International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Segmenting and Identifying Spinal Tuberculosis Disease using An Enhanced CSA and Rider Optimization Technique

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Submitted: 12/12/2023 **Revised**: 16/01/2024 **Accepted**: 01/02/2024

Abstract: Tuberculosis disease of the vertebral causes damage to the spinal cord, which causes permanent or temporary loss of sensitivity and muscle function. Tuberculosis disease infection of the Spinal cord should be detected early and treated if the patient's neurological condition is to improve. This paper proposes a Spinal cord segmentation and Tuberculosis disease detection method using an Enhanced Crow search –Rider optimization method to accurately diagnose Spinal Tuberculosis. First, segmentation of CT image of Spinal cord is done using Adaptive thresholding method followed by localization of disk with the help of Sparse FCM clustering algorithm. The Enhanced CSROA algorithm is used to perform classification with high accuracy. In this paper, mainly three evaluation methods have been used. It can be seen that all of them have achieved good results. Accuracy 86%, sensitivity 88% and specificity 88% have been obtained. Therefore, the proposed method proves to be an effective method for detecting spinal tuberculosis disease.

Keywords: *Computed tomography, Optimization, Spinal Tuberculosis detection*

1. Introduction

Tuberculosis of the spine is a assuredly life threatening infection caused by Mycobacterium tuberculosis. Bacteria enters the spine through hematogenous spread, there by affecting the vertebral bodies [1]. Computed Tomography (CT) provides accurate details about the bone structure, vertebrae etc. in the spines. The modified sagittal and three-dimensional images help to understand the power of the spinal cord [2]. The spinal cord is the arrangement for conducting electrical activity through our two vital nervous systems [3]. Tuberculosis infection of spinal cord sometimes involves little or no conduction through it, causing sensory or motor function to be adversely affected.

Many clinical studies and research activities are essential in the field of automatic spine segmentation, which is useful for disease detection and analysis [5]. In other words, the stomach and its adjacent anatomy [29] spatial reference points are used for identification and position, thus providing information about the whole-body scan [6]. Regarding picture registration, the segmented spine supply utility characteristics, that are efficient rectifying the obligatory body structure positioning over every portion [7]. In addition, completing the pathologic analysis given the segmented spine structure fits easily [31]. Besides that, all the spinal cord [8] is based on division Simply put, this provides a way to determine the dose of radiotherapy that may be harmful to properly functioning nerves [9].At last, Ulti-modal imaging has contributed greatly to the segmentation of spines in the form of accretion as well as to the arrangement of that type of joint[10]. A method for extracting the spinal cord and all associated structures is performed using knowledge-based segmentation [4]. In particular, the dynamic contour technique has been implemented in two dimensional slices based on a seed point [31]. A mechanical method of segmenting the spinal canal using mathematical structures and growing regions was performed [11]. Spinal canal identification method was performed using circular Hough transform by automatic method. CT images are best used for this purpose.[12]. Cerebrospinal fluid and the existence of inter vertebral disk calcification cause problems in segmentation. The key purpose of the paper is to create system for dividing and detecting existing Tuberculosis infections effective on the spine. Disks are localized by adopting the new method to recognize disks by all features unique to the clusters. Characteristics required for proper classification method extract disks for extraction feature. After the features are extracted by this method and combined with the DCNN-based classification module, DCNN is trained using Enhanced CS-ROA DCNN.This approach, which combines CSA and ROA, presents the advantages of two algorithms for accurate classification leading to Spinal cord Tuberculosis findings.

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2. Related works

De Leaner et al. [13] presented vertebral size recognition technique that was very powerful to different perspectives and contrasts, but the reproducibility of PropSeg needs to be evaluated in different subject groups before engaging in patient studies. Korez et al. [14] introduced an automatic technique for detecting and dividing spines and vertebrae, here a new optimization method is used in different view images, such as MRI, of all Spinal structures. Xiaoxia Han et al. [15] presented CSA was well brought up using the spiral search method. Additionally, the algorithm was protected from falling into local optimization by using random perturbation and Gaussian variation. ISCSA was more accurate and had a faster convergence rate than local optima. The practical optimization problem is also successfully resolved. Qian wang et al. [16] developed a classification based on PBT that can be used with relatively large datasets obtained from multi-site surveys. Hence the redundancy in the calculation should be reduced.

In [32],M Nisha et al.presented a Deep learning based semi supervised generative Adversarial Networks(GAN)for automatic Hippocampus segmentation with efficient accuracy. Charley Gros et al. [17] designed a new method from MRI data of patients with and without MS. A set of two CNNs was prepared to make this method. Compared to other approaches, our spinal cord segmentation performed better on clinical data that was very heterogeneous and from several sites. Christian. Peron et al. [18] developed a deep learning-based method for segmenting the grey matter of the human spinal cord. This approach has a significant network parameter decrease when correlated to conventional imaging methods. The method was only applicable to 2D slices. Guohu Wang et al. [19] developed combining force exploration approach and current ROA to obtain an improved ROA (IROA). Three standard optimization issues, performance of IROA's was examined. The IROA demonstrated great reliability and dependable exploration performances. IROA was also used to assess the specifications for the front axle of an automobile. In terms of accuracy and computing efficiency, it is also extremely competitive.

Challenges

- The size difference of spinal cord images, high-quality analysis, etc. vary greatly, which affects the strength of the automated segmentation method [16].
- Osteoporosis and the resulting intrinsic blurring in the CT data cause segmentation errors to occur often in elderly people. But when moving transversely, the vertebral body has an impact on the healing process when using a deformable model because of the significant curvature present. Direct application of spinal pedicle segmentation is not possible since the spinal cords outside edges form the spinal pedicle, which is housed inside the vertebra [5].
- It is quite difficult to identify a vertebra automatically because, despite the fact that different vertebrae display the common traits [5].

3. Material and Methods

The aim is to develop a modern strategy for segmenting the spinal cord and Tuberculosis disease detection using the Enhanced CS-ROA. Suggested method involves four steps for detecting tuberculosis disease: i) segmenting the Spinal cord ii) disc localization iii) feature extraction iv) classification. An adaptive thresholding method was initially used to extract the spinal cord from the CT images [23]. The disc localization process allows the identification of discs by the distinct characteristics of the clusters by applying the sparse FCM clustering technique [24] to the segments. Feature extraction is the step of extracting key features from the disc for accurate classification of Spinal cord infections. Thus all the features that are collected very accurately make the classification possible with the help of DCNN.DCNNs training was conducted using the enhanced CS-ROA, designed by adding CSA [25]to the Enhanced ROA [26][27] rule for that purpose. Proposed approach changes ideal weights in DCNN as CS-ROA demonstrates the advantages of both methods.

3.1. Spinal cord segmentation with an adaptive thresholding technique

To identify tuberculosis in the spinal cord, the first step entails segmenting the spinal cord from CT images applying an adaptive thresholding technique. Modified version of Wellner approach [28], all elements are comparison by the average of neighboring elements, is where the adaptive thresholding method is derived. The technique is important because it ignores soft gradient changes and uses hard contrast lines, that is the comparison between the captured pixel and its neighboring pixel.

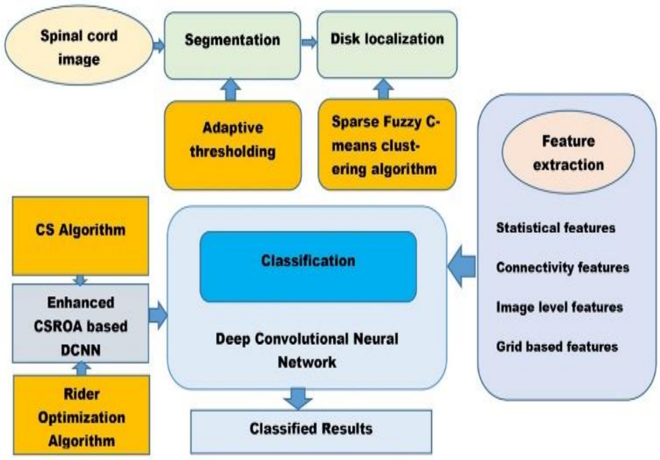

Fig 1: Diagram of Segmentation and detection of Spinal Tuberculosis.

This approach has one major benefit, which is that it only requires one pass across the image. Also, this method is a simple. An independent result is produced. To locate discs using adaptive thresholding, Disc localization works by using segments in the spinal cord[33]

3.2. Disc localization

The Sparse FCM clustering method is used for disc localized process to find discs with distinctive cluster features. The proper clustering of spinal cord segment samples affects the accuracy of disc localization. The segments obtained through the earlier segmentation process are the input to this method. This method divides all segment to clusters on their distinctive qualities. M is no. of segment, matrix ,$A_{al} \in P^{r\times p}$.

Disc localization steps:

a) Initialize $w = w1^k = w2^k = \cdots \ldots \ldots \ldots .. = wp^k = \frac{1}{\sqrt{p}}$ where w =weights (1)

b) Corrected partition matrix

$$K_{ab}\begin{cases} \frac{1}{H_b} & \text{If } Wab = 0 \text{ and } H_p = c\,\{j\,; Wap = 0 \\ 0\,, & \text{if } Wab \neq 0 \quad Wax = 0 \\ \frac{1}{\sum_{b=1}^{c}\frac{Wab(\frac{1}{\beta-1})}{Wxb}} & \text{otherwise} \end{cases} \tag{2}$$

Width is specified as follows in the conventional sparse-FCM:

$$W_{ab}=\sum_{l=1}^{c} \delta 1(Lal - Lbl)^2 \tag{3}$$

Let w and P be fixed and θ(h) is minimized if h_{bl}

$$\begin{cases} 0 & \text{if } w1 = 0 \\ \frac{\sum_{b=1}^{c} \alpha_{ab}^{\beta}.Aal}{\sum_{b=1}^{c} \alpha_{ab}^{\beta}} & \text{if } w1 \neq 0 \end{cases} . \tag{4}$$

The dissimilarity measure is shown as P, the l^{th} variable shown in its function is written as w1

c) Level Calculation

The Level Cl ,$\max_w \sum_{l=1}^{E} w1.C$ such that $\|w\|_2^2 \leq 1, \|w\|_0^0 \leq y$ to get w*

$$\|w\|_0^0 = \sum_{l=1}^{E} |wl|^0$$

d) Finish state Repeat previous method until finishing state is met

Finishing state is

$$\frac{\sum_{l=1}^{c} |w1^* - w1^k|}{\sum_{l=1}^{E} |w1^*|} < 10^{-4} \tag{5}$$

SFCM output isSEg=SE1,SE2,…..SEϵ…SEτ (6)

Where SEϵ is the ϵth disk and total is τ

3.3. Feature extraction.

Feature extraction is the step of extracting key features from the disc for accurate classification of Spinal cord infections. At last, all the characteristics that are collected very accurately make the classification possible with the help of DCNN

Connectedness properties

The connectedness property determines whether the ends of disc of spinal cord are tied. If the ends of the disc in the spinal cord are all linked, it can be understood that there is no infection there. On the other side, the danger of infection is substantial if any disconnected edges occur. The connectivity feature is[1x1] in size.

ii) Analytical properties

Measures including mean, kurtosis, and variance influence the analytical properties of the disc.

(a) Mean

The mean is expressed as follows:

$$\frac{1}{n}\sum_{s=1}^{n} S \tag{7}$$

Where total pixel n , and S pixel sum

(b) Variance

$$\text{Variance}\,,\ \mu^2 = \frac{1}{n}\sum_{s=1}^{n}(S - \bar{S})^2 \tag{8}$$

(c) Kurtosis

$$\text{Kurtosis}\,, K = \frac{\sum_{s=1}^{n}\frac{S-\bar{S}}{n}}{\sigma^4} \tag{9}$$

The features of above measures are [1x1] in size, where σ is the standard deviation.

iii) Image-level features:

When using sequential data fetching from localized disc ,a histogram is employed to accurately describe the distribution of a picture. The image-level feature has the following dimensions: [1x64]

iv) Network type structures:

The disk shape maps into a network with a specific structure starting in the upper left corner. If the form completely or partially covers the grid cells, they are given the number 1, and if the cell is outside the border, it is given the number 0. As a result, a series of 0s and 1s are obtained that represent group and its border .It has a feature size of [1x 9].

$$F = \{ f1, f2, f3, f4\} \tag{10}$$

is used to represent the feature vector, where f1 stands for connectivity features, f2 for statistical features, f3 for image-level characteristics, and f4 for Grid-based form features. The size of the feature vector is [1x 80].

3.4. Classification using the DCNN method with Enhanced CSROA

Proposed optimization approach is used to train the DCNN [29]. DCNN planning consists of 3 layers given below.

1.Convection Layer

$(K_x^y)_{i,j}=(\rho_x^y)_{i,j} + \sum_{e=1}^{1^{\sqrt{e-1}}} \sum_{g=-U_1^s}^{U_1^s} \sum_{t=-U_2^s}^{U_2^s} (\vartheta_x^y, e)c, t*(K_e^{y-1})_{i+c, j+t}$ (11)

Here , * represents Conv operator, assist in extracting internal design of alternate convolution level ,$(K_x^y)_{i,j}$. Result of (y- 1)th convection layer serves as raw data for the y-th convection layer.(ϑ_x^ye) shows that y th convection layer weight and bias is (ρ_x^y).

2.Rectifier layer

Result of yth ReLU layer is denoted as

$(K_x^y)=Afn(K_x^{y-1})$ (12)

3.FC layer

$(T_x^y) = \gamma\ K_x^y$ with $K_x^y = \sum_{e=1}^{1^{\sqrt{e-1}}} \sum_{g=-U_1^s}^{U_1^s} \sum_{t=-U_2^s}^{U_2^s} (\vartheta_x^t, e)$ $c,t*(K_e^{y-1})_{i+c, j+t}$ (13)

3.5. Proposed Method

Classification process created by integrating CSA and ROA is carried out utilizing the Enhanced CS-ROA algorithm [31]. Here the riders are classified as follows.1. Bypass riders 2. Follower 3.Overtaker 4.Attacker. All of them are working hard to reach their desired destination. A certain number of riders can only win if they all travel to the same place. This group of riders all follows a different method to arrive the Attacker is the group that uses maximum speed. Among all the riders, the one who gets ahead in the shortest time wins.

The steps involved in the algorithm as

1.Initialising parameters

The method starts with 4 rider set denoted as T ,here location is initialized arbitrarily. The rider set initialization as follows:

$A\alpha = A\alpha(a,b) \quad 1 \le a \le X\ , 1 \le b \le Y$ (14)

Here Aα(a,b) is position of the a[th] rider at time α, No .of riders is X ,which equals T, and Y denotes the dimension of co-ordinate .The total riders of each set will provide information about this and as

$X=P+Q+R+S$ (15)

Here, P is the number of bypass riders, Q is number of pursuers, R represent number of overtakers and S denotes number of attackers. Relationship between these are

$P=Q=R=S = \frac{X}{4}$ (16)

These equation is used to calculate position and parameter of rider like accelerator .

Steering angle :

$S\alpha = \{S_{a,b}^{\alpha}\}\ ; 1 \le a \le X\ , 1 \le b \le Y$ (17)

Here $\{S_{a,b}^{\alpha}\}$ denotes a th rider vehicle steering angle , 0^{th} time

Steering angle at initial time is

$$Sa,b = \begin{cases} \rho a & \text{for } b = 1 \\ Sa, b+\theta & b+\theta \le 360 \\ Sa, b+\theta-360 & \text{otherwise} \end{cases} \quad (18)$$

Here, position angle ρ and co-ordinate angle θ.

Position angle= Max angle360 /no .of riders, at the same time.

Gear of ath riders vehicle in the set is

$M=\{Ma\}\ \ 1 \le a \le X$ (19)

Ma denotes the gear angle.First value is zero at time α , The value given in this set can be taken {0,1,2,3,4}.

Accelerator :

$L=\{La\}\ \ 1 \le a \le X$ (20)

Here, La is ath rider vehicle accelerator and first value 0 similar to gear of the vehicle and value in between 0 and 1.

Brake:

$O=\{Oa\} \quad 1a \le X$ (21)

Here Oa is ath rider vehicle brake and initial value fixed at 1 and the brake value is constantly between 0 and 1. The rider adjusts the vehicle's speed as it moves towards its destination depends on 2 border points. As a result , The highest vehicle speed rate that a rider can handle is

$T_{max}^a = \frac{T_U^a - T_L^a}{\alpha_{off}}$ (22)

Where T_U^a and T_L^a stand for max and min of a th rider respectively. α_{off} stands for off time, which reaches highest aftermost of an iteration.

Speed limit:

$T_a^e = \frac{T_{max}^a}{|e|}$ (23)

Where T_{max}^a highest speed and no. of gear |e|

2.Fitness Measure

Fitness measure, also known as the success rate, is calculated using MSE and it is

$\text{Mean Square Error} = \frac{1}{m}(\text{Original value} - \text{Estimated value})$ (24)

Here m is no. of iterations. Fitness measure must be minimum for system to be effective in detecting tuberculosis disease.

3. Calculation the rider in front

Success rate fa is used to calculate the rider in front and has a chance to reach the target very quickly.

4. Upgrade rider location

Each set, rider's location is modified to determine who has the best chance of arriving at the destination first.

a)Upgrade bypass rider point

Update of bypass rider position is done using public route

Equation is

$$Y^{U}_{\alpha+1}(a,b) = \beta[Y\alpha(\varphi,b) * \mu(b) + Y\alpha\ (\sigma,\ b)\ * [1-\mu(b)] \quad (25)$$

Here , α denotes a no. in 0 &1 and φ and σ in 1 & Q.

b) Update follower location

For certain values of Y, new equation obtained using the co-ordinate selector.

$$Y^{v}_{\alpha+1}(a,Csel) = Y^{L}(L,Csel) + \left[\cos\left(B^{\alpha}_{a,Cs}\right) * Y^{L}(L,Csel) * V^{\alpha}_{a}\right] \quad (26)$$

Here co-ordinte selector Csel ,top rider point Y^{L} and L is index of top rider.

c)Update overtaker location

Co-ordinate selector, relative success rate, and direction indicator are the variables that affect the overtaker's position update.

$$Y^{w}_{\alpha+1}(a,Csel) = Y_{\alpha}(a\ ,\ Csel) + [t^{D}_{\alpha}(a) * Y^{L}(L,Csel)] \quad (27)$$

d)Update attacker location

This upgrade all co-ordinate points. Equation is

$$Y^{a}_{\alpha+1}(a\,,b\,) = X^{L}(\,L\,,b\,) + \left[\cos\left(B^{\alpha}_{a\,,b}\right) * Y^{L}(\,L\,,b\,) * V^{\alpha}_{a}\,\right] \quad (28)$$

5.Determination of success rate

The success rate of the riders is decided after the update process.

6.Update parameter for riders

The optimal solution is generated by updating the parameters of all riders

7. Activity counter:

When the riders location is upgraded , parameters and activity counter are also included. Its value is always 1, unless a single attempt has a higher success rate than the prior attempt. The activity counter's current value is 0, therefore it has no value. Equation is

$$c[a]= \begin{cases} 1 & f_{\propto+1}(a) > f\alpha(a) \\ 0 & \text{else} \end{cases} \quad (29)$$

a)Update steering angle

$$S^{\alpha+1}_{a\,,b} = \begin{cases} S^{\alpha}_{a+1\,,b} & c(a) = 1 \\ S^{\alpha}_{a-1,b} & c(a) = 0 \end{cases} \quad (30)$$

b)Update gear

Based on activity counter and fullest potential use of Gear and expressed as

$$M^{\alpha+1}_{a} = \begin{cases} M^{\alpha}_{a} + 1 & c(a) = 1 \quad Gr^{t}_{a} + 1 \neq |Gr| \\ M^{\alpha}_{a} - 1 & c(a) = 0 \quad Gr^{t}_{a} + 1 \neq 0 \\ M^{\alpha}_{a} & \text{else} \end{cases} \quad (31)$$

c)Update acceleration

$$L^{\alpha+1}_{a} = \frac{M^{\alpha+1}_{a}}{|M|} \quad (32)$$

d)Update brake value

$$O^{\alpha+1}_{a} = 1 - \frac{M^{\alpha+1}_{a}}{|M|} \quad (33)$$

8. Down time riding

Thus the above step is repeated until the off-time is reached before finding either the winner or the front row rider.Overtaker's point upgrade method in ROA has been updated by adopting CSA's method.

Equation for CSA is

$$Y_{\alpha+1}(a,Csel) = Y_{\alpha}(a,Csel)+j1XF^{\alpha}_{L}(a,Csel)\ X\ (M\alpha(Xs,Csel)-Y_{a}(a,Csel)) \quad (34)$$

$Y_{\alpha+1}(a,Csel)$ is location of the a th crow in Csel th length at $(\alpha+1)^{th}$ repetition.

Using eq (29)

$$Y_{\alpha+1}(a\,,Csel\,) = Y_{\alpha}(a\ ,Csel)[(1\text{-}j1)\ X\ F^{\alpha}_{L}(a\ ,Csel\,)]+j1XF^{\alpha}_{L}(a\ ,Csel\,)(M\alpha(\ Xs,\ Csel) \quad (35)$$

$$Y_{\alpha}\ (a\ ,Csel\ )=\frac{1}{(1-j1)XF^{\alpha}_{L}(a\ ,Csel\,)]}[Y_{\alpha+1}(a\,,Csel\,)] - j1X\ F^{\alpha}_{L}\ (a\ ,Csel\ )(M\alpha\ (Xs,Csel) \quad (36)$$

Sub eq (36) in eg (27)

When overtaker placed in top point & stated as,

$$Y^{w}_{\alpha+1}\ (a,Csel\ )= \frac{1}{(1-j1)XF^{\alpha}_{L}(a\ ,Csel\,)]}\ [Y_{\alpha+1}\ (a\,,Csel\,)] - j1XF^{\alpha}_{L}(a,Csel)\ (M\alpha(Xs,Csel)]+t^{D}_{\alpha}(X)*Y^{L}(L,C_{Sel}) \quad (37)$$

Using Eq. (37), the position of the front row rider can be determined by using the previous iteration of the rider's position, as well as the crow's flight length, the crow's memory, etc.The advantages of adopting the above formula in the proposed method are given better result.

Algorithm 1 : Position evaluation using proposed algorithm

Input → Rider Arbitrary spot = Yg

Output → Front row rider point = Y^L

Initialize people

Initialization → Steering angle $S_{a,b}^{\alpha+1}$

Gear $M_a^{\alpha+1}$

Accelerator $L_a^{\alpha+1}$

Brake $O_a^{\alpha+1}$

Calculate fx

While tm $<\propto_{off}$

For a = 1 to X

Upgrade equation 25

Upgrade equation 26

Upgrade equation 27

Upgrade equation 28

Rank all riders by success rate

Sort out the rider with the highest success rate.

Upgrade all parameter values

Replace the front row rider point depend on equation 37

t+=1

end while

4. Results

The success of the Enhanced CSROA DCNN algorithm was evaluated using three criteria including accuracy, sensitivity, and specificity. The proposed system is implemented simply and effectively in the experiment using the MATLAB program . Table 1 contains the parameters and values of the method presented here.

Table 1 : Parameters and values

Parameters	*Value*
DCNN	
Total layer	10
Loss function	Cross Entropy
Enhancer	Adam
NN	
Total layer	5
Not visible Neuron	10
Loss function	MSE
Enhancer	Levenberg– Marquardt
ROA- DCNN	
Total layer	10
Loss function	Cross Entropy
Enhancer	ROA
Enhanced CS-ROA DCNN	
Total layer	10
Loss function	Cross Entropy
Enhancer	CS - ROA

The below image shows an example miniature result for a patient's spinal cord imaging using the suggested method. It shows the Spinal cord's real image, localized image, threshold image respectively.

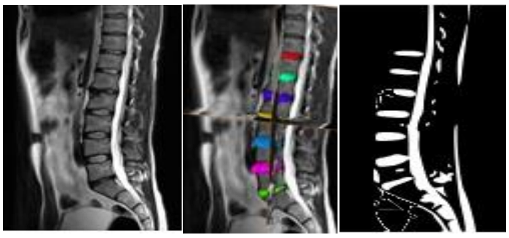

Fig. 2 : 1)spinal cord's original image 2)localized image 3)threshold image

Dataset :The dataset includes MRI images of the intervertebral discs of the lower spine(L5-T11). A binary mask is used to provide the reference manual segmentation for each vertebra, and keep in NIFTI file format.

Performance evaluation of Enhanced CS-ROA DCNN for detecting tuberculosis disease and segmenting the spinal cord

In Table 2, the model used here shows that the accuracy increases as the epoch increases. Similarly, the highest value of the epoch used has the highest sensitivity value. It can be seen the measures increase accordingly as training percentage is increased by this model.

Table 2 : Execution evaluation of the Enhanced CSROA model

Training percentage	*CS-ROADCNN epoch 10*	*CS-ROADCNN epoch 20*	*CS-ROA DCNN epoch 30*
Accuracy			
50% to 90%	0.86	0.86	0.88
Sensitivity			

50% to 90%	0.85	0.86	0.88
Specificity			
50% to 90%	0.86	0.85	0.89

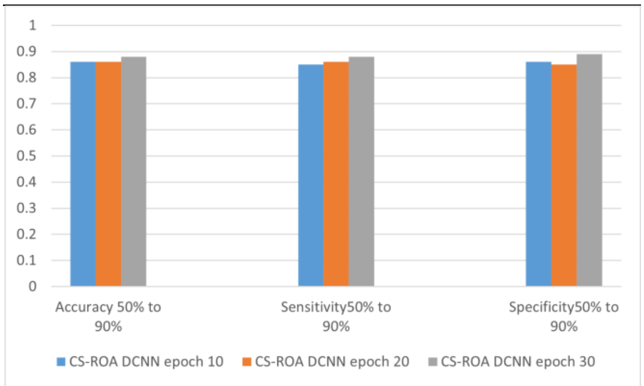

Fig 3 . Performance evaluation

Comparative methods for segmenting the spinal cord and detecting tuberculosis disease.

The analysis is carried out using hold out and K-fold cross-validation. Cross-validation is used to evaluate machine learning methods using limited samples. The dataset is divided into two sets, training set and testing set. The holdout method is such a cross-validation method. In this method, 50% is taken to train the classifier for use on the dataset and the next 50% is taken for testing the data. To perform k-fold cross-validation, the data set is divided into k subsets, and the holdout method is replicated k times in each subset.For example, when using the 5-fold cross-validation method, 80% of the data is taken to train the classifier, 20% is taken for testing, and other 20% is taken as the test set in subsequent iterations.This process continues five times until all the data taken in this way is given as testing data once.

Comparable evaluation using difference in k-fold and training percentage

Table 3 shows a comparison of the techniques used to segment the spinal cord and diagnose tuberculosis depending on the difference in the training percentage .The model used here shows that the accuracy increases as the training percentage increases. In the analysis algorithms, accuracy is 0.77, 0.80, 0.83, 0.85 and the sensitivity is 0.85, 0.86, 0.88, 0.88 respectively. The specificity is 0.76, 0.83, 0.83 and 0.88.This method outperforms current methods in terms of accuracy, sensitivity, and specificity.

Table 3 : Comparable evaluation using difference

Training percentage	*DCNN Max. value*	*NN Max. value*	*ROA – DCNN Max. value*	*Enhanced CS-ROA DCNN Max. value*
Accuracy				
50 % to 90%	0.77	0.80	0.83	0.85
Sensitivity				
50% to 90%	0.85	0.86	0.88	0.88
Specificity				
50% to 90%	0.76	0.83	0.83	0.88

Table 4 shows a comparison of the techniques used to segment the spinal cord and diagnose tuberculosis depending difference in K—fold

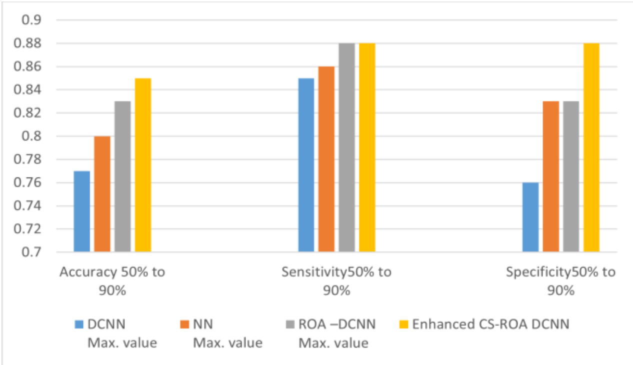

Fig 4. Performance evaluation

Table 4: K—fold difference evaluation

k fold	*DCNN Max. value*	*NN Max. value*	*ROA – DCNN Max. value*	*Enhanced CS-ROA DCNN Max. value*
Accuracy				
2 to 6	0.77	0.81	0.83	0.86
Sensitivity				
2 to 6	0.84	0.86	0.88	0.88
Specificity				
2 to 6	0.80	0.85	0.86	0.88

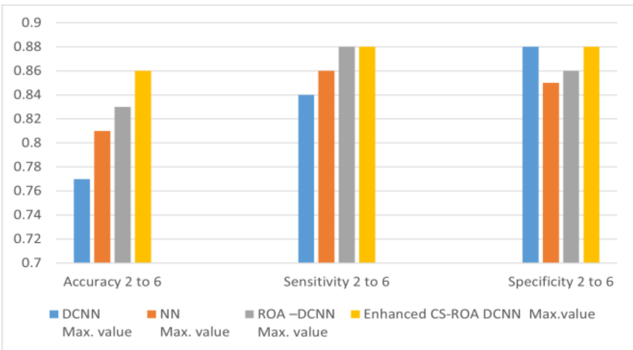

Fig 5. Performance evaluation

5. Conclusion

The proposed approach, which is based on Enhanced CS-ROA DCNN, is used to diagnose spinal cord Tuberculosis disease accurately. At first segment the Spinal cord in the CT image. Following that, segments are used in the disc localization to find disc with distinct properties of clusters. The discs are then prepared for feature extraction, which is the extraction of features taken for classification after the end of disc localization. After the features are extracted by this method and combined with the DCNN-based classification module . Proposed Algorithm that combines CSA with ROA, is used for training the DCNN. Accuracy, sensitivity, and specificity are the three evaluation measures used in the experiment. This method achieved high accuracy, sensitivity, and specificity of 0.86, 0.88, and 0.88, respectively, indicating the effectiveness of the Enhanced CS-ROA DCNN in detecting Spinal Tuberculosis disease. Analyzing the performance of the proposed strategy by taking a dataset , and it can be improved further. Additionally, Mult institutional investigations using larger datasets will be necessary to validate the results so far. Future work will resolve these issues. Additionally, using a mix of different optimization techniques, we hope to identify the disease tuberculosis in the spinal cord in the future.

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Acknowledgements

The authors are thankful to Karpagam Academy of Higher Education for providing the necessary infrastructure for the completion of the study

Conflicts of interest

There is no conflict of interest regarding the publication of this paper.