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# Disc Herniation Diagnosis and Binary Classification of Spinal Cord Injury using Ensemble Machine Learning Vote Algorithms

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**ABSTRACT:** Spinal cord injury (SCI) is a complex neurological disorder that often results in a reduced quality of life and considerable functional impairment. Early and accurate detection and classification of SCI cases into injury and non-injury categories is essential for clinical decision-making, rehabilitation and treatment planning. The majority of conventional diagnostic methods rely on medical imaging and expert interpretation, which can be time-consuming and prone to inter-observer variability. To address this challenge, paper provides a binary classification framework for spinal cord injury by combining ensemble machine learning with voting methods. A hard and soft voting ensemble comprises a range of base classifiers, including k-Nearest Neighbors, Support Vector Machines, Probabilistic Neural Networks and Naïve Bayes, to improve prediction accuracy and robustness. In terms of accuracy, precision, recall and F1-score, the ensemble technique outperforms individual models, according to the evaluation of the proposed system on benchmark medical datasets. The results show that ensemble learning with classification accuracy of 96.67% has the potential to be a reliable technique for automated SCI classification, which could help develop intelligent clinical support systems and improve diagnostic processes.

## 1. INTRODUCTION

The spinal cord is a long, thin, tubular bundle of nervous tissue and support cells that extends from the medulla oblongata in the brainstem down to the lumbar region of the vertebral column. It serves as the primary transmission pathway for information between the brain and the rest of the body [1]. Through signal transmission between the brain and the body, the lumbar spinal cord regulates bladder, bowel and sexual functions in addition to directing movement and sensation in the legs. It offers vital protection for the sensitive nerves that are situated inside the spinal canal [2]. SCI occurs when there is damage to the spinal cord or the nerves (cauda equina) at the end of the spinal canal. SCI results in damage to the bundle of nerves and tissue that transmits signals between the brain and the rest of the body, often resulting in permanent changes in strength, sensation, and other bodily functions below the site of the injury [3]. These injuries are generally categorized as complete and incomplete. In complete injury all sensory (feeling) and motor (ability to control movement) functions are lost below the SCI. In case of incomplete injury some motor or sensory function are affected below the affected area. The physiological impact affecting the mobility is determined by the level of the injury [4]. A lumbar SCI affects the lower back's lumbar vertebrae (L1-L5), causing paralysis, weakness, or sensory loss in the hips and legs due to damage to the lumbar nerves [5].

Diagnosing a SCI requires a combination of clinical physical examinations and advanced medical imaging. SCI diagnosis begins with an immediate clinical assessment focusing on the patient's motor function and sensory perception. Medical professional tests specific muscle groups for strength and dermatomes for sensitivity to light touch and pinpricks. If the patient is unconscious or has severe head trauma, doctors look for signs of spinal shock such as loss of reflexes or muscle flaccidity, to determine if the spinal cord has been compromised [6]. To confirm the physical extent of the damage, several imaging modalities are employed which includes X-ray, CT scan and MRI. X-rays are used to identify vertebral fractures, dislocations or significant spinal instability immediately following trauma. CT scans are superior for detecting bone fragments, blood clots, or vessel damage that might be compressing the spinal cord. MRI uses strong magnetic fields to identify herniated discs, ligament tears and bruising or swelling within the spinal cord itself. MRI is considered the gold standard for diagnosing SCI as it provides superior visualization of soft tissues, including the spinal cord itself, intervertebral discs, ligaments and the vascular system [7]. An MRI scan is a non-invasive procedure that uses powerful magnets and radio waves to create detailed images of the body. The MRI is basically three dimensional imaging technique. MRI scans has ability to visualize the body from multiple perspectives without moving the patient. These perspectives are essential for SCI diagnosis as it allow radiologists to see the spinal cord, vertebrae and surrounding soft tissues from every angle. The three standard views used in clinical practice are Sagittal, Axial and Coronal [8].

The Axial view provides a top-down or cross-sectional slice of the body. If the sagittal view identifies where a problem is along the length of the spine, the axial view identifies exactly how much space is left for the spinal cord at that specific level. It is the best view for determining if a bone fragment or a tumor is pushing into the spinal canal from the left, right or centre, which dictates the surgical approach needed for decompression [8, 9].

The Coronal view provides a front-to-back perspective, similar to looking at a person face-to-face. While less commonly the primary focus for acute spinal trauma compared to sagittal or axial slices, the coronal view is indispensable for evaluating lateral curvatures like scoliosis or identifying nerve root compression as the nerves exit the spinal column toward the limbs [8,10].

The sagittal view is often considered the most critical orientation in the initial MRI assessment of SCI. By providing a lateral (side-profile) perspective of the entire vertebral column, this view allows clinicians to visualize the spine as a continuous structural unit. It is uniquely suited for evaluating the alignment of the vertebrae and the canal space available for the spinal cord. As the sagittal plane captures the longitudinal relationship between the bony segments and the neural tissue, it serves as the primary roadmap for identifying the exact level of trauma. One of the primary categories of injury diagnosed through this view is vertebral displacement, such as subluxations or spondylolisthesis, where one vertebra slides forward or backward over another. These shifts can be easily missed in a cross-sectional view but are immediately apparent in the sagittal plane, where the stepping of the spinal line indicates instability. This view is the best choice for diagnosing disc herniation or protrusions. Radiologists can observe the intervertebral discs bulging posteriorly into the spinal canal, directly compressing the cord or the descending nerve roots. Beyond structural bone and disc issues, the sagittal view is essential for identifying injuries occurring within the spinal cord itself. In the acute phase of an SCI, this view reveals edema (swelling) or haemorrhage (bleeding) as changes in signal intensity along the length of the cord [8, 11, 12 and 13].

Keeping sagittal view of MRI, this paper is focused to detect SCI for disc hernation with image processing techniques of machine learning. The experimental results are presented for detection of injury location and the performance metrics of image processing techniques are discussed for accuracy, precision, F1 score etc.

## 2. RELATED LITERATURE

The detection of disc herniation and protrusions through MRI-based image processing has evolved from manual inspection to sophisticated automated pipelines [14]. These systems typically begin with image pre-processing, which includes noise reduction and intensity normalization to account for variations in MRI scanners [15]. Because the sagittal view provides a comprehensive profile of the vertebral column, it is the primary orientation used for vertebral body and intervertebral disc (IVD) segmentation [16]. MRI can clearly reveal abnormalities such as disc protrusion, extrusion or sequestration, along with associated changes like nerve root impingement and spinal canal narrowing. T1-weighted and T2-weighted sequences are commonly used, where T2-weighted images are particularly effective in highlighting hydrated disc material and pathological changes [17].

The primary issue with SCI diagnosis with MRI is observer interpretation variability due to subjective judgment, experience level and fatigue [18]. Since task being time consuming, abnormalities such as mild disc bulges or early-stage herniation can be easily overlooked, especially in complex spinal regions with overlapping anatomical structures. The image quality issues such as noise, motion artifacts, and low contrast between tissues can make it difficult to distinguish between normal and pathological structures. Thus the manual inspection suffers with limited quantitative assessment and hence automated or computer-aided diagnostic systems is essential to support clinicians, reduce variability and improve overall reliability in MRI-based disc herniation detection [19].

To address these challenges, computer-aided diagnostic (CAD) systems have been developed to assist in the accurate and efficient identification of disc abnormalities. Early CAD systems for disc herniation detection primarily utilized conventional image processing and machine learning techniques. These approaches involved pre-processing steps of noise reduction and contrast enhancement, followed by segmentation of spinal regions and extraction of handcrafted features, including texture, intensity and shape descriptors [20]. Classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) were then employed to distinguish between normal and pathological discs. While these methods demonstrated promising results, their performance was often limited by the quality of feature engineering and sensitivity to variations in MRI data [21].

Among the machine learning models, SVM has been particularly effective due to its ability to handle high-dimensional feature spaces and provide robust classification boundaries [22]. Studies have demonstrated that ML-based classifiers can achieve reliable performance in distinguishing between normal, bulging, and herniated discs when trained on well-curated datasets [23]. The hybrid approaches combining multiple classifiers or integrating feature selection techniques have further improved detection accuracy and reduced computational complexity [24].

Despite their advantages, machine learning-based approaches face several challenges. The performance of these systems heavily depends on the quality of feature extraction and the availability of labelled training data. Variability in MRI acquisition protocols and patient-specific anatomical differences can also affect model generalization. The traditional ML methods often require manual intervention during feature design, which can introduce bias and limit scalability. These limitations have led to a gradual transition toward deep learning-based methods, although classical ML techniques remain relevant in scenarios with limited data or computational resources [25].

Convolutional Neural Networks (CNNs), have been widely adopted for segmentation and classification tasks in spinal MRI analysis. These models can learn complex hierarchical representations from large datasets, leading to improved accuracy and robustness compared to traditional methods. The fully convolutional networks and 3D CNNs have been successfully applied to segment intervertebral discs and detect herniation with high precision [26, 27]. The integrated frameworks combining localization, segmentation and classification have further enhanced diagnostic performance [28].

Ensemble learning has emerged as an effective strategy for improving the accuracy and robustness of disc herniation diagnosis from MRI data [29]. Unlike single-model approaches, ensemble methods combine the predictions of multiple classifiers to reduce variance, bias, and the risk of overfitting. This is particularly beneficial in medical imaging tasks such as disc herniation detection, where variability in image quality, anatomical differences and limited labelled datasets can significantly impact model performance [30, 31].

For disc herniation diagnosis, ensemble learning is typically applied after feature extraction or as part of deep learning frameworks. Classical ensemble techniques such as bagging, boosting, and stacking have been widely explored. Random Forest has been used to classify intervertebral disc conditions based on texture and intensity features extracted from MRI scans [32]. Boosting methods like Ada Boost and Gradient Boosting iteratively focus on misclassified samples, improving the detection of subtle abnormalities like early-stage disc bulges. Stacking approaches combine multiple base learners and use a meta-classifier to generate final predictions leading to improved generalization performance [33].

Recent advancements integrate ensemble strategies with deep learning models to further enhance diagnostic capability. Multiple CNN architectures are trained independently on MRI datasets and their outputs are combined using techniques like majority voting, weighted averaging, or meta-learning. These hybrid ensemble frameworks leverage the strengths of different architectures in capturing diverse feature representations, resulting in higher classification accuracy and robustness compared to individual models [34]. Multi-view ensembles incorporating sagittal and axial MRI slices have shown improved performance by capturing complementary spatial information of the spine [35].

Despite their advantages, ensemble learning methods introduce certain challenges, including increased computational complexity, longer training times, and difficulties in model interpretability. The effectiveness of ensemble methods depends on the diversity and independence of the base models; redundant or highly correlated models may not yield significant performance gains. Addressing these issues requires careful model selection, optimization and the integration of AI techniques [36].

## 3. DATASET

A sagittal plane MRI scan shows the body a side view of the spine and spinal cord for assessing vertebral alignment, inter-vertebral disc height and herniation, spinal cord structure and signal alterations, etc. The dataset is prepared for 300 T1-weighted and T2-weighted sagittal images. The figure 1 shows a sample image of sagittal view of spinal cord with MRI scan.

**Figure 1:** Sagittal view of Spinal Cord

For testing of image processing model for disc herniation diagnosis, a total of 240 images of spinal cord sagittal view are taken to form a dataset [42] of 1339 images and for model training 850 images are used. These images are arranged as indicated in table 1.

**Table 1.** Dataset particulars

| | Normal | Injured | Total |
|---|---|---|---|
| Training | 350 | 500 | 850 |
| Testing | 98 | 142 | 240 |

## 4. METHODOLOGY

The figure 2 shows the SCI detection framework using machine learning and ensemble techniques with MRI data. The process starts with a Clinical Spinal Cord Dataset, which consists of sagittal view MRI images collected from patients. These images undergo pre-processing for improving data quality and consistency with noise removal, intensity normalization and resizing. This step ensures that irrelevant variations do not negatively impact model performance. The processed dataset is divided into two parts: the training dataset and test cases. The training dataset is used to build and learn the classification models, while the test set is reserved for evaluating the generalization capability of the trained system. This separation is essential to avoid over fitting and to obtain an unbiased estimate of performance.

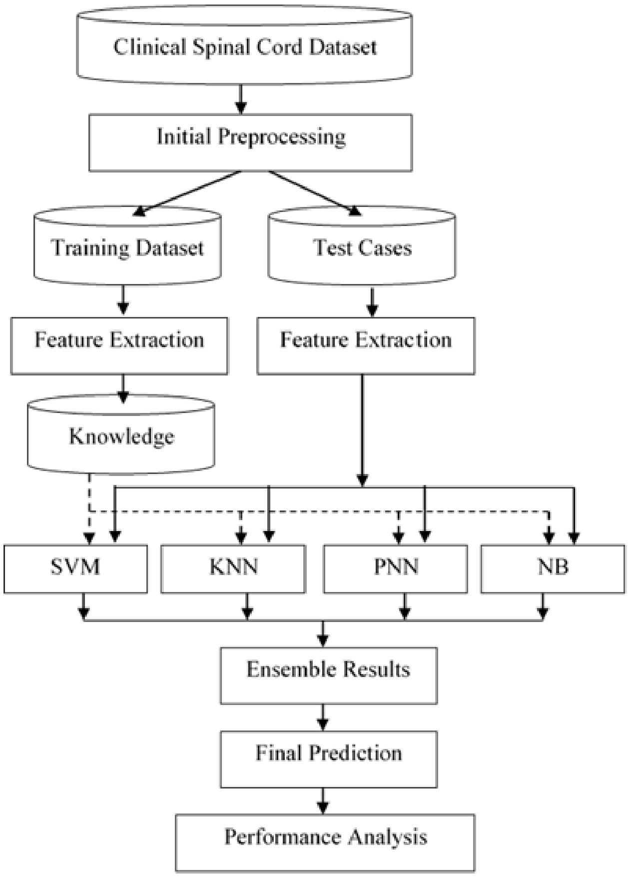



**Figure 2** Proposed Classification Model.

Both datasets then undergo feature extraction, where meaningful characteristics are derived from MRI images. These features include GLCM texture descriptors, intensity statistics, shape features and spatial information of disc regions. In the training branch, extracted features contribute to a knowledge base, which represents learned patterns or statistical relationships between features and diagnostic labels.

The SCI detection is carried out with multiple machine learning classifiers: Support Vector Machine (SVM), k-Nearest Neighbours (KNN), Probabilistic Neural Network (PNN), and Naïve Bayes (NB). Each classifier processes the extracted features independently and produces its own prediction. The use of diverse classifiers is intentional, as each model has different strengths. SVM is effective in high-dimensional spaces, KNN is simple and instance-based, PNN is probabilistic and fast in classification and NB is efficient with probabilistic assumptions.

The outputs from these classifiers are then combined in the ensemble learning stage. Instead of relying on a single model, ensemble methods aggregate predictions using voting algorithm. Hard voting chooses the class that most models predict for classification, whereas soft voting finds the class with the highest summed probability using the models' projected probabilities. The combined output produces the ensemble results, which are then used to generate the final prediction classifying a disc as normal or injured. The performance analysis is carried out by evaluating accuracy, sensitivity, specificity, precision, recall and F1-score using the test dataset.

**5. RESULTS AND DISCUSSION**

The step by step pre-processing of acquired MRI sagittal view is seen through figure 3(a) – (f). In this stage the input MRI is processed through background removal and the region of interest determined with masking the unwanted part. This background removed image is processed through k-mean segmentation. The feature extraction is carried out in terms of geometrical features and haralick texture features [41]. The details of extracted features are listed in table 2. Noise removal is done with thresholding and an image is constructed for highlighting the disc positions of the spinal cord.

**Figure 3(a)** Input Image

**Figure 3(b)** ROI Mask

**Figure 3(c)** Background removal

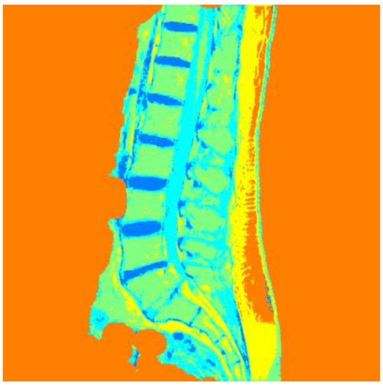


**Figure 3(d)** K mean

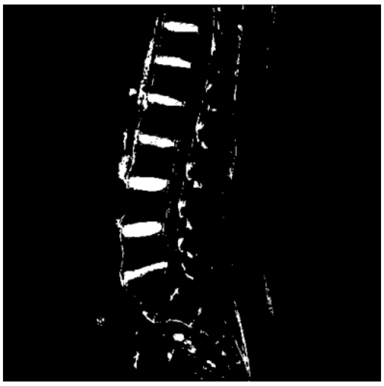


**Figure 3(e)** ROI with Noise

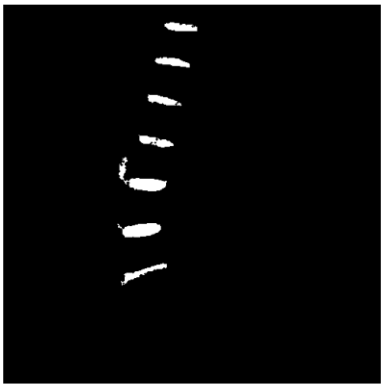


**Figure 3 (f)** Final ROI

For each image total 15 features are extracted and stored in knowledge base in csv format. This knowledge base is used to train the machine learning classifier for injury detection. The dataset of 350 normal and 500 injured images is used for training. The training data of these machine learning models is used in the ensemble voting algorithm and injury detection is carried out. The location of the injury is denoted with bounding box.

The test dataset of 240 images is used for testing of the machine learning and ensemble learning models. The sample images of injury detection with ensemble learning are shown in figure 4. The injury in the spinal cord for disc herniation is indicated with red coloured bounding box.

**Table 2.** Geometric and Haralick Texture Features

| Category | Feature Name | Description |
|---|---|---|
| **Geometrical Features** | Area | Area of disc in pixels |
| | Perimeter | Perimeter of disc |
| | Minor Axis Length | Length of the shortest axis of a disc |
| | Major Axis Length | Length of the longest axis of a disc |
| | Inter Disc Distance | Distance between each disc |
| **Haralick Texture Features** | Entropy | Measure of randomness or disorder in image |
| | Energy | Measures the local uniformity of grey levels |
| | Contrast | Measures local variations in an image |
| | Homogeneity | Evaluates how closely GLCM diagonal elements are distributed |
| | Correlation | Measures linear dependency of grey levels of neighbouring pixels |

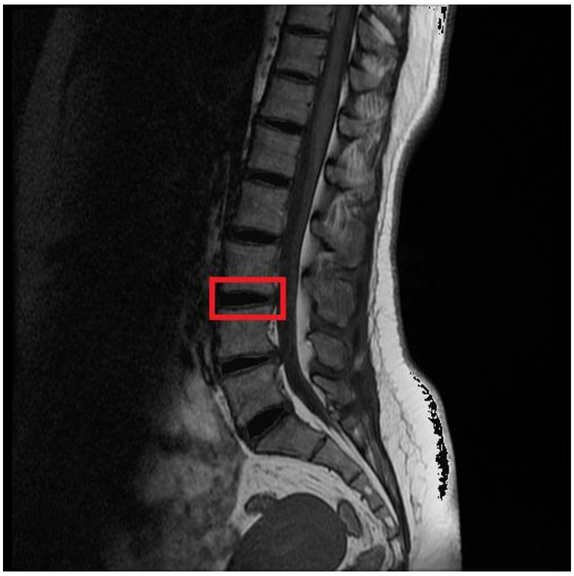


**Figure 4 (a)** Sample image of spinal cord injury detection

**Figure 4 (b)** Sample image of spinal cord injury detection

The confusion matrix and ROC curve are indicated in figure 5 and figure 6 respectively

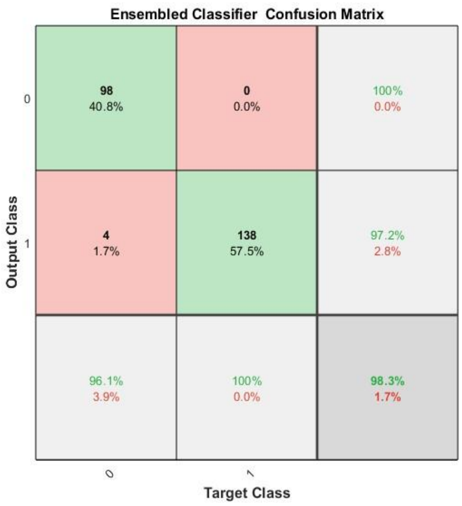



**Figure 5:** Confusion Matrix

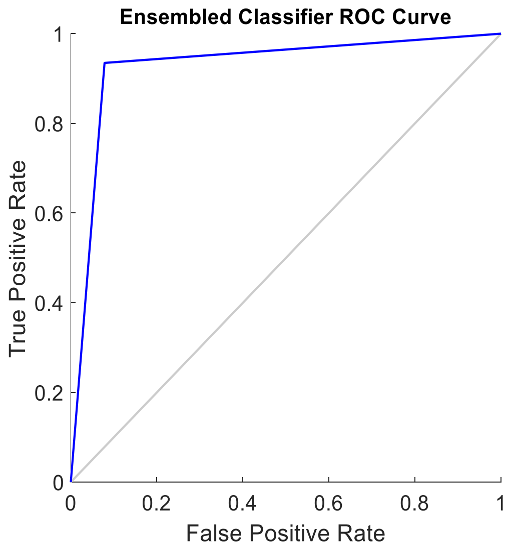
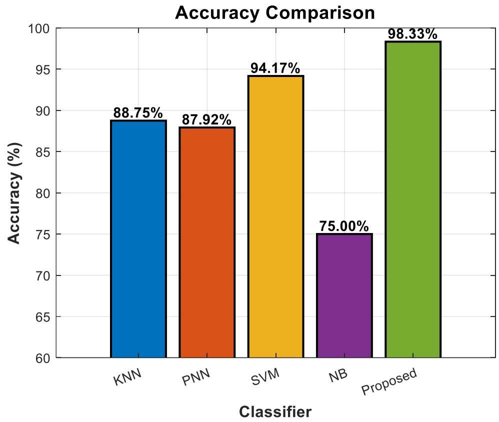
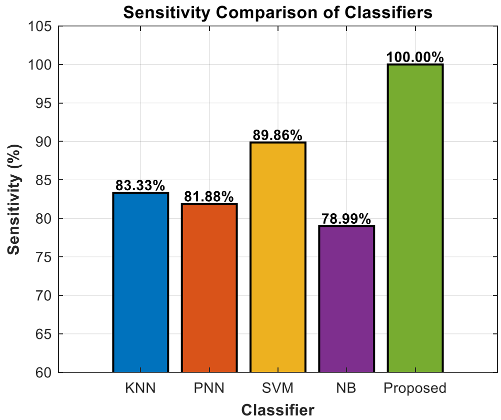



**Figure 6:** ROC Curve

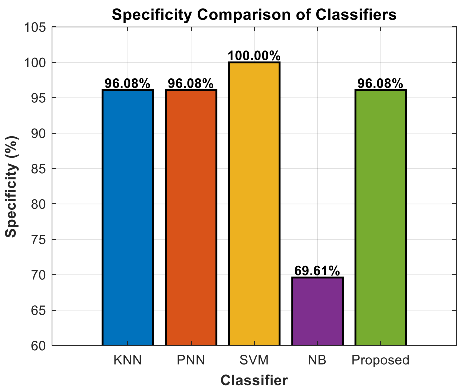
For test dataset True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) are found and the performance metrics for accuracy, sensitivity, specificity, true positive value, false positive value, recall, precision and F1 score are calculated for each of the classifier with kNN, PNN, SVM, NB and ensemble learning. The graphical comparison of these parameter for all classifiers is shown through figure 7(a) – figure 7(f).



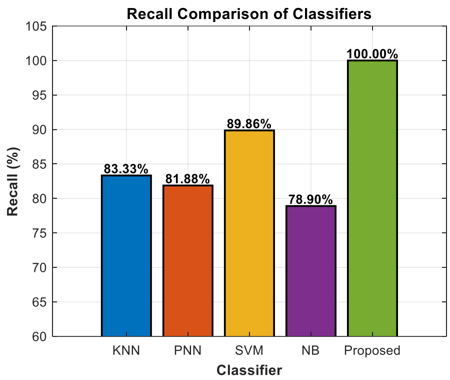

(a) Accuracy Comparisons



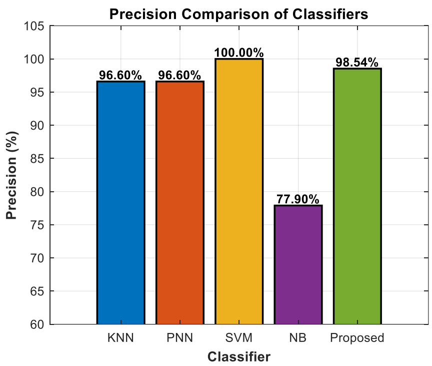

(b) Sensitivity Comparisons



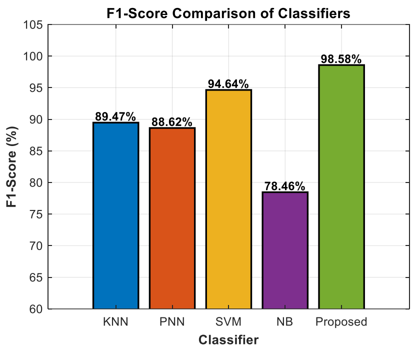

(c) specificity Comparisons




(d) Recall Comparisons




(e)Recall Comparisons




(f) F1-Score Comparisons

**Figure 7:** Performance Metrics comparisons

**Table 3.** Comparisons of performance

| Parameter | KNN | PNN | SVM | NB | Ensemble |
|---|---|---|---|---|---|
| Accuracy | 88.75% | 87.92% | 94.17% | 75.00% | 98.33% |
| Sensitivity | 83.33% | 81.88% | 89.86% | 78.99% | 100.00% |
| Specificity | 96.08% | 96.08% | 100.00% | 69.61% | 96.08% |
| TPV | 96.64% | 96.58% | 100.00% | 77.86% | 97.18% |
| FPV | 3.92% | 3.92% | 100.00% | 30.39% | 3.92% |
| Recall | 83.33% | 81.88% | 89.86% | 78.9% | 100.00% |
| Precision | 96.6% | 96.6% | 100.00% | 77.9% | 98.54% |
| F1-score | 89.47% | 88.62% | 94.64% | 78.46% | 98.58% |

As seen from graphs of figure 7 and table 3 the proposed Ensemble voting method outperforms the machine learning techniques of single classifiers with 98.33% accuracy. The accuracy of state of the art model of kNN [27] was 83%, 2D-CNN model [40] was recorded to be 92.2% and non-linear SVM approach [28] with 96.67%. Thus the proposed ensemble learning model is observed to perform well with designated dataset size.

## 6. CONCLUSION

The ensemble approaches that include voting algorithms greatly enhance machine learning model performance, outperforming single or conventional models. The best model for classifying spinal cords is ensemble voting using SVM+KNN+PNN+NB. This model outperforms other ensemble stacking models and the individual classifiers in terms of classification accuracy (98.33%) and F1-Score (0.985. Compared to the other four individual models, the suggested ensemble voting (SVM+KNN+PNN+NB) yields a high recall (1.00) and a high precision (0.985). For the appropriate spinal cord classification, the suggested ensemble voting (SVM+KNN+PNN+NB) aids in the deployment of effective methods.

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## AUTHOR CONTRIBUTIONS

**Jyoti M. Waykule:** Conceptualization, Investigation, Laboratory Analysis, Manuscript Preparation.

**M.P. Mattada:** Methodology, Result Validation, Review and editing.

**Santosh Nejkar:** Formal Analysis, Review and editing.

## CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

## ETHICS STATEMENT

During data collection, a formal consent was obtained from patients.

## DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

## REFERENCES

[1] Kiernan, J.A., 2013. Barr's The Human Nervous System: An Anatomical Viewpoint, 10th ed. Lippincott Williams & Wilkins, Philadelphia, PA, USA.

[2] Standring, S., 2016. *Gray's Anatomy: The Anatomical Basis of Clinical Practice*, 41st ed. Elsevier, London, U.K.

[3] Fehlings, M., Cadotte, D., 2007. The pathophysiology of spinal cord injury. Spine, 32(21S), S9–S13.

[4] Kirshblum, J. et al., 2011. International standards for neurological classification of spinal cord injury. Journal of Spinal Cord Medicine, 34(6), 535–546.

[5] Munavar Jasim, K., Brindha, T., 2021. Injury classification and level detection of the spinal cord based on the optimized recurrent neural network. Bio-Algorithms and Med-Systems, 17(1), 25–40.

[6] Guarnieri, G., Izzo, R., Muto, M., 2016. The role of emergency radiology in spinal trauma. The British Journal of Radiology, 89(1061), 20150833.

[7] Hussain, O., Kaushal, M., Agarwal, N., Kurpad, S., Shabani, S., 2023. The role of magnetic resonance imaging and computed tomography in spinal cord injury. Life, 13(8), 1680.

[8] Westcott, S.J., Dyke, J.P., 2020. Foundations of magnetic resonance imaging. Radiologic Technology, 91(3), 241–256.

[9] Guarnieri, G., Izzo, R., Muto, M., 2016. The role of emergency radiology in spinal trauma. The British Journal of Radiology, 89(1061), 20150833.

[10] Lee, S. et al., 2010. A practical MRI grading system for lumbar foraminal stenosis. American Journal of Roentgenology, 194(4), 1095–1102.

[11] Lee, S., 2010. A practical MRI grading system for lumbar foraminal stenosis. American Journal of Roentgenology, 194(4), 1095–1102.
[12] Ellingson, B.M., Salamon, N., Holly, L.T., 2014. Imaging techniques in spinal cord injury. World Neurosurgery, 82(6), 1351–1358.
[13] Bozzo, A., Marcoux, J., Radhakrishna, M., Pelletier, J., Goulet, B., 2011. The role of magnetic resonance imaging in the management of acute spinal cord injury. Journal of Neurotrauma, 28(8), 1401–1411.
[14] Al-U'ani, R.S., 2023. Automatic detection and classification of lumbar spinal stenosis and disc herniation: A review. IEEE Access, 11, 31568–31589.
[15] Paul, J.S., Madhuranthakam, A.J., Rofsky, N.M., 2020. Preprocessing of MRI: A review of standard techniques. Journal of Magnetic Resonance Imaging, 51(2), 345–358.
[16] Kim, S.H. et al., 2021. Automated segmentation of vertebral body and intervertebral disc on sagittal MRI using deep learning. Scientific Reports, 11(1), 11504.
[17] Shinde, N.G., Bhirud, S.G., 2017. Intensity normalization and noise reduction in MRI: A survey. In: Proceedings of the IEEE International Conference on Advanced Computing, Communication and Control, pp. 1–6.
[18] Jha, J.K., Singh, M.P., Singh, R.K., 2017. Automated detection of lumbar disc herniation from MRI images: A survey. In: Proceedings of the IEEE International Conference on Computing, Communication and Automation, pp. 1162–1167.
[19] Al-Khafaji, A.S., Mohamad, H.J., 2021. A review of computer-aided diagnosis systems for spinal cord injuries based on MRI images. Journal of Physics: Conference Series, 1973(1), 012133.
[20] Zhang, J. et al., 2023. A survey of computer-aided diagnosis for spinal diseases based on deep learning. IEEE Access, 11, 12450–12468.
[21] Mensah, E.O., Chalif, J.I., Johnston, B.R., Chalif, E., Parker, T., Izzy, S., He, Z., Saigal, R., Fehlings, M., Lu, Y., 2025. Traumatic spinal cord injury: A review of the current state of art and future directions—What do we know and where are we going? North American Spine Society Journal, 22, 100601.
[22] Wang, S., Liu, Z., Shen, Y., Zhang, L., 2019. Automatic detection of lumbar disc herniation using deep convolutional neural networks. IEEE Access, 7, 150–160.
[23] Uzunova, M.G., Ehrhardt, J., Handels, H., 2018. Memory-efficient CNN-based detection of lumbar spine pathologies. Computerized Medical Imaging and Graphics, 67, 137–146.
[24] Alomari, A., Corso, S., Chaudhary, V., 2017. Label-free detection of lumbar disc herniation using machine learning. In: Proceedings of the IEEE International Symposium on Biomedical Imaging, pp. 114–117.
[25] Litjens, G. et al., 2017. A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88.
[26] Paul, J.S., Madhuranthakam, A.J., Rofsky, N.M., 2020. Deep learning in spinal MRI: Applications and future directions. Journal of Magnetic Resonance Imaging, 51(2), 345–358.
[27] Handayani, I., 2019. Application of K-nearest neighbor algorithm on classification of disk hernia and spondylolisthesis in vertebral column. Indonesian Journal of Information Systems, 2(1).
[28] Ahammad, S.H., Rajesh, V., Rahman, M.Z.U., 2019. Fast and accurate feature extraction-based segmentation framework for spinal cord injury severity classification. IEEE Access, 7, 46092–46103.
[29] Mishra, D., Tripathi, S.M., Chaurasia, A., Chaurasia, P.K., Chaurasia, P.K., 2025. A review on ensemble learning methods: Machine learning approach. International Journal of Research Publication and Reviews, 6(2), 3795–3803.
[30] Jadama, A.F., Jobarteh, B., Islam, M.M., Toray, M.K., 2024. Ensemble learning: Methods, techniques and application. ResearchGate.
[31] Kato, C., Uemura, O., Sato, Y., Tsuji, T., 2023. Functional outcome prediction after spinal cord injury using ensemble machine learning. American Congress of Rehabilitation Medicine.
[32] Li, P., Wang, Y., 2025. A novel disc herniation prediction utilizing the power of random forest base predictive models. Journal of the Institution of Engineers (India): Series B, 106.
[33] Dietterich, T.G., 2000. Ensemble methods in machine learning. In: Proceedings of the International Workshop on Multiple Classifier Systems, pp. 1–15.
[34] Wang, S., Liu, Z., Shen, Y., Zhang, L., 2019. Automatic detection of lumbar disc herniation using deep convolutional neural networks. IEEE Access, 7, 150–160.
[35] Jamaludin, A., Kadir, T., Zisserman, A., 2017. SpineNet: Automated classification and evidence visualization in spinal MRIs. In: Proceedings of MICCAI, pp. 721–729.

[36] Raju, P.R.S.S.V., Asanambigai, V., Mudunuri, S.B., 2023. A learning-based correlated graph model for spinal cord injury prediction from magnetic resonance spinal images. International Journal of Advanced Computer Science and Applications, 14(1).
[37] Sunday, B., Abdullahi, Y.M., Matemilola, A.S., Sahabi, Y.A., Abdullahi, M., 2025. Voting ensemble learning model with dynamic weighting for improved network intrusion detection. Franklin Open, 12, 100375.
[38] Kumar, R., Singh, A., 2023. Feature extraction and classification of lumbar spine herniation using MRI image processing. In: Proceedings of the IEEE International Conference on Image Processing, pp. 456–460.
[39] Brown, M., Davis, L., 2024. Quantitative analysis of spinal canal stenosis using 3D MRI reconstruction. IEEE Journal of Biomedical and Health Informatics, 27(2), 889–898.
[40] Raju, P.R.S.S.V., Asanambigai, V., Mudunuri, S.B., 2024. Design of a novel deep network model for spinal cord injury prediction. International Journal of Artificial Intelligence, 13(2), 2131–2142.
[41] Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Textural features for image classification. IEEE Transactions on Systems, Mad Cybernetics, SMC-3(6), 610–621.
[42] Waykue, Jyoti , 2026, MRI Images Dataset of Spine (Sagittal View), Mendeley Data, V1, doi: 10.17632/wsw32tffvk.1