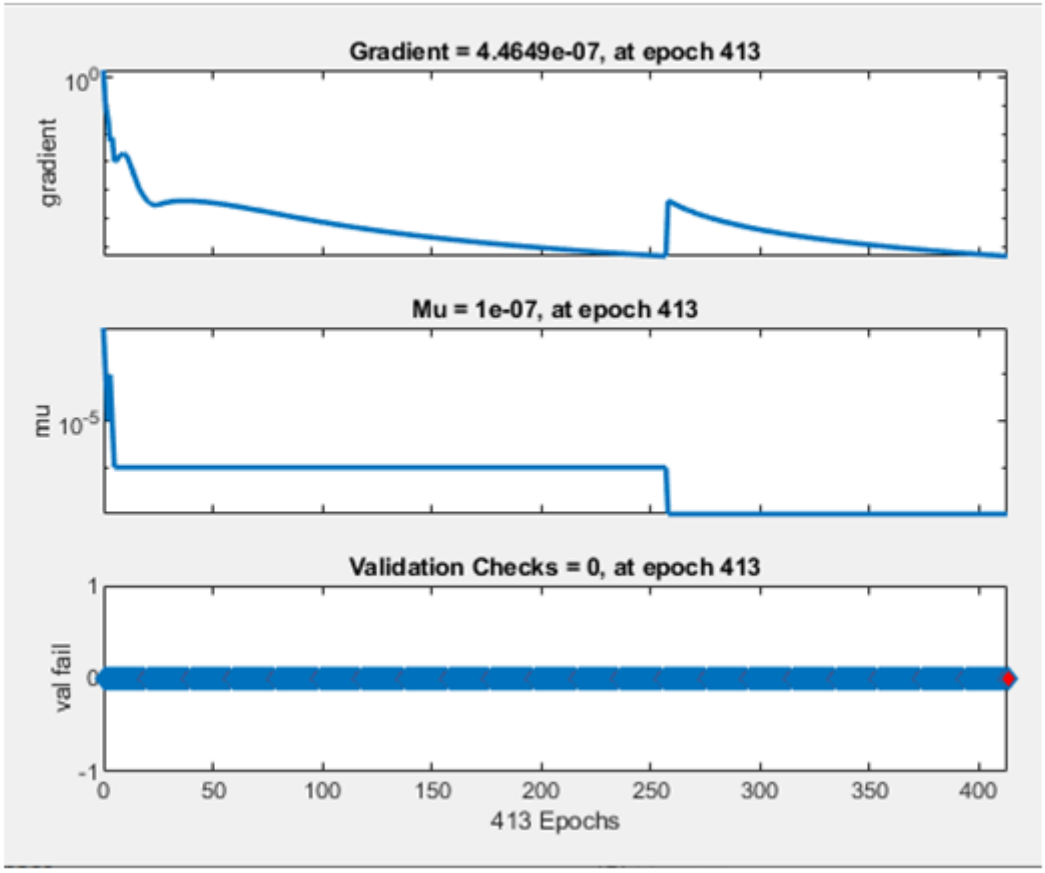


Figure 7

Number of epochs vs. training state parameters for normal bone.

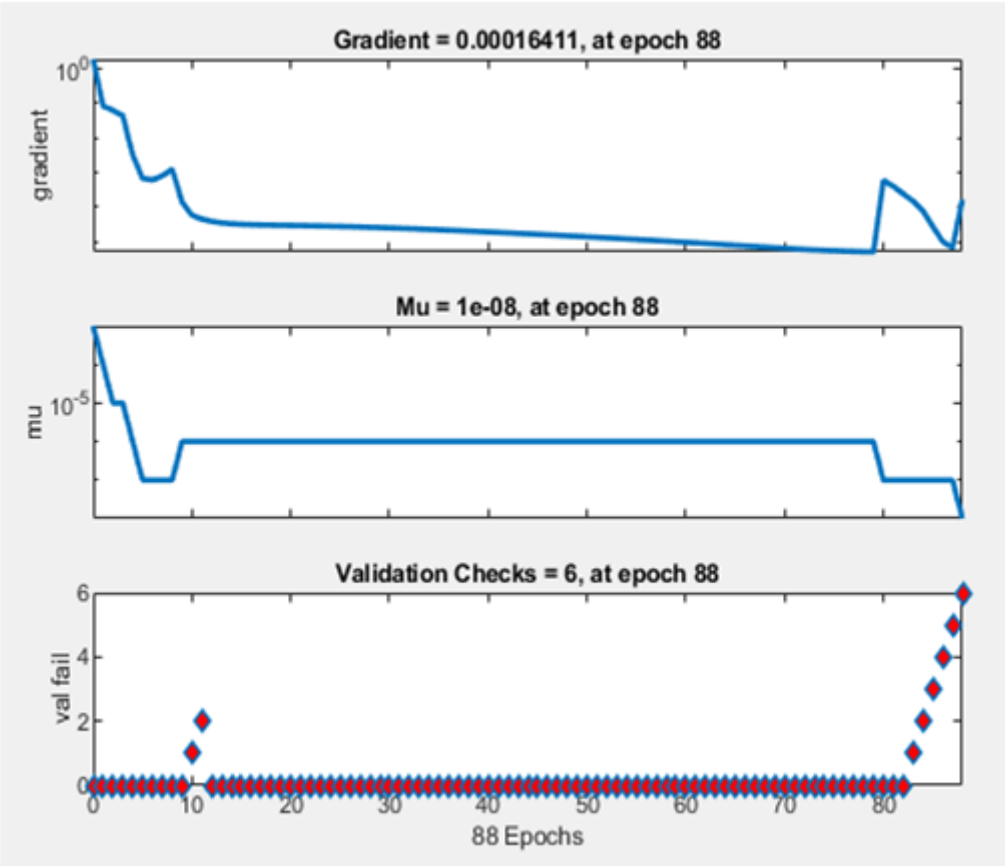


Figure 8

Number of epochs vs. training state parameters for OP bone

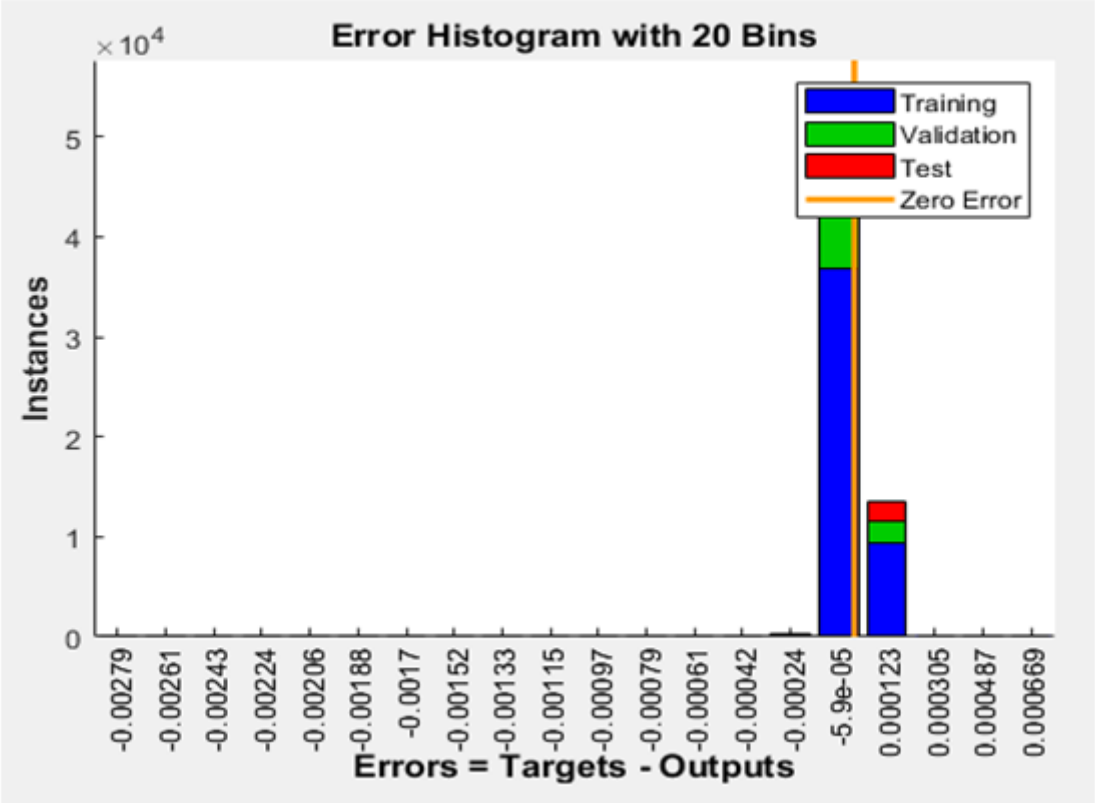


Figure 9

Error vs. Instances for normal bone

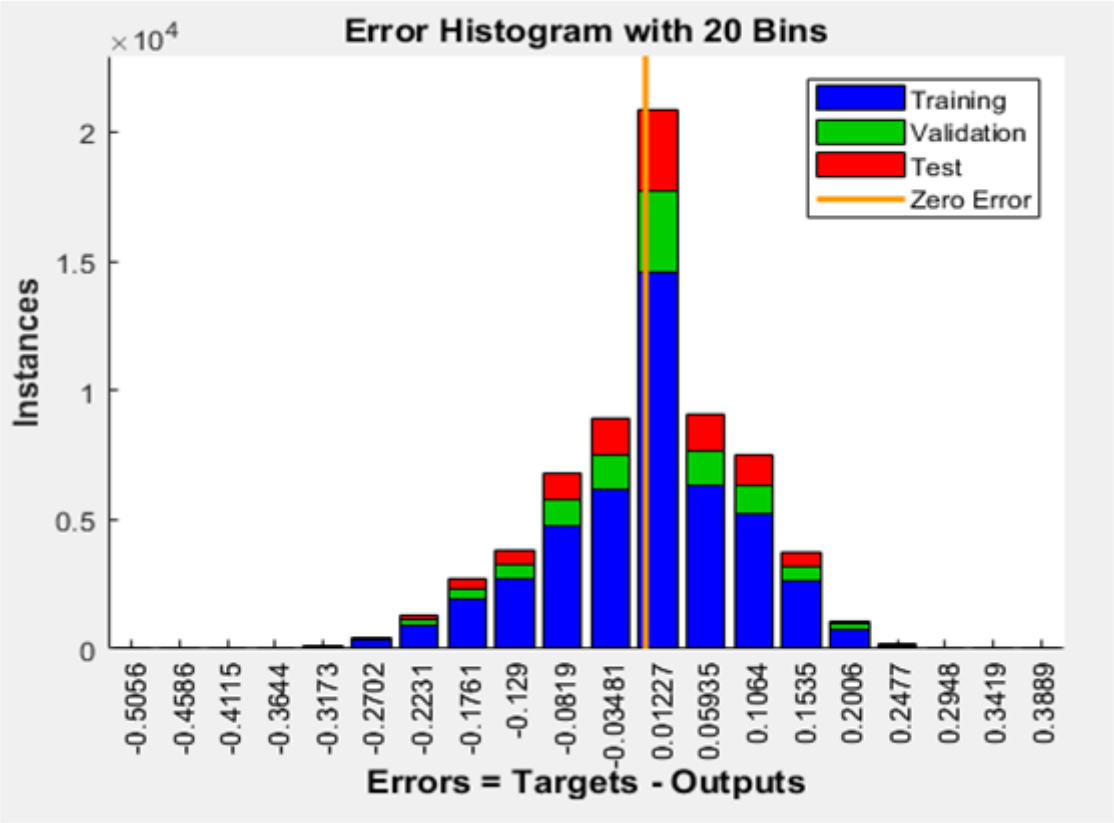


Figure 10

Error vs. Instances for OP bone

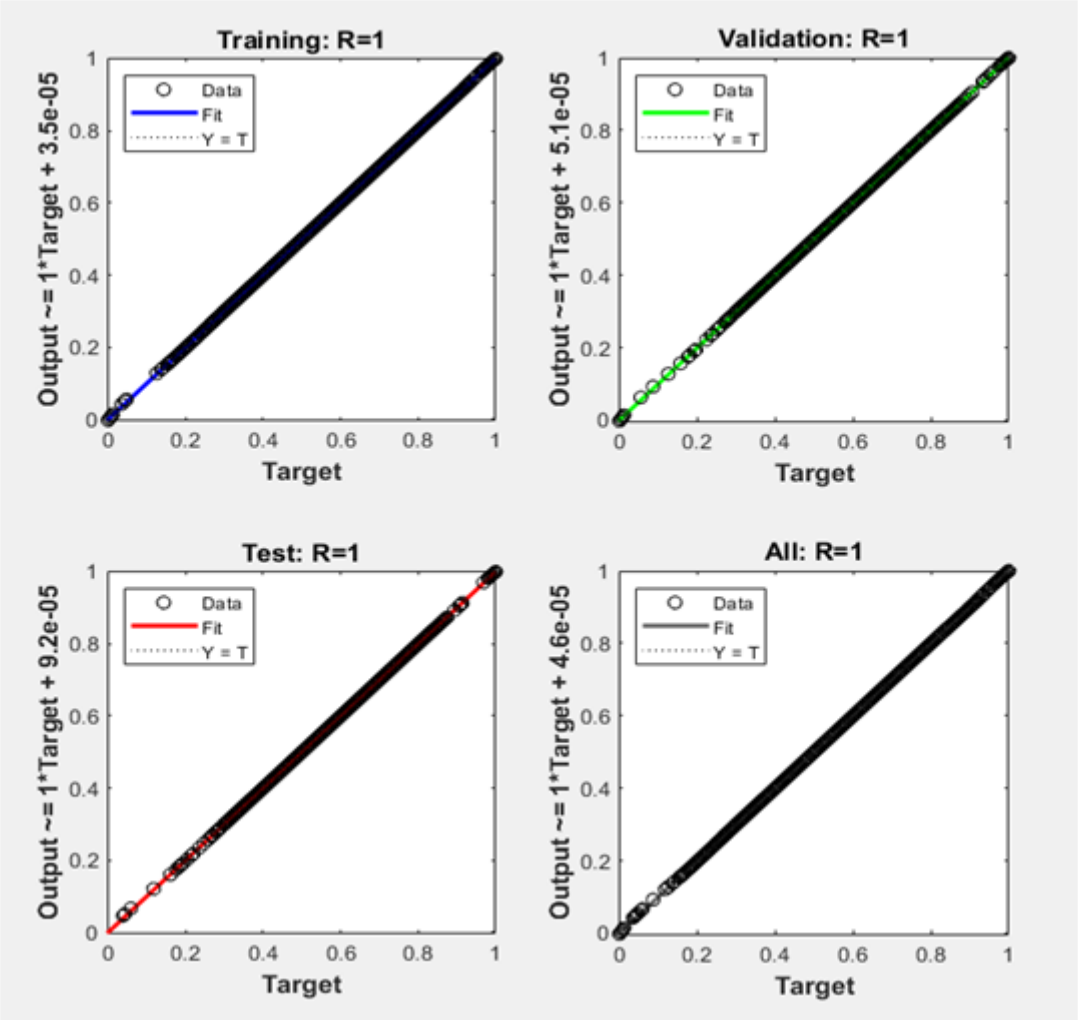
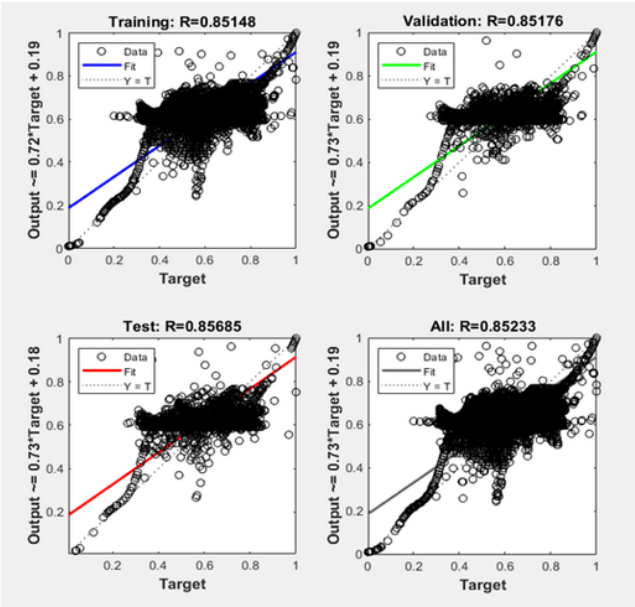


Figure 11

Regression plot for normal bone



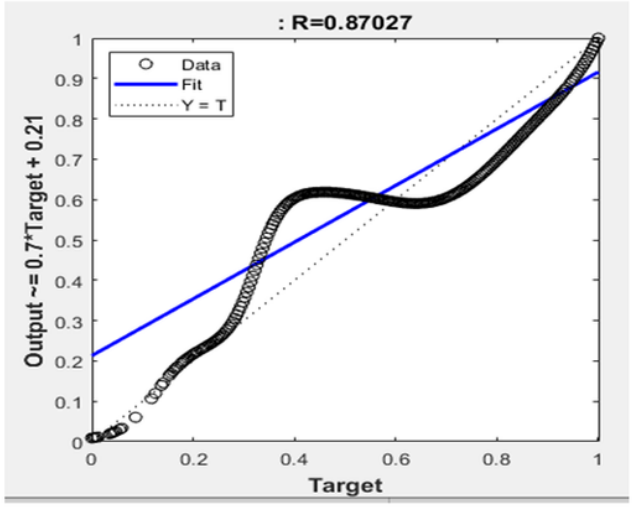


Figure 12

Regression plot for OP bone