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An Implementation of Osteoporosis Diagnosis Using Pulsed S-Transform Thermal Wave Imaging Technique

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Abstract

Medical diagnosis plays an important role in determining bone fracture disorders. In this research work osteoporosis disease diagnosis investigation can be performed through 11-bit pulsed s-transform coded thermal wave imaging. In addition to that the realization of osteoporosis disease diagnosis is established. The bone fracture, damage percentage, density and area are calculated by this implementation with MATLAB 2015b software. These numerical values are constrained with earlier methods. The final output performance measures such as density variance signal to noise ratio and thermal properties are deliberate. It is known that the approach proposed is outperforming the experimental results and competing with current technology. SNR is 136.4 dB, sensitivity 99.95%, predictivity 99.935%, true positive rate 99.91% has been attained.

Keywords: 11-bit barker code, pulsed s-transform, thermal image, osteoporosis.

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1 Introduction

The diagnosis of osteoporosis disease scanning possible with bone density scanning. This bone density scanning (BDS) can identifies the risk of bone fracture and needful treatment. Moreover bone mineral density (BMD) continuously examines the strength of bones with energy x-ray absorption. Osteoporosis is classified as BMD according to the WHO criteria, and is 2.5 standardized deviation or more above the mean value for safe young women (a T-score of <-2.5 SD) (1,6). This criterion has been generally recognized and establishes both a diagnosis and procedure threshold in several Member States.

A further procedure used to detect such bone conditions is blood testing. Osteoporosis, where blood tests are used to assess risk factors and ruling out other diseases, is one case.

Osteoporosis allows the bones to grow fragile and brittle, so brittle that a fracture may be triggered by dropping or even minor pressures such as bent over or coughing. In the shoulder, forearm or back, osteoporosis-related fractures most frequently occur. The bone is a live organ that is breaking away and replaced continually.

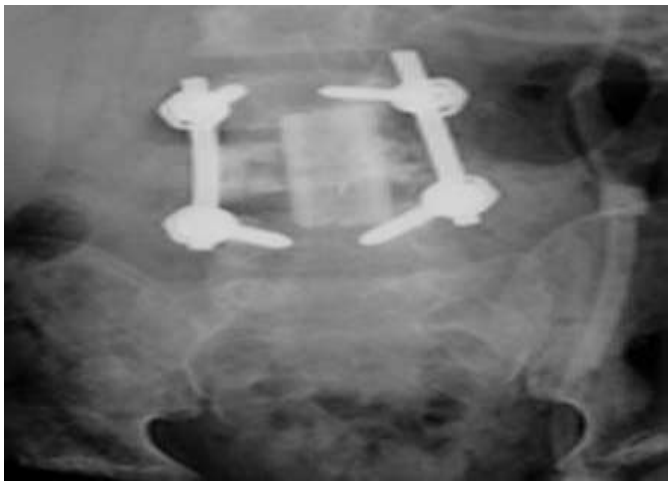


Figure 1 Osteoporosis Fractured Image.

Fig 1 clearly explains about high risk condition of osteoporosis bone fractured image. This type of disease finding can be possible with many scanning mechanisms. But, thermal image with barker code can give the more accurate diagnosis for better treatment.

Thermal image processing is playing an important key role in medical applications.The medical research is offering many applications for human beings with prior diagnosis, this diseases finding gives an accurate treatment and life to patients. The osteoporosis is a bone and skeletal disease; it can

diminish the bone strength and reduces the immunity, grounds to bone damage. Therefore an advanced application is required to diagnosis the osteoporosis disorder, in this work 11-bit s-transform barker code is designed with thermal wave imaging. This implementation estimates the bone fracture and damage, density and region percentage respectively. At final calculating the performance measures such as density variation, signal to noise ratio and thermal properties, also these are compared with earlier methods.

2 Literature Survey

The non-destructive testing methods are used to acquire the scanned image with surface temperature adjustments. The variable temperature and data profile to detecting the many features of bone and giving the accurate diagnosis. The 7-bit barker code is used to identifying the defecting bone area and density with thermal characteristics [1]. The skeletal disorders continuously reducing the bone strength leads to increases the risk of factor. The non-stationary thermal imaging models can easily find outs the bone disorders and offering accurate diagnosis. In [2] multi layered bone damages are differentiated such as tissue risk, skin and muscle models. The test sensitivity is high compared to density variations in the thermal images.

Ref.No.	Technique	Key point
Venkatasubbaraogh ali et.al[3]	3D pulse compression model	In this work finite element based pulse compression approach is used to identifying the various densities of bone fracture. Different temperature profiles are easily analyzing the strength of bone and giving the accurate outcomes.
Md. M. Pasha et.al[4]	CFRP thermal wave imaging	The principal component analysis methodology is used to identifying the thermal wave images and their abnormalities. The sub surface thermal wave imaging process can helps the test samples extraction.
B Suresh[5]	Chirp z-transform model	In this work chirp z-transform thermal image processing techniques are used to validate the bone defects and abnormalities compared to other models. The signal to noise ratio is attains more with chirp z-transform methodology.

Sk. Subhani et.al[6]	Frequency modulator thermal wave imaging	The spectral zooming Fourier transform methodology is used to identify the quantitative depth analysis and bone fractured density. This analysis is giving more solutions at thermal image processing for identifying the bone disorders.
Sk. Subhani et.al[7]	Quadratic frequency modulated thermal image analysis	In this work a non-stationary thermal image defects are identifying through integrity fiber reinforce methodology.
Erhirhie et.al[8]	Oxidants stress disorder	In this work an electronic thermal image processing techniques are used to identify the bone strength and disorders.
Prasad et.al[9]	Cardiovascular and bone risk factor analysis	In this article an expert suggestions are used to estimating the bone fractures and risk of disorders. The CVD scale variations re easily find out the abnormalities of bone fractures with easy way.
Mrs.S.Mythili [10]	Dexa scan vibration technique	In this work a bone quality is estimating through dexa scan methodology. For this work human leg bone samples are collected from BMD dataset. This work giving the information of bone quality and acquire the disease of bones.
Shalaka S[11]	Dual x-ray BMD technique	In this work bone mineral density can be identified through dual x-ray modeling. The osteoporosis and its risks are easily identified with this dual x-ray modelling.
Paola Pisani[12]	Ultra sound and x-ray diagnosis for bone disorders.	In this work the qualitative ultra sound scanning and x-ray scanning mechanisms are screening the early diagnosis of osteoporosis. The t-score can decided the disease % and giving the better treatment for the abnormality.
TaeKeunYoo [13]	SVM and ANN models.	Osteoporosis risk diagnosis can be verified through SVM and ANN models. This work giving the accuracy of 76.7%, sensitivity is 78% and specificity is 77%.

Nitin V Jadhav[14]	Artificial neural network technique.	In this work an advanced artificial neural networks are used to identifying the bone abnormalitiesand osteoporosis.Bone mineral density database is easily detecting the osteoporosis diseases with ANN.
Preeti Singh[15]	Photometric biosensor ANN technique.	Artificial neural networks technology is used to identifying the osteoporosis disease, it is a bio-sensor application and giving the mean square error 0.002 and accuracy of 93%
R.Mulaveesala [16]	Thermal wave imaging with modulated lock-in system	In this experiment bone abnormalities are easily identifying through non distractive thermal wave imaging model. The BMD samples are taken as dataset and real time samples are collecting for testing. This model giving the more accurate results compared to earlier models.
R.Mulaveesala [17]	Coded excitation with barker	In this work a barker code excitation model is used to identifying the bone fracture. The pre and post processing phase analysis models are giving the more signal to noise ratio.
V.S.Ghali[18]	Thermal wave analysis with barker code.	In this work an infrared active thermal waves are analyzed through 7-bit barker code pulse phasing system. This work is more helpful to identifying the abnormalities in the bones. The efficient analysis of barker thermal imaging system providing the effective reialable disease identification.
G.Dua[19]	Lock-in thermal wave imaging	In this work a matched filter technique is used to identifying the bone strength and mineral density. Moreover barker code and Hilbert transform mechanism is analyzing osteoporosis disease effectively.
Ghali V S[20]	Quadratic thermal wave imaging	This experiment offering pulse compression modulation technique. It is giving thermal image disorders at non-linear conditions.

The above all literature survey is giving the limitations of thermal wave imaging techniques at the time of bone fracture diagnosis. The performance

measures like pulse to signal noise ratio, t-score and accuracy is further improve to getting the unique results.

3 Methodology

The osteoporosis diagnosis is an complex task through many scanning models such as x-ray, CT scan, ultra sound and gamma ray scanning's. Therefore an advanced scanning mechanism is compulsory to diagnosis the osteoporosis bone disease. In this research work pulsed s-transform based 11 bit barker codes thermal wave imaging model is implemented on MATLAB 2015b software. This model is a novel design operating with s-transform technique and giving the accurate results.

3.1 Barker Code

Barker codes are usually a binary numbers; these are starts from 2 to 13 bit length shown in table 1 clearly. These frames have unique auto correlation functions so that the adjacent pulse of correlation tens to zero. This functionality is more useful in radar, satellite and medical applications. Barker code technique usually working based on binary phase modulation.

Table 1 Barker codes

BC 2	10
BC3	110
BC4	1011
BC5	11101
BC7	1110010
BC11	11100010010
BC13	1111100110101

3.2 Pulsed S- Transforms

The Pulsed S-transformation is obtained from the basic-transform (BT) technique [30]. The PST is like S-transform which additionally consists of two positive constants. The PST of a continuous time pulsex (t) is presented by

$$PST(t,f) = \int_{-\infty}^{+\infty} x(\tau) * \frac{1}{\sigma(f)\sqrt{2\pi}} * exp^{-(t-\tau)^2/2\sigma(f)^2} * exp^{-2i\pi f\tau}\, d\tau \quad (1)$$

Where σ (f) represents the standard deviation of the Gaussian window given by

$$\sigma(f) = \frac{1}{|f|} \quad (2)$$

The standard deviation for a modified Gaussian window can be taken as

$$\sigma(f) = \frac{k}{p + q\sqrt{f}} \quad (3)$$

Whereas, p and q are the positive constants, and k≤ $\sqrt{p^2 + q^2}$.

Similarly, the adaptive S-transform of continuous time signal x(t) is given by

$$PST(t,f) = \int_{-\infty}^{+\infty} N(£) * x(\tau) * G(t-\tau,f) * exp^{-2i\pi f\tau}\, d\tau \quad (4)$$

$$= \int_{-\infty}^{+\infty} N(£) * x(\tau) * \frac{1}{\sigma(f)\sqrt{2\pi}} * exp^{-(t-\tau)^2/2\sigma(f)^2} * exp^{-2i\pi f\tau}\, d\tau \quad (5)$$

Where $N(£)$ represents normalization function. $N(£)$Separates the signal from noise and improves the signal energy. Therefore, the Gaussian function of the AST can be written as

$$G(t,f) = N(£) * \frac{p+q\sqrt{|f|}}{k\sqrt{2\pi}} * exp^{-\left(\left(p+q\sqrt{|f|}\right)^2 t^2/2k^2\right)}, k > 0 \quad (6)$$

Therefore, the PST of a Gaussian window can be represented as

$$PST(\tau,f) = \int_{-\infty}^{\infty} N(£) * X(\alpha+f) * exp^{(-2\pi^2 m^2 k^2)/(p+q\sqrt{|f|})^2} * exp^{2i\alpha\pi\tau} d\alpha \quad (7)$$

Then, the discrete form of PST signal can be obtained as

$$S[j,n] = \sum_{m=0}^{N-1} N(£) * X(m+n) * exp^{(-2\pi^2 m^2 k^2)/(p+q\sqrt{|f|})^2} * exp^{i\left(\frac{2\pi mj}{N}\right)} \quad (8)$$

Finally, the DFT of x(k) is shifted by n in order to get X [m + n] · X(m) being given by

$$X[m] = \frac{1}{N} * \sum_{k=0}^{N-1} N(£) * x(k) * exp^{-j(2\pi mk/N)} \quad (9)$$

Further PST of signal x(t) and noise n(t) is given by

$$N(£) * S\big(x(t)+n(t)\big) = N(£) * S(x(t)) + N(£) * S(n(t)) \quad (10)$$

The above equation clearly explains about removal of noise and original signal with normalized function. Figure 2 shows Thermal Image of Bone.

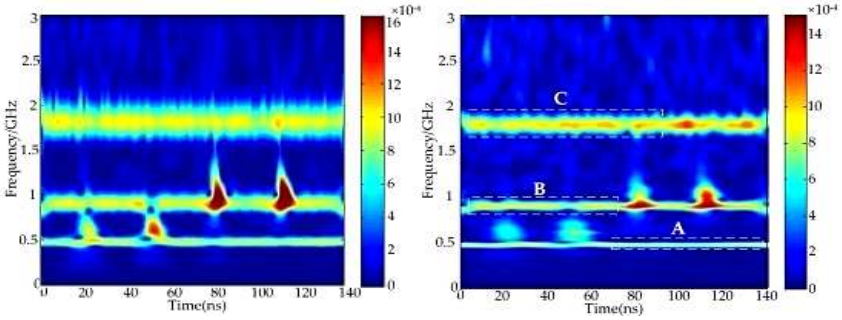


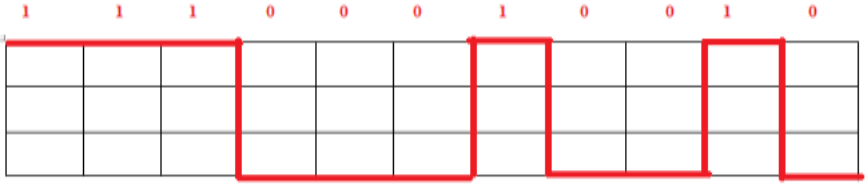
Figure 2 Thermal Image of Bone

3.3 Detection and Correction of True 'Barker Code' Pulses

After obtaining the normalization of complex locations, the threshold values are obtained based on the amplitude of the thermal wave pulse is applied for detecting the disorder. Then, to locate true R-Real positions, the detected disorder is further processed. The maximum pulse location inside the window of ±25 miss-centered at the observed pulse location by the algorithm is validated in the ground-truth annotation file for the window position of the same length. Figure 3 shows Block Diagram.

Algorithm: Pulse S-transform with 11-bit barker code

Step: 1 apply input as thermal wave image
Step: 2 correlate with 11-bit barker code



Step: 3apply pulsed S-transform
Step: 4 identify the osteoporosis
Step: 5calculate the performance measures
Step: 6 stop the process

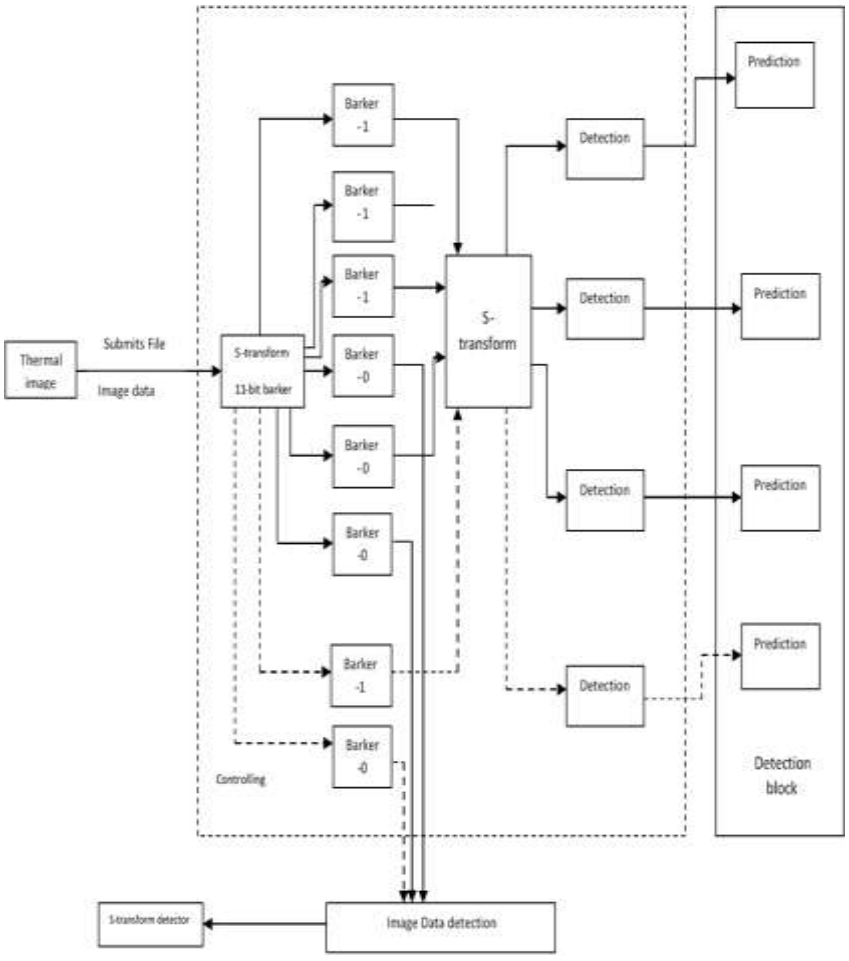


Figure 3 Block Diagram

4 Performance Measures

There are various measures used to evaluate the performance of S-transform pulse detection algorithms and a classifier. To test the efficiency of the proposed algorithm, three measures were considered such as,

1. Recall (Sensitivity (SN): Measures the rate of correctly classified pulses among all pulse points. It is basically the ratio of truly positive samples to the actual positive samples. The value of '1' specifies the best specificity value and '0' indicates the worst case.

$$SN = \frac{TP}{TP+FN} \quad (11)$$

2. Precision (Positive Predictivity (PP)): Precision computes the number of positive predicted samples which are most significant. It can be defined as the ratio of true positive samples to the total number of positive samples. The value of '1' specifies the best specificity value and '0' indicates the worst case.

$$PP = \frac{TP}{TP+FP} \quad (12)$$

3. Failed detection Rate (FDR): It is the ratio of total number of false positives and false negatives to true positive samples.

$$FDR = \frac{FP+FN}{TP} \quad (13)$$

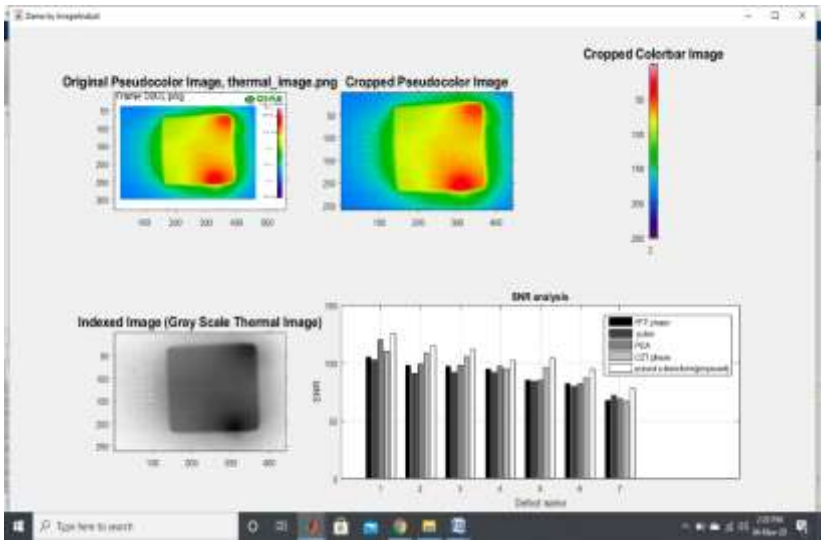


Figure 4 Disease Detection

Fig 4 demonstrates that thermal image analysis for osteoporosis disease. In this color cropping is applied at various thermal densities to getting the disorder of region.

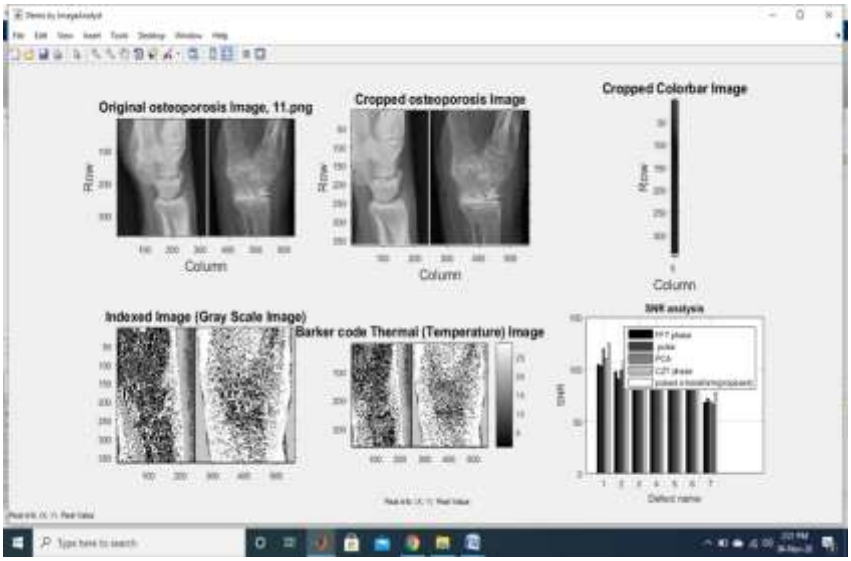


Figure 5 osteoporosis Detection

Fig 5 clearly explains about exact location of disease where specific heat, thermal conductivity, region density can be adjusted for disorder identification.

Different post processing techniques
Region Bone, B1, B2, B3,B4, B5, B6, Muscle, Fat, skin
Region Density = 2390, 1470, 1898, 1190, 1930, 2040, 2200, 2310, 1090, 911, 1109
Thermal conductivity = 0.616, 0.25, 0.32, 0.34 , 0.504, 0.532, 0.560, 0.588, 0.49, 0.21, 0.37
Specific Heat = 1430, 1200, 1313, 1000, 1170, 1235, 1300, 1365, 3421 2348, 3391

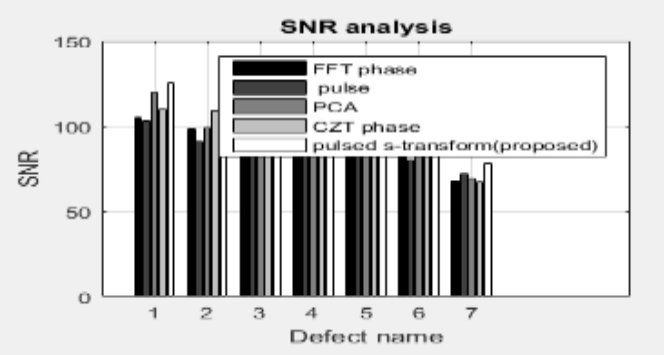


Figure 6 SNR analyses

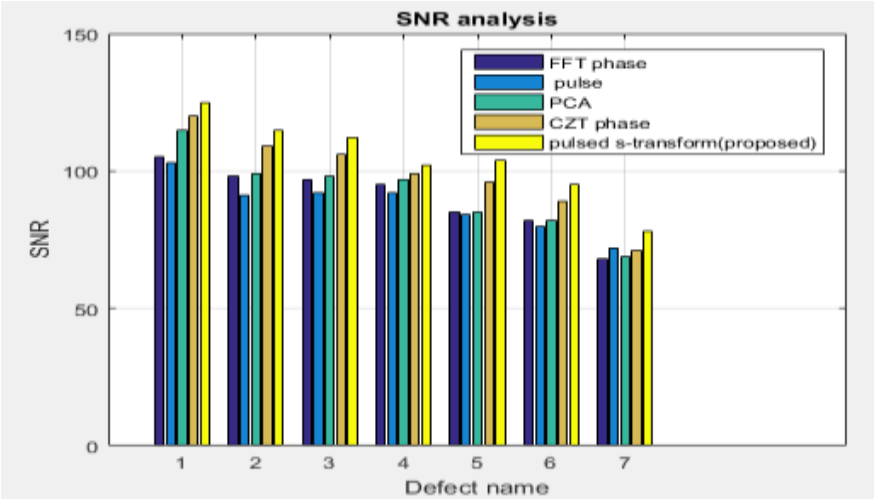


Figure 7 SNR Deep Analyses

Fig 6 and 7 explains about SNR vs proposed method analysis which is represented in dB. Here compared to FFT phase, pulse, PCA, CZT models proposed s-transform technique attains more improvement.

Proposed results
Region Bone, B1, B2, B3,B4, B5, B6, Muscle, Fat, skin
Region Density = 2385, 1465, 1893, 1185, 1925, 2035, 2150, 2290, 990, 891, 1009
Thermal conductivity = 0.605, 0.23, 0.29, 0.24 , 0.494, 0.522, 0.549,

Table 2 Comparison of Results

Sl. No.	Method	Sensitivity (%)	Predicatively (%)
1	FFT phase [5]	99.54	99.75
2	Pulse compression [6]	99.94	99.92
3	PCA [11]	99.86	99.84
4	CZT [3]	99.84	99.89
5	Symlet [6]	99.67	99.92
6	PST proposed	99.954	99.935

Table: 2 clearly explains about many earlier models comparison, in this FFT, pulse compression, PCA, and CZA methods. In this discussion proposed model attains more sensitivity and predictivity.

Table 3 Performance Measures

True Positive Count	False Positive Count	False Negative Count	TPR	PPV	sensitivity
2141	3	2	99.914	99.825	99.945

Table: 3 clearly explain about false positive rate, false negative rate, True positive and sensitivity analysis. It is clearly identified that proposed model attains more improvement compared to earlier models.

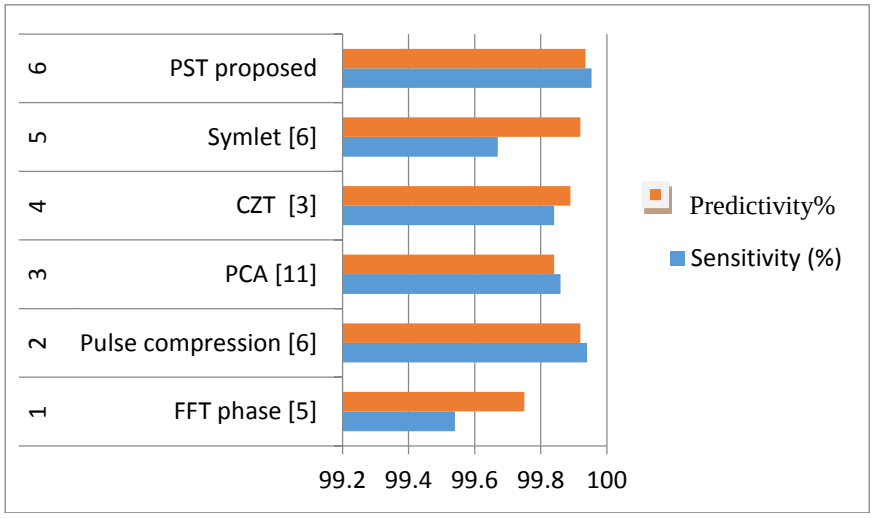


Figure 8 Sensitivity and Predictivity Analysis

In figure 8, sensitivity and predictivity analysis is observed clearly, here FFT, Symlet, CZT, PCA, pulse compression models are differentiated with proposed PST model. In these at all instances designed model attains more improvement and outperforms the methodology.

5 Conclusion

In this research work osteoporosis bone disorder can be attained through 11bit Barker code s-transform technique. The earlier methods like FFT phase, pulse compression, PCA and CZT methods getting less accurate disease detection. Therefore an automatic efficient osteoporosis disease identification method is compulsory. In this work 11bit Barker code with s-transform mechanism is implemented on MATLAB 2015b software. At last SNR is 136.4dB, sensitivity 99.95%, prediction rate 99.935%, true positive rate 99.91% has been attained. These are improved compared to earlier diagnosis mechanisms.

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