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Real-world applications of deep convolutional neural networks in diagnostic cancer imaging

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Ultrasound is integral to the management of thyroid nodules. However, the interpretation of thyroid ultrasound studies is time- and training-intensive and has inherent inter-observer inconsistencies, resulting in a decrement in its positive predictive value (1). Compounding these limitations, fine-needle aspiration (FNA) yields 15% to 30% cytologically indeterminate nodules, which often leads to unnecessary diagnostic surgeries (2). This spurred the initiation of a new research space where artificial intelligence (AI) is steered to improve preoperative sonographic risk stratification of thyroid nodules, and to minimize overdiagnosis and overtreatment of thyroid cancer. Li *et al*. conducted a multi-institutional effort to use AI-enabled algorithms that appear to supersede the previous machine learning sonographic classifiers of thyroid nodules (3). To that end, they used a large sonographic set of more than 300,000 images, thereby eliminating a common barrier to similar studies—the

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lack of sufficiently large curated datasets. Li *et al*. compared their deep convolutional neural network (DCNN) model's performance against the judgment of expert radiologists per the standard Thyroid Imaging Reporting and Data System (TI-RADS) guidelines and pathological examination results, which represent the gold standard for diagnosis (4).

Previously, there has been an unmet clinical need to grow out of the traditional machine learning thyroid nodule classifiers with their inherent pitfalls such as dependence on expert-designated features as inputs (5). However, Li *et al*. successfully demonstrate the capacity of a performance-weighted combination of two of the most popular deep learning classification models (i.e., ResNet-50 and Darknet-19 CNN architectures) to rapidly-produce promising results in a real-world setting. The DCNN model from Li *et al*. showed superior specificity and accuracy, and similar sensitivity to expert radiologists' judgment, all in the setting of an externally validated study. The latter suggested model generalizability.

Appropriately, the authors reported caveats to their work including the absence of multicenter training cohorts and not fully accounting for the potential confounding effect of nodule size and thyroid cancer subtypes, and an almost exclusively northern Han Chinese population. Nevertheless, this study offers valuable insights into the implications of deep learning in thyroid nodules sonographic risk stratification. Notably, deep learning performs better than conventional computer-assisted diagnosis (CAD) systems designed for thyroid nodule recognition especially in overcoming the challenge of heterogeneity (e.g., thyroid nodule biology, different ultrasound equipment manufacturers, etc.). CAD, given its more user-friendly nature, has a lower implementation barrier. Hence, we need to acknowledge the effort by Li *et al*. to introduce a result report interface that instantly projects to a graphical processing unit and has the potential to be integrated into ultrasound equipment. Complementing AI projects with ready-to-use application programming interfaces (API) serves as a bridge between developers and clinical stakeholders and to expedite new AI tools FDA clearance, adoption, and potential commercialization (6).

Importantly, embracing AI into clinical research and mainstream practices should be done responsibly and openly to maximize the benefits and avoid any potential or collateral damage (7). To ensure the generalizability of these results, a commitment to promoting data sharing in accordance with the FAIR guiding principles for scientific data management should be promoted (8). Li *et al*. are to be commended for going beyond just publishing "significant" results to the development of a freely available online platform that executes the deep learning framework. This under-construction website will permit prospective validation and ensure health equity across underserved regions and countries where expertise in radiological imaging interpretation might require optimization. The premise of reduced financial toxicity and psychological burden of unnecessary interventions, therefore, is encouraging indeed as is the opportunity to provide expertise required to assess thyroid nodules that may not be available in all areas of the world.

AI is invariably changing the oncology landscape and the efforts by Li *et al*. represent one benchmark for future AI algorithm development for thyroid nodules risk stratification. They provide a real potential for transforming this capability into a widely applicable clinical tool. However, what Li *et al*. make abundantly clear is that their model is complementary to rather than a substitute for manual diagnosis of thyroid cancer, reinforcing the importance of the partnership between clinicians and AI experts. Consequently, the oncology community must embrace and invest in AI via personnel education, collaborative research, and resource allocation in order to create more innovative solutions for real-world clinical challenges.

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