SUPPLEMENTARY MATERIAL / SUPPORTING INFORMATION

Magnetic Field Sensing Bolstered by Deep Learning on Scattering Images from Random and Conventional Laser Illumination

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1. Calibration and calculation of experimental accuracy

The standard laboratory calibration was performed by observing the current passing through the coils, measured using a Minipa ET-2076A multimeter, and plotted as a function of the magnetic field recorded on a Teslameter (Phywe digital, serial No. 319900040863, sensitivity $10\,\mu T$, ranges 20-200-1000 mT) coupled with an axial Hall probe. For each magnetic field value, we took 50 consecutive electric current measurements and the graph is represented in Fig. S1. The experimental accuracy is then calculated as:

$$accuracy = \left\langle \left[\left(1 - \frac{\sigma_i}{\mu_i} \right) \times 100 \right] \right\rangle$$

Where σ_i is the standard deviation of the electric current related to magnetic field i and μ_i is the average intensity of the current related to magnetic field i.

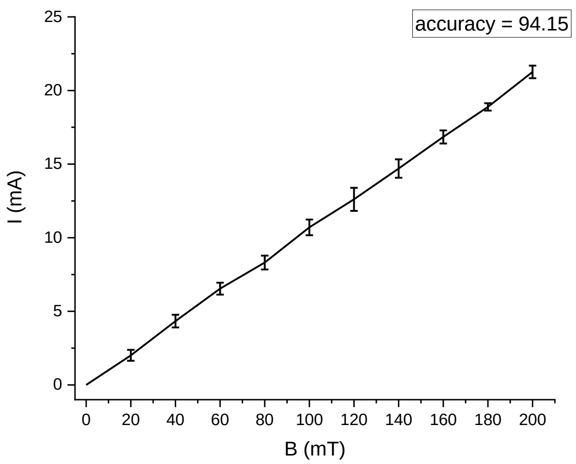

Figure S1. Calibration of the magnetic field using a multimeter coupled to the Phywe Stelltrafo mit Gleichrinter source for 20 consecutive measurements for each field value.

2. Entropy of the difference of two images

Considering two images, we calculate the value of Shannon's entropy (equation 4 of the main article). To understand the mechanism of entropy under the difference of images, in Figure S2 we show, initially (first line) the entropy of the difference of two identical images, resulting in the value zero, as expected. For an image generated by a conventional laser and another generated by a random laser (second line), the difference of these two generates an image whose entropy is 3.68. In the third line we have the entropy of the difference of the speckle with a blue background image and, in the last case (fourth line), we have for the speckle and a random image.

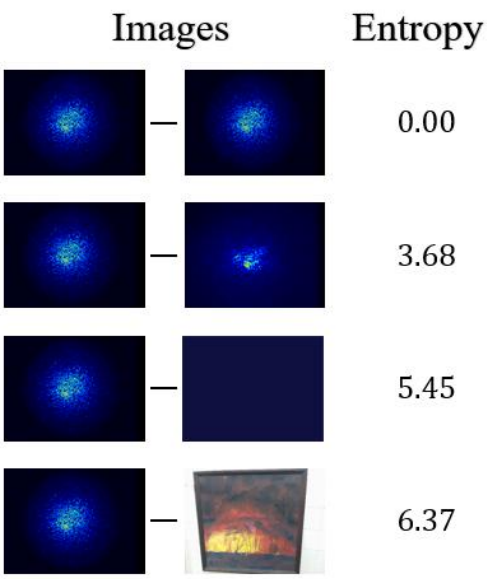

Figure S2. Entropy calculated on the image resulting from the subtraction of two images.

3. Feature maps

The feature maps applied to the convolutional layers of CNN and MHCNN models are important because each filter detects specific patterns in the image, such as edges, textures, or high-contrast regions, allowing the network to extract features relevant to the classification task, visually showing how the CNN interprets and represents the information contained in the image. The more filters that are applied, the more features can be defined for an image.

In Figure S3, we randomly selected an image from the 80 mT class, just to exemplify, and applied 5 convolutional filters to display its feature maps. Essentially, each convolutional filter is a small weight matrix that modifies the original image pixel by pixel, performing a convolution, that is, multiplying the values of the image window by the filter weights and summing the results to generate a single value. By repeating this process across the entire image, the filter generates a feature map, which highlights specific patterns that it was designed or trained to detect. Thus, the model can learn well what each image (speckle) represents.

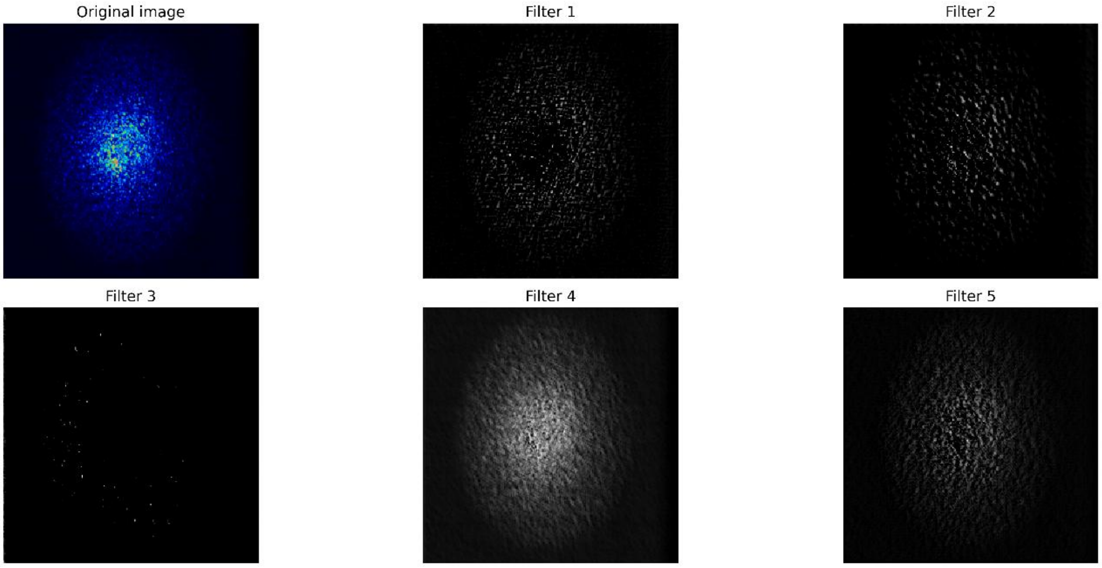

Figure S3. Some feature maps analyzed by the models from the convolutional layers.

4. Graphical User Interface

An interesting proposal is to develop a graphical user interface (GUI) that can serve as a quick and easy access platform for the scientific community. Using the MHCNN model presented in the main article and the python language, we created a simple GUI (Figure S3) in which the user can upload an image and, based on the trained model, the interface shows what the magnetic field of that image is.

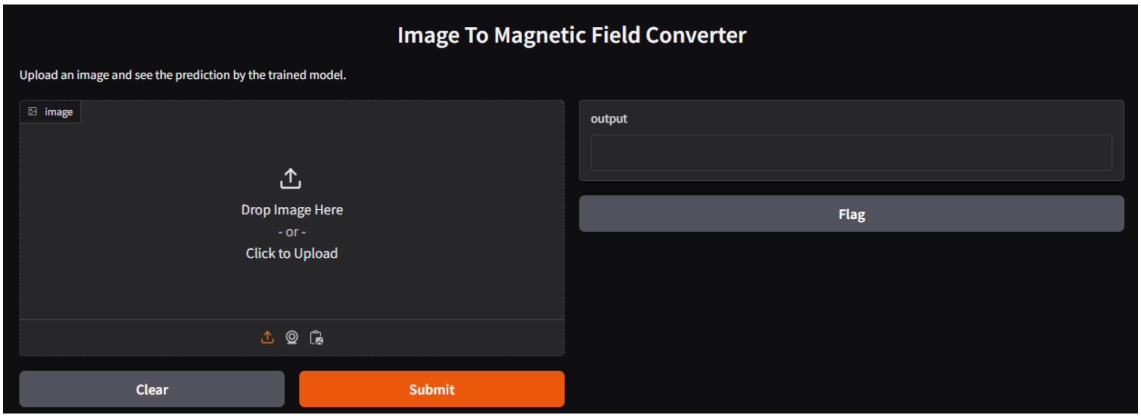

Figure S4. Graphical user interface (https://youtu.be/AUOiQjnVmVg).