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REVIEW

Artificial intelligence in gastroenterology and hepatology: Status and challenges

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Abstract

Originally proposed by John McCarthy in 1955, artificial intelligence (AI) has achieved a breakthrough and revolutionized the processing methods of clinical medicine with the increasing workloads of medical records and digital images. Doctors are paying attention to AI technologies for various diseases in the fields of gastroenterology and hepatology. This review will illustrate AI technology procedures for medical image analysis, including data processing, model establishment, and model validation. Furthermore, we will summarize AI applications in endoscopy, radiology, and pathology, such as detecting and evaluating lesions, facilitating treatment, and predicting treatment response and prognosis with excellent model performance. The current challenges for AI in clinical application include potential inherent bias in retrospective studies that requires larger samples for validation, ethics and legal concerns, and the incomprehensibility of the output results. Therefore, doctors and researchers should cooperate to address the current challenges and carry out further investigations to develop more accurate AI tools for improved clinical applications.

Key Words: Artificial intelligence; Gastroenterology; Hepatology; Status; Challenges

interest.

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Core Tip: Artificial intelligence (AI) technologies are widely used for medical image analysis in the gastroenterology and hepatology fields. Several AI models have been developed for accurate diagnosis, treatment, and prognosis based on images of endoscopy, radiology, pathology, achieving high performance comparable to experts. However, we should be aware of the certain constraints that limit the acceptance and utilization of AI tools in clinical practice. To use AI wisely, doctors and researchers should work together to address the current challenges and develop more accurate AI tools to improve patient care.

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INTRODUCTION

Originally proposed by John McCarthy in 1955, artificial intelligence (AI) which involves machine learning (ML) and problem solving, has achieved a breakthrough and revolutionized the processing methods of clinical medicine with the increasing workloads of medical records and digital images. In clinical practice, AI consists of several overlapping technologies such as ML, artificial neural networks (ANNs), deep learning (DL), convolutional neural networks (CNNs), and recurrent neural networks[1,2] (Figure 1). Since the 1980s, ML has been performed to construct a mathematical model and predict outcomes based on input data, and it is roughly divided into supervised (labeled data), unsupervised (unlabeled data), and semi-supervised (both labeled and unlabeled data) learning techniques[3]. Recently, as a subset of ML, ANNs have received increased interest because they can identify and learn input data by themselves instead of being labeled by experts[4]. In the last decade, DL, a new model of ML, holds great promise in clinical medicine. DL is particularly suitable for enormous complex or highly dimensional medical image analysis and predictive modeling tasks using the multilayers of ANNs, including CNNs and recurrent neural networks[5,6]. Notably, given that convolutional and pooling layers can extract distinct features and fully connected layers can make a final classification, CNNs have demonstrated excellent performance in image recognition such as endoscopy, radiology, and pathology[7,8].

In the fields of gastroenterology and hepatology, doctors are paying attention to AI technologies for the diagnosis, treatment, and prognosis of various diseases due to the heterogeneous expertise levels of doctors (majoring in endoscopy, radiology, and pathology), time-consuming procedures, and increasing workloads. Specifically, doctors usually assess medical images visually to detect and diagnose diseases based on personal expertise and experience. As the maturity of digitalization increases, a quantitative assessment of imaging information has become the reality instead of relatively inaccurate qualitative reasoning[9,10]. Although a lot of time is necessary to review and check image analysis traditionally, little information can be obtained. For example, using AI technologies to process pathology images can assess the histopathological classification and predict gene mutations in liver cancer[11], while only the mass nature can be identified by conventional pathology assessment. As a country with a high population, China has produced rapidly increasing medical records, which result in the high workloads[12]. Despite the progression of AI, gastroenterologists and hepatologists should always be aware of its limitations such as the retrospective manner of included studies and the utilization of not particularly suitable databases. In addition, it demands that doctors prepare for the effects and changes of AI on clinical practice in the real world.

In this review, we aim to (1) introduce how AI technologies process input data, learn from input data, validate the established model; (2) summarize the AI applications in endoscopy, radiology, pathology for accurate diagnosis, treatment, and prognosis; and (3) discuss the current limitations and future considerations of AI

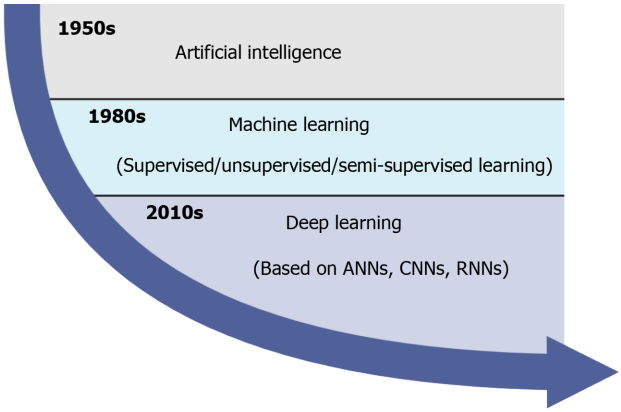

Figure 1 Timeline and related technologies of artificial intelligence. AI: Artificial intelligence; ANN: Artificial neural network; CNN: Convolutional neural network; RNN: Recurrent neural network.

applications in the fields of gastroenterology and hepatology (Figure 2).

METHODS IN DEEP LEARNING

As the most suitable approach for medical image analysis, the DL approach does not require shaped regions of interest on images to complete feature selection and extraction based on a neural network structure[13,14]. After data collection and processing, the correct neural network is chosen to establish a model, followed by model validation to assess its true generalizability.

Data processing

Raw data are collected and analyzed, and corrupt data are identified and cleaned in the processing phase. Data selection methods are provided in Scikit-Learn[15], a Python machine learning library, which consist of univariate selection, feature importance, correlation matrix, and recursive feature elimination or addition. Other programming languages such as R Studio (http://www.r-project.org) or MATLAB software (University of New Mexico, New Mexico, United States) also offer a successful environment for AI, and they provide similar approaches to address specific tasks. Useful data and relevant variables from multiple data sources, which are applied to predict outcomes, are selected and divided into an initial training set and a testing set that allow training and internal validation of the model. Data in the training set should be different and nonredundant from that in the testing set. Notably, for small datasets, a higher proportion of data should be included in the testing set to measure the performance of the trained model accurately through cross-validation or in a bootstrapping procedure.

Modeling

After transforming the data into an appropriate format, different tools are developed for implementing ML. Although several programming tools such as Python, R Studio, and MATLAB vary among themselves, they provide similar options and algorithms to adjust the parameters based on specific tasks. The major classification algorithms for testing are Naive Bayes, Decision Trees, Support Vector Machine, K-Nearest Neighbor, and Ensemble Classifiers. Oversampling or undersampling of the unbalanced training data can be utilized to improve the representation of classes and prevent model bias during the modeling stage. Currently, as the calculation workload of the batch learning process is heavy, minibatch learning is more popularized with repeating epochs, which usually decreases errors for the training and testing phases. However, an early stopping technique would be adopted to address the overfitting problem if repeating epochs cannot ensure error reduction. Based on the evaluations of model performance, developers conduct feature engineering again to manipulate the features and approve the predictive values of the model. After the optimization phase, selection for the model is primarily based on trial-and-error and the best performance for specific problem-solving. Finally, model optimization is performed with adjusted parameters by testing different configurations.

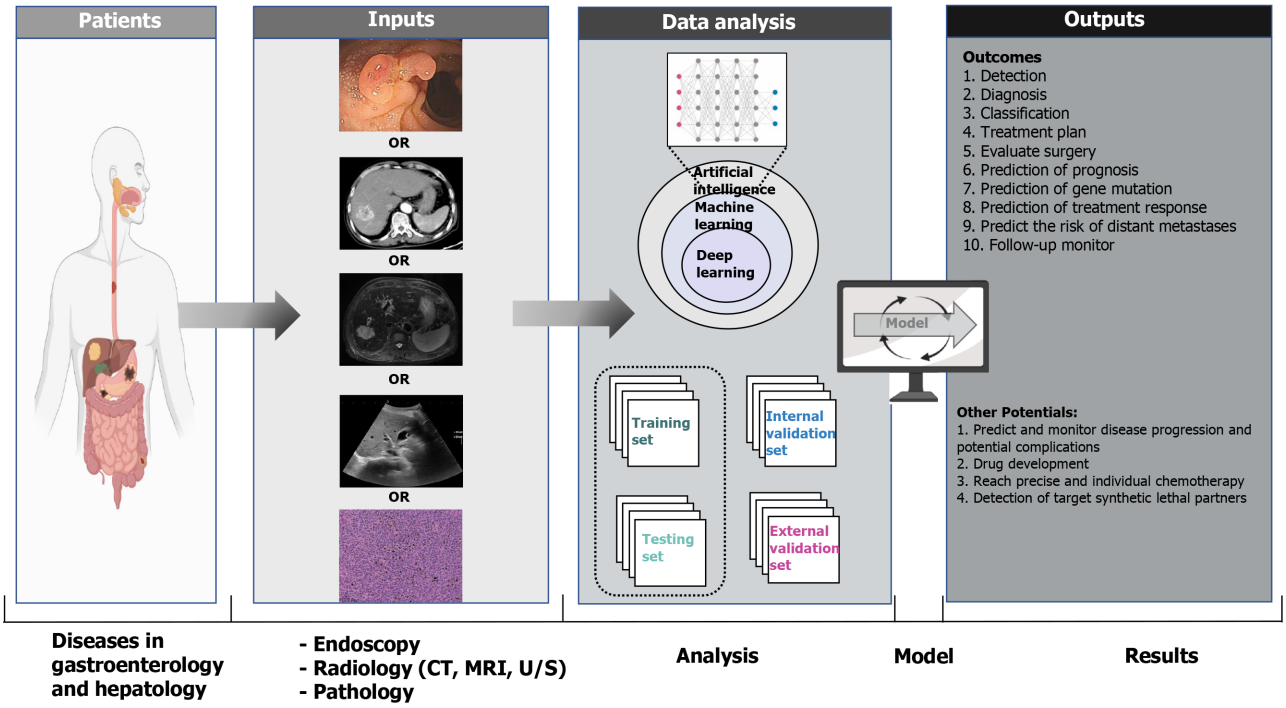

Figure 2 Artificial intelligence-assisted endoscopy, radiology, and pathology applications for medical image analysis in the fields of gastroenterology and hepatology, including detecting and evaluating lesions, facilitating treatment, and predicting treatment response and prognosis, and other potentials, using several deep learning models. CT: Computed tomography; MRI: Magnetic resonance imaging.

Model validation

To evaluate the AI approaches, one of the most significant requirements is external validation, which is called the blind test. Any model developed within one dataset will merely reflect its idiosyncrasies, and will have poor performance in analyzing new settings. In addition, models can also be validated by internal data testing (*e.g.*, *k*-fold cross-validation). In *k*-fold cross-validation, the dataset is separated into *k* subsets, including one subset for testing and the remaining (*k*-1) subsets for training a model. With all data used in both training and testing sets, the cross-validation process is repeated *k* times. The model performance is finally calculated as the average value of all *k* iterations. The *k* varies depending on the size of the dataset. For example, leave-one-out validation may be used in a small training set (< 200 data points), which means that *k* is equivalent to the dataset size. The appropriate and robust predictive model should have consistent performance between training and testing sets, preventing overfitting discrepancies.

ARTIFICIAL INTELLIGENCE IN ENDOSCOPY

With the advent and continuous improvement of fiberoptics, endoscopy has been playing a significant role in the diagnosis and treatment of gastrointestinal diseases. However, gastrointestinal diseases remain an enormous economic burden and lead to high mortality worldwide. AI is applicable in the gastroenterology fields within endoscopy[16-18], such as identification of esophageal and gastric neoplasia in esophago-gastroduodenoscopy (EGD), detection of gastrointestinal bleeding in wireless capsule endoscopy (WCE), and polyp detection and characterization in colonoscopy, *etc*[19-63] (Table 1).

EGD

Inadequate examination of the upper gastrointestinal tract is one of the reasons for misdiagnosing several EGD diseases. Based on AI-assisted EGD, the upper gastrointestinal tract can be divided into the pharynx, esophagus, stomach (upper, middle, lower), and duodenum with high values of the area under the curve (AUC)[19]. Furthermore, several AI technologies have classified the images of the stomach within EGD to significantly monitor the blind spots, and their accuracy has reached the ability

Table 1 Summary of key studies on artificial intelligence-assisted endoscopy in gastroenterology fields

Ref.	Country	Disease studied	Design of study	Application	Number of cases	Type of machine learning algorithm	Outcomes (%)	
							Accuracy	Sensitivity/Specificity
Esophagogastroduodenoscopy								
Takiyama *et al*[19], 2018	Japan	Anatomical location of upper gastrointestinal tract	Retrospective	Recognition of the anatomical location of upper gastrointestinal tract	Training: 27335 images: 663 larynx, 3252 esophagus, 5479 upper stomach, 7184 middle stomach, 7539 lower stomach, and 3218 duodenum; Testing: 17081 images: 363 larynx, 2142 esophagus, 3532 upper stomach, 6379 middle stomach, 3137 lower stomach, and 1528 duodenum	CNNs	Larynx: 100; Esophagus: 100; Stomach: 99; Duodenum: 99	Larynx: 93.9/100; Esophagus: 95.8/99.7; Stomach: 98.9/93; Duodenum: 87/99.2
Wu *et al*[20], 2019	China	Diseases of upper gastrointestinal tract	Prospective	Monitor blind spots of upper gastrointestinal tract	Training: 1.28 million images from 1000 object classes; Testing: 3000 images for DCNN1, and 2160 images for DCNN2	CNNs	90.4	87.57/95.02
van der Sommen *et al*[21], 2016	Netherlands	EN-BE	Retrospective	Detection of EN in BE	21 patients with EN-BE (60 images), 23 patients without EN-BE (40 images)	SVM	NA	86/87
Swager *et al*[22], 2017	Netherlands	EN-BE	Retrospective	Detection of EN in BE	60 images: 40 with EN-BE and 30 without EN-BE	SVM	95	90/93
Hashimoto *et al*[23], 2020	United States	EN-BE	Retrospective	Detection of EN in BE	Training: 916 images with EN-BE; Testing: 458 images: 225 dysplasia and 233 non-dysplasia	CNNs	95.4	96.4/94.2
Ebigbo *et al*[24], 2020	Germany	EAC-BE	Retrospective	Detection of EAC in BE	Training: 129 images; Testing: 62 images: 36 EAC and 26 normal BE	CNNs	89.9	83.7/100
Horie *et al*[25], 2019	Japan	EAC and ESCC	Retrospective	Detection of EAC and ESCC	Training: 384 patients with 32 EAC and 397 ESCC (8428 images); Testing: 47 patients with 8 EAC and 41 ESCC (1118 images)	CNNs	98	98/79
Kumagai *et al*[26], 2019	Japan	ESCC	Retrospective	Detection of ESCC	Training: 240 patients (4715 images: 1141 ESCC and 3574 benign lesions); Testing: 55 patients (1520 images: 467 ESCC and 1053 benign)	CNNs	90.9	92.6/89.3
Zhao *et al*[27], 2019	China	ESCC	Retrospective	Detection of ESCC	165 patients with ESCC and 54 patients without ESCC (1383 images)	CNNs	89.2	87.0/84.1
Cai *et al*[28], 2019	China	ESCC	Retrospective	Detection of ESCC	Training: 746 patients (2438 images: 1332 abnormal and 1096 normal); Testing: 52 patients (187 images)	CNNs	91.4	97.8/85.4
Nakagawa *et al*[29], 2019	Japan	ESCC	Retrospective	Determination of invasion depth	Training: 804 patients with ESCC (14338 images: 8660 non-ME and 5678 ME); Testing: 155 patients with ESCC (914 images: 405 non-ME and 509 ME)	CNNs	SM1/SM2, 3: 91.0; Invasion depth: 89.6	SM1/SM2, 3: 90.1/95.8; Invasion depth: 89.8/88.3
Tokai *et al*[30], 2020	Japan	ESCC	Retrospective	Determination of invasion depth	Training: 1751 images with ESCC; Testing: 42 patients with ESCC (293 images)	CNNs	80.9	84.1/80.9

Ali *et al*[31], 2018	Pakistan	EGC	Retrospective	Detection of EGC	56 patients with EGC, 120 patients without EGC	SVM	87	91.0/82.0
Sakai *et al*[32], 2018	Japan	EGC	Retrospective	Detection of EGC	Training: 58 patients (348943 images: 172555 EGC and 176388 normal); Testing: 58 patients (9650 images: 4653 EGC and 4997 normal)	CNNs	87.6	80.0/94.8
Kanesaka *et al*[33], 2018	Japan	EGC	Retrospective	Detection of EGC	Training: 126 images: 66 EGC and 60 normal; Testing: 81 images: 61 EGC and 20 normal	SVM	96.3	96.7/95.0
Wu *et al*[34], 2019	China	EGC	Retrospective	Detection of EGC	Training: 9691 images: 3710 EGC and 5981 normal; Testing: 100 patients: 50 EGC and 50 normal	CNNs	92.5	94.0/91.0
Horiuchi *et al*[35], 2020	Japan	EGC	Retrospective	Detection of EGC	Training: 2570 images: 1492 EGC and 1078 gastritis; Testing: 285 images: 151 EGC and 107 gastritis	CNNs	85.3	95.4/71.0
Zhu *et al*[36], 2019	China	Invasive GC	Retrospective	Determination of invasion depth	Training: 245 patients with GC and 545 patients without GC (5056 images); Testing: 203 images: 68 GC and 135 normal	CNNs	89.2	76.5/95.6
Luo *et al*[37], 2019	China	EAC, ESCC, and GC	Prospective	Detection of upper gastrointestinal cancers	Training: 15040 individuals (125898 images: 31633 cancer and 94265 control); Testing: 1886 individuals (15637 images: 3931 cancer and 11706 control)	CNNs	91.5-97.7	94.2/85.8
Nagao *et al*[38], 2020	Japan	GC	Retrospective	Determination of invasion depth	1084 patients with GC (16557 images); Training: Testing = 4:1	CNNs	94.5	84.4/99.4
Wireless capsule endoscopy								
Ayaru *et al*[39], 2015	United Kingdom	Small bowel bleeding	Retrospective	Prediction of outcomes	Training: 170 patients with small bowel bleeding; Testing: 130 patients with small bowel bleeding	ANNs	Recurrent bleeding 88; Therapeutic intervention: 88; Severe bleeding: 78	Recurrent bleeding: 67/91; Therapeutic intervention: 80/89; Severe bleeding: 73/80
Xiao *et al*[40], 2016	China	Small bowel bleeding	Retrospective	Detection of bleeding in GI tract	Training: 8200 images: 2050 bleeding and 6150 non-bleeding; Testing: 1800 images: 800 bleeding and 1000 non-bleeding	CNNs	99.6	99.2/99.9
Usman *et al*[41], 2016	South Korea	Small bowel bleeding	Retrospective	Detection of bleeding in GI tract	Training: 75000 pixels: 25000 bleeding and 50000 non-bleeding; Testing: 8000 pixels: 3000 bleeding and 5000 non-bleeding	SVM	91.8	93.7/90.7
Sengupta *et al*[42], 2017	United States	Small bowel bleeding	Retrospective	Prediction of 30-d mortality	Training: 4044 patients with small bowel bleeding; Testing: 2060 patients with small bowel bleeding	ANNs	81	87.8/90/9
Leenhardt *et al*[43], 2019	France	Small bowel bleeding	Retrospective	Detection of GIA	Training: 600 images: 300 hemorrhagic GIA and 300 non-hemorrhagic GIA; Testing: 600 images: 300 hemorrhagic GIA and 300 non-hemorrhagic GIA	CNNs	98	100.0/96.0
Aoki *et al*[44], 2020	Japan	Small bowel bleeding	Retrospective	Detection of small bowel bleeding	Training: 41 patients (27847 images: 6503 bleeding and 21344 normal); Testing: 25 patients (10208 images: 208 bleeding and 10000 non-bleeding)	CNNs	99.89	96.63/99.96
Yang *et al*[45],	China	Small bowel polyps	Retrospective	Detection of small bowel	1000 images: 500 polyps and 500 non-polyps	SVM	96.00	95.80/96.20

2020				polyps				
Vieira *et al*[46], 2020	Portugal	Small bowel tumors	Retrospective	Detection of small bowel tumors	39 patients (3936 images: 936 tumors and 3000 normal)	SVM	97.6	96.1/98.3
Colonoscopy								
Fernández-Esparrach *et al*[47], 2016	Spain	Colorectal polyps	Retrospective	Detection of polyps	24 videos containing 31 different polyps	Energy maps	79	70.4/72.4
Komeda *et al*[48], 2017	Japan	Colorectal polyps	Retrospective	Detection of polyps	Training: 1800 images: 1200 adenoma and 600 non-adenoma; Testing: 10 cases	CNNs	70.0	83.3/50.0
Misawa *et al*[49], 2017	Japan	Colorectal polyps	Retrospective	Detection of polyps	Training: 1661 images: 1213 neoplasm and 448 non-neoplasm; Testing: 173 images: 124 neoplasm and 49 non-neoplasm	SVM	87.8	94.3/71.4
Misawa *et al*[50], 2018	Japan	Colorectal polyps	Retrospective	Detection of polyps	196631 frames: 63135 polyps and 133496 non-polyps	CNNs	76.5	90.0/63.3
Chen *et al*[51], 2018	China	Colorectal polyps	Retrospective	Detection of diminutive colorectal polyps	Training: 2157 images: 681 hyperplastic and 1476 adenomas; Testing: 284 images: 96 hyperplastic and 188 adenomas	DNNs	90.1	96.3/78.1
Urban *et al*[52], 2018	United States	Colorectal polyps	Retrospective	Detection of polyps	Training: 8561 images: 4008 polyps and 4553 non-polyps; Testing: 1330 images: 672 polyps and 658 non-polyps	CNNs	96.4	96.9/95.0
Renner *et al*[53], 2018	Germany	Colorectal polyps	Retrospective	Differentiation of neoplastic from non-neoplastic polyps	Training: 788 images: 602 adenomas and 186 non-adenomatous polyps; Testing: 186 images: 52 adenomas and 48 hyperplastic lesions	DNNs	78.0	92.3/62.5
Wang *et al*[54], 2018	United States	Colorectal polyps	Retrospective	Detection of polyps	Training: 5545 images: 3634 polyps and 1911 non-polyps; Testing: 27113 images: 5541 polyps and 21572 non-polyps	CNNs	98	94.4/95.9
Mori *et al*[55], 2018	Japan	Colorectal polyps	Prospective	A diagnose-and-leave strategy for diminutive, non-neoplastic rectosigmoid polyps	Training: 61925 images; Testing: 466 cases (287 neoplastic polyps, 175 nonneoplastic polyps, and 4 missing specimens)	SVM	96.5	93.8/91.0
Byrne *et al*[56], 2019	Canada	Colorectal polyps	Retrospective	Detection and classification of polyps	Training: 60089 frames of 223 videos (29% NICE type 1, 53% NICE type 2 and 18% of normal mucosa with no polyp); Testing: 125 videos: 51 hyperplastic polyps and 74 adenoma	CNNs	94.0	98.0/83.0
Blanes-Vidal *et al*[57], 2019	Denmark	Colorectal polyps	Retrospective	Detection of polyps	131 patients with polyps and 124 patients without polyps	CNNs	96.4	97.1/93.3
Lee *et al*[58], 2020	South Korea	Colorectal polyps	Retrospective	Detection of polyps	Training: 306 patients (8593 images: 8495 polyp and 98 normal); Testing: 15 patients (15 polyps videos)	CNNs	93.4	89.9/93.7
Gohari *et al*[59], 2011	Iran	CRC	Retrospective	Determination of prognostic factors of CRC	1219 patients with CRC	ANNs	Colon cancer: 89; Rectum cancer: 82.7	NA/NA

Biglarian *et al*[60], 2012	Iran	CRC	Retrospective	Prediction of distant metastasis in CRC	1219 patients with CRC	ANNs	82	NA/NA
Takeda *et al*[61], 2017	Japan	CRC	Retrospective	Diagnosis of invasive CRC	Training: 5543 images: 2506 non-neoplasms, 2667 adenomas, and 370 invasive cancers; Testing: 200 images: 100 adenomas and 100 invasive cancers	SVM	94.1	89.4/98.9
Ito *et al*[62], 2019	Japan	CRC	Retrospective	Diagnosis of cT1b CRC	Training: 9942 images: 5124 cTis + cT1a, 4818 cT1b, and 2604 cTis + cT1a; Testing: 5022 images: 2604 cTis + cT1a, and 2418 cT1b	CNNs	81.2	67.5/89.0
Zhou *et al*[63], 2020	China	CRC	Retrospective	Diagnosis of CRC	Training: 3176 patients with CRC and 9003 patients without CRC (464105 images: 28071 CRC and 436034 non-CRC); Testing: 307 patients with CRC and 1956 patients without CRC (84615 images: 11675 CRC and 72940 non-CRC)	CNNs	96.3	91.4/98.0

AI: Artificial intelligence; CNN: Convolutional neural network; EN: Early-stage neoplasia; BE: Barrett's esophagus; SVM: Support vector machine; NA: Not available; EAC: Esophageal adenocarcinoma; ESCC: Esophageal squamous cell carcinoma; EGC: Early-stage gastric cancer; GC: Gastric cancer; ANN: Artificial neural network; GI: Gastrointestinal; GIA: Gastrointestinal angioectasia; DNN: Deep neural network; CRC: Colorectal cancer.

of experienced endoscopists[20,34].

Endoscopic surveillance for Barrett's esophagus (BE) is the potential risk factor for esophageal adenocarcinoma (EAC), of which the prognosis is related to disease staging[64,65]. However, accurate detection of esophageal neoplasia and early EAC remains difficult for experienced endoscopists[66]. An AI system developed by Ebigbo *et al*[24] enabled early detection of EAC with high sensitivity and specificity, they subsequently designed a real-time system for neoplasia classification in magnification. Both accurate detection of early EAC is important in BE images and the novel system of high invasion accuracy also deserves clinical attention[23]. In esophageal squamous cell carcinoma (ESCC), these tumors are often diagnosed at advanced stages, while early ESCC seems to be detected based on endoscopists' experience because they are almost impossible to visualize with white light endoscopy. Fortunately, with AI technologies, small esophageal lesions (< 10 mm) are recognized, and there is an AI system showing diagnostic accuracy of 91.4%, which is higher than that of high-level (with experience of > 15 years, 88.8%), mid-level (with experience of 5-15 years, 81.6%), and junior-level (with experience of < 5 years, 77.2%) endoscopists[28]. In addition, the prognosis of ESCC can be proved by differentiating tumor invasion depth[29,30].

The prognosis of gastric cancer (GC) mainly depends on the early detection and invasion depth of the disease. It is extremely difficult for endoscopists to recognize early gastric cancer (EGC), which is often accompanied by gastric mucosal inflammation, and the false-negative rate of EGC in EGD has reached nearly 25.0%[67,68]. AI-assisted EGD has the potential to address tough tissues. However, the first reported CNNs-based AI system for detection of EGC had a low positive predictive value of 30.6%, leading to misdiagnosis of gastritis and misinterpretation of the gastric angle as GC[69]. In 2019, Wu *et al*[34] examined the detection of GC by AI and

validated 200 endoscopic images, with increased accuracy, sensitivity, and specificity values (92.5%, 94%, and 91%, respectively). Furthermore, the AI system, named GRAIDS, has achieved diagnostic sensitivity close to that of expert endoscopists (94.2% *vs* 94.5%), and it demonstrated a robust performance showing high diagnostic accuracy in a multicenter study[37]. Besides detection, one of the most important criteria for curative resection is the invasion depth. The invasion depth prediction of GC by AI was first developed by Kubota *et al*[70], and the model showed the accuracy of T-stages (T1 = 77%, T2 = 49%, T3 = 51%, T4 = 55%, respectively). Considering that endoscopic mucosal resection is appropriate for intramucosal cancers (M) and submucosal cancers (invasion < 500 μm) (SM1), a more detailed classification is urgently needed. Therefore, an AI system was developed to differentiate the depths of M or SM1 and SM2 (submucosal invasion ≥ 500 μm) for GC with significantly higher sensitivity, specificity, and accuracy than those of skilled endoscopists[38].

WCE

AI-assisted WCE enables endoscopists to highlight suspicious regions on examination of the digestive tract noninvasively, including detection of small bowel bleeding, ulcers, and polyps, celiac disease, *etc*. Based on specific AI classifiers and validation techniques (mainly *k*-fold cross-validation), these models utilized still frames, pixels, or real-time videos to identify patients with small bowel bleeding with accuracy above 90% for most studies[40,41,43,44]. A CNNs-based algorithm, established in a retrospective analysis of 10000 WCE images (8200 and 1800 in the training and testing set, respectively) and validated by 10-fold cross-validation, was proposed for automatic detection of small bowel bleeding. The model was performed with a high *F*-1 score of 99.6% and precision of 99.9% for both active and inactive bleeding frames[40]. Besides detection, several emerging AI tools have been developed to stratify patients for the possibility of recurrent bleeding, treatment requirement, and mortality estimate to prevent repeated endoscopies in a significant proportion of patients with potential recurrent upper or lower gastrointestinal bleeding[39,42].

Colonoscopy

Colorectal polyp detection and appropriate polypectomy during colonoscopy is the standard way to prevent colorectal cancer (CRC). Since missed colorectal polyps can potentially progress into CRC, AI-assisted colonoscopy has been developed for polyp detection and characterization, and predicting the prognosis of CRC. In terms of polyp detection, an automated AI system using an energy map was developed in 2016, and it showed barely satisfactory performance[47]. Urban *et al*[52] used 8641 labeled images and 20 colonoscopy videos as the training and testing set to establish a CNNs model to identify colonic polyps, and the model had an accuracy of 96.4%[52]. Notably, the models should be validated to improve accuracy. After validating the model developed by Wang *et al*[54] with 27113 newly collected images from 1138 patients, the model showed acceptable performance (sensitivity = 94.38%, specificity = 95.2%, and AUC = 0.984). In addition, polyp characterization with magnifying endoscopic images is useful for identifying pit or vascular patterns to improve performance. AI tools with narrow-band imaging[51] or endoscopic videos[56] can be used to differentiate diminutive hyperplastic polyps and adenomas with high accuracy. Specifically, diminutive polyps (≤ 5 mm) may also be identified during colonoscopy[55]. In addition, AI may assist doctors in predicting the prognosis of CRC. An ANNs model, which was developed from a dataset of 1219 CRC patients, may predict patient survival and influential factors more accurately than a Cox regression model[59], and it also enables doctors to predict the risk of distant metastases[60].

ARTIFICIAL INTELLIGENCE IN RADIOLOGY

There is a disproportionate growing rate between radiological imaging data and the number of trained radiologists, and it has forced radiologists to compensate by increasing productivity[71]. The emergence of AI technologies has eased the current dilemma and dramatically advanced radiology image analysis, including ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) in the fields of gastroenterology and hepatology. In addition, the rise of radiomics, which is a new technology in radiology and cancer, can extract abundant quantifiable objective data to evaluate surgical resection and predict treatment response[72-112] (Table 2).

Table 2 Summary of key studies on artificial intelligence-assisted radiology in hepatology fields

Ref.	Country	Disease studied	Design of study	Application	Number of cases	Type of machine learning algorithm	Outcomes (%)	
							Accuracy	Sensitivity/Specificity
Ultrasound-based medical image recognition								
Gatos *et al*[72], 2016	United States	Hepatic fibrosis	Retrospective	Classification of CLD	85 images: 54 healthy and 31 CLD	SVM	87	83.3/89.1
Gatos *et al*[73], 2017	United States	Hepatic fibrosis	Retrospective	Classification of CLD	124 images: 54 healthy and 70 CLD	SVM	87.3	93.5/81.2
Chen *et al*[74], 2017	China	Hepatic fibrosis	Retrospective	Classification of the stages of hepatic fibrosis in HBV patients	513 HBV patients with different hepatic fibrosis (119 S0, 164 S1, 88 S2, 72 S3, and 70 S4)	SVM, Naive Bayes, RF, KNN	82.87	92.97/82.50
Li *et al*[75], 2019	China	Hepatic fibrosis	Prospective	Classification of the stages of hepatic fibrosis in HBV patients	144 HBV patients	Adaptive boosting, decision tree, RF, SVM	85	93.8/76.9
Gatos *et al*[76], 2019	United States	Hepatic fibrosis	Retrospective	Classification of CLD	88 healthy individuals (88 F0 fibrosis stage images) and 112 CLD patients (112 images: 46 F1, 16 F2, 22 F3, and 28 F4)	CNNs	82.5	NA/NA
Wang *et al*[77], 2019	China	Hepatic fibrosis	Prospective	Classification of the stages of hepatic fibrosis in HBV patients	Training: 266 HBV patients (1330 images); Testing: 132 HBV patients (660 images)	CNNs	F4: 100; ≥ F3: 99; ≥ F2: 99	F4: 100.0/100.0; ≥ F3: 97.4/95.7; ≥ F2: 100.0/97.7
Kuppili *et al*[78], 2017	United States	MAFLD	Retrospective	Detection and characterization of FLD	63 patients: 27 healthy and 36 MAFLD	ELM, SVM	ELM: 96.75; SVM: 89.01	NA/NA
Byra *et al*[79], 2018	Poland	MAFLD	Retrospective	Diagnosis of the amount of fat in the liver	55 severely obese patients	CNNs, SVM	96.3	100/88.2
Biswas *et al*[80], 2018	United States	MAFLD	Retrospective	Detection and risk stratification of FLD	63 patients: 27 healthy and 36 MAFLD	CNNs, SVM, ELM	CNNs: 100; SVM: 82; ELM: 92	NA/NA
Cao *et al*[81], 2020	China	MAFLD	Retrospective	Detection and classification of MAFLD	240 patients: 106 healthy, 57 mild MAFLD, 67 moderate MAFLD, and 10 severe MAFLD	CNNs	95.8	NA/NA
Guo *et al*[82], 2018	China	Liver tumors	Retrospective	Diagnosis of liver tumors	93 patients with liver tumors: 47 malignant lesions (22 HCC, 5 CC, and 10 RCLM), and 46 benign lesions	DNNs	90.41	93.56/86.89
Schmauch *et al*[83], 2019	France	FLL	Retrospective	Detection and characterization of FLL	Training: 367 patients (367 images); Testing: 177 patients	CNNs	Detection: 93.5; Characterization: 91.6	NA/NA
Yang *et al*[84], 2020	China	FLL	Retrospective	Detection of FLL	Training: 1815 patients with FLL (18000 images); Testing: 328 patients with FLL (3718 images)	CNNs	84.7	86.5/85.5

CT/MRI-based medical image recognition								
Choi *et al*[85], 2018	South Korea	Hepatic fibrosis	Retrospective	Staging liver fibrosis by using CT images	Training: 7461 patients: 3357 F0, 113 F1, 284 F2, 460 F3, 3247 F4; Testing: 891 patients: 118 F0, 109 F1, 161 F2, 173 F3, 330 F4	CNNs	92.1–95.0	84.6–95.5/89.9–96.6
He *et al*[86], 2019	United States	Hepatic fibrosis	Retrospective	Staging liver fibrosis by using MRI images	Training: 225 CLD patients; Testing: 84 patients	SVM	81.8	72.2/87.0
Ahmed *et al*[87], 2020	Egypt	Hepatic fibrosis	Retrospective	Detection and staging of liver fibrosis by using MRI images	37 patients: 15 healthy and 22 CLD	SVM	83.7	81.8/86.6
Hectors *et al*[88], 2020	United States	Liver fibrosis	Retrospective	Staging liver fibrosis by using MRI images	Training: 178 patients with liver fibrosis; Testing: 54 patients with liver fibrosis	CNNs	F1-F4: 85; F2-F4: 89; F3-F4: 91; F4: 83	F1-F4: 84/90; F2-F4: 87/93; F3-F4: 97/83; F4: 68/94
Vivanti *et al*[89], 2017	Israel	Liver tumors	Retrospective	Detection and segmentation of new tumors in follow-up by using CT images	246 liver tumors (97 new tumors)	CNNs	86	70/NA
Yasaka *et al*[90], 2018	Japan	Liver masses	Retrospective	Detection and differentiation of liver masses by using CT images	Training: 460 patients with liver masses (1068 images: 240 Category A, 121 Category B, 320 Category C, 207 Category D, 180 Category E); Testing: 100 images with liver masses: 21 Category A, 9 Category B, 35 Category C, 20 Category D, 15 Category E	CNNs	84	Category A: 71/NA; Category B: 33/NA; Category C: 94/NA; Category D: 90/NA; Category E: 100/NA
Ibragimov *et al*[91], 2018	United States	Liver diseases requiring SBRT	Retrospective	Prediction of hepatotoxicity after liver SBRT by using CT images	125 patients undergone liver SBRT: 58 liver metastases, 36 HCC, 27 cholangiocarcinoma, and 4 other histopathologies	CNNs	85	NA/NA
Abajian *et al*[92], 2018	United States	HCC	Retrospective	Prediction of HCC response to TACE by using MRI images	36 HCC patients treated with TACE	RF	78	62.5/82.1
Zhang *et al*[93], 2018	United States	HCC	Retrospective	Classification of HCC by using MRI images	20 patients with HCC	CNNs	80	NA/NA
Morshid *et al*[94], 2019	United States	HCC	Retrospective	Prediction of HCC response to TACE by using CT images	105 HCC patients received first-line treatment with TACE	CNNs	74.2	NA/NA
Nayak *et al*[95], 2019	India	Cirrhosis; HCC	Retrospective	Detection of cirrhosis and HCC by using CT images	40 patients: 14 healthy, 12 cirrhosis, 14 cirrhosis with HCC	SVM	86.9	100/95
Hamm *et al*[96], 2019	United States	Common hepatic lesions	Retrospective	Classification of common hepatic lesions by using MRI images	Training: 434 patients with common hepatic lesions; Testing: 60 patients with common hepatic lesions	CNNs	92	92/98
Wang *et al*[97], 2019	United States	Common hepatic lesions	Retrospective	Demonstration of a proof-of-concept interpretable DL system by using MRI images	60 common hepatic lesions patients	CNNs	NA	82.9/NA

Jansen *et al*[98], 2019	Netherlands	FLL	Retrospective	Classification of FLL by using MRI images	95 patients with FLL (125 benign lesions: 40 adenomas, 29 cysts, and 56 hemangiomas; and 88 malignant lesions: 30 HCC and 58 metastases)	RF	77	Adenoma: 80/78; Cyst: 93/93; Hemangioma: 84/82; HCC: 73/56; Metastasis: 62/77
Mokrane *et al*[99], 2020	France	HCC	Retrospective	Diagnosis of HCC in patients with cirrhosis by using CT images	Training: 106 patients: 85 HCC and 21 non-HCC; Testing: 36 patients: 23 HCC and 13 non-HCC	SVM, KNN, RF	70	70/54
Shi *et al*[100], 2020	China	HCC	Retrospective	Detection of HCC from FLL by using CT images	Training: 359 lesions: 155 HCC and 204 non-HCC; Testing: 90 lesions: 39 HCC and 51 non-HCC	CNNs	85.6	74.4/94.1
Alirr *et al*[101], 2020	Kuwait	Liver tumors	Retrospective	Segmentation of liver tumors	Training: 100 images with liver tumors;Testing: 31 images with liver tumors	CNNs	95.2	NA/NA
Zheng *et al*[102], 2020	China	Pancreatic cancer	Retrospective	Pancreas segmentation by using MRI images	20 patients with PDAC	CNNs	99.86	NA/NA
Radiomics								
Liang *et al*[103], 2014	China	HCC	Retrospective	Prediction of recurrence for HCC patients who received RFA	83 patients with HCC receiving RFA as first treatment (18 recurrence and 65 non-recurrence)	SVM	82	67/86
Zhou *et al*[104], 2017	China	HCC	Retrospective	Characterization of HCC	46 patients with HCC: 21 low-grade (Edmondson grades I and II) and 25 high-grade (Edmondson grades III and IV)	Free-form curve-fitting	86.95	76.00/100.00
Abajian *et al*[105], 2018	United States	HCC	Retrospective	Prediction of response to intra-arterial treatment	36 patients undergone trans-arterial treatment	RF	78	62.5/82.1
Ibragimov *et al*[91], 2018	United States	Liver tumors	Retrospective	Prediction of hepatobiliary toxicity of SBRT	125 patients undergone liver SBRT: 58 metapatients, 36 HCC, 27 cholangiocarcinoma, and 4 other primary liver tumor histopathologies	CNNs	85	NA/NA
Morshid *et al*[94], 2019	United States	HCC	Retrospective	Prediction of HCC response to TACE	105 patients with HCC: 11 BCLC stage A, 24 BCLC stage B, 67 BCLC stage C, and 3 BCLC stage D	CNNs	74.2	NA/NA
Ma *et al*[106], 2019	China	HCC	Retrospective	Prediction of MVI in HCC	Training: 110 patients with HCC: 37 with MVI and 73 without MVI; Testing: 47 patients with HCC: 18 with MVI and 29 without MVI	SVM	76.6	65.6/94.4
Dong *et al*[107], 2020	China	HCC	Retrospective	Prediction and differentiation of MVI in HCC	Prediction: 322 patients with HCC: 144 with MVI and 178 without MVI; Differentiation: 144 patients with HCC and MVI	RF, mRMR	Prediction: 63.4; Differentiation: 73.0	Prediction: 89.2/48.4; Differentiation: 33.3/80.0
He *et al*[108], 2020	China	HCC	Prospective	Prediction of MVI in HCC	Training: 101 patients with HCC; Testing: 18 patients with HCC	LASSO	84.4	NA/NA
Schoenberg *et al*[109], 2020	Germany	HCC	Prospective	Prediction of disease-free survival after HCC resection	Training: 127 patients with HCC; Testing: 53 patients with HCC	RF	78.8	NA/NA
Zhao *et al*[110],	China	HCC	Retrospective	Prediction of ER of HCC	Training: 78 patients with HCC: 40 with ER and	LASSO	80.8	80.0/81.6

2020				after partial hepatectomy	38 without ER; Testing: 35 patients with HCC: 18 with ER and 17 without ER			
Liu *et al*[111], 2020	China	HCC	Retrospective	Prediction of progression-free survival of HCC patients after RFA and SR	RFA: Training: 149 HCC patients undergone RFA Testing: 65 HCC patients undergone RFA; SR: Training: 144 HCC patients undergone SR Testing: 61 HCC patients undergone SR	Cox-CNNs	RFA: 82.0; SR: 86.3	NA/NA
Chen *et al*[112], 2021	China	HCC	Retrospective	Prediction of HCC response to first TACE by using CT images	Training: 355 patients with HCC; Testing: 118 patients with HCC	LASSO	81	85.2/77.2

AI: Artificial intelligence; CLD: Chronic liver disease; SVM: Support vector machine; HBV: Hepatitis-B virus; RF: Random forests; KNN: K-nearest neighbor; CNN: Convolutional neural network; NA: Not available; MAFLD: Metabolic associated fatty liver disease; FLD: Fatty liver disease; ELM: Extreme learning machine; HCC: Hepatocellular carcinoma; CC: Cholangiocarcinoma; RCLM: Colorectal cancer liver metastases; DNN: deep neural network; FLL: Focal liver lesions; CLD: Chronic liver disease; SBRT: Stereotactic body radiation therapy; TACE: Transarterial chemotherapy; PDAC: Pancreatic ductal adenocarcinoma; RFA: Radiofrequency ablation; BCLC: Barcelona clinic liver cancer staging; MVI: Microvascular invasion; mRMR: Minimum redundancy maximum relevance; LASSO: Least absolute shrinkage and selection operator; ER: Early recurrence; SR: Surgical resection.

Abdominal ultrasound

AI technologies have been applied to abdominal ultrasound-based medical images for the assessment of liver diseases, such as hepatic fibrosis and mass lesions. A support vector machine-derived approach was developed by Gatos *et al*[72] to detect and classify chronic liver disease (CLD) based on abdominal ultrasound. After quantifying 85 ultrasound images (54 healthy and 31 with CLD), the proposed model showed superior results (accuracy = 87.0%, sensitivity = 83.3%, and specificity = 89.1%), which greatly improved the diagnostic and classification accuracy of CLD. Furthermore, CNNs are employed to identify and isolate regions of different stiffness temporal stability under ultrasound to explore the impact on CLD diagnosis. The updated detection algorithm has augmented the accuracy to 95.5% after excluding unreliable areas and reducing interobserver variability[76]. Detecting and classifying hepatic mass lesions as benign or malignant is equally important. Schmauch *et al*[83] performed supervised training (367 ultrasonic images together with the radiological reports) to build a DL model, and the resulting algorithm had high receiver operating characteristic curves of 0.93 and 0.916 in lesion detection and characterization, respectively. Although the model could increase the diagnostic accuracy and detect potential malignant mass lesions, it should be further validated. In addition, combining AI technologies with contrast-enhanced ultrasound may improve the performance to identify and characterize liver cancer. For example, after AI-assisted contrast-enhanced ultrasound was applied to detect liver lesions in the arterial, portal, and late phases, the accuracy, sensitivity and specificity of the examination were markedly increased[82]. Due to the misty demonstration of gastroenterology within ultrasound, an AI-assisted ultrasound tool was limited.

CT/MRI

Liver diseases often present indeterminate behaviors on abdominal CT, and a biopsy is

recommended according to the European Association for the Study of the Liver guidelines[113]. Based on a large dataset of CT images (7461 patients diagnosed with liver fibrosis), a CNNs model was developed and it outperformed the radiologists' interpretation[85]. Furthermore, depending on ANNs-based contrast-enhanced CT images from 460 patients, Yasaka *et al*[90] conducted a retrospective study to classify liver masses into five categories with high accuracy, including (1) primary hepatocellular carcinoma (HCC); (2) malignant tumors apart from HCC; (3) early HCC, indeterminate masses, or dysplastic nodules; (4) hemangiomas; and (5) cysts. For patients diagnosed with liver tumors or pancreatic cancer, it is crucial to complete the liver or pancreas segmentation to assess the lesions and make the ideal treatment plan. Instead of conventional manual segmentation, a CNNs model was proposed to segment liver tumors based on CT images, with an accuracy of more than 80.0%, favoring suitable decision-making[101]. Additionally, a CNNs model was also developed for pancreas localization and segmentation using CT images[102]. Furthermore, monitoring tumor recurrence plays an important role in follow-up CT. Vivanti *et al*[89] collected and integrated the initial appearance of tumors, CT behaviors, and quantification of the tumor loads throughout the disease course, and then they designed an automated detection model of tumor recurrence with an accuracy of 86%.

Besides depending on CT images, a DL approach for pancreas segmentation can also be designed from MRI images. Several AI-assisted studies have shown promising results in classifying MRI liver lesions with/without risk factors and patients' clinical data, improving the accuracy and yields of reference models[93,96,98,102].

Radiomics

Currently, radiomics has received great interest from doctors because this AI-assisted technology can extract indiscoverable quantifiable objective data of the radiological images and reveal the association with potential biological processes[114,115]. Preoperative stratification of patients at different risk of recurrence and prediction of survival after resection is fundamental to improve prognosis. As an independent risk factor of recurrence, microvascular invasion (MVI) cannot be provided in conventional radiological techniques[116]. Several studies have managed to use radiomic algorithms based on ultrasound, CT, or MRI to elaborate radiomic signatures for preoperative prediction of MVI[106-108]. Besides the prediction of recurrence, radiomics may also be utilized to predict survival after surgical resection. However, compared to the excellent AI models based on pathologic images, radiomics-based predictive models merely attain a low value of 0.78[109].

Beyond recurrence and survival prediction purposes, radiomics can also be utilized for prediction of patients' response to transarterial chemoembolization (TACE) and radiofrequency ablation (RFA), and post-radiotherapy hepatotoxicity. A CNNs model developed from 105 HCC patients' CT images had higher accuracy in predicting response to TACE than the Barcelona Clinic Liver Cancer stages[94]. In addition, Chen *et al*[112] designed an excellent clinical-radiomic model to predict objective response to first TACE based on 595 HCC patients' CT images, which could assist the selection of HCC patients for TACE. Another study used radiomics of MRI images with clinical data to perform prediction of TACE response[105]. For HCC in the early stages, RFA is a recommended option. Based on radiomics, Liang *et al*[103] designed a model to predict the RFA response and HCC recurrence after RFA, obtaining high AUC, sensitivity, and specificity. Additionally, post-radiotherapy hepatotoxicity should be monitored to adjust the position and dose of radiotherapy. A CNNs model not only identified that irradiation of the proximal portal vein was associated with poor prognosis, it also predicted post-radiotherapy hepatotoxicity with an AUC of 0.85[91]. Ibragimov *et al*[91] applied a CNNs model to determine the consistent patterns in toxicity-related dose plans, and the AUC of the model for dose planned analysis was increased from 0.79 to 0.85 after the combination with some pre-treatment clinical features, showing that the combined framework can indicate the accurate position and dose of radiotherapy.

ARTIFICIAL INTELLIGENCE IN PATHOLOGY

Pathological analysis is considered the gold standard for the diagnosis of diseases in the fields of gastroenterology and hepatology. Currently, there is a shortage of pathologists around the world, which has become an obstruction for maintaining the accuracy of pathological analysis[117]. With the development of the whole-slide imaging (WSI) scanner and AI technologies, a combination of both technologies can ease the medical burden, improve the diagnosis accuracy, and even predict gene mutations and

prognosis[118-147] (Table 3).

Basic AI-assisted pathology: diagnosis

The basic role of pathology is disease diagnosis. In the fields of gastroenterology, there is an increasing need for automatic pathological analysis and diagnosis of GC. Based on the virtual version of pathological slices, several studies were performed to identify and classify GC automatically with high AUCs[120-122,126]. For example, a CNNs model was developed to distinguish gastric mass lesions including gastric adenocarcinoma, adenoma and non-neoplastic lesions, and it has achieved the highest AUC of 0.97 for the identification of gastric adenocarcinoma[126]. With regard to colorectal lesions, Wei *et al*[128] trained an AI-assisted model to classify colorectal polyps on WSIs, and notably, the performance of the model was similar to that of local pathologists whether in a single institution or other institutions. Besides diagnosis, a model based on more than 400 WSIs was developed to differentiate five common subtypes of colorectal polyps with accuracy of 93%[127]. In CRC, Shapcott *et al*[129] performed a retrospective study to develop a CNNs model for diagnosis based on 853 hand-marked images with an accuracy of 84%.

In the fields of hepatology, AI-assisted pathology is applied in patients with hepatitis B virus (HBV), metabolic associated fatty liver disease, HCC, *etc*. An automated, stain-free AI system can quantify the amount of fibrillar collagen to evaluate the degree of HBV-related fibrosis with the AUC > 0.82[132]. For patients with metabolic associated fatty liver disease, AI-assisted pathology tools were used to identify and quantify pathological changes including steatosis, macrosteatosis, lobular inflammation, ballooning, and fibrosis[133], and the algorithm output scores for quantitative comparison with experienced pathologists achieved good agreement. However, limited AI-assisted pathology tools have been built for HCC diagnosis. Notably, the MFC-CNN-ELM program was designed for nuclei grading of biopsy specimens from HCC patients, which revealed high performance in classifying tumor cells of different differentiation stages[134].

Advanced AI-assisted pathology: prediction of gene mutations and prognosis

Apart from AI-assisted pathology tools in diagnosis, it is no surprise that many tools have been developed for the prediction of gene mutations and prognosis in the fields of gastroenterology and hepatology. In CRC, AI tools have shown great effectiveness in predicting prognosis across all tumor stages based on WSIs[139,140], and several prospective multicenter studies have further validated the high prognosis performance[142]. Notably, a subset of genetic defects occurring in gastroenterology is related to some morphological features detected on WSIs. Among screened genetic defects, microsatellite instability and mismatch-repair deficiency are associated with the survival of gastrointestinal and colorectal cancer patients receiving immunotherapy. Therefore, an AI tool was designed to predict microsatellite instability and mismatch-repair deficiency directly from pathology, and it finally showed reasonably good performance in assisting immunotherapy[138,141]. Notably, Kather *et al*[140] further validated the above model's performance in predicting overall survival from CRC pathology slides with a hazard ratio of 2.29 in CRC-specific overall survival (OS) and an hazard ratio of 1.63 in OS, respectively. However, besides the above-mentioned studies that have focused on tumor detection of CRC, few studies were designed to predict gene mutations and prognosis due to the more complicated and heterogeneous histomorphology in gastric diseases than that in the colon[136,137].

In the fields of hepatology, AI tools are mainly used to predict gene mutations and prognosis in HCC. For example, a model has higher accuracy in predicting survival postoperatively than using a composite score of clinical and pathological factors in HCC. In addition, the model may generalize well after validating the performance in an external dataset with different staining and scanning methods[146]. Chen *et al*[11] investigated a CNN (Inception V3) for automatic classification (benign/malignant classification with 96.0% accuracy, and differentiation degree with 89.6% accuracy) and gene mutation prediction from WSIs after resection of HCC. It was found that *CTNNB1, FMN2, TP53,* and *ZFX4* could be predicted from WSIs with external AUCs from 0.71 to 0.89. Currently, after integrating clinical data, biological data, genetic data, and pathological data, the novel model may also be a promising approach. The first multi-omics model combined ribonucleic acid (RNA) sequencing, miRNA sequencing and methylation data from The Cancer Genome Atlas, and then employed AI technologies to predict and differentiate survival of HCC patients[145]. Other attempts have been made to develop models that can predict gene mutations directly based on WSIs of HCC. Using AI-assisted pathology, some approaches can predict gene expression and RNA sequencing, which may have the potential for clinical

Table 3 Summary of key studies on artificial intelligence-assisted pathology in the gastroenterology and hepatology fields

Ref.	Country	Disease studied	Design of study	Application	Number of cases	Type of machine learning algorithm	Outcomes (%)	
							Accuracy	Sensitivity/Specificity
Basic AI-based pathology: diagnosis								
Tomita *et al*[118], 2019	United States	BE and EAC	Retrospective	Detection and classification of cancerous and precancerous esophagus tissue	Training: 379 images with 4 classes: normal, BE-no-dysplasia, BE-with-dysplasia, and adenocarcinoma; Testing: 123 images with 4 classes: normal, BE-no-dysplasia, BE-with-dysplasia, and adenocarcinoma	CNNs	Mean: 83; BE-no-dysplasia: 85; BE-with-dysplasia: 89; Adenocarcinoma: 88	Normal: 69/71 BE-no-dysplasia: 77/88; BE-with-dysplasia: 21/97; Adenocarcinoma: 71/91
Sharma *et al*[119], 2017	Germany	GC	Retrospective	Classification and necrosis detection of GC	454 patients (6810 WSIs: 4994 for cancer classification and 1816 for necrosis detection) (HER2 immunohistochemical stain and HE stained)	CNNs	Cancer classification: 69.90; Necrosis detection: 81.44	NA/NA
Li *et al*[120], 2018	China	GC	Retrospective	Detection of GC	700 images: 560 GC and 140 normal (HE stained)	CNNs	100	NA/NA
Leon *et al*[121], 2019	Colombia	GC	Retrospective	Detection of GC	40 images: 20 benign and 20 malignant	CNNs	89.72	NA/NA
Sun *et al*[122], 2019	China	GC	Retrospective	Diagnosis of GC	500 WSIs of gastric areas with typical cancerous regions	DNNs	91.6	NA/NA
Ma *et al*[123], 2020	China	GC	Retrospective	Classification of lesions in the gastric mucosa	Training: 534 WSIs (1616713 images: 544925 normal, 544624 chronic gastritis, and 527164 cancer) (HE stained) Testing: 153 WSIs (399240 images: 135446 normal, 125783 chronic gastritis, and 138011 cancer) (HE stained)	CNNs, RF	Benign and cancer: 98.4; Normal, chronic gastritis, and GC: 94.5	Benign and cancer: 98.0/98.9; Normal, chronic gastritis, and GC: NA/NA
Yoshida *et al*[124], 2018	Japan	Gastric lesions	Retrospective	Classification of gastric biopsy specimens	3062 gastric biopsy specimens (HE stained)	CNNs	55.6	89.5/50.7
Qu *et al*[125], 2018	Japan	Gastric lesions	Retrospective	Classification of gastric pathology images	Training: 1080 patches: 540 benign and 540 malignant; Testing: 5400 patches: 2700 benign and 2700 malignant	CNNs	96.5	NA/NA
Iizuka *et al*[126], 2020	Japan	Gastric and colonic epithelial tumors	Retrospective	Classification of gastric and colonic epithelial tumors	4128 cases of human gastric epithelial lesions and 4036 of colonic epithelial lesions (HE stained)	CNNs, RNNs	Gastric adenocarcinoma: 97; Gastric adenoma: 99; Colonic adenocarcinoma: 96; Colonic adenoma: 99	NA/NA
Korbar *et al*[127], 2017	United States	Colorectal polyps	Retrospective	Classification of different types of colorectal polyps on WSIs	Training: 458 WSIs; Testing: 239 WSIs	A modified version of a residual network	93	88.3/NA
Wei *et al*[128], 2020	United States	Colorectal polyps	Retrospective	Classification of colorectal polyps on WSIs	Training: 326 slides with colorectal polyps: 37 tubular, 30 tubulovillous or villous, 111 hyperplastic, 140 sessile serrated, and 8 normal;	CNNs	Tubular: 84.5; Tubulovillous or villous: 89.5; Hyperplastic: 85.3;	Tubular: 73.7/91.6; Tubulovillous or villous: 97.6/87.8; Hyperplastic: 60.3/97.5; Sessile

					Testing: 238 slides with colorectal polyps: 95 tubular, 78 tubulovillous or villous, 41 hyperplastic, and 24 sessile serrated		Sessile serrated: 88.7	serrated: 79.2/89.7
Shapcott *et al*[129], 2018	UnitedKingdom	CRC	Retrospective	Diagnosis of CRC	853 hand-marked images	CNNs	84	NA/NA
Geessink *et al*[130], 2019	Netherlands	CRC	Retrospective	Quantification of intratumoral stroma in CRC	129 patients with CRC	CNNs	94.6	91.1/99.4
Song *et al*[131], 2020	China	CRC	Retrospective	Diagnosis of CRC	Training: 177 slides: 156 adenoma and 21 non-neoplasm; Testing: 362 slides: 167 adenoma and 195 non-neoplasm	CNNs	90.4	89.3/79.0
Wang *et al*[132], 2015	China	Hepatic fibrosis	Retrospective	Assessment of HBV-related liver fibrosis and detection of liver cirrhosis	Training: 105 HBV patients; Testing: 70 HBV patients	SVM	82	NA/NA
Forlano *et al*[133], 2020	UnitedKingdom	MAFLD	Retrospective	Detection and quantification of histological features of MAFLD	Training: 100 MAFLD patients; Testing: 146 MAFLD patients	K-means	Steatosis: 97; Inflammation: 96; Ballooning: 94; Fibrosis: 92	NA/NA
Li *et al*[134], 2017	China	HCC	Retrospective	Nuclei grading of HCC	4017 HCC nuclei patches	CNNs	96.7	G1: 94.3/97.5; G2: 96.0/97.0;G3: 97.1/96.6; G4: 99.5/95.8
Kiani *et al*[135], 2020	United States	Liver cancer (HCC and CC)	Retrospective	Histopathologic classification of liver cancer	Training: 70 WSIs: 35 HCC and 35 CC Testing: 80 WSIs: 40 HCC and 40 CC	SVM	84.2	72/95
Advanced AI-based pathology: prediction of gene mutations and prognosis								
Steinbuss *et al*[136], 2020	Germany	Gastritis	Retrospective	Identification of gastritis subtypes	Training: 92 patients (825 images: 398 low inflammation, 305 severe inflammation, and 122 A gastritis) (HE stained) Testing: 22 patients (209 images: 122 low inflammation, 38 severe inflammation, and 49 A gastritis) (HE stained)	CNNs	84	A gastritis: 88/89; B gastritis: 100/93; C gastritis: 83/100
Liu *et al*[137], 2020	China	Gastrointestinal neuroendocrine tumor	Retrospective	Prediction of Ki-67 positive cells	12 patients (18762 images: 5900 positive cells, 6086 positive cells, and 6776 background from ROIs) (HE and IHC stained)	CNNs	97.8	97.8/NA
Kather *et al*[138], 2019	Germany	GC and CRC	Retrospective	Prediction of MSI in GC and CRC	Training: 360 patients (93408 tiles); Testing: 378 patients (896530 tiles)	CNNs	84	NA/NA
Bychkov *et al*[139], 2018	Finland	CRC	Retrospective	Prediction of CRC outcome	420 CRC tumor tissue microarray samples	CNNs, RNNs	69	NA/NA
Kather *et al*[140], 2019	Germany	CRC	Retrospective	Prediction of survival from CRC histology slides	Training: 86 CRC tissue slides (> 100000 HE image patches); Testing: 25 CRC patients (7180 images)	CNNs	98.7	NA/NA

Echle *et al*[141], 2020	Germany	CRC	Retrospective	Detection of dMMR or MSI in CRC	Training: 5500 patients; Testing: 906 patients	A modified shufflenet DL system	92	98/52
Skrede *et al*[142], 2020	3R23 Song 2020	CRC	Retrospective	Prediction of CRC outcome after resection	Training: 828 patients (> 12000000 image tiles); Testing: 920 patients	CNNs	76	52/78
Sirinukunwattana *et al*[143], 2020	UnitedKingdom	CRC	Retrospective	Identification of consensus molecular subtypes of CRC	Training: 278 patients with CRC; Testing: 574 patients with CRC: 144 biopsies and 430 TCGA	Neural networks with domain-adversarial learning	Biopsies: 85; TCGA: 84	NA/NA
Jang *et al*[144], 2020	South Korea	CRC	Retrospective	Prediction of gene mutations in CRC	Training: 629 WSIs with CRC (HE stained) Testing: 142 WSIs with CRC (HE stained)	CNNs	64.8-88.0	NA/NA
Chaudhary *et al*[145], 2018	United States	HCC	Retrospective	Identification of survival subgroups of HCC	Training: 360 HCC patients' data using RNA-seq, miRNA-seq and methylation data from TCGA; Testing: 684 HCC patients' data (LIRI-JP cohort: 230; NCI cohort: 221; Chinese cohort: 166, E-TABM-36 cohort: 40, and Hawaiian cohort: 27)	DL	LIRI-JP cohort: 75; NCI cohort: 67; Chinese cohort: 69; E-TABM-36 cohort: 77; Hawaiian cohort: 82	NA/NA
Saillard *et al*[146], 2020	France	HCC	Retrospective	Prediction of the survival of HCC patients treated by surgical resection	Training: 206 HCC (390 WSIs); Testing: 328 HCC (342 WSIs)	CNNs (SCHMOWDER and CHOWDER)	SCHMOWDER: 78; CHOWDER: 75	NA/NA
Chen *et al*[11], 2020	China	HCC	Retrospective	Classification and gene mutation prediction of HCC	Training: 472 WSIs: 383 HCC and 89 normal liver tissue; Testing: 101 WSIs: 67 HCC and 34 normal liver tissue	CNNs	Classification: 96.0; Tumor differentiation: 89.6; Gene mutation: 71-89	NA/NA
Fu *et al*[147], 2020	UnitedKingdom	EAC, GC, CRC, and liver cancers	Retrospective	Prediction of mutations, tumor composition and prognosis	17335 HE-stained images of 28 cancer types	CNNs	Variable across tumors/gene alterations	NA/NA

AI: Artificial intelligence; BE: Barrett's esophagus; EAC: Esophageal adenocarcinoma; CNN: Convolutional neural network; GC: Gastric cancer; WSI: Whole-slide image; NA: Not available; DNN: Deep neural network; RF: Random forests; RNN: Recurrent neural network; CRC: Colorectal cancer; HBV: Hepatitis-B virus; SVM: Support vector machine; MAFLD: Metabolic associated fatty liver disease; HCC: Hepatocellular carcinoma; CC: Cholangiocarcinoma; ROI: Region of interest; IHC: Immunohistochemistry; MSI: Microsatellite instability; dMMR: Mismatch-repair deficiency; TCGA: The Cancer Genome Atlas; DL: Deep learning.

translation[147]. Interestingly, some gene expression such as PD-1 and PD-L1 expression, inflammatory gene signatures, and biomarkers of inflammation did trend with improved survival and response in HCC patients[148].

LIMITATIONS AND FUTURE CONSIDERATIONS

This review retrospectively summarized some key and representative articles with the possibility of missing some publications in AI-related journals. Although various studies have shown promising results in the fields of AI-assisted gastroenterology and

hepatology, there are still several limitations to be discussed and resolved. One of the major criticisms is the lack of high-quality training, testing, and validation datasets for the development and validation of AI models. Due to the retrospective manner of most studies, selection bias must be considered at the training stage, meanwhile, overfitting and spectrum bias may result in overestimation of the model accuracy and generalization. According to the rigorous "six-steps" translation pipelines[149], doctors and AI researchers should join the calls that advocate for developing interconnected networks of collecting raw acquisition data which was shifted from processed medical images over the world and training AI on a large scale to obtain robust and generalizable models. Furthermore, the black-box nature of AI technologies has become a barrier to clinical practice, because developers and users do not know the details about how computers output the conclusion. Explainable AI for reliable healthcare is worth investigating to reach clinical interpretability and transparency. In addition, from the perspective of ethics and legal liabilities, AI models may potentially cause errors and challenge the patient-doctor relationship despite the fact that they improve the clinical workflow with enhanced precision. Especially in the fields of gastroenterology and hepatology, cancer discrimination may mean a completely different treatment. If misdiagnosis occurs during AI application, who should take responsibility- the doctor, the programmer, the company providing the system, or the patient? Issues such as ethics and legal liabilities should be demonstrated in the early phase to maintain the balance between minimal error rates and maximal patient benefits[150,151].

There have been an increasing number of studies applying AI to gastroenterology and hepatology over the past decade. In the future, the trend will continue and larger studies will be carried out to compare the performance of medical professionals with AI *vs* professionals without AI to highlight the importance of AI assistance. AI technologies will be utilized to develop more accurate models to predict and monitor disease progression and potential complications, and these models may ameliorate the insufficiency of medical resources in the remote underserved or developing regions. Besides, AI-assisted personalized imaging protocols and immediate three-dimensional reconstruction may further improve the diagnostic efficiency and accuracy. Researchers will be able to realize the mechanism of disease progression and treatment response through the combination of multi-modality images or multi-omics data. In addition, there is an emerging trend applying AI to drug development, such as prediction of compound toxicity, physical properties, and biological activities, which may assist chemotherapy for digestive system malignancy. Furthermore, AI could be used to process the data generated from the tissue-on-a-chip platform which could better summarize the tumor microenvironment, thus reach precise and individual chemotherapy in gastroenterology and hepatology. As synthetic lethality becomes a promising genetically targeted cancer therapy[152,153], AI could also be used for the detection of target synthetic lethal partners of overexpressed or mutated genes in tumor cells to kill cancers. Finally, AI tools could not replace endoscopists, radiologists, and pathologists in the near and even distant future. Computers would make predictions and doctors would make the final decision, in other words, they would always work together to benefit patients.

CONCLUSION

AI is rapidly developing and becoming a promising tool in medical image analysis of endoscopy, radiology, and pathology to improve disease diagnosis and treatment in the fields of gastroenterology and hepatology. Nevertheless, we should be aware of the constraints that limit the acceptance and utilization of AI tools in clinical practice. To use AI wisely, doctors and researchers should cooperate to address the current challenges and develop more accurate AI tools to improve patient care.

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REFERENCES

1 **Laskaris R**. Artificial Intelligence: A Modern Approach, 3rd edition. Library Journal, 2015; **140**: 45-45

2 **Colom R**, Karama S, Jung RE, Haier RJ. Human intelligence and brain networks. *Dialogues Clin Neurosci* 2010; **12**: 489-501 [PMID: 21319494 DOI: 10.31887/DCNS.2010.12.4/rcolom]

3 **Darcy AM**, Louie AK, Roberts LW. Machine Learning and the Profession of Medicine. *JAMA* 2016; **315**: 551-552 [PMID: 26864406 DOI: 10.1001/jama.2015.18421]

4 **Esteva A**, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S, Dean J. A guide to deep learning in healthcare. *Nat Med* 2019; **25**: 24-29 [PMID: 30617335 DOI: 10.1038/s41591-018-0316-z]

5 **Yang YJ**, Bang CS. Application of artificial intelligence in gastroenterology. *World J Gastroenterol* 2019; **25**: 1666-1683 [PMID: 31011253 DOI: 10.3748/wjg.v25.i14.1666]

6 **Le Berre C**, Sandborn WJ, Aridhi S, Devignes MD, Fournier L, Smaïl-Tabbone M, Danese S, Peyrin-Biroulet L. Application of Artificial Intelligence to Gastroenterology and Hepatology. *Gastroenterology* 2020; **158**: 76-94. e2 [PMID: 31593701 DOI: 10.1053/j.gastro.2019.08.058]

7 **Bengio Y**, Courville A, Vincent P. Representation learning: a review and new perspectives. *IEEE Trans Pattern Anal Mach Intell* 2013; **35**: 1798-1828 [PMID: 23787338 DOI: 10.1109/TPAMI.2013.50]

8 **Kumar A**, Kim J, Lyndon D, Fulham M, Feng D. An Ensemble of Fine-Tuned Convolutional Neural Networks for Medical Image Classification. *IEEE J Biomed Health Inform* 2017; **21**: 31-40 [PMID: 28114041 DOI: 10.1109/JBHI.2016.2635663]

9 **Ambinder EP**. A history of the shift toward full computerization of medicine. *J Oncol Pract* 2005; **1**: 54-56 [PMID: 20871680 DOI: 10.1200/jop.2005.1.2.54]

10 **Chen H**, Sung JJY. Potentials of AI in medical image analysis in Gastroenterology and Hepatology. *J Gastroenterol Hepatol* 2021; **36**: 31-38 [PMID: 33140875 DOI: 10.1111/jgh.15327]

11 **Chen M**, Zhang B, Topatana W, Cao J, Zhu H, Juengpanich S, Mao Q, Yu H, Cai X. Classification and mutation prediction based on histopathology H&E images in liver cancer using deep learning. *NPJ Precis Oncol* 2020; **4**: 14 [PMID: 32550270 DOI: 10.1038/s41698-020-0120-3]

12 **Fu Y**, Schwebel DC, Hu G. Physicians' Workloads in China: 1998–2016. *Int J Environ Res Public Health* 2018; **15** [PMID: 30081497 DOI: 10.3390/ijerph15081649]

13 **Miotto R**, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. *Brief Bioinform* 2018; **19**: 1236-1246 [PMID: 28481991 DOI: 10.1093/bib/bbx044]

14 **Shen D**, Wu G, Suk HI. Deep Learning in Medical Image Analysis. *Annu Rev Biomed Eng* 2017; **19**: 221-248 [PMID: 28301734 DOI: 10.1146/annurev-bioeng-071516-044442]

15 **Pedregosa F**, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay E. Scikit-learn: Machine Learning in Python. *J Mach Learn Res* 2011; **12**: 2825-2830

16 **Yu H**, Singh R, Shin SH, Ho KY. Artificial intelligence in upper GI endoscopy - current status, challenges and future promise. *J Gastroenterol Hepatol* 2021; **36**: 20-24 [PMID: 33448515 DOI: 10.1111/jgh.15354]

17 **Mori Y**, Neumann H, Misawa M, Kudo SE, Bretthauer M. Artificial intelligence in colonoscopy - Now on the market. What's next? *J Gastroenterol Hepatol* 2021; **36**: 7-11 [PMID: 33179322 DOI: 10.1111/jgh.15339]

18 **Wu J**, Chen J, Cai J. Application of Artificial Intelligence in Gastrointestinal Endoscopy. *J Clin Gastroenterol* 2021; **55**: 110-120 [PMID: 32925304 DOI: 10.1097/MCG.0000000000001423]

19 **Takiyama H**, Ozawa T, Ishihara S, Fujishiro M, Shichijo S, Nomura S, Miura M, Tada T. Automatic anatomical classification of esophagogastroduodenoscopy images using deep convolutional neural networks. *Sci Rep* 2018; **8**: 7497 [PMID: 29760397 DOI: 10.1038/s41598-018-25842-6]

20 **Wu L**, Zhang J, Zhou W, An P, Shen L, Liu J, Jiang X, Huang X, Mu G, Wan X, Lv X, Gao J, Cui N, Hu S, Chen Y, Hu X, Li J, Chen D, Gong D, He X, Ding Q, Zhu X, Li S, Wei X, Li X, Wang X, Zhou J, Zhang M, Yu HG. Randomised controlled trial of WISENSE, a real-time quality improving system for monitoring blind spots during esophagogastroduodenoscopy. *Gut* 2019; **68**: 2161-2169 [PMID: 30858305 DOI: 10.1136/gutjnl-2018-317366]

21 **van der Sommen F**, Zinger S, Curvers WL, Bisschops R, Pech O, Weusten BL, Bergman JJ, de With PH, Schoon EJ. Computer-aided detection of early neoplastic lesions in Barrett's esophagus. *Endoscopy* 2016; **48**: 617-624 [PMID: 27100718 DOI: 10.1055/s-0042-105284]

22 **Swager AF**, van der Sommen F, Klomp SR, Zinger S, Meijer SL, Schoon EJ, Bergman JJGHM, de With PH, Curvers WL. Computer-aided detection of early Barrett's neoplasia using volumetric laser endomicroscopy. *Gastrointest Endosc* 2017; **86**: 839-846 [PMID: 28322771 DOI: 10.1016/j.gie.2017.03.011]

23 **Hashimoto R**, Requa J, Dao T, Ninh A, Tran E, Mai D, Lugo M, El-Hage Chehade N, Chang KJ, Karnes WE, Samarasena JB. Artificial intelligence using convolutional neural networks for real-time detection of early esophageal neoplasia in Barrett's esophagus (with video). *Gastrointest Endosc* 2020; **91**: 1264-1271. e1 [PMID: 31930967 DOI: 10.1016/j.gie.2019.12.049]

24 **Ebigbo A**, Mendel R, Probst A, Manzeneder J, Prinz F, de Souza LA Jr, Papa J, Palm C, Messmann H. Real-time use of artificial intelligence in the evaluation of cancer in Barrett's oesophagus. *Gut* 2020; **69**: 615-616 [PMID: 31541004 DOI: 10.1136/gutjnl-2019-319460]

25 **Horie Y**, Yoshio T, Aoyama K, Yoshimizu S, Horiuchi Y, Ishiyama A, Hirasawa T, Tsuchida T, Ozawa T, Ishihara S, Kumagai Y, Fujishiro M, Maetani I, Fujisaki J, Tada T. Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks. *Gastrointest Endosc* 2019; **89**: 25-32 [PMID: 30120958 DOI: 10.1016/j.gie.2018.07.037]

26 **Kumagai Y**, Takubo K, Kawada K, Aoyama K, Endo Y, Ozawa T, Hirasawa T, Yoshio T, Ishihara S, Fujishiro M, Tamaru JI, Mochiki E, Ishida H, Tada T. Diagnosis using deep-learning artificial intelligence based on the endocytoscopic observation of the esophagus. *Esophagus* 2019; **16**: 180-187 [PMID: 30547352 DOI: 10.1007/s10388-018-0651-7]

27 **Zhao YY**, Xue DX, Wang YL, Zhang R, Sun B, Cai YP, Feng H, Cai Y, Xu JM. Computer-assisted diagnosis of early esophageal squamous cell carcinoma using narrow-band imaging magnifying endoscopy. *Endoscopy* 2019; **51**: 333-341 [PMID: 30469155 DOI: 10.1055/a-0756-8754]

28 **Cai SL**, Li B, Tan WM, Niu XJ, Yu HH, Yao LQ, Zhou PH, Yan B, Zhong YS. Using a deep learning system in endoscopy for screening of early esophageal squamous cell carcinoma (with video). *Gastrointest Endosc* 2019; **90**: 745-753. e2 [PMID: 31302091 DOI: 10.1016/j.gie.2019.06.044]

29 **Nakagawa K**, Ishihara R, Aoyama K, Ohmori M, Nakahira H, Matsuura N, Shichijo S, Nishida T, Yamada T, Yamaguchi S, Ogiyama H, Egawa S, Kishida O, Tada T. Classification for invasion depth of esophageal squamous cell carcinoma using a deep neural network compared with experienced endoscopists. *Gastrointest Endosc* 2019; **90**: 407-414 [PMID: 31077698 DOI: 10.1016/j.gie.2019.04.245]

30 **Tokai Y**, Yoshio T, Aoyama K, Horie Y, Yoshimizu S, Horiuchi Y, Ishiyama A, Tsuchida T, Hirasawa T, Sakakibara Y, Yamada T, Yamaguchi S, Fujisaki J, Tada T. Application of artificial intelligence using convolutional neural networks in determining the invasion depth of esophageal squamous cell carcinoma. *Esophagus* 2020; **17**: 250-256 [PMID: 31980977 DOI: 10.1007/s10388-020-00716-x]

31 **Ali H**, Yasmin M, Sharif M, Rehmani MH. Computer assisted gastric abnormalities detection using hybrid texture descriptors for chromoendoscopy images. *Comput Methods Programs Biomed* 2018; **157**: 39-47 [PMID: 29477434 DOI: 10.1016/j.cmpb.2018.01.013]

32 **Sakai Y**, Takemoto S, Hori K, Nishimura M, Ikematsu H, Yano T, Yokota H. Automatic detection of early gastric cancer in endoscopic images using a transferring convolutional neural network. *Annu Int Conf IEEE Eng Med Biol Soc* 2018; **2018**: 4138-4141 [PMID: 30441266 DOI: 10.1109/EMBC.2018.8513274]

33 **Kanesaka T**, Lee TC, Uedo N, Lin KP, Chen HZ, Lee JY, Wang HP, Chang HT. Computer-aided diagnosis for identifying and delineating early gastric cancers in magnifying narrow-band imaging. *Gastrointest Endosc* 2018; **87**: 1339-1344 [PMID: 29225083 DOI: 10.1016/j.gie.2017.11.029]

34 **Wu L**, Zhou W, Wan X, Zhang J, Shen L, Hu S, Ding Q, Mu G, Yin A, Huang X, Liu J, Jiang X, Wang Z, Deng Y, Liu M, Lin R, Ling T, Li P, Wu Q, Jin P, Chen J, Yu H. A deep neural network improves endoscopic detection of early gastric cancer without blind spots. *Endoscopy* 2019; **51**: 522-531 [PMID: 30861533 DOI: 10.1055/a-0855-3532]

35 **Horiuchi Y**, Aoyama K, Tokai Y, Hirasawa T, Yoshimizu S, Ishiyama A, Yoshio T, Tsuchida T, Fujisaki J, Tada T. Convolutional Neural Network for Differentiating Gastric Cancer from Gastritis Using Magnified Endoscopy with Narrow Band Imaging. *Dig Dis Sci* 2020; **65**: 1355-1363 [PMID: 31584138 DOI: 10.1007/s10620-019-05862-6]

36 **Zhu Y**, Wang QC, Xu MD, Zhang Z, Cheng J, Zhong YS, Zhang YQ, Chen WF, Yao LQ, Zhou PH, Li QL. Application of convolutional neural network in the diagnosis of the invasion depth of gastric cancer based on conventional endoscopy. *Gastrointest Endosc* 2019; **89**: 806-815. e1 [PMID: 30452913 DOI: 10.1016/j.gie.2018.11.011]

37 **Luo H**, Xu G, Li C, He L, Luo L, Wang Z, Jing B, Deng Y, Jin Y, Li Y, Li B, Tan W, He C, Seeruttun SR, Wu Q, Huang J, Huang DW, Chen B, Lin SB, Chen QM, Yuan CM, Chen HX, Pu HY, Zhou F, He Y, Xu RH. Real-time artificial intelligence for detection of upper gastrointestinal cancer by endoscopy: a multicentre, case-control, diagnostic study. *Lancet Oncol* 2019; **20**: 1645-1654 [PMID: 31591062 DOI: 10.1016/S1470-2045(19)30637-0]

38 **Nagao S**, Tsuji Y, Sakaguchi Y, Takahashi Y, Minatsuki C, Niimi K, Yamashita H, Yamamichi N, Seto Y, Tada T, Koike K. Highly accurate artificial intelligence systems to predict the invasion depth of gastric cancer: efficacy of conventional white-light imaging, nonmagnifying narrow-band imaging, and indigo-carmine dye contrast imaging. *Gastrointest Endosc* 2020; **92**: 866-873. e1 [PMID: 32592776 DOI: 10.1016/j.gie.2020.06.047]

39 **Ayaru L**, Ypsilantis PP, Nanapragasam A, Choi RC, Thillanathan A, Min-Ho L, Montana G. Prediction of Outcome in Acute Lower Gastrointestinal Bleeding Using Gradient Boosting. *PLoS One* 2015; **10**: e0132485 [PMID: 26172121 DOI: 10.1371/journal.pone.0132485]

40 **Xiao Jia**, Meng MQ. A deep convolutional neural network for bleeding detection in Wireless Capsule Endoscopy images. *Annu Int Conf IEEE Eng Med Biol Soc* 2016; **2016**: 639-642 [PMID: 28268409 DOI: 10.1109/EMBC.2016.7590783]

41 **Usman MA**, Satrya GB, Usman MR, Shin SY. Detection of small colon bleeding in wireless capsule endoscopy videos. *Comput Med Imaging Graph* 2016; **54**: 16-26 [PMID: 27793502 DOI: 10.1016/j.compmedimag.2016.09.005]

42 **Sengupta N**, Tapper EB. Derivation and Internal Validation of a Clinical Prediction Tool for 30-Day Mortality in Lower Gastrointestinal Bleeding. *Am J Med* 2017; **130**: 601.e1-601. e8 [PMID: 28065767 DOI: 10.1016/j.amjmed.2016.12.009]

43 **Leenhardt R**, Vasseur P, Li C, Saurin JC, Rahmi G, Cholet F, Becq A, Marteau P, Histace A, Dray X; CAD-CAP Database Working Group. A neural network algorithm for detection of GI angiectasia during small-bowel capsule endoscopy. *Gastrointest Endosc* 2019; **89**: 189-194 [PMID: 30017868 DOI: 10.1016/j.gie.2018.06.036]

44 **Aoki T**, Yamada A, Kato Y, Saito H, Tsuboi A, Nakada A, Niikura R, Fujishiro M, Oka S, Ishihara S, Matsuda T, Nakahori M, Tanaka S, Koike K, Tada T. Automatic detection of blood content in capsule endoscopy images based on a deep convolutional neural network. *J Gastroenterol Hepatol* 2020; **35**: 1196-1200 [PMID: 31758717 DOI: 10.1111/jgh.14941]

45 **Yang J**, Chang L, Li S, He X, Zhu T. WCE polyp detection based on novel feature descriptor with normalized variance locality-constrained linear coding. *Int J Comput Assist Radiol Surg* 2020; **15**: 1291-1302 [PMID: 32447521 DOI: 10.1007/s11548-020-02190-3]

46 **Vieira PM**, Freitas NR, Valente J, Vaz IF, Rolanda C, Lima CS. Automatic detection of small bowel tumors in wireless capsule endoscopy images using ensemble learning. *Med Phys* 2020; **47**: 52-63 [PMID: 31299096 DOI: 10.1002/mp.13709]

47 **Fernández-Esparrach G**, Bernal J, López-Cerón M, Córdova H, Sánchez-Montes C, Rodríguez de Miguel C, Sánchez FJ. Exploring the clinical potential of an automatic colonic polyp detection method based on the creation of energy maps. *Endoscopy* 2016; **48**: 837-842 [PMID: 27285900 DOI: 10.1055/s-0042-108434]

48 **Komeda Y**, Handa H, Watanabe T, Nomura T, Kitahashi M, Sakurai T, Okamoto A, Minami T, Kono M, Arizumi T, Takenaka M, Hagiwara S, Matsui S, Nishida N, Kashida H, Kudo M. Computer-Aided Diagnosis Based on Convolutional Neural Network System for Colorectal Polyp Classification: Preliminary Experience. *Oncology* 2017; **93** Suppl 1: 30-34 [PMID: 29258081 DOI: 10.1159/000481227]

49 **Misawa M**, Kudo SE, Mori Y, Takeda K, Maeda Y, Kataoka S, Nakamura H, Kudo T, Wakamura K, Hayashi T, Katagiri A, Baba T, Ishida F, Inoue H, Nimura Y, Oda M, Mori K. Accuracy of computer-aided diagnosis based on narrow-band imaging endocytoscopy for diagnosing colorectal lesions: comparison with experts. *Int J Comput Assist Radiol Surg* 2017; **12**: 757-766 [PMID: 28247214 DOI: 10.1007/s11548-017-1542-4]

50 **Misawa M**, Kudo SE, Mori Y, Cho T, Kataoka S, Yamauchi A, Ogawa Y, Maeda Y, Takeda K, Ichimasa K, Nakamura H, Yagawa Y, Toyoshima N, Ogata N, Kudo T, Hisayuki T, Hayashi T, Wakamura K, Baba T, Ishida F, Itoh H, Roth H, Oda M, Mori K. Artificial Intelligence-Assisted Polyp Detection for Colonoscopy: Initial Experience. *Gastroenterology* 2018; **154**: 2027-2029. e3 [PMID: 29653147 DOI: 10.1053/j.gastro.2018.04.003]

51 **Chen PJ**, Lin MC, Lai MJ, Lin JC, Lu HH, Tseng VS. Accurate Classification of Diminutive Colorectal Polyps Using Computer-Aided Analysis. *Gastroenterology* 2018; **154**: 568-575 [PMID: 29042219 DOI: 10.1053/j.gastro.2017.10.010]

52 **Urban G**, Tripathi P, Alkayali T, Mittal M, Jalali F, Karnes W, Baldi P. Deep Learning Localizes and Identifies Polyps in Real Time With 96% Accuracy in Screening Colonoscopy. *Gastroenterology* 2018; **155**: 1069-1078. e8 [PMID: 29928897 DOI: 10.1053/j.gastro.2018.06.037]

53 **Renner J**, Phlipsen H, Haller B, Navarro-Avila F, Saint-Hill-Febles Y, Mateus D, Ponchon T, Poszler A, Abdelhafez M, Schmid RM, von Delius S, Klare P. Optical classification of neoplastic colorectal polyps - a computer-assisted approach (the COACH study). *Scand J Gastroenterol* 2018; **53**: 1100-1106 [PMID: 30270677 DOI: 10.1080/00365521.2018.1501092]

54 **Wang P**, Xiao X, Glissen Brown JR, Berzin TM, Tu M, Xiong F, Hu X, Liu P, Song Y, Zhang D, Yang X, Li L, He J, Yi X, Liu J, Liu X. Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy. *Nat Biomed Eng* 2018; **2**: 741-748 [PMID: 31015647 DOI: 10.1038/s41551-018-0301-3]

55 **Mori Y**, Kudo SE, Misawa M, Saito Y, Ikematsu H, Hotta K, Ohtsuka K, Urushibara F, Kataoka S, Ogawa Y, Maeda Y, Takeda K, Nakamura H, Ichimasa K, Kudo T, Hayashi T, Wakamura K, Ishida F, Inoue H, Itoh H, Oda M, Mori K. Real-Time Use of Artificial Intelligence in Identification of Diminutive Polyps During Colonoscopy: A Prospective Study. *Ann Intern Med* 2018; **169**: 357-366 [PMID: 30105375 DOI: 10.7326/M18-0249]

56 **Byrne MF**, Chapados N, Soudan F, Oertel C, Linares Pérez M, Kelly R, Iqbal N, Chandelier F, Rex DK. Real-time differentiation of adenomatous and hyperplastic diminutive colorectal polyps during analysis of unaltered videos of standard colonoscopy using a deep learning model. *Gut* 2019; **68**: 94-100 [PMID: 29066576 DOI: 10.1136/gutjnl-2017-314547]

57 **Blanes-Vidal V**, Baatrup G, Nadimi ES. Addressing priority challenges in the detection and assessment of colorectal polyps from capsule endoscopy and colonoscopy in colorectal cancer screening using machine learning. *Acta Oncol* 2019; **58**: S29-S36 [PMID: 30836800 DOI: 10.1080/0284186X.2019.1584404]

58 **Lee JY**, Jeong J, Song EM, Ha C, Lee HJ, Koo JE, Yang DH, Kim N, Byeon JS. Real-time detection of colon polyps during colonoscopy using deep learning: systematic validation with four independent datasets. *Sci Rep* 2020; **10**: 8379 [PMID: 32433506 DOI: 10.1038/s41598-020-65387-1]

59 **Gohari MR**, Biglarian A, Bakhshi E, Pourhoseingholi MA. Use of an artificial neural network to determine prognostic factors in colorectal cancer patients. *Asian Pac J Cancer Prev* 2011; **12**: 1469-1472 [PMID: 22126483]

60 **Biglarian A**, Bakhshi E, Gohari MR, Khodabakhshi R. Artificial neural network for prediction of distant metastasis in colorectal cancer. *Asian Pac J Cancer Prev* 2012; **13**: 927-930 [PMID:

22631673 DOI: 10.7314/apjcp.2012.13.3.927]
61 **Takeda K**, Kudo SE, Mori Y, Misawa M, Kudo T, Wakamura K, Katagiri A, Baba T, Hidaka E, Ishida F, Inoue H, Oda M, Mori K. Accuracy of diagnosing invasive colorectal cancer using computer-aided endocytoscopy. *Endoscopy* 2017; **49**: 798-802 [PMID: 28472832 DOI: 10.1055/s-0043-105486]
62 **Ito N**, Kawahira H, Nakashima H, Uesato M, Miyauchi H, Matsubara H. Endoscopic Diagnostic Support System for cT1b Colorectal Cancer Using Deep Learning. *Oncology* 2019; **96**: 44-50 [PMID: 30130758 DOI: 10.1159/000491636]
63 **Zhou D**, Tian F, Tian X, Sun L, Huang X, Zhao F, Zhou N, Chen Z, Zhang Q, Yang M, Yang Y, Guo X, Li Z, Liu J, Wang J, Wang B, Zhang G, Sun B, Zhang W, Kong D, Chen K, Li X. Diagnostic evaluation of a deep learning model for optical diagnosis of colorectal cancer. *Nat Commun* 2020; **11**: 2961 [PMID: 32528084 DOI: 10.1038/s41467-020-16777-6]
64 **Shaheen NJ**, Falk GW, Iyer PG, Gerson LB; American College of Gastroenterology. ACG Clinical Guideline: Diagnosis and Management of Barrett's Esophagus. *Am J Gastroenterol* 2016; **111**: 30-50; quiz 51 [PMID: 26526079 DOI: 10.1038/ajg.2015.322]
65 **Fitzgerald RC**, di Pietro M, Ragunath K, Ang Y, Kang JY, Watson P, Trudgill N, Patel P, Kaye PV, Sanders S, O'Donovan M, Bird-Lieberman E, Bhandari P, Jankowski JA, Attwood S, Parsons SL, Loft D, Lagergren J, Moayyedi P, Lyratzopoulos G, de Caestecker J; British Society of Gastroenterology. British Society of Gastroenterology guidelines on the diagnosis and management of Barrett's oesophagus. *Gut* 2014; **63**: 7-42 [PMID: 24165758 DOI: 10.1136/gutjnl-2013-305372]
66 **Schölvinck DW**, van der Meulen K, Bergman JJGHM, Weusten BLAM. Detection of lesions in dysplastic Barrett's esophagus by community and expert endoscopists. *Endoscopy* 2017; **49**: 113-120 [PMID: 27855466 DOI: 10.1055/s-0042-118312]
67 **Menon S**, Trudgill N. How commonly is upper gastrointestinal cancer missed at endoscopy? *Endosc Int Open* 2014; **2**: E46-E50 [PMID: 26135259 DOI: 10.1055/s-0034-1365524]
68 **Hosokawa O**, Hattori M, Douden K, Hayashi H, Ohta K, Kaizaki Y. Difference in accuracy between gastroscopy and colonoscopy for detection of cancer. *Hepatogastroenterology* 2007; **54**: 442-444 [PMID: 17523293]
69 **Hirasawa T**, Aoyama K, Tanimoto T, Ishihara S, Shichijo S, Ozawa T, Ohnishi T, Fujishiro M, Matsuo K, Fujisaki J, Tada T. Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images. *Gastric Cancer* 2018; **21**: 653-660 [PMID: 29335825 DOI: 10.1007/s10120-018-0793-2]
70 **Kubota K**, Kuroda J, Yoshida M, Ohta K, Kitajima M. Medical image analysis: computer-aided diagnosis of gastric cancer invasion on endoscopic images. *Surg Endosc* 2012; **26**: 1485-1489 [PMID: 22083334 DOI: 10.1007/s00464-011-2036-z]
71 **Boland GW**, Guimaraes AS, Mueller PR. The radiologist's conundrum: benefits and costs of increasing CT capacity and utilization. *Eur Radiol* 2009; **19**: 9-11; discussion 12 [PMID: 18766347 DOI: 10.1007/s00330-008-1159-7]
72 **Gatos I**, Tsantis S, Spiliopoulos S, Karnabatidis D, Theotokas I, Zoumpoulis P, Loupas T, Hazle JD, Kagadis GC. A new computer aided diagnosis system for evaluation of chronic liver disease with ultrasound shear wave elastography imaging. *Med Phys* 2016; **43**: 1428-1436 [PMID: 26936727 DOI: 10.1118/1.4942383]
73 **Gatos I**, Tsantis S, Spiliopoulos S, Karnabatidis D, Theotokas I, Zoumpoulis P, Loupas T, Hazle JD, Kagadis GC. A Machine-Learning Algorithm Toward Color Analysis for Chronic Liver Disease Classification, Employing Ultrasound Shear Wave Elastography. *Ultrasound Med Biol* 2017; **43**: 1797-1810 [PMID: 28634041 DOI: 10.1016/j.ultrasmedbio.2017.05.002]
74 **Chen Y**, Luo Y, Huang W, Hu D, Zheng RQ, Cong SZ, Meng FK, Yang H, Lin HJ, Sun Y, Wang XY, Wu T, Ren J, Pei SF, Zheng Y, He Y, Hu Y, Yang N, Yan H. Machine-learning-based classification of real-time tissue elastography for hepatic fibrosis in patients with chronic hepatitis B. *Comput Biol Med* 2017; **89**: 18-23 [PMID: 28779596 DOI: 10.1016/j.compbiomed.2017.07.012]
75 **Li W**, Huang Y, Zhuang BW, Liu GJ, Hu HT, Li X, Liang JY, Wang Z, Huang XW, Zhang CQ, Ruan SM, Xie XY, Kuang M, Lu MD, Chen LD, Wang W. Multiparametric ultrasomics of significant liver fibrosis: A machine learning-based analysis. *Eur Radiol* 2019; **29**: 1496-1506 [PMID: 30178143 DOI: 10.1007/s00330-018-5680-z]
76 **Gatos I**, Tsantis S, Spiliopoulos S, Karnabatidis D, Theotokas I, Zoumpoulis P, Loupas T, Hazle JD, Kagadis GC. Temporal stability assessment in shear wave elasticity images validated by deep learning neural network for chronic liver disease fibrosis stage assessment. *Med Phys* 2019; **46**: 2298-2309 [PMID: 30929260 DOI: 10.1002/mp.13521]
77 **Wang K**, Lu X, Zhou H, Gao Y, Zheng J, Tong M, Wu C, Liu C, Huang L, Jiang T, Meng F, Lu Y, Ai H, Xie XY, Yin LP, Liang P, Tian J, Zheng R. Deep learning Radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis in chronic hepatitis B: a prospective multicentre study. *Gut* 2019; **68**: 729-741 [PMID: 29730602 DOI: 10.1136/gutjnl-2018-316204]
78 **Kuppili V**, Biswas M, Sreekumar A, Suri HS, Saba L, Edla DR, Marinho RT, Sanches JM, Suri JS. Extreme Learning Machine Framework for Risk Stratification of Fatty Liver Disease Using Ultrasound Tissue Characterization. *J Med Syst* 2017; **41**: 152 [PMID: 28836045 DOI: 10.1007/s10916-017-0797-1]
79 **Byra M**, Styczynski G, Szmigielski C, Kalinowski P, Michałowski Ł, Paluszkiewicz R, Ziarkiewicz-Wróblewska B, Zieniewicz K, Sobieraj P, Nowicki A. Transfer learning with deep

convolutional neural network for liver steatosis assessment in ultrasound images. *Int J Comput Assist Radiol Surg* 2018; **13**: 1895-1903 [PMID: 30094778 DOI: 10.1007/s11548-018-1843-2]

80 **Biswas M**, Kuppili V, Edla DR, Suri HS, Saba L, Marinhoe RT, Sanches JM, Suri JS. Symtosis: A liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm. *Comput Methods Programs Biomed* 2018; **155**: 165-177 [PMID: 29512496 DOI: 10.1016/j.cmpb.2017.12.016]

81 **Cao W**, An X, Cong L, Lyu C, Zhou Q, Guo R. Application of Deep Learning in Quantitative Analysis of 2-Dimensional Ultrasound Imaging of Nonalcoholic Fatty Liver Disease. *J Ultrasound Med* 2020; **39**: 51-59 [PMID: 31222786 DOI: 10.1002/jum.15070]

82 **Guo LH**, Wang D, Qian YY, Zheng X, Zhao CK, Li XL, Bo XW, Yue WW, Zhang Q, Shi J, Xu HX. A two-stage multi-view learning framework based computer-aided diagnosis of liver tumors with contrast enhanced ultrasound images. *Clin Hemorheol Microcirc* 2018; **69**: 343-354 [PMID: 29630528 DOI: 10.3233/CH-170275]

83 **Schmauch B**, Herent P, Jehanno P, Dehaene O, Saillard C, Aubé C, Luciani A, Lassau N, Jégou S. Diagnosis of focal liver lesions from ultrasound using deep learning. *Diagn Interv Imaging* 2019; **100**: 227-233 [PMID: 30926443 DOI: 10.1016/j.diii.2019.02.009]

84 **Yang Q**, Wei J, Hao X, Kong D, Yu X, Jiang T, Xi J, Cai W, Luo Y, Jing X, Yang Y, Cheng Z, Wu J, Zhang H, Liao J, Zhou P, Song Y, Zhang Y, Han Z, Cheng W, Tang L, Liu F, Dou J, Zheng R, Yu J, Tian J, Liang P. Improving B-mode ultrasound diagnostic performance for focal liver lesions using deep learning: A multicentre study. *EBioMedicine* 2020; **56**: 102777 [PMID: 32485640 DOI: 10.1016/j.ebiom.2020.102777]

85 **Choi KJ**, Jang JK, Lee SS, Sung YS, Shim WH, Kim HS, Yun J, Choi JY, Lee Y, Kang BK, Kim JH, Kim SY, Yu ES. Development and Validation of a Deep Learning System for Staging Liver Fibrosis by Using Contrast Agent-enhanced CT Images in the Liver. *Radiology* 2018; **289**: 688-697 [PMID: 30179104 DOI: 10.1148/radiol.2018180763]

86 **He L**, Li H, Dudley JA, Maloney TC, Brady SL, Somasundaram E, Trout AT, Dillman JR. Machine Learning Prediction of Liver Stiffness Using Clinical and T2-Weighted MRI Radiomic Data. *AJR Am J Roentgenol* 2019; **213**: 592-601 [PMID: 31120779 DOI: 10.2214/AJR.19.21082]

87 **Ahmed Y**, Hussein RS, Basha TA, Khalifa AM, Ibrahim AS, Abdelmoaty AS, Abdella HM, Fahmy AS. Detecting liver fibrosis using a machine learning-based approach to the quantification of the heart-induced deformation in tagged MR images. *NMR Biomed* 2020; **33**: e4215 [PMID: 31730265 DOI: 10.1002/nbm.4215]

88 **Hectors SJ**, Kennedy P, Huang KH, Stocker D, Carbonell G, Greenspan H, Friedman S, Taouli B. Fully automated prediction of liver fibrosis using deep learning analysis of gadoxetic acid-enhanced MRI. *Eur Radiol* 2020 [PMID: 33201285 DOI: 10.1007/s00330-020-07475-4]

89 **Vivanti R**, Szeskin A, Lev-Cohain N, Sosna J, Joskowicz L. Automatic detection of new tumors and tumor burden evaluation in longitudinal liver CT scan studies. *Int J Comput Assist Radiol Surg* 2017; **12**: 1945-1957 [PMID: 28856515 DOI: 10.1007/s11548-017-1660-z]

90 **Yasaka K**, Akai H, Abe O, Kiryu S. Deep Learning with Convolutional Neural Network for Differentiation of Liver Masses at Dynamic Contrast-enhanced CT: A Preliminary Study. *Radiology* 2018; **286**: 887-896 [PMID: 29059036 DOI: 10.1148/radiol.2017170706]

91 **Ibragimov B**, Toesca D, Chang D, Yuan Y, Koong A, Xing L. Development of deep neural network for individualized hepatobiliary toxicity prediction after liver SBRT. *Med Phys* 2018; **45**: 4763-4774 [PMID: 30098025 DOI: 10.1002/mp.13122]

92 **Abajian A**, Murali N, Savic LJ, Laage-Gaupp FM, Nezami N, Duncan JS, Schlachter T, Lin M, Geschwind JF, Chapiro J. Predicting Treatment Response to Intra-arterial Therapies for Hepatocellular Carcinoma with the Use of Supervised Machine Learning-An Artificial Intelligence Concept. *J Vasc Interv Radiol* 2018; **29**: 850-857. e1 [PMID: 29548875 DOI: 10.1016/j.jvir.2018.01.769]

93 **Zhang F**, Yang J, Nezami N, Laage-Gaupp F, Chapiro J, De Lin M, Duncan J. Liver Tissue Classification Using an Auto-context-based Deep Neural Network with a Multi-phase Training Framework. *Patch Based Tech Med Imaging (2018)* 2018; **11075**: 59-66 [PMID: 32432233 DOI: 10.1007/978-3-030-00500-9_7]

94 **Morshid A**, Elsayes KM, Khalaf AM, Elmohr MM, Yu J, Kaseb AO, Hassan M, Mahvash A, Wang Z, Hazle JD, Fuentes D. A machine learning model to predict hepatocellular carcinoma response to transcatheter arterial chemoembolization. *Radiol Artif Intell* 2019; **1** [PMID: 31858078 DOI: 10.1148/ryai.2019180021]

95 **Nayak A**, Baidya Kayal E, Arya M, Culli J, Krishan S, Agarwal S, Mehndiratta A. Computer-aided diagnosis of cirrhosis and hepatocellular carcinoma using multi-phase abdomen CT. *Int J Comput Assist Radiol Surg* 2019; **14**: 1341-1352 [PMID: 31062266 DOI: 10.1007/s11548-019-01991-5]

96 **Hamm CA**, Wang CJ, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Duncan JS, Weinreb JC, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part I: development of a convolutional neural network classifier for multi-phasic MRI. *Eur Radiol* 2019; **29**: 3338-3347 [PMID: 31016442 DOI: 10.1007/s00330-019-06205-9]

97 **Wang CJ**, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. *Eur Radiol* 2019; **29**: 3348-3357 [PMID: 31093705 DOI: 10.1007/s00330-019-06214-8]

98 **Jansen MJA**, Kuijf HJ, Veldhuis WB, Wessels FJ, Viergever MA, Pluim JPW. Automatic

classification of focal liver lesions based on MRI and risk factors. *PLoS One* 2019; **14**: e0217053 [PMID: 31095624 DOI: 10.1371/journal.pone.0217053]

99 **Mokrane FZ**, Lu L, Vavasseur A, Otal P, Peron JM, Luk L, Yang H, Ammari S, Saenger Y, Rousseau H, Zhao B, Schwartz LH, Dercle L. Radiomics machine-learning signature for diagnosis of hepatocellular carcinoma in cirrhotic patients with indeterminate liver nodules. *Eur Radiol* 2020; **30**: 558-570 [PMID: 31444598 DOI: 10.1007/s00330-019-06347-w]

100 **Shi W**, Kuang S, Cao S, Hu B, Xie S, Chen S, Chen Y, Gao D, Zhu Y, Zhang H, Liu H, Ye M, Sirlin CB, Wang J. Deep learning assisted differentiation of hepatocellular carcinoma from focal liver lesions: choice of four-phase and three-phase CT imaging protocol. *Abdom Radiol (NY)* 2020; **45**: 2688-2697 [PMID: 32232524 DOI: 10.1007/s00261-020-02485-8]

101 **Alirr OI**. Deep learning and level set approach for liver and tumor segmentation from CT scans. *J Appl Clin Med Phys* 2020; **21**: 200-209 [PMID: 33113290 DOI: 10.1002/acm2.13003]

102 **Zheng H**, Chen Y, Yue X, Ma C, Liu X, Yang P, Lu J. Deep pancreas segmentation with uncertain regions of shadowed sets. *Magn Reson Imaging* 2020; **68**: 45-52 [PMID: 31987903 DOI: 10.1016/j.mri.2020.01.008]

103 **Liang JD**, Ping XO, Tseng YJ, Huang GT, Lai F, Yang PM. Recurrence predictive models for patients with hepatocellular carcinoma after radiofrequency ablation using support vector machines with feature selection methods. *Comput Methods Programs Biomed* 2014; **117**: 425-434 [PMID: 25278224 DOI: 10.1016/j.cmpb.2014.09.001]

104 **Zhou W**, Zhang L, Wang K, Chen S, Wang G, Liu Z, Liang C. Malignancy characterization of hepatocellular carcinomas based on texture analysis of contrast-enhanced MR images. *J Magn Reson Imaging* 2017; **45**: 1476-1484 [PMID: 27626270 DOI: 10.1002/jmri.25454]

105 **Abajian A**, Murali N, Savic LJ, Laage-Gaupp FM, Nezami N, Duncan JS, Schlachter T, Lin M, Geschwind JF, Chapiro J. Predicting Treatment Response to Image-Guided Therapies Using Machine Learning: An Example for Trans-Arterial Treatment of Hepatocellular Carcinoma. *J Vis Exp* 2018 [PMID: 30371657 DOI: 10.3791/58382]

106 **Ma X**, Wei J, Gu D, Zhu Y, Feng B, Liang M, Wang S, Zhao X, Tian J. Preoperative radiomics nomogram for microvascular invasion prediction in hepatocellular carcinoma using contrast-enhanced CT. *Eur Radiol* 2019; **29**: 3595-3605 [PMID: 30770969 DOI: 10.1007/s00330-018-5985-y]

107 **Dong Y**, Zhou L, Xia W, Zhao XY, Zhang Q, Jian JM, Gao X, Wang WP. Preoperative Prediction of Microvascular Invasion in Hepatocellular Carcinoma: Initial Application of a Radiomic Algorithm Based on Grayscale Ultrasound Images. *Front Oncol* 2020; **10**: 353 [PMID: 32266138 DOI: 10.3389/fonc.2020.00353]

108 **He M**, Zhang P, Ma X, He B, Fang C, Jia F. Radiomic Feature-Based Predictive Model for Microvascular Invasion in Patients With Hepatocellular Carcinoma. *Front Oncol* 2020; **10**: 574228 [PMID: 33251138 DOI: 10.3389/fonc.2020.574228]

109 **Schoenberg MB**, Bucher JN, Koch D, Börner N, Hesse S, De Toni EN, Seidensticker M, Angele MK, Klein C, Bazhin AV, Werner J, Guba MO. A novel machine learning algorithm to predict disease free survival after resection of hepatocellular carcinoma. *Ann Transl Med* 2020; **8**: 434 [PMID: 32395478 DOI: 10.21037/atm.2020.04.16]

110 **Zhao Y**, Wu J, Zhang Q, Hua Z, Qi W, Wang N, Lin T, Sheng L, Cui D, Liu J, Song Q, Li X, Wu T, Guo Y, Cui J, Liu A. Radiomics Analysis Based on Multiparametric MRI for Predicting Early Recurrence in Hepatocellular Carcinoma After Partial Hepatectomy. *J Magn Reson Imaging* 2020 [PMID: 33217114 DOI: 10.1002/jmri.27424]

111 **Liu F**, Liu D, Wang K, Xie X, Su L, Kuang M, Huang G, Peng B, Wang Y, Lin M, Tian J. Deep Learning Radiomics Based on Contrast-Enhanced Ultrasound Might Optimize Curative Treatments for Very-Early or Early-Stage Hepatocellular Carcinoma Patients. *Liver Cancer* 2020; **9**: 397-413 [PMID: 32999867 DOI: 10.1159/000505694]

112 **Chen M**, Cao J, Hu J, Topatana W, Li S, Juengpanich S, Lin J, Tong C, Shen J, Zhang B, Wu J, Pocha C, Kudo M, Amedei A, Trevisani F, Sung PS, Zaydfudim VM, Kanda T, Cai X. Clinical-Radiomic Analysis for Pretreatment Prediction of Objective Response to First Transarterial Chemoembolization in Hepatocellular Carcinoma. *Liver Cancer* 2021; **10**: 38-51 [PMID: 33708638 DOI: 10.1159/000512028]

113 **European Association for the Study of the Liver**. EASL Clinical Practice Guidelines: Management of hepatocellular carcinoma. *J Hepatol* 2018; **69**: 182-236 [PMID: 29628281 DOI: 10.1016/j.jhep.2018.03.019]

114 **Gillies RJ**, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. *Radiology* 2016; **278**: 563-577 [PMID: 26579733 DOI: 10.1148/radiol.2015151169]

115 **Lambin P**, Leijenaar RTH, Deist TM, Peerlings J, de Jong EEC, van Timmeren J, Sanduleanu S, Larue RTHM, Even AJG, Jochems A, van Wijk Y, Woodruff H, van Soest J, Lustberg T, Roelofs E, van Elmpt W, Dekker A, Mottaghy FM, Wildberger JE, Walsh S. Radiomics: the bridge between medical imaging and personalized medicine. *Nat Rev Clin Oncol* 2017; **14**: 749-762 [PMID: 28975929 DOI: 10.1038/nrclinonc.2017.141]

116 **Erstad DJ**, Tanabe KK. Prognostic and Therapeutic Implications of Microvascular Invasion in Hepatocellular Carcinoma. *Ann Surg Oncol* 2019; **26**: 1474-1493 [PMID: 30788629 DOI: 10.1245/s10434-019-07227-9]

117 **Metter DM**, Colgan TJ, Leung ST, Timmons CF, Park JY. Trends in the US and Canadian Pathologist Workforces From 2007 to 2017. *JAMA Netw Open* 2019; **2**: e194337 [PMID: 31150073

DOI: 10.1001/jamanetworkopen.2019.4337]

118 **Tomita N**, Abdollahi B, Wei J, Ren B, Suriawinata A, Hassanpour S. Attention-Based Deep Neural Networks for Detection of Cancerous and Precancerous Esophagus Tissue on Histopathological Slides. *JAMA Netw Open* 2019; **2**: e1914645 [PMID: 31693124 DOI: 10.1001/jamanetworkopen.2019.14645]

119 **Sharma H**, Zerbe N, Klempert I, Hellwich O, Hufnagl P. Deep convolutional neural networks for automatic classification of gastric carcinoma using whole slide images in digital histopathology. *Comput Med Imaging Graph* 2017; **61**: 2-13 [PMID: 28676295 DOI: 10.1016/j.compmedimag.2017.06.001]

120 **Li Y**, Li X, Xie X, Shen L. Deep learning based gastric cancer identification. Proceedings of the 2018 IEEE 15th International Symposium on Biomedical Imaging; 2018: 182-185 [DOI: 10.1109/ISBI.2018.8363550]

121 **Leon F**, Gelvez M, Jaimes Z, Gelvez T, Arguello H. Supervised Classification of Histopathological Images Using Convolutional Neuronal Networks for Gastric Cancer Detection. Proceedings of the 2019 XXII Symposium on Image, Signal Processing and Artificial Vision; 2019: 1-5 [DOI: 10.1109/STSIVA.2019.8730284]

122 **Sun M**, Zhang G, Dang H, Qi X, Zhou X, Chang Q. Accurate Gastric Cancer Segmentation in Digital Pathology Images Using Deformable Convolution and Multi-Scale Embedding Networks. IEEE Access 2019; 7: 75530-75541 [DOI: 10.1109/ACCESS.2019.2918800]

123 **Ma B**, Guo Y, Hu W, Yuan F, Zhu Z, Yu Y, Zou H. Artificial Intelligence-Based Multiclass Classification of Benign or Malignant Mucosal Lesions of the Stomach. *Front Pharmacol* 2020; **11**: 572372 [PMID: 33132910 DOI: 10.3389/fphar.2020.572372]

124 **Yoshida H**, Shimazu T, Kiyuna T, Marugame A, Yamashita Y, Cosatto E, Taniguchi H, Sekine S, Ochiai A. Automated histological classification of whole-slide images of gastric biopsy specimens. *Gastric Cancer* 2018; **21**: 249-257 [PMID: 28577229 DOI: 10.1007/s10120-017-0731-8]

125 **Qu J**, Hiruta N, Terai K, Nosato H, Murakawa M, Sakanashi H. Gastric Pathology Image Classification Using Stepwise Fine-Tuning for Deep Neural Networks. *J Healthc Eng* 2018; **2018**: 8961781 [PMID: 30034677 DOI: 10.1155/2018/8961781]

126 **Iizuka O**, Kanavati F, Kato K, Rambeau M, Arihiro K, Tsuneki M. Deep Learning Models for Histopathological Classification of Gastric and Colonic Epithelial Tumours. *Sci Rep* 2020; **10**: 1504 [PMID: 32001752 DOI: 10.1038/s41598-020-58467-9]

127 **Korbar B**, Olofson AM, Miraflor AP, Nicka CM, Suriawinata MA, Torresani L, Suriawinata AA, Hassanpour S. Deep Learning for Classification of Colorectal Polyps on Whole-slide Images. *J Pathol Inform* 2017; **8**: 30 [PMID: 28828201 DOI: 10.4103/jpi.jpi_34_17]

128 **Wei JW**, Suriawinata AA, Vaickus LJ, Ren B, Liu X, Lisovsky M, Tomita N, Abdollahi B, Kim AS, Snover DC, Baron JA, Barry EL, Hassanpour S. Evaluation of a Deep Neural Network for Automated Classification of Colorectal Polyps on Histopathologic Slides. *JAMA Netw Open* 2020; **3**: e203398 [PMID: 32324237 DOI: 10.1001/jamanetworkopen.2020.3398]

129 **Shapcott M**, Hewitt KJ, Rajpoot N. Deep Learning With Sampling in Colon Cancer Histology. *Front Bioeng Biotechnol* 2019; **7**: 52 [PMID: 30972333 DOI: 10.3389/fbioe.2019.00052]

130 **Geessink OGF**, Baidoshvili A, Klaase JM, Ehteshami Bejnordi B, Litjens GJS, van Pelt GW, Mesker WE, Nagtegaal ID, Ciompi F, van der Laak JAWM. Computer aided quantification of intratumoral stroma yields an independent prognosticator in rectal cancer. *Cell Oncol (Dordr)* 2019; **42**: 331-341 [PMID: 30825182 DOI: 10.1007/s13402-019-00429-z]

131 **Song Z**, Yu C, Zou S, Wang W, Huang Y, Ding X, Liu J, Shao L, Yuan J, Gou X, Jin W, Wang Z, Chen X, Chen H, Liu C, Xu G, Sun Z, Ku C, Zhang Y, Dong X, Wang S, Xu W, Lv N, Shi H. Automatic deep learning-based colorectal adenoma detection system and its similarities with pathologists. *BMJ Open* 2020; **10**: e036423 [PMID: 32912980 DOI: 10.1136/bmjopen-2019-036423]

132 **Wang TH**, Chen TC, Teng X, Liang KH, Yeh CT. Automated biphasic morphological assessment of hepatitis B-related liver fibrosis using second harmonic generation microscopy. *Sci Rep* 2015; **5**: 12962 [PMID: 26260921 DOI: 10.1038/srep12962]

133 **Forlano R**, Mullish BH, Giannakeas N, Maurice JB, Angkathunyakul N, Lloyd J, Tzallas AT, Tsipouras M, Yee M, Thursz MR, Goldin RD, Manousou P. High-Throughput, Machine Learning-Based Quantification of Steatosis, Inflammation, Ballooning, and Fibrosis in Biopsies From Patients With Nonalcoholic Fatty Liver Disease. *Clin Gastroenterol Hepatol* 2020; **18**: 2081-2090. e9 [PMID: 31887451 DOI: 10.1016/j.cgh.2019.12.025]

134 **Li S**, Jiang H, Pang W. Joint multiple fully connected convolutional neural network with extreme learning machine for hepatocellular carcinoma nuclei grading. *Comput Biol Med* 2017; **84**: 156-167 [PMID: 28365546 DOI: 10.1016/j.compbiomed.2017.03.017]

135 **Kiani A**, Uyumazturk B, Rajpurkar P, Wang A, Gao R, Jones E, Yu Y, Langlotz CP, Ball RL, Montine TJ, Martin BA, Berry GJ, Ozawa MG, Hazard FK, Brown RA, Chen SB, Wood M, Allard LS, Ylagan L, Ng AY, Shen J. Impact of a deep learning assistant on the histopathologic classification of liver cancer. *NPJ Digit Med* 2020; **3**: 23 [PMID: 32140566 DOI: 10.1038/s41746-020-0232-8]

136 **Steinbuss G**, Kriegsmann K, Kriegsmann M. Identification of Gastritis Subtypes by Convolutional Neuronal Networks on Histological Images of Antrum and Corpus Biopsies. *Int J Mol Sci* 2020; **21** [PMID: 32932860 DOI: 10.3390/ijms21186652]

137 **Liu Y**, Li X, Zheng A, Zhu X, Liu S, Hu M, Luo Q, Liao H, Liu M, He Y, Chen Y. Predict Ki-67

Positive Cells in H&E-Stained Images Using Deep Learning Independently From IHC-Stained Images. *Front Mol Biosci* 2020; **7**: 183 [PMID: 32903653 DOI: 10.3389/fmolb.2020.00183]

138 **Kather JN**, Pearson AT, Halama N, Jäger D, Krause J, Loosen SH, Marx A, Boor P, Tacke F, Neumann UP, Grabsch HI, Yoshikawa T, Brenner H, Chang-Claude J, Hoffmeister M, Trautwein C, Luedde T. Deep learning can predict microsatellite instability directly from histology in gastrointestinal cancer. *Nat Med* 2019; **25**: 1054-1056 [PMID: 31160815 DOI: 10.1038/s41591-019-0462-y]

139 **Bychkov D**, Linder N, Turkki R, Nordling S, Kovanen PE, Verrill C, Walliander M, Lundin M, Haglund C, Lundin J. Deep learning based tissue analysis predicts outcome in colorectal cancer. *Sci Rep* 2018; **8**: 3395 [PMID: 29467373 DOI: 10.1038/s41598-018-21758-3]

140 **Kather JN**, Krisam J, Charoentong P, Luedde T, Herpel E, Weis CA, Gaiser T, Marx A, Valous NA, Ferber D, Jansen L, Reyes-Aldasoro CC, Zörnig I, Jäger D, Brenner H, Chang-Claude J, Hoffmeister M, Halama N. Predicting survival from colorectal cancer histology slides using deep learning: A retrospective multicenter study. *PLoS Med* 2019; **16**: e1002730 [PMID: 30677016 DOI: 10.1371/journal.pmed.1002730]

141 **Echle A**, Grabsch HI, Quirke P, van den Brandt PA, West NP, Hutchins GGA, Heij LR, Tan X, Richman SD, Krause J, Alwers E, Jenniskens J, Offermans K, Gray R, Brenner H, Chang-Claude J, Trautwein C, Pearson AT, Boor P, Luedde T, Gaisa NT, Hoffmeister M, Kather JN. Clinical-Grade Detection of Microsatellite Instability in Colorectal Tumors by Deep Learning. *Gastroenterology* 2020; **159**: 1406-1416. e11 [PMID: 32562722 DOI: 10.1053/j.gastro.2020.06.021]

142 **Skrede OJ**, De Raedt S, Kleppe A, Hveem TS, Liestøl K, Maddison J, Askautrud HA, Pradhan M, Nesheim JA, Albregtsen F, Farstad IN, Domingo E, Church DN, Nesbakken A, Shepherd NA, Tomlinson I, Kerr R, Novelli M, Kerr DJ, Danielsen HE. Deep learning for prediction of colorectal cancer outcome: a discovery and validation study. *Lancet* 2020; **395**: 350-360 [PMID: 32007170 DOI: 10.1016/S0140-6736(19)32998-8]

143 **Sirinukunwattana K**, Domingo E, Richman SD, Redmond KL, Blake A, Verrill C, Leedham SJ, Chatzipli A, Hardy C, Whalley CM, Wu CH, Beggs AD, McDermott U, Dunne PD, Meade A, Walker SM, Murray GI, Samuel L, Seymour M, Tomlinson I, Quirke P, Maughan T, Rittscher J, Koelzer VH; S:CORT consortium. Image-based consensus molecular subtype (imCMS) classification of colorectal cancer using deep learning. *Gut* 2021; **70**: 544-554 [PMID: 32690604 DOI: 10.1136/gutjnl-2019-319866]

144 **Jang HJ**, Lee A, Kang J, Song IH, Lee SH. Prediction of clinically actionable genetic alterations from colorectal cancer histopathology images using deep learning. *World J Gastroenterol* 2020; **26**: 6207-6223 [PMID: 33177794 DOI: 10.3748/wjg.v26.i40.6207]

145 **Chaudhary K**, Poirion OB, Lu L, Garmire LX. Deep Learning-Based Multi-Omics Integration Robustly Predicts Survival in Liver Cancer. *Clin Cancer Res* 2018; **24**: 1248-1259 [PMID: 28982688 DOI: 10.1158/1078-0432.CCR-17-0853]

146 **Saillard C**, Schmauch B, Laifa O, Moarii M, Toldo S, Zaslavskiy M, Pronier E, Laurent A, Amaddeo G, Regnault H, Sommacale D, Ziol M, Pawlotsky JM, Mulé S, Luciani A, Wainrib G, Clozel T, Courtiol P, Calderaro J. Predicting Survival After Hepatocellular Carcinoma Resection Using Deep Learning on Histological Slides. *Hepatology* 2020; **72**: 2000-2013 [PMID: 32108950 DOI: 10.1002/hep.31207]

147 **Fu Y**, Jung AW, Torne RV, Gonzalez S, Vöhringer H, Shmatko A, Yates LR, Jimenez-Linan M, Moore L, Gerstung M. Pan-cancer computational histopathology reveals mutations, tumor composition and prognosis. *Nature Cancer* 2020; **1**: 800-810 [DOI: 10.1038/s43018-020-0085-8]

148 **Sangro B**, Melero I, Wadhawan S, Finn RS, Abou-Alfa GK, Cheng AL, Yau T, Furuse J, Park JW, Boyd Z, Tang HT, Shen Y, Tschaika M, Neely J, El-Khoueiry A. Association of inflammatory biomarkers with clinical outcomes in nivolumab-treated patients with advanced hepatocellular carcinoma. *J Hepatol* 2020; **73**: 1460-1469 [PMID: 32710922 DOI: 10.1016/j.jhep.2020.07.026]

149 **Stead WW**. Clinical Implications and Challenges of Artificial Intelligence and Deep Learning. *JAMA* 2018; **320**: 1107-1108 [PMID: 30178025 DOI: 10.1001/jama.2018.11029]

150 **Sung JJ**, Poon NC. Artificial intelligence in gastroenterology: where are we heading? *Front Med* 2020; **14**: 511-517 [PMID: 32458189 DOI: 10.1007/s11684-020-0742-4]

151 **Poon NC**, Sung JJ. Self-driving cars and AI-assisted endoscopy: Who should take the responsibility when things go wrong? *J Gastroenterol Hepatol* 2019; **34**: 625-626 [PMID: 30920688 DOI: 10.1111/jgh.14641]

152 **Li S**, Topatana W, Juengpanich S, Cao J, Hu J, Zhang B, Ma D, Cai X, Chen M. Development of synthetic lethality in cancer: molecular and cellular classification. *Signal Transduct Target Ther* 2020; **5**: 241 [PMID: 33077733 DOI: 10.1038/s41392-020-00358-6]

153 **Topatana W**, Juengpanich S, Li S, Cao J, Hu J, Lee J, Suliyanto K, Ma D, Zhang B, Chen M, Cai X. Advances in synthetic lethality for cancer therapy: cellular mechanism and clinical translation. *J Hematol Oncol* 2020; **13**: 118 [PMID: 32883316 DOI: 10.1186/s13045-020-00956-5]

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