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ADVANCES IN THE APPLICATION OF DEEP LEARNING IN CERVICAL OSSIFICATION OF THE POSTERIOR LONGITUDINAL LIGAMENT

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Abstract: Cervical ossification of the posterior longitudinal ligament (OPLL) is relatively common among Asian populations. Its progression can cause spinal canal stenosis and compression of the spinal cord and nerve roots, leading to neurological dysfunction and increasing surgical complexity and the risk of complications. In recent years, early identification, precise evaluation, and appropriate intervention for OPLL have become major focuses in radiology and spine surgery. Artificial intelligence, particularly deep learning, has shown new potential in the detection, lesion segmentation, and prognostic evaluation of this disease. This article integrates existing studies to summarize the advances of deep learning in multimodal imaging and discusses its value in clinical decision support, aiming to provide methodological references and clinical insights for related disciplines.
Keywords: Deep learning; Cervical ossification of the posterior longitudinal ligament; Multimodal medical imaging; Risk prediction

1 INTRODUCTION

Cervical ossification of the posterior longitudinal ligament (OPLL) is a distinctive subtype of degenerative spinal disease. Its defining feature is ectopic ossification of the posterior longitudinal ligament, with ossified lesions protruding into the spinal canal, resulting in canal stenosis, spinal cord compression, and subsequent neurological dysfunction[1–4]. The prevalence of OPLL is markedly higher in Asian populations than in Western countries. Epidemiological data indicate that middle-aged and elderly men in Korea and other East Asian regions are more susceptible to OPLL, which is closely related to genetic predisposition, metabolic abnormalities, and long-term mechanical stress[5]. As the disease progresses, the ossified mass gradually thickens and compresses the spinal cord, leading to symptoms such as upper-limb numbness, gait disturbance, and limb weakness. Even minor trauma can precipitate central cord injury in advanced cases[6-9]. Previous surgical follow-up studies have demonstrated that OPLL is one of the major causes of cervical myelopathy and a key factor influencing surgical strategy and prognosis[10]. Therefore, early detection and timely intervention are essential for preventing disease progression and improving neurological outcomes.

At present, radiographic screening primarily relies on anteroposterior and lateral cervical X-rays, which can reveal characteristic ossified lesions or high-density shadows within the spinal canal. However, this approach is insensitive to early or segmental lesions, with a reported miss rate of approximately 48%[11]. In comparison, computed tomography (CT) provides detailed visualization of bony structures and is regarded as the preferred modality for diagnosing OPLL. CT enables accurate assessment of ossification morphology, thickness, and segmental distribution, thereby assisting in canal stenosis evaluation and preoperative planning. Systematic studies consistently report that CT surpasses plain radiography in both lesion detection and anatomical delineation; however, its higher radiation dose and cost limit its use in long-term follow-up, especially for postoperative patients who require periodic monitoring of ossification progression[12–14]. Magnetic resonance imaging (MRI), on the other hand, offers superior evaluation of soft tissue and spinal cord pathology, allowing direct visualization of spinal cord compression and intramedullary signal changes. Nevertheless, MRI has limited capability for depicting calcified or ossified components, and OPLL may be confounded with ligamentous hypertrophy or intervertebral disc calcification, leading to reduced diagnostic accuracy on conventional sequences[16–17].

With the advancement of artificial intelligence (AI) and deep learning technologies, novel strategies have emerged for the early diagnosis and quantitative assessment of OPLL. Current studies mainly focus on three domains: (1) automatic detection of ossified regions based on X-ray or CT images; (2) assessment of spinal cord involvement and direct identification of OPLL using MRI combined with deep learning algorithms; and (3) clinical prediction models for surgical risk and postoperative prognosis, including complication rates and functional recovery. This review systematically summarizes recent progress in the application of deep learning to multimodal imaging—X-ray, CT, and MRI—for the detection, segmentation, and prognostic evaluation of OPLL, aiming to provide methodological references and clinical perspectives for future research.

2 MATERIALS AND METHODS

A systematic literature search was conducted on September 1, 2025, across the PubMed, MEDLINE, and Web of Science databases. The search strategy followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The following medical subject headings (MeSH) and keywords were used: *"artificial intelligence"* OR *"AI"* OR *"machine learning"* OR *"ML"* OR *"deep learning"* OR *"DL"*, combined with *"ossification of the posterior longitudinal ligament"* OR *"OPLL"*. The search was primarily limited to English-language studies published within the past eight years (2017–2025).
To ensure the comprehensiveness of this review, several earlier seminal studies with substantial academic or clinical influence were also cited in the Discussion section as supplementary references.
Inclusion criteria:
(1) Studies applying artificial intelligence (AI) or machine learning (ML) techniques to cervical ossification of the posterior longitudinal ligament (OPLL);
(2) Human subject studies;
(3) English-language publications;
(4) Peer-reviewed original research articles.
Exclusion criteria:
(1) Non-original research (e.g., review articles, commentaries, conference abstracts, or case reports) and unpublished studies;
(2) Studies focusing on non-OPLL topics or using non-clinical data.
The initial database search identified 163 records. After sequentially excluding studies published outside the specified time frame, papers with inappropriate article types, and non-English publications, a total of 73 studies remained for full-text screening. Following rigorous evaluation according to predefined inclusion criteria, 12 original research articles were finally included in this review.

3 APPLICATION OF DEEP LEARNING IN THE DIAGNOSIS AND QUANTIFICATION OF OPLL

Deep learning technology has been applied to the automatic recognition and segmentation of OPLL across various imaging modalities. This article first reviews deep learning–based methods for the diagnosis and quantification of OPLL using X-ray, CT, and MRI images, and compares the similarities and differences in model performance among these different modalities.

3.1 OPLL Auxiliary Diagnosis Based on X-Ray

Traditional anteroposterior and lateral cervical X-rays are prone to missed diagnoses and misjudgments due to overlapping tissues and subtle calcified lesions. In recent years, several studies have attempted to apply deep learning to the identification of OPLL on X-rays to enhance screening capability.
Murata et al. trained a residual network model on 2,318 radiographs (672 cases) and achieved an overall accuracy of 98.9%, sensitivity of 97.0% [18], specificity of 99.4%, and an AUC of 0.99, demonstrating the potential of OPLL binary screening. Ogawa et al. conducted a small-sample study (50 OPLL cases and 50 controls) and showed that their convolutional neural network performed well in detecting OPLL on X-rays (AUC = 0.924, sensitivity 80%, specificity 100%) [19]. Miura et al. first demonstrated that using the EfficientNet-B4 model for three-category classification of lateral cervical radiographs could reach expert-level performance (accuracy 0.86) [20]; however, its performance was limited in cases with segmental or localized OPLL and in low-quality images, indicating a need for improvement. The study also emphasized the clinical potential of AI for early OPLL screening.
Notably, Chae et al. conducted an observer study showing that incorporating AI model results into film reading assistance could improve diagnostic performance [11]. When the AI model analyzed patients independently, its AUC was 0.851 (sensitivity 91%, specificity 69%); when radiologists performed a second review with AI assistance after their initial interpretation, the average patient-based AUC increased from 0.841 to 0.911, suggesting that AI is better suited as an auxiliary reading tool to enhance overall diagnostic performance.
Overall, deep learning can screen for OPLL on cervical X-rays with high sensitivity, reducing missed and incorrect diagnoses caused by limited CT examinations, and has potential value in health check-ups or primary care. AI-based automatic screening using plain radiographs can not only reduce unnecessary CT radiation exposure but also assist physicians in early diagnosis. However, differences remain among studies in sample size, external validation, and annotation standards, and further multicenter and standardized studies are needed to verify clinical generalizability.

3.2 Quantitative Segmentation of OPLL Based on CT

Cervical CT is considered the gold standard for diagnosing OPLL because ossified lesions can be clearly visualized, and manual reading maintains high sensitivity and specificity. Therefore, deep learning studies directly targeting OPLL detection on plain CT scans are relatively limited. Clinically, the advantage of CT lies more in the precise quantification of the range and volume of ossified lesions, providing an important basis for surgical planning. In recent years, as deep learning technology has matured, it has become feasible to quantify the extent and volume of OPLL ossification from CT images.

Jiang et al. conducted a dual-center study based on CT data from 307 patients [21], constructing a 3D U-Net segmentation model that simultaneously quantified the maximum ossification thickness, residual spinal canal diameter at the corresponding level, and the “spinal cord compression coefficient.” The model achieved a Dice coefficient of 0.71 and an average surface distance (ASD) of 2.63 mm on the external test set, showing little difference from manual measurement. External validation demonstrated that automatic segmentation and compression quantification on the CT platform have clinical feasibility. Overall, CT imaging—with its rich anatomical detail—is highly suitable for the segmentation and quantification of OPLL ossified lesions using deep learning. The automatically segmented results can also be applied to preoperative 3D visualization and simulated surgical planning. However, CT segmentation models require large amounts of slice-by-slice annotated data for training, which entails a heavy labeling workload. Currently, publicly reported studies of this type remain limited, but their performance demonstrates that deep learning has the potential to significantly reduce physicians’ measurement workload while maintaining high accuracy.

3.3 OPLL Auxiliary Diagnosis Based on MRI

MRI is highly sensitive for displaying soft tissue and spinal cord lesions, but its ability to visualize ossified lesions is inferior to that of CT. Nevertheless, some researchers have attempted to develop deep learning models based on MRI, hoping to identify OPLL patients directly from MRI without relying on CT.

Shemesh et al. developed an MRI-AI tool based on a single-center cohort of consecutive patients (900 cases within 36 months, including 65 OPLL cases) [22]. The tool can automatically layer and segment the vertebral bodies, posterior longitudinal ligament, and disc-ligament complex, and identify OPLL at the patient level. In a reader comparison study, the model achieved a sensitivity of 85%, specificity of 98%, and overall accuracy of 98%, and additionally detected five OPLL cases that were initially missed by manual interpretation, suggesting that MRI combined with AI also has high discriminative ability even without CT.

In addition, Qu et al. constructed MRI classification models based on ResNet34/50/101 using surgical cases (272 OPLL cases and 412 cases of degenerative stenosis) [23]. In the test set, the model accuracies reached 92.98%, 95.32%, and 97.66%, respectively. Among them, the accuracy and specificity of ResNet50/101 were significantly higher than those of three spine surgeons, and ResNet101 also achieved higher sensitivity than two of them, further demonstrating that deep neural networks can enhance the detection performance of OPLL on MRI.

Overall, MRI-AI has shown considerable potential in the automatic stratification and detection of OPLL. However, multicenter external validation and finer-grained lesion-level segmentation studies are still needed to achieve CT-equivalent quantitative assessment of ossified lesions and promote clinical application.

4 APPLICATION OF DEEP LEARNING IN PROGNOSIS

In addition to assisting diagnosis, deep learning has begun to play a role in preoperative decision support and prognosis prediction for OPLL patients. By integrating imaging and clinical data, AI models can be used to predict surgical approach selection, postoperative complication risks, and functional recovery, thereby helping clinicians develop more optimized treatment strategies. The following section summarizes several representative studies on predictive models.

4.1 Preoperative Decision Support for OPLL

The choice of surgical approach for cervical OPLL (anterior, posterior, or combined) has long been controversial. The decision requires comprehensive consideration of the ossification range, spinal canal occupancy ratio, and the K-line (cervical lordotic line). Traditionally, this judgment is qualitatively made by experienced spine surgeons based on imaging, which inevitably introduces subjectivity. Deep learning can transform such empirical knowledge into reusable and standardized models.

Li et al. proposed a two-stage process of “Dilated TransUNet + discriminative post-processing. [24]” First, a U-Net variant combining dilated convolution and Transformer was used to detect the four boundary points (C2–C7) on lateral cervical CT images and reconstruct the K-line. Then, within the ROI formed by these four points, a bimodal histogram–based dynamic threshold and left–right “white zone” continuity difference were used to distinguish the artifacts of “ossification crossing the line” and “vertebral crossing the line,” outputting the K-line determination. The test results showed an average keypoint detection error of 1.463 ± 3.007 pixels, SDR-5 of 98.49%, and SDR-9 of 98.90%; 97.8% of images had all four points located within 5 pixels. Compared with baseline models such as ASM, U-Net, and TransUNet, the new method achieved better overall accuracy and significantly reduced misidentification at the easily confused C7 level, effectively suppressing interference from “ossification crossing” or “vertebral crossing.” Converting K-line determination from manual drawing to standardized, reproducible automatic evaluation facilitates standardized surgical approach selection, surgeon–patient communication, and structured preoperative stratification.

4.2 Postoperative Risk and Prognostic Prediction for OPLL

Surgery for OPLL is technically demanding, and postoperative complications such as neurological injury, C5 nerve root palsy, dural tears, and infection are not uncommon. Identifying high-risk patients preoperatively and implementing targeted preventive measures could improve surgical safety.

Ito et al. conducted a multicenter prospective study (28 institutions, 478 cases) and trained a deep learning model using preoperative clinical and imaging features [25]. The model achieved an overall prediction accuracy for complications of 74.6%, comparable to logistic regression (74.1%); for neurological complications specifically, accuracy reached 91.7%, indicating feasibility for use in risk communication.

Kim et al. developed various machine learning models using a single-center retrospective cohort of 901 cases. The best-performing model achieved an AUC of 0.88, significantly higher than logistic regression (AUC = 0.69) [26]. The model identified age, surgical approach, involvement of the C1–C3 segments, and immediate postoperative shoulder pain as factors associated with C5 palsy, suggesting enhanced intraoperative protection and postoperative monitoring. This finding indicates that machine learning can be used for early warning of specific complications.

Regarding postoperative functional improvement, Maki et al. developed a preoperative prediction model using data from 478 cases to determine whether cervical OPLL patients would achieve “minimal clinically important difference (MCID)” at 1 year and 2 years after surgery [27]. The XGBoost model performed best at 1 year (AUC = 0.72, accuracy 67.8%), while the random forest model performed best at 2 years (AUC = 0.75, accuracy 69.6%). These results demonstrate the feasibility of constructing postoperative prognostic ML models in OPLL populations, with current discriminative power at a moderate level (evidence level 4), providing a reference for expectation management and rehabilitation planning.

For ossification progression prediction, Qin et al. developed an interpretable model to predict postoperative re-ossification and progression risks [28]. They extracted radiomics features from preoperative CT images of 473 followed-up postoperative patients and combined them with clinical variables. The combined model achieved an AUC of 0.751 on the test set, outperforming radiomics-only (AUC = 0.693) and clinical-only models (AUC = 0.620). The results support that “preoperative CT radiomics + clinical variables” can enable individualized prediction of postoperative progression risk of OPLL, facilitating clinical interpretation and personalized follow-up.

5 CURRENT RESEARCH STATUS AND LIMITATIONS

Based on existing findings, the application of deep learning to multimodal imaging in OPLL has become increasingly well defined. X-ray–based intelligent models are mainly used for rapid screening and reducing missed diagnoses. CT-based algorithms focus on lesion segmentation and quantitative feature extraction, such as ossified volume and thickness, providing objective references for preoperative planning. MRI-related models can avoid ionizing radiation and have achieved high accuracy in individualized diagnosis. Notably, integrated models combining imaging and clinical variables have demonstrated diagnostic performance comparable to or even superior to traditional methods in predicting postoperative complications and functional recovery. Overall, AI tools in the OPLL field are evolving from simple recognition toward quantitative analysis and clinical decision-support systems, showing practical value in early screening, surgical pathway selection, and risk communication.

Despite the remarkable progress, several critical bottlenecks remain at the current stage. Most models are built on retrospective, single-center data, lacking external validation and prospective study design, which limits their applicability to different populations. Meanwhile, inconsistency in the delineation of lesion boundaries and classification standards across studies and the absence of universally accepted annotation protocols hinder cross-study comparisons and affect model stability and generalization performance. In addition, model interpretability and uncertainty assessment have not received sufficient attention, reducing clinicians’ trust in algorithmic outputs and restricting their integration into real clinical workflows. Therefore, the translation of AI models into clinical practice for OPLL still requires further breakthroughs.

Future research can proceed along several directions. Strengthening multicenter collaboration and prospective study design will be essential to build diverse, high-quality datasets and improve model generalizability and robustness through cross-institutional validation. Meanwhile, establishing unified imaging annotation and grading systems to clearly define ossification boundaries and lesion types will facilitate model training and result comparison. Model transparency is equally important; techniques such as saliency visualization, feature-importance ranking, and confidence-interval estimation can help clinicians understand model reasoning and assess its reliability. Moreover, the stability of models under different scanner vendors, acquisition parameters, and image quality conditions also needs to be verified. With systematic improvements in data sharing, interpretability, and cross-domain validation, deep learning is expected to achieve a key transition—from algorithmic performance optimization to tangible patient benefit.

6 SUMMARY AND OUTLOOK

Cervical ossification of the posterior longitudinal ligament (OPLL) is a spinal disorder associated with a high risk of disability. Imaging examinations play a central role in establishing the diagnosis and formulating treatment strategies. In recent years, the rapid development of deep learning has created new opportunities for imaging-based recognition and preoperative decision-making in OPLL. Artificial intelligence–assisted analysis of multimodal imaging has demonstrated high accuracy and feasibility in multiple studies, while preoperative predictive models have shown clinical value in surgical strategy selection. Notably, deep learning–based approaches for complication risk assessment and postoperative functional prediction have achieved performance comparable to or even exceeding that of traditional models in some studies. Although these algorithms remain in the validation and optimization stage, the research direction of intelligent decision support for OPLL is becoming increasingly clear—by quantitatively evaluating preoperative risks and potential benefits, they can provide clinicians with more informative decision-making references.

Overall, deep learning is driving a paradigm shift in the diagnosis and treatment of OPLL. Its applications are expanding from image recognition to quantitative analysis and clinical decision support, leading to continuous optimization of diagnostic and therapeutic workflows. Further prospective validation and inter-institutional collaboration are required to ensure model robustness and generalizability. With the deepening integration of medicine and computational technology, deep learning is expected to become a routine tool for multidisciplinary teams in spinal disease management, enhancing the clarity of imaging interpretation, the precision of quantitative evaluation, and the reliability of therapeutic decision-making. Close collaboration among radiologists, spine surgeons, and algorithm researchers will accelerate the translation of technological advances into clinical benefits. Looking ahead, the role of deep learning in precision medicine for OPLL will continue to strengthen, ultimately aiming to provide patients with more accurate, safer, and personalized treatment strategies.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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