OP402 SUBCLASSES OF TYPE-II PIT PATTERN REVEAL ALTERNATIVE TUMORIGENIC PATHWAYS OF COLORECTAL SERRATED LESIONS

H. Aoki[1], E. Yamamoto[2], H. Yamano[3], K. Yoshikawa[4], H. Matsushita[5], R. Takagi[6], E. Harada[5], Y. Tanaka[7], T. Sugai[8], H. Suzuki[1]
[1]*Dept. Of Molecular Biology, Sapporo Medical University, Sapporo/Japan*
[2]*Dept. Of Gastroenterology, Sapporo medical university, Sapporo/Japan*
[3]*Dept. Of Gastroenterology, Akita Red Cross Hospital, Akita/Japan*
[4]*Dept. Of Gastroenterology, Akita Red Cross Hospital, Akita/Japan*
[5]*Department Of Gastroenterology, Akita Red Cross Hospital, Akita/Japan*
[6]*Department Of Gastroenterology, Akita Red Cross Hospital, Akita/Japan*
[7]*Gastroenterology, Akita Red Cross Hospital, Akita-Shi/Japan*
[8]*Dept. Of Molecular Diagnostic Pathology, Iwate Medical University, Morioka/Japan*

Contact E-mail Address: hironori_a1123@yahoo.co.jp

Introduction: Colorectal serrated lesions (SLs) include hyperplastic polyp (HP), traditional serrated adenoma (TSA) and sessile serrated adenoma/polyp (SSA/P). Emerging evidences suggest that SSA/Ps are precursor lesions of colorectal cancers (CRCs) with BRAF mutation and the CpG island methylator phenotype (CIMP). We have previously reported that Type II-Open (Type II-O) pit patterns, which is highly specific to SSA/P. However, clinicopathological and molecular features of SLs without Type II-O pits remain unclear.

Aims & Methods: We aimed to identify clinicopathological and molecular features of SLs without Type II-O pits. We analyzed the methylation of CIMP markers (MINT1, −2, −12, −31, p16 and MLH1) and BRAF and KRAS mutation in 448 premalignant and malignant colorectal tumors. By using magnifying endoscopy, surface microstructures of colorectal lesions were classified into Type II pit or tumor pit (Type III, IV or V pit) according to the Kudo's pit pattern classification system. Type II pit was subcategorized into classical Type-II pit, Type II-O pit and Type II-Long (Type II-L) pit. CIMP status (CIMP-high, -low and -negative) was determined by using the five methylation markers.

Results: Endoscopic findings were classified as 41 Type II pit, 8 Type II-L pit, 92 Type II-O pit, 21 Type II plus tumor pit, 22 Type II-L plus tumor pit, 50 Type II-O plus tumor pit and 214 tumor pit. We identified Type II-L plus tumor pit, which was specific to TSA with KRAS mutation and CIMP-low (sensitivity, 60%; specificity, 96%). As compared to lesions with only Type II-L pit, KRAS mutation and CIMP-low were more frequent in lesions with Type II-L plus tumor pits. Progression of Type II-L pit lesions to TSA was associated with KRAS mutation and accumulation of moderate DNA methylation. In contrast, BRAF mutation was frequently observed in colonic tumors with Type II plus tumor pit. These results suggest that lesions with Type II-L pit and those with Type II pit appear to develop through distinct tumorigenic pathways, though the majority of lesions with Type II or Type II-L pit were the same HP.

Conclusion: Our data suggest that Type II-L plus tumor pit is a useful hallmark of the premalignant stage of CRCs with KRAS mutation and CIMP-low.

Disclosure of Interest: All authors have declared no conflicts of interest.

OP403 ARTIFICIAL INTELLIGENCE (AI) IN ENDOSCOPY–DEEP LEARNING FOR OPTICAL BIOPSY OF COLORECTAL POLYPS IN REAL-TIME ON UNALTERED ENDOSCOPIC VIDEOS

M. F. Byrne[1], D. K. Rex[2], N. Chapados[3], F. Soudan[4], C. Oertel[4], M. Linares Perez[5], R. Kelly[6], N. Iqbal[7], F. Chandelier[8]
[1]*Gastroenterology, Vancouver General Hospital, Vancouver/Canada/BC*
[2]*Gastroenterology And Hepatology, Indiana University Medical Center, Indianapolis/United States of America/IN*
[3]*École Polytechnique de Montréal, Montreal/Canada/QC*
[4]*Imagia, Montreal/Canada/QC*
[5]*University of Buenos Aires, Buenos Aires/Argentina*
[6]*University College Cork, Cork/Ireland*
[7]*St Luke's Hospital, Kilkenny/Ireland*
[8]*Cadens Imaging, Montreal/Canada/QC*

Contact E-mail Address: mfjbyrne@gmail.com

Introduction: ASGE-PIVI guidelines support a "resect and discard" strategy for diminutive colon polyps, provided that the predictive value of technology allowing for "optical biopsy" depicts at least 90% agreement in assignment of post-polypectomy surveillance intervals using pathology as standard. In addition, in order for a technology to be used to guide the decision to leave suspected diminutive rectosigmoid hyperplastic polyps in place (without resection), the technology should provide 90% negative predictive value for adenomatous histology. Such standards with optical biopsy might be achievable with experts (although even that is unclear) but do not cross over into general clinical practice. Several groups have looked at supporting the process of optical biopsy decision making on endoscopic assessment of the histology of diminutive colorectal polyps using traditional machine learning, but to date there are significant limitations in terms of (1) using still images only, and non-realtime computer support, both of which are not clinically efficient or effective, and (2) often involving magnification endoscopy that is not yet a widespread clinical practice. Deep learning is a branch of artificial intelligence which is a siginificant advance on traditional machine learning, and with huge computational power, machines can now recognize objects in real time. We sought to apply novel deep learning techniques to optical biopsy for colon polyps.

Aims & Methods: We aimed to evaluate deep learning applied to the classification of colorectal polyps into NICE types 1 and 2, in real-time on unaltered endoscopic videos, for the support of clinically efficient optical biopsy. We used 92 videos of small colorectal polyps (<10 mm) under white light (WL) and narrow-band imaging (NBI) (38 NICE type 1, 52 NICE type 2), using Olympus 190 series colonoscopes. "Optical biopsy" was done on all polyps by an expert with >95% accuracy (using pathology as the reference standard) prior to removal and histological confirmation.

We investigated a Deep Learning Artificial Intelligence model with a proprietary deep convolutional neural network (DCNN) for the computer-assisted NICE type 1&2 differentiation. We designed a 3-class model representing Types 1, 2, and unsuitable (frames without statistically representative information–blur, bubbles, liquid). The model operated at the individual frame level, without prior segmentation.

For model training purposes, each frame was manually tagged. The final dataset was split into training and validation sets, without overlap. Finally, the analysis was performed separately for NBI and WL frames, allowing for reporting of frame processing time and classification performance.

Results: A total of 33,954 training frames were used, split equally across NBI & WL, and type 1, type 2, & unsuitable classes. We performed a 5-fold cross-validation on the tagged frames for quality control. The trained DCNN model was then used to evaluate the unaltered videos in real-time, with an accuracy for polyp classification of 90% for NBI, and 83% for WL. The confusion matrix on whole-video classification of colorectal polyps gives a sensitivity of 93% and specificity of 85% for NBI. Finally, the processing time of our DCNN model ran at between 25 and 30 frames per second (fps) using a decent gamer-grade GPU (NVIDIA Titan-X) on an unaltered video feed of 60 fps, delivering near-realtime computer support.