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Artificial intelligence and capsule endoscopy: automatic detection of enteric protruding lesions using a convolutional neural network

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Author contributions: *Study design*: MMS, JA, TR, JF, HC, PA, MP, RJ, GM. *Revision of CE videos*: MMS, HC, PA. *Construction and development of the CNN*: MMS, JA, JF, TR. *Statistical analysis*: JF. *Drafting of the manuscript*: MMS, JA, TR, RG. *Bibliographic review*: TR; RG, PC. All authors approved the final version of the manuscript.

Keywords: Capsule endoscopy, artificial intelligence, polyps, gastrointestinal hemorrhage

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Abstract

Background and aims: Capsule endoscopy (CE) revolutionized the study of the small intestine. Nevertheless, reviewing CE images is a time-consuming and prone to error. Artificial intelligence algorithms, particularly convolutional neural networks (CNN) are expected to overcome these drawbacks. Protruding lesions of the small intestine exhibit enormous morphological diversity in CE images. We aimed to develop a CNN-based algorithm for automatic detection small bowel protruding lesions.

Methods: A CNN was developed using a pool of CE images containing protruding lesions or normal mucosa from 1,229 patients. A training dataset was used for development of the model. The performance of the network was evaluated using an independent dataset. The performance of the network was evaluated by calculating its sensitivity, specificity, accuracy, positive and negative predictive values.

Results: A total of 18,625 CE images (2,830 showing protruding lesions and 15,795 normal mucosa) were included. Training and validation datasets were built with an 80%/20% distribution, respectively. After optimizing the architecture of the network, our model automatically detected small bowel protruding lesions with an accuracy of 92.5%. Our CNN had a sensitivity and specificity of 96.8%, 96.5%, respectively. The CNN analyzed the validation dataset in 53 seconds, at a rate of approximately 70 frames per second.

Conclusions: We developed an accurate CNN for automatic detection of enteric protruding lesions with a wide range of morphologies. The development of these tools may enhance the diagnostic efficiency of CE.

Introduction

Capsule endoscopy (CE) allows minimally invasive visual inspection of the full length of the digestive tract and is the standard technique for the workup of patients with suspected small bowel diseases, including small bowel tumors and inherited polyposis syndromes (1-3).

The identification of enteric protruding lesions by CE is often difficult as these lesions have significant pleomorphism (4). Gastrointestinal bleeding is a frequent manifestation of small bowel tumors (5). Therefore, their prompt identification is essential for adequate acute and long-term patient management (6). Nevertheless, each CE exam produces approximately 50,000 images, requiring approximately 30-120 minutes for reading (7). Moreover, mucosal lesions may be restricted to a very small number of frames, which increases the risk of overlooking significant lesions.

Recently, several artificial intelligence (AI) systems aiming at automatic interpretation of medical images have been developed (8-10). However, their impact in the diagnosis and characterization of small bowel protruding lesions has not been fully explored. We aimed to develop a CNN-based model for automatic detection and assessment of the bleeding potential of small bowel protruding lesions in CE images.

Methods

We retrospectively reviewed CE exams performed between 2015 and 2020 at a single tertiary center (São João University Hospital, Porto, Portugal). The full-length CE video of all participants was reviewed. Inclusion and labelling of frames were performed by three gastroenterologists with experience in CE (MMS, HC and PA). The final labelling of each frame required agreement between at least two researchers. This study was approved by the ethics committee of São João University Hospital (CE 407/2020).

Capsule Endoscopy Protocol

All procedures were conducted using the *PillCam™* SB3 system (Medtronic, Minneapolis, USA). The images were reviewed using *PillCam*™ Software version 9 (Medtronic, Minneapolis, USA). Bowel preparation was performed according to previously issued recommendations (11).

Classification of lesions

Each frame was evaluated for the presence of enteric protruding lesions (polyps, epithelial tumors, subepithelial lesions and nodules) (4). The hemorrhagic potential of these lesions was estimated according to Saurin's classification (6): P0 – no hemorrhagic potential; P1 – uncertain/intermediate hemorrhagic potential; P2 – high hemorrhagic potential. Protruding lesions were considered P2 when large (≥10 mm), ulcerated or when hemorrhagic stigmata were present. These lesions were classified as P1 when small (<10 mm) and with intact overlying mucosa (e.g., subepithelial lesions).

Development of the Convolutional Neural Network

To create the CNN, we used the Xception model with its weights trained on ImageNet (a large-scale image dataset aimed for use in development of object recognition software). To transfer this learning to our data, we kept the convolutional layers of the model. We removed the last fully connected layers and attached fully connected layers based on the number of classes we used to classify our endoscopic images. We used two blocks, each having a fully connected layer followed by a Dropout layer of 0.3 drop rate. Following these two blocks, we add a Dense layer with a size defined as the number of categories (three) to classify. The learning rate of 0.0001, batch size of 32, and the number of epochs of 100 was set by trial and error. We used Tensorflow 2.3 and Keras libraries to prepare the data and run the model. The analyses were performed with a computer equipped with a 2.1 GHz Intel® Xeon® Gold 6130 processor (Intel, Santa Clara, CA, USA) and a double NVIDIA Quadro® RTX™ 4000 graphic processing unit (NVIDIA Corporate, Santa Clara, CA, USA).

Outcome measures, model performance and statistical analysis

The labelling and classification of the bleeding potential provided by the expert gastroenterologists was compared to the CNN's prediction. The latter was considered as the *gold standard* for comparison. For each image, the CNN calculated the probability for each of the three categories (normal mucosa, P1 protruding lesions, and P2 lesions). A higher probability value translated in a greater confidence in the CNN prediction. The category with the highest probability score was outputted as the CNN's predicted classification The primary outcome measures included the sensitivity, specificity and overall accuracy of the CNN for the detection and differentiation of enteric protruding lesions with distinct bleeding potential. These variables were calculated in one iteration of the CNN and are presented as percentages. Moreover, we used receiver operating characteristic (ROC) curves analysis and area under the ROC curves (AUC) to measure the performance of the model. The computational performance of the CNN was also measured as frames/s. Statistical analysis was performed using Sci-Kit learn v0.22.2.

Results

Construction of the convolutional neural network

This study included a total of 1,229 patients, corresponding to a sum of 1,483 CE exams A total of 18,625 small bowel images were extracted: 2,830 showing protruding lesions (P1 – 1,830 frames; P2 – 1,000 frames), and the remaining displaying normal mucosa. The training dataset was constituted by 80% of the total image pool. The remaining 20% (n = 3,725) were used for testing the model. The latter subset of images was composed by 366 and 200 frames showing P1 and P2 protruding lesions, respectively, and 3,159 images with normal mucosa. For each image, the CNN calculated the probability for each category **(Figure 1).** The accuracy of the network increased as more images were being inputted into its multi-layer architecture (Figure 2). Images representing false negative and false positive CNN predictions are shown in figure 3.

Overall performance of the network

Overall, the accuracy of the CNN was 92.5%. The sensitivity and specificity of the model were 96.8% and 96.5%, respectively (Table 1).

Performance for the detection and distinction enteric protruding lesions with distinct bleeding potential

The CNN detected P1 and P2 lesions with a sensitivity of 95.9% and 97.0% and a specificity of 94.3% and 97.6%, respectively. The algorithm differentiated P1 and P2 lesions from normal mucosa with sensitivities of 99.2% and 100.0%, and specificities of 94.0% and 97.6%, respectively. P1 lesions were distinguished from P2 lesions with a sensitivity of 96.7% and a sensitivity of 97.0%. The AUCs for detection of P1 and P2 protruding lesions is shown in Figure 4.

Computational performance of the convolutional neural network

The CNN completed the reading of the entire validation dataset in approximately 53 seconds. This translates into an approximated reading rate of 70 frames per second (0.01 second per frame). At this rate, reading a full-length CE video containing 50,000 images would require approximately 12 minutes.

Discussion

We developed a pioneer CNN for automatic detection and characterization of the bleeding potential of enteric protruding lesions in CE images with high sensitivity (96.8%), specificity (96.5%) and accuracy (92.5%). Small bowel tumors often present with OGIB or iron deficient anemia (12). The detection and characterization of small bowel tumors is difficult due to their significant pleomorphism. Nevertheless, it is important for adequate management and prognostication of the patient. Furthermore, enteric protruding lesions are common sources of obscure gastrointestinal bleeding (13).

The analysis of CE videos is a time-consuming task and lesions may be restricted to a small number of frames, thus increasing the risk of overlooking significant lesions (14). The development of AI algorithms has shown promising results in overcoming these drawbacks (15-17).

Saito and coworkers were the first to develop of a CNN algorithm for automatic identification of enteric protruding lesions (18). Their CNN demonstrated a sensitivity of 90.7% and a specificity of 79.8%. The overall accuracy of their CNN was 84.5%. In this study, the main indication for CE in patients for whom a protruding lesion was ultimately diagnosed was obscure gastrointestinal bleeding. However, the bleeding potential of these lesions was not assessed.

Our network demonstrated a high image processing capacity (70 frames/second). This reading rate is higher than those reported for other CNNs for assisted CE reading (18, 19). With application of these tools to clinical practice, these performance marks may be reflected into shorter CE reading times.

This study has several limitations. First, it is a retrospective study using selected images from a single center. Second, the number of extracted images was relatively small. Therefore, multicentric studies including larger populations are warranted for assessment of the clinical utility of this tool. Additionally, all CE exams were performed using the *PillCam™* SB3 system. Therefore, these results may not be appliable to other models.

In conclusion, we developed a CNN capable of identifying protruding lesions with great accuracy. Clinical application of AI algorithms in clinical practice is expected in a near future and will be helpful in increasing diagnostic accuracy and sensitivity and diminished the diagnostic medical error.

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Tables

Table 1 – Confusion matrix and summary of results

		Expert classification		
		Normal	**P1 lesions**	**P2 lesions**
CNN classification	Normal	2,902	3	0
	P1 lesions	185	351	6
	P2 lesions	72	12	194
		Sensitivity	**Specificity**	**Accuracy**
	Overall	96.8%	96.5%	92.5%
	P1 vs. All	95.9%	94.3%	94.5%
	P2 vs. All	97.0%	97.6%	97.6%
	P1 vs. P2	96.7%	97.0%	96.8%

CNN – convolutional neural network

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Figure legends

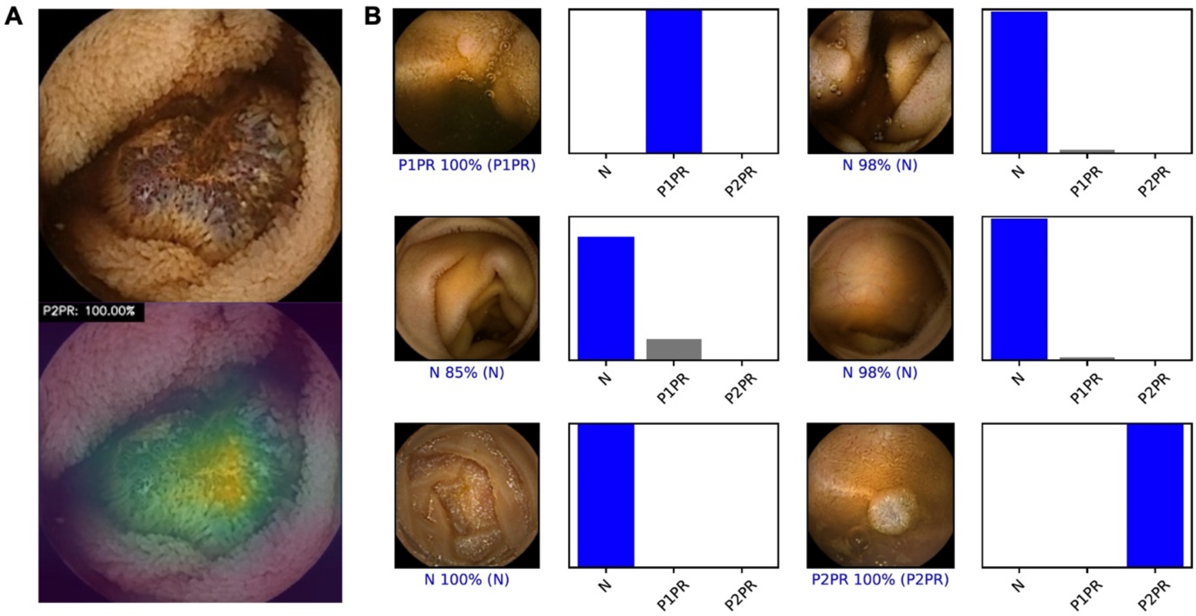

Figure 1: Heatmaps (A) and output (B) obtained from the application of the convolutional neural network. Blue and red bars represent a correct and incorrect prediction, respectively. *N: normal mucosa; P1PR – protruding lesions with intermediate bleeding potential; P2 – protruding lesions with high bleeding potential.*

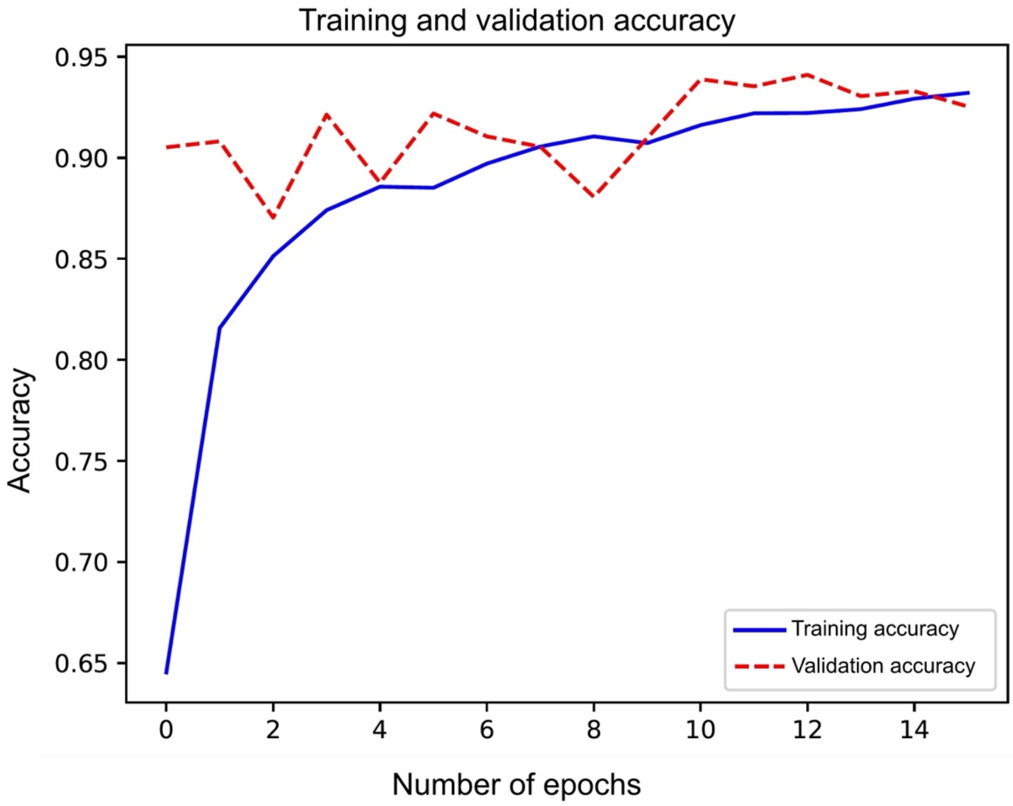

Figure 2: Evolution of the accuracy of the convolutional neural network during training and validation phases.

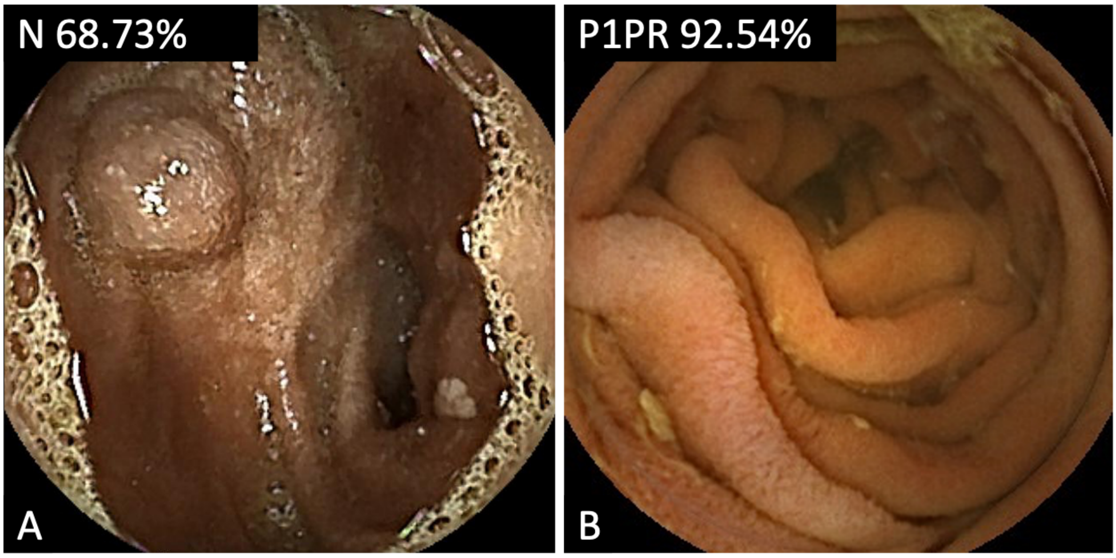

Figure 3: False negative (A) and false positive (B) predictions of the CNN. In (A), the CNN classified the frame as normal (with a probability of 68.73%) despite the presence of a P1 protruding lesion. This frame has an air-water interface which may have contributed to the

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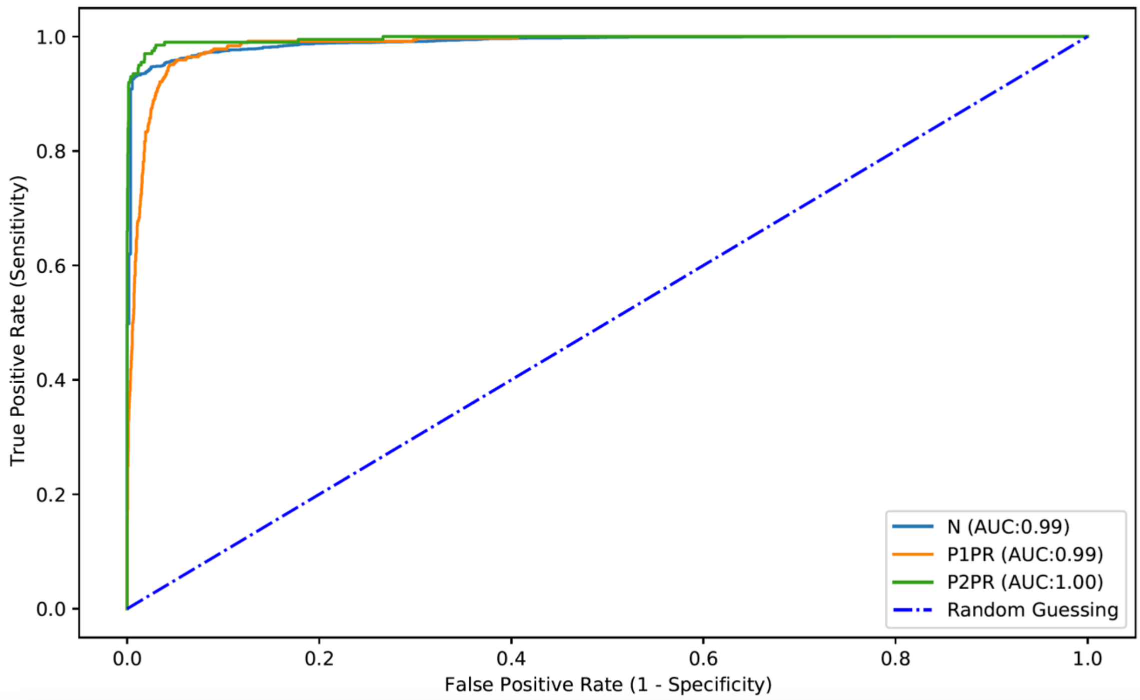
failed prediction; in (B), the CNN detected a P1PR lesion in a frame showing normal enteric mucosa. This may be due to more prominent mucosal folds. *CNN*: convolutional neural network; *N: normal mucosa; P1PR – protruding lesions with intermediate bleeding potential.*



<u>Figure 4:</u> ROC analyses of the network's performance in the detection of normal mucosa, P1 and P2 protruding lesions. *ROC – receiver operating characteristic. AUC – area under the curve. N: normal mucosa; P1PR – protruding lesions with intermediate bleeding potential; P2 – protruding lesions with high bleeding potential.*