Artificial intelligence continues to make headway in dermatology

We will elaborate on this topic using three recent and varied publications about AI in dermatology. But first, for those of you who may not be familiar with AI, here is a short glossary related to four of the most frequently employed terms in these articles (and essentially all over the press): artificial intelligence, machine learning, neural networks, deep learning.

A short glossary about artificial intelligence

Artificial intelligence (AI) can be simply defined as a computer's ability to simulate intelligent human behavior. Machine learning is a subset of AI that uses algorithms and statistical models that can learn from data. Deep learning is a specific subset of machine learning. Convolutional neural networks (or "CNNs") are computer architectures made up of highly connected processing nodes, similar to neurons in the brain, that enable computers to carry out deep learning.

In short, artificial intelligence is a very broad term that can refer to both machine learning and convolutional neural networks. All of these terms fit together like a set of Russian dolls. This is of course a very simplified explanation, and those of you who wish to learn more can do so by consulting the references listed below (1,2).

Diagnostic performance of artificial intelligence for histologic melanoma recognition compared to 18 international expert pathologists (3)

Today, the anatomo-pathological diagnosis of melanomas is based on several (naturally, somewhat subjective) histological characteristics. This means that there may be significant discordance between pathologists classifying the same lesions, and objective assistance tools could prove useful.

This study compared the ability of convolutional neural networks (CNNs) with that of 18 international expert pathologists to differentiate between melanomas and nevi. CNNs were trained and tested with images of histological slides of 50 melanomas and 50 nevi that had previously been classified by two experienced dermatopathologists who gave the reference diagnosis. The same 100 scanned slides were submitted online for diagnosis to 18 international dermatopathologists, each with at least 5 years' experience.

The pathologists achieved sensitivity, specificity, and accuracy rates of 88.88%, 91.77% and 90.33%, respectively. The CNNs, having been trained with the scanned slides, with or without prior manual annotation of the region of interest (NB: a technique that facilitates analysis by the CNN), matched the experts (in terms of average sensitivity, specificity and accuracy (unannotated slides: 88%, 88% and 88%, respectively, and area under the curve [AUC] 0.95; annotated slides: 94%, 90% and 92%, respectively, with an AUC of 0.97).

However, all slide collections tested in this study came from the laboratory of origin, so the CNNs' performance cannot be extrapolated outside of this specific environment. Despite this limitation, the authors conclude that this type of "local" CNN can be useful in a laboratory, especially as a diagnostic aid for more inexperienced pathologists.

Diagnosis of congenital pigmented macules in infants with reflectance confocal microscopy and machine learning (4)

Congenital pigmented macules (CPMs) can be clinically equivocal in infants. The differential diagnosis between café au lait stains and congenital melanocytic nevi (CMN) can therefore be difficult. Confocal reflectance microscopy (CRM) could be useful here. A retrospective study conducted by the Nantes University Hospital used CRM to study the characteristics of 49 equivocal CPMs. The diagnosis of café au lait stains or CMN was established using skin biopsy or observations made during follow-up. The images were evaluated by three blinded experts.

Finally, a convolutional neural network ("CNN") was trained to automatically classify CPMs as café au lait stains or CMN using the CRM images. Out of 30 children with CPMs (mean age of 33.7 months), 20 had café au lait stains and 10 had CMN. The average follow-up lasted 72 months. CRM images of CMN were characterized by the presence of hyper-reflective thecae (CMN: 100% vs café au lait stains: 0%, $p < 0.001$). In contrast, CRM images of café au lait stains were characterized by the presence of peripapillary rings that were both hyper-reflective (café au lait stains: 100% vs CMN: 30%, $p < 0.001$) and hypertrophied (café au lait stains: 100% vs CMN: 10% $p < 0.001$).

The convolutional neural network had an accuracy rate of 89.1% when differentiating between CMN and café au lait stains, with 85.5% and 92.8% correct predictions respectively. These results show that café au lait stains and CMN observed using CRM have different characteristics that can be used for differential diagnosis. In addition, a neural network trained with CRM images can differentiate between café au lait stains and CMN.

Automated detection of skin reactions in epicutaneous patch testing using machine learning (5)

Patch testing is the go-to method for identifying the causes of allergic contact dermatitis. That said, there are not many facilities that specialize in patch testing. In addition, the increase in consultations required to take and read tests can be tedious for patients as well as doctors.

Here, the authors describe a new application of machine learning in dermatology for diagnosing allergic reactions using patch test photographs. 77 patients who underwent patch testing at Stanford Hospital were included in this study. Allergens were placed on their backs in eight panels measuring 5x2 cm each and removed after 48 hours. Anonymized images of each panel were obtained four days after the allergens were applied. From these images, two dermatologists categorized the allergen reactions into positive (1+, 2+, 3+) and negative or irritant (0, IR) reactions. Questionable reactions (?+) and poor-quality images were excluded, resulting in a set of 3,695 images representing 118 positive and 3,577 negative patch tests).

The data set was separated into three subsets: one for training a CNN (the Google Xception network), one for validating it, and one for evaluating it. For the test subset, which included 50 positive and 2,154 negative patch test images, the CNN achieved a 99.5% accuracy rate. There were 11 misclassifications, 4 of which were false positives and 7 were false negatives.

The potential advantages of this approach include: 1) avoiding the inter-individual discrepancies that exist between dermatologists when it comes to test interpretation, 2) making it possible to diagnose the patient at home, thus saving an extra trip to read the tests, 3) and finally, given how convolutional neural networks work, test readings, as well as skin reaction recordings, could incorporate other factors such as the sensitizing potential of the tested substance, or the prevalence of contact eczema with this substance, therefore potentially allowing for improved interpretation.

In conclusion, this study provides proof of principle that machine learning can be used to interpret patch test photographs with a high degree of accuracy. The next step, which will require a larger database, will be to develop a CNN capable of quantifying the intensity of skin reactions according to the standard scale used for patch testing.

- Sources

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