Review Article

The use of machine learning for predicting candidates for outpatient spine surgery: a review

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Abstract: While spine surgery has historically been performed in the inpatient setting, in recent years there has been growing interest in performing certain cervical and lumbar spine procedures on an outpatient basis. While conducting these procedures in the outpatient setting may be preferable for both the surgeon and the patient, appropriate patient selection is crucial. The employment of machine learning techniques for data analysis and outcome prediction has grown in recent years within spine surgery literature. Machine learning is a form of statistics often applied to large datasets that creates predictive models, with minimal to no human intervention, that can be applied to previously unseen data. Machine learning techniques may outperform traditional logistic regression with regards to predictive accuracy when analyzing complex datasets. Researchers have applied machine learning to develop algorithms to aid in patient selection for spinal surgery and to predict postoperative outcomes. Furthermore, there has been increasing interest in using machine learning to assist in the selection of patients who may be appropriate candidates for outpatient cervical and lumbar spine surgery. The goal of this review is to discuss the current literature utilizing machine learning to predict appropriate patients for cervical and lumbar spine surgery, candidates for outpatient spine surgery, and outcomes following these procedures.

Keywords: Spine surgery; machine learning; outpatient

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Introduction

Background

Machine learning has become an increasingly common methodology for assessing large datasets in all fields of medicine (1). Machine learning is a form of statistical analysis which allows investigators to create highly fluid predictive models which are able to learn from a dataset with minimal to no human intervention (1,2). This stands in contrast to logistic regression (LR), which is the more traditional method for building multivariate predictive models for determining risk of an outcome. Utilization of machine learning algorithms in medical outcomes literature has grown, and unlike LR, machine learning techniques are able to assess complex linear and non-linear relationships amongst risk factors and outcomes while requiring less human intervention when developing the predictive model (3). Additionally, machine learning models have demonstrated superior predictive performance when compared with LR when compared using area under the curve (AUC) analysis (4). AUC is a method of assessing predictive efficacy of a model, with AUC of 1.0 indicating perfect predictive performance.

The popularity of machine learning has impacted spine literature as well. The use of machine learning models in the analysis of spine data has grown increasingly common in recent years (3,5,6). Many of these studies seek to employ machine learning techniques to predict diagnoses, treatment options, and patient outcomes (4,7). Spine patients often have complex pathologies alongside complex pre-existing comorbidities; as such, these studies aim to create predictive algorithms that can incorporate numerous patient-centered variables to develop patient-specific outcome predictions. As personalized medicine becomes increasingly desired by both patients and physicians, machine learning-based research seeks to facilitate this paradigm shift.

Rationale and knowledge gap

In addition to the push for personalized medicine, spine surgery has been making a push towards increasing the number of surgeries that can be performed in the outpatient setting. Outpatient cervical and lumbar spine surgery has become increasingly common (8,9). Outpatient spine surgery can provide a safe, efficient, and cost-effective alternative to traditional inpatient surgery (10-12). However, when considering a shift to outpatient surgery for procedures that have traditionally been done in the inpatient setting, it is paramount to consider potential acute complications for which identification and treatment might be delayed in the outpatient setting when compared with the inpatient setting. Alongside this, it is important to identify appropriate candidates for outpatient surgery, who would be less likely to suffer from these acute complications.

Objective

Machine learning techniques have previously been employed to identify appropriate candidacy for outpatient surgery in other areas of orthopedics such as shoulder, hip, and knee arthroplasty (13,14). Recently, machine learning has been employed in the spine literature as a predictive tool to determine which patients would be appropriate candidates for outpatient spine surgery. The goal of this review is to investigate the ways in which machine learning techniques have been utilized in the spine literature to predict appropriate candidates for cervical and lumbar surgery, predict patient outcomes for various cervical and lumbar surgeries, and how these predictive models are used to determine candidacy for outpatient spine surgery.

Lumbar spine

Indications for surgery

A variety of pathologies of the lumbar spine are debilitating and a threat to the functional status of patients. However, deciding who to operate on and how to most effectively treat a particular lumbar pathology can be challenging. Surgical decision making in spine surgery often differs from surgeon to surgeon, and with so many factors (anatomy, pathology, symptoms, patient expectations, other medical comorbidities) influencing which treatment options are utilized, it can be difficult to decide the “best option” for a patient. Machine learning models have been a recent area of focus in aiding surgical decision-making during lumbar spine surgery. Xie *et al.* utilized an artificial neural network (ANN) to predict the need for progression to requiring surgical intervention for patients with lumbar spine pathology. In their predictive model they included 55 patient factors, of which 8 were included in the final algorithm, including patient symptoms, medical history, and imaging findings. Their model showed a high degree of accuracy with an AUC of 0.90. They concluded that they can predict surgical candidacy with a high degree of accuracy cutting down potential wait-lists times for surgical evaluation and more targeted surgical referrals (7).

Machine learning also was utilized to predict spinal surgery candidacy based on imaging data. Wilson *et al.* utilized a machine learning model and MRI scans to analyze whether particular patients are surgical candidates for spinal stenosis. The model displayed an AUC of 0.88 for correctly predicting whether a patient should be referred to a surgical subspecialist. They concluded that their model could be utilized as a triage modality to make the outpatient surgical referral process more efficient (15). Another area of application for machine learning was improving surgical triage in the spine clinic. This was exemplified in a study conducted by Broida *et al.*, in which the authors created a model that used patient demographic data to accurately predict outpatient surgical candidacy in order to optimize surgical referrals and clinical triage (16). Overall, machine learning models have shown promising evidence that will allow surgeons to predict the likelihood their patient will require surgery with high degree of accuracy potentially saving time, money, and resources.

Predicting postoperative complications

Predicting complications has been a significant primary application of machine learning in spine surgery. Kim *et al.* illustrated this in a study in which they used the ACS-NSQIP database to examine ANN machine learning models to predict complications following posterior lumbar spine fusions. They conclude that their ANN exceeds the previously utilized linear regression models in identifying risk factors of developing complications following posterior lumbar spine fusions (4). This shows promising support that models can be created incorporating multiple variables in order to predict future obstacles to patient recovery. Another study looked at the use of predictive modeling and machine learning to identify patients at risk of venous thromboembolism following posterior lumbar fusions. This study found that their predictive model could be identified as a tool to identify patients at risk of developing venous thromboembolism after a posterior lumbar fusion (17). Another group that investigated the ability for machine learning to predict post-operative complications conducted a large-scale study involving 23,264 patients from the NSQIP database to investigate the ability of machine learning to predict 30-day readmissions after posterior lumbar fusion. This model had a mean positive predictive value (PPV) of 78.5% and a mean AUC of 0.812. The authors concluded that the model was able to predict readmissions up to 60% with a 0% false positivity rate which may suggest a need for creating a new system to reduce hospital readmission penalties after lumbar spine surgery (18). These studies exemplify the endless potential of predictive models and their applications to reduce costs, post-operative complications, and optimization of patient care in spine surgery and suggest that these models will likely have a clinical role in the future.

Predicting outpatient candidacy

Machine learning has also been utilized to predict outpatient surgery candidacy. Goyal *et al.* examined machine learning's ability to predict discharge to non-home facilities as well as early unplanned readmissions following spinal fusion. They found their machine learning algorithms had the ability to reliably predict non-home discharge as well as unplanned readmissions (19). This study demonstrates a practical application in which a model may help set appropriate postoperative expectations early on and prepare for readmissions or certain discharge dispositions ahead of time. Another application was exemplified by Li *et al.*, who investigated machine learning approaches to define candidates for ambulatory single level laminectomy surgery (20).

Discharge placement was another point of emphasis for several other studies. Ogink *et al.* looked at the ability of machine learning to predict discharge placement after elective lumbar spinal stenosis. They found their models could accurately predict discharge placement after lumbar spinal stenosis surgery, thereby avoiding delayed discharge and possibly resulting in lower healthcare costs (21). In the same year, Ogink *et al.* showed similar efficacy of a predictive machine learning algorithm to determine discharge placement following surgical intervention for lumbar spondylolisthesis (22). Stopa *et al.* utilized machine-learning models to predict non-routine discharge after elective lumbar spine surgery. They created a model that could predict non-routine discharge after lumbar disc surgery, which if applied could help institutions allocate appropriate resources to those at increased risk for unexpected changes in discharge dispositions (23).

Lastly, Kalagara *et al.* utilized machine learning models to predict hospital readmission following lumbar laminectomy. They found using their model that readmission can be predicted accurately using only preoperative input variables (24). In practice, this model could be utilized to increase the discharge care for higher risk patients to help reduce readmission following lumbar laminectomy. Overall, the use of predictive models in predicting ambulatory lumbar spine surgery or discharge planning can ultimately help save money, time, resources, and optimize care for patients undergoing lumbar spine surgery.

Cervical spine

Similar to lumbar spine surgery, cervical spine pathology can be debilitating and surgery has many indications and procedure options. Commonly treated pathologies include myelopathy, instability, radiculopathy, infection, and tumors. The number of spine procedures performed each year continues to increase (25-27). Therefore, the ability for surgeons to predict whether a patient will benefit from a surgery, have a high likelihood for improved function, and have a low risk for complication is of increasing importance.

Indications for surgery

Machine learning has increasingly been utilized to investigate how to better identify candidates for cervical spine surgery to augment clinical decision making. Wang *et al.* developed a predictive model using 12,492 patients undergoing single-level outpatient anterior cervical discectomy and fusion (ACDF) using an ANN to identify "safe" patients who may qualify for outpatient single-level ACDF. Their results were compares to legacy metrics and they found the predictive model had an AUC of 0.757, higher than both legacy risk-stratifications measured. They concluded that their model could aid in identification of safe candidates for single-level outpatient ACDF (28). Another study used MRI reports and a screening questionnaire of 478 patients to predict whether a patient would be recommended for cervical spinal surgery using an ANN. They found an AUC of 0.821 with a PPV of 83% and a negative predictive value (NPV) of 85% (16). This model could effectively screen patients to reduce nonsurgical patient burden in a surgical clinic without excluding patients that require surgery. This would reduce unnecessary visits, improve patient care, and potentially increase the proportion of operative cervical spine candidates seen by surgeons (16).

Another application of machine learning for identifying surgical candidates was performed by Khan *et al.* using seven different machine learning algorithms. Khan *et al.* aimed to develop an algorithm that predicts mild degenerative cervical myelopathy (DCM) patients that would most likely benefit form cervical spine surgery by using demographic variables and clinical presentation characteristics. After evaluating 193 patients who underwent surgical decompression, they found that their generalized boosted model (GBM) and earth models performed the best with AUCs of 0.77 and 0.78, respectively. They concluded that their model with further external validation would be beneficial for identifying patients with mild DCM who would benefit from surgery (29).

Predicting postoperative outcomes

Predicting the risk of post-operative complications before surgery is another application of machine learning that has been explored. Arvind *et al.* identified 20,879 patients who underwent ACDF and applied ANN, LR, support vector machine (SVM), and random forest decision tree (RF) models to compare with the American Society of Anesthesiologists physical status classification to predict surgical complications. This study found ANN and LR outperformed ASA for predicting post-operative complications, and ANN had greater sensitivity than LR when predicting mortality and wound complications (30). Maki *et al.* created a prognostic model with 478 patients using multiple model types to predict surgical outcomes for patients with cervical ossification of the posterior longitudinal ligament (OPLL). They found that the XGBoost model had the highest AUC of 0.72 and an accuracy of 67.8% after 1-year for predicting their set minimal clinically important difference (MCID) of a JOA score of greater than 2.5. Additionally, Maki *et al.* determined their RF model had the highest AUC of 7.5 and accuracy of 69.6% for predicting MCID after 2-years (31).

Merali *et al.* applied a supervised machine learning model to predict patient outcomes following surgery for DCM. They included 605 patients in a multi-center study which found the best performing predictive model was a RF structure with an AUC of 0.70. They found worse pre-operative disease, longer duration of DCM symptoms, older age, higher body weight, and smoking status as associated with worse surgical outcomes (32). Passias *et al.* utilized a Conditional Inference Decision Tree model to develop a risk index for developing distal junctional kyphosis (DJK) following cervical corrective surgery. Their analysis of 101 patients found a 23.8% incidence of DJK radiographically. Baseline malalignments, combined approaches and usage of Smith-Petersen osteotomy were the greatest risk factors for post-operative DJK at 1 year (33). Shah *et al.* retrospectively reviewed 6,822 patients for readmission or major complication and utilized an ensemble model compared to LR and standard machine learning techniques to predict major perioperative complications and readmission after posterior cervical fusion. The ensemble ML model had a modest risk prediction advantage over LR and standard ML models. They also found that the ensemble models most valued features were markedly less important than those most important in the LR model (34).

Another study, performed by Wang *et al.* utilized a SVM model evaluating 184 patients with cervical myelopathy after posterior laminectomy and fusion for clinical and imaging variables. They aimed to use this information to develop a model for predicting C5 palsy following this procedure. Their model achieved an AUC of 0.923 and an accuracy of 0.918 (35). Veeramani *et al.* evaluated the efficacy of many machine learning models for predicting the risk of unplanned intubation following ACDF. A total of 54,502 patients met inclusion criteria and found using the NSQIP database. The machine learning algorithms produced accuracy ranging from 72–100% and AUCs ranging from

0.52–0.77 with LR having the best AUC, but the worst accuracy (36). Wong *et al.* investigated if they could predict the early onset of adjacent segment degeneration following ACDF by evaluating the morphometry of preoperative deep neck muscles. They utilized an SVM model with demographic, radiographic and muscle parameters to develop this prediction model. Their model achieved high accuracy of 96.7% and an AUC of 0.97 (37). Goyal *et al.* wanted to develop a model to predict nonhome discharge and unplanned readmissions following spinal fusion (19).

All of these examples of machine learning models investigate our ability to predict various complications following cervical spine surgery from a pre-operative time point. The clinical value of this utility of machine learning is immense, as it allows us to understand what factors put patients at risk for various complications and can allow clinicians to better plan intra-operative and/or post-operative care. Additionally, these predictive potentials can allow surgeons to better predict a patient's post-operative prognosis before beginning surgery, which can further aid in decision-making regarding a patient's candidacy for outpatient spinal surgery.

Predicting length of stay (LOS) and outpatient candidacy

Another focus researchers have been exploring with machine learning is the risk factors involved in LOS following cervical spine surgery. Predicting the LOS for a procedure helps determine the appropriateness of outpatient versus inpatient surgery. Russo *et al.* implemented multiple machine learning models to evaluate 2,159 patients retrospectively, split between two LOS groups, less than two midnights or greater than two midnights in the hospital. The models aimed to predict the probability of a greater than two midnight stay. Their best performing ACDF Predictive Scoring System (APSS) was modeled after a LASSO, with an AUC from the receiver operating characteristic (AUROC) of 0.68 with a specificity of 0.78 and a sensitivity of 0.49. They concluded that this scoring system could be used in the inpatient or outpatient setting for predicting LOS following ACDF (38). Valliani *et al.* retrospectively examined EMRs from large, urban academic centers to identify patients who underwent cervical spine fusion for the development of a model to predict LOS following this procedure. Their Gradient-boosted tree model predicted LOS with an AUROC of 0.87 on a single-center validation set and 0.84 on a nationwide National Inpatient Sample data set (39). Zhang *et al.* endeavored to create a model to predict LOS following posterior spinal fusion surgery for adult spinal deformity. They utilized the ACS NSQIP dataset to find patients undergoing this procedure and analyzed the patients with several modalities with a prolonged LOS set at greater than or equal to 9 days. A total of 1,281 patients were included, with prediction accuracies ranging from 68% to 83% and AUC ranging from 0.566 to 0.821, with LR having the greatest accuracy and RF having the best AUC for predicting prolonged LOS (40).

Predicting symptomatic improvement

Postoperative functionality and symptom improvement are the ultimate goals of cervical spine surgery. Unfortunately, some patients do not improve as expected following cervical spine surgery. An investigation into functionality following cervical spine surgery was performed by Khan *et al.* They evaluated 757 patients retrospectively, who underwent surgical decompression for DCM. The modified Japanese Orthopedic Association score (mJOA) was used as a measure for functionality, along with other demographics and patient characteristics, were analyzed with multiple machine learning modalities. They found their highest performing algorithm to be a polynomial SVM, which demonstrated an AUC of 0.834 with an accuracy of 74.3%. Khan *et al.* concluded that worsening mJOA following surgical decompression of DCM was multifactorial, though they were able to identify predicting factors, and could successfully predict worsening status (29). Another application of machine learning to predict functional status following cervical spine surgery was performed by Hoffman *et al.*, who implemented multivariate linear regression and support vector regression models to predict a postoperative Oswestry disability index for any given patient requiring surgical decompression due to cervical spondylotic myelopathy. They included 20 patients in their study and found their SVR model to be more accurate than the MLR model, concluding that the SVR could be used preoperatively to create a risk/benefit analysis for a patient to supplement shared decision-making regarding surgical intervention (41).

Conclusions

As machine learning techniques are refined and advanced, they will continue to be utilized in the medical literature. This technology presents a new frontier for the analysis of large datasets and their application in regard to clinical decision making. Research surrounding machine learning in spine surgery has focused on clinically impactful uses of this technology. In time, machine learning will likely become more omnipresent within spine outcomes literature, with the goal of discovering ways to incorporate its usage within clinical practice.

While the growth of this technology is exciting, it is important to consider its limitations. Predominantly, the external validity of the predictive algorithms being published upon is unclear. The accuracy of the algorithms produced using machine learning techniques are dependent upon the data with which they are trained and refined. Thus, a highly accurate algorithm produced using one researcher's patient database may not be accurately applied to a new and different set of patients. Further research is needed to determine how applicable predictive algorithms are to patients from outside the dataset used in their production.

It is also important to consider the broader implications of machine learning's predictive capabilities on healthcare as a whole. While researchers are currently beginning to apply these predictive models to patient data, it is likely that entities such as health insurance companies will employ machine learning principals to their own datasets, if this isn't happening already. These models may become commonplace in determining if a patient will have a procedure approved for coverage. While this may in theory expedite approval processes, and allow for potentially more accurate decisions, these predictive models will be subject to the same limitations as all others, namely questionable generalizability. Furthermore, this could theoretically take some of the medical decision-making power away from the treating physician. Ultimately, more research is warranted to understand the greater impacts this technology may have on healthcare as a whole.

Machine learning will likely become an integral part of spine research, with an increasing number of investigators becoming familiar with its uses and drawbacks. The studies presented in this review are likely the first of many that seek to apply machine learning to the questions regarding cervical and lumbar spine surgery indications and outcomes.

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Footnote

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