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ESC Congress 2019

Machine Learning—state of the art

The critical role that machine learning can play in advancing cardiology was outlined at a packed session at ESC 2019

Speakers examined what machine learning can offer cardiology in the future, and also—in the abstract-based element of the session—focused on specific examples and studies where machine learning has been embraced to deliver results that may not otherwise have been attainable. In providing a perspective on machine learning, Professor Nicholas Duchateau from the University of Lyon noted that it was not a new concept and that there were previous machine learning booms in the 1960s and 1980s. 'The difference with the boom we are undergoing is the spread of it and our access to more data—Big Data—and much more computational power'.

As part of Artificial Intelligence (AI), with deep learning a subspecialty of machine learning, he emphasized the key to harnessing its power lies in putting forward the right question (s), choosing the data and model. 'Learning performance increases with experience and specific tasks but you have to adapt your models to your data', he said. However, there were still challenges in the field, such as the fusion of multiple data, unsupervised and semi-supervised, and various uncertainties.

In the first of a series of abstracts presented during the session—where the power of machine learning had delivered important results in the context of cardiology—Daniel Treiman, AI team lead at AliveCor, outlined how a deep neural network was able to predict atrial fibrillation (AF) from normal electrocardiograms (ECGs) recorded on a smartphone-enabled device.

Working with colleagues from the University of Oklahoma, the AliveCor team had hypothesized that a deep learning model could identify patterns predictive of AF during normal sinus rhythm. To test this, they trained a deep convolutional neural network to detect features of AF that are present in single-lead ECGs with normal sinus rhythm using a smartphone-enabled device.

Some 27 526 patients and almost 2 million ECGs were covered. The results showed that among 8259 patients in the test set, 3467 patients had at least 30% of their ECGs with an automated finding of AF. When the deep learning model was run on 841 776 normal ECGs, it was able to predict whether the ECG was from a patient with no AF or with 30% or more AF.

Using an operating point with equal sensitivity and specificity, the model's sensitivity and specificity were 73.1%. Mr Treiman concluded: 'A deep learning model was able to predict AF from ECGs in normal sinus rhythm that were recorded on a smartphone-enabled device. The use of deep learning, if prospectively validated, may facilitate AF screening in patients with paroxysmal disease or warn patients who are at high risk for developing AF'.

A study conducted by a team from the Department of Cardiology at Peking University First Hospital in Beijing showed how machine learning could be used to predict contrast-related acute kidney injury (AKI) from clinical data repositories (CDRs), including electronic health records (EHR). Dr Yuxi Li explained that while CDRs have great potential for outcome prediction and risk modelling, most are only used for data displaying. 'Using data from CDR for outcome prediction often requires careful study design and sophisticated modelling techniques before a hypothesis can be tested', he said.

However, the Peking University team built a prediction tool integrated with CDR, based on pattern discovery aiming to bridge that gap and successfully demonstrated a case study on contrast-related acute kidney injury with the system. To do this, a cardiovascular CDR integrated with multiple hospital informatics systems was established which included patients undergoing cardiac catheterization from January 2015 to April 2017, excluding those with dialysis, end-stage renal disease, renal transplant, and missing pre- or post-procedural creatinine. 'To build predictive modelling, we selected 17 variables covered in existing AKI models. Pattern discovery was recently developed as an interpretable predictive model which works on incomplete noisy data', he said. From the pattern discovery-based visual analytics tool, the results showed that among 2560 patients in the final dataset with 17 pre-procedure variables derived from CDR data, 169 (7.3%) had AKI.

In conclusion, Dr Li said: 'We developed a novel pattern-discovery-based outcome prediction tool integrated with CDR and purely using EHR data. In the case of predicting contrast related AKI, the tool showed user-friendliness by physicians, and demonstrated a competitive performance in comparison with the state-of-the-art models'. He said that future plans included external validation and that the predictive model was not the final destination, with risk classification and evaluation and further decision-making seen as being more important. There are also plans to build a patient-level risk evaluation tool based on pattern discovery and to design studies to investigate whether using such tools to direct clinical pathways can improve outcome or efficiency.

He added: 'We also want to encourage more physicians to collaborate with the IT guys'.

Dr Marton Tokodi from the Heart and Vascular Center at Semmelweis University, Budapest, Hungary, outlined how a machine learning-based risk stratification system was able to predict survival in patients undergoing cardiac resynchronization therapy (CRT).

Against a background of mortality rates remaining high in the CRT patient population, the researchers felt that a precise risk stratification would add significant value. 'Nonetheless, the currently available risk scores have several shortcomings which hamper their utilization in the everyday clinical practice', he said. 'Therefore, more precise and personalized methods are required'.

To help address this, the team's objective was to design and evaluate a machine learning-based risk stratification system to predict 1-, 2-, 3-, 4-, and 5-year mortality from pre-implant parameters of patients undergoing CRT implantation. After selecting 33 pre-implant clinical features, they trained multiple machine learning models on a retrospective database of 1510 patients undergoing CRT implantation to predict 1- to 5-year all-cause mortality. Then, the best performing model (the random forest based SEMMELWEIS-CRT score), along with pre-existing scores (Seattle Heart Failure Model, VALID-CRT, EAARN, Screen, CRT-score), was tested on an independent cohort of 158 CRT patients.

Results showed that using commonly available clinical variables, the SEMMELWEIS-CRT score was capable of effectively predicting all-cause mortality in patients undergoing CRT implantation. To enable an interactive and personalized calculation of predicted mortality, they have also developed an on-line calculator (semmelweiscrtscore.com).

Dr Tokodi said: 'Our results indicate that machine learning based risk assessment tools such as the SEMMELWEIS-CRT score can outperform the already existing linear model-based scores. By capturing the non-linear association of predictors, the utilization of these state-of-the-art approaches may facilitate optimal candidate selection and prognostication of patients undergoing CRT implantation'.

In wrapping up the session, Professor Partho Sengupta outlined a vision of the future for machine learning in cardiology. Chief of the Division of Cardiology and Director of Cardiac Imaging at West Virginia University School of Medicine, he said: 'Machine learning is going to completely disrupt the way we live and practice medicine. The first thing we have to do is let our guard down and accept this change'. Projected roles of AI, he said, are: improved risk prediction, improved efficiency and workflows, precision phenotyping, risk stratification scores, and greater contribution from synthetic modelling and datasets.

He said that as more patients present with an array of chronic disease the question will no longer be 'how are we going to treat patients as a cardiologist' but 'what are we going to do to make the patient able to live better'. 'It is about understanding a cluster of diseases', he said. 'There will be a continued growth in wearables, but we need to use machine learning to make sense of the data that is coming out of those wearables. We will see changes in how patients present—they will no longer be presenting symptoms but will present signs of symptoms coming from their apps. Once we have identified a high-risk individual there will be more emphasis on modelling our solution'.

He forecast that all diagnostic work in cardiology will eventually be supervised by machine learning. 'While we are currently training machine learning models to identify diseases as we understand them, in the near future we will learn cardiovascular diseases in new ways using unsupervised algorithm', he said. 'It is likely the whole taxonomy of how we understand cardiovascular disease and the 'progression of risk in disease space will change'. He pointed to the health kiosk model which will offer face assessments or blood volume from fingers placed on a monitor with data entered into a risk algorithm and outline cardiovascular health. He also suggested that smart bathrooms at home may have sensors that will pick up potential diseases when the household uses the room.

However, he urged the need for caution with machine learning because of the biases involved and added that: 'The patient–doctor relationship will not be replaced by AI. AI will not replace us but people who do not use AI will be replaced by people who do use AI'.

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