

Modified Deep Convolutional Neural Network for Lumbar Spine Degenerative Classification with Improved Multikernel Fuzzy C-Means Segmentation

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Abstract

Nowadays back pain is the most emerging health issue which is affecting the people around the world. The main reasons causing this back pain problem is damage or deterioration of the lower part of the spine, this is referred to as the lumbar spine. The lower spine supports our body weight and helps us to stand, sit or move. As the cases of lumbar spine chronic diseases are increasing at a rapid rate, it is highly important to do the correct diagnosis and that too at the correct span of time. Currently, doctors are mainly using MRI scans to diagnose these types of spine related problems. In contrast the diagnosis is followed by manual analysis of the images which takes time and can also generate errors. Doing this manually is not always consistent and also fail in detecting the issues at early stages, which in case plays a important role in proper treatment. To solve the arising problems, the reasear proposes a new deep learning based method which can detect lumbar spine degenerative conditions at early stage and also classify them accordingly. This method works in four main steps. The first step includes preprocessing in which the MRI images are analysed and cleaned by the use of Gaussian filter. This step decreases the noise, increasing the overall image quality. The next step is segmentation in which all the importance region of image are detached using a technique called Modified Multikernel Fuzzy C-Means (MMKFCM). This step gives better partitioning by using multiple kernels at a time and nearby pixels information. This step is then followed by feature extraction in which after the partitioning, all useful information is taken from image which includes shape, texture and positioning of spine by using methods like monogenic binary coding and improved Gradient Local Ternary Pattern (IGLT_eP). The last step is classification in which all the information and features are passed by Modified Deep Convolution Neural Network (MDCNN) which uses advanced technologies like rank based average pooling and HardELiSh activateon with batch normalisation to increase the effectiveness and results in more accurate and reduced computation time. This complete system provides a reliable and efficient way for detection and classification of lumbar spine degenerative diseases. In comparison to other existing methods, the proposed model works better, resulting in 93.7% accuracy, 91.1% F-measure and 95.1% specificity. According to the result, this approach is more accurate and effective than other traditional methods.

Keywords: Gaussian Filter, Modified Multi-Kernel Fuzzy C-means algorithm, Improved Gradient Local Ternary Pattern, Modified DCNN

1. INTRODUCTION

Degenerative conditions of the lumbar spine, including intervertebral disc degeneration (IDD), degenerative lumbar spinal stenosis (DLSS), and lumbar disc herniation (LDH), pose a substantial healthcare burden, especially among elderly individuals [1]. These conditions can lead to severe chronic pain, functional impairment, and decreased quality of life, highlighting the urgent need for accurate and timely diagnosis [2]. Traditional diagnostic methods, primarily relying on radiographic imaging and clinical evaluations, are often hindered by subjectivity and variability, which can result in inconsistent diagnoses and less effective treatment strategies [3].

Recent advancements in machine learning (ML) and deep learning (DL) technologies have shown promise in improving the diagnosis and classification of lumbar spine degenerative diseases [4] [5]. For example, unsupervised ML techniques have been applied to analyze functional impairment and identify distinct patient clusters, revealing patterns that are not always apparent with traditional methods [6] [7]. Similarly, deep convolutional neural networks (CNNs) have demonstrated the ability to automate the grading of IDD from Magnetic Resonance Imaging (MRI) images with high accuracy, presenting a more efficient alternative to manual grading [8] [9].

➤ Proposing a modified Multikernel Fuzzy C-Means (MMKFCM) algorithm for segmenting the preprocessed images. Unlike the conventional MFCM method, the objective function is enhanced

by incorporating a modified kernel function. This enhancement significantly improves segmentation accuracy by effectively capturing both the texture and intensity features of the image.

➤ Introducing a new feature extraction method, which incorporates an improved Gradient Local Ternary Pattern feature with a Sobel operator to effectively capture texture and gradient information, even in low-resolution images.

➤ Introducing a modified DCNN model for the classification of lumbar spine degeneration. The key enhancements are made in this architecture, including the incorporation of multiheaded DCNN layers, Rank-based Average Pooling layers, and the proposed HardELiSH activation function, which is a combination of HardSigmoid and Exponential Linear Unit functions, along with batch normalization layers. These architectural improvements significantly reduce computational complexity, enabling more efficient training while simultaneously achieving enhanced classification performance.

The Introduction is presented in Section 1, followed by a detailed Literature Review, presented in Section 2. Subsequently, the Proposed Classification Model is explained in Section 3, while their results are described in Section 4. Finally, the Conclusion is provided in Section 5.

2. LITERATURE REVIEW

In 2023, Liawrungrueang W *et al.*, [19] has proposed a deep CNN model to automatically detect, classify, and grade intervertebral disc degeneration (IDD) using T2-weighted sagittal MRI images. Leveraging the Pfirrmann grading system, it achieved over 95% accuracy in classifying IDD grades, representing its potential as a rapid and efficient tool for routine diagnostic use.

In 2023, Singh D *et al.*, [20] has proposed a comprehensive approach for detecting LSDs by integrating optimized feature extraction using a differential SMO method and feature selection via a CNN-based linearity model.

In 2023, Abbas J *et al.*, [21] has proposed using machine learning, specifically the random forest and decision tree models, to identify key predictors of symptomatic DLSS. The anteroposterior diameter of the bony canal at L5 in males and L4 in females, along with other lumbar spine characteristics, were found to strongly predict the onset of DLSS.

In 2023, Zhang W *et al.*, [22] has proposed a DL-based diagnostic model using Faster Region-Based Convolutional Neural Network (R-CNN) and ResNeXt101 to automatically detect and classify lumbar disc herniation (LDH) on axial T2-weighted MR images. Utilizing the Michigan State University (MSU) classification criterion, the model demonstrated high detection accuracy and agreement with specialist evaluations, achieving a high classification area under the curve (AUC) on internal and external datasets.

In 2023, Yi W *et al.*, [23] has suggested a DL model to identify lumbar degenerative conditions from T2-weighted MRI scans utilizing 3D ResNet18 and transformer architecture, and assessed how well it performs in detecting cervical degenerative disease.

In 2024, Abuhayi BM *et al.*, [29] has introduced a novel approach for classifying lumbar diseases using an Involutional Neural-Based VGG Nets (InVGG), which integrates the VGG architecture with involutional neural networks. By using location-specific and channel-agnostic involution kernels, the InVGG is better able to adapt to a variety of visual patterns found in medical images.

In 2025, Dastgir A *et al.*, [30] has created a model for the automated categorization of spine lesions called Multi-Scale Attention Feature Fusion MobileNetv3 (MAFMv3). By including Attention and Atrous Spatial Pyramid Pooling (ASPP) modules, this model improves multi-scale feature collection and lesion region focus, building upon MobileNetv3.

2.1 Problem Definition

The diagnosis and classification of lumbar spine degenerative conditions remain significant challenges due to their heavy reliance on manual interpretation of medical images. This process is not only time-consuming but also prone to inter-observer variability and subjective judgment, limiting diagnostic consistency and efficiency. These challenges highlight the pressing need for a robust, scalable, and clinically adaptable system for the classification of lumbar spine degenerative conditions. Hence, this paper addresses the above limitations by proposing a comprehensive deep learning framework that leverages the MMKFCM-based segmentation approach and the extraction of improved GLTeP feature and the modified DCNN approach

together contribute to improved classification accuracy while reducing computational complexity and are significantly better than the existing methods.

3. PROPOSED MODEL FOR LUMBAR SPINE DEGENERATIVE CLASSIFICATION MODEL

This paper intends to enhance the classification of lumbar spine degenerative conditions through a comprehensive method integrating advanced deep learning techniques. The proposed approach comprises four important stages, namely, preprocessing, segmentation, extraction of features and classification. Initially, the MRI images are applied for preprocessing using the Gaussian filtering. Figure 1 shows the Lumbar Spine Degenerative Classification process.

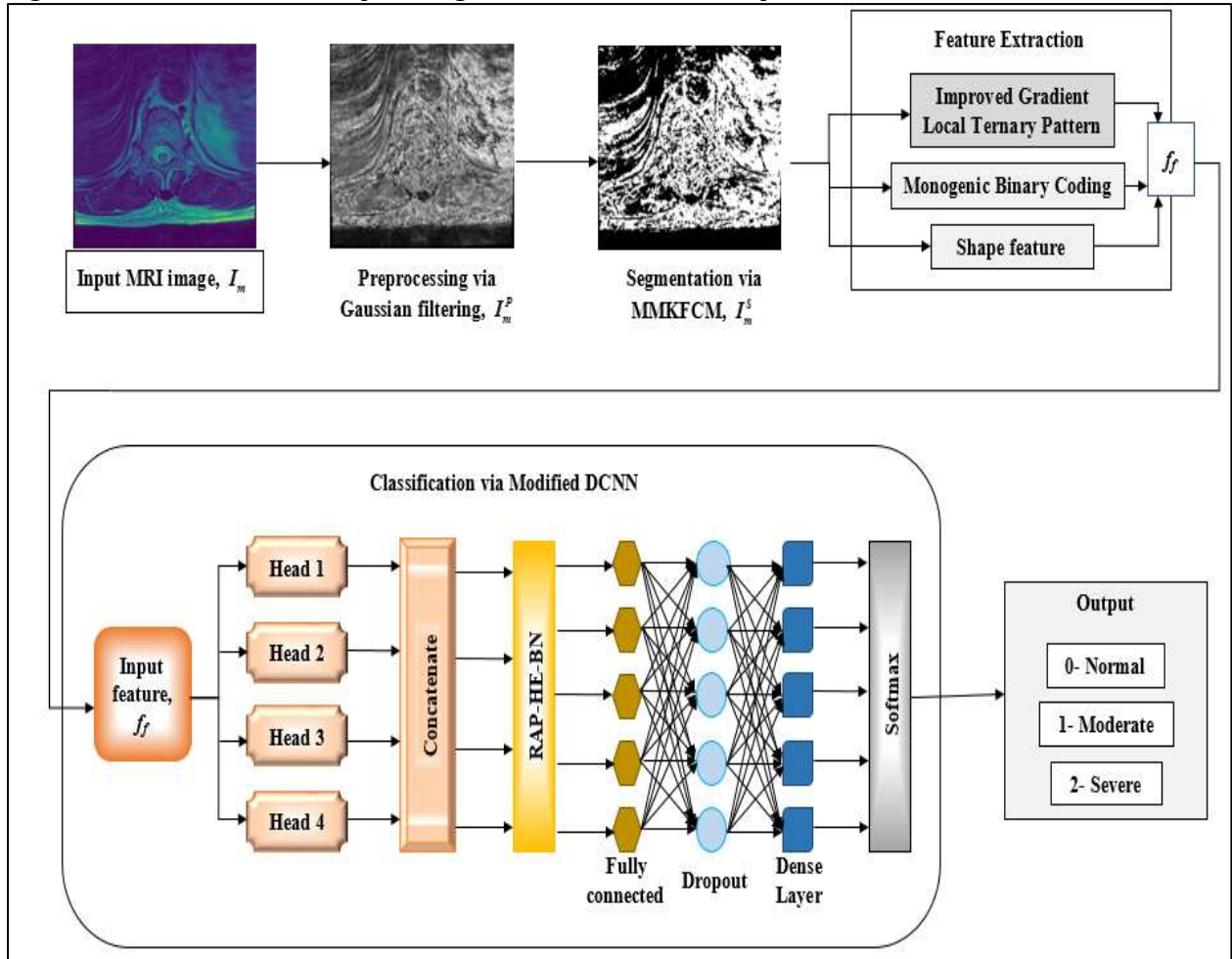


Figure 1: Lumbar Spine Degenerative Classification Process

3.1 Preprocessing via Gaussian filtering

In the Preprocessing phase, the input MRI images, I_m is processed via Gaussian filtering [31] techniques to enhance their quality and reduce noise, resulting in the preprocessed image denoted as I_m^P . Compared to other preprocessing techniques, Gaussian filtering is a linear smoothing method that applies a weighted value to every pixel, where the weights are determined by the Gaussian distribution centered at the target pixel. The values of the elements in the Gaussian smoothing filter are calculated according to the Gaussian function presented in Eq. (1). Here, the standard deviation is symbolized as σ and the normalization constant is denoted as $\hat{N}$, is included to ensure that the sum of the filter's weights equals one. This technique effectively reduces high-frequency noise, providing cleaner images for further stages of analysis.

$$gf(x, y) = \frac{1}{\hat{N}} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

3.2 Segmentation via Modified Multikernel Fuzzy C Means (MMKFCM)

Segmentation is the crucial step in medical image analysis. The Fuzzy C-Means (FCM) algorithm is a widely used clustering technique based on partitioning. Hence, this research proposes a

Modified Multikernel Fuzzy C-Means (MMKFCM) algorithm to segment the preprocessed MRI image, I_m^P effectively. The conventional Multikernel Fuzzy C-Means (MKFCM) approach [34] considers multiple kernel functions, such as Gaussian model-based kernels $\hat{k}_1$ and $\hat{k}_2$. They are used to simultaneously regulate the best degree of membership for each pixel and to identify the ideal kernel weights, combining them in a non-negative manner to represent the underlying structure of the image. The objective function, $\hat{f}$ of the conventional MKFCM, is given in Eq. (2). Where v_{ij} represents the membership degree of the pixel x_j belonging to centroid L_i , n indicates the fuzziness parameter, and $\hat{k}_n$ is the kernel function, computed as per Eq. (3).

The gaussian kernel functions $\hat{k}_1$ and $\hat{k}_2$ are defined by using Eq. (4) and Eq. (5), respectively. where, x_j represents the pixel values of I_m^P , σ_1^2 and σ_2^2 are the variances associated with the kernel functions $\hat{k}_1$ and $\hat{k}_2$ respectively.

$$\hat{f} = \sum_{i=1}^l \sum_{j=1}^m v_{ij}^n \left(1 - \hat{k}_n(x_j - L_i) \right) \quad (2)$$

$$\hat{k}_n = \hat{k}_1 * \hat{k}_2 \quad (3)$$

$$\hat{k}_1 = \exp \left(- \frac{\|x_j - L_i\|^2}{\sigma_1^2} \right) \quad (4)$$

$$\hat{k}_2 = \exp \left(- \frac{\|x_j - L_i\|^2}{\sigma_2^2} \right) \quad (5)$$

The key issue with the conventional MKFCM lies in its dependence on the appropriate selection of kernel functions and their corresponding parameters ($\sigma_1^2 + \sigma_2^2$). If the kernels are not aligned well with the underlying image structure, the segmentation results may not be effective.

To overcome this limitation, an MMKFCM algorithm is proposed to improve the segmentation performance of images. To address these issues, the objective function for MMKFCM is proposed as per Eq. (6), where $\hat{k}'_n$ denotes the modified kernel function, which is the combination of two kernels, $\hat{k}'_1$ and $\hat{k}'_2$. This proposed objective function provides relative scaling and enabling a better sensitivity to subtle textural and gradient differences for accurate detection. Also, allows the model to focus on relevant local variations, improving the discriminative power of the features.

$$f' = \frac{\sqrt{\sum_{i=1}^l \sum_{j=1}^m v_{ij}^n \left[\left(1 - \hat{k}'_n \right) \left(\left(|x_j| \right) - \left(|L_i| \right) \right)^2 \right]}}{\min \left[\left(\sqrt{\sum_{i=1}^l \left(|x_j| \right)^2} \right), \left(\sqrt{\sum_{j=1}^m \left(|L_j| \right)^2} \right) \right]} \quad (6)$$

(i) Calculation of modified first Kernel function $\hat{k}'_1$

The modified first kernel $\hat{k}'_1$ is calculated using the following step-by-step process:

Step 1: Calculate the first kernel function, $\hat{k}'_1$ based on averaging the hyperbolic kernel and the Laplacian kernel [35] as per Eq. (7), where, x, y signifies the pixel value of the preprocessed image, σ denotes the standard deviation, α represents scalar and c denotes the constant in the hyperbolic kernel, which controls the steepness of the non-linearity, as well as contributes to helping the kernel to focus on relevant local structures.

$$\hat{k}_1 = \frac{\left[\tanh(\alpha x^T y + c) + \exp\left(-\frac{\|x - y\|}{\sigma}\right) \right]}{2} \quad (7)$$

Step 2: Subsequently, Normalized the first kernel function as per Eq. (8). where, x, y signifies the normalized kernel, t, r_1 and r_2 are the parameters in the range of (0,1).

$$\hat{k}_1' = \begin{cases} \frac{1}{1 + \exp\left(-2\left(\hat{k}_1 - t\right)/r_1\right)} & \text{if } \hat{k}_1 < t \\ \frac{1}{1 + \exp\left(-2\left(\hat{k}_1 - t\right)/r_2\right)} & \text{if } \hat{k}_1 \geq t \end{cases} \quad (8)$$

(ii) Calculation of modified second Kernel function $\hat{k}_2'$

The calculation of the modified second kernel function $\hat{k}_2'$ is defined in the following step-by-step process:

Step 1: Calculate the second kernel function, $\hat{k}_1'$ based on summing the hyperbolic kernel and the polynomial kernel [35] as per as per Eq. (9), where, d signifies the degree of polynomial, c denotes the constant, x_1 and x_2 represents the vectors, which would model higher-order, non-linear relationship between features and also avoids overfitting.

$$\hat{k}_2 = \left[\tanh(\alpha x^T y + c) + (x_1 \cdot x_2 + 1)d \right] \quad (9)$$

Step 2: Subsequently, Normalized the first kernel function as per Eq. (10), where, x, y signifies the normalized kernel, t, r_1 and r_2 are the parameters in the range of (0,1).

$$\hat{k}_2' = \begin{cases} \frac{1}{1 + \exp\left(-2\left(\hat{k}_2 - t\right)/r_1\right)} & \text{if } \hat{k}_2 < t \\ \frac{1}{1 + \exp\left(-2\left(\hat{k}_2 - t\right)/r_2\right)} & \text{if } \hat{k}_2 \geq t \end{cases} \quad (10)$$

(iii) Calculation of Modified Kernel Function $\hat{k}_n'$

From Eq. (8) and Eq. (10), the final modified kernel function is calculated in the objective function of MMKFCM, which is defined in Eq. (11).

$$\hat{k}_n' = \left\{ \frac{\hat{k}_1' * \hat{k}_2'}{1 + e^{-\left(\hat{k}_1' * \hat{k}_2'\right)}} \right\} \quad (11)$$

Thus, the proposed MMKFCM algorithm addresses the limitations of conventional MKFCM by integrating a normalized kernel that combines both pixel intensity and local spatial information. This provides more accurate segmentation by considering both the texture and intensity features of the image. The kernel functions adapt to the underlying image structure, enhancing the algorithm's performance. Moreover, the normalized kernels help to effectively incorporate the information from neighboring pixels, improving segmentation in challenging conditions. The segmented image resulting from the MMKFCM is signified as I_m^S .

3.3 Feature Extraction

In this phase, several features are extracted from the segmented image, I_m^S including Improved Gradient Local Ternary Pattern (IGLTep), Monogenic Binary Coding and shape features

3.3.1 Improved Gradient Local Ternary Pattern-based features, f_{IGLTp}

The Improved Gradient Local Ternary Pattern (IGLTp) is a key technique in the feature extraction phase, designed to capture the fine-grained texture details as well as gradient information from the segmented MRI image, I_m^S .

A binary code reflecting the image's local texture information is produced as a result of this operation. Mathematically, the LBP for a pixel is computed in Eq. (12), here: G_p and G_c are the intensity values of the neighboring pixel and the central pixel, respectively, P denotes the number of neighboring pixels considered in the pattern. $S(x)$ denotes a threshold function.

$$LBP = \sum_{p=0}^{P-1} S(G_p - G_c) 2^p \quad (12)$$

The Improved Local Binary Pattern (ILBP) is mathematically expressed as per Eq. (13). Here, $t \cdot G_p$ represents the gradient values obtained through the Sobel operator, capturing edge and structural information from the image. $S(G_p - G_c)$ denotes the binary threshold comparison between the neighbor pixel G_p and the central pixel G_c . The sums are weighted differently for the texture and gradient components, ensuring that both texture details and edge information are incorporated. μ denotes the mean of neighbor pixel by using Eq. (14), t denotes the threshold parameter [37], which is defined in Eq. (15), where AM signifies the arithmetic mean of G_p , RM denotes the regional average of the image with the centre pixel, and GM indicates the geometric mean. The GM , AM and RM play a crucial role in capturing rich and robust texture and gradient information. Specifically, GM enhances sensitivity to local contrast variations by emphasizing multiplicative relationships among neighboring pixels. On the other hand, AM captures the average local intensity, serving as a baseline for identifying subtle changes in brightness and texture. RM provides a broader contextual understanding by averaging intensities over a larger region centered on the target pixel, which helps in capturing gradient consistency. These measures enrich the ternary encoding process by incorporating both local and regional variations, improving robustness against low-contrast conditions. GM computed as per Eq. (16), here s denotes the total neighbors, G_c represent the gray value of central pixel and G_p denotes the gray value of neighboring pixel.

$$ILBP = \left[\sum_{p=0}^{P-1} S(G_p - G_c) 2^{p-1} \cdot t \cdot G_p + \sum_{p=4}^{P-7} S(G_p - G_c) \cdot 2^{P/2+1} \cdot t \cdot G_p \right] \mu ; N = 8 \quad (13)$$

$$\mu = \frac{1}{P} \sum_{p=0}^{P-1} G_p \quad (14)$$

$$t = \begin{cases} 1 & \text{if } GM \geq G_c \text{ and } AM \leq G_p \\ 0 & \text{if } AM \geq G_c \text{ and } RM > G_p \\ 1 & \text{if } RM < G_c \text{ and } AM \leq G_p \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

$$GM = \left(\prod_{G=1}^s G_p \right)^{1/s} \quad (16)$$

The Improved Gradient Local Ternary Pattern (IGLTp) based features, f_{IGLTp} offers several key advantages over conventional LBP. By integrating Sobel gradients with LBP, ILBP combines fine-grained texture details with coarse structural features, creating a more comprehensive set of image descriptors.

3.3.2 Monogenic Binary Coding, f_{MBC}

Monogenic binary coding (MBC) [38] f_{MBC} is utilized to extract detailed local features from the segmented image by analyzing it from multiple perspectives. Based on monogenic signal theory, three key attributes are derived such as amplitude $\hat{A}$, phase θ and orientation ψ , which together capture the comprehensive characteristics of the image. The feature images decomposed from these attributes are referred to as Monogenic Binary Coding (MBC) amplitude image ($I_m^S - \hat{A}$), MBC phase image ($I_m^S - \theta$) and MBC orientation image ($I_m^S - \psi$). These coding images comprise two primary components such as the intensity coding of the monogenic local imaginary part and the monogenic local variable coding. Eq. (17) illustrates the coding formula that merges these features. Here, z_c refers to the central pixel of the selected region. This approach effectively captures local variations in intensity, phase, and orientation, providing a rich set of discriminative features for detailed image analysis.

$$I_m^S - \hat{N}(z_c) = [C_x(z_c), C_y(z_c), C_{\hat{N}}(z_c)] \quad \hat{N} = \hat{A}, \theta, \psi \quad (17)$$

3.3.3 Shape features, f_{shape}

The extraction of shape features f_{Shape} from segmented images plays a major role in characterizing the structural properties of lumbar spine regions. Key shape features [39] include the perimeter, diameter, eccentricity, and curvature, all of which provide valuable geometric insights into the image's structural patterns. These features are vital for differentiating between varying degenerative conditions.

3.4 Classification via Modified DCNN

The classification phase in this paper employs a Modified Deep Convolutional Neural Network (MDCNN) for the classification of lumbar spine degeneration.

3.4.1 Conventional DCNN

A Deep Convolutional Neural Network (DCNN) [40] consists of several key architectural components. Initially, input features f_f pass through multiple convolutional layers that apply filters to extract low-level features like textures and edges. Following each convolution, pooling layers (max-pooling or average-pooling) reduce the spatial dimensions of the feature maps and help the model stay invariant to small translations of the input. The main drawbacks of Deep Convolutional Neural Networks (DCNNs) are their complexity, overfitting potential, and slow convergence. As the network grows in depth, the number of layers and parameters like filter coefficients and fully connected weights creates significant challenges in terms of computational demand.

3.4.2 Modified DCNN (MDCNN)

The Modified DCNN (MDCNN) model incorporates several improvements, such as the use of multiheaded DCNN and Rank-based Average Pooling with HardELiSH Batch Normalization (RAP-HE-BN), making it more efficient in terms of computation and contributing to enhancing the classification accuracy.

The MDCNN architecture is shown in Figure 2, which begins with an input feature f_f from the feature extraction phase fed into the model. Instead of a conventional single convolutional path, this modified DCNN utilizes a multiheaded approach with four parallel convolutional heads, each processing the input data in a unique manner. These four parallel convolutional heads enable a multi-perspective feature learning. This concatenated output is passed through a RAP-HE-BN layer, which combines Rank-based Average Pooling (RAP) and HardELiSH Activation (HE) with batch normalization (BN), enhancing feature extraction and improving network stability. Specifically, the RAP mechanism incorporates ranking feature activations within a given region. This approach allows the network to retain the most informative features while reducing sensitivity to outliers. Following this, the HardELiSH activation function, a hybrid of HardSigmoid and ELU, introduces a smooth, non-linear transformation that maintains small negative outputs. Also, the HardELiSH is significantly more computationally efficient due to the use of HardSigmoid function. Finally, Batch Normalization further stabilizes the learning process by normalizing activation distributions, and accelerating convergence. Together, the RAP-HE-BN layer provides

a balanced combination of robust feature selection, non-linear expressiveness, and training stability, contributing to improved classification performance. After the RAP-HE-BN layer, the data flows into a fully connected layer, further refining the extracted features. To avoid overfitting, a dropout layer is incorporated, randomly dropping connections between layers during training. Finally, the processed features pass through a dense layer, followed by a softmax layer that outputs the final classification probabilities for the three classes, such as “0” denotes “Normal”, “1” denotes “Moderate” and “2” denotes “Severe”.

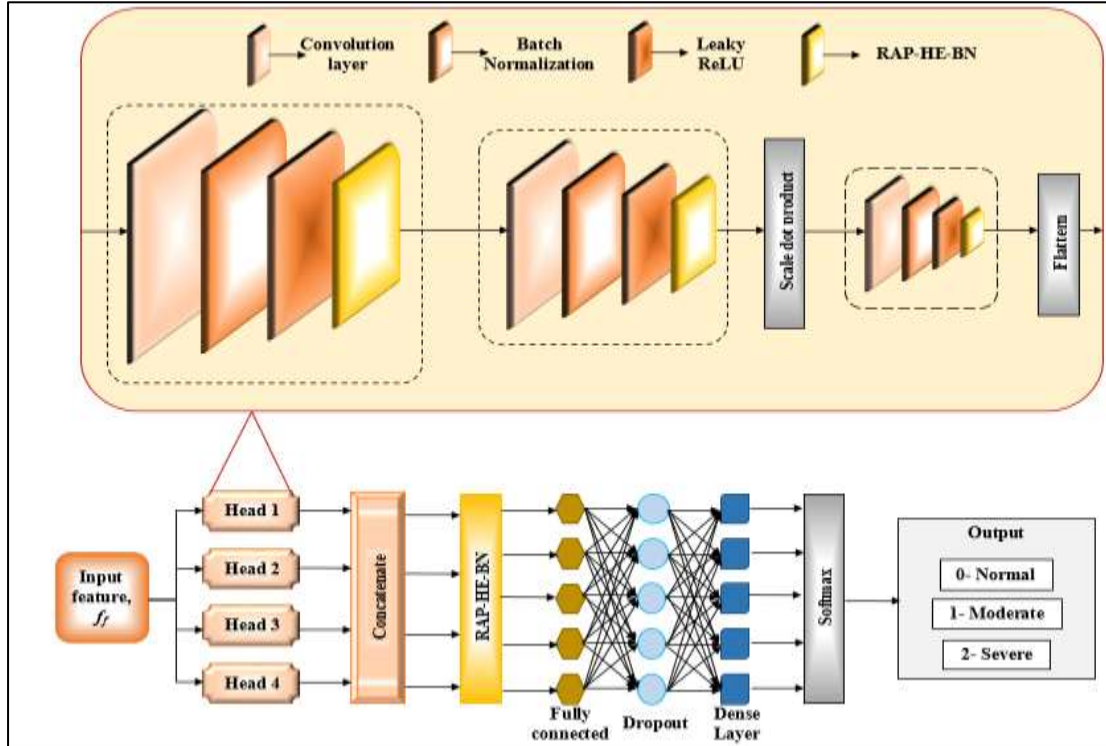


Figure 2: MDCNN model

Multiheaded layers:

In the proposed Modified DCNN model, each head includes a sequence of layers designed to efficiently extract and refine features. Initially, the input feature, f_f is inputted to a convolutional layer, which applies filters to extract local features from the input. This is followed by batch normalization, which helps to standardize the activations and speeds up training. After batch normalization, the output is passed through a Leaky ReLU activation function, introducing non-linearity to allow the model to learn complex patterns. The Leaky ReLU output is then passed through the Rank-based Average Pooling with HardELiSH response and batch normalization (RAP-HE-BN) layer, which helps to preserve important discriminative information while mitigating the loss of useful features often caused by traditional max pooling or average pooling.

RAP-HE-BN Layer (Rank-based Average Pooling with HardELiSH Batch Normalization)

The RAP-HE-BN layer is a crucial innovation in the proposed model, which improves features and stability during training by combining several advanced techniques.

Step 1: Rank-based Average Pooling (RAP)

The RAP technique [41] is introduced to overcome the limitations of conventional pooling methods, such as max pooling and average pooling, that either throw away useful information or downplay significant activations. RAP helps preserve discriminative features by ranking the activations in a given region and averaging only the most important ones. The mathematical expression of Rank-based average pooling is expressed in Eq. (19), where, a_i denotes the feature value at location i within the pooling region R_j , $\hat{t}$ denotes the index of each activation function.

x' denotes the rank-based average pooling.

$$RAP, x' = \frac{1}{\hat{t}} \sum_{i \in R_j, r_i < \hat{t}} a_i \quad (19)$$

Step 2: HardELiSH Activation function

HardELiSH [42] is a variant of the ELiSH activation function that combines both the HardSigmoid function and Exponential Linear Units (ELU). The proposed HardELiSH activation function plays a crucial role in enhancing the performance of the modified DCNN model. Unlike ReLU, which completely suppresses negative activations and can lead to dead neurons, HardELiSH allows small, informative negative outputs, thereby preserving critical low-intensity patterns. While ELU also retains negative gradients, it is computationally expensive due to the use of exponential operations. In contrast, HardELiSH combines the HardSigmoid and ELU functions. In this proposed model, HardELiSH is the activation function applied to the Rank-based Average Pooling's output, which is expressed in Eq. (20), where, x' represents the output of Rank-based Average Pooling, and $f(x')$ denotes the HardELiSH activation function applied to x' . Compared to the This activation function allows for better handling of both positive and negative activations, improving the model's learning capabilities.

$$f(x') = \begin{cases} x' \times \max\left(0, \min\left(1, \frac{x'+1}{2}\right)\right), & x' \geq 0 \\ (e^{x'} - 1) \times \max\left(0, \min\left(1, \frac{x'+1}{2}\right)\right), & x' < 0 \end{cases} \quad (20)$$

Step 3: RAP-HE-BN

After applying RAP and HardELiSH activation, batch normalization [43] is used to stabilize the training process by normalizing the activations across the mini-batch. The formula for RAP-HE-BN involves calculating the mean $\mu_c^{(k)}$ and variance, $(\sigma_c^{(k)})^2$ of the batch, normalizing the activations, and then applying the HardELiSH function as per Eq. (21), where ϵ denotes a small constant added for numerical stability.

$$RAP - HE - BN = \left\{ \frac{x'^{(k)} - \mu_c^{(k)}}{\sqrt{(\sigma_c^{(k)})^2 + \epsilon}} * f(x') \right\} \quad (21)$$

Therefore, Modified DCNN with RAP-HE-BN reduces computational complexity by minimizing parameter adjustments in fully connected layers, allowing more focus on convolutional learning. ReLU was used as the primary activation function due to its proven ability to mitigate vanishing gradient problems, with additional use of Leaky ReLU and Batch Normalization to stabilize training and improve convergence. The Adam optimizer was selected for its adaptive learning rate capabilities. A batch size of 32 and a training duration of 100 epochs were sufficient for achieving high accuracy without overfitting, using MSE as the loss function suitable for regression-based classification outputs. These settings collectively contribute to the robustness of the proposed classification framework.

4. RESULTS AND DISCUSSION**4.1 Simulation Procedure**

The proposed Lumbar Spine Degenerative Classification was implemented in PYTHON, specifically "Version 3.7". The processor employed "AMD Ryzen 5 3450U with Radeon Vega Mobile Gfx 2.10 GHz and the Installed RAM was 16.0 GB". Further, the Lumbar Spine Degenerative Classification was analyzed using RSNA 2024 Lumbar Spine Degenerative Classification [44].

4.2 Dataset Description

RSNA had teamed up with the "American Society of Neuroradiology (ASNR)" to organize the competition to discover whether AI can be utilized to assist in degenerative spine conditions detection and classification via lumbar spine MRI.

4.3 Performance Assessment

A wide-ranging assessment was conducted among the MDCNN and existing strategies for Lumbar Spine Degenerative Classification. The evaluation included a comprehensive set of performance measures, including "Sensitivity, Negative predictive Vlaue (NPV), Specificity, F-measure, False

negative rate (FNR), Precision, False positive rate (FPR), Matthews correlation coefficient (MCC), and Accuracy.” The comparison utilized the Radiological Society of North America (RSNA) 2024 Lumbar Spine Degenerative Classification dataset for MDCNN and conventional methods. Moreover, Figure 3 presents the original images alongside their Gaussian filter images after preprocessing.

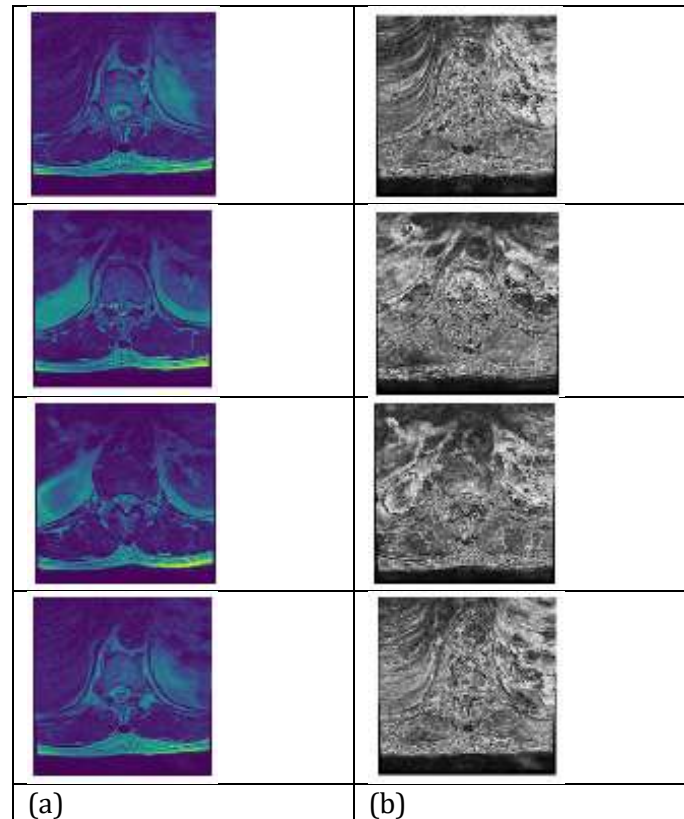
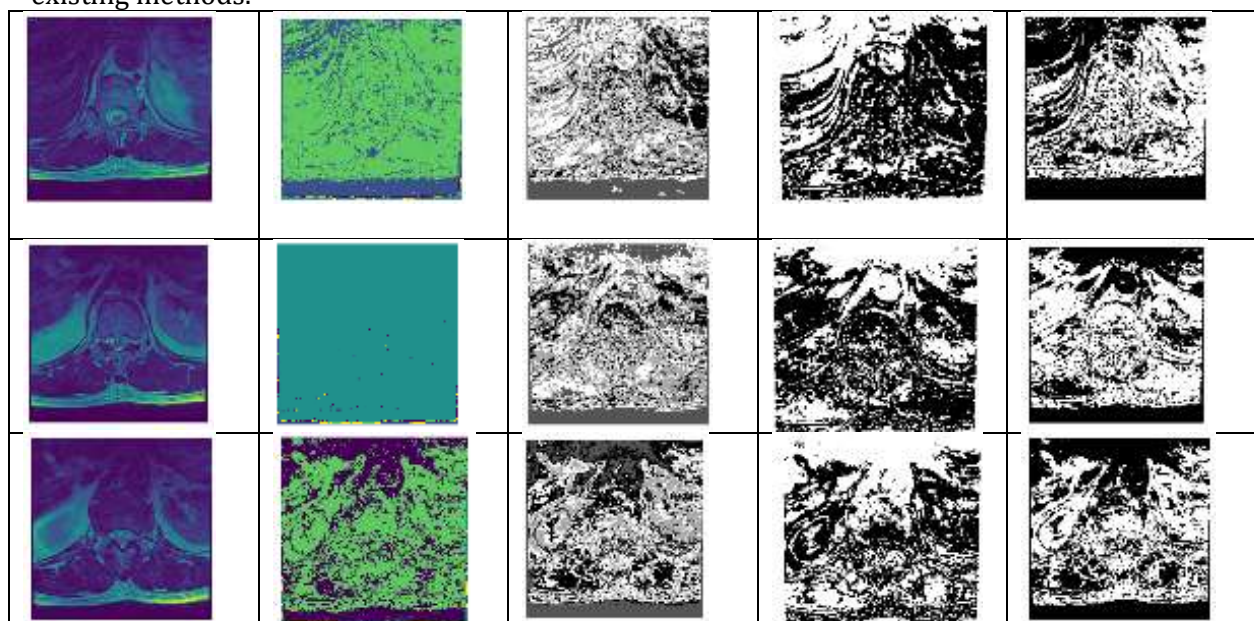


Figure 3: Pre-processed Outcomes a) Sample Images and b) Gaussian Filtering

4.4 Analysis of Segmentation Methods

Figure 4 displays an assessment of sample images together with their respective segmented outcomes for Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), Conventional MKFCM, U-Net and MMKFCM for Lumbar Spine Degenerative Classification. Therefore, the MMKFCM algorithm achieves superior segmentation performance compared to existing methods.



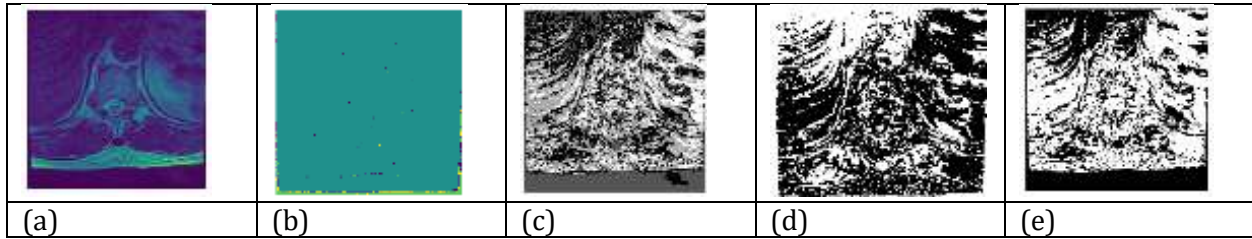


Figure 4: Segmented Outcomes a) Sample Images b) BIRCH c) Conventional MKFCM d) U-Net and e) MMKFCM

4.4.1 Analysis of Dice and Jaccard

Table 1 provides an assessment of MMKFCM and compares it with U-Net, BIRCH and Conventional MKFCM for Lumbar Spine Degenerative classification. The MMKFCM approach attains a Jaccard score of 0.912, this is greatest among the models compared. This outperforms U-Net (0.776), BIRCH (0.714) and Conventional MKFCM (0.827), signifying exceptional segmentation accuracy. In terms of Dice, the MMKFCM leads with a score of 0.940, compared to 0.846 for U-Net, 0.767 for Birch and 0.905 for Conventional MKFCM. In MMKFCM, the used parameters balance the importance of pixel intensities and local spatial information in the Kernel space. The Normalized Kernel is used for intensities but also for texture information.

Table 1: Dice and Jaccard analysis on MMKFCM and Conventional Methods

Metrics	U-Net	BIRCH	Traditional MKFCM	MMKFCM
Dice	0.846	0.767	0.905	0.940
Jaccard	0.776	0.714	0.827	0.912

4.4.2 Segmentation performance analysis with varying values of parameter t

The results presented in the Table 2 highlight the effectiveness of the proposed MMKFCM algorithm for image segmentation across different values of the parameter t , ranging from 0 to 1. As t increases from 0.25 to 1, the Dice score and segmentation accuracy show a general improvement, indicating that the method becomes more precise in segmenting the lumbar spine degenerative conditions. For instance, at $t=0.25$, the Dice score is 0.905, while at $t=0.5$, it increases to 0.918, reflecting a notable enhancement in segmentation performance. Similarly, the segmentation accuracy rises from 0.923 at $t=0.25$ to 0.934 at $t=0.5$, further confirming the efficacy of the MMKFCM algorithm. The Jaccard coefficient, however, does not exhibit as pronounced an improvement across different t -values, showing a more stable range of values from 0.872 to 0.900. This suggests that while the method excels at achieving high segmentation accuracy and Dice scores, the Jaccard coefficient remains slightly less sensitive to the changes in t . Overall, the results demonstrate that the MMKFCM algorithm performs robustly across the different values of t , with the best overall performance observed at $t=0.5$, where the balance between segmentation accuracy and computational efficiency is likely optimal.

Table 2: Analysis on segmentation performance of the proposed MMKFCM

t	Metrics	Proposed MMKFCM
0.25	Dice score	0.905
0.25	Jaccard coefficient	0.900
0.25	segmentation accuracy	0.923
0.5	Dice score	0.918
0.5	Jaccard coefficient	0.900
0.5	segmentation accuracy	0.934
0.75	Dice score	0.897
0.75	Jaccard coefficient	0.872
0.75	segmentation accuracy	0.903

1	Dice score	0.913
1	Jaccard coefficient	0.887
1	segmentation accuracy	0.924

4.5 Analysis on Feature Extraction

Table 3 presents a comparative analysis of different feature extraction techniques such as MAFMv3 [30], MobileNetv2 [18], and the proposed feature set comprising Improved Gradient Local Ternary Pattern, Monogenic Binary Coding, and shape-based features. The evaluation is based on key performance metrics including sensitivity, specificity, accuracy, precision, NPV, F-measure, MCC, and FPR. The proposed feature set outperforms both MAFMv3 and MobileNetv2 across all evaluated metrics. Most notably, it achieves the highest accuracy of 0.937, meanwhile, the MAFMv3 is 0.916, and MobileNetv2 is 0.915. In case of sensitivity, the proposed feature set achieves 0.848, compared to 0.792 and 0.778 for MAFMv3 and MobileNetv2, respectively. Similarly, improvements are observed in precision (0.863) and F-measure (0.856), achieved by the proposed feature set, suggesting a balanced performance between precision and recall. These results indicate that the combination of IGLTeP, MBC, and shape features yields more discriminative and robust feature representations compared to state-of-the-art models like MAFMv3 and MobileNetv2. The enhanced classification performance of the proposed feature set comprising IGLTeP, Monogenic Binary Coding, and shape features enables from its ability to extract detailed, domain-specific characteristics that state-of-the-art deep learning models like MobileNetv2 and MAFMv3 often fail to capture. Specifically, the IGLTeP captures fine-grained texture and edge information with gradient-based enhancements, enabling better differentiation of subtle degenerative changes in spinal structures. Monogenic Binary Coding enriches the representation, and offering strong resilience to variations in rotation and illumination. Additionally, shape descriptors such as perimeter, eccentricity, diameter, and curvature offer valuable insights into the geometrical representation. In contrast, MobileNetv2 and MAFMv3, which rely solely on automatically learned features and may struggle in fine-detail scenarios, the proposed approach integrates handcrafted texture, structural, and morphological features into a unified and highly discriminative representation. This combined feature enables a more robust and precise classification of lumbar spine degenerative conditions compared to the state-of-the-art models like MAFMv3 and MobileNetv2.

Table 3: Assessment on feature extraction techniques

Measures	MAFMv3	MobileNetv2	Proposed feature set f_f (IGLTeP, Monogenic Binary Coding, Shape Features)
Accuracy	91.60%	91.50%	93.70%
Sensitivity	79.20%	77.80%	84.80%
Specificity	94.90%	95.10%	96.20%
Precision	80.80%	80.80%	86.30%
F-measure	80.00%	79.20%	85.60%
MCC	74.70%	74.00%	81.60%
NPV	94.40%	94.20%	95.80%
FPR	5.10%	4.90%	3.80%
FNR	20.80%	22.20%	15.20%

4.6 Performance comparison of the Proposed IGLTeP and the Conventional GLTeP Feature

The comparison between the conventional GLTeP and the proposed IGLTeP presented in Table 4 demonstrates a clear improvement across most performance metrics, highlighting the enhanced effectiveness of the IGLTeP in capturing fine-grained details for the classification of lumbar spine degenerative conditions. Notably, the accuracy increases from 0.919 for the conventional GLTeP to 0.937 for the proposed IGLTeP, indicating that the proposed approach delivers better overall classification performance. Similarly, sensitivity rises from 0.797 to 0.848, showing that the proposed method is better at correctly identifying true positive cases of degeneration. The

precision and F-measure also demonstrate significant gains, moving from 0.817 to 0.863 and from 0.807 to 0.856, respectively, suggesting that the proposed method not only improves the number of true positives but also enhances the balance between precision and recall. The experimental results clearly demonstrate that IGLTeP is more effective in capturing fine-grained features and distinguishing subtle differences in low-resolution images compared to the conventional GLTeP. The image outcomes of the conventional GLTeP and the proposed IGLTeP technique are visually shown in Figure 5.

Table 4: Comparing the performance of the proposed IGLTeP with conventional GLTeP

Metrics	Conventional GLTeP	Proposed IGLTeP
Accuracy	0.919	0.937
Sensitivity	0.797	0.848
Specificity	0.952	0.962
Precision	0.817	0.863
F-measure	0.807	0.856
MCC	0.756	0.816
NPV	0.946	0.958
FPR	0.048	0.038
FNR	0.203	0.152

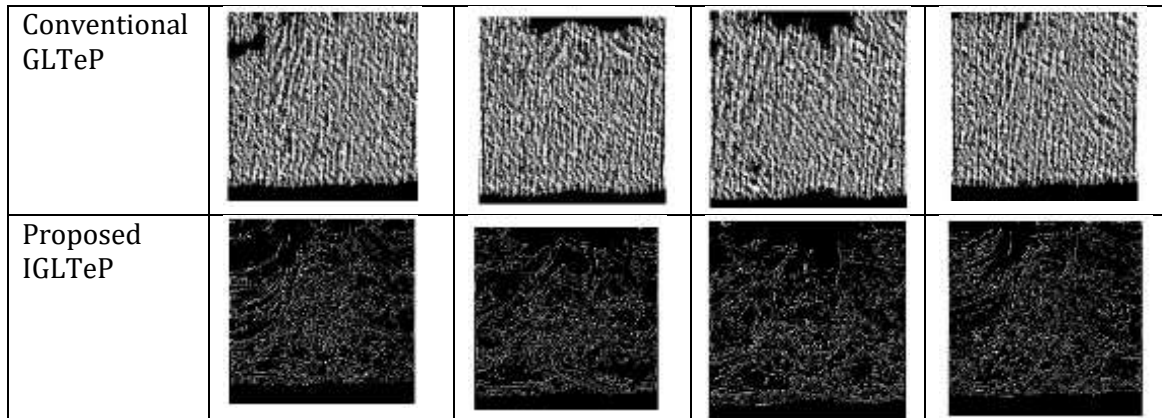


Figure 5: Image outcomes of conventional GLTeP and the proposed IGLTeP featuring techniques

4.7 Comparative Analysis

To analyze the efficiency of the MDCNN scheme for Lumbar Spine Degenerative Classification, its performance is contradicted by existing methodologies, such as CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN [27], 3D ResNet18 [28] and InVGG [29] as exposed in figure 6, figure 7 and figure 8. The investigation focuses on Positive, Neutral and Negative measures, which are important for effective classification of lumbar spine degenerative. Greater positive and neutral metric values signify superior performance in exactly categorizing lumbar spine degenerative. For 60% of training data, the MDCNN scheme attains an accuracy of 0.914, surpassing the existing methods with CNN at 0.861, Bi-LSTM at 0.830, RNN at 0.850, SqueezeNet at 0.881, DBN at 0.904, DCNN [27] at 0.864, 3D ResNet18 [28] at 0.873, and InVGG [29] at 0.880, respectively. By means of the training data improved to 70%, 80% and 90%, the MDCNN scheme continues to exhibit outstanding performance reaching a highest accuracy rate of 0.943 (training data=90%). The proposed MDCNN consistently achieves higher sensitivity compared to conventional methods. At 90% training data, it attains a sensitivity of 0.856, outperforming several established models, including CNN [27] (0.806), Bi-LSTM (0.776), RNN (0.714), SqueezeNet (0.769), DBN (0.757), DCNN [27] (0.793), 3D ResNet18 [28] (0.786), and InVGG [29] (0.778). By integrating Sobel gradients with LBP, the IGLTeP model provides a more comprehensive feature set that

incorporates both fine-grained texture details from LBP and coarse structural information from Sobel.

In 80% of training data, the MDCNN scheme attains the greatest NPV of 0.958, which is extremely higher than CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN [27], 3D ResNet18 [28], and InVGG [29]. This finding emphasizes the MDCNN method's effectiveness in achieving optimal classification performance in lumbar spine degenerative. In order to attain effective classification, it is important that the negative measure scores are diminished. In 70% of training data, the FPR for the MDCNN approach is 0.041, exhibiting a noteworthy enhancement over the traditional strategies. In contrast, the FPRs for CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN [27], 3D ResNet18 [28] and InVGG [29] are greater with values of 0.081, 0.101, 0.065, 0.090, 0.045, 0.074, 0.065, and 0.061 respectively. This substantial lessening in FPR for the MDCNN scheme specifies its upgraded capability to precisely classify Lumbar spine degenerative, minimalizing error values and enhancing the classification accuracy. These results collectively demonstrate that the MDCNN model incorporating Gaussian filtering-based preprocessing, precise MMKFCM segmentation, enriched feature extraction, and a proposed deep learning classifier offers a comprehensive, efficient, and accurate solution for lumbar spine degeneration classification. The modular architecture and enhanced performance contribute meaningfully to the domain of automated spinal diagnosis, particularly in supporting reliable clinical decision-making under resource-constrained settings.

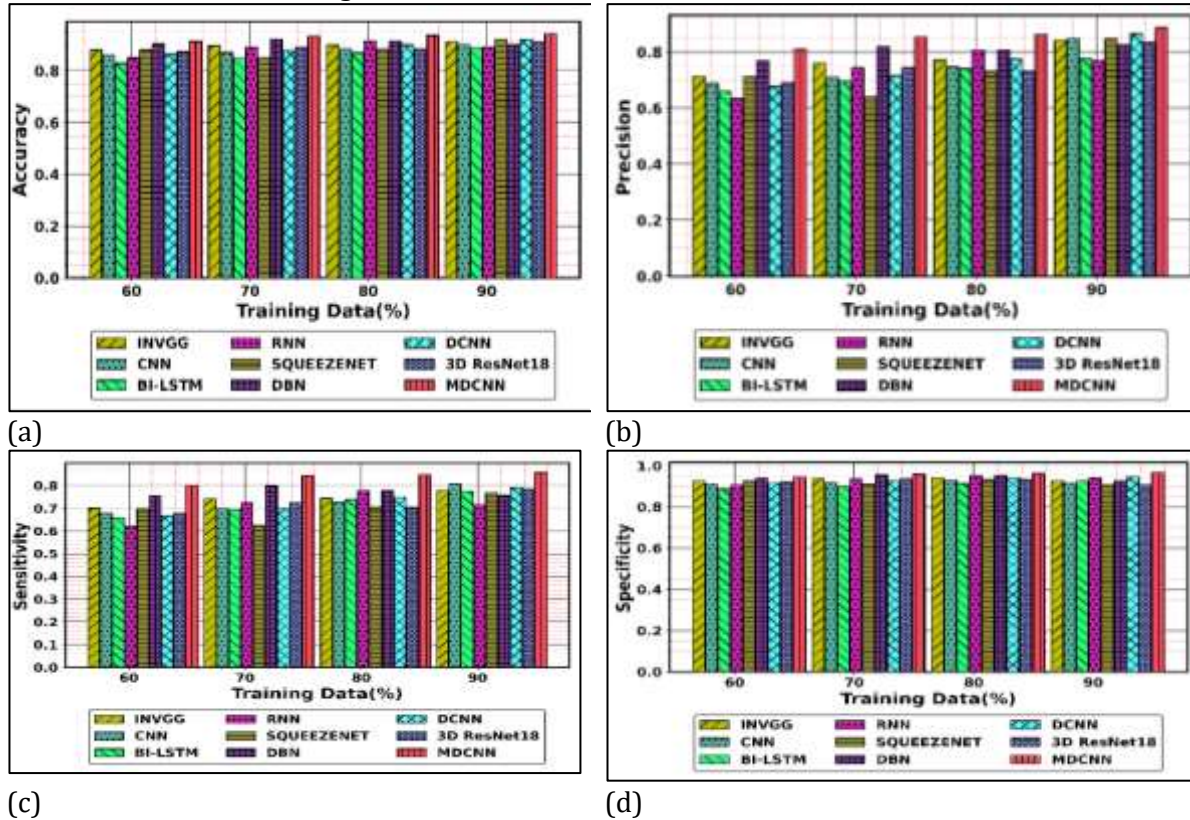


Figure 6: Comparison of Positive metrics on MDCNN and the existing methods a) Accuracy b) Precision c) Sensitivity and d) Specificity

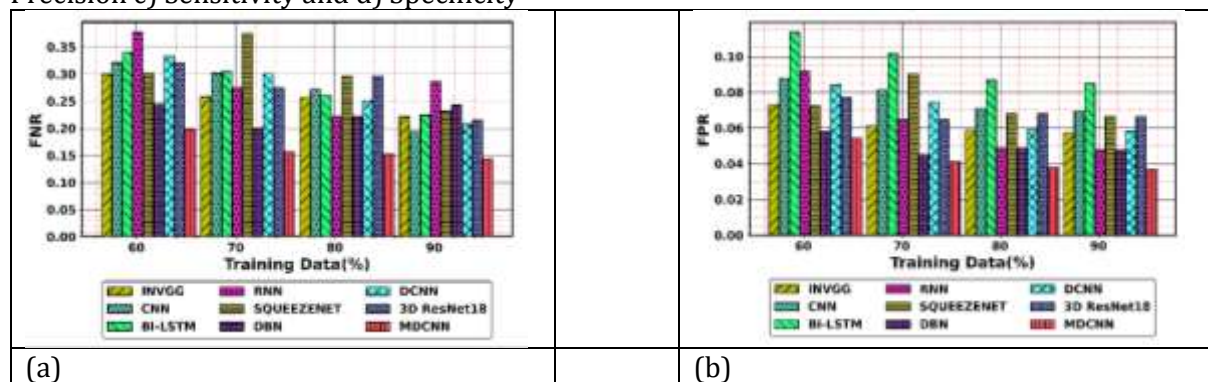
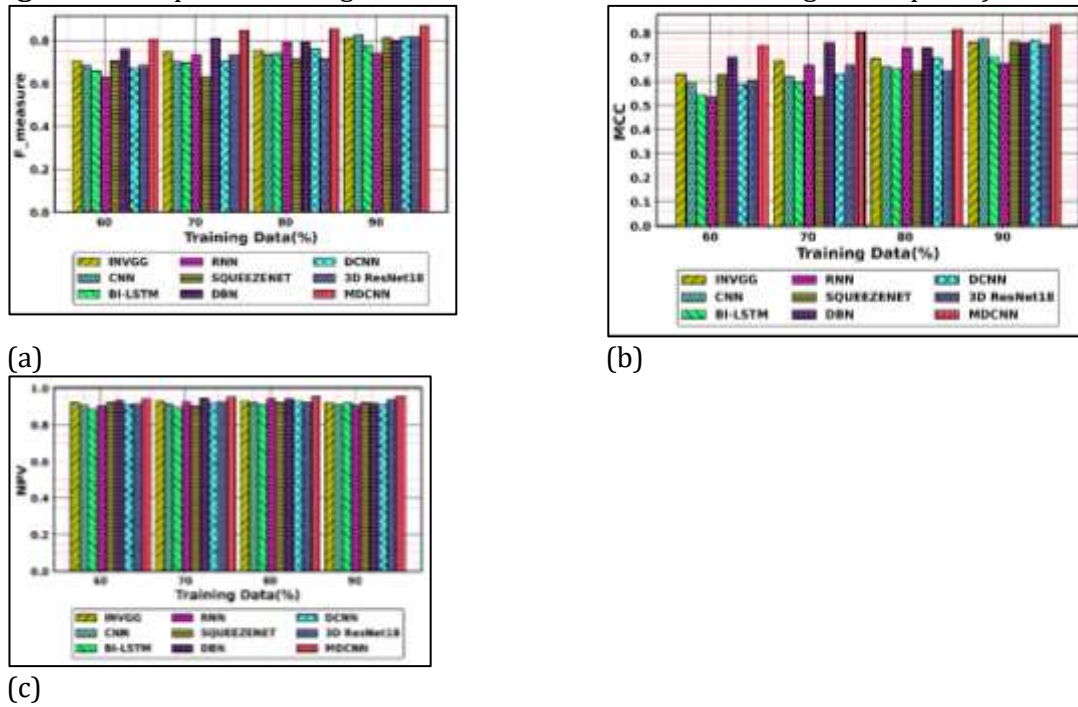


Figure 7: Comparison of Negative metrics on MDCNN and existing techniques a) FNR and b) FPR**Figure 8:** Comparison of other Metrics on MDCNN and Existing Techniques a) F-Measure b) MCC and c) NPV

4.8 Statistical Analysis in terms of Accuracy

Table 5 provides a statistical evaluation comparing the MDCNN scheme with existing approaches, such as CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN [27], 3D ResNet18 [28] and InVGG [29] for Lumbar Spine Degenerative Classification. Considering the Maximum statistical metric, the MDCNN scheme acquired the highest accuracy rate of 0.943, whereas the Bi-LSTM, CNN, RNN, 3D ResNet18 [28], and InVGG [29] acquired the least accuracies of 0.888, 0.902, 0.915, 0.912 and 0.912. The SqueezeNet, DBN and DCNN [27] scored slightly improved accuracy of 0.923. However, the MDCNN scheme accomplished greater accuracy values. The MMKFCM provides a fused different pixel information in the image segmentation problem. Also, it takes advantage of local spatial information. Further, the IGLTeP with the Sobel operator works very fast and accurately with low resolution. The MDCNN recorded a peak accuracy rate of 0.935 in the Median statistical measure, indicating improved performance in Lumbar Spine Degenerative Classification. In comparison, CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN [27], 3D ResNet18 [28], and InVGG [29] generated lesser accuracies. By drastically reducing the weight adjustment procedure in a fully connected layer, Modified DCNN concentrates learning on convolutional layers, lowers computing complexity, and accelerates convergence.

Table 5: Statistical Evaluation in terms of Accuracy

	INVGG	CNN	BI-LSTM	RNN	SqueezeNet	DBN	DCNN	3D ResNet18	MDCNN
Mean	89.80%	88.00%	85.90%	88.70%	88.50%	91.10%	89.10%	89.10%	93.20%
Median	89.90%	87.80%	85.90%	89.20%	88.30%	91.00%	88.90%	88.80%	93.50%
Std	1.10%	1.50%	2.20%	2.40%	2.60%	0.90%	2.20%	1.40%	1.10%
Min	88.00%	86.10%	83.00%	85.00%	85.10%	90.20%	86.40%	87.30%	91.40%
Max	91.20%	90.20%	88.80%	91.50%	92.30%	92.30%	92.30%	91.20%	94.30%

4.9 Ablation Study

An ablation study describes the impact on performance by removing the residual connections, and investigating how that disturbs the model's performance. Table 6 provides an ablation assessment of MDCNN approach in Lumbar spine degenerative classification, contrasting its performance with numerous variants such as MDCNN without Feature Extraction, MDCNN with

Existing MKFCM, MDCNN with Existing GLTeP, MDCNN without MKFCM and MDCNN without preprocessing. The MDCNN scheme attains the highest F-measure at 0.911, signifying its excellent capability in accurately categorizing lumbar spine degenerative. This value is notably greater compared to MDCNN without feature extraction (0.857), MDCNN with Existing MKFCM (0.832), MDCNN with Existing GLTeP (0.883), MDCNN without MKFCM (0.792), and MDCNN without preprocessing (0.772), respectively. The model omits preprocessing achieved lower performance, underscoring the vital role of noise reduction and image enhancement through Gaussian filtering in supporting subsequent analysis. The minimal FPR attained using the MDCNN technique is 0.049, signifying reduced error values compared to MDCNN omitting Feature Extraction, MDCNN with Existing MKFCM, MDCNN with Existing GLTeP, MDCNN without MKFCM and MDCNN without preprocessing. Moreover, these findings collectively affirm that the MDCNN model integrating Gaussian filtering for preprocessing, accurate segmentation through MMKFCM, advanced feature extraction techniques, and a tailored deep learning classifier delivers an efficient, and highly accurate framework for classifying lumbar spine degenerative conditions.

Table 6: Ablation Assessment on MDCNN Approach, MDCNN without Feature Extraction, MDCNN with Existing MKFCM, MDCNN with Existing GLTeP, MDCNN without MKFCM and MDCNN without Preprocessing

Metrics	MDCNN without extraction of features	MDCNN with traditional MKFCM	MDCNN with traditional GLTeP	MDCNN without MKFCM	MDCNN without preprocessing	MDCNN
Accuracy	90.40%	89.40%	91.50%	91.50%	90.50%	93.70%
FPR	8.00%	8.50%	7.50%	6.30%	5.70%	4.90%
F-measure	85.70%	83.20%	88.30%	79.20%	77.20%	91.10%
Sensitivity	84.30%	81.40%	87.30%	77.80%	76.40%	89.60%
FNR	15.70%	18.60%	12.70%	22.20%	23.60%	10.40%
Specificity	92.00%	91.50%	92.50%	93.70%	94.20%	95.10%
NPV	91.20%	90.40%	92.00%	93.20%	93.70%	95.80%
Precision	87.20%	85.10%	89.30%	80.80%	78.00%	91.60%
MCC	83.70%	80.60%	86.90%	74.00%	71.20%	87.60%

4.10 Analysis on Computing Time

Table 7 presents the computing time required by various DL models to process and classify lumbar spine MRI images. The analysis highlights the computational efficiency of the proposed MDCNN in comparison with several established models, such as INVGG, CNN, BI-LSTM, RNN, SqueezeNet, DBN, DCNN, and 3D ResNet18. Among all the models, the proposed MDCNN demonstrates the lowest computing time at 27.506 seconds, indicating a significant improvement in processing speed. In contrast, traditional models such as the RNN, DBN, and INVGG exhibit higher computing times of 62.775s, 50.495s and 55.323s, respectively. Other CNN-based models like 3D ResNet18 take 51.053s, and SqueezeNet takes 45.981s, also demonstrating relatively higher computational time. These models contribute to longer inference times. Additionally, the computational time of models such as Bi-LSTM (29.868s), DCNN (39.349s), SqueezeNet (45.981s), CNN (38.285s) and DCNN (39.349s) shows moderate computing times but still fall short of the efficiency achieved by MDCNN. Overall, the reduction in computing time can be attributed to the architectural enhancements such as Rank-based Average Pooling, and HardELiSH activation with Batch Normalization, which streamline feature learning and optimization while minimizing computational overhead and make it well-suited for real-time clinical applications, where both speed and accuracy are critical.

Table 7: Computing time analysis on the proposed MDCNN method vs traditional methods

Models	Computing Time (sec)
INVGG	50.495
CNN	38.285

Bi-LSTM	29.868
RNN	62.775
SqueezeNet	45.981
DBN	55.323
DCNN	39.349
3D ResNet18	51.053
Proposed MDCNN	27.506

4.11 Analysis on Space complexity

Table 8 presents a comparative assessment of space complexity (in megabytes) of the suggested MDCNN model and the traditional deep learning techniques, such as INVGG, CNN, Bi-LSTM, RNN, SqueezeNet, DBN, DCNN, and 3D ResNet18, particularly for lumbar spine degeneration. Among all models evaluated, the MDCNN approach demonstrates the lowest space complexity at 40.377 MB, indicating its superior memory efficiency. In contrast, 3D ResNet18 and BI-LSTM exhibit the highest space requirements, consuming 74.402 MB and 72.731 MB, respectively. Other traditional models like CNN (51.066 MB) and RNN (49.095 MB) fall within a moderate space range. Specifically, SqueezeNet, which is generally known for its lightweight architecture, has a relatively high space complexity of 97.960 MB in this context. Models such as INVGG (48.073 MB), DBN (61.309 MB), and DCNN (59.622 MB) also indicate greater space usage. This is especially noteworthy given that MDCNN integrates advanced components such as Rank-based Average Pooling and HardELiSH-based Batch Normalization, which evidently do not impose a substantial memory overhead. This efficiency makes MDCNN well-suited for deployment in environments with limited hardware resources and offers a portable diagnostic tool.

Table 8: Assessment on Space complexity

Models	Space complexity (MB)
INVGG	48.073
CNN	51.066
BI-LSTM	72.731
RNN	49.095
SQUEEZENET	97.960
DBN	61.309
DCNN	59.622
3D ResNet18	74.402
Proposed MDCNN	40.377

4.12 Analysis on FLOPS

Table 9 presents a comparative analysis of the proposed MDCNN and the different DL techniques, such as INVGG, CNN, BI-LSTM, RNN, SqueezeNet, DBN, DCNN, and 3D ResNet18, based on their Floating-point operations per second (FLOPS), which serves as an indicator of computational complexity and efficiency. A lower FLOPS value typically signifies a more computationally efficient model, assuming similar performance metrics. Among the listed models, the MDCNN achieves the lowest FLOPS value (7.601 GFLOPS), indicating the highest computational efficiency. This suggests that MDCNN requires fewer operations to process input data. The DCNN also shows a relatively low FLOPS (7.921 GFLOPS), underscoring its computational feasibility. The slight improvement in MDCNN highlights the effectiveness of the modifications made, such as the use of Rank-based Average Pooling, HardELiSH activation, and Batch Normalization, in reducing complexity without sacrificing model performance. In contrast, models like BI-LSTM (11.014 GFLOPS) and CNN (10.589 GFLOPS) exhibit higher FLOPS, indicating greater computational demands. Additionally, the 3D ResNet18 (10.098 GFLOPS), SqueezeNet (10.017 GFLOPS), RNN (8.337 GFLOPS) and DBN (9.045 GFLOPS). Overall, the results highlight MDCNN as the most efficient model in terms of FLOPS, making it well-suited for high-throughput diagnostic environments. Its efficiency advantage, combined with the reported improvements in classification accuracy, supports its potential as a robust solution for the classification of lumbar spine degenerative conditions.

Table 9: Assessment on MDCNN Vs existing methods based on FLOPS

Models	FLOPS (GFLOPS)
INVGG	9.019
CNN	10.589
BI-LSTM	11.014
RNN	8.337
SQUEEZENET	10.017
DBN	9.045
DCNN	7.921
3D ResNet18	10.098
MDCNN	7.601

4.13 Analysis on K-fold Cross-Validation

The K-fold cross-validation is conducted in this study to assess the generalizability and robustness of the model across real-world clinical settings. The analysis of the K-fold validation is shown in Table 10. The dataset was divided into five equal folds (K=5) for this evaluation, with one fold being used for testing and four folds for training in each iteration. Each fold was used as the test set once during the five iterations of this procedure. Each fold's performance indicators have been recorded to give a more thorough and objective assessment of the model's classification accuracy. This validation approach mitigates overfitting and ensures that the reported results are not dependent on a particular train-test split. The results presented in Table 13 reveal that the MDCNN consistently outperforms the state-of-the-art models and comparative models such as INVGG, CNN, BI-LSTM, RNN, SqueezeNet, DBN, DCNN, and 3D ResNet18 across all five folds. The MDCNN achieved the highest accuracy in every fold, with scores of 0.942 at fold 1, indicating remarkable stability and generalization. Meanwhile, the existing models such as INVGG=0.916, CNN=0.873, Bi-LSTM=0.856, RNN=0.873, SqueezeNet=0.892, DBN=0.873, DCNN=0.875, and 3D ResNet18=0.931. Also, findings demonstrate that the suggested MDCNN model consistently shows exceptional performance across all folds owing to the integrated methods, including Gaussian filtering, MMKFCM-based segmentation, advanced feature extraction, and DL models in accurately capturing diagnostic features from lumbar spine images in comparison to the existing techniques.

Table 10: Analysis on K-fold cross-validation

Folds	INVGG	CNN	BI-LSTM	RNN	SqueezeNet	DBN	DCNN	3D ResNet18	MDCNN
Fold=1	0.916	0.873	0.856	0.873	0.892	0.873	0.875	0.931	0.942
Fold=2	0.916	0.902	0.873	0.902	0.815	0.881	0.904	0.932	0.941
Fold=3	0.902	0.928	0.850	0.872	0.795	0.868	0.878	0.918	0.939
Fold=4	0.893	0.909	0.895	0.852	0.889	0.883	0.863	0.922	0.935
Fold=5	0.915	0.919	0.893	0.852	0.915	0.906	0.917	0.926	0.941

4.14 Activation Function Comparison

The performance evaluation presented in Table 11 highlights the effectiveness of the proposed model using the HardELiSH activation function compared to traditional activation functions such as ReLU, ELU, and LeakyReLU. The proposed model achieved the highest accuracy (0.937), outperforming ReLU (0.899), ELU (0.907), and LeakyReLU (0.921), indicating its superior ability to correctly classify lumbar spine degenerative conditions. The precision (0.863) and F-measure (0.856) of the proposed model also surpassed those of other models, demonstrating enhanced balance between recall and precision. Notably, the proposed model achieved the lowest FPR of 0.038 and FNR of 0.152, as well as the highest NPV of 0.958, further emphasizing its reliability. Overall, the use of HardELiSH activation in the MDCNN significantly enhances classification performance across all key evaluation metrics.

Table 11: Performance evaluation on activation functions

Metrics	Model with ReLU	Model with ELU	Model with LeakyReLU	Proposed model using HardELiSH
Accuracy	0.899	0.907	0.921	0.937
Sensitivity	0.789	0.784	0.806	0.848
Specificity	0.929	0.940	0.952	0.962
Precision	0.816	0.812	0.822	0.863
F-measure	0.802	0.797	0.814	0.856
MCC	0.759	0.749	0.764	0.816
NPV	0.921	0.932	0.947	0.958
FPR	0.071	0.060	0.048	0.038
FNR	0.211	0.216	0.194	0.152

5. CONCLUSION

Thus, this paper presented an advanced and integrated approach for classifying lumbar spine degenerative conditions. The methodology started with Gaussian filtering in the preprocessing stage to decrease noise and increase the clarity of MRI images. In the segmentation stage, a Modified Multikernel Fuzzy C-Means (MMKFCM) algorithm was employed to segment images effectively by utilizing fused pixel and local spatial information. The feature extraction phase incorporates an Improved Gradient Local Ternary Pattern (IGLT_{EP}) combined with a Sobel operator, along with additional features like Monogenic Binary Coding and shape descriptors, to capture discriminative patterns from segmented regions. The classification is performed using a MDCNN that combines RAP-HE-BN to optimize the learning process by reducing computational complexity. Additionally, the suggested model has undergone a thorough evaluation in comparison to both conventional and cutting-edge models. At 90% training data, the proposed model achieved a superior accuracy of 0.943, outperforming DCNN (0.922), 3D ResNet18 (0.912), InVGG (0.912), CNN (0.902), Bi-LSTM (0.888), RNN (0.892), SqueezeNet (0.923), and DBN (0.902). In addition to higher accuracy, the model demonstrated improved efficiency, achieving a faster computation time of 27.506 seconds. Despite these promising results, several limitations remain. While Gaussian filtering is effective for noise reduction in the preprocessing stage, the overall pipeline may still require some parameter tuning, limiting scalability. The model relies solely on MRI data, which represent a major challenge. It does not incorporate additional clinical parameters such as symptoms or functional scores, which could enhance diagnostic performance and clinical relevance. To address these challenges, future studies should investigate the use of feature selection and augmentation approaches to further increase classification accuracy and decrease redundancy, as well as the incorporation of metaheuristic optimization techniques for automatic fine-tuning of model parameters. Moreover, validating the proposed framework on real-world clinical datasets, including real-time patient data, is essential to assess its performance and robustness.

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