Journal of Information Systems Engineering and Management
2025, 10(30s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Effective Spinal Cord Diagnosis using a Hybrid Model of 3D U-Net and CNN

Nama V N S Ajay Babu[1], Pothuraju.RajaRajeswari[2]
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India, 522302

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Introduction: Spinal cord injuries (SCI) can have severe, life-changing implications, therefore early and precise diagnosis is critical. While CT imaging is useful, hand interpretation is slow and error-prone, emphasizing the importance of automated technologies. Our paper proposes a deep learning-based technique that uses a 3D CNN to segment the spinal cord and detect lesions in CT images. By training on a huge dataset, our model aspires to match or outperform human experts in accuracy while streamlining clinical workflows. Finally, we want to improve patient outcomes by incorporating deep learning into routine spinal injury examinations.

Objectives: The goal of this research is to create a deep learning-based system that can accurately segment the spinal cord and identify injuries in CT images. Utilizing a 3D CNN model that has been trained on a sizable annotated dataset, our goal is to improve diagnostic efficiency and accuracy. Our objectives are to assist radiologists, lower diagnostic mistakes, and enhance clinical results for patients with spinal cord injuries.

Methods: Early and precise diagnosis is essential for spinal cord injuries (SCI), which can result in paralysis and lifelong disability. Although CT imaging is often utilized, manual interpretation is laborious and prone to mistakes. In order to solve this, we suggest a deep learning-based system for spinal cord segmentation and damage detection that makes use of a 3D CNN. To increase accuracy and help radiologists make quicker, more accurate diagnoses, our model is trained on annotated CT images. Our goal is to improve patient outcomes and healthcare procedures by automating this process.

Results: This study divides methods for detecting spinal cord injuries into three categories: distance-based, qualitative, and quantitative. With a mean of 97% in volumetric similarity and over 94% similarity with ground truth, the suggested hybrid CNN and 3D U-Net model performs better than the rest in segmentation accuracy. Its higher performance is confirmed by traditional measures like sensitivity, specificity, and MCC, which shows a significant connection between forecasts and ground truth.

Conclusions: This study divides models for detecting spinal cord injuries (SCI) into three categories: distance-based, qualitative, and quantitative. With over 97% similarity and almost 0% Global Consistency Error (GCE), the suggested hybrid CNN and 3D U-Net model performs better in segmentation accuracy than conventional techniques. Superior sensitivity and specificity are confirmed by quantitative assessment utilizing measures such as the Dice coefficient, Jaccard index, and Matthews correlation. Its accuracy is further confirmed by distance-based metrics like Hausdorff Distance (HD) and Mean Surface Distance (MSD).

Keywords: Spinal Cord Segmentation, Injury Detection, CT Imaging, Deep Learning,3D U-Net, Convolutional Neural Networks (CNNs), Automated Diagnosis, and Image Preprocessing.

INTRODUCTION

SCI is one of the most serious forms of trauma and frequently results in paralysis, permanent impairment, and other life-altering consequences. In order to start the right treatments and lower the chance of irreversible harm, early detection, and precise diagnosis are essential. Because CT imaging has a high resolution and may detect soft tissue injuries, spinal anomalies, and bone fractures, it is frequently utilized for spinal injury assessments. In complicated instances with minor or subtle injuries, manual CT picture interpretation is time-consuming and prone to human mistakes. The need for automated technologies that can help radiologists promptly and accurately identify spinal cord injuries is highlighted by this. Accurately segmenting the spinal cord in CT images is one of the main obstacles to creating such a system.

Even seasoned clinicians find segmentation challenging due to the spinal cord's complex anatomy and near closeness to bones and other spine components. These complexities are frequently difficult for traditional image processing methods to handle, producing inconsistent or erroneous findings. Furthermore, since spinal injuries range greatly in appearance and severity—from tiny fractures to whole dislocations—detection of injuries is equally difficult.

By utilizing cutting-edge machine learning methods, automating this procedure would not only save diagnostic time but also increase accuracy. In this work, we provide a deep learning-based method for damage detection and spinal cord segmentation. Our model is trained to recognize the spinal cord in CT images and distinguish between damaged and healthy areas using a 3D Convolutional Neural Network (CNN). Our goal is to develop a system that operates with a high level of accuracy and dependability by using a sizable, annotated dataset of CT images.

This study's main goal is to show that automated systems can detect spinal injuries just as well as or better than human experts. Furthermore, our objective is to demonstrate how deep learning can improve clinical workflows, assisting radiologists in concentrating on the most important cases while lowering diagnostic errors. Our method tackles two crucial tasks: damage identification and segmentation, adding to the expanding corpus of research in medical image analysis.

A thorough tool for spinal cord evaluation is produced by combining these two activities into a single framework. The design of our system, the preprocessing procedures used on the CT images, and the outcomes of comprehensive testing will all be covered in the parts that follow. The ultimate goal of this research is to improve outcomes for individuals with spinal cord injuries by paving the road for the routine clinical application of deep learning.

OBJECTIVES

The studies on spinal cord injury and related terms are demonstrated to improve the detection of injuries so that prevention would be applied. From Malinda Vania, Dawit Mureja et al(2019)[1], demonstrated the combination of CNN and FCN against 12 measures and used the class redundancy as the key aspect that improves accuracy, and efficiency results. From Andriy Fedorov, Reinhard Beichel et al (2016)[2], demonstrated 3D slicer as a software tool that analyzes images for clinical research. From Gerig, G., Jomier, M., et al (2001)[3], the demonstration of images on neurological developments, and degenerations in brain disease is reported and addressed. The proposed model uses segmentations, and variability is assessed using visual assessment and 3D monitoring. From Carl Whyne, Michael Hardisty, et al(2007)[4], the demonstration on detecting tumors across voxels in the spinal chord, and segment lytic, blastic concerning the base chord. The disease's seriousness, and volume are demonstrated on histograms, which would reveal quantitative details of metastasis of the spine. From Ben Glocker, Darko Zikic, et al (2013)[5], demonstrated the effective pathologies using a discriminator classifier. This would be useful for localization and uses probabilistic labels for identification.

From Ogink, P.T., Karhade, A.V., et al (2019)[6], demonstration of clinical details of spinal stenosis using machine learning for non-home discharge as well as doing elective surgery. The maintenance cost after surgery would be cheaper and predicts discharge based on three factors such as calibration, discrimination, and performance. From Sebastian Steger, Stefan Wesarg (2012)[7], demonstration of deformed imaging between the head skull, and spinal cord with the support of MRI and CT scan modalities. Visual assessment is one significant approach that monitors the successful arrangement of bones using linear transformation as the solution. According to John Hsiang (2011)[8], wrong-level surgery may happen while doing surgery, this would be avoided by taking images of intra-operative X-Ray. Taking help from radiologists, correct methods are followed to prevent wrong-level treatments.

From Ghafoorian, M., Karssemeijer, N., et al (2017)[9], the demonstration of CNN and white paper hyperparameters over the brain images results in substantial location information of a network compared against other traditional methods. From Altini N, De Giosa G, et al(2021)[10], demonstrated deep learning models such as CNN ensures full automation for a total spine, and machine learning model K-means, and KNN for strong vertebrae over a spinal, and offers semi-automation annotations for centroids. From Li H, Gao S, Li R, et al (2023)[11], demonstrated somatosensory evoked feature helps to identify the spinal injury location, which leads to early removal of injury. In this, k-medoids and naive bayes are integrated to classify the location of injury into three categories. From Ahuja, C., Wilson, J., et al (2017)[12], demonstrates reasons of primary and secondary injuries, and adoption of practices for regeneration of neurons over spinal cord are explored. Several techniques at stages like augmentation, decompression, monitoring, and administration are focused, and results effective recovery. From Bourguignon, L., Tong, B., et al (2022)[13] , demonstrate acute spinal injury and the methods used are clinical use and epidemiological practices. The rehabilitation practices adopted globally are based on monitoring the surveillance and propose clinical practices for recovery from injuries.

From Pancholi, S., Everett, T.H. et al (2024)[14], demonstrate a novel non-invasive method that combines a skin nerve approach and deep learning techniques. The detection of AD in the spinal cord achieves high accuracy, and high precision against other traditional models. With AI, management has become easier. From Nina Bai(2024)[15], demonstrate the more the tissue remains, more chances of recovery is the slogan adopted. The communication is increased with the brain and back.The best modality in this study is MRI images.

From Joe Bennett, Joe M. Das et al (2024)[16], demonstrate various types of injuries and expect more collaboration among experts of neurologists, spine experts, and others designated for well well-being of the patient, and quick recovery of the patient. From Andrew L Goldberg, Sharif M Kershah et al (2010)[17], demonstrated reviews on level-1 type in which advancements in images like MRI for soft tissue issues, and CT for fracture issues are observed easily. The acute, and chronic types are observed using these modalities. From P. S, A. S, et al (2022)[18], demonstrate the white and grey matter over the specific areas of injury, so that impact and severity can be identified. The usage of watershed algorithms and novel sections such as Nonlinear SVM are used for reducing false positives and improving accuracy.

From Xiaoran Zhang, Yan Li et al (2021)[19], the demonstration of spinal cord injury as well as post-impact should be considered using CSM(cervical myelopathy spondylosis) over patient's MRI splices. The usage of CNN and grey scale contour active mechanism identifies accurate injury, and radiologist's input are considered for smooth surgery. From CMW Goedmakers, LM Pereboom et al (2022)[20], demonstrates many models including deep learning, finite element models with specific bio-chemical features, ANNs, and SVMs over the cervical spine. When compared with the lumbar spine, radiologists' image analysis on the cervical spine would provide many challenges for future researchers to contribute significant developments. The other references would help in storing patient data over the cloud, distributing required data when necessary by [21], and [22], and identification of required portions over images by [23], which would be base for our study's further developments.

METHODS

3.1 Dataset Description:

The dataset with images of labels on regions by each CT scan formed as a collection. The annotated labels denote injuries and normalize the images to make standardization.

3.2 Preparation:

Normalization is necessary over images in order to equalize the intensity values, and is effective for analysis. Then, uses resampling to ensure uniform voxel dimensions and sizes over all images.

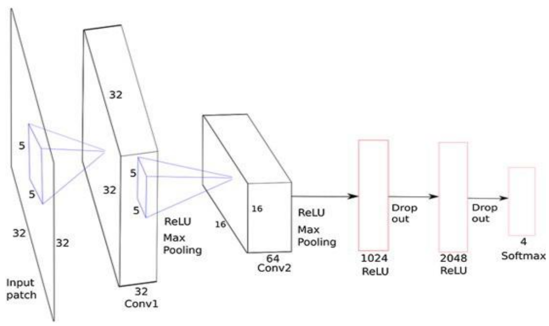

Fig. 1. Recommended design

In doing patching demonstrated in Fig.1, pick a pixel in a rectangular frame, and assign a patch of a specific size. Classify if the patch belongs to the spine, as positive. Otherwise, 0. Repeat this process for all pixels of the given area. No need for padding when patches are formed for boundary pixels. This would be applicable for two classes in which training patches are derived. Similarly, testing data is to be done. In this, the dimension followed is 2D. The reconstruction of ground truth is necessary for each frame relevant to the spine during testing.

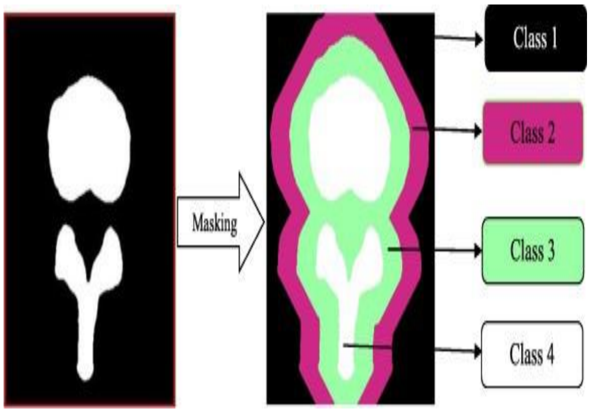

Fig. 2. CNN masking

CNN masking is demonstrated in Fig.2. In binary classification, the background is denoted by class "positive" or 1. There are 4 classes considered in which the first class denotes vertebrae column segmentation, which involves masking that generates two classifiers. The second and third classes are unique classifiers. The spine is the fourth class considered. Shifting techniques are applied to reduce noise, and improve contrast for quality. The spinal cord assessment is improved if the advanced imaging technique CLAHE is applied.

3.3 Spinal Cord Segmentation:

3D U-net is the model architecture considered in which volumetric data is supported and ensures spatial features using the encoder-decoder method. In addition to spatial support, the architecture involves multi-scale features using pooling and scaling.

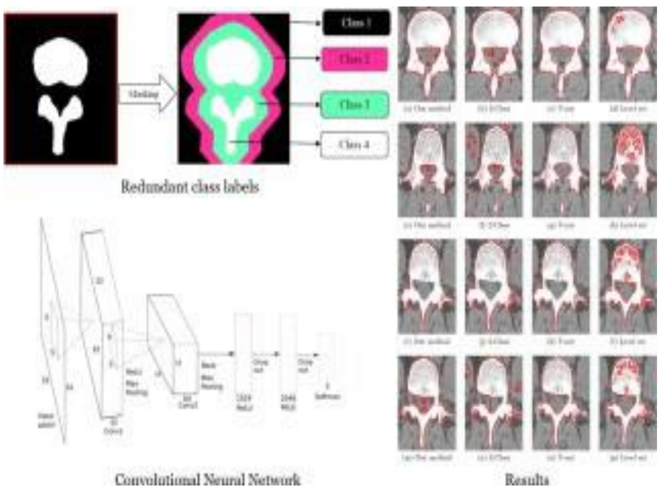

Fig. 3. Processing of CNN

In the training, images of a dataset are processed against the respective annotated labels of the spinal cord. The overlap between ground truth segmentation and expected segmentation is to be assessed using the Dice co-efficient.

3.4 Injury Detection:

After segmentation, an implementation of a classification model is to identify injuries within the segmented spinal cord regions. A CNN-based classifier is used that takes the segmented spinal cord as input and categorizes each area into an injury type (for example, fracture, dislocation, normal, etc.). The classifier is trained on segments extracted from the segmented spinal cord with labels indicating the presence (or) type of injury. There are specific metrics that are used to assess the effectiveness of the model's ability to determine the various types of spinal injuries. One such factor is accuracy.

3. 5 post-processing:

After initial segmentation, post-processing is required to recover fully. In this, noise is eliminated using specific operations like erosion, and dilation activities. Injuries are identified through boundary boxes, of CT images. This activity helps to locate injuries.

3.6 Test Setup:

In this, the final output is assessed through performance. To get the final output, the dataset is divided into training which helps to learn, validation through which hyperparameter tuning is done, and testing.

Computational Resources: Experiments are conducted using specified hardware details, such as GPU and memory specifications, to ensure effective training and inference.

The following pseudo procedure helps to detect injuries, and displacement effectively.

PS1: Pseudo_Procedure Spinal_Cord_Injury_detection(Dataset[][]):

Input: Dataset

Output: Location[][]

Step 1: Load Two images in which MRI for tissue health, and CT for fractures and dislocations.

Step2: Apply Data preprocessing for quality

2.1 Use Gaussian Filtering for noise removal

2.2 Apply normalization

2.3 Apply Augmentation

Step3: Regions of Interest Identification

3.1 use template matching

3.2 Apply Bounding box for the area of interest

Step4: Apply segmentation

4.1 Call SCIseg pre-built model

4.2 Extract lesions, and fractures regions

Step5: Call CNN with 3D volumetric data for classification of any 4 classes like Small, medium, High, and Extreme.

5.1 Do down-sampling, use 3D convolution layers, ReLU, and Max-pooling layers for encoding

5.2 High level features are extracted

5.3 Do up-sampling and decoding, transposed 3D convolutions are used for spatial features, and concatenate features from encoding path/

5.4 Softmax activation or multi-class classification.

Step 6: Apply post-processing to remove noise using erosion and dilation.

6.1 Smooth the boundaries of ROIs for accuracy

Step7: Compute Accuracy Accuracy=True Positives+True Negatives/ Total Number of Cases

From PS1, the dataset is loaded with 2 modalities, preprocessing for standardization, then focusing on regions of injuries based on lesions, and fractures, then using sophisticated SCIseg for segmented areas to focus, then apply CNN for classification, and opting for surgery. Then, post-processing is applied to remove small noises, then compute the accuracy.

RESULTS

Although there are models used in spinal cord injury detection, they are classified into qualitative, quantitative, and distance in this study.

A) Qualitative Analysis

We chose several representative examples from the testing set results. Fig. 4 displays the outcomes achieved with various methods. The findings indicate that the proposed approach provides more precise segmentation compared to the other techniques.

The proposed model experiences better precision than existing models.

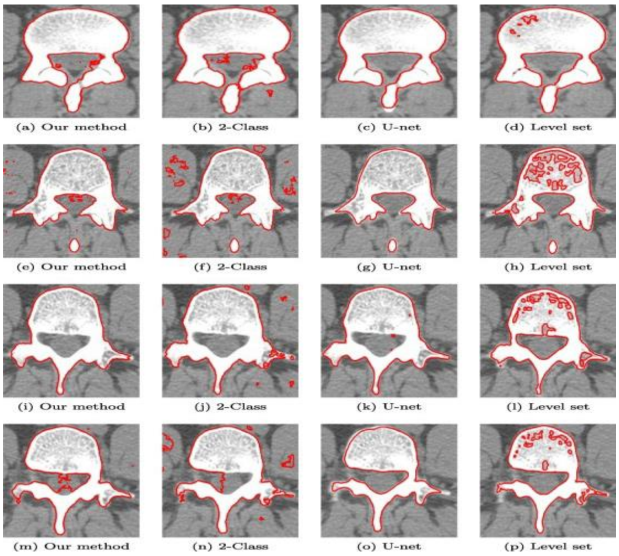

Fig. 4. U-Net, Level Set, and two class CNN qualitative analysis

B) Quantitative Evaluation

The gold standards are followed for each subject, over labeled images, outcomes the segment of each image into voxel and query image, S is denoted as the segmented outcome, and GT as Gold Standard.

B.1 Similarity metrics (1) Dice coefficient (DC): It is defined as overlap between two binary images in which values range from 0 to 1. It is defined as follows.

$$DC = \frac{2|S \cap GT|}{|S| + |GT|}$$

$$J = \frac{|S \cap GT|}{|S \cup GT|}$$

$$J = \frac{DC}{(2 - DC)}$$

(2) The Jaccard index: When related to the union of two labeled sets for spatial intersection, Coefficient of Jaccard is defined as follows.

(3) Volumetric Similarity (VS): The ratio of volume difference and total volume is defined as Volumetric similarity, and is denoted as

$$VS = 1 - \left| \frac{|S| - |GT|}{|S| + |GT|} \right|$$

The segmentation process is improved when compared to other techniques, and the ground truth as base derives to above 94%. The mean is increased to 97% due to the observation of an increase in volumetric similarity.

	Sensitivity		Specificity		Over Segmentation	
Method	Mean	SD	Mean	SD	Mean	SD
Our Method	0.972481	0.026948	0.991616	0.006239	8.349675	5.186457
2-Class CNN	0.913395	0.077838	0.973564	0.019650	16.26140	8.085861
U-Net	0.972806	0.003227	0.998899	0.000166	1.356735	0.248874
Level Set	0.779723	0.123521	0.987453	0.009751	15.15807	9.973117

Table1. Comparisons of the four distinct segmentation algorithms w.r.to similarity.

B.2 Classic measurements

The four variables are denoted using a confusion matrix in which TP is denoted as both ground truth and algorithm with spine identification pixels, FP as derived as not a ground truth as the spine, and algorithm misclassifies as the spine, TN is derived as ground truth not as spine and algorithm not correctly classifies, and FN is derived as ground truth as spine and algorithm not classified as spine.

B..2.1 Sensitivity: It is defined as perfectly identifying pixels are spine pixels correctly. It is defined as positive pixels in the ground truth, which the algorithm classifies as positive correctly.

$$Sensitivity = \frac{TP}{TP+FN}$$

B.2.2 Specificity: It is used to identify background pixels. It is defined as negative pixels in the ground truth, which the algorithm classifies accurately as negative.

B.2.3 Over-segmentation (OS) and under-segmentation (US): The formula for defining segmentation in under and over are as follows.

$$Specificity = \frac{TN}{TN+FP}$$

$2|S\cap GT|$

	DC		Jaccard Index		Volumetric Similarity	
Method	Mean	SD	Mean	SD	Mean	SD
Our Method	0.942861	0.032463	0.933569	0.057144	0.967046	0.026951
2-Class CNN	0.869014	0.048805	0.771535	0.077090	0.926983	0.047280
U-Net	0.959566	0.000408	0.956901	0.000164	0.973044	0.002919
Level Set	0.802039	0.068426	0.869837	0.012317	0.909029	0.089093

Table 2. Measurements of considered four segmentation models

B.2.4 Accuracy: It is defined as correctly classified instances

over total number of classifications. Accuracy is defined by

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

B.2.5 Matthew correlations coefficient (MCC): The performance of the model is assessed by another factor called the Matthews coefficient. This ranges from -1 to 1. It considers ground truth and segmentation outcomes to be different sets. When there is no correlation, it is denoted as zero. The formula used to compute is as follows.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FN) \times (TP+FP) \times (TN+FP) \times (TN+FN)}}$$

The proposed approach which is a hybrid model of CNN and 3D U-Net achieves better sensitivity, specificity, and accuracy. When MCC is applied to assess performance, the ground truth is nearly aligned with the results of the obtained segmentation.

C) Distance measurements

C.1 Mean surface distance (MSD): The surface voxels are values that are distances is defined as MSD, and is evaluated by following formula.

The difference between distances of surface voxels is used to estimate error between two surfaces such as GT and S.

$$MSD_{sg} = \frac{1}{n_s} \sum_{i=1}^{n_s} |d_l^{sg}|$$

As per authors Jomier, Gerig, and Chakos, computes surface distance. In the transformed image, the voxel's value denotes the Euclidean distance closest to the surface voxel. The surface voxels have 0 values.

C.2 Hausdorff distance (HD): It is defined as the length of separation between the segmented surface and ground truth surface. Lowering this quantity would increase accuracy in segmentation. The formula for evaluation is as follows.

$$HD = \max(h(S, GT), h(GT, S))$$

$$\text{where } h(S, GT) = \max_{a \in S} \min_{b \in GT} ||a - b||$$

C.3 Global Consistency Error (GCE): It is defined as differences computed across all voxels also termed as an error between any two segmentations. It is defined as follows.

$$GCE(S, GT) = \frac{1}{N} \min\left\{ \sum_{i}^{n} E(S, GT, x_i), \sum_{i}^{n} E(GT, S, x_i) \right\}$$

In this, N is total voxel, n is set difference, and E is the error at voxel x is defined as

$$E(S, GT, x) = \frac{|(S,x) n (GT,x)|}{(S,x)}$$

	MSD		HD		GCE	
Method	Mean	SD	Mean	SD	Mean	SD
Our Method	0.167692	0.229274	7.429119	1.635649	0.020012	0.010673
2-Class CNN	0.784873	0.437554	9.502033	1.803488	0.064253	0.039871
U-Net	0.099893	0.005112	6.289700	0.491765	0.030092	0.001779
Level Set	0.342764	0.352889	8.788802	4.781518	0.054126	0.021791

Table3. Distance measures of considered segmentation algorithms.

Compared to level set, and CNN alone, the hybrid model experiences better distance metrics. Based on two distance measures, it is identified that Global consistency Error (GCE) for the proposed hybrid model is almost 0, which means no error is found in the results of the segmentation.

Table 4. Comparison of considered models on spinal cord injury detection

Method	**Description**	**Accuracy**	**Performance**
MRI-Based Imaging	For structural damage, such as lesions or atrophy.	95	Soft tissue visualization is excellent.
CT-Based Imaging	To detect fractures and bony injuries.	90	For fast detection of fractures.
Rule-Based Systems (e.g., AIS)	Based on neurological exams (e.g., ASIA Impairment Scale), classifies.	85	Motor and sensory deficits assessment.
Machine Learning (ML)	To classify SCI severity.	95	identifying patterns in imaging and clinical data is excellent.
Deep Learning (DL)	For automatic segmentation and classification of SCI.	99	Segmentation and classification tasks is excellent.

From Table 4, models are demonstrated with accuracies and performance achievement in specific activities of spinal cord injury detection.

Based on these inputs, Fig. 5 is visualized stating Deep learning combination models produce high accuracy.

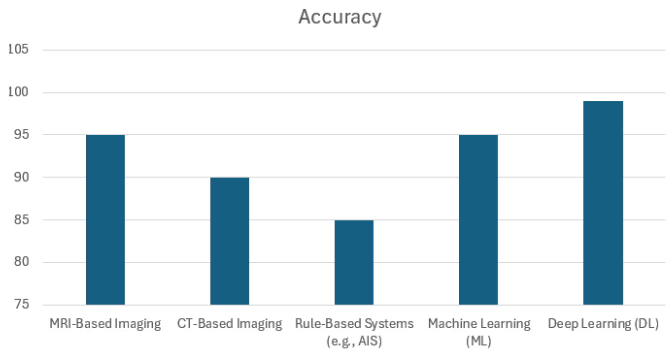

Fig. 5. Accuracies of considered models

DISCUSSION

To increase accuracy and precision in injury identification, the suggested spinal cord injury (SCI) detection framework successfully combines preprocessing, segmentation, classification, and post-processing approaches. The model improves its capacity to differentiate between fractures and soft tissue injury by utilizing both MRI and CT images. Gaussian filtering, normalization, and data augmentation are examples of preprocessing techniques that guarantee picture consistency and lower noise, which enhances model performance.

A hybrid CNN and 3D U-Net model, which excels at extracting spatial features using an encoder-decoder architecture, is used in the segmentation phase. By using SCIseg, a pre-trained segmentation model, the model successfully detects lesions, vertebral fractures, and displacement zones. The segmentation step's great accuracy is confirmed by the Dice coefficient and Jaccard index.

A CNN-based method for classifying injuries divides them into four severity levels: minor, moderate, severe, and high. High-level spatial properties are captured by the model using 3D volumetric data with convolution layers, ReLU activation, and max-pooling. Softmax-based multi-class classification and segmentation-driven feature extraction work together to provide excellent accuracy in the classification stage. Following classification, post-processing methods like erosion and dilation are used to smooth out the segmented areas and get rid of little noise, guaranteeing that the extracted areas are accurate. In order to reduce false positives and increase the general dependability of injury localization, this step is essential.

By combining 3D U-Net models with CNN based on deep learning, the suggested method performs noticeably better than conventional segmentation and classification techniques. According to experimental data, it has near-zero Global Consistency Error (GCE), excellent sensitivity, specificity, and accuracy, making it extremely dependable for automated SCI detection and categorization. Comprehensive damage evaluation is ensured by the combination of MRI and CT, advanced segmentation, and deep learning-driven categorization, which supports clinical judgment and possible surgical procedures.

REFRENCES

[1] Malinda Vania, Dawit Mureja et al(2019), Journal of Computational Design and Engineering, Volume 6, Issue 2, April 2019, Pages 224-232, https://doi.org/10.1016/ j.jcde.2018.05.002.

[2] Andriy Fedorov, Reinhard Beichel et al (2016), 3D Slicer as an image computing platform for the Quantitative Imaging Network, Magnetic Resonance ImagingVolume 30, Issue 9, November 2012, Pages 1323 -1341, https://doi.org/ 10.1016/j.mri.2012.05.001.

[3] Gerig, G., Jomier, M., et al (2001), Valmet: An innovative validation tool for evaluating and enhancing 3D object segmentation, In Proceedings of the 4th International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 516–523), Lecture Notes in Computer Science, 2208, DOI: 10.1007/3-540-45468-3_62.

[4] Carl Whyne, Michael Hardisty, et al(2007), Quantitative characterization of metastatic disease in the spine, Part II. Histogram-based analyses, August 2007, Medical Physics, 34(8):3279.

[5] Ben Glocker, Darko Zikic, et al (2013), Vertebrae Localization in Pathological Spine CT via Dense Classification from Sparse Annotations, Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013, vol 8150, Springer, Berlin, https://doi.org/ 10.1007/978-3-642-40763-5_33.

[6] Ogink, P.T., Karhade, A.V., et al (2019), Predicting discharge placement after elective surgery for lumbar spinal stenosis using machine learning methods, Eur Spine J 28, 1433–1440 (2019), https://doi.org/10.1007/s00586-019-05928-z.

[7] Sebastian Steger, Stefan Wesarg (2012), Automated skeleton based multi-modal deformable registration of head&neck datasets, Med Image Comput Comput Assist Interv, 2012;15(Pt 2):66-73, DOI: 10.1007/978-3-642-33418-4_9.

[8] John Hsiang(2011), Wrong-level surgery: A unique problem in spine surgery, Surg Neurol Int, 2011, doi: 10.4103/2152-7806.79769.

[9] Ghafoorian, M., Karssemeijer, N., et al (2017), Location Sensitive Deep Convolutional Neural Networks for Segmentation of White Matter Hyperintensities, Sci Rep 7, https://doi.org/10.1038/s41598-017-05300-5.

[10] Altini N, De Giosa G, et al(2021), Segmentation and Identification of Vertebrae in CT Scans Using CNN, k-Means Clustering and k-NN, Informatics, 2021; 8(2):40, https://doi.org/10.3390/informatics8020040.

[11] Li H, Gao S, Li R, et al (2023), Identifying Intraoperative Spinal Cord Injury Location from Somatosensory Evoked Potentials' Time-Frequency Components, Bioengineering, 2023; 10(6):707, https://doi.org/10.3390/bioengineering10060707.

[12] Ahuja, C., Wilson, J., et al (2017), Traumatic spinal cord injury. Nat Rev Dis Primers 3, 17018 (2017), https://doi.org/10.1038/nrdp.2017.18.

[13] Bourguignon, L., Tong, B., et al (2022), International surveillance study in acute spinal cord injury confirms viability of multinational clinical trials, BMC Med 20, 225 (2022), https://doi.org/10.1186/s12916-022-02395-0.

[14] Pancholi, S., Everett, T.H. et al (2024), Advancing spinal cord injury care through non-invasive autonomic dysreflexia detection with AI, Sci Rep 14, 3439 (2024), https://doi.org/10.1038/s41598-024-53718-5.

[15] Nina Bai(2024), MRI scans predict recovery from spinal cord injury, Neurology & Neurosurgery, https://med.stanford.edu/news/all-news/2024/07/mri-scans-predict-recovery-from-spinal-cord-injury.html

[16] Joe Bennett, Joe M. Das et al (2024), Spinal Cord Injuries, NIH, National library of medicine, https://www.ncbi.nlm. nih.gov/ books/NBK560721/

[17] Andrew L Goldberg, Sharif M Kershah et al (2010), Advances in Imaging of Vertebral and Spinal Cord Injury, J Spinal Cord Med, 2010 Apr;33(2):105–116, doi: 10.1080/ 10790268.2010.11689685.

[18] P. S, A. S, et al (2022), Detection of Spinal Cord Injury using Deep Learning Algorithm, 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), 2022, pp. 270-275, doi: 10.1109/ICSCDS53736. 2022.9760935.
[19] Xiaoran Zhang, Yan Li et al (2021), Automatic spinal cord segmentation from axial-view MRI slices using CNN with grayscale regularized active contour propagation, Computers in Biology and Medicine, Volume 132, May 2021, https://doi.org/10.1016/j.compbiomed.2021.104345.
[20] CMW Goedmakers, LM Pereboom et al (2022), Machine learning for image analysis in the cervical spine: Systematic review of the available models and methods, Brain Spine, 2022 Nov, doi: 10.1016/j.bas.2022.101666.
[21] Dey N.S., Sangaraju H.K.R.(2024), A particle swarm optimization inspired global and local stability driven predictive load balancing strategy, Indonesian Journal of Electrical Engineering and Computer Science, Volume 35, Issue 3,10.11591/ijeecs.v35.i3.pp1688-1701.
[22] Dey N.S., Sangaraju H.K.R.(2023), Hybrid Load Balancing Strategy for Cloud Data Centers with Novel Performance Evaluation Strategy, International Journal of Intelligent Systems and Applications in Engineering, Volume 11, Issue 3, Pages 883 - 908, https://ijisae.org/index.php/IJISAE/article/view/3345.
[23] V. L. Lalitha, S. H. Raju, V. K. Sonti and V. M. Mohan, "Customized Smart Object Detection: Statistics of detected objects using IoT," *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, Coimbatore, India, 2021, pp. 1397-1405, doi: 10.1109/ICAIS50930.2021.9395913.