A Survey on Spinal Cord Injury Detection Using Improved U Net Segmentation With Hybrid Classification

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Abstract:

Spinal cord injury (SCI) is a serious medical condition. Spinal Cord Injury limits the movement of the body, blocks the nervous system and affects the quality of life of an injured patient. Spinal cord injury (SCI) detection is one of the major problems. Earlier, to detect spinal cord injury, radiologists analyze SCI images manually but manual interpretation of high dimensional feature space makes it difficult to predict the exact category and level of severity of injury. For better analysis of the spinal cord injury, technology must be used . Recent advances in the medical field of SCI has played a significant role in improving diagnosis, stabilization and well being of injured patient. Technology, like machine learning, deep learning, image segmentation can help to detect spinal cord injury in an improved manner. This paper focuses on study of related work done on detection of Spinal Cord Injury and also proposes a novel model for detection of spinal cord injury.

Keywords: *Spinal cord injury, Machine learning, deep learning.*

1.Introduction

The spinal cord serves as the path to transmit the electrical activity, such as sensation or afferent information and motor or efferent information between central nervous system (CNS) and Peripheral nervous system (PNS) [9] [10]. The spinal cord, one of the intricate and well-organized components of the CNS, is in charge of the neural signal transmission to the PNS from the brain, also known as motor data, and to the brain from PNS, also known as sensory data [11] [12]. In simple terms, this data is conveyed and regulated by spinal interneurons, which are typically found in the gray matter (GM), and is conveyed by myelinated motor and sensory axons, which are located in the white matter (WM). Additionally, the GM of the spinal cord has intrinsic neural circuits that are employed to support particular tasks including movement [13]. The majority of spinal cord injuries (SCI) are caused by trauma from accidents or falls. Any spinal cord injury, whether whole or partial, has an impact on the conduction along these pathways, which leads to the impairment of motor and/or sensory function [14] [15].

The World Health Organization (WHO) estimates that between 2,50,000 and 5,00,000 people suffer from spinal cord injuries each year worldwide, which is a significant global health issue [16] [17]. SCI is currently the third-highest cause of death in the world, and by 2030, it is predicted to overtake all other causes of death. The diagnostic imaging procedure is quite important throughout the diagnosis of SCI. Thus, several research projects and clinical investigations are required in order to deploy automated spine segmentation as a tool for disease detection and statistical analysis [18] [19].

In the field of computer vision and image analysis, segmentation of images is viewed as a crucial step. Researchers have tried a number of research methods, including active contour, growing area approach, and others, to automatically or semi-automatically segment the spinal cord [20]. This method's main goal is to divide an image plane into many non-overlapping areas. Multilevel threshold is used in the majority of real-time applications to reduce error rates and boost accuracy. In the past, radiologists manually examined SCI images to look for unusual spinal abnormalities. However, due to manual interpretation of higher dimensional feature space, the precise category and level of degree of severity remains challenging to be determined. In addition, an architecture based on deep learning (DL) facilitates rapid and accurate diagnosis. Automatic classification of normal and abnormal SCI images is done using DL methods.

2.RELATED WORK:

Ahammad *et al.* [1] provided a DL system for aiding in the diagnosis of SCI characteristics in 2020. The framework relies on the segmenting procedure. This article used sensor SCI image data to apply a unique CNN segmentation oriented boosting classifier. The data on spinal cord disorders was captured using a real-time portable sensor with various forms and orientations. According to experimental findings, the current CNN boosting classifier has a higher computational SCI prediction than the CNN oriented classifiers currently in use. Experimental findings have shown that the current approach outperforms existing SCI detection models.

A new segment-based categorization approach was published by Ahammad *et al.* in 2019 [2], and it was necessary to determine the extent of SCI and to forecast patterns of disease on the over-segmented areas and features. The spinal cord areas in the current model are segmented using a hybrid imaging threshold technique in order to employ SVM classification strategy. The suggested SVM was more accurate for SCI detection than the conventional models. The outcomes demonstrated that the current methodology is more effective than the previous methods.

The introduction of an automated MR spinal cord segment model by América *et al.* [3] in 2022 allowed for the automated and smooth evaluation of spinal cord weakness. An MRI dataset of 121 individuals with multiple sclerosis (MS) was used to build the method. The manual labeling was overseen by skilled radiologists and was set as ground-truth. The 2D CNN included a hybrid residual segmenting technique that was developed to identify the central spinal cord. The automated model produced accurate segmentation outcomes.

In 2022, Andrew *et al.* [4] examined the connections between lesion-site features of spared spinal cord tissue and standing capacity using scES. According to our hypothesis, unbiased expansion in the contralateral lower limb would be correlated with the quantity of lateral cord tissue spared. Eleven people with chronic, clinically complete SCI with spinal cord MRIs done before scES were included. An overground research using scES evaluated patterns of activity and standing ability. In order to examine the connections among standing and imaging results, regression analysis was utilized. In this investigation, standing results with scES were substantially correlated with MRI assessments of spinal cord tissues.

Xiaoran *et al.* in 2021 [5] suggested a fully automated method for segmenting spinal cord from 2D MRI slices from individuals with CSM. The suggested approach was trained and evaluated with the use of medical data from 20 CSM patients. Utilizing quantitative measurements, the reliability meter, and visual evaluation, the suggested method's accuracy was assessed. The MSE was lower using the suggested strategy. The findings were of statistical significance when comparing the suggested approaches to extant techniques.

An approach based on super pixel was proposed by Xing *et al.* [6] in 2022 to detect the necrotic spinal cord areas in chronic SCI MRI. Intensity statistical data, Gabor texture features, GLCM features, LBP features, and super pixel regions were combined to create feature sets, which were then used to create super pixels using a linear iterative clustering approach. Then, the accuracy and processing times of the SVM and random forest (RF) classification models were compared.

In 2019, Charley *et al.* [7] created a fully-automatic model for segmentation of the spinal cord from conventional MRI data of non-MS and MS patients. The sequence of two CNNs formed the foundation of the suggested chord and lesion automated segmentation method. A first CNN with 2D dilated convolutions identified the spinal cord centerline before a second CNN with 3D convolutions segments the spinal cord and/or lesions to account for the relatively tiny fraction of spinal cord over the remaining part of the volume. In this paper, a reliable approach was presented for segmenting intramedullary MS lesions and spinal cord lesions on various MRI contrasts.

Munavar *et al.* [8] in 2021 developed a system for segmenting and detecting SCI based on the suggested Crow search-Rider Optimization-based DCNN (CS-ROA DCNN) approach. This system was capable of accurately detecting SCIs. The adaptive thresholding approach was first used to segment the spinal cord in the CT image, and then the Sparse FCM clustering algorithm (Sparse-FCM) was used to locate the disc. The features required for the classification procedure were taken from the localized discs via a feature extraction phase. The suggested CS-ROA, which combines the "Crow Search Algorithm (CSA) and Rider Optimization Algorithm (ROA)", is used to train DCNN for the classification process.

F. Inanici et al.[9],in 2021 conducted a study on 6 volunteers between the age limit 21 and 71 years, who are suffering from SCI to show the results. Authors used transcutaneous electric stimulation of spinal cord which leads to fast and sustained recovery of hand and arm function.Transcutaneous simulations help to activate the spinal cord via sensory pathways in the dorsal roots to provide excitation within a spinal cord.

Soshi Samejima et al. [10] in 2021 conducted a study on rats to show the role of brain computer interface for spinal cord injury intervention which can be used to recreate actions in paralyzed limb. By creating a complete brain, an artificial connection has been established in the brain and paralyzed limbs to restore the actions in upper limbs. The suggested BCSI i.e Brain-Computer Spinal interface is demonstrated for restoring upper limb movement. Through demonstration authors found good results in forelimb functions.

R. Cheng et al.[13] in 2019 conducted a study for analyzing muscle synergies in SCI patients where muscle synergies , extracted using novel algorithms, are kept as a key physiological mechanism to generate motor functions. Results shows that, even after spinal cord injury, muscle synergies remain unbroken which can be used to enable standing ability, using spinal cord stimulation.

3. RESEARCH GAP:

From the above literature study, e tried to find the research gap which is enlisted below:

- According to researchers, traditional methods are not efficient to process high dimensional feature space due to high computational memory and time.[1]
- Experimental results shown that, accuracy is decreased in older age SCI images and variations happened in accuracy in case of change in gender.Also,noise in the T1 and T2 weighted regions is more in older age SCI images.[2]
- Many researchers through their research focused the issue that,with small size SCI images, variability in results found to detect severity of diverse injury.Also,Stimulation and Binding off SCI images is difficult to achieve due to sensation associated with stimulation.[9]

4. PROBLEM STATEMENT:

Inlined with research gap, we focused on improvement of spinal cord injury detection. We aim to solve the above problems using problem statements as below:

- Due to the wide range of acquisition settings and image artifacts, robust and accurate segmentation of multi-site spinal cord information can be difficult. The spinal canal was segmented in traditional works using an automated process based on mathematical anatomy and the growing region. Utilizing the circular Hough transform, it was possible to automatically recognize the spinal canal. Due to the significant variations between CT and MRI images, these approaches can be utilized in CT images but are not employed in MRI data. Due to the distance among uneven transmit fields and the coil, the shortcomings of the MRI oriented segmentation merge the bias field of intensity. Additionally, segmentation problems are caused by the absence of CSF over the spinal cord and the frequent occurrence of intervertebral disk calcification [8].
- As, in large size SCI image data, it is difficult to find essential disorder or injury regions so deep learning framework can be designed to improve classification accuracy in large SCI images with Hadoop approach.
- In order to improve accuracy in older age SCI images and to maintain the accuracy in case of change in gender, a novel multi-level segmentation based classification approach can be implemented on gender wise and age wise spinal cord images to improve accuracy and error rate.
- Noise in older age image data is more so it can be optimized to improve classification in older age image data.

5.Proposed Methodology:

Detecting SCI remains a main challenge in employing feature sets to identify affected portions of the spinal cord in MRI images. Since the WM, size, and structure of the spinal cord fluctuate, automatic identification of atrophy in the spinal cord is challenging. The key elements that affect the identification of spinal cord weakness and its severity are the delineation of GM and WM. The severity of the SCI may be accurately detected using automatic segmentation and classification. Therefore, through this paper, we introduce a novel SCI detection model that includes various phases including (i) Preprocessing, (ii) Segmentation, (iii) Feature extraction, and (iii) Classification. Initially, the input image is subjected to the preprocessing phase. Subsequently, the preprocessed image is subjected to the segmentation phase, in which the Improved UNet architecture is used for disc localization. From the segmented image, texture features, Improved Local Gabor Binary Pattern, shape features and statistical features are extracted. Moreover, the extracted features are subjected to the classification phase, for which Deep Maxout Network (DMO) as well as Recurrent Neural network (RNN) will be used. The outputs from DMO and RNN will be averaged and final SCI detected results will be obtained. Figure 1 shows the diagram of proposed methodology.

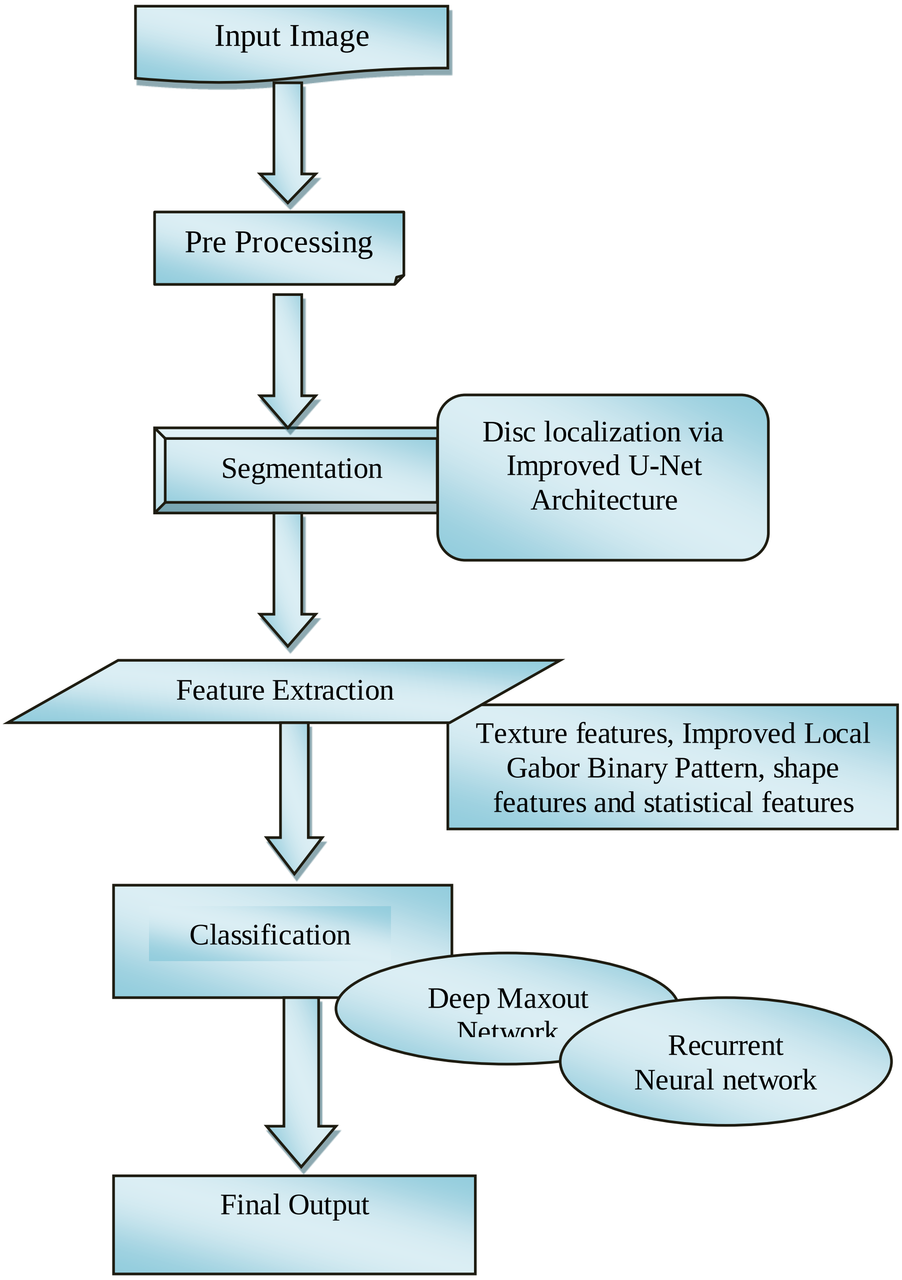

Fig1.Diagram of Proposed Methodology

6.CONCLUSION:

Spinal cord injury (SCI) is a serious medical condition.Recent advances in the medical field of SCI has played a significant role in improving diagnosis, stabilization and well being of injured patients. Technology, like machine learning, deep learning, image segmentation can help to detect spinal cord injury in an improved manner. The proposed method based on SCI detection will be implemented in PYTHON and the experimental investigation will be carried out. The analysis on performance will be done by comparing the Type I and Type II measures of the proposed model over others.

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