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Explaining Machine Learning-based Classifications of in-vivo Gastral Images

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***Abstract*—This paper proposes an explainable machine learning tool that can potentially be used for decision support in medical image analysis scenarios. For a decision-support system it is important to be able to reverse-engineer the impact of features on the final decision outcome. In the medical domain, such functionality is typically required to allow applying machine learning to clinical decision making. In this paper, we present initial experiments that have been performed on in-vivo gastral images obtained from capsule endoscopy. Quantitative analysis has been performed to evaluate the utility of the proposed method. Convolutional neural networks have been used for training the validating of the image data set to provide the bleeding classifications. The visual explanations have been provided in the images to help health professionals trust the black box predictions. While the paper focuses on the in-vivo gastral image use case, most findings are generalizable.**

***Keywords:* Explainable artificial intelligence, Convolutional neural networks, Black box explanations, LIME**

I. Introduction

In domains such as scientific research, medicine, forensics, finance, and education [1], it is typically important to justify explain the decisions made by the model in order to justify the results (Figure 1). Explainable Artificial Intelligence (XAI) has emerged as a scientific discipline that studies the predictions of any *artificially intelligent* agent, classifier, or regressor. For example, when providing image classification-based decision support, it might be beneficial for the user if the system highlights the super pixels with positive weight for a particular class to give a justification for why the model thinks that it should be present in that class. Such explanations increase trust in the decisions made by the classifier even if the predicted class is wrong as it depicts that it is not behaving in an unreasonable manner. The proposed approach tries to provide the global understanding for the machine learning models by providing explanations for individual instances in the context of medical (in-vivo gastral) image analysis. The approach is model-agnostic, and can also be used to enhance the understanding of models in a *test data set* context. To understand the rationale for a decision made by a black box machine learning model with sophisticated layers, it is important to layout fundamental factors that have informed the decision. Below are several important aspects that motivate the requirement of XAI functionality.

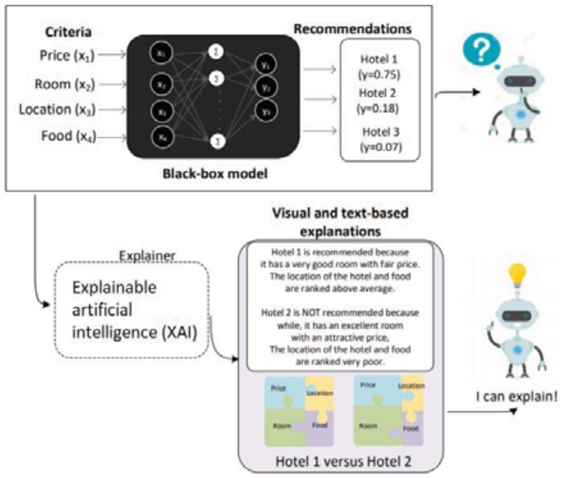

Fig. 1. Explaining the decisions made by a machine learning model using an XAI approach [2]

1) System testing: a black box is *per se* not trustworthy; systematic testing is required to assure the model's decisions can be considered reasonable from a human perspective.
2) System as a teacher: machine learning models excel at finding correlations in massive amounts of high-dimensional data; this ability exceeds human capabilities by far. Hence, humans can learn from ML-based systems if the systems are capable of explaining the decisions taken at any instance.
3) Legal compliance: many decisions can potentially have disastrous consequences that result in legal litigation, huge financial and reputation penalties, and even cause the loss of human life. If the black box machine learning model is able to explain the driving factors for a decision, then a human-in-the-loop approach can avoid machine errors that would have been easily detectable by humans.

Below are the major contributions of this paper:

1) We describe a machine learning-based diagnosis decision-support system for the semi-automatic assessment of in-vivo gastral images obtained from capsule endoscopy.

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2) We supplement the ML-based system with LIME-based explanation capabilities.
3) We introduce an architecture/pipeline for the integrated classification and explanation of capsule endoscopy image frames.
4) We provide an open source implementation of code that allows for the evaluation of the core *explainable machine learning* functionality of the architecture.

The rest of the paper is organized as follows. In Section II we provide the literature review of contemporary explainable models as a motivation for this research. Section III describes the proposed method for image classification and explanation. An overview of the system implementation is provided in Section IV. The experimental results are presented in Section V. Finally, the presented work and its limitations are discussed in Section VI, before Section VII concludes the paper by outlining future research directions.

II. Literature Review

Although there is an increasing number of works on interpretable and transparent machine learning algorithms, most research is primarily directed at explanations for technical users. Recently published papers provide comprehensive surveys on XAI research [3]. Anjomshoae et al. [4] provide a systematic literature review of works on explainable intelligent agents. A systemantic review of XAI methods for explaining black-box models is given by Guidotti et al. [5]. Machine learning models can be considered reliable but they lack in explainability. An early approach for explaining the decision of machine learning models is based on the notion of the *contextual importance and utility* of features [6], [7], [7]. With the rise of deep learning as a mainstream data analysis method, additional approaches emerged providing ML model explanations, for example; LIME (Local Interpretable Model-Agnostic Explanations) [8], CIU (Contextual Importance and Utility) [6], ELI5 [9], Skater [10], SHAP (SHapley Additive exPlanations) [11] etc. These model interpretation techniques provide model prediction explanations with local interpretation, model prediction values with shape values, building interpretable models with surrogate tree based models and much more.

A. Explainability of deep learning models

In [12] an explainable deep learning approach for image classification has been studied. The work also proposes two approaches for deep learning explanation of sensitivity in regard to input changes, and second decomposes the decision for its responsible input variables. Another interesting review has been provided by [13] about machine learning, information visualization and analytics along with future directions and current challenges of explainable deep learning. It has explained six application opportunities (a) providing external human knowledge (b) user driven generative models (c) progressive visual analytic (d) Training set reduction (e) robustness enhancement for AI and (f) deep learning visual analytics with advanced architectures.

An interpretation of XAI in a comprehensive form has been studied in [14]. The work has been broadly grouped into three classes to understand, diagnose and refine respectively. Relevant examples from current state-of-the-art has been provided along with future possibilities. Basic conceptual and example application have been provided by [1] for the areas of security, medicine, transportation, finance military and legal advices for example. This DARPA project is really an interesting literature to follow the motivation and contemporary state of work of XAI. In [15] has studied plant stress phenotyping using machine vision based deep learning explainable system. A soybean plant has been studied for foliar stress using feature maps with unsupervised learning to measure stress severity. About 25,000 images have been considered for fungal and bacterial diseases along with nutrition deficiency or injury with promising accuracy.

B. Explainability in the medical domain

Local Interpretable Model-agnostic Explanations (LIME), a novel explanation technique developed by Ribeiro et al. [8] was proposed to explain the classifier's predictions in a faithful and interpretable way. It learns the interpretable model in a local manner around the prediction [8]. The flexibility of the model is demonstrated by providing the explanations for different models for text and images. It helped with both experts and non-experts users in making decisions between models while assessing their trust and to improve the untrustworthy models by having an insight into predictions. Andreas et al. [16] explained the need of the explainable AI in the medical domain to help the medical professionals to make the decisions transparent, explainable and understandable. It will help in facilitating the machine learning implementation in medical domain by helping in trusting the decisions. The author also discussed the challenges of explainable AI in digital pathology in his another paper [17] where they use the artificial intelligence to understand the decisions in context of an application task for making decisions transparent and explainable.

In [18] a systematic review on deep learning in medical imaging and radiation therapy has been provided. The work gives an overview of the history and present status of research, identifies challenges along with strategies, and finally lays out future research directions.

C. Machine learning methods for WCE

[19] proposes a modern technique to detect bleeding signs by employing color features out of regions of digital images by computing skewness, energy, mean, and standard deviation. Initially, the order histogram using the RGB color plane is considered in contrast to gray scale to obtain bleeding-related features. They are considered in pathology images via content based retrieval systems. Basically, the strength of the aforementioned paper is to use a content-based retrieval system for the color features of digital images to analyse bleeding in capsule endoscopy. All possible subsets are considered involving the feature options in detail to search for best accuracy results and it achieves 89% of accuracy.

A clustering-based approach using the K-nearest neighbors (KNN) algorithm to detect bleeding in CE images is presented in [20]. The algorithm considers the R/G ratio of pixel intensity instead of RGB matrices of colored images. Afterwards it

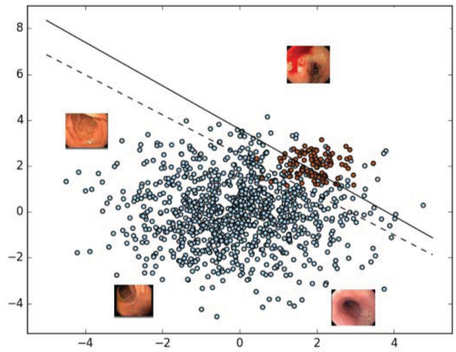

Fig. 2. Example of imbalanced data classification for CE bleeding detection. Blue and brown points are non-bleeding and bleeding instances respectively

calculates mean, maximum, minimum, skewness and kurtosis of R/G elements to obtain the spatial attributes' variation for R/G components. A publicly available data set is tested for this approach and achieves an accuracy of 98.5%, sensitivity of 98%, and specificity of 99%. A more sophisticated bleeding detection idea which is based upon probabilistic neural network (PNN) is presented in [21]. It computes the classification function to filter out bleeding instances using distinguishing features of WCE images. A specificity 85.6% and a sensitivity 93.1% are reported to have been achieved. A support vector machine (SVM)-based approach is proposed in [22] for bleeding diagnosis decision support provided to gastroenterologists. It is able to achieve a sensitivity of 94% and a specificity of 83%.

III. Methods - Applying LIME to Explain Classification Decisions in Capsule Endoscopy

Currently, in medical domain, XAI functionality is a necessary requirement for many machine learning-based medical research, education and clinical decision making scenarios. Systems for solving the medical domain's explainability/interpretability problem can be distinguished into two types; post-hoc systems and ante-hoc systems. Post-hoc systems help in providing local explanations for a particular decision made by machine learning so that it can be made interpretable on demand rather than explaining the whole systems behavior. One of the algorithms that enables post-hoc explainability is LIME. Ante-hoc systems are interpretable by design and referred to as *glass-box* approaches in the literature [16]; examples are decision trees, linear regression and fuzzy inference systems. In an applied science context, LIME has already been used for explaining machine learning models for the heat failure detection in air handling units [23].

The image classification problem for the CE procedure can be visualized as an imbalanced data distribution problem shown in Figure 2. Here, dark brown dots on the upper right edge signify bleeding instances and blue dots show non-bleeding majority negative class instances. The solid and broken lines are various options of classifiers depending upon different priority weight assigned to bleeding instances.

The complete classification and explanation process has been depicted in Figure 3, which describes the classification procedure by machine learning model as well as explanation

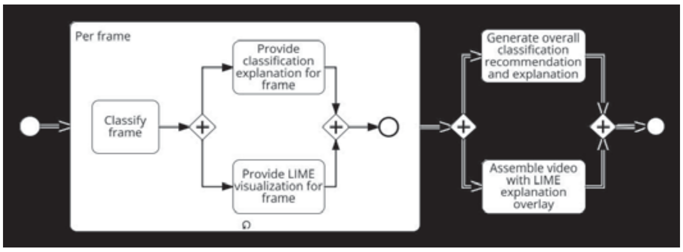

Fig. 3. Classification and Explanation Process

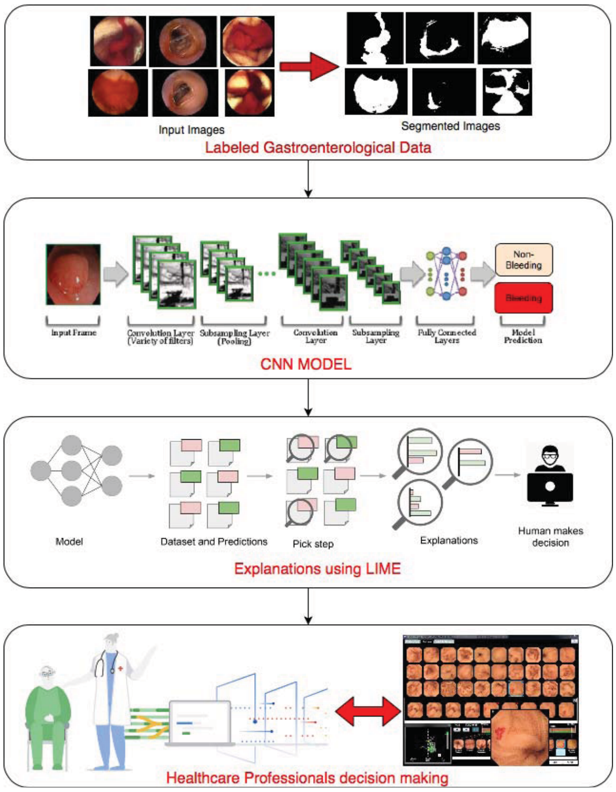

Fig. 4. The Architecture for the proposed model

and visualization by LIME for each image frame. The image data set is trained with a machine learning model (CNN in our example) The trained model is given to our proposed model for providing classifications and explanations underlying these classifications. The overall explanations for the whole test data can be provided to the medical professionals for assisting them in decision making. The overall recommendation and explanation is provided by the health-care professional by making an aggregate ranking system for providing the severity of the intestinal bleeding in the patient. The architecture of the proposed model is depicted in Figure 4 where the whole process can be divided into four segments: Pre-processing, applying the CNN model, explanation-generation using LIME, and decision-assistance for healthcare professionals.

IV. Implementation

We implemented a prototype that realizes the learning and explanation pipeline of the architecture in an *offline* manner with a Python-based technology stack[1].

- **Neural network: TensorFlow.** TensorFlow [24] is an open source platform for machine learning. We use TensorFlow to train the neural network that classifies the gastroenterological images.
- **Local interpretable model-agnostic explanations: LIME.** LIME [8] is the original Python implementation of the LIME explanation technique. LIME takes the neural network as generated by TensorFlow and the result of a specific frame to generate a matrix representation of the regions that triggered the corresponding classification.

The code and its documentation are available at https://github.com/Madhikermi/CNN_LIME.

V. Results

A. Use Case: Wireless capsule endoscopy

Wireless Capsule Endoscopy (WCE) is a non-invasive procedure to visualize a patient's entire gastroenterological tract for signs of bleeding or polyp [25]. A disposable capsule containing radio frequency transmitter, battery, imaging sensor, an illuminator, and an optical dome is swallowed by the patient for the procedure after 8 hours of fasting (empty stomach). It gets pushed down the digestive tract by peristalsis while scanning interior mucosa and capturing images at a speed of about two images/second. Images are transmitted to an outside receiver worn by the patient on their waist. Altogether the procedure captures about 55,000 square images of size 256 $\times$ 256 while travelling through the patient's digestive tract. Traditionally these captured video frames are examined manually by the physician to check for potential bleeding symptoms. This manual procedure is time-consuming, tedious, and dependent upon extended concentration of the doctor, who is required to watch thousands of images in the form of a video. Using machine learning techniques, this process can be automated with convincing accuracy in bleeding detection, which saves manual effort as well as time. In machine learning, negative and positive data refers to non-bleeding and bleeding images. Actually, bleeding classification in WCE is an example of imbalance data classification problem where negative examples outnumber positive data by a big margin, sometimes 1000:1. To handle the data imbalance problem there are two basic class of techniques: data-oriented and algorithm-oriented. If the initial data processing involves majority class undersampling or minority class oversampling then it is defined under data oriented approach category. If the data distribution analysis is performed by algorithm itself then it belongs to algorithmic category. As an example ensemble model or by considering features of data distribution is a type of algorithm oriented approach.

B. Image data set

The data set of 3,295+600 images was obtained from [26] as shown in table I. The images are representative of the medical application scenario and include normal as well as bleeding cases. Set 1 consists of 3,295 images of which 90% of the data have been used for training and rest of the 10% data have been used for testing. For fast and consistent computation, all 3,895 images have been re-sized to 150×150 pixels. The labels of the images were created based on the segmentation of the same data set as performed by [26]. The sample CE images from the data set are shown in Figure 5.

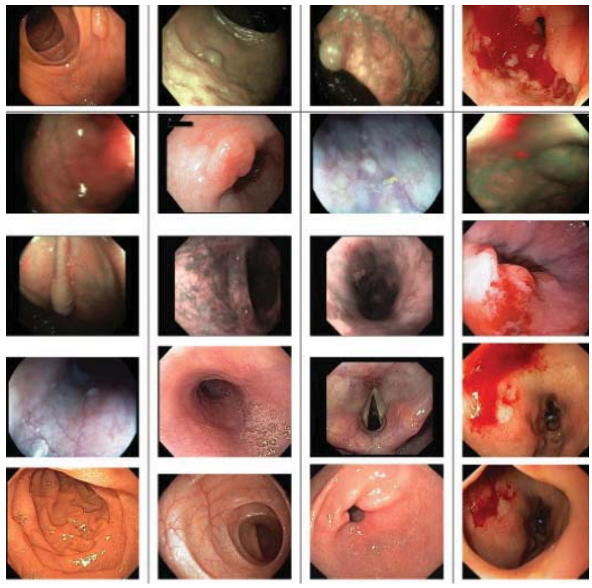

Fig. 5. Sample CE images (First three columns correspond to non bleeding and normal case and right most column shows example bleeding images)

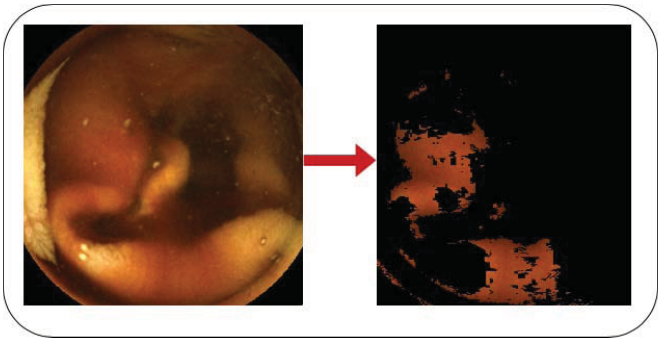

Fig. 6. Annotating the red lesions in capsule endoscopy images

TABLE I. Data set description of normal and bleeding images considered for training and testing sets (Coelho et al [26])

Data sets	Normal	Bleeding	Total
Set 1 - training	1969	1024	2993
Set 2 - testing	195	107	302
Total	2164	1131	3295

C. Black box predictions and explanations

The code trains on the Red Lesion Endoscopy data set that is provided at https://rdm.inesctec.pt/dataset/nis-2018-003. Note that we train on labels and not on graphical annotations. The labels were created from the annotated images provided in the repository and the labels were used for training our

[1]In fact, Python mostly provides a developer abstraction of the underlying tools; much of the code of the underlying libraries is C and C++.

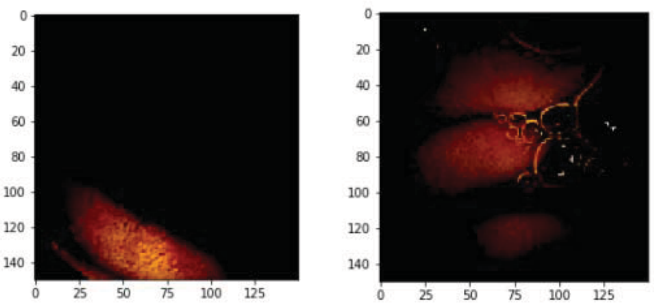

Fig. 7. The bloody regions are shown to give the glimpse of the areas due to which the image is classified as bloody image

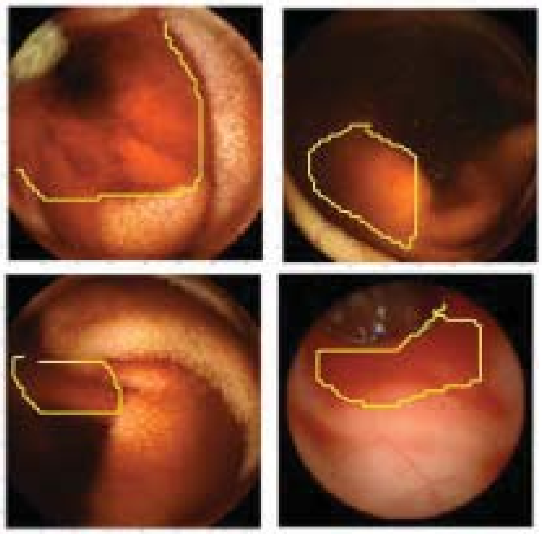

Fig. 8. Explanations for black box model by LIME

CNN model. First, we prepared our data and then we split data and labels into train and validation sets (randomly assigned). For each set, separate bleeding and non-bleeding images with Data length: 3295; label length: 3295 Training data length: 2993; validation data length: 302. The data set is trained using a CNN model with 50 epochs with batch size of 16 and achieves a validation accuracy of **97.92%**. Then we try to read the images from the validation data set that have been classified as bleeding images and finally providing the explanations for bleeding images with the help of LIME. It provides explanations for bleeding images by marking the boundaries of the bloody areas in the image. Figure 6 gives the annotations for a particular instance of the bleeding image. Figure 7 tries to explain the black box decision for particular bleeding image instances by highlighting the features or areas due to which the image is classified as bleeding image. The explanations provided by LIME are depicted in Figure 8 in the form of highlighted boundaries around the important features of the images which contributed in making the decisions by black box model. The LIME has been tested for all the bleeding images in the validation data set and the results are shown in Figure 9. The prediction probabilities for bleeding class have also been calculated for few of the sample bleeding images as shown in table II.

TABLE II. PREDICTION PROBABILITIES FOR BLEEDING CLASS FOR FEW OF THE SAMPLE VALIDATED IMAGES

Images	Prediction Probability
Image 1	0.3362
Image 2	0.9999
Image 3	0.3933
Image 4	0
Image 5	0.5084

VI. Discussion

The provide approach to XAI for medial image analysis can help medical professionals to trust the decisions made by the black-box models and also help them explaining the decisions to the patients in the form of visualizations. According to our knowledge, such XAI approaches have not yet found their way into state-of-the-art literature in the medical domain. While the generated LIME explanations are in many cases ”correct” from a human perspective, in some of the cases the explanations do not seem fully plausible, as can be seen in Figure 9. A likely reason is the small size of the training data, as well as the only minimally customized machine learning model generator. The explanations have been provided to the partner hospital, which has provided positive feedback as to the value of the approach and research direction.

Machine learning in the context of medical decision making must take explainability into account, to ensure that machine errors do not cause disastrous consequences that can be prevented by a human-in-the-loop approach, which requires that medical professionals must have a possibility to understand how and why a machine decision has been made. Further, transparent algorithms can appropriately enhance the trust of medical professionals in artificial intelligence systems. If machine learning models complement human intelligence, and even overrule it in some cases, the decisions needs to be understandable and interactively influenced by humans. Highly autonomous systems cannot be deployed unless the machine learning decisions can be presented in a way that allows for human interpretation.

VII. Conclusion and Future Work

In this paper, we have proposed and prototyped an explainable machine learning tool that can potentially be used by medical experts as a decision-support system to detect gastroenterological bleeding faster and in a more reliable manner. However, the following work should be conducted to allow for real-world applicability of the presented tool:

1) **Strengthen the architecture’s implementation and technical evaluation.** In this paper, we have presented the implementation of a prototype of the machine learning-explainability part of the proposed tool chain. However, a more systematic assessment of the capabilities of class label-based classifications and LIME in contrast to graphical annotation-based machine learning in terms of classification accuracy, explainability, and labelling effort needs to be made. Also, the full architecture should be implemented to allow for a practical/use case-oriented evaluation.

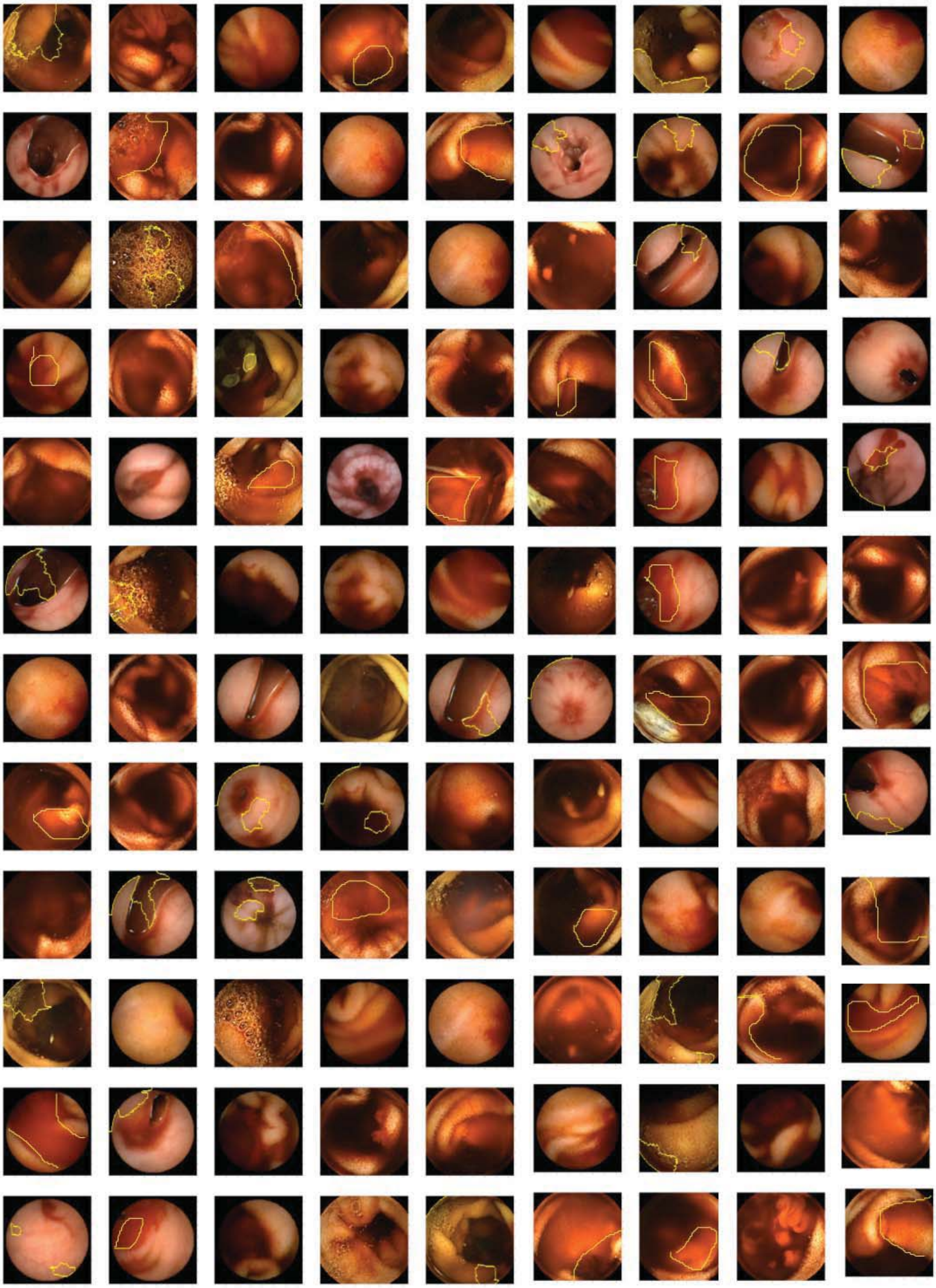

Fig. 9. LIME explanations provided in the form of boundaries for bloody regions from the validated CE data set

2) **Evaluate the tool's applicability in user studies with medical experts.** While we have provided a prototype that shows the workings of a tool to help solve the real-world challenge of automating diagnosis support for gastroenterological bleeding detection, its exact usability has not been assessed in practice (or practice-like scenarios). User studies with medical experts should be conducted as future research to detect potential pitfalls and shortcomings.
3) **Provide a full application that can be used *out-of-the-box* by medical practitioners.** The introduced tool implements an end-to-end pipeline for classifying and explaining gastroenterological images for bleeding detection, but does not come with a graphical user interface that is tailored for simple and safe use by medical practitioners. Implementing such a user interface and assessing it (see Point *1.*), is important future research domain.
4) **Enable learning from expert feedback.** Ideally, the tool would allow experts to provide online feedback if image sequences are incorrectly classified (in particular: false negatives) to continuously improve the accuracy of the machine learning model.
5) **Generalize to other medical image analysis scenarios.** The presented architecture and implementation can potentially be utilized for other medical image analysis scenarios that require a combination of ML-based classification and decision explanation. Applying the architecture and implementation to other sets of medical images, evaluating and refining it in the light of further medical decision support and automation scenarios can lead to a more widely applicable solution. Also, given that the binary-decision problem at hand may not require deep machine learning methods in a practical setting, more complex medical image classification scenarios should be studies that inevitably depend on black-box models.

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REFERENCES

[1] D. Gunning, "Explainable artificial intelligence (xai)," *Defense Advanced Research Projects Agency (DARPA), nd Web*, vol. 2, 2017.

[2] S. Anjomshoae, K. Främling, and A. Najjar, "Explanations of black-box model predictions by contextual importance and utility," in *Proceedings of the 1st International Workshop on EXplainable TRansparent Autonomous Agents and Multi-Agent Systems*, pp. 1–15, Springer Nature, 2019.

[3] A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence (xai)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

[4] S. Anjomshoae, A. Najjar, D. Calvaresi, and K. Främling, "Explainable agents and robots: Results from a systematic literature review," in *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems*, pp. 1078–1088, International Foundation for Autonomous Agents and Multiagent Systems, 2019.

[5] R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, and D. Pedreschi, "A survey of methods for explaining black box models," *ACM computing surveys (CSUR)*, vol. 51, no. 5, p. 93, 2018.

[6] K. Främling, *Modélisation et apprentissage des préférences par réseaux de neurones pour l'aide à la décision multicritère*. PhD thesis, INSA de Lyon, 1996.

[7] K. Främling and D. Graillot, "Extracting explanations from neural networks," in *Proceedings of the ICANN*, vol. 95, pp. 163–168, Citeseer, 1995.

[8] M. T. Ribeiro, S. Singh, and C. Guestrin, ""why should I trust you?": Explaining the predictions of any classifier," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016*, pp. 1135–1144, 2016.

[9] "ELI5." https://github.com/TeamHG-Memex/eli5, 2019. [Online; accessed 04-June-2019].

[10] "Skater." https://github.com/oracle/Skater, 2019. [Online; accessed 04-June-2019].

[11] "shap." https://github.com/slundberg/shap, 2019. [Online; accessed 04-June-2019].

[12] W. Samek, T. Wiegand, and K.-R. Müller, "Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models," *arXiv preprint arXiv:1708.08296*, 2017.

[13] J. Choo and S. Liu, "Visual analytics for explainable deep learning," *IEEE computer graphics and applications*, vol. 38, no. 4, pp. 84–92, 2018.

[14] S. Liu, X. Wang, M. Liu, and J. Zhu, "Towards better analysis of machine learning models: A visual analytics perspective," *Visual Informatics*, vol. 1, no. 1, pp. 48–56, 2017.

[15] S. Ghosal, D. Blystone, A. K. Singh, B. Ganapathysubramanian, A. Singh, and S. Sarkar, "An explainable deep machine vision framework for plant stress phenotyping," *Proceedings of the National Academy of Sciences*, vol. 115, no. 18, pp. 4613–4618, 2018.

[16] A. Holzinger, C. Biemann, C. S. Pattichis, and D. B. Kell, "What do we need to build explainable ai systems for the medical domain?," *arXiv preprint arXiv:1712.09923*, 2017.

[17] A. Holzinger, B. Malle, P. Kieseberg, P. M. Roth, H. Müller, R. Reihs, and K. Zatloukal, "Towards the augmented pathologist: Challenges of explainable-ai in digital pathology," *arXiv preprint arXiv:1712.06657*, 2017.

[18] B. Sahiner, A. Pezeshk, L. M. Hadjiiski, X. Wang, K. Drukker, K. H. Cha, R. M. Summers, and M. L. Giger, "Deep learning in medical imaging and radiation therapy," *Medical physics*, vol. 46, no. 1, pp. e1–e36, 2019.

[19] S. Sainju, F. M. Bui, and K. Wahid, "Bleeding detection in wireless capsule endoscopy based on color features from histogram probability," in *2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp. 1–4, IEEE, 2013.

[20] T. Ghosh, S. K. Bashar, M. S. Alam, K. Wahid, and S. A. Fattah, "A statistical feature based novel method to detect bleeding in wireless capsule endoscopy images," in *2014 International Conference on Informatics, Electronics & Vision (ICIEV)*, pp. 1–4, IEEE, 2014.

[21] G. Pan, G. Yan, X. Qiu, and J. Cui, "Bleeding detection in wireless capsule endoscopy based on probabilistic neural network," *Journal of medical systems*, vol. 35, no. 6, pp. 1477–1484, 2011.

[22] W. Xu, G. Yan, Z. Wang, G. Liu, S. Kuang, and S. Zhao, "A method for bleeding detection in endoscopy images using svm," *Zhongguo yi liao qi xie za zhi= Chinese journal of medical instrumentation*, vol. 39, no. 1, pp. 9–12, 2015.

[23] M. Madhikermi, A. Malhi, and K. Främling, "Explainable artificial intelligence based heatrecycler fault detection in air handling unit," 2019.

[24] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, *et al.*, "Tensorflow: A system for large-scale machine learning," in *12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16)*, pp. 265–283, 2016.

[25] G. Iddan, G. Meron, A. Glukhovsky, *et al.*, "Wireless capsule endoscopy. nature," *vol*, vol. 405, p. 25, 2000.

[26] P. Coelho, A. Pereira, M. Salgado, and A. Cunha, "A deep learning approach for red lesions detection in video capsule endoscopies," in *International Conference Image Analysis and Recognition*, pp. 553–561, Springer, 2018.