EDITORIAL

Risk Scores and Neural Networks in Heart Failure Patients

Scores de riesgo y redes neuronales en pacientes con insuficiencia cardíaca

LUIS EDUARDO JUÁREZ-OROZCO MD, PHD[1]

A new reverberating era has started in artificial intelligence. The general concept of artificial intelligence corresponds with the implementation of models or algorithms to perform a task needing an intelligence level comparable to that of human beings. (1) To date, the methodological cornerstone is data analysis through iterative methods capable of extracting generalizable patterns that optimize performance in classification and prediction tasks (machine learning). This has permeated into different scientific and industrial areas at a remarkably fast pace with significant examples such as facial recognition, self-driving cars, web search engines and even visual and auditive entertainment media. (2)

Regarding the family of machine learning algorithms, a conceptual division can be made between statistical methods such as iterative logistic regression, K-nearest neighbor (for assembling), support vector machine, random forest (useful for decision trees) and combinations by means of ensemble boosting, and those using artificial neural networks (ANN), which according to their increase in depth (in number of intermediate layers) has been called deep learning. This division is artificial but sensitive to two fundamental differences between types of algorithms, interpretation ability and performance with respect to sample size. On the one hand, machine learning statistical methods can be better interpreted by the analyst. On the other hand, deep learning has only shown excellent functioning when a large volume of data is used for its training.

Another basic aspect is the goal assigned to the models, which by definition must be trained, validated and tested in separate samples. The type of learning can differ between supervised, non-supervised and reinforcement. Supervised learning means that the dependent variable (disease, adverse event, exact measurement) is already known in the data analyzed and is therefore used as a conceptual truth from which it is possible to calculate how adequately the algorithm is performing and to monitor its improvement through training cycles. Conversely, non-supervised learning implies not assuming a specific truth, generating clusters of data that may or may not be known by the analyst. This has been successful for the exploration of new subgroups in patients with heterogeneous conditions for whom a subclassification does not exist yet (for example, responders to cardiac resynchronization therapy). (3)

In medical sciences, cardiovascular medicine has started to benefit from these analytical methods in automated data processing derived from diagnostic images obtained by means of coronary computed tomography angiography (CCTA), (4, 5) single photon emission computed tomography (SPECT), (6, 7), positron emission tomography (PET) (8) and cardiac magnetic resonance (CMR). (9) In addition, deep learning of electrocardiographic analysis for triage of acute conditions has shown excellent performance together with adequate interpretation of plausible spatial patterns, though also indistinguishable for the analyst or operator. The latter emphasizes the potential of these analytical methods in the exploitation of complex patterns which are omitted in the daily clinical reality but which can be crucial for improving our approach to preventive and therapeutic decisions.

The pathway in the implementation of artificial intelligence based on machine learning in any niche that requires optimization in the identification and differentiation of pathological states and prediction of adverse events can be oriented with respect to what the accumulated experience has shown in the last 5 years. Initially, supervised learning can be used by means of machine learning statistical methods and, depending on the amount of data, deep learning can be implemented for the analysis of structured data in existing databases. Simultaneously, non-supervised learning can be applied in search of novel patient groups with potential consequences in for management and follow-up. If the data allow it, deep learning can follow in structured data or in direct imaging identification. Once these analyses have been contemplated in terms of diagnosis, prognostic analyses are of great interest, though it is necessary to clarify that literature is still limited and offers great possibilities in the near future.

Rev Argent Cardiol 2021;89:369-370. http://dx.doi.org/10.7775/rac.v89.i5.20449

SEE RELATED ARTICLE: Rev Argent Cardiol 2021;89:416-426. http://dx.doi.org/10.7775/rac.v89.i5.20434

[1] Divisie Hart en Longen. Universitair Medisch Centrum Utrecht

And it is in this niche that Gambarte et al. (10) report in this issue of the Argentine Journal of Cardiology the use of artificial neural networks for the analysis of 24 variables employed in different models generated in international samples estimating all-cause mortality risk in patients with acute heart failure hospitalized in a coronary care unit. This certainly commendable exploratory study performed in South America analyzed the performance of two types of superficial neural networks in the identification of patient mortality at three prospective cutoff points (1, 6 and 12 months) compared with previously validated and recommended linear scores. The integration of these variables showed a better performance with respect to comparative models, with a significant gain in discrimination, but still with discrete predictive values. They additionally presented a proxy of interpretation through values of standardized importance, which is an excellent aspect of the study made possible given the relative simplicity of the network used.

As every pioneering study, Gambarte's report generates a series of very interesting questions and suggests an optimization pathway of the analyses presented. Firstly, it is important to investigate, in the near future, how does the performance of this network compare with machine learning linear and statistical models incorporating the same 24 variables and in which "feature selection" is performed with respect to other estimation methods of standardized relevance. This, with the objective of exploring what proportion of the performance is due to overfitting, which can be handled to improve model functioning and generalization. It will be paramount to divide future data considering a training set, a validation one and another testing set where performance measurements will be more reliable. Secondly, it is relevant to explore how to incorporate the influence of survival time in machine learning modeling. Up to the moment, studies reported on this area have used follow-up periods as fixed points, without a means for using time-to-event data. Considering that the statistical standard in predictive studies is survival analysis through Cox regression due to the relevance of survival time, it is important to visualize its incorporation in machine learning explorations. Finally, another challenge for future studies will be to assess the performance of different neural network architectures with respect to those reported in the study by Gambarte et al. Open source libraries such as PyTorch (https://pytorch.org) offer a great variety of tools for this exploration by programming in languages such as Python. With these resources it is possible to extend this interesting line of research beyond the limits established in programs such as SPSS.

CONCLUSION

The study of Gambarte et al. contributes to the growing area of artificial intelligence implementation based on machine learning for the optimization of cardiovascular prognosis estimation, and promotes interesting challenges for the near future.

Scientific progress has as keystone the search for the truth, and the objective of generating and implementing new analytical capacities has been galvanized by this emerging era of progress in artificial intelligence. The present study embraces these purposes and orients us in the progress of cardiovascular medicine, profiting from the utilization of data and their complex interrelationships. There are no longer constraints in terms of computational capacity and data storage, and the only limit in the horizon is that of our imagination.

Conflicts of interest

None declared.

(See authors' conflicts of interest forms on the website/ Supplementary material)

Ethical considerations

Not applicable.

REFERENCES

1. Slart RH, Williams MC, Juarez-Orozco LE, Rischpler C, Dweck MR, Glaudemans AW, et al. Position paper of the EACVI and EANM on artificial intelligence applications in multimodality cardiovascular imaging using SPECT/CT, PET/CT, and cardiac CT. Eur J Nucl Med Mol Imaging. 2021;48:1399–413. https://doi.org/10.1007/s00259-021-05341-z

2. Benjamins JW, Hendriks T, Knuuti J, Juarez-Orozco LE, van der Harst P. A primer in artificial intelligence in cardiovascular medicine. Netherlands Hear J [Internet]. 2019;27:392-402. https://doi.org/10.1007/s12471-019-1286-6

3. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M, et al. Artificial Intelligence in Cardiology. J Am Coll Cardiol. 2018;71:2668–79. https://doi.org/10.1016/j.jacc.2018.03.521

4. Takx RAP, De Jong PA, Leiner T, Oudkerk M, De Koning HJ, Mol CP, et al. Automated coronary artery calcification scoring in non-gated chest CT: Agreement and reliability. PLoS One. 2014;9. https://doi.org/10.1371/journal.pone.0091239

5. Benjamins JW, Yeung MW, Maaniitty T, Saraste A, Klén R, van der Harst P, et al. Improving patient identification for advanced cardiac imaging through machine learning-integration of clinical and coronary CT angiography data. Int J Cardiol. 2021;335:130–6. https://doi.org/10.1016/j.ijcard.2021.04.009

6. Hu L-H, Betancur J, Sharir T, Einstein AJ, Bokhari S, Fish MB, et al. Machine learning predicts per-vessel early coronary revascularization after fast myocardial perfusion SPECT: results from multicentre REFINE SPECT registry. Eur Hear J - Cardiovasc Imaging. 2019;1–11. https://doi.org/10.1093/ehjci/jez177

7. Otaki Y, Singh A, Kavanagh P, Miller RJH, Parekh T, Tamarappoo BK, et al. Clinical Deployment of Explainable Artificial Intelligence of SPECT for Diagnosis of Coronary Artery Disease. JACC Cardiovasc Imaging. 2021 Jul; https://doi.org/10.1016/j.jcmg.2021.04.030

8. Juarez-Orozco LE, Martinez-Manzanera O, van der Zant FM, Knol RJJ, Knuuti J. Deep Learning in Quantitative PET Myocardial Perfusion Imaging: A Study on Cardiovascular Event Prediction. JACC Cardiovasc Imaging [Internet]. 2019 https://doi.org/10.1016/j.jcmg.2019.08.009

9. Ruijsink B, Puyol-Antón E, Oksuz I, Sinclair M, Bai W, Schnabel JA, et al. Fully Automated, Quality-Controlled Cardiac Analysis From CMR: Validation and Large-Scale Application to Characterize Cardiac Function. JACC Cardiovasc Imaging. 2020;13:684–95. https://doi.org/10.1016/j.jcmg.2019.05.030

10. Gambarte MJ, Higa C, Novo F, Ciambrone GM, Tupayachi Villagomez OD, Ginesi A, y cols. Prognostic Comparison between Risk Scores and Neural Networks to Predict Short- and Mid-Term Mortality in Acute Heart Failure . Rev Argent Cardiol 2021;89:416-26. http://dx.doi.org/10.7775/rac.es.v89.i5.20434