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Endoscopic Image Classification using Federated Learning And XAI

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Abstract

The emergence of IoT, AI, Machine Learning, and Deep Learning algorithms has completely changed the healthcare sector and given rise to data-driven medical applications. However, due to difficulties in achieving rigorous security, privacy, and quality of service standards, the adoption of AI-based medical applications is still low. With the processing of medical data at the network's edge, federated learning has come to be seen as a possible solution to these problems because it allows for the distributed training of sophisticated machine-learning models while maintaining privacy and security concerns. In this paper, we have applied some federated learning-based algorithms for endoscopic image classification. We used an open-source KVASIR dataset to conduct our research. Furthermore, we have integrated Explainable AI (XAI) to offer explanations and interpretations of the models' learning.

1 Introduction

Gastrointestinal (GI) infections and cancer is a major public health concern because it is frequently identified at an advanced stage when treatment is difficult. Gastrointestinal cancer treatment includes surgery, targeted therapy and chemotherapy but the effectiveness of these treatments depends on the cancer stage at diagnosis (Mohapatra et al., 2023). Early detection and prevention through regular screening are crucial to improving outcomes and reducing the burden of gastrointestinal cancer.

The text states that the United States has the highest number of cases of gastric cancer and a large number of people suffer from bowel infections, with new cases reported every year (Bray et al., 2018)(Sharif et al., 2021). Due to the rise of patients with GI problems, the demand for gastroenterologists is increasing Endoscopy is a diagnostic imaging technique that is particularly effective in identifying various GI tract abnormalities. Many studies have been conducted to develop automated classification algorithms for detecting and diagnosing GI tract illnesses using endoscopic pictures.

Artificial intelligence (AI) is used to detect abnormalities in medical images. The system performs several steps to analyze the images, including pre-processing (cleaning and enhancing the images), identifying important characteristics in the images, choosing the most relevant features, and classification (determining if the image shows a normal or abnormal result). This system can help with early detection of abnormalities, which can lead to earlier treatment and better outcomes for patients.

Research was also carried out in order to build automatic classification schemes that are capable of identifying and treating disorders in the gastrointestinal (GI) tract using gastrointestinal images (Khan et al., 2020). By performing feature mining and selection, classification on accessible medical pictures, these AI-based systems have shown to be effective in the early diagnosis of problems. Nevertheless, owing to the existence of numerous noises such as annotations, black borders, and other abnormalities, pre-processing of endoscopic pictures might be a difficult task (Cogan et al., 2019).

These noises can affect the accuracy of the classification model and lead to false positives or negatives, thereby compromising the system's reliability. Therefore, developing effective pre-processing techniques that can effectively remove these noises and enhance the quality of endoscopic images is crucial for improving the accuracy and reliability of automated classification systems for GI abnormalities.

This research paper aims to investigate the use of federated learning and XAI in improving the accuracy and interpretability of GI abnormality detection and classification. We propose a novel framework that uses federated learning to train a deep learning model on GI endoscopy images from multiple sources while preserving patient privacy. We also propose using XAI techniques to interpret the model's decision-making process and provide insights into the features used to classify GI abnormalities. Our suggested approach, we believe, has the chance of enhancing accuracy and privacy of GI abnormality detection and classification while also providing interpretability, thus enabling clinicians to make more informed decisions and improving patient outcomes.

2 Background and Literature Review

(Malhi et al., 2019) propose a diagnostic decision-support system that utilizes machine learning for the semi-automatic evaluation of in-vivo gastral images acquired via capsule endoscopy.To assess the utility of the proposed technique, quantitative analysis was conducted.They have developed a pipeline for the combined categorization and interpretation of capsule endoscopy image frames.To provide bleeding diagnosis, convolutional neural networks have been used for training and verifying the image data collection. To increase the trustworthiness of the black box predictions, a LIME-based explaining abilities have been added to the machine learning-based solution.

Thee research (Adnan et al., 2022) show the feasibility of using variably private federated learning in the medical field for evaluating complicated histopathology pictures. The Cancer Genome Atlas (TCGA) dataset was used to model a distributed setting and compare the efficacy of private, distributed training to traditional training.Differential privacy increases the degree of privacy security by imposing numerical constraints. Using synthetic real-world data with both independent and non-independent data distributions, they have demonstrated the efficacy of a technique known as federated learning (FedAvg). When compared to conventional centralized training, private federated learning produces comparable results, making it a feasible choice for distributed training on medical data .

In recent years, deep learning has had astonishingly good effects on medical diagnosis. In this paper(Mukhtorov et al., 2023) a new approach is proposed for classifying endoscopic images that combines the Inception-Resnet-v2, ResNet-50, MobileNetV2, ResNet-152 and VGG16 models with a Grad-CAM model designed for explainable artificial intelligence. Additionally, they have applied a data augmentation technique to boost the effectiveness of medical images.They have also used a noise reduction technique to solve the overfitting issue while utilizing a short dataset. An open-source KVASIR dataset with more than 8,000 photos of the esophagus, stomach, and colon are included in the dataset, along with annotations that show the presence of different disorders such as polyps, ulcers and inflammation has been used here. In this paper (Mukhtorov et al., 2023), they applied various widely used CNN models, including ResNet-18, ResNet-152, MobileNetv2, DenseNet201, and VGG16 for the classification of wireless endoscopic images. The most accurate classification of the endoscopic pictures was made by ResNet-152 with 98.28% training and 93.46% validation accuracy. For explainable AI, Grad-Cam showed better results to visualize the heat map.

This paper (Rustam et al., 2021) suggests a method for automatically classifying Wireless Capsule Endoscopic photos in order to find the bleedy images. In this paper[4], a deep learning approach is used to create a model named Bleedy Image Recognizer(BIR) which is a combination of MobileNet and a custom-defined CNN architecture model. MobileNet is used for feature extraction and CNN is used for training. The dataset includes 4550 normal pictures and 450 bleedy images from 33 patients, respectively. In both imbalanced and balanced datasets based on image flipping, several tests are run. The effectiveness of the BIR is assessed using the metrics of accuracy, precision, recall, F1 score, and Cohen's kappa. The obtained accuracy, precision, recall, F1 score, and Cohen's kappa values of 0.993, 1.000, 0.994, 0.997, and 0.995, respectively, show good results. The BIR model is also analyzed using an additional dataset from Google and achieves accuracy of 0.978.

The researcher (Mohapatra et al., 2023) proposes a framework to classify the endoscopic abnormal images. For classification in their paper, they used EWT and CNN networks. The KVASIR dataset is used and divided into two sections. The main motive of their work is to detect different types of diseases in the digestive system. The image recognition process is performed at two classification levels and the proposed CNN model is trained twice. The confusion matrix is used for evaluating the performance of a classification model. Framework efficiency is assessed using a confusion matrix and various performance indicators.

3 Methodology

3.1 Dataset

The KVASIR Dataset (Pogorelov et al., 2017) was released as part of the medical multimedia challenge presented by MediaEval. The dataset is composed of 8,000 endoscopic images obtained from the GI tract via an endoscopy procedure. The images are annotated and verified by medical doctors and are categorized into 8 different classes based on three anatomical landmarks, three pathological findings, and two other classes related to the polyp removal process. Each class contains 1,000 image examples, and the dataset is intended for use in developing automated classification algorithms for detecting and diagnosing GI tract illnesses using endoscopic images.

3.2 Workflow

3.3 CNN

Convolutional neural networks are feed-forward neural networks that are commonly used to evaluate visual pictures by processing data in a grid-like fashion.A convolution neural network comprises several hidden layers that aid in image information extraction.The layers are Convolution layer, ReLU layer, Pooling layer and Fully connected layer(Biswal, 2023).Typically, the first layer removes fundamental characteristics like horizontal or diagonal edges. The result is sent to the next layer, which recognizes additional characteristics like corners or combinational edges. when we get further into the network, it can recognize greater complex characteristics like objects, faces, and so forth(Mandal, 2022).

3.4 Federated Learning

Federated learning is a distributed method of training machine learning models that does not need the sharing of the data that underlies them. Algorithms are distributed to several data warehouses for local training. When trained, just the algorithm, not the data, returns to the central location. The updated predictions are then delivered to each individual dataset to keep and enhance(owk).Federated learning involves each client privately training a copy of the central model, which is represented by the model weights ω, and reporting its modifications back to the server for aggregation across clients without exposing local private data. Federated learning may be expressed as:

$$\min_{\omega \in R} f(\omega) \quad \text{with} \quad f(\omega) = \frac{1}{n} \sum_{i=1}^{n} fi(\omega)$$

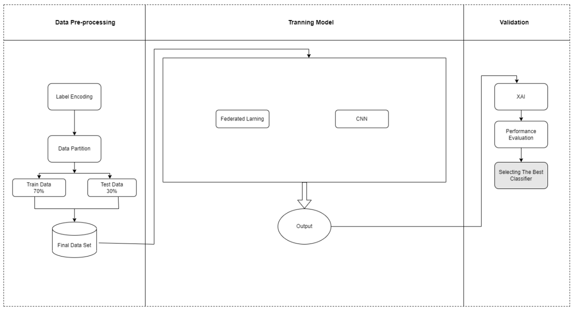

Figure 1: Workflow

4 Implementation and Result

5 Conclusion and Future Work

As IoT, AI, machine learning, and deep learning algorithms proliferated and gave rise to data-driven medical applications, the healthcare sector experienced a radical transformation. Due to difficulties in achieving strong security, privacy, and service quality standards, however, the adoption of AI-based medical applications is still low. With the processing of medical data at the network's edge, federated learning has come to be seen as a possible answer to these problems because it allows for the distributed training of sophisticated machine-learned models while maintaining privacy and security concerns. In this paper, we have used federated learning-based algorithms for endoscopic image classification with an open-source KVASIR dataset and incorporated Explainable AI (XAI) to provide explanations and interpretations of the models' learning.

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