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Letter to the Editor on "Machine Learning and Primary Total Knee Arthroplasty: Patient Forecasting for a Patient-Specific Payment Model"

To the Editor:

We read with interest the recent publication investigating the ability to utilize machine learning (ML)/artificial intelligence (AI) within a large statewide database Statewide Planning and Research Cooperative System (SPARCS) [1]. We have experience with both the SPARCS dataset and ML applications at our institution. We congratulate the authors on being the first group, to our knowledge, to publish their findings combining a large health database, ML, and total joint arthroplasty. We are believers that ML has the potential to shape how we manage large datasets and population health in the future. ML also holds promise in regards to image recognition in areas such as radiology and pathology, as well as natural language processing within electronic medical records. As the authors of the study have introduced ML technology to the journal, we would like to take this opportunity to allow further discussion on our behalf and for those readers who would like to begin to understand more about this topic. This presents a great question and answer opportunity on a cutting edge topic.

1. What resources are out there for readers who like to deepen their understanding of this topic? Is there a "machine learning for beginners" resource available?
2. Which one of the authors performed the data extraction from the SPARCS database and who was responsible for the ML algorithm design? If one of the authors was not formally trained in ML algorithm design, how did you gain experience and proficiency with this process?
3. From the Methods section of the paper, we concluded that you validated your ML algorithms based on internal SPARCS data. Have you made any attempt to validate this against an external dataset? What limitations do you currently see if you were to attempt to do this?
4. We see that you decided to utilize a naïve Bayesian machine learning algorithm in your work. We have used single-hidden layer feed-forward artificial neural network in some of our work. Can you explain why you chose naïve Bayesian machine learning algorithm vs any other algorithm and the pros and cons of one vs any other?
5. Can you describe for us some of the biggest hurdles you faced when completing your study? Specifically, what limitations did you find within the SPARCS database? As we continue to collect big data for ML/AI purposes, should we begin thinking about structuring our state and national databases in a way that facilitates ML/AI integration?

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Reference

[1] Navarro SM, Wang EY, Haeberle HS, Mont MA, Krebs VE, Patterson BM, et al. Machine learning and primary total knee arthroplasty: patient forecasting for a patient-specific payment model. J Arthroplasty 2018;33:3617–23.

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Response to Letter to the Editor on "Machine Learning and Primary Total Knee Arthroplasty: Patient Forecasting for a Patient-Specific Payment Model"

In Reply:

We thank Drs Ricciardi and Meyers for their insightful letter and kind comments. We appreciate the opportunity to further the conversation on the topic of machine learning (ML) and artificial intelligence (AI) in orthopedic surgery, particularly focusing on lower extremity arthroplasty.

We share the belief that ML is a critical tool that we in our profession should be familiar with as we continue to aggregate large amounts of data sets, known as "big data," in the form of joint registries, electronic medical records (EMRs), or picture archiving and communication systems (PACS) for musculoskeletal imaging. As computing power and server storage capacity increase in line with "Moore's Law," which forecasts that the number of transistors in a processing circuit doubles approximately every 2 years, the ability to aggregate and analyze data at a rapid speed has given rise to the commoditization of ML techniques [1]. It is our sincere belief that ML techniques may be readily applied to assist the day-to-day workflow of the overextended orthopedic surgeon on numerous fronts. From assisting our emergency medicine and radiology colleagues in clinical decision-making to quantifying the disparity between reimbursement and risk for a given arthroplasty patient, ML may be leveraged in many different ways to streamline our practice. To further explore the possibilities related to arthroplasty, AI, and ML, we have recently established the

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Machine Learning Arthroplasty Laboratory centered at the Cleveland Clinic.

1. What resources are out there for readers who like to deepen their understanding of this topic? Is there a “machine learning for beginners” resource available?

   Certainly, various resources exist for readers who desire an overview of ML topics. Our favorite review of big data and ML was published as a viewpoint article in the *Journal of American Medical Association* by Andrew L. Beam and Isaac S. Kohane [2], where the authors describe ML as a spectrum between human-controlled operations and computer-automated processes. Real-world applications from well-known technology companies, such as Google, Amazon, and Netflix, are presented. We would be remiss if we did not mention Dr Bini’s excellent narrative in the *Journal of Arthroplasty*, entitled *Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will they Impact Health Care?*[3]. However, no article supersedes the value of taking an introductory computer science class, learning the languages of Python in Anaconda and R in R Study, and practicing teaching machines how to perform pattern-oriented tasks.
2. Which one of the authors performed the data extraction from the SPARCS database and who was responsible for the ML algorithm design? If one of the authors was not formally trained in ML algorithm design how did you gain experience and proficiency with this process?

   Data extraction for the database was performed by Drs Navarro, Wang, Haeberle, and Ramkumar with an ML algorithm design by Navarro and Ramkumar. Before their careers in medicine, Navarro and Ramkumar had experience in ML topics from relevant industry experiences at Goldman Sachs and Microsoft, respectively, as well as formal education in computer science and computational analytics at the graduate level. We recommend that at least 2 members of a research team have a strong computer science background to develop the algorithm and to verify the code script, as well as a professional statistician capable of quantifying algorithm performance.
3. From the methods section of the article, we concluded that you validated your ML algorithms based on internal SPARCS data. Have you made any attempts to validate this against an external data set? What limitations do you currently see if you were to attempt to do this?

   This is an astute observation. We relied on internal validation of the ML algorithm for both this study on total knee arthroplasty (TKA) and our in-press article on total hip arthroplasty (THA), meaning it was tested on patients only within the database [4]. We used a 3:1 split in which 75% of the available patient data “built” or “trained” the algorithm, and the remaining 25% of the patients were used for “testing” to determine how well the algorithm was trained, a process that was repeated 5 times. We demonstrated “learning” using this method for both the TKA and THA populations in the SPARCS database, because the accuracy increased with each iteration. The limitation of this methodology is that the algorithm only applies to the patient population in this database. Certainly, external validation is necessary to strengthen the algorithm and to improve its generalizability. However, with the addition of multiple data sets, inconsistency with independent and dependent variables is not infrequent. Thus, only study of the common variables between the databases is possible to achieve internal and external validation. We have recently completed an analysis with both internal and external validation using a stronger ML technique with multiple data sets, and we are presently awaiting a decision from the submitted journal.
4. We see that you decided to use a naïve Bayesian machine-learning algorithm (NBML) in your work. We have used a single-hidden layer feed-forward artificial neural network in some of our work. Can you explain why you chose NBML vs any other algorithm and the pros and cons of one vs any other?

   We have used both NBML and artificial neural network (ANN) approaches in our work to date. The NBML approach described in our article is the most basic technique in ML as a classifier algorithm. This approach relies on independence of input variables, which is certainly an unrealistic assumption because in the clinical world risk factors such as diabetes, heart disease, and obesity are certainly coexisting, dependent variables. However, this represented an initial attempt to determine whether the approach was even possible with our existing orthopedic data sets. ANNs represent a more advanced ML technique that permits multiple interactions of input variables with each other, thereby allowing for more sophisticated inferences and thus a more accurate predictive algorithm. The ANN was designed after the neuron’s interconnectivity with discrete layers building upon each other (“deep” models), connections, and “axonal” directions of data propagation that permit “learning.” [5] As previously mentioned, we have strengthened our algorithm with an ANN using multiple databases for external validation and are awaiting a decision from the submitted journal. Our hope is to go beyond ML and to demonstrate that we have created a self-sustaining “deep learning” algorithm that learns with additive data and little to no human interaction or manual programming.
5. Can you describe for us some of the biggest hurdles you faced when completing your study? Specifically, what limitations did you find within the SPARCS database? As we continue to collect big data for ML/AI purposes should we begin thinking about structuring our state and national databases in a way that facilitates ML/AI integration?

   The biggest hurdle we faced, first and foremost, was communicating what ML was, its utility, and how it works. Certainly, the simultaneous analysis of thousands of patients and their associated variables cannot be fully isolated, weighted, and explained. This created a “black box” phenomenon that obfuscated the analysis. Further complicating matters is that the value of each variable cannot be fully quantified, despite the accuracy of the output. The SPARCS database is limited by the number of measurable outcome variables and its lack of generalizability as a regional state database. Expansion of outcome and more specific cost variables with a nationwide database will allow for an improved, more generalizable algorithm. Going forward, we as orthopedic surgeons should be more mindful of the software and platform used to construct these databases, beyond simply the outcome variables and population captured. A more rigorous understanding of the portability and shareability of the software architecture is required. In 2017, Ramkumar and Mont et al published a review in the *Journal of Arthroplasty* summarizing the importance of open architecture systems for the arthroplasty surgeon as our volume of stored data rapidly increases in EMRs, PACS, and registries [6]. However, a limitation of the current landscape in big data is the fragmentation and lack of interconnectivity between the myriad of data sources. One solution is to ensure that all systems implement an “open” architecture that affords universal data standards and a global interconnected network. The most recent example of a successful open architecture is the Internet. The rapid adoption and success of the Internet can be attributed to its ability to receive data from many different inputs because the transfer of data has a common denominator, the Internet protocol. This facilitated the development of the Web, an application that has engendered innovation and lowered the barrier to entry such that nearly anyone can build and customize an "online" presence with a website. Similarly, a unified registry incorporating PACS, EMR data, and continuous registry outcomes would be a monumental breakthrough in our ability to precisely forecast episodes of care, preoperatively plan, predict revision risk, and manage surgical expectations, among other applications.

We are grateful to Drs Ricciardi and Myers for the opportunity to have an open dialogue about AI and ML in lower extremity arthroplasty. Many excellent questions have been raised, and answering these uncertainties is an important focus of the Machine Learning Arthroplasty Laboratory as we continue to advance our understanding of this breakthrough technique.

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Letter to the Editor on "Routine Postoperative Laboratory Tests Are Not Necessary After Primary Total Hip Arthroplasty"

To the Editor:

We read with great interest the article by Halawi et al [1] regarding the necessity of routine postoperative laboratory tests after primary total hip arthroplasty (THA). This study adds evidence to the growing knowledge [2–4] that postoperative laboratory tests is only necessary in patients with identified risk factors in primary unilateral THA, and routinely postoperative laboratory tests should be discouraged for most patients in modern clinical practice. They are dedicated to improving the clinical practice, which impel us to redefine the necessity of the postoperative laboratory tests and re-examine the clinical utility of routine practice. The practice of ordering a "standard" battery of postoperative laboratory tests for patients after primary unilateral THA without evaluation of clinical needs could be wasteful and potentially harmful. However, when to abandon routine blood tests warrants further investigation.

First of all, order or abandon, that is the question: whether routine postoperative blood tests should be performed in patients undergoing primary THA. In this study, although more than 20% of patients had abnormal postoperative blood test results, only 17.6% (13/74) of which conveyed actionable information. These findings indicated that with the technological evolution of THA and health care, most postoperative blood test results are normal (negative), and most of the abnormal are borderline results that require no further treatment. Therefore, predicting the occurrence of abnormal postoperative

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Ethics approval or institutional review board approval: This letter was based on previous published studies; thus, no ethical approval or patient consent is required.

Submission statement: We confirm that this manuscript has not been published elsewhere and is not under consideration by another journal. All authors have approved the manuscript and agree with submission to *The Journal of Arthroplasty*.

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