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Fast and Accurate Feature Extraction-Based Segmentation Framework for Spinal Cord Injury Severity Classification

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ABSTRACT Detection of spinal cord injury (SCI) is one of the major problems in MRI images to detect the affected portion of spinal cord regions using feature sets. Automatic detection of spinal cord atrophy is complex due to change in structure, size, and white matter. Delineating gray matter and white matter are the essential factors that influence the detection of spinal cord atrophy and its severity. Automatic segmentation and classification are accurate methods for detecting the severity of the SCI. Hierarchical segmentation, partitioning segmentation, graph, and watershed segmentation methods are used to find the SCI segments in static fixed positions. Also, these segmentation models result in a high false positive rate due to over segmentation features and noise in the segmented regions. Furthermore, these classification methods fail to segment and detect the severity level in the affected region due to over segmentation. In order to overcome these issues, a novel segment-based classification model is required to find the severity of the injury and to predict the disease patterns on the over segmented regions and features. In the present model, a hybrid image threshold technique is used to segment the spinal cord regions for non-linear SVM classification approach. Among the traditional feature segmentation-based classification models, the proposed threshold-based non-linear SVM has better accuracy for SCI detection. The results proved that the present model is more efficient than the earlier approaches in terms of true positive rate (TP = 0.9783) and accuracy (0.9683).

INDEX TERMS Machine learning, spinal cord image, support vector machine, segmentation.

I. INTRODUCTION

According to the World Health Organization (WHO), every year around the globe between 2,50000 to 5,00000 patients suffering from a spinal cord injury which is a serious global health problem [1]. SCI is the fourth leading cause of death worldwide, with the mortality rate estimated to rise to the third-highest position by 2030. The process of diagnostic imaging plays a vital role during the diagnosis of spinal cord injury. The spinal cord injury mostly occurs due to trauma from falls or accidents. Generally spinal cord sequences are captured by using T1-weighted and T2-weighted regions. They are used to determine the brightness and contrast of the spinal cord tissue. T-1 weighted image is produced by short Time to echo (TE) and Repetition time (RT) whereas T-2 image is produced by long TE and RT. In case of ischemia, the T2 weighted modifications cannot be noticed immediately after the injury as shown in fig 1. But, in case of spinal cord injury, we can find hyper-intensity on T2 weighted imaging. Therefore, the T2 weighted imaging is considered the most effective diagnosis process in the preliminary stage [2]. The hyper-intensity is caused due to cytotoxic and vasogenic edema which may lead to hemorrhage. T2* is

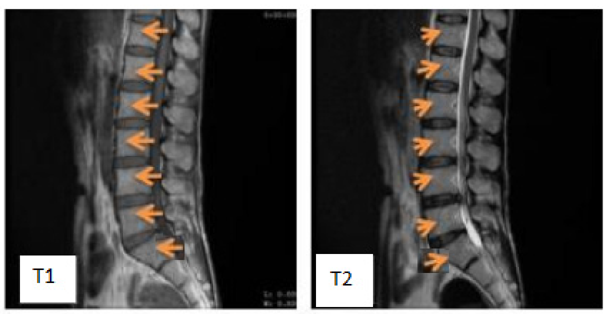

FIGURE 1. **T1 weighted and T2-weighted image.**

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the extended version of the traditional T2 weighted imaging technique [3]. Both these techniques are not efficient for the diagnosis of spinal cord injury.

Diffusion weighted magnetic resonance imaging technique [4] is better in terms of diagnostic efficiency as compared to T2 weighted imaging method. Spinal cord injury is specifically a neurological injury which may lead to dangerous medical, emotional damage. Recently, magnetic resonance imaging schemes are implemented in order to analyze the soft tissue of spinal cord injury. Most of the traditional edema and hemorrhage features in spinal cord can be analyzed more accurately with the help of magnetic resonance imaging technique. According to a recent survey, the spinal cord edema and hemorrhage interstitial fibrosis are considered as a significant modification in case of signal intensity. But these symptoms are not always helpful in the prediction of functional changes.

Image segmentation is considered an important phase in the domain of computer vision and image analysis. The prime objective of this approach is to isolate the image plane into a number of non-overlapping regions. Here, the number of thresholds can be varied according to the feature space. In most of the real time applications, multilevel thresholding technique is implemented to minimize the error rate and to improve the accuracy. In the multilevel thresholding technique, the histogram of a particular image is decomposed into different groups and a particular intensity value is allocated to each individual group. L. Guo *et al.*, proposed a guided filter approach to segment the image features into non-overlapping regions [2]. In order to detect the optimal thresholds, parametric and nonparametric techniques. are mostly preferred: For every individual class, statistical parameters are estimated depending upon initial conditions. In non-parametric techniques, threshold values are evaluated through optimization of criteria such as maximization of class variance or entropy measures. This approach is considered the most popular approach to achieve segmentation. An advanced thresholding approach can be implemented in a spinal cord injury (SCI) image as well as for detecting lesions within the brain.

V. K. Bohat implemented an advanced heuristic approach for multilevel thresholding of images [3]. Multilevel image thresholding is used to separate interesting objects from their non-interesting background. The major objective of this approach is to enhance the capability of the algorithm in order to eliminate the local optimum. Md. H. Merzban *et al.*, developed an effective solution of Otsu multilevel image thresholding [4] which has a wide range of applications in the field of image enhancement and image segmentation. One of the most popular criteria is the Otsu criterion which considers the maximization of inter class variance technique. In this paper, they presented a dynamic programming approach to develop an appropriate solution for the above issue. K. P. Baby Resma *et al.*, introduced a multilevel thresholding approach in order to carry out the process of image segmentation with the help of Krill Herd optimization approach [5]. In this work, they presented a multilevel thresholding technique with the help of a meta-heuristic krill herd optimization approach. N. Tang, *et al.*, proposed a new unsupervised pixel wise classification technique [6]. The automatic segmentation process of Chaetoceros is the most difficult challenge. They emphasized on the unsupervised pixel wise classification technique. Initially, both positive and negative samples are generated automatically. B. D. Leener, *et al.*, developed a spinal cord toolbox and termed it SCT [7]. It is basically open source software that is required for the processing of spinal cord MRI data. I. K. Kallel, *et al.*, presented an iterative probabilistic knowledge diffusion technique for medical image segmentation [8]. In this work, they introduced an efficient image segmentation approach by considering the probabilistic knowledge modeling approaches. S. Agrawal, *et al.*, introduced a new technique for automatic absolute intensity difference-based approach in optimal magnetic resonance of brain image thresholding [9]. M. Beauchemin developed a new method of image thresholding which completely depends upon theories of semi-variance [10]. In this work, a new algorithm is included in order to carry out the process of image thresholding. M. D. Budde and N. P. Skinner presented a diffusion MRI approach in cases of acute nervous system damage [11]. Diffusion weighted magnetic resonance (DWI) imaging is highly efficient in identifying the changes by caused injury. This approach is mostly implemented by to identify cases of cerebral ischemia. T. Carlsted and L. Havton emphasized on longitudinal spinal cord injury [12]. Spinal cord injury in human being specifically the nerve root avulsion injury is considered in this paper. They have performed different experiments to rescue spinal cord nerve cells and heal the spinal cord circuits. P. Chakrawarty and G. Bhatnagar focused on a new image thresholding approach that completely depends upon the local activity feature matrix [13]. The major objective of this technique is to produce a local activity feature matrix in spinal cord detection process.

M. M. D'souza, *et al.*, implemented a diffusion tensor magnetic resonance imaging in case of spinal cord injury [14]. H. Fan, *et al.*, developed an advanced automatic segmentation technique for dermoscopy images with the help of saliency and Otsu threshold [15]. The process of segmentation is considered the most vital phase for CAD diagnosis of skin cancer. T. Y. Goh, *et al.*, studied the issues and limitations of traditional image thresholding and segmentation models in medical image processing [16].

C. Gros, *et al.*, proposed an automated spinal cord localization to improve the MRI contrasts by using global curve optimization approach [17]. Y. Guo, *et al.* proposed a new image thresholding approach that completely depends upon neutrosophic similarity score [18]. Noise is considered a type of indeterminate information in case of images. Hence, the above technique can be implemented in image processing and computer vision research.M. Habba, *et al.* proposed a Gini index-based evaluation criterion for image segmentation [19]. Most of these approaches are subjective in nature and are inefficient to analyses the performance of various kinds of segmentation processes. L. He and S. Huang presented an advanced version of traditional firefly approach that exclusively depends upon multilevel thresholding in color image segmentation process [20]. The prime objective of this algorithm is to detect the optimal multilevel threshold values in case of color images. They employed minimum cross entropy, Kapur's entropy, and feature variation approach as objective functions. In this method, chaotic maps play a significant role during the initialization phase of firefly population. In other words, it is responsible for improvising the diversification.

A. K. Md Khairuzzaman *et al.*, presented a new multilevel thresholding approach with the help of grey wolf optimizer in image segmentation process [21]. Z. Li, *et al.*, developed a new statistical image thresholding and classification scheme for medical image processing [22]. The conventional statistical thresholding approaches are independent of dynamic parameter optimization during the segmentation phase. L. Li, *et al.*, proposed an unsupervised image co-segmentation approach for spinal cord image injury detection [23]. In this approach different segmented features with common structures are identified for injury detection. J. Li, *et al.*, presented a new multilevel thresholding selection scheme that depends upon variational mode decomposition in case of image segmentation [24]. This technique is implemented to split the histogram regions into different submodes. Q. Lin and C. implemented a T sallis entropy based long-range correlation process [25]. Y. Liu, *et al.*, proposed a kernel-based metric for image segmentation process [26]. The segmentation process of noisy images is considered a difficult and complex task in medical image processing. In this paper, they presented a robust variational level set model to perform the image segmentation. They included a kernel metric based on radial basis function instead of data fidelity metric for segmentation process.

H. Min, *et al.*, proposed an efficient local regional approach that depends upon salient fitting of image segmentation process [27]. H. Mittal *et al.*, introduced an optimum multilevel image thresholding segmentation with the help of non-local histogram and exponential K based gravitational search approach [28]. U. Mlakar, *et al.*, presented a hybrid differential evolution for optimal multilevel image thresholding process [29]. Image thresholding can be defined as a specific process which is responsible to find the interesting objects in the background. In this paper, they have proposed a new hybrid differential evolution technique in order to select the required optimal threshold values in segmentation and classification process. Apart from this, certain evolutionary algorithms or swarm intelligence algorithms such as particle swarm optimization, genetic algorithm are implemented during the process of thresholding. M. S. R. Naidu, *et al.*, implemented a Fuzzy entropy-based image thresholding technique in image segmentation process [30]. The prime objective of image segmentation process is to isolate the foreground image from the background image. They have introduced new firefly algorithm that completely depends upon multilevel image thresholding technique.

F. Nie, *et al.*, focused on generalization of entropy and its applications in the domain of image thresholding [31]. In this work, they presented an advanced approach that can manage the additive or non-extensive information present within a physical system. They used a tunable entropic parameter r during the process of image segmentation.

S. Pare, *et al.*, introduced an advanced approach for the multilevel color image thresholding that completely depends upon modified version of fuzzy entropy and Lévy flight firefly technique [32]. which is used to enhance the image segmentation and classification process.

The main contributions of this paper are as follows:

1. Implementing an improved multi-level image thresholding method.
2. Implementing a hybrid image segmentation approach to minimize the over-segmented regions.

The rest of the paper is organized as follows. Section 2, Section 2, describes the proposed solution to the spinal cord injury region detection. Section 3 describes the experimental results of proposed model to the existing models. Finally, we conclude the paper in section 4.

II. PROPOSED FEATURE SELECTION BASED SEGMENTATION AND CLASSIFICATION

Image segmentation is the process of partitioning the image into smaller regions with common homogenous features. Every individual sub-region must have homogeneous pixels. So, there is necessity of some standard segmentation approach that can be implemented in most kinds of SCI images. Image segmentation is considered the initial and standard operation to analyze and interpret spinal cord images. Thresholding based segmentation approach is used to partition the input image into smaller segments. It considers single or multiple grey level values in order to detect the boundary. Therefore, it is quite complex to select the appropriate threshold value by using histogram peaks.

The issue of thresholding becomes more complicated if the number of thresholds grows. Hence, a multilevel thresholding is the most preferred area of research in medical image processing. In case of multiple thresholding, an image can be segmented with the help of multiple threshold values. The multilevel thresholding approaches play an important role during the process of image analysis. In Otsu's technique, optimal threshold values are responsible for maximization of variance between different clusters. Here, the computational time increases rapidly with increase in the number of thresholds. Hence, there is necessity of an optimization approach in order to generate the optimal solution within specified time.

In the proposed model as shown in fig 2, an optimized feature selection measure is developed using the improved particle swarm optimization (IPSO) approach. IPSO is applied on the input spinal cord images to extract the essential features for segmentation process. IPSO is an extension of traditional

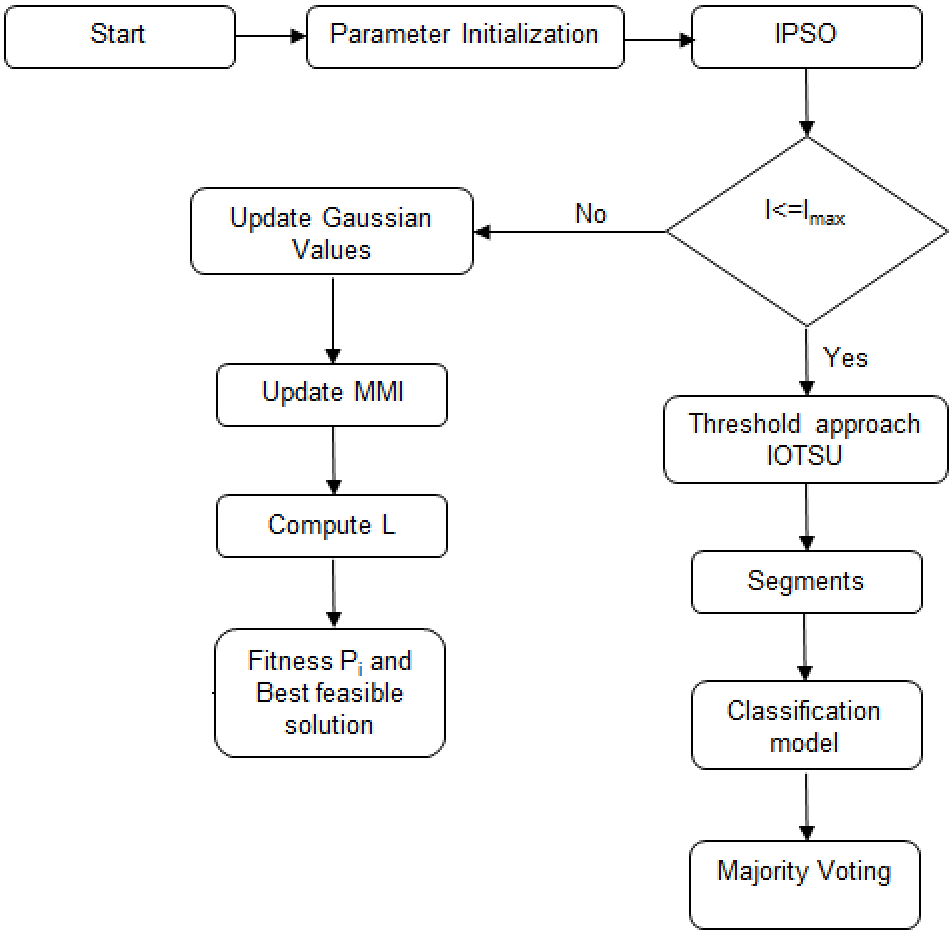


FIGURE 2. Proposed feature selection-based segmentation and classification.

PSO approach. In the proposed IPSO, a randomized Gaussian chaotic function and modified mutual information measure are optimized to extract the filtered features in the SCI images. Here 'L' represents the similarity measure computed between each particle to the local best particle. After computing the MMI and L measure, the local best and global best particles are used to find the feasible features in the image. I and I_{max} are the current iteration and maximum iterations in the IPSO approach. After the completion of IPSO approach, essential features are marked to find the segmented regions using improved OTSU's method.

A. FEATURE SELECTION AND SEGMENTATION

In the proposed model, a hybrid feature selection-based image segmentation and classification process is implemented on spinal cord image datasets. As shown in figure 2, initially, spinal cord images are filtered using the improved particle swarm optimization (IPSO) model in order to detect the essential features in the spinal cord images for training data. Proposed IPSO is repeated until all the features in the spinal cord image are extracted for thresholding-based segmentation process. In the threshold-based segmentation process, an enhanced OSTU's method [3] is implemented on the feature space to minimize the over-segmentation regions in the spinal cord injury detection. Finally, these segmented regions are classified using the non-linear SVM model to find the optimal SCI region in the over-segmented regions. Here, an ensemble learning based classification model is designed to choose the majority voted region among the segmented regions.

In the algorithm 1, spinal cord images are processed in order to extract the hidden features using the IPSO approach. In this approach, a hybrid particle swarm optimization is developed using the mutual information and Gaussian chaotic measure for feature extraction process. The threshold value is dependent on pixel position in local swarm optimization models. Additionally, thresholding approaches can be categorized into parametric approaches and non-parametric approaches. In parametric approaches, every individual class must have previously defined statistical distributions. In non-parametric approaches, no distribution is considered. The nonparametric approaches completely depend upon the optimization of a single criterion. According to the kind of information used, the thresholding techniques can also be categorized. The outcomes of a particular thresholding approach completely dependent on the image properties and

Algorithm 1 Feature Selection Using Improved Otsu's Model

1. Read input image I(x,y)←SCIDB[]
2. Randomly initialize the search agents $P_i(i = 1, 2 \ldots .n)$ in the search space S.
3. K = 1;
4. Calculate the optimized fitness of each agent to find the best feasible solution P_{best}.
5. For I in $[1,2 \ldots I_{max}]$ do
   a. Initialize Gaussian chaotic values using

$$\text{GuassianChaotic}\ (GC_i)$$
$$= \max\{\mu.\varphi_j^k(1-\varphi_j^k), \frac{1}{\sqrt{2\pi\sigma_{I(x,y)}}} e^{-\frac{(I-\mu_{I(x,y)})^2}{\sigma_{I(x,y)}{}^2}}\}$$
$$K = 1, 2 \ldots n$$
$$\varphi_j^k \in (0, 1)$$

   b. Compute distance between P_i and P_{best} as

$Sim(P_{best}, P_i) = Max\{Cor(P_{best}), CorP_i\}$
$\vec{L} = |\vec{H}_i\Box\ \vec{P}_{best} - \vec{P}_i|;\ \text{if Sim}\ (P_{best}, P_i) < 0.5$
$\vec{L} = \left|\vec{H}_i - MMI\right|;\ \text{if Sim}\ (P_{best}, P_i) > 0.5$
$\text{ModifiedMutualInformation(MMI)} = -P_i \log(\sqrt[3]{P_i})$
$H_i = 2^*\left(\vec{C}_i\Box\ \overset{->}{C_j}\right)$
where $\vec{C}_i, \vec{C}_j \in GC_k$
$\vec{P}_{i+1} = \vec{L}\Box\exp(s.l)\Box\cos ine(2.\pi.s) + \lambda \cdot \vec{P}_{best}$
s is shape parameter, l is random number taken from GC.
End for

6. Compute the fitness value of the agent to find P_{best}.

its content. In real world images, various approaches generate different outcomes when implemented on a particular image. There is no significant approach that can obtain good performance in all types of images.

B. MULTI-LEVEL IMAGE SEGMENTATION MODEL USING OPTIMIZED OTSU'S METHOD

Let spinal cord image be represented as I(x,y) with grey levels $0, 1 \ldots \rho - 1$. The histogram of the input image I is represented as $F = \{f_0, f_1 \ldots . f\rho{-}1\}$, where $f_0, f_1 \ldots . f\rho{-}1$ represents the frequency of each grey scale level in the input image I.

Let $N = \sum_{i=1}^{\rho} f_i$ be the total number of pixels in the spinal cord image.

The probability of the ith grey scale level is computed as

$$\Pr ob_i = \frac{f_i}{N}; \Pr ob_i > 0, \quad \sum \Pr ob_i = 1$$

Proposed method is an extension of the Ostu's method. Proposed method partition the spinal cord image into T + 1 segments as $S_k = \{S_o, S_1 \ldots . S_k\}$. Here T is selected from the set of thresholds $T = \{t[r], t[r+1], \ldots ..t[r+1] - 1\}$; Each segmented region is the set of grey scale levels taken from T.

To each segment S compute, the weighted probability and mean weighted grey scale levels η as

$$ws_k = \sum_{i \in s_k} \Pr ob_i$$
$$\eta = \sum_{i \in s_k} \frac{\Pr ob_i . \max\{i, g * \log(i)\}}{ws_k}; \quad g \in GC$$

Weighted mean grey scale intensity μ_{WI} and mean inter-class variance σ_{VS}^2 between the segments of whole image is given by

$$\mu_{WI} = \sum_{i=0}^{\rho} i^* \Pr ob_i$$
$$\sigma_{VS}^2 = \sum_{i=0}^{\rho} ws_k . \eta^2 - \mu_{WI}^2$$
$$(\sigma_{VS}^2)^* = \sum \max\{\sigma_{VS}^2(S_i), \sigma_{VS}^2(S_j)\}$$

In the proposed model, optimal thresholds are determined to each grey scale level of the segmented region by maximizing the inter-class variance as

$$\{t^*[1], t^*[2] \ldots t^*[n]\} = \text{argmax}\ \{\sigma_{VS}^{2*}(t[1], t[2] \ldots . t[T])\}$$

In this algorithm, image automatic threshold technique is proposed to perform the image segmentation on spinal cord image. The inter class variation between the foreground and background objects is processed to estimate the noise level in the over-segmentation process. The segmented regions of the spinal cord detection are used to classify the best pattern among the over-segmented region using the following non-linear SVM formulation.

C. NON-LINEAR SVM CLASSIFICATION

In the proposed SVM classification model, a novel non-linear kernel optimization function is implemented on the segmented regions of the spinal cord regions. Proposed kernel optimization function is used to improve the classification accuracy rate and to minimize the classification error rate.

Input: Over-segmented spinal cord regions
Step 1: Initialize the classification parameters.
Step 2: For each segmented region do
do
Step 3: Apply nonlinear SVM classification model using the following objective function.

$$\min_{W_k, a_k} \frac{1}{2} m_1 \|W_k\|_1^2 + \max\{m_2, \alpha\} \sum_{i=1}^{n} \xi_i^n . ker < s_i, s_j > + \tau_m$$
$$\text{s.t}\ \ W_k^T s_i + b_k \geq 1 - \xi_i^n - \tau_m, \quad \text{if } y_i = k$$
$$W_k^T s_i + b_k \leq -1 + \xi_i^n + \tau_m, \quad \text{if } y_i \neq k$$
$$\xi_i^n > 0$$
$$\tau_m > 0; \quad m = 1 \ldots \text{segments}$$

FIGURE 3. Sample of pre-processed test spinal cord injured image.

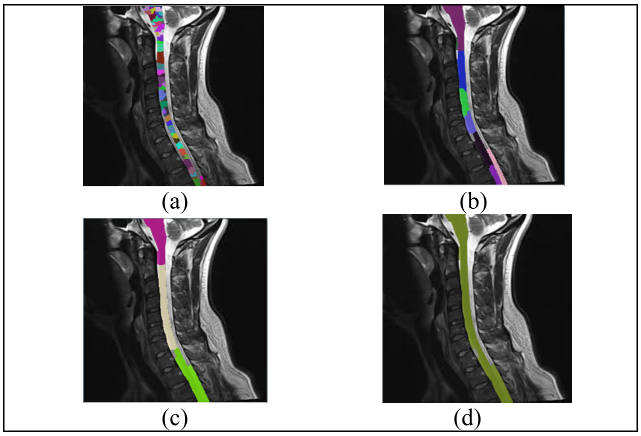


FIGURE 4. Segmentation of the proposed approach with different levels of segments. (a) Segmentation of the proposed approach with over-segmented regions (b). Segmentation of the proposed model with number of segments = 7 (c). Segmentation of the proposed model with segments count = 3. (d) Segmentation process of the proposed approach with a single segmented region.

Here kernel function $ker < s_i, s_j >$ defines the s_i input segments that are mapped to s_j dimensional space as:

$$\begin{aligned} ker\langle s_i, s_j\rangle &= \alpha e^{-\gamma-\log\left(\sum\|s_i-s_j\|^2\right)} \quad \text{if } s_i = s_j \\ &= \alpha e^{-\gamma-log\left(\sum\|s_i\|^2\right)} \quad \text{if } s_i < s_j \\ &= \alpha e^{-\gamma-log\left(\sum\|s_j\|^2\right)} \quad \text{if } s_i > s_j \end{aligned}$$

Step 4: A new sample is predicted to the class s_j based on the largest decision values as

$$\text{argmax}\,\{W_k^T s_i + b_k\}$$

In the proposed non-linear SVM classifier, each segmented region is classified to filter the noisy segmented over-segmented regions in the spinal cord image. The main difference between the traditional SVM to the proposed classifier is that the proposed classifier improves the overall classification accuracy compared to the traditional models for large feature segmented regions.

III. EXPERIMENTATION AND PERFORMANCE ANALYSIS

A. EXPERIMENTAL SETUP AND DATASETS

Experimental results are carried out on SCI images taken from the Manipla hospital, Vijayawada. Here, training spinal cord vertebra dataset is used to segment the regions using the proposed thresholding-based segmentation model. The dataset is a collection of spinal cord patterns with computed

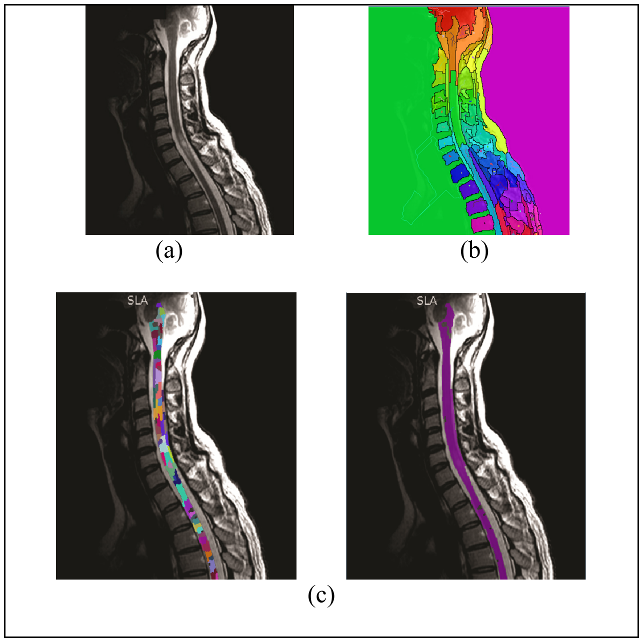


FIGURE 5. Segmentation of the proposed approach with different levels of segmented regions (a) Test medical spinal cord image (b). Over-segmented regions for data classification (c). Minimized Over-segmented regions for data classification.

TABLE 1. Average classification recall and precision of proposed model to the existing models on SCI dataset.

Models	Recall	Precision
PCA Ensemble	0.8264	0.8425
PSO Ensemble	0.8635	0.8733
SVM + linear kernel	0.9384	0.9063
SVM + Quadratic kernel	0.9484	0.9294
Proposed Model	0.9745	0.9782

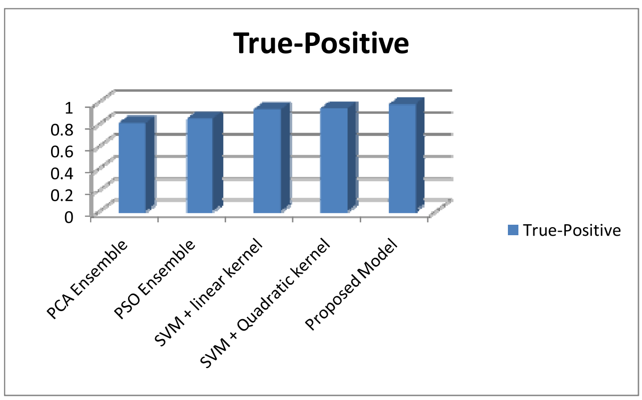


FIGURE 6. Comparison of true positive rate of proposed model to the existing models on SCI dataset.

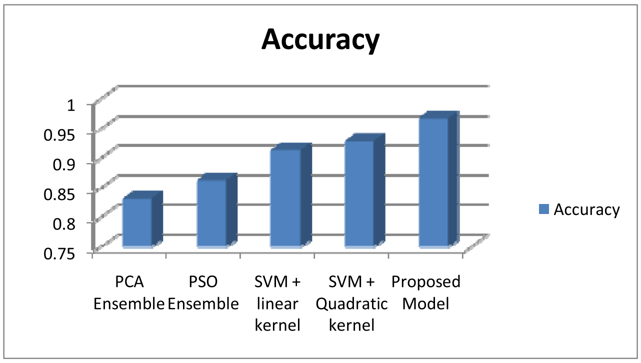


FIGURE 7. Classification accuracy of present approach to the existing Models on SCI dataset.

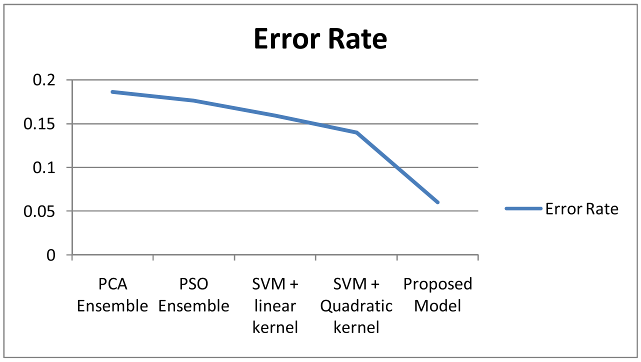


FIGURE 8. Comparative analysis of proposed model to existing models in terms of error rate.

TABLE 2. Performance analysis of proposed approach to the traditional approaches in terms of PSNR and SSIM measures.

Models	PSNR	SSIM
OTSU	28.44	0.783
Entropy	32.43	0.835
Whale Optimization +OTSU	35.34	0.913
PSO+OTSU	34.83	0.9219
Proposed Model	39.24	0.9682

data in nii format, where all the images are related to both male and female. To evaluate the proposed segmentation-based classification model, amazon AWS server with 20GB of RAM is configured as shown in fig 9. The experimental results are developed using the python programming in Amazon AWS server. For testing purpose, proposed model is evaluated on the real-time spinal cord vertebra injury detection taken from the different hospitals. Proposed model classifies the test spinal cord images with high true positive rate and less error rate.

Figure 3, describes the test medical spinal cord image taken from hospital to test the segmented regions for automatic data classification problem.

B. SIMULATION RESULTS

Figure 4(a) describes the segmentation of the proposed model for 25 segmented regions. Here, each color represents one

TABLE 3. Comparative analysis of average proposed gaussian chaotic and modified mutual information measures to the existing measures on SCI image database.

Particle Iteration	Gaussian random [16]	Gaussian Chaotic GC	MI [21]	MMI
P1	0.75	0.96	0.77	0.96
P2	0.88	0.92	0.82	0.92
P3	0.78	0.95	0.85	0.94
P4	0.83	0.95	0.83	0.94
P5	0.86	0.93	0.87	0.96
P6	0.88	0.95	0.84	0.96
P7	0.8	0.92	0.87	0.93
P8	0.78	0.92	0.78	0.91
P9	0.71	0.94	0.77	0.94
P10	0.8	0.95	0.82	0.96
P11	0.79	0.92	0.9	0.97
P12	0.71	0.95	0.9	0.93
P13	0.71	0.94	0.86	0.92
P14	0.83	0.96	0.9	0.93
P15	0.88	0.93	0.79	0.93
P16	0.73	0.95	0.81	0.96
P17	0.86	0.94	0.78	0.94
P18	0.77	0.96	0.9	0.92
P19	0.71	0.93	0.87	0.91
P20	0.79	0.96	0.82	0.92
P21	0.77	0.93	0.86	0.94
P22	0.83	0.93	0.88	0.97
P23	0.71	0.96	0.82	0.95
P24	0.75	0.93	0.84	0.92
P25	0.86	0.92	0.84	0.92
P26	0.81	0.92	0.86	0.94
P27	0.74	0.93	0.86	0.91
P28	0.78	0.95	0.92	0.95
P29	0.8	0.96	0.82	0.93
P30	0.76	0.95	0.88	0.93
P31	0.74	0.94	0.87	0.97
P32	0.75	0.95	0.89	0.97
P33	0.89	0.95	0.77	0.95
P34	0.85	0.95	0.76	0.97
P35	0.88	0.93	0.88	0.96
P36	0.89	0.95	0.78	0.93
P37	0.7	0.94	0.88	0.95
P38	0.74	0.91	0.8	0.92
P39	0.82	0.93	0.78	0.93
P40	0.79	0.92	0.82	0.97
P41	0.81	0.94	0.88	0.94
P42	0.87	0.94	0.76	0.92
P43	0.79	0.94	0.78	0.96
P44	0.73	0.91	0.86	0.96
P45	0.78	0.95	0.88	0.94
P46	0.78	0.91	0.79	0.96
P47	0.82	0.94	0.86	0.95
P48	0.88	0.91	0.88	0.93
P49	0.74	0.95	0.84	0.93
P50	0.85	0.96	0.91	0.92

TABLE 4. Comparison of average inter and intra region variances on the SCI image database.

Threshold T	Intra Variance [14]	Proposed Intra Variance	Inter Variance [14]	Proposed Inter Variance
T=1	1.93	2.15	1.69	2.53
T=2	2.55	3.07	2.4	2.93
T=3	1.83	2.3	2.78	3.56
T=4	1.21	2.25	1.82	2.93
T=5	1.48	3.35	1.6	3.71
T=6	3.26	3.53	2.58	2.59
T=7	0.94	1.68	3.38	3.44
T=8	1.66	1.75	0.65	2.71
T=9	0.76	2.24	1.97	1.99
T=10	1.23	1.68	0.53	2
T=11	2.73	3.62	1.74	3.71
T=12	1.66	2.52	0.59	3.2
T=13	2.36	2.82	0.6	3.2
T=14	2.57	3.59	1.68	1.81
T=15	**1.5**	**2.71**	**0.45**	**3.79**
T=16	0.88	1.18	1.76	3.31
T=17	1.99	2.74	1.05	2.97
T=18	1.75	3.41	1.19	2.21
T=19	1.37	3.3	1.03	3.24
T=20	2.06	2.48	3.32	3.38
T=21	2.24	3.38	1.44	2.05
T=22	1.66	1.98	2.04	3.28
T=23	0.79	2.61	1.1	2.21
T=24	0.57	3.04	0.89	2.55
T=25	2.36	3.04	0.85	1.41
T=26	1.98	2.83	1.27	3.38
T=27	1.71	2.89	1.24	2.81
T=28	2.64	3.09	0.79	0.99
T=29	1.06	2.18	1.3	3.5
T=30	2.18	3.24	2.22	2.33
T=31	0.86	0.9	2.01	3.73
T=32	3.59	3.74	0.72	3.74
T=33	0.79	2.36	0.86	1.12
T=34	2.07	3.44	2.94	3.04
T=35	1.57	1.74	1.52	2.68
T=36	1.51	2.12	0.71	2.57
T=37	0.5	2.37	1.29	2.52
T=38	0.79	1.68	2.66	3.51
T=39	3.19	3.51	1.14	2.91
T=40	1.36	3.71	1.92	3.32
T=41	3.46	3.5	0.55	0.86
T=42	1.2	1.8	0.98	1.17
T=43	2.93	3.03	2.33	2.66
T=44	0.91	2.53	1.1	1.3
T=45	3.24	3.75	1.94	2.04
T=46	1.6	3.62	0.45	3.17
T=47	0.68	3.63	1.36	2.21
T=48	2.52	3.6	1.15	3.59
T=49	1.83	2	1.67	2.73
T=50	1.35	3.14	2.62	2.66

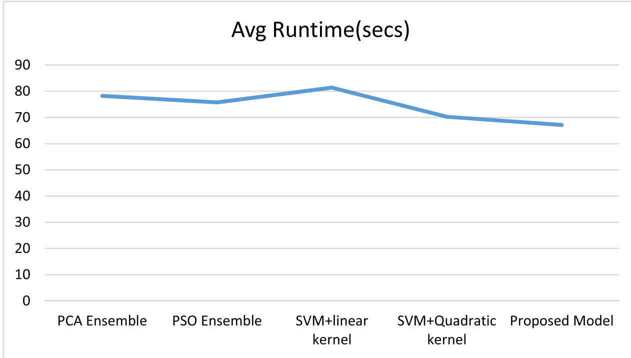


FIGURE 9. Comparative analysis of proposed model to traditional approaches in terms of runtime (secs).

segmented region for data classification problem. As the size of the segmented regions increases, proposed model efficiently classifies the regions by using the scalable classification model.

Figure 4(b) describes the segmentation of the proposed model for 7 segmented regions. Here, each color represents one segmented region for data classification problem. As the size of the segmented regions increases, proposed model efficiently classifies the regions by using the scalable classification model. Figure 4(c) describes the segmentation of the proposed model for 3 segmented regions. Here, each color represents one segmented region for data classification problem. As the size of the segmented regions increases, proposed model efficiently classifies the regions by using the scalable classification model. Figure 4(d) describes the segmentation of the proposed model for single region merging after classification problem.

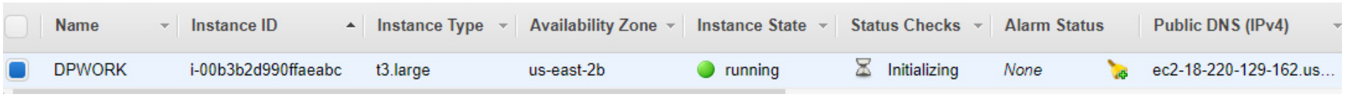
Figure 5(a), describes the test medical spinal cord image taken from SCI repository to test the segmented regions for automatic data classification problem.

Figure 5 b) describe the segmentation of the proposed model for 25 segmented regions. Here, each color represents one segmented region for data classification problem. As the size of the segmented regions increases, proposed model efficiently classifies the regions by using the scalable classification model. Figure 5 c), describes the segmentation of the proposed model for minimization of over-segmented regions after classification approach.

C. PERFORMANCE ANALYSIS

Experimental results are simulated and tested on various spinal cord images to detect the segmentation quality and classification accuracy. Different types of computational measures have been used to improve the image quality of the spinal cord vertebra injury. The mean square error, PSNR and SSIM are used to evaluate the performance of the proposed model to the existing segmentation models [5].

$$\mathrm{MSE} = \frac{1}{MN}\sum\sum(s_i\text{-}s_j)$$



Name	Instance ID	Instance Type	Availability Zone	Instance State	Status Checks	Alarm Status	Public DNS (IPv4)
DPWORK	i-00b3b2d990ffaeabc	t3.large	us-east-2b	running	Initializing	None	ec2-18-220-129-162.us...

FIGURE 10. Amazon AWS server and its configurations.

$$\mathrm{PSNR} = 20^{*} \log\left(\frac{255}{\mathrm{MSE}}\right)$$

$$\mathrm{m(A, B)} = \frac{2\overline{\mathrm{A}} \cdot \overline{\mathrm{B}} + \theta_1}{\overline{\mathrm{A}}^2 + \overline{\mathrm{B}}^2 + \theta_1}$$

$$\mathrm{cn(A, B)} = \frac{2\mathrm{SD(A)SD(B)} + \theta_2}{\mathrm{Var(A)} + \mathrm{Var(B)} + \theta_2}$$

$$\mathrm{sc(A, B)} = \frac{\mathrm{SD(AB)} + \theta_3}{\mathrm{SD(A)SD(B)} + \theta_3}$$

$$\mathrm{SSIM} = \mathrm{m(A,B)}^{\mathrm{r1}}.\mathrm{cn(A,B)}^{\mathrm{r2}}.\mathrm{sc(A,B)}^{\mathrm{r3}}$$

$$\mathrm{SSIM} = \frac{\left(2\overline{\mathrm{AB}} + \theta_1\right)(2\mathrm{SD(AB)} + \theta_2)}{\left(\overline{\mathrm{A}}^2 + \overline{\mathrm{B}}^2 + \theta_1\right)(\mathrm{Var(A)} + \mathrm{Var(B)})}$$

Here, A and B represent two adjacent segmented regions in spinal cord injury regions. θ_1 and θ_2 represents the average mean and variance of the segmented regions of A and B [6]. Three evaluation metrics were used to assess the proposed segmentation and classification performance with the traditional models. Here, SSIM gives the similarity between the two regions during the segmentation process [8]. Similarly, classification accuracy is computed using the true positive rate, recall, precision, accuracy measures.

Table 1 shows the performance of the present technique on the SCI disease dataset on large feature space. Here, a novel PSO based multi-class SVM is used in the ensemble model to improve the recall and precision. Proposed classification model is better in terms of feature identification and SCI region classification. In the table1, recall and precision of the proposed model is compared with the traditional SCI classification models. The recall and precision of the proposed model is better than the traditional classification models for large over-segmented regions.

Figure 6 describes the performance of the present technique on the SCI disease dataset on large data size. Here, the proposed classification model optimizes the true positive rate of the spinal cord detection compared to the existing models. Proposed classification model is better in terms of feature identification and SCI region classification.

Figure 7 describes the performance of the present technique on the SCI disease dataset by using segmented feature set. In the figure, true positive rate and accuracy of the proposed model is compared with the traditional SCI classification models. The true positive rate and the accuracy of the proposed model is better than the traditional classification models for large over-segmented regions.

Figure 8 shows the performance of the present technique on the SCI disease dataset on large feature space. Here, a novel PSO based multi-class SVM is used in the ensemble model to improve the true positive and accuracy rate. From the figure 7, it is clearly observed that the proposed SCI region classification model has less error rate compared to the traditional models on large segmented regions.

From the table, it is observed that the proposed segmentation model has high SSIM measure and PSNR ratio compared to the existing techniques. Here, the inter and intra segmentation variation between the regions is improved due to optimal feature selection measure.

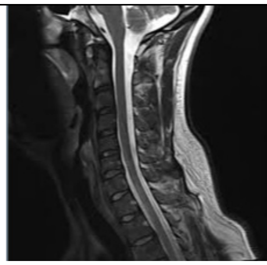
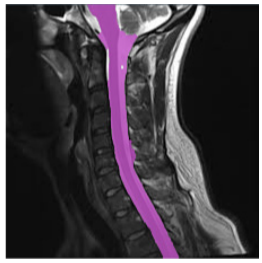
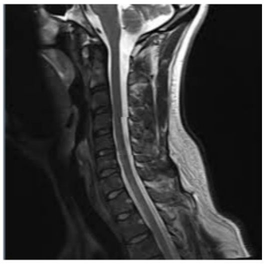
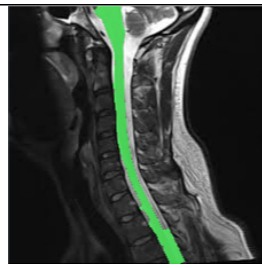
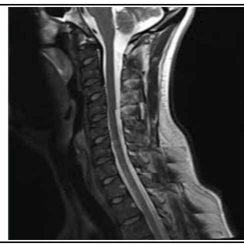
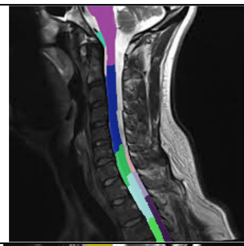
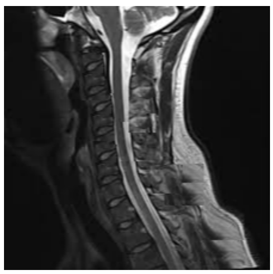
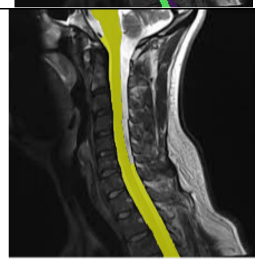
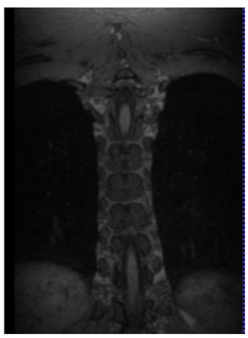
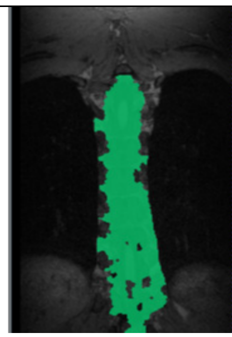
Table 3 illustrates the comparison of the average proposed Gaussian chaotic and modified mutual information measures to the existing measures on SCI image database. In this table, the Gaussian randomization values in the proposed measure and existing measures are tabulated. Here, the Gaussian randomization in each particle initialization process is optimal compared to the existing values for local best and global best computation. Also, the mutual information of the proposed MMI measure is optimal for selecting the features in the IPSO approach than the existing MI measure.

Table 4 illustrates the comparison of average inter and intra cluster variances on the SCI image database. To each threshold T, the variation of inter and intra cluster regions are computed and tabulated. From the table, it is noted that the least 0.45 value in the intra cluster variance and maximum 3.79 value in the inter cluster variance are selected in the threshold $T = 15$.

Figure 10, describes the computational server and its memory computational details for the simulation results. Here, the amazon web services are used for the simulation results with 48GB of RAM. In the above screenshot, amazon t3.large instance is used to simulate the segmentation-based classification approach on the SCI image dataset.

Table 5, illustrates the experimental results of proposed framework on the input spinal cord injury images. Here, five sample input SCI images are taken to test the segmentation and classification accuracy. Also, these five sample images have different disorders in terms of orientation and shape. From the table, it is noted that the proposed model has high computation accuracy in the first four input images with accuracy $> 96\%$. Last image is the older age SCI image which contains noise in the T1-weighted and T2-weighted regions and hence the accuracy of the last image is slightly lower than the previous sample of images.

TABLE 5. Experimental result of five sample input images and its classified segmented region(s) along with accuracy.

S.No	Type of Image	Patent Category	Disorder	Input Image	Classified Segmented Region	Accuracy
1	Image – 1	Male(age=37)	Spinal cord orientation			0.968
2	Image – 2	Female(age=43)	Spinal cord shape			0.973
3	Image – 3	Male(age=34)	Spinal cord orientation			0.978
4	Image – 4	Male(age=53)	Spinal cord shape			0.985
5	Image - 5	Female(age=57)	Spinal cord orientation and shape			0.9475

IV. CONCLUSION

Disease prediction in high dimensional spinal cord images is one of the major issues in real-time applications due to noise or feature selection problem. Most of the traditional models are independent of segmented features for spinal cord classification problem. As the size of the spinal cord vertebra segments increases, these models fail to classify the newly added spinal cord images due to high computational time and memory. In order to overcome these issues, a novel segment-based classification model is required to find the severity of the injury and to predict the disease patterns on the over segmented regions and features. As the number of segmented features in the SCI increase, a hybrid principal component analysis (IPCA) technique is developed to minimize the over segmented features and to optimize the noisy regions in the SCI images. In the present model, a hybrid image threshold-based segmentation approach is developed to minimize the over-segmented regions in the spinal cord images. These segmented regions are used to classify the image using the non-linear SVM classification approach. Experimental results proved that the present model is efficient than the existing approaches in terms of accuracy, SNR, SSIM and runtime. Experimental results proved that the present model is better in terms of accuracy, true positive, and error rate than the traditional models. In the future work, a novel multi-level segmentation-based classification approach will be implemented on the gender wise spinal cord images to improve the error rate and accuracy. Also, the noises in the T1-weighted and T2-weighted regions are optimized in order to improve the classification accuracy in the older age SCI images.

CONSENT TO PUBLISH
The consent to publish has been obtained from the participant to report individual's data.

ETHICS APPROVAL
Not applicable

AVAILABILITY OF DATA AND MATERIALS
Not applicable

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The authors declare that they have no competing interests.

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