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Original Article

Use artificial neural network to recommend the lumbar spinal endoscopic surgical corridor

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Abstract

Objectives: The transforaminal and interlaminar approaches are the two main surgical corridors of full endoscopic lumbar surgery. However, there are no quantifying methods for assessing the best surgical approach for each patient. This study aimed to establish an artificial intelligence (AI) model using an artificial neural network (ANN). **Materials and Methods:** Patients who underwent full endoscopic lumbar spinal surgery were enrolled in this research. Fourteen pre-operative factors were fed into the ANN. A three-layer deep neural network was constructed. Patient data were divided into the training, validation, and testing datasets. **Results:** There were 899 patients enrolled. The accuracy of the training, validation, and test datasets were 87.3%, 85.5%, and 85.0%, respectively. The positive predictive values for the transforaminal and interlaminar approaches were 85.1% and 89.1%, respectively. The area under the curve of the receiver operating characteristic was 0.91. The SHapley Additive exPlanations algorithm was utilized to explain the relative importance of each factor. The surgical lumbar level was the most important factor, followed by herniated disc localization and migrating disc zone level. **Conclusion:** ANN can effectively learn from the choice of an experienced spinal endoscopic surgeon and can accurately predict the appropriate surgical approach.

Keywords: *Artificial intelligence, Artificial neural network, Deep learning, Machine learning, Spinal endoscope*

INTRODUCTION

The use of spinal endoscopes for treating lumbar degenerative diseases had been increasing in recent years [1,2]. With advancements in endoscopic instruments and techniques, these devices are applied to not only herniated disc but also facet cyst, tumor, and lumbar stenosis [3-5]. The transforaminal and interlaminar approaches are the two main surgical corridors of full endoscopic lumbar surgery. Dr. Parviz Kambin introduced the Kambin's triangle in1973. This paved a road for Dr. Yeung and Dr. Hoogland to invent the transforaminal route [6-8]. In 2005, Dr. Rutten presented the interlaminar approach [9]. These two corridors are the foundation of modern full endoscopic lumbar spinal surgery. Several studies have discussed the indications and benefits of each surgical corridor [4,5,10]. However, there are no quantifying methods for assessing the best surgical approach for each patient. Decision-making is highly dependent on the surgeons' experiences and may be challenging for novice surgeons.

The use of artificial intelligence (AI) had been increasing in recent years. AI had been a good tool for facilitating medical decision-making or predicting prognosis [11-17]. Artificial neural network (ANN) is a machine learning model that imitates human neurons [12]. ANN comprised several nodes, which can be human neurons [Figure 1]. Each node receives several inputs (x_1, x_2,…x_n), and each input multiplies a weight (x_1, x_2,…x_n). Then, a bias is added (b). The weighted sum of the input signals is passed through an activation function, and an output $y = \varphi(wx+b)$ is generated [Figure 1a]. The input could be seen as the dendrite and the output as the axon. Several of these neurons can construct a neural network [Figure 1b]. Deep neural network is commonly defined as greater than or equal to three-layer ANNs. The total output of the whole ANN could then be compared with the actual results using the loss function to generate a loss value. Then, via back-propagation, every weight in the ANN can be updated to a new value. Each update process is called an epoch. The whole learning process

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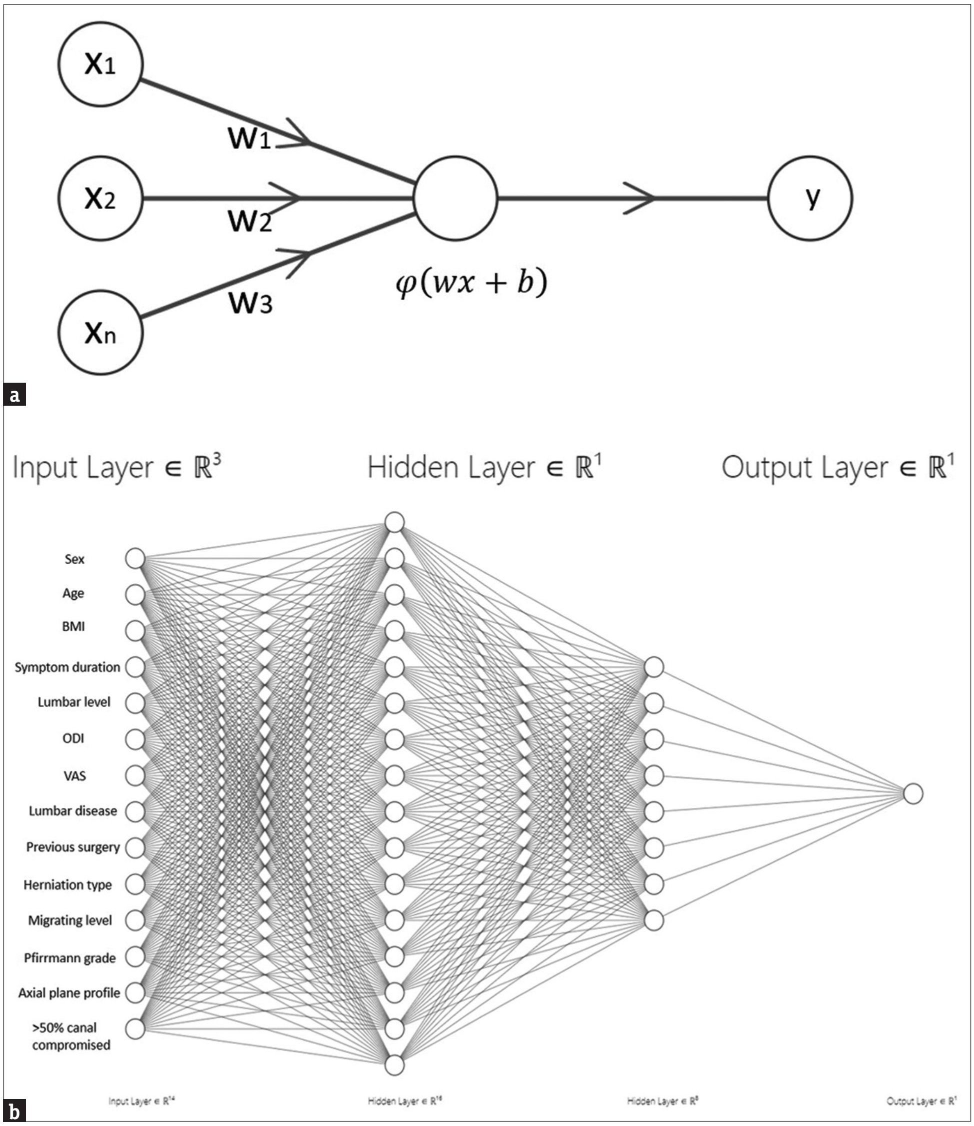

Figure 1: (a) A neuron node receives inputs (x_1, x_2,…x_n). Then, it enters the weight sum into the activation function to yield the output y. (b) A deep neural network comprising 14 inputs and 3 hidden layers. This was also the deep neural structure used in this study

aims to minimize the loss value and to maximize the accuracy between the outputs and the actual results. The ANNs work just like a human brain, which learns from errors.

This study aimed to establish a deep learning model that could learn from the experience of an endoscopic spinal surgeon who performed more than 1000 full endoscopic surgeries. The model was designed to provide suggestions regarding which surgical methods (transforaminal versus interlaminar approach) are preferred based on the patients' preoperative status. After the AI model was learned from the dataset, its efficacy was validated using multiple methods. To the best of our knowledge, this study first applied ANN in full endoscopic lumbar spinal surgery.

Materials and Methods

Dataset

From March 2009 to May 2021, all patients who underwent full endoscopic lumbar spinal surgery were enrolled in the study. Patients who require endoscopic surgeries for sacroiliac joint pain, juxtafacet cyst, and fracture were excluded. Factors included in the analysis could be divided into three main categories: Basic information including sex, age, and body mass index (BMI); preoperative status such as surgical lumbar level, preoperative Oswestry disability index (ODI), preoperative visual analog scale (VAS) score, previous surgical history, and duration of symptom before surgery; and information obtained from magnetic resonance imaging including the type of lumbar disease, classification of disc migration, Pfirrmann grade, herniated disc localization, stenosis versus herniated intervertebral disc (HIVD), and >50% canal stenosis. Patients who had any missing preoperative information were excluded from our study. Finally, 899 patients were included in the final analysis. The study protocol was approved by the ethics review board of Changhua Christian Hospital, Taiwan (IRB No. 190905).

The three herniation types were as follows: Prolapse, extrusion, and sequestration [10]. Previous surgical history was considered only if the previous surgery was performed at the same spinal level. Disc migration was classified into five based on a previous research article [1]: far-upward (zone 1), near-upward (zone 2), near-downward (zone 3), far-downward (zone 4), and no migration [1]. The Pfirrmann grading system was used to define the degree of disc degeneration, and the condition was graded from I (normal) to V (most severe) [10,18]. Lesion localization at the axial plane was classified as central, subarticular, foraminal, and extraforaminal types [10]. Surgical lumbar levels were divided into the following: T12/L1, L1/L2, L2/L3, L3/L4, L4/L5, L5/S1, L4/L5 + L5/S1, and two levels other than L4/L5 + L5/S1. The types of lumbar disease included disc herniation, lumbar stenosis, and foraminal stenosis.

To simplify the model, we transformed all continuous variables into categorical variables. The patients were grouped as follows: age, ≤65 and >65 years; BMI, ≤30 and >30 years old; ODI, ≤20, 20 < ODI ≤40, 40 < ODI ≤60, 60 < ODI ≤80, and >80; and VAS ≤4 and >4. The symptom duration before surgery was divided into ≤3 and >3 months.

Artificial neural network mode

TensorFlow Keras was utilized to build the ANN and train the model. We constructed a three-layer deep neural network. There were 14 neurons in the input layer, 16 in the first hidden layer, and 8 in the second hidden layer [Figure 1b]. We used binary categorical cross-entropy in the loss function. Thus, there was only one output layer. It showed the percentage of results for the transforaminal or interlaminar approach. All layers were fully connected. Figure 1b shows the complete structure of the model.

We divided 899 patients into three for the training, validation, and testing groups [Figure 2]. The validation dataset was used to tune the hyperparameter and to prevent overfitting during training. The testing dataset was used to evaluate the efficacy of our model in the final stage. We shuffled the data to prevent the AI model from learning the pattern via time series. For example, a spinal endoscopic surgeon might prefer the interlaminar approach over the transforaminal approach in early practice. The patients were under general anesthesia, and the surgical route was more familiar. Thus, our dataset was imbalanced since it comprised 621 and 278 patients who underwent surgery using the transforaminal and interlaminar approaches, respectively. Due to this imbalance, the AI model will prefer the dominant group. For example, if the Al model simply decided that all patients who will undergo surgery using the transforaminal approach, it still achieves an accuracy rate of 69.1% (621/899). However, it will generate a positive predictive value (PPV) of 0% in the interlaminar group. To overcome potential bias, we needed to add more loss function weight (transforaminal: interlaminar = 1:2.24) to the interlaminar group. Therefore, the Al model could be punished more if it has a wrong prediction in the interlaminar group.

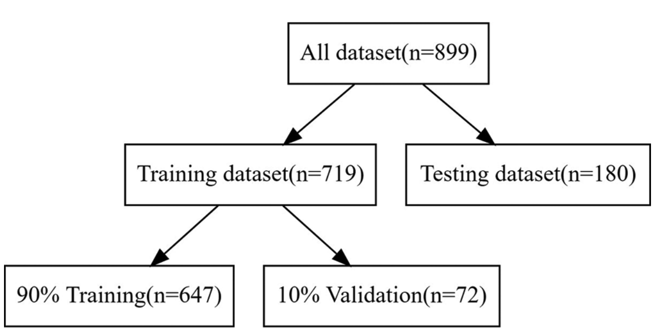

Figure 2: In total, the data of patients (n = 899) were first divided into the training and testing datasets. The training data were further divided into training and validation datasets for hyperparameter tuning and validation during the training process. The test dataset can provide an unbiased estimate of the final model

We evaluated the model in terms of not only accuracy but also PPV, negative predictive value, confusion matrix, and receiver operating characteristic (ROC) curve. The confusion matrix was useful as it saw our attempt to well manage the imbalance data work.

Software and hardware

Python 3.8, TensorFlow 2.4.1, and Scipy 1.6.3 were used to establish the model. Moreover, the Chi-square test was utilized for calculating the difference between the two groups in traditional statistical analysis. Training of the ANN was performed in an Intel i5 9400F equipped with an Nvidia RTX2070.

Results

Table 1 shows the demographic characteristics of the two surgical groups. Patients who underwent transforaminal surgery were older (>65 years old, ratio: 28.2% vs. 10.1%) and had a high BMI (>30 kg/m^2, ratio: 17.1% vs. 10.1%) longer preoperative symptoms (>3 months, ratio: 37.2% vs. 25.9%), and more >50% spinal canal stenosis (12.6% vs. 3.6%). On the contrary, the interlaminar group had a higher proportion of patients who underwent surgery at L5/S1 (78.4% vs. 11.8%) and had a more downward migrating disc (54.7% vs. 35.7%). Moreover, their ODI was more severe (>20, ratio: 82.8% vs. 72.4%). Of 22 patients who had lumbar surgery at the previous level, only one underwent secondary surgery using the interlaminar approach. Lesions localized at the central spinal canal were more likely managed using the interlaminar approach (45.7% vs. 27.9%). The mean preoperative ODI and the postoperative ODI were 26.0 (±7.3) and 1.5 (±2.8), respectively. The mean preoperative VAS and the postoperative VAS were 7.3 (±2.2) and 0.2 (±0.8), respectively. There was a significant improvement in ODI and VAS after the surgery (P < 0.001, P < 0.001).

In total, data from 719 patients were used to train the model, and those from 180 patients were used to validate the accuracy of the model. Data from 72 of 719 patients were randomly divided for model validation during the training process. The accuracy at the training, validation, and test datasets were 87.3%, 85.5%, and 85.0%, respectively. Based on the validation results, with the training progress, the validation loss was decreasing, and the validation accuracy was increasing [Figure 3]. Hence, the model did not overfit. Overfitting was a pattern that the AI model only performed well only on the training model, not on the validation or testing model. Figure 4 shows the confusion matrix. The PPVs for transforaminal and interlaminar approaches were 85.1%

Table 1: Patient demographics and comparisons between the transforaminal and interlaminar groups

	Transforaminal (%)	Interlaminar (%)	*P*
Patient number	621 (69.1)	278 (30.9)	
Sex			
Male	384 (61.8)	164 (59.0)	0.419
Female	237 (38.2)	114 (41.0)	
Age			
≤65	446 (71.8)	252 (89.9)	<0.001
>65	175 (28.2)	26 (10.1)	
BMI			
≤30	515 (82.9)	252 (89.9)	0.006
>30	106 (17.1)	26 (10.1)	
Symptom duration (months)			
≤3	390 (62.8)	206 (74.1)	0.001
>3	231 (37.2)	72 (25.9)	
Lumbar level			
L2/L3	35 (5.6)	1 (0.4)	<0.001
L3/L4	107 (17.2)	3 (1.1)	
L4/L5	392 (63.1)	47 (16.9)	
L5/S1	73 (11.8)	218 (78.4)	
Other 2 levels	7 (1.1)	1 (0.4)	
L4/L5+ L5/S1	1 (0.2)	7 (2.5)	
L1/L2	4 (0.6)	1 (0.4)	
T12/L1	2 (0.3)	0	
ODI			
≤20	171 (27.5)	48 (17.3)	0.001
20-40	438 (70.5)	219 (78.8)	
40-60	12 (1.9)	11 (4.0)	
60-80	0	0	
>80	0	0	
VAS			
≤4	71 (11.4)	24 (8.6)	0.206
>4	550 (88.6)	254 (91.4)	
Lumbar disease			
HIVD	506 (81.5)	267 (96.0)	<0.001
Canal stenosis	78 (12.6)	10 (3.6)	
Foraminal stenosis	37 (6.0)	1 (0.4)	
Previous surgical history*			
No	600 (96.6)	277 (99.6)	0.006
Yes	21 (3.4)	1 (0.4)	
Herniation type			
Prolapse	23 (3.7)	13 (4.7)	0.147
Extrusion	436 (70.2)	177 (63.7)	
Sequestration	153 (26.1)	88 (31.7)	
Migrating level			
Zone I	30 (4.8)	7 (2.5)	<0.001
Zone II	22 (3.5)	8 (2.9)	
Zone III	123 (19.8)	82 (29.5)	
Zone IV	99 (15.9)	70 (25.2)	
No migrating	347 (55.9)	111 (39.9)	
Pfirrmann grade			
Grade I	2 (0.3)	0	0.122
Grade II	128 (20.6)	64 (23.0)	
Grade III	439 (70.7)	203 (73.0)	
Grade IV	50 (8.1)	10 (3.6)	
Grade V	2 (0.3)	1 (0.4)	

Contd...

Table 1: Contd...

	Transforaminal (%)	Interlaminar (%)	*P*
Lesion localization at axial plane			
Central	173 (27.9)	127 (45.7)	<0.001
Subarticular	209 (33.7)	104 (37.4)	
Foraminal	180 (29.0)	38 (13.7)	
Extraforaminal	59 (9.5)	9 (3.2)	
>50% canal compromised			
No	555 (89.4)	243 (87.4)	0.389
Yes	66 (10.6)	35 (12.6)	

HIVD: Herniated intervertebral disc, VAS: Visual Analog Scale, ODI: Oswestry disability index

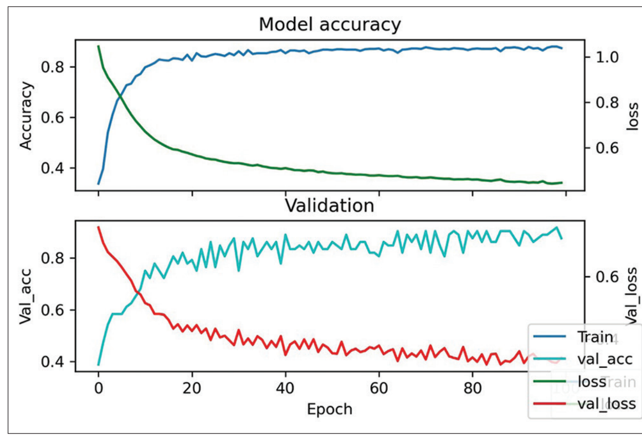

Figure 3: Training process of the model. With each epoch, the accuracy increased, and the loss decreased in both training and validation datasets

and 89.1%, respectively. Our class weight balance worked well. Thus, the model was equally effective in predicting the transforaminal and interlaminar approaches. Figure 5 depicts the ROC curve. The AUC was 0.91, which was considered an outstanding result [19].

Importance of each factor

Machine learning, particularly deep learning, was commonly considered a black box because it was challenging to explain how it generated the results [15]. In ANNs, all the nodes were fully connected in each layer. Thus, the factors that contributed more to the results cannot be identified using the traditional method. The SHapley Additive exPlanations (SHAP) algorithm was used to explain the relative importance of each factor contributing to our model. SHAP was based on the game theory and local explanations to explain the AI models [20,21]. Using SHAP's DeepExplainer, the average impact on model output magnitude could not be plotted, as shown in Figure 6. The surgical lumbar level was the most important factor in deciding the surgical approach, after the migrating disc zone level and herniated disc localization.

Graphical user interface for deploying the model

We wrote a graphical user interface (GUI) using Tkinter, which was established in the python library. After selecting the patients' factors in the interface, the GUI used the model we trained to provide suggestions. Figure 7 shows two examples. After inputting the patients' characteristics, the AI model gave the correct surgical suggestions in both cases.

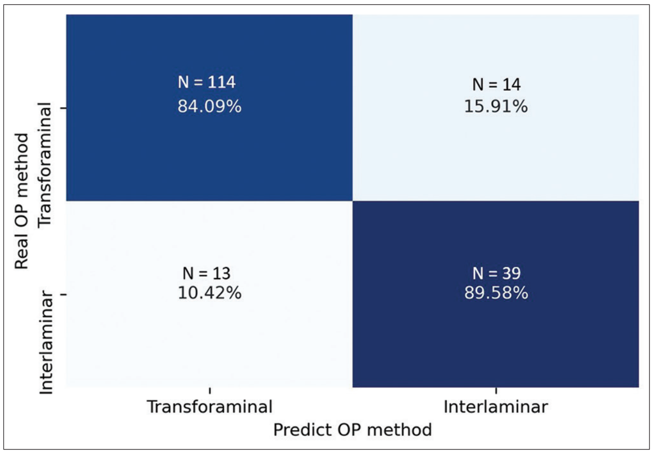

Figure 4: The confusion matrix of the artificial intelligence model. The confusion matrix can present true positive, true negative, false positive, and false negative data. This can overcome the blind spot of accuracy ([(true positive) + (true negative)]/total data) when evaluating an artificial intelligence model

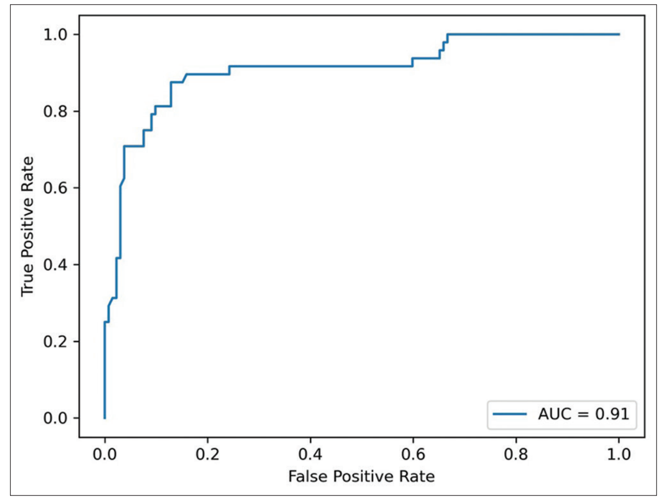

Figure 5: The receiver operating characteristic curve of the AI model. The receiver operating characteristic curve represents the diagnostic ability of a binary classifier system. The area under the curve was 0.91, which is considered outstanding discrimination

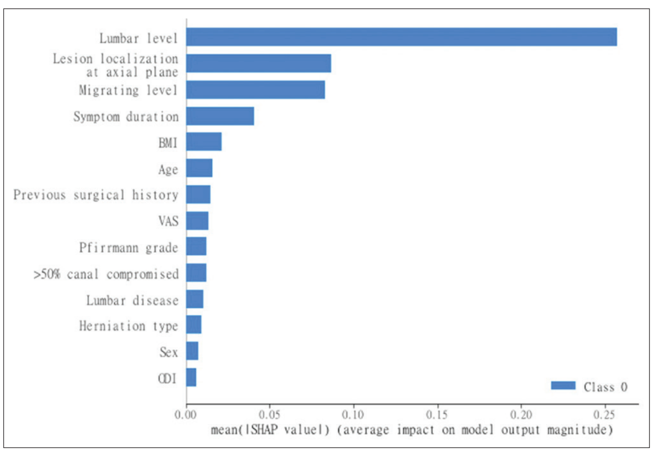

Figure 6: In the SHapley Additive exPlanations model, which was used to evaluate the important factors of the model, surgical lumbar level was the most important factor, followed by herniated disc localization at the axial plane and migrating disc zone level

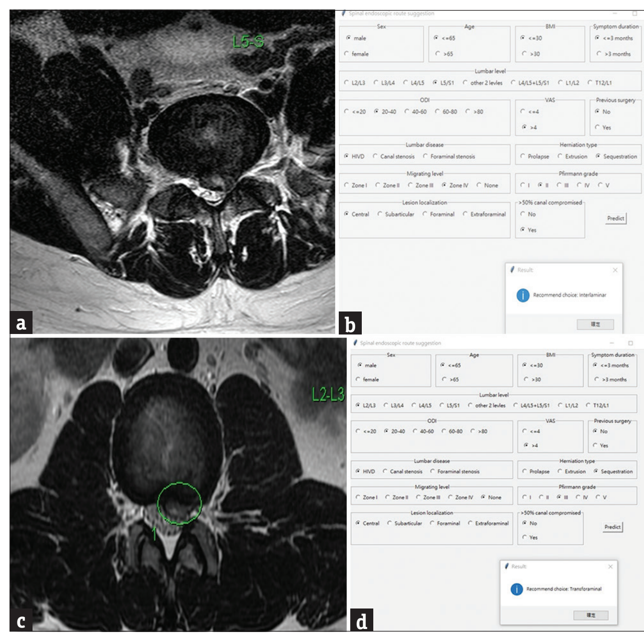

Figure 7: For demonstration, we applied the AI model into two cases. (a) a 21-year-old male who had herniated disc at L5/S1 level for 30 days and received interlaminar endoscopic surgery. (c) a 37-year-old male who had herniated disc at L2/L3 level for 7 days and received transforaminal endoscopic surgery. (b and d) the artificial intelligence model predict the surgical approach the same as the surgeon

Discussion

Previous studies comparing the transforaminal or interlaminar approach for lumbar diseases were usually based on individual parameters, rather than a combination. Our study did not only systemically compare two surgical groups of patients in terms of demographic characteristics but also train an AI model based on multiple preoperative patient factors. The AI model, particularly the deep learning-like ANN, was commonly considered a black box. We will analyze how the model learns in the following discussion. Results showed that it was extremely similar to a surgeon's thinking process.

The interlaminar approach was preferred for surgeries at the L5/S1 region [Table 1] because it had the widest interlaminar window and the narrowest neural foramen. The iliac crest sometimes blocked the surgical route that made the transforaminal approach challenging at this level [3,9]. By contrast, the neural foramen widened, and the gap between the disc and the interlaminar window was larger when the lumbar level went up. The transforaminal approach was more favorable at the upper lumbar level [5]. Thus, it was not surprising that in our relative importance analysis, the AI model considered the surgical lumbar level as the most important factor.

If lumbar spinal stenosis or HIVDs were localized at the central spinal canal, the interlaminar approach was more feasible, and the transforaminal approach was technically more challenging. On the contrary, if the lesions were localized more laterally, then the transforaminal approach was preferred, particularly in cases of extraforaminal HIVD, in which the interlaminar approach is extremely difficult to use unless a lot of bony structures are sacrificed. The AI model considered herniated disc localization as the second most important.

Moreover, based on the AI model, the migrating disc zone level is the third most import variable. In terms of demographic data, patients with migrating discs, particularly at zones III and IV (54.7% vs. 35.7%), were more likely to be managed using the interlaminar approach (60.1% vs. 44.1) [Table 1]. The result was reasonable since the transforaminal approach, which was used to manage the migrating disc, was challenging and even resulted in residual disc [22-24]. In addition, the use of the transforaminal approach to managing the downward migrating disc (zones III and IV) was considered an advanced spinal endoscopic technique and was often required to sacrifice a lot of bony structures [23]. It might even lead to instability due to the extensive destruction of the facet, the pedicle, and, even, the vertebral body [25].

Elderly patients might have a higher incidence of morbidity, which can inhibit them from receiving general anesthesia. Thus, the transforaminal approach was preferred. Since the endoscopic sheath and instruments were shorter, the interlaminar approach might be more challenging if a patient was obese (BMI: >30 kg/m^2). Patients who had longer symptoms might have a better pain tolerance. Thus, the transforaminal approach under local anesthesia was performed. Patients who had a higher ODI might not tolerate local anesthesia. Therefore, the interlaminar approach was preferred. Foraminal stenosis can be easily managed using the transforaminal approach since this route was direct and simple. Patients who had a previous lumbar surgical history usually had scars at the interlaminar route. Therefore, the transforaminal route could prevent from managing the scar tissues.

Some factors might not significantly differ between these two surgical methods. However, they are fed into the AI model for learning because we attempted to follow the surgeons' actual experience when patients visit the clinic. For example, the VAS score did not significantly differ in the traditional Chi-square analysis. Nevertheless, it might play a role in the decision-making of surgeons. If patients are in extreme pain, the surgeons might believe that they could not tolerate the prone position for too long when undergoing surgery using the transforaminal approach under local anesthesia. Therefore, the interlaminar approach under general anesthesia was preferred.

Our research is advantageous because the number of patients was relatively large compared with other studies that used AI models in medical predictions or decision-making [1,12-14,16]. Unnecessary variables were not fed into the AI model to prevent garbage in and garbage out. However, the study still had some limitations. First, some potential variables might have not been recognized and recorded. For example, with the evolving of the FESS instrument, the surgeon might change his surgical approach during the time. Second, the type of surgical route is highly dependent on each surgeon's training and experience. The variables we included in the article might not be important to each surgeon. Third, we only included one surgeon's experience in the article which might cause some bias. However, it might be an advantage too. If we included surgeons who had <1000 FESS experiences or a lot of missing data, then the AI might be confused during the training process. Finally, the Al model was not used to replace an expert's decision. Rather, it was utilized as an advisor, particularly for inexperienced surgeons in the field. Fourth, some factors were not included. For example, in lumbar disease classification, we did not include epidural hematoma, tumor, and infection.

Conclusion

ANN can effectively learn from the choice of an experienced spinal endoscopic surgeon and can accurately predict the appropriate surgical approach for lumbar spine disease. The AI model may be useful for novice spinal endoscopic surgeons as it can assist them in proper surgical decision-making.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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