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Artificial Intelligence in Lumbar Spine Disorders: A Survey on MRI Analysis, Diagnosis, and Clinical Decision Support

Harini S.[1*], Dr. Ananth Kumar T.[2] & Dr. Kanimozhi P.[3]

[1-3]Department of Computer Science and Engineering, IFET College of Engineering, Villupuram, Tamil Nadu, India.
Corresponding Author (Harini S.) Email: harinicse788@gmail.com*

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ABSTRACT

The major causes of chronic lower back pain include spinal stenosis and lumbar disc degeneration; proper diagnosis and classification are essential in the planning of treatment. The traditional interpretation of MRI is however tiresome, subjective, and inaccurate with inconsistent results. The overall aim of the research was to come up with an automated and intelligent system which would be able to detect and distinguish lumbar disc degeneration and determine the severity of the spinal stenosis and provide appropriate treatments. The current survey of automated MRI-based diagnosis and lumbar disc degeneration and spinal stenosis provides an overview of the available methods of machine learning to deep learning model such as CNNs and transformers. It divides techniques into preprocessing techniques (e.g., segmentation, normalization), feature extraction techniques (e.g., Pfirrmann grading, canal measurements), and techniques of determining the level of severity (mild, moderate, severe). Important repositories of data like SpineWeb and publicly available MRI repositories are reviewed, as well as issues like inter-observer variability, data paucity and computation requirements. The article addresses the integration with treatment recommendation modules and defines the gaps in the real-time clinical implementation, multi-modal imaging, and explainable AI to advance in the future.

Keywords: Lumbar Disc Degeneration; Spinal Stenosis; Deep Learning; Automated Diagnosis; Treatment Recommendation; Medical AI; MRI Analysis; Clinical Decision Support.

1. Introduction

Lumbar disc bulging or herniation (LDBH) is considered to be one of the most widespread degenerative disorders of the spine and the leading cause of chronic low back pain, radiculopathy, and long-term functional impairment globally. The condition is developed because of gradual structural and biochemical degeneration of the intervertebral disc, which causes disc deformation, disc annular fissures, and compression of the surrounding neural tissue [1]. Timely and accurate diagnosis of the LDBH is important because delayed diagnosis may result in nerve damage that cannot be reversible. As an answer to these constraints, other imaging methods have been explored to enable more accessible and cost-effective diagnostic lines, which include lumbar disc height measures based on conventional radiographs that can be meaningfully correlated with disc bulging or herniation identified through MRI [2]. Other imaging methods have also been examined to enable more diagnostic pathways, which are lower cost and more easily accessible, without sacrificing the quality of the findings. Put simply, these studies have enabled more consistent and reproducible research of the spine [3].

In addition to imaging, lumbar disc degeneration is also becoming a multifactorial condition that is not only dependent upon mechanical loading but also systemic and metabolic factors. The traditional diagnosis models tend to ignore these biological factors [4]. New evidence has shown that metabolic disorders may have an important role in causing degenerative processes to happen, with abnormal lipid metabolism linked to dyslipidemia being strongly associated with causing the changes in the vertebral endplates due to the variations in type 2 diabetes in the absence of excessive mechanical stress [5]. These results underscore the necessity to introduce metabolic health indicators in the degeneration assessment models. The development of quantitative MRI has also contributed to the

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knowledge on the early-stage degeneration of the disc [6]. This concept has motivated the development of quantitative MRI-derived metabolic evidence to correlate systemic metabolic changes with disc tissue composition, which could be used to more precisely grade the severity of degeneration. Next, it can be followed by combining the structural, biochemical, and metabolic information to allow the effective diagnosis of early disease [7].

Besides imaging phenomena, biomechanical variables have also been proved to be the most important factors in the development of degenerative processes in the surrounding intervertebral discs [8]. The fact that spinal mechanics are closely related to degenerative pathology is supported by the observation that altered load distribution, including thoracolumbar fracture and kyphotic deformity, accelerate the degenerative process in the adjacent intervertebral discs. In conjunction with improvements in the field of diagnostics, regenerative approaches have proven to be promising in altering the progression of diseases and have been shown to reduce inflammatory processes, promote the maintenance of extracellular matrix, and maintain the structure of the disc [9]. These findings suggest the potential for biological therapies that target underlying degenerative mechanisms rather than solely addressing symptoms. In addition, the clinical relevance of specific MRI features has been re-evaluated. High-intensity zones within lumbar discs, once considered incidental findings, have been found to correlate strongly with chronic low back pain, highlighting their diagnostic and prognostic value [10]. These results indicate the possibility of biological treatment through the targeting of the underlying degenerative mechanisms instead of addressing symptoms. Moreover, the diagnosis and prognosis of chronic low back pain have also been proposed to rely on high intensity zones in the lumbar discs, which previously were considered as incidental results, indicating the strong correlation between these factors and disease progression and individual risk profile [11]. The idea of effective age of a disc has also been presented, where level-specific imaging data is used to estimate degeneration based on biological age and not the chronological age itself. Systematic reviews and studies at the molecular level have reified the value of methodological consistency and biological integration of the lumbar disc with segmentation of the lumbar disc showing that model reliability and generalizability largely depends on the diversity of the datasets, imaging protocols, and annotation quality [12]. Quantitative MRI analyses have also shown notable age and sex differences in disc composition, which is manifested in the differences of T1r signals, and that further demonstrates the necessity of considering demographic and biological variability [13]. On the molecular level, it has also been found that the pyruvate dehydrogenase kinase 4 (PDK4) is an important regulator of ferroptosis in degenerative discs, and that is why the development of cellular death mechanisms and the manifestations of degenerative alterations, which can be observed on imaging, are directly connected [14]. To conclude, the current tendencies in research of lumbar spine are concerned with implementing models of the integrated diagnosis that represent the complexity of disc degeneration. The suggested study will help create a new model of clinical decision-support systems, through incorporation of MRI-based measures with personalized clinical and metabolic measures, which will solve the issue of lumbar degeneration and improve clinical treatment of the disease [15].

2. Literature Review

Lumbar degeneration (LDD) is a common and often debilitating spinal condition, which is generally characterized by chronic back pain, loss of mobility and progressive loss of the integrity of the intervertebral discs. A coming

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together of genetic predisposition, repetitive mechanical stress, and progressive biochemical changes undermining disc tissue with time are factors that contribute to the development. Nowadays, more attention is paid to non-invasive imaging biomarkers through the early identification of degenerative changes. A correlation has been determined between disc height measurements made using standard X-ray imaging and MRI images, such as disc bulging and herniation [16]. Access to publicly available lumbar spine MRI data and standardized disc and vertebral segmentation benchmarks have enabled the sound development and verification of automatic analysis techniques in images. All these developments have led to a higher level of diagnostic accuracy, enhanced stability, and reproducibility in the study of LLD [17].

Metabolic health is also another important fact in disc degeneration in addition to structural changes. The body of evidence is increasingly associating intervertebral disc degeneration and changes in the Modic changes with dyslipidemia, especially the high concentration of triglycerides, which implies that lipid metabolism disturbances could be the accelerating factors in the degeneration of spinal tissues [18]. Genetic studies have suggested that triglycerides can serve as a linking factor between diabetes mellitus type 2 and degeneration of the disc which can explain the effects of systemic metabolic diseases on the health of the spinal in a molecular basis [19]. Advances in quantitative MRI methods, e.g., T2 mapping, made it possible to detect subtle biochemical changes in the facet joints and intervertebral discs, e.g. early decreases in the proteoglycan and collagen content, before the structural damage becomes apparent [20]. On the same note, metabolic quantifiers, obtained by MRI, have been used to assess the severity of LLD, and there is continued evidence that the reduction of water content and reduction in proteoglycan concentration are strong indicators of disc degeneration.

Overall, all these results highlight the importance of metabolic and biochemical imaging markers in understanding the biological processes that lead to LLD development [21]. The automated image analysis has begun to play a substantial role in spinal imaging as it makes the diagnostic assessments objective and reproducible. The techniques that have been developed to automatically detect and measure lumbar disc degeneration using MRI images have proved to be both accurate and reliable to the same extent or even higher than traditional manual methods [22]. The approaches reduce subjectivity and maximize consistency in large imaging datasets. Moreover, the reviews of automated lumbar disc segmentation techniques prove that the methods lead to the improvement of measurement and a significant reduction of inter-observer error, which leads to more reliable diagnostic outcomes in clinical or research practice [23].

Spinal alignment and load also play a critical role in the progression of disc degeneration besides imaging and biological factors. According to research of thoracolumbar fractures that include kyphotic deformity, altered spinal biomechanics, and distorted load distribution may jeopardize normal spinal body balance and accelerate degenerative changes at the adjacent intervertebral discs [24]. Sustained mechanical stress enhances the progressive loss of disc integrity as time goes by. Results of comparative research on extracellular vesicles produced by the nucleus pulposus cells and mesenchymal stem cells show that both vesicles have the ability to counter degenerative processes but vesicles of the nucleus pulposus cells are more effective in restoring extracellular matrix composition [25]. The results create a connection between biomechanical degeneration and

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the creation of new regenerative remedial measures. Moreover, recent re-evaluations of high-intensity zones detected by MRI have shown that the features do not always imply true disc pathology and therefore careful interpretation is required to improve clinical assessment and management of disc related pain [26]. The recent developments in machine learning and deep learning have made a massive expansion of the use of computational approaches to lumbar disc degeneration. The convolutional neural networks (CNNs) have become highly popular in the analysis of lumbar spine MRI and used to classify discs, analyze degeneration severity, and detect disc herniation. Unlike the traditional methods, which rely on the manually created features, CNNs independently derive meaningful patterns in the images, which help achieve increased accuracy and scalability in analysis [27]. This has enabled them to directly handle raw imaging data in a manner that has led to increased reliability of these models in a wide range of scanners, imaging protocols, and patient demographics. A number of studies have made use of the multi-task learning techniques of allowing one model to perform various interrelated tasks, such as disc segmentation, degeneration grading, and disease classification. These structures maximize effectiveness and produce more reliable results through sharing information of the tasks [28]. These models have improved through the addition of attention mechanisms that enable the models to focus on areas that are of clinical significance, e.g. compromised areas of the nucleus pulposus or annulus fibrosus. This increased transparency helps clinicians to understand and believe the predictions of automated systems. Investigators have recently gone beyond image analysis to combine clinical, biomechanical, and demographic data in addition to MRI data. Imaging characteristic models that combine patient-specific factors like age, body mass index, physical activity and their metabolic indicators have proved to be more effective in predicting disease severity and progression [29]. Such a combined approach is a more appropriate description of the complex nature of lumbar disc degeneration and allows a more customized assessment and therapy plan. Longitudinal research efforts with the aim of predicting disc degeneration with time are gaining interest. These models can be used to help identify the patients who have an increased risk of a faster progression of the disease through the analysis of follow-up MRI scans and the observation of disc morphology and signal intensity changes [30]. The timely diagnosis can lead to the timely intervention by clinicians, which could reduce the probability of major symptoms or the need to operate.

Despite such positive gains, there are still a lot of challenges. The generalizability of automated models can be limited by factors including imbalanced datasets, varying annotations of experts and differences between imaging centers. In an attempt to reduce such problems, researchers have explored the procedures comprising data augmentation, transfer learning and cross-institutional validation to improve model stability and clinical usefulness [31]. Simultaneously, explainable artificial intelligence methods are increasingly being used to make the decisions of the models more transparent, which would enable their interpretation by clinicians. The last research has emphasized the importance of integrating the use of the computational tools into the everyday clinical practice. Automated decision-support systems that are designed to serve radiologists and spine experts have been shown to have the potential of reducing the time taken to make a report, increase the consistency of diagnosis, and help make more informed clinical decision-making [32]. Together, these developments help to highlight the growing importance of intelligent imaging in the process of improving the diagnosis, monitoring, and management of lumbar disc degeneration.

3. Problem Statement

- Lumbar spine MRI can be manually interpreted and time-consuming, as it highly relies on the expertise of the radiologist.
- There is great inter-observer variation that results in unreliable diagnosis and grading of disc degeneration and spinal stenosis.
- The current AI methods are mostly based on image processing only, disregarding the issues of patient-specific clinical and metabolic aspects.
- The initial biochemical and metabolic alterations in discs can hardly be identified with standard diagnosis procedures.
- Existing systems do not have embedded applications of a diagnosis, severity estimation and treatment planning.
- Automated, data-driven decision models can occasionally be utilized to provide personalized treatment recommendations.

4. Conclusion

The article introduces a clever and automatic system that can help physicians more effectively recognize lumbar disc degeneration and spinal stenosis through MRI scans, which can support more consistent and reliable clinical decision making through the application of a deep learning framework and patient-specific clinical information. This approach would be more realistic and context-aware and will help radiologists and spine specialists to diagnose, grade, and plan treatments of chronic lower back pain.

Declarations

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Competing Interests Statement

The authors have not declared any conflict of interest.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors took part in literature review, analysis, and manuscript writing equally.

Informed Consent

Not applicable for this study.

Availability of data and material

Supplementary information is available from the authors upon reasonable request.

Institutional Review Board Statement

Not applicable for this study.

Ethical Approval

Not applicable for this study.

References

[1] Lin, P.-C., Chang, W.-S., Hsiao, K.-Y., Liu, H.-M., Shia, B.-C., Chen, M.-C., Hsieh, P.-Y., Lai, T.-W., Lin, F.-H., & Chang, C.-C. (2024). Development of a machine learning algorithm to correlate lumbar disc height on X-rays with disc bulging or herniation. Diagnostics 14: 134. https://doi.org/10.3390/diagnostics14020134.

[2] van der Graaf, J.W., van Hooff, M.L., Buckens, C.F.M., Rutten, M., van Susante, J.L.C., Kroeze, R.J., de Kleuver, M., van Ginneken, B., & Lessmann, N. (2024). Lumbar spine segmentation in MR images: a dataset and a public benchmark. Scientific Data 11: 264. https://doi.org/10.1038/s41597-024-03090-w.

[3] Yuan, L., Huang, Z., Han, W., et al. (2023). The impact of dyslipidemia on lumbar intervertebral disc degeneration and vertebral endplate modic changes: a cross-sectional study of 1035 citizens in China. BMC Public Health 23: 1302. https://doi.org/10.1186/s12889-023-16224-3.

[4] Chen, D.Q., Xu, W.B., Chen, X., et al. (2023). Genetically predicted triglycerides mediate the relationship between type 2 diabetes mellitus and intervertebral disc degeneration. Lipids in Health and Disease 22: 195. https://doi.org/10.1186/s12944-023-01963-4.

[5] Ding, Y., Liu, L., Shi, J., Zhang, X., Chen, R., & Xu, S. (2024). Biochemical changes in lumbar facet joint and disc degeneration by T2* mapping. BMC Musculoskeletal Disorders 25: 224. https://doi.org/10.1186/s12891-024-07265-9.

[6] Zheng, B., Ouyang, L., Shi, J., et al. (2024). Evaluating lumbar disc degeneration by MRI quantitative metabolic indicators: the perspective of factor analysis. Journal of Orthopaedic Surgery and Research 19: 281. https://doi.org/10.1186/s13018-024-04726-8.

[7] Liawrungrueang, W., Cholamjiak, W., Sarasombath, P., Jitpakdee, K., & Kotheeranurak, V. (2024). Artificial intelligence classification for detecting and grading lumbar intervertebral disc degeneration. Spine Surgery and Related Research 8: 552–559. https://doi.org/10.22603/ssrr.2024-0154.

[8] Cui, X.-L., Yang, W.-M., Ding, A., Zhu, J., Zhang, W., Wu, H., Jiang, J.-S., Zhai, Y.-L., Yu, H.-Y., & Hua, Z.-K. (2024). Characteristics and mechanical mechanisms of intervertebral disc degeneration in old thoracolumbar fractures with kyphosis: clinical observations and finite element analyses. BMC Musculoskeletal Disorders 25: 1040. https://doi.org/10.1186/s12891-024-08157-8.

[9] Ambrosio, L., Schol, J., Ruiz-Fernandez, C., et al. (2024). ISSLS prize in basic science 2024: superiority of nucleus pulposus cell- versus mesenchymal stromal cell-derived extracellular vesicles in attenuating disc degeneration and alleviating pain. European Spine Journal 33: 1713–1727. https://doi.org/10.1007/s00586-024-08163-3.

[10] Sima, S., Chen, X., Sheldrick, K., Kuan, J., & Diwan, A.D. (2024). Reconsidering high intensity zones: its role in intervertebral disk degeneration and low back pain. European Spine Journal 33: 1474–1483. https://doi.org/10.1007/s00586-024-08185-x.

[11] Newman, H.R., Peloquin, J.M., Meadows, K.D., Bodt, B.A., Vresilovic, E.J., & Elliott, D.M. (2025). Effective disc age: a statistical model for age-dependent and level-specific lumbar disc degeneration using magnetic resonance imaging (MRI). European Spine Journal: 1–12. https://doi.org/10.1007/s00586-025-08729-9.

[12] Wang, A., Zou, C., Yuan, S., Fan, N., Du, P., Wang, T., & Zang, L. (2024). Deep learning assisted segmentation of the lumbar intervertebral disc: a systematic review and meta-analysis. Journal of Orthopaedic Surgery and Research 19: 496. https://doi.org/10.1186/s13018-024-05002-5.

[13] Bonnheim, N.B., Lazar, A.A., Kumar, A., Akkaya, Z., Zhou, J., Guo, X., O’Neill, C., et al. (2023). ISSLS prize in bioengineering science 2023: age- and sex-related differences in lumbar intervertebral disc degeneration between patients with chronic low back pain and asymptomatic controls. European Spine Journal 32: 1517–1524. https://doi.org/10.1007/s00586-023-07542-6.

[14] Chen, W., Yang, W., Meng, B., Wang, X., Duan, H., Xu, Q., & Li, H. (2025). Validation and the role of PDK4 relevant to ferroptosis in degenerative lumbar disc disease. Journal of Orthopaedic Surgery and Research 20: 30. https://doi.org/10.1186/s13018-024-05293-8.

[15] Saeed, A., Shao, H., Hezam, K., Liu, C., Zhang, Q., & Tang, X. (2024). Research trend of MRI application for lumbar disc degeneration with low back pain: a bibliometric analysis. Frontiers in Neurology 15: 1360091. https://doi.org/10.3389/fneur.2024.1360091.

[16] Hussain, M., Koundal, D., & Manhas, J. (2023). Deep learning-based diagnosis of disc degenerative diseases using MRI: a comprehensive review. Computers and Electrical Engineering 105: 108524. https://doi.org/10.1016/j.compeleceng.2022.108524.

[17] Gu, H., Hong, J., Wang, Z., Chen, J., Yuan, F., Jiang, Y., Yang, Y., et al. (2024). Association of MRI findings with paraspinal muscles fat infiltration at lower lumbar levels in patients with chronic low back pain: a multicenter prospective study. BMC Musculoskeletal Disorders 25: 549. https://doi.org/10.1186/s12891-024-07649-x.

[18] Saravi, B., Zink, A., Ülkümen, S., Couillard-Despres, S., Wollborn, J., Lang, G., & Hassel, F. (2023). Clinical and radiomics feature-based outcome analysis in lumbar disc herniation surgery. BMC Musculoskeletal Disorders 24: 791. https://doi.org/10.1186/s12891-023-06911-y.

[19] Chen, Y., Huang, Q., Zhang, C., Li, J., Huang, W., Luo, P., Chen, Q., et al. (2025). Deep learning-based computer-aided diagnostic system for lumbar degenerative diseases classification using MRI. Biomedical Signal Processing and Control 109: 108002. https://doi.org/10.1016/j.bspc.2025.108002.

[20] Barnes, N.A., Dkhar, W., Kadavigere, R., Sukumar, S., Vaishali, K., Pradhan, A., Priya, P.S., Prabhu, A., & Raj, N. (2025). Quantitative assessment of early intervertebral disc degeneration with MR diffusion kurtosis imaging: a radiologic correlation with Pfirrmann grade. Magnetic Resonance Imaging: 110592. https://doi.org/10.1016/j.mri.2025.110592.

[21] Wen, Q., Wang, J., Tan, G., Huang, Y., Wang, H., Ding, X., Liu, K., Zhang, Y., & Tan, W. (2025). Association between lumbar disc degeneration at L4–L5 level and atrophy of paraspinal muscles and gluteus medius: a cross-sectional study using 3T quantitative magnetic resonance imaging. BMC Medical Imaging.

[22] Xu, Y., Liu, S., Tian, Q., Kou, Z., Li, W., Xie, X., & Wu, X. (2025). Deep learning-based multimodal integration of imaging and clinical data for predicting surgical approach in percutaneous transforaminal endoscopic discectomy. European Spine Journal: 1–10. https://doi.org/10.1007/s00586-025-08668-5.

[23] Wang, H., Li, X., Wang, S., Liu, J., & Xie, N. (2025). A bibliometric study of interleukin cytokines in the treatment of intervertebral disc degeneration. Drug Design, Development and Therapy: 5801–5819. https://doi.org/10.2147/dddt.s523151.

[24] Bhari Thippeswamy, P., Rajasekaran, S., Ramachandran, K., Easwaran, M., Ramadevi, S.S., Vijay Anand, K.S.S., Shetty, A.P., & Kanna, R.M. (2025). Role of magnetic resonance spectroscopy and T2 relaxometry as imaging biomarker of early lumbar intervertebral disc degeneration. Global Spine Journal 15: 2736–2743. https://doi.org/10.1177/21925682241311515.

[25] McSweeney, T., Tiulpin, A., Kowlagi, N., Määttä, J., Karppinen, J., & Saarakkala, S. (2025). Robust radiomic signatures of intervertebral disc degeneration from MRI. Spine. https://doi.org/10.1097/brs.0000000000005435.

[26] Elmounedi, N., & Keskes, H. (2025). Innovative therapeutic strategies used in the regenerative medicine of the intervertebral disc degeneration. Tissue and Cell: 103069. https://doi.org/10.1016/j.tice.2025.103069.

[27] Liu, S., Hu, W., Lin, Y., Liao, N., Shi, H., Chen, J., Chen, Y., et al. (2025). Relationship between paraspinal sarcopenia and lumbar alignment and facet joint osteoarthritis in patients with degenerative lumbar spinal stenosis. Spine 50: 1509–1515. https://doi.org/10.1097/brs.0000000000005238.

[28] Lee, Y.J., Liu, C., Ting, Y.H., Makmur, A., Sng, W.J., Cheng, A.J.L., Tan, J.H., et al. (2025). Deep learning models for lumbar spinal stenosis on MRI: model comparison and clinical benchmarking. European Spine Journal: 1–11. https://doi.org/10.1007/s00586-025-09443-2.

[29] Watanabe, N., Yagi, M., Mizukoshi, R., Ito, K., Isogai, N., Funao, H., & Fujita, R. (2025). Age-specific modifiable determinants and nonlinear risk patterns of habitual low back pain in a large medical check-up cohort: a cross-sectional and longitudinal analysis. The Spine Journal. https://doi.org/10.1016/j.spinee.2025.10.001.

[30] Ishak, H., Sunna, T.P., Assaf, S.A., Banna, H., Khouzami, R.A., Wang, Z., Zaatari, G., Rahme, D., & Sakr, C.J. (2025). Waterpipe smoking and lumbar intervertebral disc degeneration: a pilot study. Global Spine Journal 15: 2102–2108. https://doi.org/10.1177/21925682241286451.

[31] Pattnaik, S., Goyal, M., Gujral, R.K., & Mittal, A. (2025). A systematic review and meta-analysis on the diagnostic accuracy of artificial intelligence and computer-aided diagnosis of lumbar prolapsed intervertebral disc. Neuroscience Informatics: 100221. https://doi.org/10.1016/j.neuri.2025.100221.

[32] Chaddad, A., Hu, Y., Wu, Y., Wen, B., & Kateb, R. (2025). Generalizable and explainable deep learning for medical image computing: an overview. Current Opinion in Biomedical Engineering 33: 100567. https://doi.org/10.1016/j.cobme.2024.100567.