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People go the extra mile for food

In the United States, cardiometabolic diseases are rife — and on the rise. Efforts to understand this trend typically look at how local access to healthy food varies across the country. But a study of 94 million visits to food retailers shows that most people venture beyond their neighbourhoods to buy food, as Xu *et al*. report in *Nature Communications* (R. Xu *et al. Nature Commun.* **14**, 7326; 2023). The authors found that people travel a median distance of 5.95 kilometres each time they buy food.

Using GPS tracking data, Xu *et al*. calculated the percentage of food-buying visits that people from a given area made to retailers selling healthy food. They found that this measure was a better predictor of rates of obesity, high cholesterol and high blood pressure than is the percentage of such retailers in the local area, which is a standard way to measure food-access disparities. The findings could shift policy priorities away from improving local food access, to instead focusing on health education and the affordability of healthy food.

Abigail Klopper

Artificial intelligence

The deep route to low-field MRI with high potential

Patricia M. Johnson & Yvonne W. Lui

A type of magnetic resonance imaging, known as low-field MRI, could make the technique more widely accessible, but only if the image quality can be improved. A deep-learning protocol might hold the key.

Magnetic resonance imaging (MRI) is an essential tool in medical diagnostics; however, its utility has often been limited by factors such as high costs and the necessity for advanced infrastructure. Conventional MRI is therefore unavailable in many health-care settings, especially in low- and middle-income countries. One approach to counter these challenges is the development of MRI that uses low magnetic-field strengths. However, low-field MRI also introduces its own set of problems – notably, longer scan times and a diminished signal-to-noise ratio compared with conventional MRI. Writing in *Science Advances*, Man *et al.*[1] report a promising solution to these limitations that uses deep-learning techniques to enhance the images obtained with ultra-low-field MRI. The approach is a key contribution to efforts aimed at using deep learning to make MRI affordable and widely accessible.

An MRI system is typically used to help physicians to distinguish one type of tissue from another. In simple terms, this is achieved by sending radio-frequency pulses through the tissue while it is subjected to the system's magnetic field, and then measuring how the magnetic response of the hydrogen nuclei in the tissue varies across the sample. Since the introduction of MRI half a century ago[2], there has been a trend towards using ever higher magnetic field strengths, because they produce inherently stronger signals than do weak fields. Early clinical MRI scanners[3] operated at field strengths of up to 0.5 tesla, whereas scanners with strengths of 1.5 T and 3 T are now widely used, and systems with even higher field strengths are popular in some areas of research.

But interest in low-field MRI is burgeoning, and ultra-low-field systems are now emerging with field strengths of less than 0.1 T (refs 4,5). The system that Man and colleagues used operates at a mere 0.055 T. Ordinarily, such a system would generate noisy, low-resolution images, but the authors showed that they could enhance the image quality using state-of-the-art deep learning, rendering some anatomical details more visible (Fig. 1).

The image protocol involved acquiring two types of 3D image, each with a different contrast, at low spatial resolution and with a low

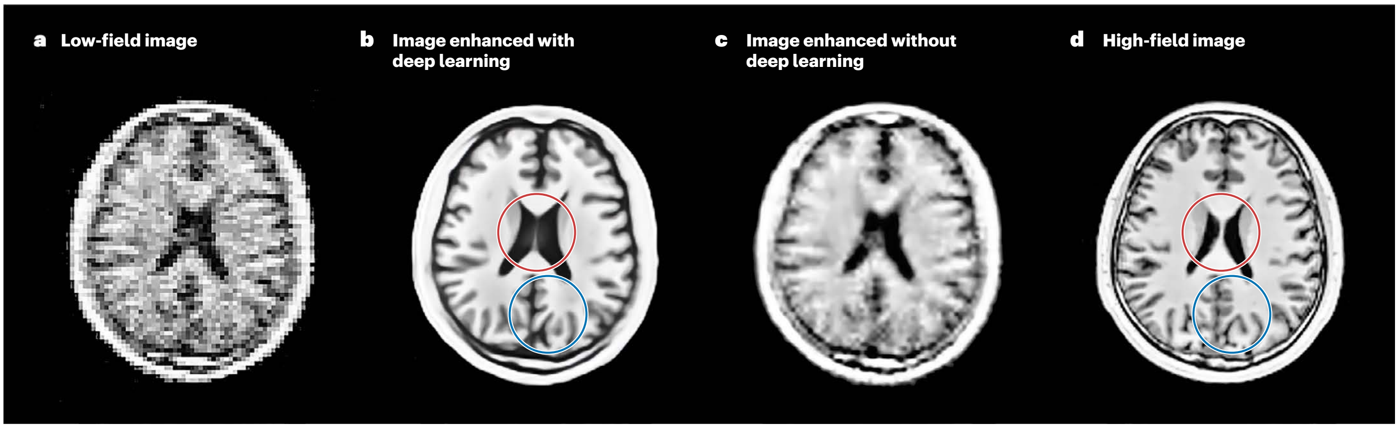

Figure 1 | Enhancing MRI images of the brain. Conventional magnetic resonance imaging (MRI) requires expensive magnets to produce large magnetic fields that are difficult to generate. **a**, Alternative MRI systems with low magnetic-field strengths are cheaper and more portable, but they produce low-quality, noisy images, such as the one shown here of the brain of a 33-year-old volunteer. **b**, Man *et al.*[1] developed a protocol to enhance the quality of these images using deep-learning techniques. **c**, The approach improves the quality of enhancements made with other techniques that do not involve deep learning. **d**, Its images are close in appearance to images generated by systems with higher, standard magnetic-field strengths. However, some inconsistencies are apparent in the deep-learning-enhanced image, such as larger ventricles (fluid-containing compartments inside the brain; red) and a simplified brain-surface folding pattern (blue). (Adapted from Fig. 4a of ref. 1.)

signal-to-noise ratio. The images were also undersampled, using a technique known as partial Fourier sampling. By undersampling, the authors reduced the scan times for these images to around three minutes — more than three times faster than the scan times that members of the same group were able to achieve previously with a different method[6].

The 3D images then served as inputs for the team's deep-learning model, which aims to create high-resolution images from lower-resolution images, thereby achieving 'super-resolution'. The approach was inspired by a network model for achieving super-resolution in 2D images of natural scenes[7], which the authors extended to 3D to better capture the features of brain structures.

The model needed to be trained on pairs of ultra-low-field and 3-T MRI images of the human brain. However, such data are currently scarce. To address this challenge, the team used a publicly available data set of human brain images generated by 3-T MRI systems. They then simulated the characteristics of undersampled, low-resolution, noisy ultra-low-field images. This innovative approach provided the authors with a robust training data set for their model — showcasing a promising technique for the future development of deep-learning methods for ultra-low-field imaging.

Man *et al.* demonstrated the efficacy of their protocol by evaluating two key metrics for image quality across 200 synthetic data, and showed that the processed images were quantitatively better on average than the raw ultra-low-field images. MRI data from healthy volunteers reaffirmed these findings. The authors' technique also produced results that were qualitatively less noisy than those generated with conventional image reconstruction and denoising methods, and the images were closer in appearance to scans obtained using an MRI machine with a 3-T magnetic field.

Although Man and colleagues' results are promising, their study did not include a thorough evaluation of how useful the information in the images would be in a clinical setting. To truly assess the diagnostic potential of the images obtained through this approach, a broader clinical evaluation with a diverse cohort of individuals with varied brain pathologies is required. Indeed, one concern associated with deep-learning methods in medical imaging is that they have the potential to remove abnormal features from the images. This phenomenon, termed pseudo-normalization, has already been observed in deep-learning reconstructions of brain images obtained with highly accelerated MRI (ref. 8).

At their core, deep-learning super-resolution methods aim to enhance the resolution of an image beyond that of the originally acquired image. These models learn to predict and fill in missing high-resolution details on the basis of patterns contained in the vast data sets on which they train. Therefore, a model trained on healthy individuals alone lacks exposure to pathologies and might not represent them accurately. Conversely, super-resolution models can sometimes introduce 'hallucinations' by generating details that might appear realistic, but do not exist in the original image. Both problems underscore the need for rigorous clinical validation of deep-learning technologies.

Man *et al.* focused on using deep learning for image enhancement, which differs from deep learning for image reconstruction. Deep-learning methods for reconstruction often incorporate data-fidelity measures, which potentially reduce the chances of generating hallucinations. These approaches might be more accurate than deep-learning methods designed for image enhancement because they leverage the inherent redundancies in the data during image formation, rather than relying solely on patterns from previous data sets to enhance resolution. Continuing work aims to develop methods that can accurately estimate errors in images that are reconstructed or enhanced with deep learning[9,10].

Nonetheless, Man and colleagues' method for ultra-low-field imaging offers an exciting step towards cost-effective and accessible MRI. Ensuring the reliability of their approach will be crucial, especially in terms of detecting abnormalities. Future studies must tread carefully, balancing the allure of cutting-edge imaging techniques with the rigorous demands of clinical accuracy.

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