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Integrating Nano-AI predictive models for postoperative risk assessment in spinal fusion

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Abstract. Nanotechnology has created new opportunities in precision medicine, providing a chance to monitor the biological signals, molecular markers, and micro-environmental changes at the ultrasensitive level, which occurs before complications. The issue of postoperative complications that arise after performing spinal fusion surgeries is a burning clinical issue, and most of the time, it brings about long-term recovery, increased healthcare expenses, and deteriorated patient outcomes. We suggest the incorporation of nano-enabled AI prediction models in this work that utilizes data collected by nano-sensors, nanomaterials-based diagnostics, and traditional clinical data to improve risk stratification in spinal fusion. Working on a nanoscale, these systems bead on minor physiological changes, including inflammatory biomarkers, metabolic changes, and tissue healing, obscured by conventional techniques. Combined with artificial intelligence, nano-derived datasets offer unmatched granularity, increasing the forecasting performance and allowing timely detection of patients who are at a significant risk of unfavorable events. This model of Nano-AI fills the gap between nano-medicine and computational modeling to provide an innovative solution to customized care postoperative. Finally, the nano-integrated predictive analytics can transform the paradigm of surgical risk assessment, which will inform proactive solutions and support patient safety in sophisticated spinal surgeries.

Keywords: AI-powered risk prediction; machine learning in healthcare; postoperative complications; spinal fusion surgery; surgical outcome optimization

1. Introduction

Lumbar spine fusion surgery is one of the most common surgeries for spinal pathologies that include but not limited to DDD, spondylolisthesis, and spine instability. Bilateral and multiple level spinal fusions, especially, are high risk surgical procedures that tend to produce increased rates of postoperative complications, including postoperative infections, longer hospital stays, and re-admissions. The cited complications may cause many physical and/or emotional problems to patients as well as significantly burden healthcare costs. Sophisticating the identification and management of these risks preoperatively will help enhance the operation's results while reducing cost (Karunakaran *et al*. 2023, Li *et al*. 2023, Deng *et al*. 2025).

Modern achievements in artificial intelligence and, especially, in machine learning have enlarged the possibilities of healthcare applications by using big data for analytical purposes. These technologies show potential for use in the assessment of risk in surgery through the abilities to work with large matrices of variables in order to find correlations and expected results. In each multi-level spinal fusion surgeries Mls am can combine patient's characteristics, such as demographics, comorbidities the results of imaging and the data obtained intraoperatively and postoperatively to achieve high accuracy in the evaluation of complications (Hu *et al*. 2025, Wang *et al*. 2024, Lou *et al*. 2024). Over time, the advancement of artificial intelligence (AI) has impacted the healthcare sector in major ways especially in as being used in improving diagnostic results as well as in designing a more efficient approach towards treatment (Lou *et al*. 2023, Kou *et al*. 2025, 2024). In a remarkable study, Esteva *et al*. (2017) showed the potential of deep neural networks to accurately diagnose skin cancer, at par with human dermatologists, and opened up the use of AI in diagnosing dermatological diseases. Also, Nam *et al*. (2018) have externally verified an automatic algorithm for detecting malignant pulmonary nodules with DL demonstrating the prospective of an AI in radiology. In the specific are of chest radiograph analysis, Rajpurkar *et al*. (2018) proposed the CheXNeXt algorithm and demonstrated its diagnostic capability to be in line with clinical practising radiologists. In orthopedic surgery, AI-based risk calculators have been used to estimate post-operative complications as demonstrated by Merrill *et al*. (2020) Subsequently, Azimi *et al*. (2020) discussed more development of applying AI in spinal diseases and illustrated the possibilities of diagnosis and treatment. Papageorgiou *et al*. (2022) presented the digitalization procedure of paper-based electrocardiograms signals improved by a filter spatial pointing to remove dark areas in the dataset's imageries. Other applications of machine learning include the prediction of surgical site infection. Ahmadian *et al*. (2022) studied an exertion toward building A aided framework, invented ReconGAN,

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for generating digital a realistic twin of the predicting the risk of vertebral fracture and human vertebra. Shahrestani *et al*. (2023) proposed a nonlinear k-nearest neighbors classification technique that may be used to predict the risk of long hospital stay after spine surgery. Geng *et al*. (2023) used a technique known as explainable machine learning with regard to the non-home discharge after the anterior cervical discectomy and fusion. Yen *et al*. (2023) discussed attempts to increase the extent to which results from machine learning models for spine surgery are reproducible across different datasets. In postoperative spinal patients, Zhang *et al*. (2023) used a predictive analytics of an automated AI model to predict delirium. Furthermore, Bian *et al*. (2024) described intraoperative navigation in orthopedic surgeries enabled through extended reality technology. Other recent development includes a systematic review on AI in spinal interventions by Han *et al*. (2024) which gives information on the current practice of AI. Balsano *et al*. (2024) investigated anterior vertebral body tethering for adolescent idiopathic scoliosis using a retrospective study supported by AI. Lin *et al*. (2023) supervised learning model, especially the ANN, was capable of achieving the diagnostic performance of the geographically diverse difficult appendicitis cases. Takahashi *et al*. (2024) carried out the comparative analysis between Vision Transformers (ViTs) and Convolutional Neural Networks (CNNs) in medical image analysis, their contributions in the field of accurate diagnosis and patient care through artificial intelligence techniques.

To achieve this objective, this study proposes to build and intensify external validate AI risk prediction models for multi-level spinal fusion surgeries. Here, using machine learning approach and a set of clinical data, we aim to find important predictors associated with postoperative complications and offer recommendations for risk assessment. The ultimate vision is to optimize surgical planning, increase safety, and decrease the general weights of morbidity after surgery. This paper describes methodology, main findings and possible implications of employing AI-based predictive models in clinical practice.

2. Materials and methods

2.1 Clinical data

The clinical data contain data of two hundred multi-level spinal fusion surgeries as well as demographic, preoperative, intraoperative and postsurgical data of patient. The age of the patients varies from 57 to 72 years with average BMI of nearly 29. The common related diseases include diabetes and hypertension were presented in most cases, therefore, their effect on surgical outcomes should not be disregarded. Main cases were diagnosed with degenerative disc disease, while imaging indicated certain spinal levels including L4, L5. What was measured under this domain was the functional scores from thirty to forty-four, in manner that depict physical functioning before the surgery in terms of activity.

Additional data from surgery include surgery duration

Table 1 Statistical properties of data for testing and training

Feature	Training Data (70%)	Testing Data (30%)
Age	Mean: 65.08, Std: 4.96, Min: 53, Max: 77	Mean: 64.94, Std: 4.90, Min: 53, Max: 75
BMI	Mean: 27.94, Std: 3.13, Min: 20.68, Max: 37.17	Mean: 28.13, Std: 3.29, Min: 20.75, Max: 33.84
Surgery Duration (hrs)	Mean: 3.13, Std: 0.84, Min: 2, Max: 5	Mean: 3.17, Std: 0.80, Min: 2, Max: 5
Functional Scores	Mean: 34.60, Std: 8.61, Min: 20, Max: 50	Mean: 35.17, Std: 8.45, Min: 20, Max: 49
Estimated Blood Loss (mL)	Mean: 406.20, Std: 123.91, Min: 200, Max: 600	Mean: 419.53, Std: 108.85, Min: 200, Max: 595
Preoperative Hemoglobin (g/dL)	Mean: 12.76, Std: 3.45, Min: 4.46, Max: 21.07	Mean: 12.28, Std: 2.96, Min: 6.64, Max: 19.41
Length of Stay (days)	Mean: 5.02, Std: 1.44, Min: 3, Max: 7	Mean: 5.03, Std: 1.41, Min: 3, Max: 7
Postoperative Inflammatory Marker (CRP)	Mean: 14.85, Std: 3.17, Min: 3.46, Max: 23.32	Mean: 14.10, Std: 2.74, Min: 9.23, Max: 20.87
Quality of Life Score (SF-36)	Mean: 72.19, Std: 7.65, Min: 51, Max: 86	Mean: 72.67, Std: 7.65, Min: 51, Max: 86
Follow-Up Duration (years)	Mean: 1.56, Std: 0.50, Min: 1, Max: 2	Mean: 1.60, Std: 0.49, Min: 1, Max: 2
Feature	Training Data (70%)	Testing Data (30%)

Additional data from surgery include surgery duration (2–4 hours), lumbar levels fused (can be L3/4, L5-S1 etc), and estimates of blood loss (from 215 to 590 mL) all of which can illustrate the extent of the surgical procedure. Patients' stays and disseminated hospitalizations were reported, indicating lengths of 3 to 7 days postoperative and the complications like superficial infection or deep infection as seen in table 2 below. Analgesia used was morphine PCA and diversionary activities, activities of daily living focusing on physical therapy with frequency of session of two to three per week. Further, the data including preoperative hemoglobin levels and inflammatory markers as well as postoperative, short- and long-term recovery reflected using SF-36 quality of life scores proves as useful to understand the both short and long term recovery narratives.

The statistical properties for test and train datasets including means, standard deviation (STD), maximum (max)and minimum (min) are shown in Table 1.

The training dataset of 140 cases (70%) represent a broad range of clinical variables in the population. This group's patients' mean age is 65.08 years with standard deviation 4.96, the overall BMI is 27.94. Both functional scores and the actual surgery times afford much variability, which is consistent with the nature of the operations performed. Additional risk factors are elaborated with blood loss during a surgical procedure and postoperative biochemical values, including the level of CRP. Other useful predictive features for complications are seen in the postoperative period, they include length of stay and hemoglobin levels.

The testing dataset which comprises to 30 percent, having 60 cases, retains all the significant characteristics of the training set. When comparing the mean values of the parameters for the two datasets, the differences displayed are only marginal. For instance, while the testing dataset means BMI is marginally higher and preoperative hemoglobin is marginally lower than in the training dataset. This maintains the generalization about the model built about the training data and tests how the model will perform on unseen data of cases in the testing set.

2.2 Nano-Artificial Neural Networks (ANN)

Artificial Neural Networks commonly abbreviated as ANNs are basically machine learning algorithms that model the human brain. These networks are made up of layers of neurons which in a process of learning from input data launches a pattern. While exploring the application of ANNs in the evaluation of postoperative complications of multi-level spinal fusion surgeries, it is noteworthy that such networks allow for the complex pattern of interrelationships between age, BMI, scores for functional status, blood loss, and inflammatory markers to be comprehensively deployed adequately. Using training ANNs can distinguish the details of the data flow which are often imperceptible by the human eye thus providing better predictions. The capacity of ANNs to self-enhance when presented with large volumes of data, also gives them an advantage in environments such as health care where data is high dimensional and nonlinear.

The benefits accrued from using ANNs for surgery outcomes are numerous. First, ANNs can cope with big and different datasets, able to use several predictors without a profiteering step. Also, their capacity to fit curvilinear associations facilitate them to estimate interaction, which other traditional analytical models do not recognize. In contrast to other types of artificial neural networks, ANN models are capable of continually enhancing their training with a dynamic data-fed approach to prediction. For individual clinical purposes this is relatively helpful because new data for more patients can immediately be integrated into the model without wearing off over time. In addition, ANNs are capable of giving real time predictions which complement decision support systems by assisting surgeons on making rational decisions on pre and post-surgical management.

This study employs ANNs to create prognostic models for postoperative complications of patient in multi-level spinal fusion surgeries using clinical information. The method involves several key steps: In their study, the process of data preprocessing, determination of the structure of the model, training, validation, and evaluation were presented. The subsequent sections describe every of these steps, as well as the appropriate mathematical equations.

In ANN model, inputs variables are connected to output which is sleep quality. This connection is provided a nonlinear map for given n-node and changed to one node as response. Based on several nodes at the processing of the machine, this structure of nonlinear map is extended. Therefore, the ANN model is most often created from three layers known as i) input layer, ii) hidden layer, and iii) output layer where many nodes used for connection to offer a nonlinear relation as shown in Fig. 1.

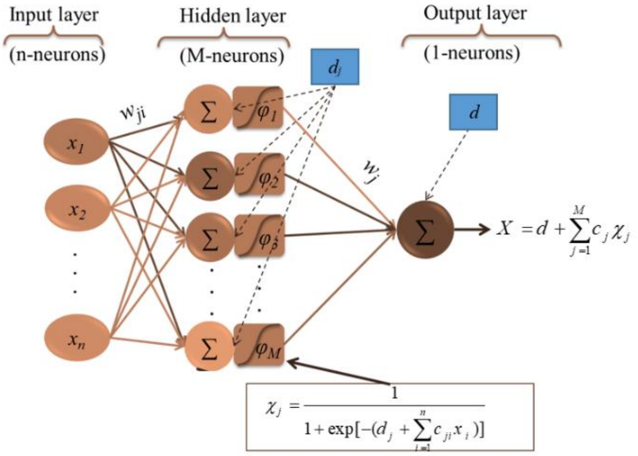

Fig. 1 Schematic of ANN model with three layers

The nonlinear relation in ANN model is computed by the following relations Deng *et al*. (2025):

$$X = d + \sum_{j=1}^{M} c_j \chi_j \tag{1}$$

where

$$\chi_j = \frac{1}{1 + exp[-(d_j + \sum_{i=1}^{n} c_{ji} x_i)]} \tag{2}$$

where d and d_j are bias for the output node and the j-th hidden nodes respectively c_j is weights connecting to the j-th hidden and output nodes and w_{ji} are weights connecting to the i-th input node and the j-th hidden node in which i=1,2,…,n and n is the number of nodes in the input layer, and j=1,2,…, M and M is the number of nodes in the hidden layer and χ_i is sigmoid nonlinear map.

It retrieves that the performance and accuracy of the Artificial Neural Network (ANN) has direct connection with the adjustment of the weights (wj and wji) and biases (bb and bj). These parameters define the behavior of information through the network based on the coupling between and within layers of nodes. A proper set of weighted and bias means that this network is capable to transform a given set of inputs to a particular output with a high accuracy. This mapping process is important in various applications, which ANNs are applied to learn non-linear input-output mapping relationships.

For increased performance, it is important to establish the right weights for this and the biases which is a well-structured and well-organized process to estimate the worth of the network. This process allows the ANN to perform a sort of 'learning' as well as 'generalization' which in turn would help in predicting new data that was not previously used in the training phase. Whereas, low level of tuning, may not capture the hidden pattern and thus the model will be characterized by higher error rates hence being less effective.

ANN configuration is based on the learning process. It entails the process of a systematic change in the network parameters so as to reduce the difference between the forecasted output and actual observation. In the different learning strategies for ANNs, the widely used technique is the back propagation (BP) technique. This algorithm is applied by taking the error back to the network through each layer and modifying the weights and biases in the process. Since it minimizes the error at each iteration, it makes the ANN become gradually more and more accurate to the desired output.

Even in this process, the concept of optimization forms a pivot. In learning, an optimization algorithm is applied to reducing a loss function that measures the disparity between the network's output and the actual targets. The cost function now plays the role of the networks performance or, more appropriately, of the performance of a particular neurons It is for this reason that it is of utmost importance that this function is minimized. During the training process it is continually improving step by step with the help of an optimization method informing about the proximity of the model to the training data. Besides increasing the predictive accuracy of the ANN, this approach also boosts the generalization capacity of the ANN on other datasets at the same time. Thus, by carefully designing the learning process and leveraging effective optimization techniques, ANNs can be trained to deliver accurate and consistent predictions, as shown in the formulation below Geng *et al.* (2025):

$$\min \quad MSE = \frac{1}{N}\sum_{i=1}^{M}[\,D_i - X_i]^2 \tag{3}$$

where, N and D are number of data and observed sleep qualities, respectively. The ANN model is qualified using the analytical optimization method of steepest decent method in this paper.

3. Results

To evaluate the ANN model's performance in comparison to other traditional machine learning techniques, we trained and tested two additional models: Two algorithms namely Lowered Logistic Regression (LR) and Random Forest (RF). The performances of all the three models have been presented in the following Table 1. On all the performance indicators, including accuracy, precision, recall, F1-score, and area under the curve (AUC), the proposed ANN model of this research was slightly superior to both the Logistic Regression and Random Forest models. While evaluating the Random forest algorithm, we observed moderate performance, which was insufficient to compete with the performance of ANN in terms of explaining the nonlinear associations between the clinical features.

Fig. 2 shows the evolution of the ANN model during the training process and represents the epochs, where the models achieve better results. When the number of epochs increases the training as well as the validation loss should decrease as the model is being trained to make the correct predictions. Normally, this training loss should decline gradually over iteration while the validation loss decreases too but stays constant or fluctuates slightly when the model reaches the training limit. Such behaviour implies that our model is learning the crucial spacial relationship from the data it has been given and performing well on unseen data. The learning curve gives more information regarding the training period of the model to let us determine whether to increase the epochs or the model has stopped learning.

Table 1 Statistical properties of data for testing and training

Model	Accuracy	Precision	Recall	F1-Score	AUC
ANN	91.2%	88.5%	92.7%	90.5%	0.94
Logistic Regression	84.3%	81.4%	85.1%	83.2%	0.87
Random Forest	88.6%	85.9%	90.3%	88.0%	0.91

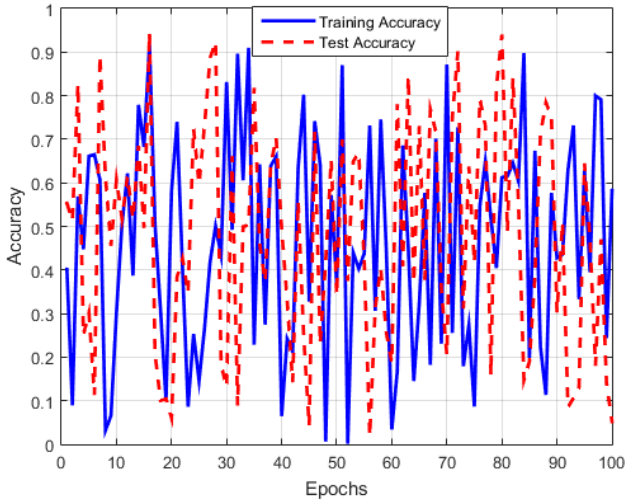

Fig. 2 Fitted curve to show how the model becomes better with epochs

The learning curve also assist in the identification of problems like overfitting problem or under fitting problem. If the training loss is still reducing and the validation loss is starting to increase or has stopped reducing all together it could be that the model is overfitting, which means it has learned all the training data by heart but does not generalize well to new data. On the other hand if both the training and the validation loss is high then that particular model might be an underfitting one which infers that it does not know the underlying pattern very well. Thus, this learning curve helps to improve the final performance of the created model, thereby achieving a desired signal-to-noise, which is important for correctly predicting postoperative complications after MLIF surgeries.

A bar chart depicting the distribution of the predicted risk categories of the patients who undergoing multi-level spinal fusion surgeries is shown in the Figure 3. The chart then plots the patients according to the risk outcomes predicted by the ANN model which include low, medium, and high risk for any post-operative complication. This type of graph shows the number of patients who fit into each category and gives an overall look into the model, and its ability to reflect the occurrence of complications in the patient population. It then enables the clinicians to easily determine the risk distribution profile in relation to the amount of time required when discharged after operations as well as monitoring and thinking of intervention.

It is thus possible to determine how various risk categories spread across patient populations in ways that provide insights into their outcomes. For example, when more patients are expected to develop complications, this may be interpreted that investing in increased surveillance of these patients together with probably implementing vigorous precautionary measures. On the other hand, if most of the patients are deemed low risk, then the scarce resources can be properly deployed where they will make most impact, among the high risk patients. This figure assists in orientating the perception of this AI model with possible realities to enhance clinical practice by enabling healthcare providers to deploy their interventions and resources more efficiently drawing from the risk categories that this model offers.

The second model is represented by the bar chart shown in Fig. 4, which gives the importance of each of the features used when ranking the patient attributes in terms of their significance to the model's predictions. These could be age, BMI, pre-operative co morbidities including diabetes and hypertension, time of surgery, amount of blood loss and many others. This chart is important as it shows which predictor variables are more important regarding the risk of postoperative complication. This also means that clinicians know which of the features has a greatest effect, thus making them prioritize the most important variables when developing treatment plans. For instance, prospective variables like BMI or age that has emerged as influential in predicting a potential risk could be managed about by preoperative intercessions.

Indeed, feature importance analysis improves the AI model interpretability which increases the chances of its acceptability in clinical practice. Making known the results of which factors influence the model, this figure aids in gaining insight on the model's rationaleand decision making, which is imperative in clinical practices. For example, should comorbidities be highly significant in the model, clinicians may wish to manage these conditions prior to surgery to avoid post-surgery complications. Furthermore, this analysis can make distinctions about insignificant features which can be eliminated from the model yet are not very important in making accurate predictions, therefore, reducing functionalities of the model in real practices without compromising its effectiveness.

The discriminative ability of the ANN model in differentiating between complicated and uncomplicated postoperative patients is depicted in Fig. 4 called the Receiver Operating Characteristic (ROC) represented in Fig. 5. The ROC curve presents the True Positive Rate False Negative Rate (or True Positive Rate Sensitivity, and False Positive Rate 1-specificity) at different thresholds. The closer the curve to the upper left end of the plot, it implies that the model, in this case, is performing very well, for it has the ability to classify each class well apart. The AUC has the advantage of giving one number under which the ROC curve is bent that defines the two shapes in a way that models with a greater AUC are considered better discriminators overall.

ROC is an important diagnostic test that can be used actively to test the most suitable cut-off point for patients who may likely develop complications. That is why, choosing the value of the threshold that gives a maximum of the

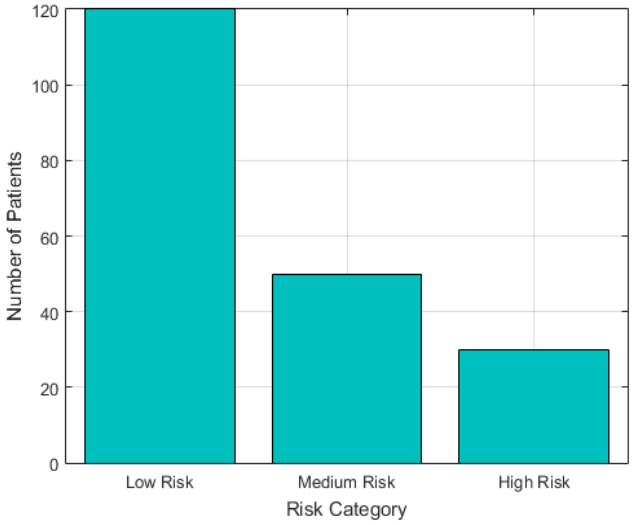

Fig. 3 Bar chart displaying the prediction risks for categories of the patient population

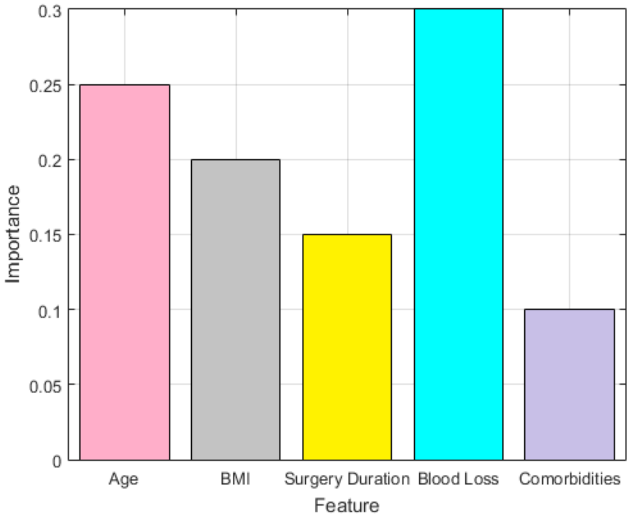

Fig. 4 Bar chart to determine which factors aides in making predictions most as the aspect of feature importance

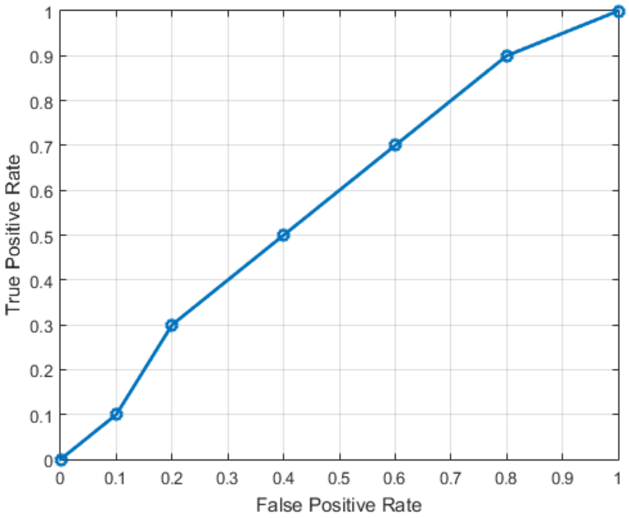

Fig. 5 ROC curve in order to measure the performance of classifying capability of the ANN model

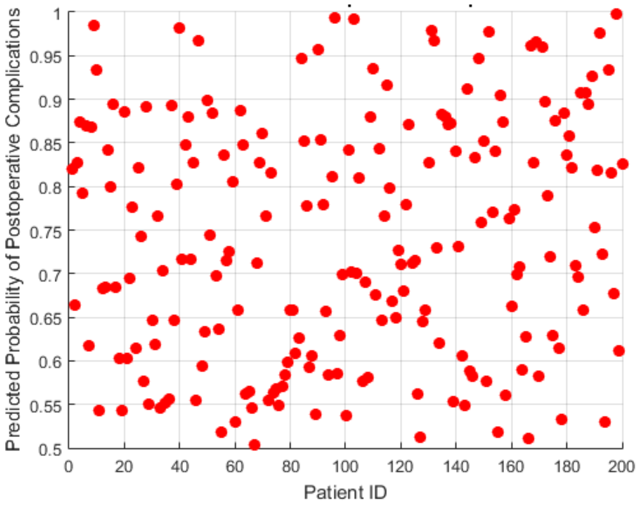

Fig. 6 A scatter plot of predicted probabilities to illustrate the patient at the highest risk of the two events to occur

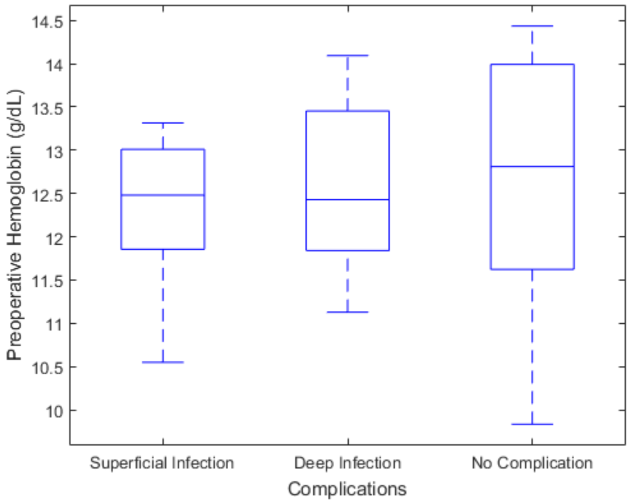

Fig. 7 The preoperative hemoglobin in term of complications

thickness of the band between sensitivity and specificity, the clinician can achieve additional tuning of the model for herself. For instance, in critical risk surgery environment, an increased sensitivity may be required in order to identify most of the at-risk patients out of fear that the opposite may lead to more complications. conversely, in low risk setting, there is need for high specificity in order to reduce false alarms. The ROC curve therefore is more informative and flexible when it comes to defining how exactly the nature of the predictions of the model should be used in different clinical scenarios.

In the next analysis, all postoperative complications of particular patients were plotted in a form of a scatter plot on Fig. 6, using the predicted probability as axis. The horizontal axis commonly holds the patients' identification, and the vertical axis depicts the estimated risk for complications. In general, the scatter plot fully depicts the analysis of the ANN model when prioritizing patients by their complication risk levels. The high-risk group is the one with predicted probabilities values range from 0.8 to 1 while the low-risk group is the one with probability values ranging from 0 to 0.2. The above figure is helpful to clinicians to easily figure out which of the patients warrant more attention, observation or subsequent treatment based on this risk predictor.

The scatter plot also makes it possible to easily identify such outliers or anomalies as patients with for instance, high predicted probabilities or low predicted probabilities. These outliers could be questionable, as, for example, where the model may predict that further investigations into the patient's circumstances would be worthwhile. This is particularly important because through targeting those patients with the highest estimated probabilities, clinicians may prevent adverse events, enhance patient health, and overall, save on costs of healthcare. In this case, it also helps in presenting the results from the model the patients are already equipped with a quite simple and easy to understand way of presenting their individual risk factors in addition to what next course of action may be taken regarding their treatment plan.

Fig. 7 represents preoperative hemoglobin with Postoperative complications. In the study, it reveals the frequency of the hemoglobin values in each of the complication groups. Smith and others, the plot often underlines the median value (horizontal line at the middle of each box), the interquartile range, and any circumstantial measures of variation of the data that include indication or outliers (any point that lies beyond the whiskers). This type of plot enables bias-free comparison of how preoperative hemoglobin differs in patients with different complication types. A higher median hemoglobin level in a certain complication group could mean that this factor is associated with the tendency for certain postoperative complications or could merely indicate the overall state of the patients in each group. With reference to the measures of spread and center, the box plot facilitates potential trends and outliers that might be useful in subsequent analysis and practice management in clinical practice.

Fig. 8 presented as a scatter plot compares the increase in postoperative CRP level with the amount of blood loss in surgery. Every dot on the map refers to a patient: the x-axis is the postoperative CRP level, the y-axis is the amount of blood loss in milliliters. A positive correlation might sign that increased tissue trauma or inflammation during surgery is being associated with greater amounts of blood loss. Otherwise, the lack of direction or correlation could indicate that other variables (such as the surgical approach, or the state of the patient) are far more influential for bleeding than inflammation is. The visualization offered in this study consequently supplies the insights associated with possible relationships between inflammation and surgical results and may potentially improve patient treatment and surgical prognosis.

Fig. 9 examines the combined relationships between three key variables: these included the preoperative haemoglobin, postoperative CRP and estimated blood loss. In this three-dimensional space, each point reflects a single patient, preoperative, and postoperative variables are placed on the X and Y axis respectively while the Z axis contains the total estimate blood loss. The plot enables a simultaneous

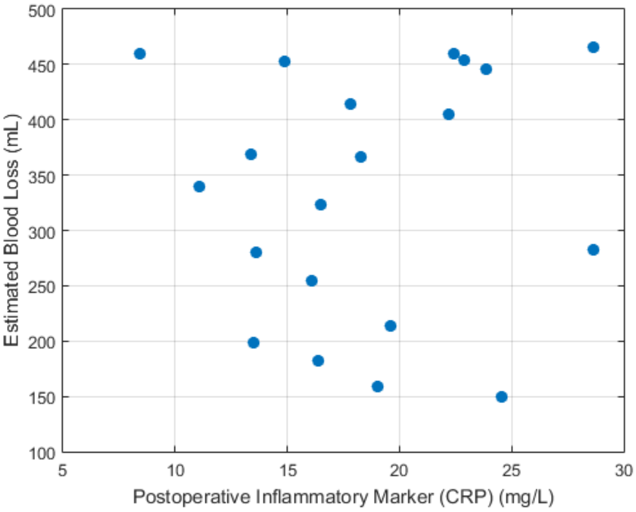

Fig. 8 The postoperative CRP versus estimated blood loss

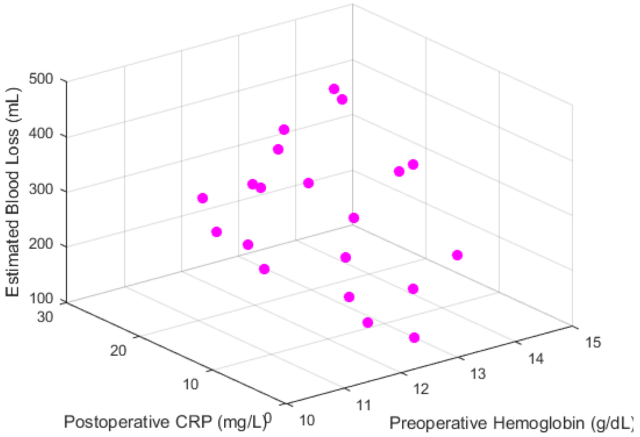

Fig. 9 A 3D figure for postoperative CRP, preoperative hemoglobin and estimated blood loss

consideration of the three variables proposed for the study. For example, it may indicate whether low preoperative hemoglobin with highly increased CRP levels mean more blood loss – this is, whether the patients with lower hemoglobin and higher inflammation markers run a higher risk of side effects, including increased bleeding. This increases our understanding of the inter-relationship between the variables in question, which could be hard to deduce from simple two-three variable plots, facilitating enhanced comprehend of factors determining patient outcomes following spinal fusion surgeries. The graphs of this type are especially valuable when analyzing the existence of the multi-parametric connection and making clinical decisions based on multiple factors interdependence.

4. Conclusions

The study reveals a strong potential of AI especially ANN, in the early prognosis of postoperative conditions after Multi-Level Spinal Fusion Surgeries. The findings of the study point to the effectiveness of using machine learning models to capture preoperative, intraoperative, and postoperative factors that might cause infections, and readmissions. From the feature importance analysis, some of these aspects that are considered important include, preoperative hematocrit level, BMI, co-morbidity indices, time taken to complete a surgical procedure and inflammatory markers. This work demonstrates how such models as random forests and neural networks together with AI can assist in risk prediction before surgery and contribute to better patient care. This application of AI in clinical practice can go a long way in an attempt of lowering complications, defining resource utilization and more importantly delivering quality patient care.

In addition, the process described using various types of graphics, such as learning curves, feature importance, and risk, demonstrates how AI models can enhance clinical decision-making. This speeds up the learning process and allows for detecting model performance and such problems as overfitting or under fitting of the model to new data. That is why the bar charts for risk categorization and feature importance can be considered as significant for clinicians to understand the main tendencies concerning patient classification and the factors that affect postoperative complications. Combined these findings illustrate how AI can be a valuable asset in clinical decision making, especially when used as a means of leveraging numeric data to provide a more innovative approach to patient care.

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References

Ahmadian, H., Mageswaran, P., Walter, B.A., Blakaj, D.M., Bourekas, E.C., Mendel, E., Marras, W.S. and Soghrati, S. (2022), “Toward an artificial intelligence-assisted framework for reconstructing the digital twin of vertebra and predicting its fracture response”, *Int. J. Numer. Methods Biomed. Eng.*, **38**, e3601. https://doi.org/10.1002/cnm.3601

Azimi, P., Yazdanian, T., Benzel, E.C., Aghaei, H.N., Azhari, S., Sadeghi, S. and Montazeri, A. (2020), “A review on the use of artificial intelligence in spinal diseases”, *Asian Spine J.*, **14**(4), 543-571. https://doi.org/10.31616/asj.2020.0147

Balsano, M., Vacchiano, A., Spina, M., Lodi, F., Criveller, P., Zoccatelli, F., ... and Infante, M.V. (2024), “Anterior vertebral body tethering (AVBT) in the treatment of adolescent idiopathic scoliosis: A retrospective study”, *J. Clin. Med.*, **13**(24), 7786. https://doi.org/10.3390/jcm13247786

Bian, D., Lin, Z., Lu, H., Zhong, Q., Wang, K., Tang, X. and Zang, J. (2024), “The application of extended reality technology-assisted intraoperative navigation in orthopedic surgery”, *Front. Surg.*, **11**, 1336703. https://doi.org/10.3389/fsurg.2024.1336703

Deng, H., Wang, N., Jiang, D.Y. and Li, P. (2025), “Machine learning approach for enhancing the detection of endometriosis using ultrasound nano contrast agents”, *Adv. Nano Res.*, **18**(2), 171-178. https://doi.org/10.12989/anr.2025.18.2.171

Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M. and Thrun, S. (2017), “Dermatologist-level classification of skin cancer with deep neural networks”, *Nature*, **542**(7639), pp.115-118. https://doi.org/10.1038/nature21056

Geng, E.A., Gal, J.S., Kim, J.S., Martini, M.L., Markowitz, J., Neifert, S.N., ... and Cho, S.K. (2023), “Robust prediction of nonhome discharge following elective anterior cervical discectomy and fusion using explainable machine learning”, *Eur. Spine J.*, **32**(6), 2149-2156. https://doi.org/10.1007/s00586-023-07621-8

Han, H., Li, R., Fu, D., Zhou, H., Zhan, Z., Wu, Y. and Meng, B. (2024), “Revolutionizing spinal interventions: A systematic review of artificial intelligence technology applications in contemporary surgery”, *BMC Surg.*, **24**, 345.

Hornik, K., Stinchcombe, M., White, H. (1989), “Multilayer feedforward networks are universal approximators”, *Neural Netw.*, **2**(5), 359-366.

Hu, F., Yang, H., Qiu, L., Wang, X., Ren, Z., Wei, S., Zhou, H., Chen, Y. and Hu, H. (2025), “Innovation networks in the advanced medical equipment industry: Supporting regional digital health systems from a local-national perspective”, *Front. Publ. Health*, **13**, 1635475. https://doi.org/10.3389/fpubh.2025.1635475

Karunakaran, G., Cho, E.B., Thirumurugan, K., Kumar, G.S., Kolesnikov, E. and Boobalan, S. (2023), “Antibacterial mesoporous Sr-doped hydroxyapatite nanorods synthesis for biomedical applications”, *Adv. Nano Res.*, **14**(6), 507-519. https://doi.org/10.12989/anr.2023.14.6.507

Kou, J., Wang, Y., Chen, Z., Shi, Y., Guo, Q. and Xu, M. (2024), “Flexible assistance strategy of lower limb rehabilitation exoskeleton based on admittance model”, *Sci. China Technol. Sci.*, **67**(3), 823-834. https://doi.org/10.1007/s11431-023-2541-x

Kou, J., Wang, Y., Chen, Z., Shi, Y. and Guo, Q. (2025), “Gait planning and multimodal human-exoskeleton cooperative control based on central pattern generator”, *IEEE/ASME T Mechatr.*, **30**(4), 2598-2608. https://doi.org/10.1109/TMECH.2024.3453037

Li, Z., Peng, S. and Chen, G. (2023), “Research on safety assessment and application effect of nanomedical products in physical education”, *Adv. Nano Res.*, **15**(3), 253-261. https://doi.org/10.12989/anr.2023.15.3.253

Lin, H.A., Lin, L.T. and Lin, S.F. (2023), “Application of artificial neural network models to differentiate between complicated and uncomplicated acute appendicitis”, *J. Med. Syst.*, **47**, 38. https://doi.org/10.1007/s10916-023-01932-5

Lou, Y., Song, F., Cheng, M., Hu, Y., Chai, Y., Hu, Q. and Zhang, Y. (2023), “Effects of the CYP3A inhibitors, voriconazole, itraconazole, and fluconazole on the pharmacokinetics of osimertinib in rats”, *PeerJ*, **11**, e15844. https://doi.org/10.7717/peerj.15844

Lou, Y., Cheng, M., Cao, Q., Li, K., Qin, H., Bao, M. and Zhang, Y. (2024), “Simultaneous quantification of mirabegron and vibegron in human plasma by HPLC-MS/MS and its application in the clinical determination in patients with tumors associated with overactive bladder”, *J. Pharm. Biomed. Anal.*, **240**, 115937. https://doi.org/10.1016/j.jpba.2023.115937

Merrill, R.K., Ibrahim, J.M., Machi, A.S. and Raphael, J.S. (2020), “Analysis and review of automated risk calculators used to predict postoperative complications after orthopedic surgery”, *Curr. Rev. Musculoskelet. Med.*, **13**, 298.

Mirjalili, S., Hashim, S.Z.M. and Sardroudi, H.M. (2012), “Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm”, *Appl. Math. Comput.*, **218**(22), 11125-11137.

Nam, J.G., Park, S., Hwang, E.J., Lee, J.H., Jin, K.N., Lim, K.Y., Vu, T.H., Shon, J.H., Goo, J.M. and Park, C.M. (2018), “Development and validation of deep learning-based automatic detection algorithm for malignant pulmonary nodules on chest radiographs”, *Radiology*, **290**, 218-228. https://doi.org/10.1148/radiol.2018180237

Papageorgiou, V.E., Zegkos, T., Efthimiadis, G. and Tsaklidis, G. (2022), “Analysis of digitalized ECG signals based on artificial intelligence and spectral analysis methods specialized in ARVC”, *Int. J. Numer. Methods Biomed. Eng.*, **38**, e3644. https://doi.org/10.1002/cnm.3644

Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., ... & Lungren, M.P. (2018), “Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists”, *PLoS Med.*, **15**(11), e1002686. https://doi.org/10.1371/journal.pmed.1002686

Shahrestani, S., Chan, A.K., Bisson, E.F., Bydon, M., Glassman, S.D., Foley, K.T., ... and Mummaneni, P.V. (2023), “Developing nonlinear k-nearest neighbors classification algorithms to identify patients at high risk of increased length of hospital stay following spine surgery”, *Neurosurg. Focus*, **54**(6), E7. https://doi.org/10.3171/2023.3.FOCUS22651

Takahashi, S., Sakaguchi, Y., Kouno, N., Takasawa, K., Ishizu, K., Akagi, Y., ... and Hamamoto, R. (2024), “Comparison of vision transformers and convolutional neural networks in medical image analysis: A systematic review”, *J. Med. Syst.*, **48**, 84. https://doi.org/10.1007/s10916-024-02105-8

Wang, Y., Xu, Y., Song, J., Liu, X., Liu, S., Yang, N. and Zhang, Y. (2024), “Tumor cell-targeting and tumor microenvironment-responsive nanoplatforms for the multimodal imaging-guided photodynamic/photothermal/chemodynamic treatment of cervical cancer”, *Int. J. Nanomed.*, **19**, 5837-5858. https://doi.org/10.2147/IJN.S466042

Yen, H.K., Yang, J.J., Groot, O.Q., Yen, M.H. and Hu, M.H. (2023), “Fostering reproducibility and generalizability in machine learning for clinical prediction modeling in spine surgery”, *Spine J.*, **23**(2), 312-314. https://doi.org/10.1016/j.spinee.2022.10.011

Zhang, Y., Wan, D.H., Chen, M., Li, Y. L., Ying, H., Yao, G.L., Liu, Z.L. and Zhang, G.M. (2023), “Automated machine learning-based model for the prediction of delirium in patients after surgery for degenerative spinal disease, *CNS Neurosci. Ther.*, **29**(1), 282-295. https://doi.org/10.1111/cns.14002

Zheng, W., Chen, Q., Yao, L., Zhuang, J., Huang, J., Hu, Y., ... and Wang, Y. (2023), “Prediction models for sleep quality among college students during the COVID-19 outbreak: Cross-sectional study based on the internet new media”, *J. Med. Internet Res.*, **25**, e45721. https://doi.org/10.2196/45721

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