ColoSensus: A Spatiotemporal CNN-based Application for Gastrointestinal Disease Classification

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Abstract. The incidence cases of gastrointestinal diseases continue to rise in developing countries such as the Philippines. Some of these diseases such as colorectal cancer, ulcerative colitis, and colon polyps are a common sight during colonoscopy, a procedure used to detect abnormalities in the colon. Clinicians and medical students manually identifying gastrointestinal diseases may take time especially when lengthy videos are analyzed. Using models with spatiotemporal convolutional neural networks, colonoscopy videos instead of images can now be ingested by these models to predict gastrointestinal diseases. ColoSensus, an application that detects the gastrointestinal diseases mentioned, and uses one out of the 12 trained models from hyperparameter tuning, garnered a weighted average of 82% accuracy, 87% precision, 82% recall, and 79% F1 score. The performance of the current model could be further improved so that it could generalize better to new inputs and be finally used by clinicians as a support decision tool.

Keywords: spatiotemporal convolutional neural network, gastrointestinal disease, hyperparameter tuning, colonoscopy, support decision tool

1 INTRODUCTION

The incidence of colon diseases is showing a concerning trend globally. One such disease which is colorectal cancer (CRC) is a prevalent malignancy affecting the colon and rectum. It arises when healthy cells in the colon or rectum exhibits uncontrolled growth, forming tumors. It has shown a 157% increase from 1990 to 2019, totalling 2.17 million cases worldwide [1]. Furthermore, recent data shows a significant increase in early-onset colorectal cancer (EOCRC) cases in low sociodemographic index (SDI) countries [2], and there has also been a steady increase of CRC in the mean age of cases over the years [3].

Colorectal cancer can start from a colon polyp or a clump of cell that forms on the lining of the colon. Majority of developed colon polyps are benign. But there are instances where some colon polyps turn into cancer [4].

In addition, there has also been a global incidence of Inflammatory Bowel Disease (IBD), particularly in developed and industrialized countries [5] [6]. Recent data shows that 147 of 204 countries or territories experienced a gradual

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increase in the age-standardised rate of IBD for 29 years since 1990. Moreover, there are ongoing reports that IBD is also a health problem among developing countries aside from the developed and industrialized ones. However, there is very little data to confirm this as it was revealed that out of the 4601 publications focusing on Ulcerative Colitis (UC), only 21 have publications describing individuals with Colitis in low-and-lower-middle income countries [7] [8].

IBD is a progressive inflammatory condition that debilitates the gastrointestinal tract lining. It is characterized by a chronic inflammation of the gastrointestinal tract. Moreover, IBD encompasses UC. UC is known for its continuous mucosal inflammation in the large intestine, and is mainly diagnosed through endoscopic findings of continuous inflammation from the rectum to the more proximal colon [18]. The exact cause of UC is still unknown. However, risk factors of UC include gastrointestinal infections, diet, medications, lifestyle factors, genetic factors, and more [9] [10].

Since there have been increasing cases of colon diseases in developing countries, the challenge to differentiate and diagnose using minimal resources becomes more crucial than ever.

Machine learning, specifically deep learning and its application to healthcare has shown promising results in predicting diseases. With the rapid advancement of technology, there is now a way to utilize colonoscopy videos which serve as a good dataset for carefully configured models to use in training to detect any indicators of these diseases. This was demonstrated by several studies showing that deep learning models predict diseases more accurately than clinicians diagnosing specific diseases [6] [19] [20].

1.1 Related Work

As the uptrend of colon diseases continues, so are the advancements of technologies. There were attempts to use artificial intelligence in the healthcare setting to reduce the time it takes to diagnose diseases, and this was also tested on classifying diseases occuring in a specific region. Image or video inputs are used to train models that will classify the disease of interest, and models imitate how the brain works by using a network of neurons to extract useful features in an input, which is also called deep learning. Deep learning algorithms have the capacity to analyze patient data in real time, allowing for more precise diagnoses and individualized treatment approaches [22]. This also applies to finding abnormalities in the gastrointestinal tract using endoscopic images, garnering accuracy scores as high as 98.37% without human assistance [23].

State-of-the-art deep learning models showed that its performance in different image processing situations also performs well on identifying patterns and characteristics in medical images to aid in the detection of diseases [25]. Using colonoscopy images, a CNN-based model showed a 91.5% accuracy on identifying UC and classifying its severity [24]. The same model also scored an 82.8% and 92.4% sensitivity and specificity score, respectively, implying a successful application of a deep learning model with minimal false positive and false negative predictions.

Colon polyps signifies a mass that could potentially be CRC. Moreover, UC puts patients at higher risk of developing CRC due to the lesions developed. Since CNN showed a successful identification of UC, CRC, and polyps, researchers attempted to solve the lapses of the existing research by creating a model that classifies if a colon is healthy, has CRC, or has colon polyps. A CNN-based model was used to do the classification, and colonoscopy images were used to train the model. The model garnered an accuracy score of 60%, implying that the model was trained enough to successfully classify said diseases [4].

1.2 Motivation, contribution, and organization

Despite the feasibility of predicting CRC, UC, and polyps successfully, more research is still required as the aforementioned studies only used colonoscopy images. To date, there is limited research on using colonoscopy videos as inputs. One approach for the model to learn from videos is through spatiotemporal convolution where the spatial aspect or the length and width of each frame and the temporal aspect which is time are combined for enhanced data analysis [11]. Unlike CNN models taking in single images at a time, these networks can effectively capture sequential relationships among frames in videos. Spatiotemporal CNNs have been utilized to automate the identification of anatomical landmarks, aiding in comprehensive examinations such as colonoscopy examinations [12]. Currently, there are emerging studies that look into using spatiotemporal CNNs for disease classification where colonoscopy videos are the input. Moreover, the data only includes doing polyp segmentation and phase detection during colonoscopy procedures [13].

With this, solutions to create a web application that utilizes a model for clinicians to use is formulated. One way to achieve this is to serialize the model and then the researcher will export the model and integrate it into an application [26]. Said model can then be used by its designated users by giving an input, and then the model will process the data to create an output. Very limited data was available on an application that detects and predicts CRC, UC, and polyps using colonoscopy videos. UC-NfNet, a deep-learning enabled assessment of ulcerative colitis is the only closest related web application from the web application to be created. It uses colonoscopy images to assess whether the patient has Ulcerative Colitis, and evaluates the severity given, if any. Moreover, a review of the current state of practice and research in artificial intelligence and colonoscopy shows that most models are tailored to be integrated in colonoscopy devices, meaning most literature only detects colon diseases in real time, and were not integrated in a standalone application to analyze colonoscopy videos [14].

The contribution of this study is the creation of a potential colon disease detector using deep learning along with spatiotemporal data as an input. Through the creation of a web-based application for disease classification, this study aims to reduce the burden of specific colon disease classification of clinicians having difficulties in predicting said diseases through endoscopy results alone. The creation of this application also provides convenience to clinicians manually analyzing videos with longer lengths. In addition, this project will contribute to the body of knowledge on using deep learning in the healthcare setting, with emphasis on utilizing spatiotemporal data as inputs.

In creating a robust model, there is a need to use a credible dataset. The HyperKvasir dataset is a significant collection of images and videos of the gastrointestinal tract, primarily gathered during real gastrointestinal and colonoscopy examinations at Baerum Hospital in Norway [27]. It comprises of approximately 110,000 images and 370 videos, including various landmarks, normal findings, and pathological conditions. The special problem will only use the colonoscopy videos of patients with a normal colon, with CRC, UC, or polyps.

2 PROPOSED APPROACH

2.1 Data augmentation

The dataset used is the HyperKvasir dataset, which is a comprehensive multi-class image and video dataset. Within the dataset, the colonoscopy videos classified as patients with CRC, UC, and polyps will be used. Medical data such as colonoscopy data is sparse and hard to obtain due to ethical and legal restrictions. Using a credible data such as the HyperKvasir dataset will ensure the model was trained with reliable data [27]. Moreover, the creators of the dataset established that HyperKvasir is primarily intended to be explored more on the applications of artificial intelligence in the context of endoscopy and gastroenterology in general.

The problem with the dataset is the lack of data from the CRC and UC classes. The HyperKvasir dataset only offers 3 videos for CRC and 14 videos for UC. In order to address this, Python's VidAug package was used. Several augmentation techniques were used. Moreover, these techniques imitate the inaccuracies occurring during video procedures such as added noise, flips, increased or decreased contrast, and varying brightness. This is further combined with reversing frame orders to act as a new video. 100 videos from each class were finally created and partitioned into a 80-10-10 training, validation, and test datasets

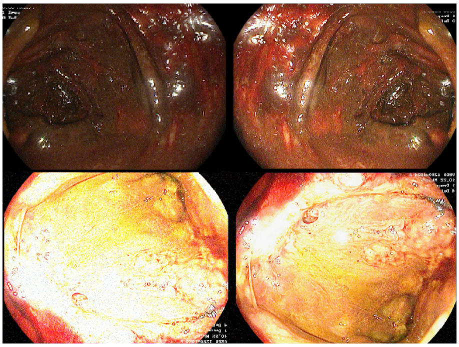

Fig. 1. Different augmentation techniques done in a single frame. The original frame (at the upper left) is augmented using horizontal and vertical flips, salt and pepper noises, video reversals, and intensity changes

2.2 Spatial-temporal CNN

CNNs are a class of deep neural networks that are used in image recognition to extract features from images and classify them accurately. This neural network utilizes deep learning architectures to automatically learn hierarchical representations of images, enabling them to capture complex patterns and structures. Like a 2D CNN, a spatiotemporal CNN uses three dimensions to extract data: the spatial dimension and the temporal dimension. When the dataset consists mainly of videos, a spatiotemporal CNN can be used. In this case, the videos from the HyperKvasir dataset is used by the model [28].

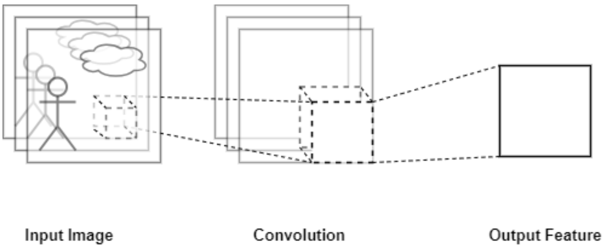

Fig. 2. A standard 3D CNN model. A temporal dimension is added during convolution

In this study, a 3D convolutional neural network variant was used for computational efficiency: the R(2+1)D convolutional neural network. A 3D convolutional neural network is done using a filter size of $t \times w \times h$ at a time. This means given a fixed value of stride and slide, the convolution operation is applied simultaneously. In R(2+1)D convolution however, the convolution operation is decomposed into two parts. The first convolution involves using the spatial dimensions or the height and width of the video first on t frames independently, and then using the output vector for each frame to proceed with the second convolution using the temporal dimension. Figure 3 highlights the difference between 3D CNN and (2 +1)D CNN models [28].

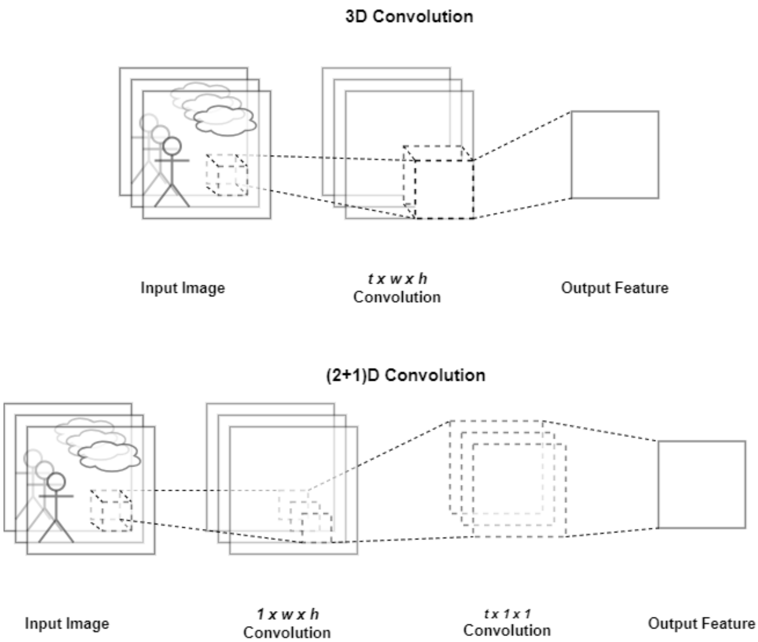

Fig. 3. Difference between how 3D CNN and (2+1)D CNN processes data inputs

2.3 Django model integration

The Django web framework is known for its ability to create strong and scalable web applications with a user-friendly interface that is simple to maintain [29]. It is built using the Python programming language and is known for its wide range of libraries and tools that enable developers to create sophisticated and feature rich applications [30]. Moreover, integrating serialized CNN models into Django is feasible and is widely practiced in web development. Using its flexibility and support for various Python libraries, Django can handle the deployment of machine learning models and load the serialized model within a view or an API endpoint. The framework provides a robust environment for preprocessing input data, making predictions, and responding to client requests. The figure illustrates how a CNN-based web application works using Django.

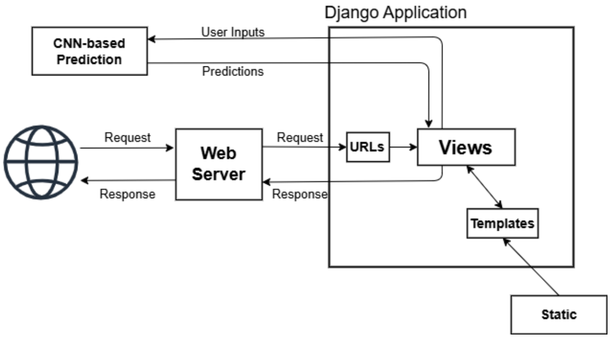

Fig. 4. CNN-based web application using Django and its components

3 HYPERPARAMETER TUNING

Hyperparameter tuning using a grid search approach was done to find the best model. The search space includes the number of filters, the learning rate, and the drop out rate of the model during fitting.

The following pipeline in Figure 5 was followed in order to obtain the most efficient model for the analysis of colonoscopy videos. The specified hyperparameters are added in a grid search function to determine which of the following combinations of hyperparameters produce the model with the best training and validation score. The model used is a R(2+1)D convolutional neural network (CNN) that was a ResNet-inspired neural network that makes convolutions in the spatial dimension followed by a convolution in the temporal dimension. This is different from a standard 3D convolution model as it makes convolutions for spatial and temporal dimensions simultaneously. Although both 3D convolutional neural networks and R(2+1)D convolutional neural networks have their own strengths, R(2+1)D CNN generally outperforms 3D CNN for working in non-volumetric data, such as colonoscopy videos [28].

This study establishes several hyperparameters to ensure that the model can perform better given a search space of: 0.0001, 0.00001 learning rate; 16, 32 filters; 20%, 50%, 80% dropout rate.

For medical applications, especially with complex spatiotemporal models like R(2+1)D CNN, the authors have agreed that lower learning rates tend to be more appropriate as complex datasets like colonoscopy videos make spatiotemporal CNN prone to overfitting to the data [15]. This also applies to the number of filters used for training the model. The authors decided to balance between capturing broad features in early layers and capturing more intricate details from frames, especially in later layers when the model needs to discern finer nuances such as polyp textures, or abnormal tissue structures [16]. Lastly, the authors also chose varying dropout rates in hopes to find the correct value of dropping neurons to force the model to learn more robust patterns [17].

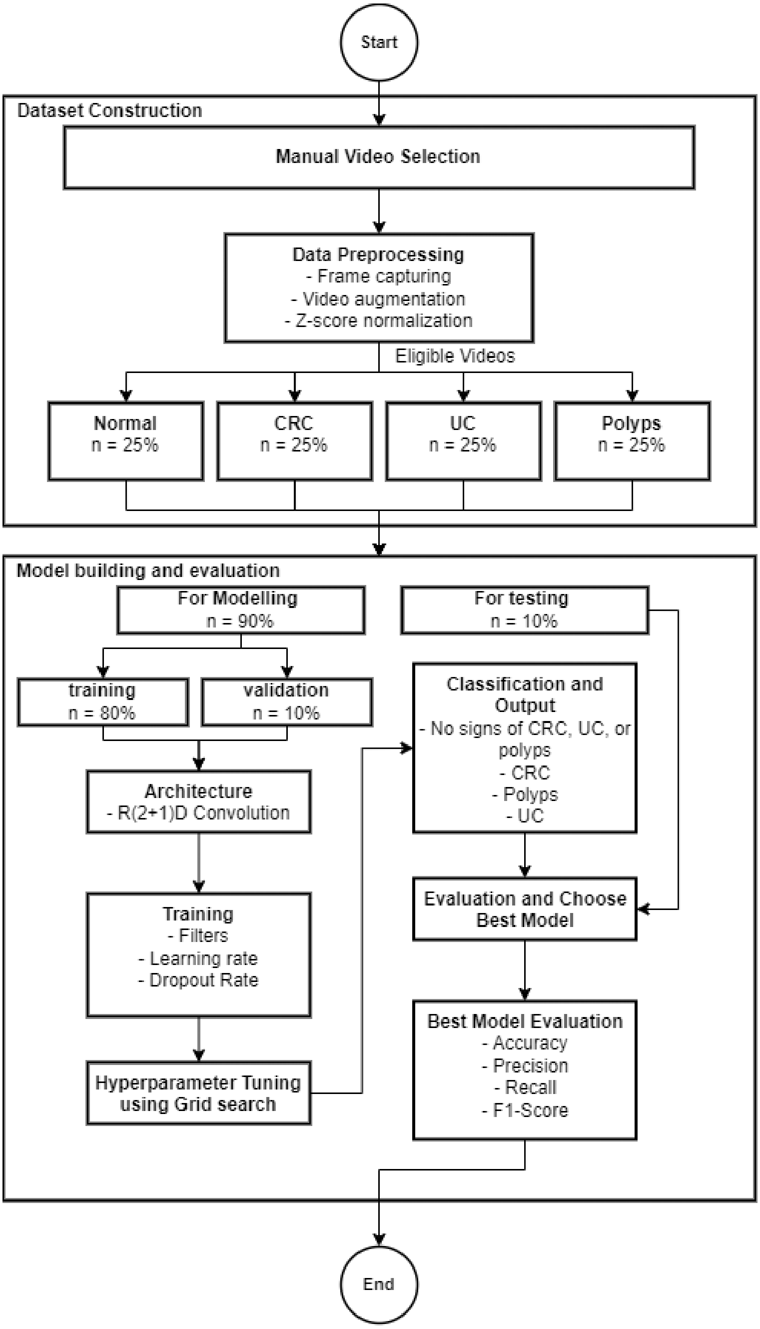

Fig. 5. Modeling Pipeline for CRC, UC, and polyps detection

Table 1 shows all hyperparameters and their performances during model fitting. 100 videos from each class were finally created and partitioned into a 80-10-10 training, validation, and test datasets. The table below shows the results of all combinations of hyperparameters specified in the objectives of the study. The best model was determined by evaluating the performances of each model using a test dataset. Specifically, each model was assessed using the weighted average of its accuracy, precision, recall, and F1 score metrics. The best model is determined by the highest F1-Score. Moreover, in order to establish a model that is acceptable for effective medical decision-making, it must have a score between 0.7 to 0.9 [21]. All possible combinations of the established hyperparameters were tested through individual training and individual validation, and unintroduced data was fed to each trained model to obtain each of its accuracy, precision, recall, and F1-score. Due to time constraints, only R(2+1)D CNN was used as the model for predicting the diseases mentioned in this study. Furthermore, only 3 colon diseases were fed to the model as increasing the number of classes significantly increases the time it takes to train a model with a particular set of hyperparameters. Colonoscopy videos having no manifestations of any of the diseases will be labeled as "No manifestations of CRC, UC, and polyps."

Trial ID	Hyperparameters	Accuracy	Precision	Recall	F1 Score
00	0.0001 Learning Rate 0.2 Dropout 16 Filters	0.75	0.76	0.75	0.74
01	0.0001 Learning Rate 0.2 Dropout 32 Filters	0.70	0.69	0.70	0.68
02	**0.0001 Learning Rate** **0.5 Dropout** **16 Filters**	**0.82**	**0.87**	**0.82**	**0.79**
03	0.0001 Learning Rate 0.5 Dropout 32 Filters	0.68	0.64	0.68	0.64
04	0.0001 Learning Rate 0.8 Dropout 16 Filters	0.57	0.47	0.57	0.51
05	0.0001 Learning Rate 0.8 Dropout 32 Filters	0.65	0.67	0.65	0.62
06	0.00001 Learning Rate 0.2 Dropout 16 Filters	0.62	0.66	0.62	0.61

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Trial ID	Hyperparameters	Accuracy	Precision	Recall	F1 Score
07	0.00001 Learning Rate 0.2 Dropout 32 Filters	0.55	0.59	0.55	0.54
08	0.00001 Learning Rate 0.5 Dropout 16 Filters	0.40	0.38	0.40	0.36
09	0.00001 Learning Rate 0.5 Dropout 32 Filters	0.45	0.48	0.45	0.45
10	0.00001 Learning Rate 0.8 Dropout 16 Filters	0.53	0.46	0.53	0.46
11	0.00001 Learning Rate 0.8 Dropout 32 Filters	0.57	0.67	0.58	0.52

Table 1: Hyperparameter tuning results.

Trial 02 was shown as the best model with an F1-score of 0.79, implying a balance between precision and recall, or the true positives and true negatives correctly identified from the test dataset fed into the model. It was then serialized and integrated into the web application for sample predictions.

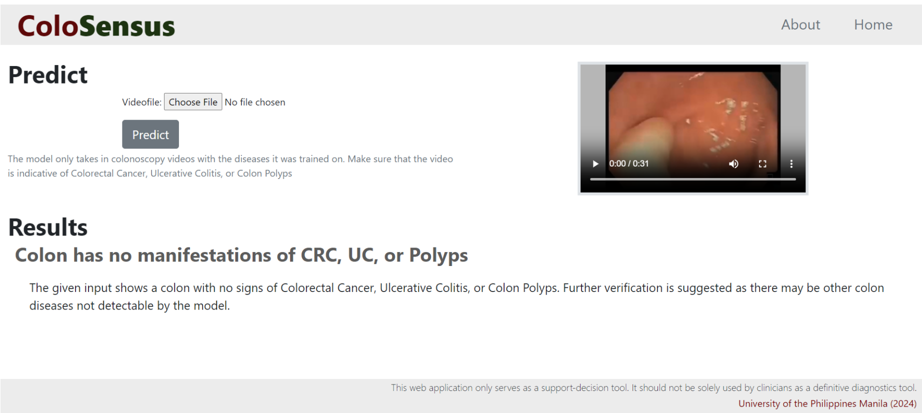

Fig. 6. ColoSensus predicting a colon with no manifestations of CRC, UC, or polyps from video input

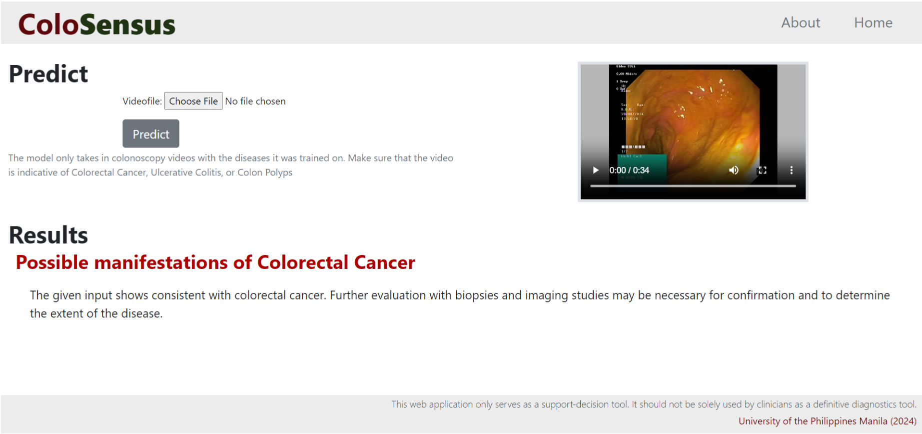

Fig. 7. ColoSensus predicting colorectal cancer from video input

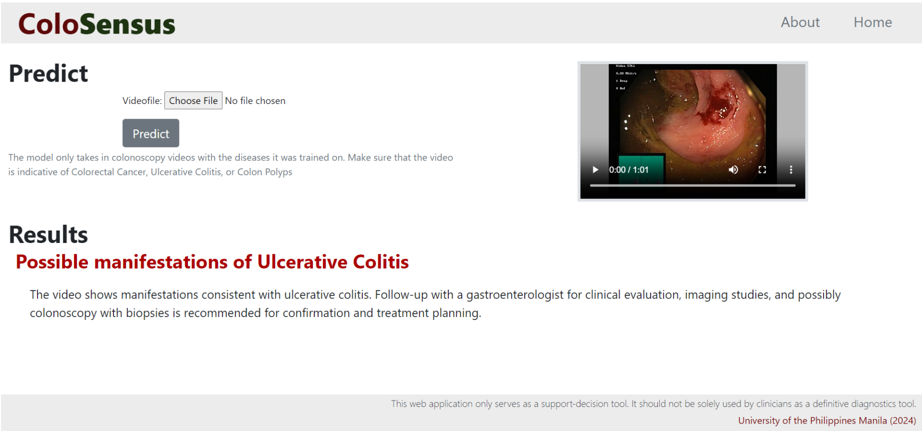

Fig. 8. ColoSensus predicting ulcerative colitis from video input

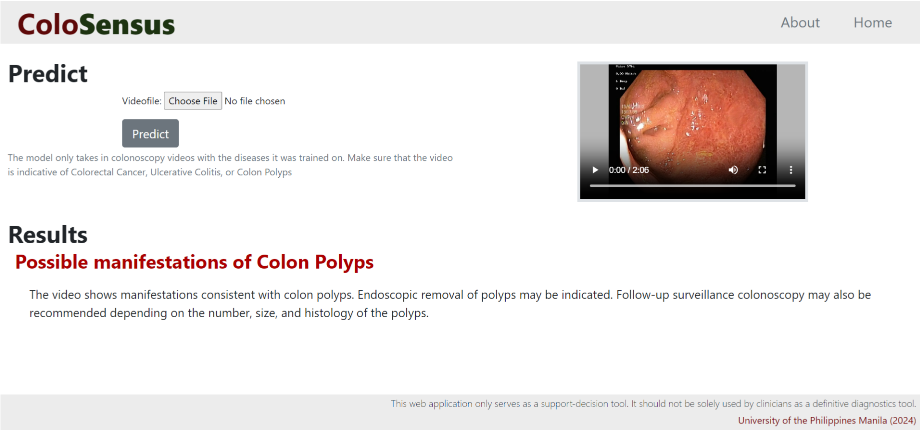

Fig. 9. ColoSensus predicting colon polyps from video input

4 DISCUSSION AND CONCLUSION

This CNN-based system is an application that was developed to serve as a clinical support decision tool for clinicians to use. It allows its users to upload a video of a colonoscopy procedure and let a model process it to make a final prediction. The model was tailored to take in spatiotemporal data, meaning it reduces the burden of clinicians to take a key frame from a colonoscopy procedure for prediction as the model was trained to handle this tedious step. The model used is a R(2+1)D convolutional neural network (CNN) that was a ResNet-inspired neural network that makes convolutions in the spatial dimension followed by a convolution in the temporal dimension.

The colonoscopy videos used were obtained from the publicly available HyperKvasir Dataset where it contains various colonoscopy videos with different diseases. The model only used colonoscopy videos of patients with a healthy colon, CRC, UC, and polyps [27]. The number of videos from each class were scarce, so video augmentation techniques, such as video flipping, frame reversals, and salt and pepper noises, were ultimately used as an attempt to create unfamiliar videos to the model, and prevent overfitting. After video augmentation, the training, validation, and test datasets were split in an 80-10-10 ratio respectively.

It is important to note that there may be signs of overfitting on predicting CRC. The scarcity of colonoscopy videos with CRC led to the creation of several colonoscopy videos that may be slightly similar to the original colonoscopy videos with the same disease.

All in all, the ability of the model to analyze colonoscopy videos instead of images using spatiotemporal CNNs opened up the possibilities of creating more clinical support decision tools not only exclusive to the three diseases mentioned in this study, but also to different d iseases o bservable u sing v ideo i nputs i n a healthcare setting.

5 RECOMMENDATIONS AND FUTURE WORK

While ColoSensus aids in the classification o f c olonoscopy v ideos, f urther improvements can enhance its clinical utility, particularly in providing actionable evidence to clinicians. In addition to classification, future versions of ColoSensus could include the following features:

1. Timestamp and Region of Interest Identification. The tool could mark timestamps where abnormalities are detected, allowing clinicians to investigate specific segments. Furthermore, highlighting regions of interest could provide visual cues to aid in diagnosis, reducing the need for manual video review.
2. Make a larger model trained with a significantly increased data size. Colosensus relied only on a few original colonoscopy videos and heavy video augmentation to create 100 videos for each class. Expanding the dataset with more diverse and annotated colonoscopy videos would improve generalizability and robustness.
3. Include the number of epochs as a hyperparameter. The training and validation graphs showed a slight fluctuation during fitting. Increasing the number of epochs may resolve this and help the model find more complex patterns in the dataset.
4. Explore other network architectures besides R(2+1)D CNN.

Since the machine can only handle 4 classes for model development, the application can also be extended to cater to different gastrointestinal diseases such as Crohn's Disease, Gastrointestinal Tuberculosis, and more.

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