International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Advanced Classification of Lumbar Spine Degenerative Disorders Using Spine-CNN Attenuation Model

Dr. Viral H. Borisagar*[1], Kaushikkumar Keshavlal Rana[2], Dr. Sheshang Degadwala[3] and Dhairya Vyas[4]

Submitted: 25/01/2024 **Accepted :** 05/03/2024 **Accepted:** 12/03/2024

Abstract*:* This study offers a new method for classifying lumbar degenerative sicknesses using the nice backbone-CNN attenuation version. Lumbar spine pathologies, inclusive of herniated disc, spinal stenosis, and facet joint arthritis, pose notable demanding situations in prognosis and treatment making plans due to their distinctive diagnoses and overlapping signs and symptoms. backbone-CNN slimming version become proposed together with deep studying strategies with special algorithms for medical statistics evaluation, with unique awareness on the slimming sample within the lumbar area. The layout consists of a multilayer convolutional neural community (CNN) optimized for feature extraction and classification, enabling correct discrimination of various degenerative diseases. The principal benefit of this version is that it can create tough radiographic photographs and dispose of landmarks related to positive diseases. A comprehensive database of different lumbar degenerative diseases changed into used to assess the effectiveness of the version. The assessment and validation technique has been completed, demonstrating the version's effectiveness, high accuracy, and generality in many patients. The effects highlight the potential of the backbone-CNN attenuation version as a crucial device for radiologists and physicians to improve diagnostic accuracy, train clinical selection-making, and make sure patient effects. additionally, this study contributes to clinical imaging studies via the use of deep getting to know to remedy complicated problems in musculoskeletal imaging. future directions consist of enhancing the structure of the model, expanding the dataset for more applicability, and integrating scientific information to enhance predictive electricity and remedy use. universal, this looks at demonstrates the evolution of cognitive competencies in healthcare reform, especially inside the field of musculoskeletal disorders, and demonstrates the need for continued research and innovation on this swiftly changing surroundings.

Keywords: *Lumbar Spine, Degenerative Disorders, Transfer Learning, Spine-CNN, Attenuation Layer.*

1. Introduction

The prevalence state-of-the-art lumbar spine degenerative disorders has been regularly growing, posing large challenges in scientific control and healthcare aid allocation. The primary clinical manifestations encompass decrease returned pain, radicular signs and symptoms, and functional impairment, leading to decreased first-class cutting-edge existence and monetary burden. contemporary diagnostic strategies heavily rely on clinical evaluation, conventional radiography, and superior imaging modalities along with magnetic resonance imaging (MRI) and computed tomography (CT). however, the accurate category and precise localization state-of-the-art unique degenerative pathologies continue to be complicated obligations state-of-the-art overlapping medical presentations and variability in radiographic findings [1,3].

In reaction to these demanding situations, there was a growing interest in leveraging superior computational strategies, especially synthetic intelligence (AI) and deep studying, to enhance the diagnostic accuracy and prognostic capabilities in lumbar spine degenerative issues. Deep trendy algorithms, mainly convolutional neural networks (CNNs), have established excellent performance in various clinical imaging tasks, which include segmentation, category, and detection modern day pathological features [2,13]. Fig. 1 shows MRI scan of the normal and degenerative disorders lumbar spine.

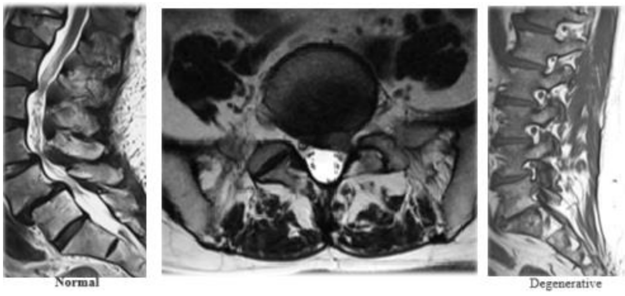


Fig. 1.MRI Scan of Lumbar Spine Degenerative Disorders

This paper pursuits to discover the application brand new a complicated spine-CNN Attenuation model for the category state-of-the-art lumbar spine degenerative problems. The proposed

[1]Assistant Professor, Computer Engineering Department, Vishwakarma Government Engineering College, Chandkheda, Ahmedabad, Gujarat, India
ORCID ID : 0000-0002-4816-7374, Email: viralborisagar@gmail.com
[2] Assistant Professor, Computer Engineering Department, Vishwakarma Government Engineering College, Chandkheda, Ahmedabad, Gujarat, India
ORCID ID : 0009-0001-5358-0198, Email:kkr@vgecg.ac.in
[3]Professor & HOD, Dept. of Comp. Eng., Sigma University, Vadodara, Gujarat, India
ORCID ID : 0000-0002-2385-7790, Email:sheshang13@gmail.com
[4] The Maharaja Sayajirao University of Baroda, Vadodara, Gujarat, India
ORCID ID : 0000-0001-7636-4167
Email:dhairya.vyas-cse@msubaroda.ac.in
** Corresponding Author Email: viralborisagar@gmail.com*

version carries deep modern techniques, specialised algorithms for attenuation evaluation, and a comprehensive dataset contemporary radiological photograph representing numerous degenerative pathologies. via rigorous assessment and validation, this examine seeks to demonstrate the efficacy, reliability, and scientific software contemporary the Spine-CNN version in accurately differentiating between numerous lumbar backbone degenerative issues, thereby contributing to the advancement latest precision medicine and tailored remedy techniques in this hard medical area.

2. Literature Study

Various categorization systems have been proposed to classify lumbar illnesses, aiming to beautify diagnostic accuracy and remedy efficacy. Abuhayi et al. delivered the Involutional neural primarily based VGG Nets (INVGG) system, leveraging deep studying techniques for lumbar sickness categorization. This approach capitalizes on the abilities of convolutional neural networks (CNNs) and the VGG structure to enhance disease category, providing a promising road for extra unique clinical tests [1].

The medical and Radiographic Degenerative Spondylolisthesis (cards) classification gadget, as delineated through Turcotte et al., provides a stratified framework for comparing consequences in sufferers undergoing lumbar fusion. This system integrates scientific and radiographic parameters to tailor remedy techniques, highlighting the importance of customized procedures in handling degenerative spinal conditions and optimizing patient consequences [2].

Staartjes et al. explored the usage of unsupervised learning techniques to identify clusters of objective useful impairment in patients with degenerative lumbar spinal sickness. by means of employing algorithms which can figure styles and institution patients primarily based on purposeful impairment profiles, this examine contributes to a deeper expertise of disease heterogeneity and probably informs targeted interventions for stepped forward patient control [3].

Soydan et al. proposed a novel qualitative morphometric MRI-primarily based disc degeneration class device, focusing on tracing the disc's structural adjustments. This category framework pursuits to enhance the diagnostic precision of disc degeneration, supplying clinicians with a complete toolset to evaluate disorder severity and progression as it should be [4].

Rangwalla and co-workers performed an evaluation of existing classifications for degenerative lumbar spondylolisthesis and placed forth a unique category gadget. Their paintings underscore the continuing efforts to refine sickness categorizations, reflecting the evolving panorama of spinal pathology evaluation and the quest for extra nuanced diagnostic paradigms [5].

Molina and Vial conducted a comprehensive literature evaluation to elucidate the principle radiological type structures for degenerative lumbar spine sickness. Their synthesis of current systems contributes to the information base surrounding disorder characterization, facilitating informed clinical decision-making and advancing standardized processes to ailment assessment [6].

Wang et al. delved into compensatory class in backbone sagittal malalignment coupled with lumbar degeneration, shedding mild at the complex interplay between spinal alignment and degenerative tactics. Their study underscores the multifactorial nature of spinal pathology, emphasizing the importance of holistic checks in medical practice [7].

Bharadwaj et al. leveraged deep mastering techniques for automated and interpretable category of lumbar spinal stenosis and aspect arthropathy from axial MRI scans. with the aid of harnessing the energy of deep mastering fashions, this research contributes to the improvement of strong diagnostic tools capable of dealing with complicated imaging data and helping in accurate disorder category [8].

Issa et al. evaluated the application of seated lateral radiographs in diagnosing and classifying lumbar degenerative spondylolisthesis, highlighting the importance of imaging modalities in refining diagnostic accuracy. Their findings underscore the role of radiographic tests in complementing clinical opinions, especially in elucidating degenerative spinal pathologies [9].

Soydan et al. offered an automatized deep segmentation and category version particularly tailored for lumbar disk degeneration. This version no longer only enables precise disorder category but additionally elucidates its impact on medical selection-making, bridging the space among advanced imaging analyses and therapeutic strategies [10].

Zhang et al. advanced a deep gaining knowledge of-based model for the detection and type of lumbar disc herniation on magnetic resonance pix. Their approach showcases the ability of deep gaining knowledge of algorithms in automating the analysis of complicated imaging facts, thereby improving diagnostic accuracy and efficiency [11].

Xuan et al. proposed a spinal disease diagnosis assistant based totally on MRI pictures using deep switch learning methods. This innovative technique harnesses the abilities of transfer learning to leverage pre-present knowledge and optimize diagnostic accuracy inside the context of spinal disorder assessment [12].

Abbas et al. applied a device learning set of rules approach to pick out predictive elements for degenerative lumbar spinal stenosis. Their model contributes to a greater complete information of the disorder's prognostic signs, helping in customized remedy strategies [13].

Zhang et al. advanced an automatic machine gaining knowledge of-primarily based version for predicting delirium in sufferers after surgical treatment for degenerative spinal sickness. This version showcases the capability of machine learning in predicting postoperative complications, thereby enhancing patient care and management [14].

Tamagawa et al. discussed advances and demanding situations in quantitative MRI for imaging evaluation of intervertebral disc degeneration and painful discs. Their evaluation presents insights into the evolving techniques and methodologies in quantitative MRI for assessing spinal pathology [15].

Zheng et al. evolved a deep learning-primarily based excessive-accuracy quantitation method for lumbar intervertebral disc degeneration from MRI. Their paintings highlight the ability of deep mastering algorithms in appropriately quantifying disorder severity, aiding in scientific decision-making [16].

Fraiwan et al. utilized deep transfer learning to locate scoliosis and spondylolisthesis from X-ray photographs. Their method demonstrates the versatility of deep learning strategies in automating the detection and class of spinal situations [17].

Kora et al. performed a assessment on transfer getting to know strategies for medical photo evaluation. Their complete evaluation highlights the capacity of switch mastering in advancing diagnostic accuracy and performance in clinical imaging [18].

Stephens et al. evaluated the application of machine mastering algorithms in degenerative cervical and lumbar backbone disease via a systematic evaluation. Their overview provides insights into the present-day panorama of machines getting to know packages in spinal sickness evaluation [19].

Müller et al. developed a device-getting to know primarily based model for predicting multidimensional consequences after surgical procedure for degenerative issues of the backbone. Their version contributes to customized medicinal drug methods by using predicting postoperative results based totally on affected person-specific traits [20].

Xie et al. explored using machine getting to know to model surgical decision-making in lumbar backbone surgical procedure. Their look highlights the capability of system getting to know in aiding surgeons with choice support tools for optimizing surgical effects [21].

Zheng et al. evolved a excessive-accuracy quantitation technique for lumbar intervertebral disc degeneration through the use of deep learning techniques. Their paintings underscore the ability of deep mastering algorithms in precisely quantifying disorder severity, aiding in clinical decision-making [22].

Grob et al. externally established the deep learning system 'SpineNet' for grading radiological features of degeneration on MRIs of the lumbar backbone. Their validation looks at reinforces the reliability and accuracy of deep getting to know structures in radiological exams of spinal pathology [23].

Cho et al. advanced an automatic dimension device for lumbar lordosis on radiographs the use of device learning and computer imaginative and prescient. Their paintings showcase the combination of device getting to know algorithms with imaging technology for precise anatomical measurements [24].

Khan et al. discussed the usage of device studying and artificial intelligence to pressure personalized medication tactics for spine care. Their assessment highlights the capacity of superior technologies in tailoring remedy strategies for spinal issues [25].

Gille et al. proposed a new category machine for degenerative spondylolisthesis of the lumbar spine. Their category system contributes to refining disorder categorization, aiding in more diagnostic and treatment strategies [26]

Ruchi et al. (2023) propose an enhanced Convolutional Neural Network (CNN) model for detecting lumbar spine diseases, achieving improved classification accuracy. Published in IEEE Access, their study demonstrates the model's superior performance in accurately identifying various spine conditions, highlighting the potential of CNNs in advancing medical diagnostics [27].

As from above the literature regarding lumbar spinal sicknesses consist of the capability for bias in patient choice or statistics series techniques, restrained pattern sizes that may not completely constitute the diversity of patients with those conditions, and the inherent demanding situations associated with retrospective research. Additionally, many of these studies depend heavily on advanced imaging technology and device mastering algorithms, which may not be comfortably available or viable in all healthcare settings, consequently proscribing the generalizability of their findings. Furthermore, the speedy improvements in technology and type structures might also render some of the proposed frameworks or models old or in want of steady updates to maintain relevance. lastly, whilst device gaining knowledge of and deep learning algorithms offer promising avenues for automated class and prediction, there remains a want for scientific validation and integration into habitual scientific exercise to ensure their efficacy and reliability in real-world situations.

3. Proposed Methodology

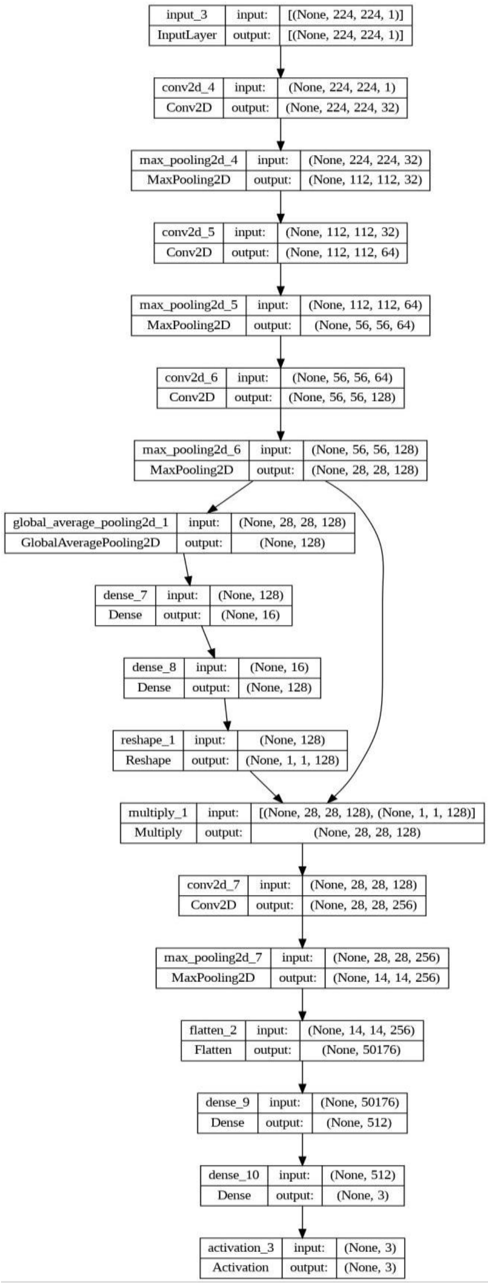


Fig. 2. Proposed Spine-CNN Model

As shown in fig. 2 the proposed model is an advanced Convolutional Neural network (CNN) designed for the superior classification of lumbar backbone degenerative issues into three distinct categories: everyday/slight, moderate, and excessive. This model employs an input layer in particular tailor-made to manner grayscale photos of length 224x224 pixels. Preprocessing steps ensure that input pix are normalized and resized correctly, optimizing them for neural network processing.

The preliminary layers of the version include a sequence of convolutional layers aimed at extracting hierarchical features from the input snap shots. The first convolutional layer incorporates 32 filters with a kernel size of 3x3, the use of the ReLU activation feature and 'equal' padding to maintain the spatial dimensions of the characteristic maps. that is accompanied through a max-pooling layer with a pool length of 2x2 to reduce the spatial dimensions, thereby concentrating the important features. This pattern is repeated with the next convolutional

layers, which steadily increase the number of filters to sixty-four after which 128, each accompanied by max-pooling layers to down sample the feature maps whilst maintaining critical records.
A key thing of the version is the inclusion of an interest mechanism, designed to enhance the community's awareness at the maximum relevant functions for class. This attention block begins with a global common pooling layer that condenses each channel's information right into a single cost, representing the average activation. This pooled statistic is then passed through dense layers: the primary reduces the dimensionality to a fraction of the authentic (specifically channels // 8) the use of ReLU activation, and the second restores the dimensionality to healthy the authentic number of channels with a sigmoid activation, generating channel-wise attention weights. Those weights are reshaped to align with the authentic characteristic maps and then extended with them, efficiently emphasizing the maximum essential functions.
Following the attention block, an extra convolutional layer with 256 filters and a kernel size of 3x3 in addition refines the characteristic extraction manner, again the usage of ReLU activation and 'equal' padding. This layer is likewise followed by using a max-pooling operation to keep the down sampling manner.
The characteristic maps are then flattened right into a one-dimensional vector, which is fed into a fully connected dense layer with 512 gadgets and ReLU activation, facilitating high-level reasoning. sooner or later, the output layer consists of a dense layer with 3 devices, every like one of the 3 classes: regular/moderate, moderate, and excessive. This accretion employs a SoftMax activation characteristic to output probabilities for each elegance, ensuring that the sum of possibilities equals one.
The version is compiled the usage of the Adam optimizer, recognized for its performance and adaptive studying rate abilities, and is educated the usage of the categorical move-entropy loss characteristic, that is well-proper for multi-elegance classification obligations. Accuracy is used because the primary metric to assess the version's performance, reflecting the percentage of accurate predictions.
In summary, this CNN model, augmented with an attention mechanism, affords a robust framework for the type of lumbar backbone degenerative problems. With the aid of specializing in applicable functions and efficaciously handling spatial hierarchies within the statistics, it pursuits to supply specific and dependable type results.

4. Results Analysis

The World Health Organization reports that low back pain was the leading cause of disability globally in 2020, impacting 619 million people. This condition is common, especially as people age, often due to degenerative spine issues such as spondylosis. Spondylosis encompasses the degeneration of intervertebral discs
The RSNA has partnered with the American Society of Neuroradiology (ASNR) [28] to host a competition aimed at determining if artificial intelligence can assist in identifying and classifying degenerative spine conditions using lumbar spine MRI scans.
This challenge will focus on classifying five specific lumbar spine degenerative conditions: Left Neural Foraminal Narrowing, Right Neural Foraminal Narrowing, Left Subarticular Stenosis, Right Subarticular Stenosis, and Spinal Canal Stenosis. Each MRI study in the dataset includes severity scores (Normal/Mild, Moderate, or Severe) for these conditions across the intervertebral disc levels L1/L2, L2/L3, L3/L4, L4/L5, and L5/S1 [28].
To develop the ground truth dataset, the RSNA challenge planning task force compiled imaging data from eight sites across five continents. This carefully curated, multi-institutional dataset aims to standardize the classification of degenerative lumbar spine conditions and support the development of automated tools for accurate and rapid disease classification [28].
As shown in fig. 3 first Train Label Coordinates CSV file is reading which contains study_id, serial_id, instant_number, coordinates, level, x and y.

	study_id	series_id	instance_number	condition	level	x	y
0	4003253	702807833	8	Spinal Canal Stenosis	L1/L2	322.831858	227.964602
1	4003253	702807833	8	Spinal Canal Stenosis	L2/L3	320.571429	295.714286
2	4003253	702807833	8	Spinal Canal Stenosis	L3/L4	323.030303	371.818182
3	4003253	702807833	8	Spinal Canal Stenosis	L4/L5	335.292035	427.327434
4	4003253	702807833	8	Spinal Canal Stenosis	L5/S1	353.415929	483.964602

Fig. 3. Train Label Coordinates CSV

As shown in fig. 4 first Train CSV file is reading which contains study_id, and different conditions types.

	study_id	spinal_canal_stenosis_l1_l2	spinal_canal_stenosis_l2_l3	spinal_canal_stenosis_l3_l4
0	4003253	Normal/Mild	Normal/Mild	Normal/Mild
1	4646740	Normal/Mild	Normal/Mild	Moderate
2	7143189	Normal/Mild	Normal/Mild	Normal/Mild
3	8785691	Normal/Mild	Normal/Mild	Normal/Mild
4	10728036	Normal/Mild	Normal/Mild	Normal/Mild

Fig. 4. Train csv

As shown in fig. 5 first combining above two file is and generate new csv which contain all information.

	study_id	series_id	instance_number	condition	level	x	y	output
0	4003253	702807833	8	Spinal Canal Stenosis	L1/L2	322.831858	227.964602	Normal/Mild
1	4003253	702807833	8	Spinal Canal Stenosis	L2/L3	320.571429	295.714286	Normal/Mild
2	4003253	702807833	8	Spinal Canal Stenosis	L3/L4	323.030303	371.818182	Normal/Mild
3	4003253	702807833	8	Spinal Canal Stenosis	L4/L5	335.292035	427.327434	Normal/Mild
4	4003253	702807833	8	Spinal Canal Stenosis	L5/S1	353.415929	483.964602	Normal/Mild

Fig. 5. Combine File

As shown in fig. 6 first final datasetCSV file is generating which contains images path.

	study_id	series_id	instance_number	condition	level	x	y	output	image_file_path
0	4003253	702807833	8	Spinal Canal Stenosis	L1/L2	322.831858	227.964602	Normal/Mild	4003253_702807833_8.dcm
1	4003253	702807833	8	Spinal Canal Stenosis	L2/L3	320.571429	295.714286	Normal/Mild	4003253_702807833_8.dcm
2	4003253	702807833	8	Spinal Canal Stenosis	L3/L4	323.030303	371.818182	Normal/Mild	4003253_702807833_8.dcm
3	4003253	702807833	8	Spinal Canal Stenosis	L4/L5	335.292035	427.327434	Normal/Mild	4003253_702807833_8.dcm
4	4003253	702807833	8	Spinal Canal Stenosis	L5/S1	353.415929	483.964602	Normal/Mild	4003253_702807833_8.dcm

Fig. 6. Final dataset csv

As shown in fig. 7 reading all imges of 3 different classes of mri normal_mild, severe, moderate.

Fig. 7. Reading DCM MRI images

As shown in fig. 8 shows alexnet training & validation data accuracy and loss plots.

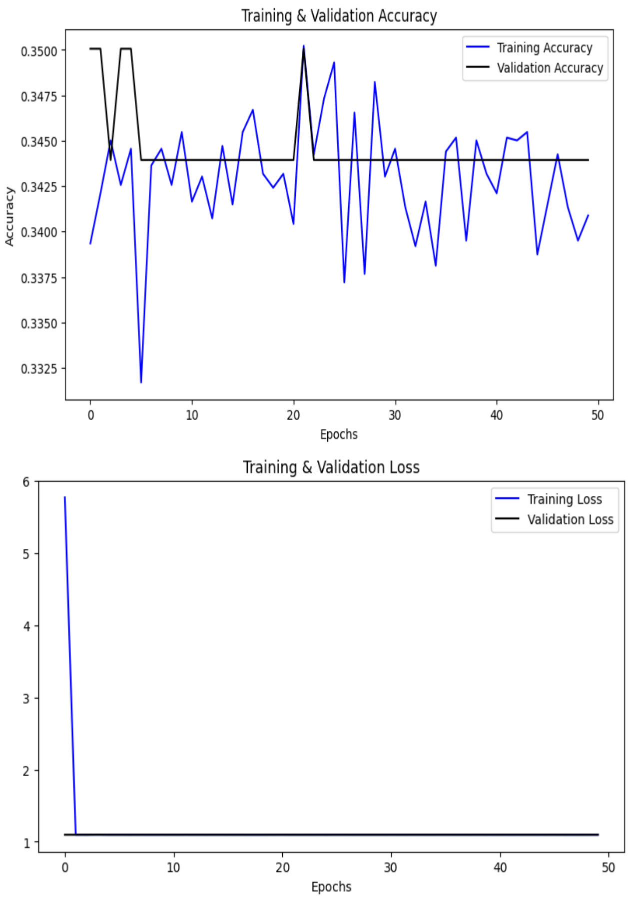
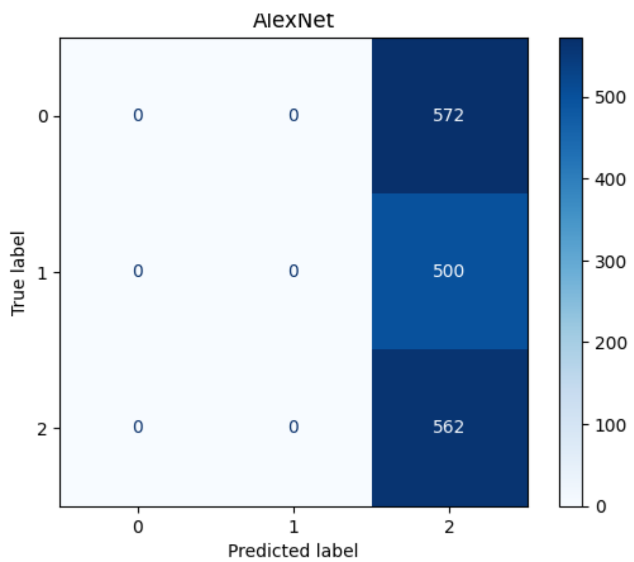


Fig. 8. AlexNet Model Training

As shown in fig. 9 shows alexnet model parameters confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.00	0.00	0.00	572
1	0.00	0.00	0.00	500
2	0.34	1.00	0.51	562
accuracy			0.34	1634
macro avg	0.11	0.33	0.17	1634
weighted avg	0.12	0.34	0.18	1634

Fig. 9. AlexNet Parameters

As shown in fig. 10 shows vgg-16 training & validation data accuracy and loss plots.

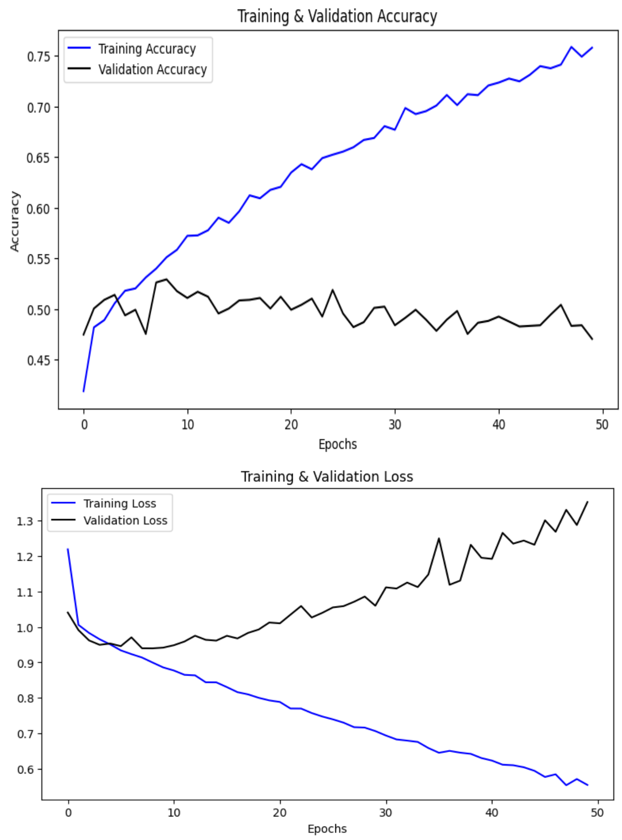
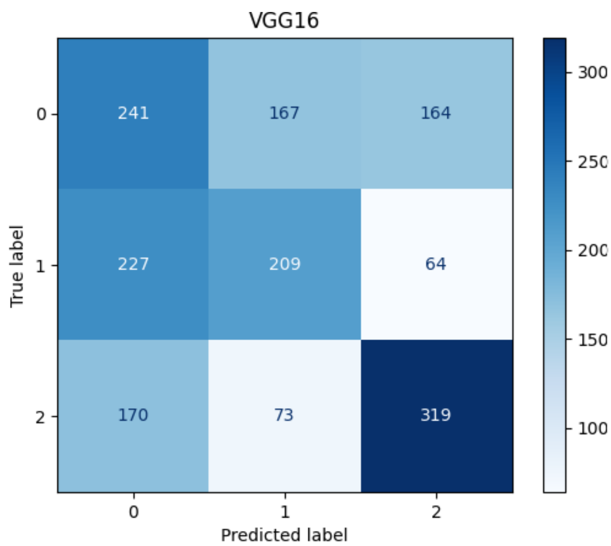


Fig. 10. Vgg-16 Model Training

As shown in fig. 11 shows vgg-16 model parameters confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.38	0.42	0.40	572
1	0.47	0.42	0.44	500
2	0.58	0.57	0.58	562
accuracy			0.47	1634
macro avg	0.48	0.47	0.47	1634
weighted avg	0.48	0.47	0.47	1634

Fig. 11. Vgg-16 Parameters

As shown in fig. 12 shows resnet-50 training & validation data accuracy and loss plots.

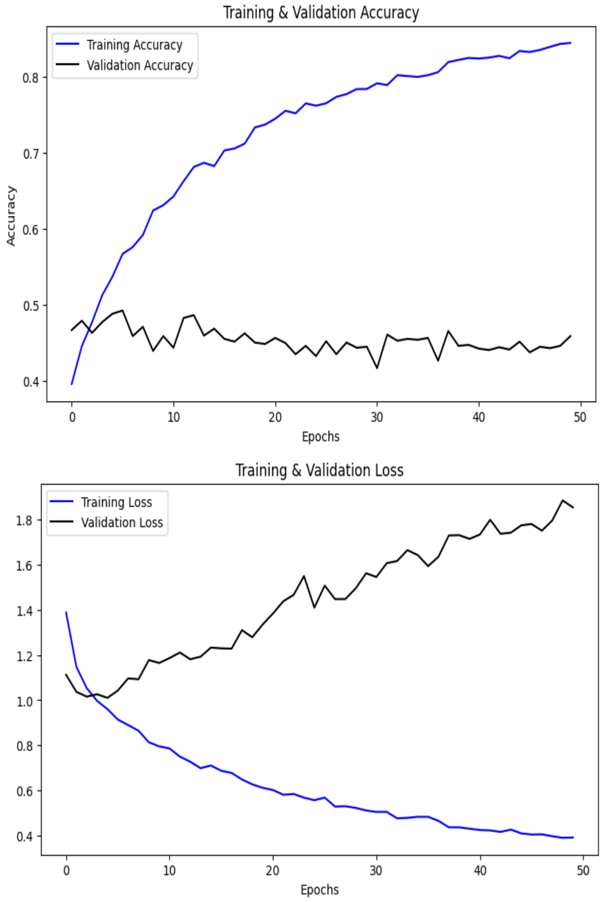
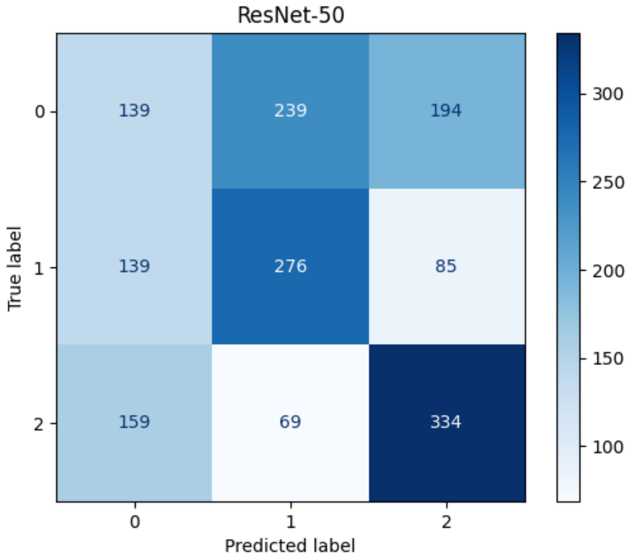


Fig. 12. ResNet-50 Model Training

As shown in fig. 13 shows resnet-50 model parameters confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.32	0.24	0.28	572
1	0.47	0.55	0.51	500
2	0.54	0.59	0.57	562
accuracy			0.46	1634
macro avg	0.45	0.46	0.45	1634
weighted avg	0.44	0.46	0.45	1634

Fig. 13. ResNet-50 Parameters

As shown in fig. 14 shows proposed spine-cnn training & validation data accuracy and loss plots.

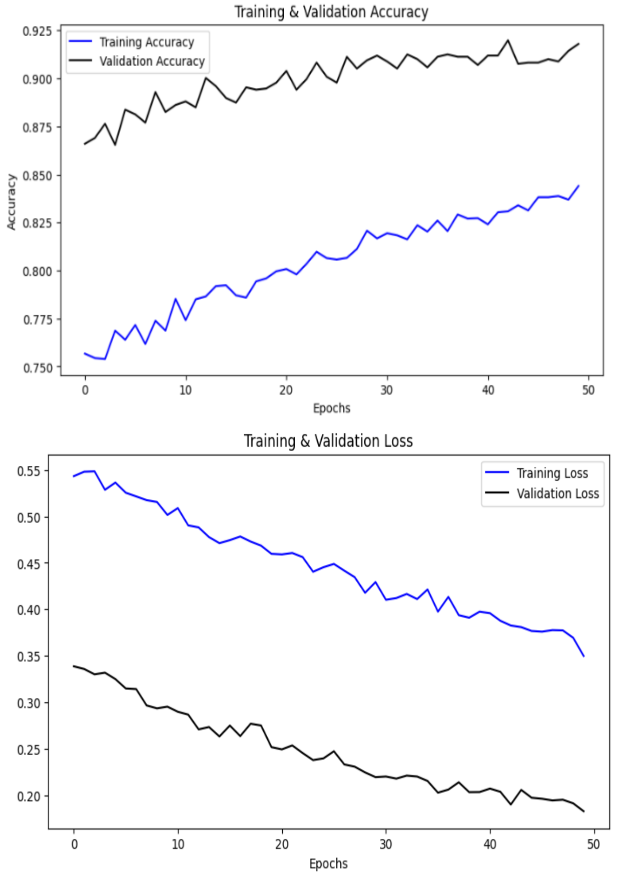
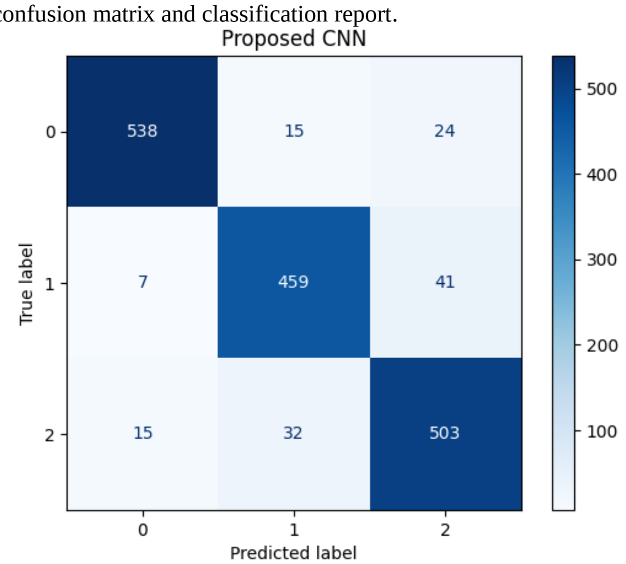


Fig. 14. Proposed Spine-CNN Model Training

As shown in fig. 15 shows proposed spine-cnn model parameters confusion matrix and classification report.



	precision	recall	f1-score	support
0	0.96	0.93	0.95	577
1	0.91	0.91	0.91	507
2	0.89	0.91	0.90	550
accuracy			0.92	1634
macro avg	0.92	0.92	0.92	1634
weighted avg	0.92	0.92	0.92	1634

Fig. 15. Proposed Spine-CNN Parameters

Table. 1. Comparative Analysis

Model	Precision [P]	Recall [R]	F1-Score [F1]	Accuracy [ACC]
AlexNet	11%	33%	17%	34%
Vgg-16	48%	47%	47%	47%
ResNet-50	45%	46%	45%	46%
Proposed Spine-CNN	92%	92%	92%	92%

Table 1 presents a comparative analysis of four models. The Proposed Spine-CNN outperforms AlexNet, Vgg-16, and ResNet-50 significantly across all metrics, achieving a precision, recall, F1-score, and accuracy of 92%. In contrast, Vgg-16 and ResNet-50 have balanced but lower metrics around 45-47%, while AlexNet shows the weakest performance with values ranging from 11% to 34%.

5. Conclusion

The consequences of this research at conclusively exhibit the advanced performance of the Proposed spine-CNN Attenuation model inside the classification of lumbar backbone degenerative issues. With a precision, do not forget, F1-rating, and accuracy of 92%, the Spine-CNN version significantly outperforms AlexNet, Vgg-16, and ResNet-50, which exhibit considerably decrease metrics. This high level of accuracy underscores the effectiveness of the Spine-CNN model in clinical diagnosis, highlighting its potential to enhance the diagnostic process and improve patient outcomes by providing more accurate and reliable classifications of spine conditions.

Looking forward, future research should focus on further validating the Spine-CNN model across more diverse and larger datasets to ensure its robustness and generalizability in various clinical scenarios. Additionally, integrating this model with other diagnostic tools and exploring its application in real-time diagnostic systems could further enhance its utility. Investigating the model's performance in detecting other spinal disorders and its adaptability to different imaging modalities could expand its clinical relevance. Continuous refinement of the model's architecture and training methods will also be essential to maintaining its state-of-the-art performance and ensuring it remains an asset in medical diagnostics.

6. References and Footnotes

Author contributions

Conceptualization—Dr. Viral H. Borisagar and KaushikkumarKeshavlal Rana; Methodology—Dr. Sheshang Degadwala; Software—Dhairya Vyas; Validation— Dr. Viral H. Borisagar and KaushikkumarKeshavlal Rana; Formal Analysis—Dr. Sheshang Degadwala and Dhairya Vyas; Investigation— Dr. Viral H. Borisagar and KaushikkumarKeshavlal Rana; Resources—Dhairya Vyas; data curation—Mr. Kalpesh Patel; Writing—review and editing—Dr. Sheshang Degadwala and Dhairya Vyas; Visualization— Dr. Viral H. Borisagar and KaushikkumarKeshavlal Rana; supervision— Dr. Viral H. Borisagar; Project administration— Dr. Viral H. Borisagar and KaushikkumarKeshavlal Rana.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] B. M. Abuhayi, Y. A. Bezabh, and A. M. Ayalew, "Lumbar disease classification using an Involutional neural based VGG Nets (INVGG).," IEEE Access, 2024.

[2] J. J. Turcotte, J. C. Brennan, P. Rana, A. H. Johnson, and C. Patton, "Outcomes in Lumbar Fusion Patients Stratified by the Clinical and Radiographic Degenerative Spondylolisthesis (CARDS) Classification System," Cureus, vol. 16, no. 2, 2024.

[3] V. E. Staartjes, A. M. Klukowska, V. Stumpo, W. P. Vandertop, and M. L. Schröder, "Identifying clusters of objective functional impairment in patients with degenerative lumbar spinal disease using unsupervised learning," European Spine Journal, vol. 33, no. 4, pp. 1320–1331, 2024.

[4] Z. Soydan, E. Bayramoglu, D. U. Urut, A. C. Iplikcioglu, and C. Sen, "Tracing the disc: The novel qualitative morphometric MRI based disc degeneration classification system," JOR spine, vol. 7, no. 1, p. e1321, 2024.

[5] K. Rangwalla et al., "Degenerative lumbar spondylolisthesis: review of current classifications and proposal of a novel classification system," European Spine Journal, pp. 1–11, 2023.

[6] M. Molina and S. Vial, "Radiological Classification for Degenerative Lumbar Spine Disease: A Literature Review of the Main Systems," Journal of Spine Research and Surgery, vol. 5, pp. 127–138, 2023.

[7] Y. Wang, X.-Y. Li, W.-G. Zhu, C.-X. Liu, C. Kong, and S.-B. Lu, "Compensatory classification in spine sagittal malalignment with lumbar degeneration," BMC Musculoskeletal Disorders, vol. 24, no. 1, p. 229, 2023.

[8] U. U. Bharadwaj et al., "Deep learning for automated, interpretable classification of lumbar spinal stenosis and facet arthropathy from axial MRI," European radiology, vol. 33, no. 5, pp. 3435–3443, 2023.

[9] T. Z. Issa et al., "Utility of Seated Lateral Radiographs in the Diagnosis and Classification of Lumbar Degenerative Spondylolisthesis," Asian Spine Journal, vol. 17, no. 4, p. 721, 2023.

[10] Z. Soydan, E. Bayramoglu, R. Karasu, I. Sayin, S. Salturk, and H. Uvet, "An Automatized Deep Segmentation and Classification Model for Lumbar Disk Degeneration and Clarification of Its Impact on Clinical Decisions," Global Spine Journal, p. 21925682231200784, 2023.

[11] W. Zhang et al., "Deep learning-based detection and classification of lumbar disc herniation on magnetic resonance images," JOR spine, vol. 6, no. 3, p. e1276, 2023.

[12] J. Xuan, B. Ke, W. Ma, Y. Liang, and W. Hu, "Spinal disease diagnosis assistant based on MRI images using deep transfer learning methods," Frontiers in Public Health, vol. 11, p. 1044525, 2023.

[13] J. Abbas, M. Yousef, N. Peled, I. Hershkovitz, and K. Hamoud, "Predictive factors for degenerative lumbar spinal stenosis: a model obtained from a machine learning algorithm technique," BMC Musculoskeletal Disorders, vol. 24, no. 1, p. 218, 2023.

[14] Y. Zhang et al., "Automated machine learning-based model for the prediction of delirium in patients after surgery for degenerative spinal disease," CNS Neuroscience & Therapeutics, vol. 29, no. 1, pp. 282–295, 2023.

[15] S. Tamagawa, D. Sakai, H. Nojiri, M. Sato, M. Ishijima, and M. Watanabe, “Imaging evaluation of intervertebral disc degeneration and painful discs—advances and challenges in quantitative MRI,” Diagnostics, vol. 12, no. 3, p. 707, 2022.
[16] H.-D. Zheng et al., “Deep learning-based high-accuracy quantitation for lumbar intervertebral disc degeneration from MRI,” Nature communications, vol. 13, no. 1, p. 841, 2022.
[17] M. Fraiwan, Z. Audat, L. Fraiwan, and T. Manasreh, “Using deep transfer learning to detect scoliosis and spondylolisthesis from X-ray images,” Plos one, vol. 17, no. 5, p. e0267851, 2022.
[18] P. Kora et al., “Transfer learning techniques for medical image analysis: A review,” Biocybernetics and Biomedical Engineering, vol. 42, no. 1, pp. 79–107, 2022.
[19] M. E. Stephens et al., “Utility of machine learning algorithms in degenerative cervical and lumbar spine disease: a systematic review,” Neurosurgical Review, pp. 1–14, 2022.
[20] D. Müller et al., “Development of a machine-learning based model for predicting multidimensional outcome after surgery for degenerative disorders of the spine,” European Spine Journal, vol. 31, no. 8, pp. 2125–2136, 2022.
[21] N. Xie, P. J. Wilson, and R. Reddy, “Use of machine learning to model surgical decision-making in lumbar spine surgery,” European Spine Journal, vol. 31, no. 8, pp. 2000–2006, 2022.
[22] H.-D. Zheng et al., “Deep learning-based high-accuracy quantitation for lumbar intervertebral disc degeneration from MRI,” Nature communications, vol. 13, no. 1, p. 841, 2022.
[23] A. Grob et al., “External validation of the deep learning system ‘SpineNet’ for grading radiological features of degeneration on MRIs of the lumbar spine,” European Spine Journal, vol. 31, no. 8, pp. 2137–2148, 2022.
[24] B. H. Cho et al., “Automated measurement of lumbar lordosis on radiographs using machine learning and computer vision,” Global spine journal, vol. 10, no. 5, pp. 611–618, 2020.
[25] O. Khan, J. H. Badhiwala, G. Grasso, and M. G. Fehlings, “Use of machine learning and artificial intelligence to drive personalized medicine approaches for spine care,” World neurosurgery, vol. 140, pp. 512–518, 2020.
[26] O. Gille et al., “A new classification system for degenerative spondylolisthesis of the lumbar spine,” European Spine Journal, vol. 26, pp. 3096–3105, 2017.
[27] Ruchi et al., "Lumbar Spine Disease Detection: Enhanced CNN Model with Improved Classification Accuracy," in IEEE Access, vol. 11, pp. 141889-141901, 2023, doi: 10.1109/ACCESS.2023.3342064.
[28] Tyler Richards, Jason Talbott, Robyn Ball, Errol Colak, Adam Flanders, Felipe Kitamura, John Mongan, Luciano Prevedello, Maryam Vazirabad.. (2024). RSNA 2024 Lumbar Spine Degenerative Classification. Kaggle. https://kaggle.com/competitions/rsna-2024-lumbar-spine-degenerative-classification.