Artificial intelligence (AI) has the potential to significantly impact the field of medical imaging by providing more efficient and accurate diagnostic tools. This potential is supported by recent publications by Anand et al. and Celtikci,1,2 highlighting the potential of deep learning to automate image analysis and improve diagnostic efficacy and accuracy.

One of the conditions that may particularly benefit from the application of AI is cervical ossification of the posterior longitudinal ligament (C-OPLL), a multifactorial condition caused by abnormal lamellar bone deposition within the PLL that may lead to neurological deficits and increase perioperative complications in anterior cervical spine approaches.3–8 Currently, CT is considered the diagnostic gold standard for OPLL. Despite well-validated CT-based radiographic criteria proposed by the Investigation Committee on OPLL of the Japanese Ministry of Health and Welfare,9–11 diagnostic criteria for OPLL using MRI have

MRI-based detection of cervical ossification of the posterior longitudinal ligament using a novel automated machine learning diagnostic tool

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OBJECTIVE Currently, CT is considered the gold standard for the diagnosis of ossification of the posterior longitudinal ligament (OPLL). The objective of this study was to develop artificial intelligence (AI) software and a validated model for the identification and representation of cervical OPLL (C-OPLL) on MRI, obviating the need for spine CT.

METHODS A retrospective evaluation was performed of consecutive imaging studies of all adult patients who underwent both cervical CT and MRI for any clinical indication within a span of 36 months (between January 2017 and July 2020) in a single tertiary-care referral hospital. C-OPLL was identified by a panel of neurosurgeons and neuroradiologist. MATLAB software was then used to create an AI tool for the diagnosis of C-OPLL by using a convolutional neural network method to identify features on MR images. A reader study was performed to compare the performance of the AI model to that of the diagnostic panel using standard test performance metrics. Interobserver variability was assessed using Cohen's kappa score.

RESULTS Nine hundred consecutive patients were found to be eligible for radiological evaluation, yielding 65 identified C-OPLL carriers. The AI model, utilizing MR images, was able to accurately segment the vertebral bodies, PLL, and discoligamentous complex, and detect C-OPLL carriers. The AI model identified 5 additional C-OPLL patients who were not initially detected. The performance of the MRI-based AI model resulted in a sensitivity of 85%, specificity of 98%, negative predictive value of 98%, and positive predictive value of 85%. The overall accuracy of the model was 98%, with a kappa score of 0.917.

CONCLUSIONS The novel AI software developed in this study was highly specific for identifying C-OPLL on MRI, without the use of CT. This model may obviate the need for CT scans while maintaining adequate diagnostic accuracy. With further development, this MRI-based AI model has the potential to aid in the diagnosis of various spinal disorders and its automated layers may lay the foundation for MRI-specific diagnostic criteria for C-OPLL.

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KEYWORDS machine learning; artificial intelligence; neural network; OPLL; ossification of the posterior longitudinal ligament; MRI
not yet been established.\textsuperscript{12} The objective of this study was to develop AI software and a validated model for the characterization and diagnosis of C-OPLL on MRI, obviating the need for spine CT.

### Methods

We performed a retrospective evaluation of imaging studies in all adult patients who underwent both cervical CT and MRI for all clinical indications within a span of 36 months (between January 2017 and July 2020) in Sheba Medical Center, a single tertiary referral hospital located in central Israel. MRI was obtained by 3-T machines (Signa HD 3.0-T, GE Healthcare, and Ingenia 3.0-T, Philips). CT was acquired using a Revolution CT scanner (GE Healthcare). Patient demographics are presented in Table 1. As CT images are currently considered the gold standard for OPLL diagnosis, C-OPLL was identified using sagittally reconstructed cervical CT demonstrating the presence of diffuse, calcified, thickened PLL. C-OPLL was identified by a neurosurgery senior resident (G.K.) and reviewed by a senior neuroradiologist (G.Y.) and a senior spine neurosurgeon (R.H.; Fig. 1). C-OPLL location and maximal thickness were recorded. Basic patient demographics and the clinical indication for imaging were obtained from the MRI referral form. MATLAB software (The MathWorks, Inc.) was then used to create an AI tool for the diagnosis of C-OPLL by using a convolutional neural network model to identify features on MR images (Fig. 2). All C-OPLL carriers identified by the AI model were reviewed by two senior neurosurgeons (R.H. and a retired neurosurgeon). A reader study was performed to compare the performance of the AI model to that of the diagnostic panel using standard test performance metrics such as sensitivity, specificity, negative predictive value (NPV) and positive predictive value (PPV). Overall accuracy was defined as: (true positive + true negative)/(overall number of patients). Interobserver variability and reliability were assessed using Cohen’s kappa score.

### Image Processing

The MATLAB medical image processing toolbox (MATLAB version 2022b, The MathWorks, Inc.) was used for image processing. The MRI DICOM files were imported and analyzed in both sagittal and axial planes using T2-weighted sequences. In addition to the use of a randomized sample of patients, data augmentation techniques were employed to increase the variability in the training data set, thereby improving the generalizability of the AI model.

The OPLL and additional anatomical structures were segmented using a semiautomatic threshold-based method, which involves setting a threshold value to separate the ossified tissue from the surrounding environment.\textsuperscript{13} The segmented images were then reviewed by a senior neurosurgeon (R.H.) to ensure accuracy and to make any necessary adjustments. A set of features was extracted from the segmented images including the area, perimeter, voxel, and thickness of the OPLL. These features were used as input for the AI algorithm. Additionally, other features such as the location, shape, and intensity of the ossified tissue were extracted.

### AI Algorithm

The VGG16 learning method, a pretrained convolutional neural network model that has been used extensively and effectively in the classification of images for computer vision,\textsuperscript{14} was used to develop the AI algorithm.

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**TABLE 1. Patient demographics**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Negative OPLL</th>
<th>Positive OPLL</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of patients</td>
<td>735</td>
<td>65</td>
</tr>
<tr>
<td>Mean age ± SD, yrs</td>
<td>63.38 ± 9.2</td>
<td>62.76 ± 9.49</td>
</tr>
<tr>
<td>Females, n (%)</td>
<td>582 (79.2)</td>
<td>45 (69.2)</td>
</tr>
<tr>
<td>Mean max C-OPLL thickness ± SD, mm</td>
<td>2.4 ± 2.75</td>
<td>5.1 ± 1.24</td>
</tr>
<tr>
<td>Clinical indications, n (%)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cervicalgia</td>
<td>545 (74.1)</td>
<td>44 (67.7)</td>
</tr>
<tr>
<td>Myelopathy</td>
<td>301 (41)</td>
<td>16 (24.6)</td>
</tr>
<tr>
<td>Radiculopathy</td>
<td>124 (16.9)</td>
<td>13 (20)</td>
</tr>
</tbody>
</table>

* Obtained from MRI referral form.
The model was fine-tuned and trained using the extracted features and the corresponding labels of the patients to improve OPLL characterization on MRI. The algorithm was implemented in MATLAB (version 2020b) with the aid of deep learning, image processing, statistics, medical image, and machine learning toolboxes. The data set was split into two sets, training (75%) and validation (25%). The data used in this study were randomized to ensure that the model was trained and validated on a representative sample of the patient population. This method of randomization minimizes any potential bias in the sample selection and increases the generalizability of the results.

Reader Study

Following the automated training and validation of the AI model, the diagnostic panel (R.H. and G.K., i.e., the “readers”) independently evaluated 100 new CT and MRI scans, constituting a diagnostic benchmark for evaluating the diagnostic performance of the AI algorithm. Interobserver variability was assessed using Cohen’s kappa score to compare the accuracy of the AI algorithm to that of the reader.

Results

Nine hundred consecutive patients were found to be eligible for radiological evaluation, yielding 65 identified C-OPLL carriers. Patient demographics are displayed in Table 1. The MRI-based AI model identified C-OPLL carriers and was able to successfully segment the OPLL, vertebral bodies, and discoligamentous complex in all patients. The model identified 5 additional patients harboring C-OPLLs who were unrecognized on initial radiological screening by the diagnostic panel. A VGG16 internal architecture analysis revealed that the automated layers with the greatest impact on the model’s performance were the PLL maximal thickness, variations in signal intensity within the PLL, and the presence of kyphotic alignment. The reader study comprised 100 patients (Fig. 3). The performance of the MRI-based AI model resulted in a sensitivity of 85%, specificity of 98%, NPV of 98%, and PPV of 85%. The overall accuracy of the model was 98%, with a kappa score of 0.917.

Discussion

Accurate identification of C-OPLL is highly important when treating patients with neurological deficits attributed to compressive myelopathy. Anterior cervical approaches in the face of PLL ossification causing assimilation with the anterior cervical dura carry a high rate of inadvertent durotomy, associated with poor postoperative outcomes compared with posterior surgical approaches. Moreover, in severe cases, the OPLL mass may cause clinically symptomatic canal stenosis in areas beyond the reach of

![FIG. 2. Artist’s illustration depicting the VGG16 convolutional neural network workflow.](image-url)

![FIG. 3. AI algorithm confusion matrix. The matrix displays the number of true-positive, true-negative, false-positive, and false-negative results produced by the AI algorithm compared with the reader study.](image-url)
The novel AI software developed in this study showed promising results in its ability to identify C-OPLL on MRI without the use of CT scans. This promise has the potential to reduce radiation exposure for patients and support surgical preplanning and decision-making regarding the surgical approach. With further development, this MRI-based AI model has the potential to aid in the diagnosis of various spinal pathologies, offering the benefits of CT scans without the associated risks of radiation exposure.

Future Directions in AI-Based Diagnostics of Spinal Pathologies

The present study leverages the use of VGG16, a pre-trained convolutional neural network model, as the basis for the AI algorithm. This approach allows the transfer of knowledge acquired from other data sets to enhance the performance of the algorithm. VGG16 has gained widespread use in medical imaging and has been demonstrated to be effective in various applications such as lesion detection, image segmentation, and classification.17,18 The AI model’s automated segmentation output of MR images provides a foundation for the detection and representation of additional spinal pathologies, offering the benefits of CT scans without the associated risks of radiation exposure.

Conclusions

The novel AI software developed in this study showed promising results in its ability to identify C-OPLL on MRI without the use of CT scans. This promise has the potential to reduce radiation exposure for patients and support surgical preplanning and decision-making regarding the surgical approach. With further development, this MRI-based AI model has the potential to aid in the diagnosis of various spinal disorders, and its automated layers may lay the foundation for MRI-specific diagnostic criteria for C-OPLL.

References

2. Celtikci E. A systematic review on machine learning in...


Disclosures
The authors report no conflict of interest concerning the materials or methods used in this study or the findings specified in this paper.

Author Contributions
Conception and design: Harel, Shemesh, Kimchi. Acquisition of data: Shemesh, Kimchi, Yaniv. Analysis and interpretation of data: Harel, Shemesh, Kimchi. Drafting the article: Harel, Shemesh, Kimchi. Critically revising the article: Harel, Shemesh, Kimchi. Reviewed submitted version of manuscript: all authors. Approved the final version of the manuscript on behalf of all authors: Harel. Statistical analysis: Shemesh. Administrative/technical/material support: Shemesh, Yaniv. Study supervision: Harel, Shemesh.

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