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Corresponding Author:	David David, M.D. Cedars-Sinai Medical Center Los Angeles, CA UNITED STATES
First Author:	David Ouyang, MD
Order of Authors:	David Ouyang, MD
	William Hiesinger, MD
	Curt Langlotz, MD
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Deep Learning Pre-Operative Risk Stratification

David Ouyang [MD](#)^{1,2,*}, William Hiesinger [MD](#)^{3,4}, Curt Langlotz [MD PhD](#)^{3,5}

1. Department of Cardiology, Smidt Heart Institute, Cedars-Sinai Medical Center
2. Division of Artificial Intelligence in Medicine, Cedars-Sinai Medical Center
3. Center for Artificial Intelligence in Medicine and Imaging, Stanford University
4. Department of Cardiothoracic Surgery, Stanford University
5. Department of Radiology, Stanford University

Correspondence.

[127 S. San Vicente Blvd.](#)

[AHSP Pavilion Suite A3100](#)

[Los Angeles, CA 90048](#)

[310-423-3475](#)

David.ouyang@cshs.org

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Preoperative risk stratification and optimization is one of the most common encounters before surgery, however physicians still prognosticate risk using tools that are imprecise and incomplete. Traditional risk calculators only capture a sliver of the patient condition. Even complex risk scores requiring significant manual effort for entering data elements, such as the Society of Thoracic Surgeons Short-Term Risk Calculator and the euroSCORE, only capture a brief glimpse of the whole picture in understanding the complex relationship between patient condition and surgical risk. In this manuscript by Raghu et al, the authors propose the application of machine learning to common pre-operative imaging studies as a useful adjunct to clinical intuition and clinical risk scores for risk stratification of pre-operative cardiac surgery patients. Using information learned from preoperative chest X-rays (CXRs), their deep learning model was trained to predict post-operative mortality and aid in this important clinical scenario. At the same time,

Preoperative risk stratification can be approached from many perspectives; it is performed by surgeons, anesthesiologists, cardiologists, and primary care physicians alike. But traditional risk calculators only capture a sliver of the patient condition. Even complex risk scores for cardiac surgery, such as the Society of Thoracic Surgeons Short-Term Risk Calculator¹ and the euroSCORE², only capture a brief glimpse of the whole picture in understanding the complex relationship between patient condition and surgical risk. Inputs for these risk calculators already expansive—requiring significant manual effort for entering of data elements from many sources,

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such as laboratory testing, imaging results, social history, and prior diagnoses. Supplementing these models with additional clinical information such as frailty³, socioeconomic status⁴, or additional co-morbidities improves prognostic ability. The clear value of clinical intuition—the ‘sick or not sick’ judgement call every physician makes upon walking into a room—highlights the value of information beyond simple metrics and lab tests for clinical decision making about the patient condition.

Machine learning and artificial intelligence enable algorithms to synthesize the complex relationship between anatomic information and patient outcomes. Machine learning approaches are well-suited for these complex clinical challenges because they can identify complex features present in medical imaging and can model discontinuities in risk that elude logistic regression. This opportunity is particularly compelling for medical imaging applications. Great strides have already been made in tackling complex non-medical computer vision tasks ranging from self-driving cars to facial recognition. With the exponential growth and availability of computational power, new insights can be gleaned from readily accessible and rapidly growing stores of medical imaging data.

Recognizing this opportunity, Raghu et al.¹ used a deep learning convolutional neural network (Inception V3 architecture) on over fifteen thousand pre-operative chest X-rays (CXRs) with the goal of improving prognostication of mortality after cardiac surgery. On a hold-out test dataset of CXRs at Massachusetts General Hospital, the deep learning model performed well in predicting mortality within 30 days post-surgery with an AUC of 0.84, and on an independent dataset of CXRs before cardiac surgery at Brigham and Woman’s Hospital, predicted 30-day mortality with an AUC of 0.74. The STS Score performed similarly in the same populations with

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an AUC of 0.88 at MGH and 0.80 at BWH respectively, ~~however the STS score is much more expensive to calculate because it requires manual review of the clinical chart and significant data entry.~~

~~Many will inquire about the reliability of such a ‘black box’ algorithm and will want to know the most important features identified on CXR by the model? While the authors do analyze these questions, including saliency maps to identify regions of interest on the CXR, machine learning interpretability methods have significant room for improvement⁵ and often serve as little more than Rorschach tests in the eye of the beholder. But~~ The authors prior work as well as others have shown that important variables in the STS risk calculator, such as age^{2,6}, sex⁷, and comorbidities⁸ can be estimated by the chest radiograph alone. If the inputs for standard risk scores can be derived from the CXR, then the downstream synthesis of this information into a risk prediction can similarly be performed by a deep learning model. A growing and increasingly robust field of literature shows that biomarkers and co-morbidity information can be picked up by medical imaging^{3,4,9,10} and signals data. Parallel work on preoperative risk stratification from pre-operative electrocardiograms^{5,11} reaffirms the richness of possible medical data that can be used to identify patients at risk.

As we examine the current study, we should keep in mind that it focused on patients who underwent CXR imaging prior to surgery – ~~which~~. ~~This subset of patients~~ might not include the most low-risk or the most high-risk ~~patients undergoing cardiac surgery~~ patients. While chest radiographs are common, chest computed tomography (CT) is increasingly being utilized for pre-operative imaging, particularly ~~for before~~ re-do operations that require evaluation of the aorta and ~~vascular structures in relation to the sternum after scar tissue has formed~~¹². It is also notable that traditional risk calculators perform well in all cohorts of this study.¹ ~~Although not~~

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~~statistically significant, the STS Score had higher numerical AUC,~~ suggesting that deep learning models may be best used as an adjunct to traditional risk evaluation methods rather than replacing standard risk stratification. ~~Ultimately, to evaluate the risk for surgery, physicians must rely both on their own clinical experience and interpretation of the patient condition, and on decision-making aids that integrate additional objective information.~~

Overall, this study demonstrates clearly how advanced computational methods can be used to derive new insights that improve prognostication for a complex disease condition. The results also offer promise of continued progress in applying measures derived from computer vision to standardize assessments and improve the precision of patient care. The authors' parallel work on other forms of disease detection²⁶ in chest radiographs in addition to concurrent work ~~being done by others~~ in CT,¹³ echocardiography,¹⁴ and electrocardiograms, show the enormous potential of the rich information available in medical imaging. Automated machine learning approaches like those described here will enable even greater precision in patient phenotyping, thereby identifying new opportunities to improve patient outcomes.

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