Artificial intelligence applications in inflammatory bowel disease: Emerging technologies and future directions

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Abstract
Inflammatory bowel disease (IBD) is a complex and multifaceted disorder of the gastrointestinal tract that is increasing in incidence worldwide and associated with significant morbidity. The rapid accumulation of large datasets from electronic health records, high-definition multi-omics (including genomics, proteomics, transcriptomics, and metagenomics), and imaging modalities (endoscopy and endomicroscopy) have provided powerful tools to unravel novel mechanistic insights and help address unmet clinical needs in IBD. Although the application of artificial intelligence (AI) methods has facilitated the analysis, integration, and interpretation of large datasets in IBD, significant heterogeneity in AI methods, datasets, and clinical outcomes and the need for unbiased prospective validations studies are current barriers to incorporation of AI into clinical practice. The purpose of this review is to summarize the most recent advances in the application of AI and machine learning technologies in the diagnosis and risk prediction, assessment of disease severity, and prediction of clinical outcomes in patients with IBD.

Key Words: Artificial intelligence; Machine learning; Inflammatory bowel disease; Crohn’s disease; Ulcerative colitis; Clinical outcomes

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**INTRODUCTION**

Inflammatory bowel disease (IBD), which includes Crohn’s disease (CD) and ulcerative colitis (UC), is a chronic inflammatory disorder of the gastrointestinal tract. IBD has emerged as a global disease with increasing incidence worldwide and associated with significant healthcare utilization[1,2]. The pathogenesis of IBD is complex and is thought to involve an interplay between loss of tolerance to commensal gut bacteria, intestinal epithelial barrier dysfunction, and immune dysregulation[3-7]. The diagnosis of IBD is based on a combination of factors including clinical data (e.g., chronicity of gastrointestinal symptoms), laboratory values (elevated inflammatory markers such as C-reactive protein and fecal calprotectin), imaging, endoscopy, and histology (gastrointestinal inflammation with architectural distortion)[8]. Although treatment algorithms based on clinical trials and experience have been developed to inform clinical management in IBD[9], there is significant heterogeneity among patients with IBD with regards to presentation, response to therapy, and long-term clinical outcomes such development of strictures and need for surgery[10,11]. There is a great need for precision medicine strategies to improve diagnostic and therapeutic approaches in IBD.

Precision medicine efforts in IBD have led to more in-depth phenotyping of patients with IBD using large scale databases from clinical trials and cohort studies, deep immunophenotyping using whole genome gene expression datasets, proteomics, transcriptomics, and metagenomics of gut microbiota, and complex predictive models incorporating computer-assisted analysis of endoscopic images and histology[12-14]. This has inevitably led to vast arrays of high dimensional data that pose significant challenges with traditional statistical and computational methods[15]. Technological advances in artificial intelligence (AI) have revolutionized the ability of clinicians and researchers to process, analyze, and interpret high dimensional data and large datasets.

AI is a broad and multidisciplinary field incorporating concepts from computer science, engineering, philosophy, and linguistics aimed at understanding and designing systems that display or mimic human intelligence. The term was first coined in 1965 by McCarthy [16,17]. Machine learning (ML) is a subdiscipline of AI where computer algorithms apply statistical models to learn associations of predictive power from examples in provided datasets (e.g., Dragon dictation, SPAM, Netflix). ML may be programmed through supervised learning or unsupervised learning. In supervised learning, computer programs are trained to learn associations between inputs and outputs in data through analysis of predefined outputs of interest (by human operator). Once associations have been learned using existing data, supervised ML classifiers could then be used to predict future examples using different datasets. Examples of supervised ML include random forest (RF) and support vector machines (SVM). In unsupervised learning, computer programs learn associations in data without external definitions of associations of interest. This method allows for the identification of previously undiscovered predictors. Deep learning, commonly known as neural networks, includes newer techniques that are based on models with fewer assumptions, rely on multiple layers of representation of the data with successive transformations that amplify aspects of the input which improves discrimination power and thus able to handle more complex data (e.g., Facebook face recognition, credit card fraud)[17]. There has been increased interest in use of AI in IBD in recent years.

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years with many prior groups applying ML methods to identify meaningful insights in diagnostics and prediction models in IBD. The purpose of this review is to provide a comprehensive summary of advances in the application of AI and ML technologies in the diagnosis and risk prediction, assessment of disease severity, and prediction of clinical outcomes in patients with IBD.

LITERATURE SEARCH

We performed a literature review using PubMed (MEDLINE) from inception to December 15, 2020 of studies applying AI in IBD. Our search strategy included the following combinations: ((((((inflammatory bowel disease[Title])) OR (ulcerative colitis[Title])) OR (Crohn's disease[Title])) AND (artificial intelligence[Title])) OR (computer-assisted[Title])) OR (computer-aided[Title])) OR (neural network[Title])) OR (machine learning[Title])) OR (deep learning[Title]). We included studies that used AI in the (1) diagnosis or risk prediction of IBD, (2) assessment of disease severity in IBD, and (3) prediction of therapy response and clinical outcomes in IBD. We excluded reviews, studies with non-human subjects (animal models), or studies that did not provide objective measures of the efficacy of AI applications (e.g., measures of precision, accuracy, area under the curve (AUC), sensitivity, specificity, etc.).

RESULTS

Our search strategy yielded 98 studies evaluating AI in IBD of which 58 studies[18-74] met inclusion criteria and were included in the final review. About 86.2% (50/58) of studies were published within the past 5 years (2015 and later). There were 23 studies[18-39] that focused on IBD diagnosis and risk prediction, 19 studies[40-58] which evaluated disease activity, and 17 studies[45,59-74] which predicted IBD clinical outcomes (response to therapy, colonic neoplasia, post-surgical complications, quality of life, IBD well-being and emotional content). There were 22 studies with combined IBD cohorts (CD and UC), 16 studies with UC patients only, 18 studies with CD only, and 5 pediatric IBD cohorts. The most common AI classifications used were neural networks (convolutional and deep) at 32.7% (19/58 studies), RF at 29.3% (17/58 studies), and SVM at 29.3% (17/58 studies).

AI in diagnosis and risk prediction of IBD

Table 1 summarizes studies included which applied AI in the diagnosis and risk prediction of IBD. There were 17 studies focused on IBD diagnosis, whereas 5 studies focused on predicting risk of IBD. Data modalities included genetic/genomic datasets (n = 16 studies), imaging and endoscopic datasets (n = 4), and protein expression/proteomics (n = 2 studies). Some groups have used ML to develop IBD risk prediction models based on gene expression datasets. In a cross-sectional study of 180 CD patients, 149 UC patients and 90 healthy controls by Isakov et al[21], RF and SVM used microarray and RNA-seq data sets to classify a list of 16390 genes. Their combined IBD risk prediction model demonstrated an AUC, sensitivity, specificity, and accuracy values of 0.829, 0.577, 0.880, and 0.808, respectively. In another cross-sectional study of 18227 CD patients and 34050 healthy controls, Romagnoni et al[20] used gradient boosted trees and artificial neural networks to analyze gene expression profiles. Using single nucleotide polymorphisms, their final predictive model for CD achieved AUC of 0.80. Likewise, a cross-sectional study of 20 UC patients and 20 healthy controls by Duttagupta et al[33] used SVM to analyze microRNA profiles. Their SVM classifier measurements revealed a predictive score accuracy of 92.8%, specificity of 96.2%, and sensitivity of 89.5% in distinguishing UC patients from normal individuals.

A major challenge in IBD diagnosis is the distinction between CD and UC which is based on clinical features such as the distribution of inflammation along the gastrointestinal tract. The misdiagnosis of IBD subtype is not uncommon[74]. Distinguishing between CD and UC is clinically important as IBD subtype informs clinical management. AI has been employed to analyze molecular data to distinguish between CD and UC. In a cross-sectional study of 59 CD patients, 26 UC patients, and 42 healthy controls applying deep belief networks (DBNs) and SVM to gene expression datasets, Smolander et al[25] explored the diagnosis UC from CD. Using DBN only, the accuracy for diagnosis of UC was 97.06% and CD was 97.07%. Using both DBN and SVM, accuracy for diagnosis of UC was 97.06% and CD was 97.03%.
Using single nucleotide polymorphisms (SNPs), final predictive model achieved AUC of 0.80.

AI classifier

CD/UC

Risk of IBD

Cross-sectional, 146 UC

Study results/validation cohort

Cross-sectional, 68 IBD

CD/UC

Risk of IBD

Cross-sectional, 180 CD

Rubin et al.[28], 2019

CITRUS supervised machine learning algorithm. No comparator

CD/UC

Peripheral blood mononuclear cells and intestinal biopsies mass cytometry

Diagnosis of IBD

An 8-parameter immune signature distinguished Crohn's disease from ulcerative colitis with an AUC = 0.845 (95% CI: 0.742-0.948). No validation cohort included

Yuan et al.[22], 2017

Sequential minimal optimization vs DisGeNET (Version 4.0)

CD/UC

Gene Expression datasets

Risk of IBD

By analyzing the gene expression profiles using minimum redundancy maximum relevance and incremental feature selection, 21 genes were obtained that could effectively distinguish samples from IBD and the non-IBD samples. Highest total prediction accuracy was 97.64% using the 1170th feature set. Validation cohort included

Hübenthal et al.[23], 2013

SVM vs RF

CD/UC

MicroRNAs

Diagnosis of IBD

Measured by the AUC the corresponding median holdout-validated accuracy was estimated as ranging from 0.73 to 1.00 and 0.89 to 0.98, respectively. In combination, the corresponding models provide tools for the distinction of CD and UC as well as CD, UC and healthy control with expected classification error rates of 3.1 and 3.3%, respectively. Validation cohort included

Tong et al.[24], 2020

RF vs convolutional neural network (CNN)

CD/UC

Colonoscopy Endoscopic Images

Diagnosis of IBD

RF sensitivities/specificities of UC/CD were 0.89/0.84, 0.83/0.82, and 0.72/0.77, respectively, while the values for the CNN of CD was 0.90/0.77. The precisions/recalls of UC-CD when employing RF were 0.97/0.97, 0.65/0.53, respectively, and when employing the CNN were 0.99/0.97 and 0.87/0.83, respectively. Validation cohort included

Smolander et al.[25], 2019

Deep belief networks (DBNs) vs SVM

CD/UC

Gene Expression datasets

Diagnosis of IBD

Using DBN only, accuracy for diagnosis of UC was 97.06% and CD was 97.07%. Using both DBN and SVM, accuracy for diagnosis of UC was 97.06% and CD was 97.03%. Validation cohort included

Abbas et al.[26], 2019

RF vs network-based biomarker discovery

Peds CD/UC

Diagnosis of IBD

For the diagnosis of IBD, highest AUC attained by top Random Forest classifiers was 0.77. No validation cohort included

Khorasani et al.[27], 2020

SVM vs recently developed feature selection algorithm (robustness-performance tradeoff, RPT)

UC

Gene Expression dataset

Diagnosis of IBD

Our model perfectly detected all active cases and had an average precision of 0.62 in the inactive cases. Validation cohort included

Rubin et al.[28], 2019

CITRUS supervised machine learning algorithm. No comparator

CD/UC

Peripheral blood mononuclear cells and intestinal biopsies mass cytometry

Diagnosis of IBD

An 8-parameter immune signature distinguished Crohn's disease from ulcerative colitis with an AUC = 0.845 (95% CI: 0.742-0.948). No validation cohort included

Wei et al.[19], 2013

SVM with gradient boosted trees (GBT) vs simple log odds method

CD/UC

Risk of IBD

Cross-sectional, 30000 IBD patients, 22000 healthy controls

AUC = 0.845 (95%CI: 0.742-0.948). No validation cohort included

Romagnoni et al.[20], 2019

Artificial neural networks (ANNs) vs penalized logistic regression (LR), and GBT

CD

Risk of IBD

Cross-sectional, 18227 CD patients, 34080 healthy controls

AUC 0.862 and 0.826 for CD and UC, respectively. Validation cohort included

Isakov et al.[21], 2017

Random forest (RF), SVM with svmPoly), extreme gradient boosting vs elastic net regularized generalized linear model (glmnet)

CD/UC

Risk of IBD

Cross-sectional, 180 CD patients, 149 UC patients, 90 healthy controls

AUC 0.862 and 0.826 for CD and UC, respectively. Validation cohort included

Mossotto et al.[18], 2017

Support vector machines (SVM) vs linear discriminant

Peds CD/UC

Diagnosis of IBD

Diagnostic accuracy of 82.7% with an AUC of 0.87 in diagnosing Crohn's disease or ulcerative colitis. Validation cohort included

**Table 1 Artificial intelligence in diagnosis and risk prediction of inflammatory bowel disease**

| Ref. | AI classifier vs comparator | IBD type | Study design and sample size | Modality | Outcome | Study results/validation cohort |
|------|-----------------------------|----------|-----------------------------|----------|---------|---------------------------------|
| Mossotto et al.[18], 2017 | Support vector machines (SVM) vs linear discriminant | Peds CD/UC | Prospective cohort, 287 IBD patients | Endoscopic and histologic inflammation | Diagnosis of IBD | Diagnostic accuracy of 82.7% with an AUC of 0.87 in diagnosing Crohn's disease or ulcerative colitis. Validation cohort included |
| Wei et al.[19], 2013 | SVM with gradient boosted trees (GBT) vs simple log odds method | CD/UC | Cross-sectional, 30000 IBD patients, 22000 healthy controls | Genetics, ImmunoChip | Risk of IBD | The SVM demonstrated very comparable performance (AUC 0.862 and 0.826 for CD and UC, respectively), whereas GBT showed inferior performance (AUC 0.802 and 0.782 for CD and UC, respectively. Validation cohort included |
| Romagnoni et al.[20], 2019 | Artificial neural networks (ANNs) vs penalized logistic regression (LR), and GBT | CD | Cross-sectional, 18227 CD patients, 34080 healthy controls | Genetics, ImmunoChip | Risk of IBD | Using single nucleotide polymorphisms (SNPs), final predictive model achieved AUC of 0.80. Validation cohort included |
| Isakov et al.[21], 2017 | Random forest (RF), SVM with svmPoly), extreme gradient boosting vs elastic net regularized generalized linear model (glmnet) | CD/UC | Cross-sectional, 180 CD patients, 149 UC patients, 90 healthy controls | Expression data (microarray and RNA-seq) | Risk of IBD | The method was used to classify a list of 16390 genes. Each gene received a score that was used to prioritize it according to its predicted association to IBD. The combined model demonstrated AUC, sensitivity, specificity, and accuracy values of 0.829, 0.577, 0.88, and 0.808, respectively. Validation cohort included |
| Yuan et al.[22], 2017 | Sequential minimal optimization vs DisGeNET (Version 4.0) | CD/UC | Cross-sectional, 59 CD patients, 26 UC patients, 42 healthy controls | Gene Expression datasets | Risk of IBD | By analyzing the gene expression profiles using minimum redundancy maximum relevance and incremental feature selection, 21 genes were obtained that could effectively distinguish samples from IBD and the non-IBD samples. Highest total prediction accuracy was 97.64% using the 1170th feature set. Validation cohort included |
| Hübenthal et al.[23], 2013 | SVM vs RF | CD/UC | Cross-sectional, 40 CD patients, 36 UC patients, 38 healthy controls | MicroRNAs | Diagnosis of IBD | Measured by the AUC the corresponding median holdout-validated accuracy was estimated as ranging from 0.73 to 1.00 and 0.89 to 0.98, respectively. In combination, the corresponding models provide tools for the distinction of CD and UC as well as CD, UC and healthy control with expected classification error rates of 3.1 and 3.3%, respectively. Validation cohort included |
| Tong et al.[24], 2020 | RF vs convolutional neural network (CNN) | CD/UC | Retrospective Cohort, 875 CD patients, 5128 UC patients | Colonoscopy Endoscopic Images | Diagnosis of IBD | RF sensitivities/specificities of UC/CD were 0.89/0.84, 0.83/0.82, and 0.72/0.77, respectively, while the values for the CNN of CD was 0.90/0.77. The precisions/recalls of UC-CD when employing RF were 0.97/0.97, 0.65/0.53, respectively, and when employing the CNN were 0.99/0.97 and 0.87/0.83, respectively. Validation cohort included |
| Smolander et al.[25], 2019 | Deep belief networks (DBNs) vs SVM | CD/UC | Cross-sectional, 59 CD patients, 26 UC patients, 42 healthy controls | Gene Expression datasets | Diagnosis of IBD | Using DBN only, accuracy for diagnosis of UC was 97.06% and CD was 97.07%. Using both DBN and SVM, accuracy for diagnosis of UC was 97.06% and CD was 97.03%. Validation cohort included |
| Abbas et al.[26], 2019 | RF vs network-based biomarker discovery | Peds CD/UC | Cross-sectional, 657 IBD patients, 316 healthy controls | Large dataset of newborn pediatric IBD metagenomics biopsy samples | Diagnosis of IBD | For the diagnosis of IBD, highest AUC attained by top Random Forest classifiers was 0.77. No validation cohort included |
| Khorasani et al.[27], 2020 | SVM vs recently developed feature selection algorithm (robustness-performance tradeoff, RPT) | UC | Cross-sectional, 146 UC patients, 60 healthy controls | Gene Expression dataset | Diagnosis of IBD | Our model perfectly detected all active cases and had an average precision of 0.62 in the inactive cases. Validation cohort included |
| Rubin et al.[28], 2019 | CITRUS supervised machine learning algorithm. No comparator | CD/UC | Cross-sectional, 68 IBD patients | Peripheral blood mononuclear cells and intestinal biopsies mass cytometry | Diagnosis of IBD | An 8-parameter immune signature distinguished Crohn's disease from ulcerative colitis with an AUC = 0.845 (95% CI: 0.742-0.948). No validation cohort included |
| Study | Methods | Disease | Design | Outcome | Results |
|-------|---------|---------|--------|---------|---------|
| Pal et al. [29], 2017 | Naive Bayes and with a consensus machine learning method vs Critical Assessment of Genome Interpretation (CAGI) 4 method | CD | Cross-sectional, 64 CD patients, 47 healthy controls | Genotypes from Exome Sequencing Data | The AUC for predicting risk of Crohn’s disease using the SNP model was 0.72. No validation cohort included |
| Aoki et al. [30], 2019 | Deep CNN. No comparator | CD | Retrospective Cohort, 115 IBD patients | Wireless capsule endoscopy images | The AUC for the detection of erosions and ulcerations was 0.958 (95% CI: 0.947-0.968). The sensitivity, specificity, and accuracy of the CNN were 98.2% (95% CI: 84.8-91.0), 90.3% (95% CI: 90.3-91.4), and 90.8% (95% CI: 90.2-91.3), respectively. Validation cohort included |
| Bielecki et al. [11], 2012 | SVM vs human reader (pathologist) | CD/UC | Cross-sectional, 14 CD patients, 13 UC patients, 11 healthy controls | Raman spectroscopic imaging of epithelium cells | Raman maps of human colon tissue sections were analyzed by utilizing innovative chemometric approaches. Using SVM, it was possible to separate between healthy control patients, patients with Crohn’s Disease, and patients with ulcerative colitis with an accuracy of 98.90%. No validation cohort included |
| Cui et al. [32], 2013 | Recursive SVM vs unsupervised learning strategy | CD/UC | Cross-sectional, 124 IBD patients, 99 healthy controls | 16S rRNA gene analysis | Selection level of 200 features results in the best leave-one-out cross-validation result (accuracy = 88%, sensitivity = 92%, specificity = 84%). Validation cohort included |
| Duttagupta et al. [33], 2012 | SVM. No comparator | UC | Cross-sectional, 20 UC patients, 20 healthy controls | MicroRNAs | SVM classifier measurements revealed a predictive score of 92.8% accuracy, 96.2% specificity and 89.5% sensitivity in distinguishing ulcerative colitis patients from normal individuals. Validation cohort included |
| Daneshjou et al. [34], 2017 | Naive bayes, neural networks, random forests vs CAGI methods | CD | Cross-sectional, 64 ICD patients, 47 healthy controls | Exome Sequencing | In CAGI4, 111 exomes were derived from a mix of 64 Crohn’s disease patients. Top performing methods had an AUC of 0.87. Validation cohort included |
| Geurts et al. [35], 2005 | RF vs SVM | CD/UC | Prospective cohort, 30 CD patients, 30 CD patients | Proteomic Mass Spectrometry | Random forest model to diagnosis IBD had a sensitivity of 81.67%, specificity of 81.17%. Support vector machine model to diagnosis IBD had a sensitivity of 87.92%, specificity of 87.87%. Validation cohort included |
| Li et al. [36], 2020 | RF vs ANN | UC | Cross-sectional, 193 UC patients, 21 healthy controls | Gene Expression Profiles | The random forest algorithm was introduced to determine 1 downregulated and 29 upregulated differentially expressed genes contributing highest to ulcerative colitis occurrence. ANN was developed to calculate differentially expressed genes weights to ulcerative colitis. Prediction results agreed with that of an independent data set (AUC = 0.9506/PR-AUC = 0.9747). Validation cohort included |
| Wingfield et al. [37], 2019 | RF vs SVM | CD | Cross-sectional, 668 CD patients | Metagenomic Data | Highest RPT measure for Crohn’s disease was random forest 0.60 and SVM 0.58. For ulcerative colitis, RPT was random forest 0.70 and SVM 0.48. Validation cohort included |
| Han et al. [38], 2018 | RF vs LR, CORG | CD/UC | Cross-sectional, 24 CD patients, 59 UC patients, 76 healthy controls | Gene Expression Profiles | The gene-based feature sets had median AUC on the validation sets ranging from 0.6 to 0.76. Validation cohort included |
| Wang et al. [39], 2019 | AVADx (Analysis of Variation for Association with Disease) vs two GWAS-based CD evaluation methods | CD | Cross-sectional, 64 CD patients, 47 healthy controls | Whole Exome or Genome Sequencing Data | AVADx highlighted known CD genes including NOD2 and new potential CD genes. AVADx identified 16% (at strict cutoff) of CD patients at 99% precision and 58% of the patients (at default cutoff) with 82% precision in over 3000 individuals from separately sequenced panels. Validation cohort included |

AI: Artificial intelligence; IBD: Inflammatory bowel disease; CD: Crohn’s disease; UC: Ulcerative colitis; AUC: Area under the curve.
a cross-sectional study of 68 IBD patients using a CITRUS supervised ML algorithm to analyze single cell immunophenotyping of peripheral blood mononuclear cells by mass cytometry, Rubin et al.[28] demonstrated that an 8-parameter immune signature distinguished CD from UC with an AUC = 0.845 [95% confidence interval (CI): 0.742-0.948]. ML algorithms have also been applied to analyze large arrays of endoscopic images to differentiate between UC and CD. In a recent retrospective cohort study of 875 CD patients and 5128 UC patients by Tong et al.[24] using RF and convolutional neural networks (CNNs) on endoscopic images, the precision of diagnosing UC/CD with RF and CNNs were 0.97/0.65 and 0.99/0.87, respectively. Taken together, these studies suggest that AI classifiers have high performance in diagnosing or predicting risk of IBD but have some variability with type of AI classifier and modality of data (molecular vs endoscopic).

**AI in assessment of disease severity in IBD**

The assessment of disease activity and grading of severity in IBD could be accomplished using validated clinical symptom scores (e.g., Harvey Bradshaw Index for CD, Mayo Score for UC)[75,76], biomarkers of inflammation (e.g., C-reactive protein, fecal calprotectin)[77,78], endoscopic inflammation indices (e.g., Mayo endoscopic score, simple endoscopic score)[79,80], and histologic scoring systems (e.g., Geboes Score, Robarts Histopathology Index)[81,82]. However, these systems may be subject to recall bias, heterogeneity in patient clinical presentation, and interobserver and interobserver variability[83]. AI has been applied to these existing systems to improve precision and accuracy of quantifying disease severity in IBD.

Table 2 summarizes studies included which applied AI in the assessment of disease severity in IBD. There were 2 studies that assessed clinical disease activity, 2 studies that assessed disease activity by biomarker (C-reactive protein), 13 studies that focused on endoscopic inflammation, and 3 studies that focused on histologic inflammation. Data modalities included electronic health records (n = 2), molecular datasets (n = 3), endoscopic datasets (n = 11 studies), and histologic datasets via endomicroscopy/endoscopcy (n = 2). Using RF to integrate and analyze clinical and laboratory data from publicly available clinical trials (UNITI-1, UNITI-2, and IM-UNITI) data consisting of 401 CD patients, Waljee et al.[42] constructed a CD remission prediction model using the week 6 albumin to C-reactive protein ratio with an AUC of 0.76 (95%CI: 0.71-0.82). Reddy et al.[44] applied gradient boosting machines to electronic health records and predicted inflammation severity in a retrospective cohort of 3335 CD patients with a very high accuracy (AUC) = 92.82%. In a CNN analysis of colonoscopy images from a retrospective cohort of 841 UC patients by Ozawa et al.[55], the CNN-based computer aided diagnostic system showed a high level of performance with AUC of 0.86 and 0.98 to identify Mayo 0 and 0-1, respectively. The performance of the CNN was better for the rectum than for the right side and left side of the colon when identifying Mayo 0 (AUC = 0.92, 0.83, and 0.83, respectively). Likewise, in an ordinal CNN analysis of wireless capsule endoscopy images in a retrospective cohort of 49 CD patients by Barash et al.[50], the classification accuracy of the algorithm was 0.91 for grade 1 vs grade 3 ulcers, 0.78 for grade 2 vs grade 3, and 0.624 for grade 1 vs grade 2. The role of AI in grading severity of histologic inflammation in IBD has also been explored. For example, in a retrospective cohort study of 187 UC patients by Maeda et al.[46], application of SVM to data derived from endomicroscopy to assess histologic inflammation provided diagnostic sensitivity, specificity, and accuracy of 74% (95%CI: 65-81), 97% (95%CI: 95-99), and 91% (95%CI: 83-95), respectively. These examples highlight the clinical utility, versatility, and performance of AI classifiers in grading the disease activity of IBD patients at the clinical, endoscopic, and histologic level. AI performance may be affected by location of inflammation and may be limited by ability to discriminate between subtle differences.

**AI in prediction of therapy response and clinical outcomes in IBD**

The armamentarium of therapies in IBD have expanded significantly in recent years with diverse mechanisms of action ranging from biologics that inhibit proinflammatory cytokines (anti-tumor necrosis factor-α, anti-interleukin-12/23) and leukocyte trafficking to the gut (anti-α4β7) to small molecule inhibitors of the JAK-STAT signaling pathway[84-86]. Despite several IBD treatment options available to clinicians, there are no effective biomarkers or tools to predict response to therapy or to guide selection of alternative therapies after a failed response. Likewise, there is also an unmet clinical need to predict long term clinical outcomes in IBD such as colon cancer. To address these challenges, several groups have applied AI and ML algorithms to existing clinical and molecular datasets.
### Table 2 Artificial Intelligence in assessment of disease severity in inflammatory bowel disease

| Ref. | AI classifier vs comparator | IBD type | Study design and sample size | Modality | Outcomes | Study results/validation cohort |
|------|----------------------------|----------|-----------------------------|---------|---------|---------------------------------|
| Kumar et al [40], 2012 | Support vector machines (SVM) vs human observers | CD | Cross-sectional, 50,000 images (number of patients not given) | Small bowel capsule endoscopy | Endoscopic Inflammation | Database of 47 studies including 50,000 capsule endoscopy images evaluating severity of small bowel lesions. Method had good precision (>90% for lesion detection) and recall (>90%) for lesions of varying severity. Validation cohort included |
| Biasci et al [41], 2019 | Logistic regression with an adaptive Elastic-Net penalty. No comparator | CD/UC | Prospective cohort, 118 IBD patients | Transcriptomics from purified CD8 T cells and/or whole blood | Disease severity, medication escalation | A 17-gene qPCR-based classifier stratified patients into two distinct subgroups. IBDhi patients experienced significantly more aggressive disease than IBDlo patients (analogous to IB2D), with earlier need for treatment escalation [HR 2.65 (CD), 3.12 (UC)] and more escalations over time [for multiple escalations within 18 months: sensitivity=72.7% (CD), 100% (UC); negative predictive value = 90.9% (CD), 100% (UC)]. Validation cohort included |
| Waljee et al [42], 2019 | RF. No comparator | CD | Post-hoc analysis of prospective clinical trials, 401 CD patients | Clinical and laboratory data from publicly available clinical trials (UNITI-1, UNITI-2, and IM-UNITI) | Crohn’s disease remission, C-reactive protein < 5 mg/L | A prediction model using the week-6 albumin to C-reactive protein ratio had an AUC of 0.76 [95% confidence interval (CI): 0.71-0.82]. Validation cohort included |
| Mahapatra et al [43], 2016 | RF. No comparator | CD | Cross-sectional, 35 CD patients | Abdominal magnetic resonance imaging | Segmentation of diseased colon (intestinal inflammation) | Model segmentation accuracy ranged from 82.7% to 92.2%. Validation cohort included |
| Reddy et al [44], 2019 | Gradient boosting machines vs logistic regression | CD | Retrospective, 3335 CD patients | Electronic medical record | Severity of intestinal inflammation (by C-reactive protein) | Machine-learning-based analytic methods such as gradient boosting machines can predict the inflammation severity with a very high accuracy (AUC = 92.82%). Validation cohort included |
| Douglas et al [45], 2018 | RF. No comparator | CD | Cross-sectional, 20 CD patients, 20 healthy controls | Shotgun metagenomics (MGS), 16S RNA gene sequencing | Disease State (Relapse/Remission) | MGS modules significantly classified samples by disease state (accuracy = 68.4%, P = 0.043 and accuracy = 65.8%, P = 0.03, respectively), 165 datasets had a maximum accuracy of 68.4% and P = 0.016 based on strain level for disease state. Validation cohort included |
| Maeda et al [46], 2019 | SVM vs human reader | UC | Retrospective cohort, 187 UC patients | Endocytoscopy | Histologic inflammation | Computer aided diagnosis (CAD) of histologic inflammation provided diagnostic sensitivity, specificity, and accuracy as follows: 74% (95%CI: 65-81), 97% (95%CI: 95-99), and 91% (95%CI: 83-95), respectively. Its reproducibility was perfect (k = 1). Validation cohort included |
| Charisis et al [47], 2016 | SVM vs human reader | CD | Retrospective cohort, 13 CD patients | Wireless capsule endoscopy (WCE) images | Endoscopic Inflammation | Experimental results, along with comparison with other related efforts, have shown that the hybrid adaptive filtering [HAF-Differential Lacunarity (DLac) analysis (HAF-DLac)] via SVM approach evidently outperforms them in the field of WCE image analysis for automated lesion detection, providing higher classification results, up to 93.8% (accuracy), 95.2% (sensitivity), 92.4% (specificity) and 92.6% (precision). Validation cohort included |
| Klang et al [48], 2020 | Convolutional neural network (CNN) vs human reader | CD | Retrospective cohort, 49 CD patients | WCE images | Endoscopic Inflammation | Dataset included 17,640 CE images from 49 patients: 739 images with mucosal ulcers and 10,249 images of normal mucosa. For randomly split images results, AUC was 0.99 with accuracies ranging from 95.4% to 96.7%. For individual patient-level experiments, the AUCs were 0.94-0.99. Validation cohort included |
| Ungaro et al [49], 2021 | Random survival forest. No comparator | Peds CD | Retrospective case-control, 265 peds CD patients | Protein biomarkers using a proximity extension assay (Olink Proteomics) | Penetrating and structuring complications | A model with 5 protein markers predicted penetrating complications with an AUC of 0.79 (95%CI: 0.76-0.82) compared to 0.69 (95%CI: 0.66-0.72) for serologies and 0.74 (95%CI: 0.71-0.77) for clinical variables. A model with 4 protein markers predicted structuring complications with an AUC of 0.68 (95%CI: 0.65-0.71) compared to 0.62 (95%CI: 0.59-0.65) for serologies and 0.52 (95%CI: 0.50-0.53) for clinical variables. Validation cohort included |
Barash et al.[50], 2021  Ordinal CNN. No comparator  CD  Retrospective cohort, 49 CD patients  WCE images  Ulcer Severity Grading  The classification accuracy of the algorithm was 0.91 (95%CI: 0.867-0.954) for grade 1 vs grade 3 ulcers, 0.78 (95%CI: 0.716-0.844) for grade 2 vs grade 3, and 0.624 (95%CI: 0.547-0.701) for grade 1 vs grade 2. Validation cohort included.

Lamash et al.[51], 2019  CNN vs semi-supervised and active learning models  CD  Retrospective cohort, 23 CD patients  Magnetic resonance imaging  Active Crohn’s Disease  CNN exhibited Dice similarity coefficient of 75% ± 18%, 81% ± 8%, and 97% ± 2% for the lumen, wall, and background, respectively. The extracted markers of wall thickness at the location of min radius (P = 0.0013) and the median value of relative contrast enhancement (P = 0.003) could differentiate active and nonactive disease segments. Other extracted markers could differentiate between segments with strictures and segments without strictures (P < 0.05). Validation cohort included.

Takenaka et al.[52], 2020  Deep neural networks vs human reader (endoscopist)  UC  Prospective cohort, 2012 UC patients  Colonoscopy images  Endoscopic inflammation  Deep neural network identified patients with endoscopic remission with 90.1% accuracy (95%CI: 89.2-90.9) and a kappa coefficient of 0.798 (95%CI: 0.780-0.814), using findings reported by endoscopists as the reference standard. Validation cohort included.

Bossuyt et al.[53], 2020  Computer algorithm based on red density (RD) vs blinded central readers  UC  Prospective cohort, 29 UC patients, 6 healthy controls  Colonoscopy Images  Endoscopic and histologic inflammation  In the construction cohort, RD correlated with rhi (r = 0.74, P < 0.0001), Mayo endoscopic subscores (r = 0.76, P < 0.0001) and Endoscopic index of severity scores (r = 0.74, P < 0.0001). The RD sensitivity to change had a standardized effect size of 1.16. in the validation set, RD correlated with rhi (r = 0.65, P = 0.00002). Validation cohort included.

Bhambhvani et al.[54], 2021  CNN vs human reader (endoscopist)  UC  Retrospective cohort, 777 UC patients  Colonoscopy images  Mayo Endoscopic Scores (MES)  The final model classified MES 3 disease with an AUC of 0.96, MES 2 disease with an AUC of 0.86, and MES 1 disease with an AUC 0.89. Overall accuracy was 77.2%. Across MES 1, 2, and 3, average specificity was 85.7%, average sensitivity was 72.4%, average PPV was 77.7%, and the average NPV was 87.0%. Validation cohort included.

Ozawa et al.[55], 2019  CNN vs human reader (endoscopist)  UC  Retrospective cohort, 841 UC patients  Colonoscopy images  MES  The CNN-based CAD system showed a high level of performance with AUC of 0.86 and 0.98 to identify Mayo 0 and 0-1, respectively. The performance of the CNN was better for the rectum than for the right side and left side of the colon when identifying Mayo 0 (AUC = 0.92, 0.83, and 0.83, respectively). Validation cohort included.

Bossuyt et al.[56], 2021  Automated CAD Algorithm vs human reader  UC  Prospective cohort, 48 UC patients  Colonoscopy images with confocal laser endomicroscopy  Histologic Remission  The current automated CAD algorithm detects histologic remission with a high performance (sensitivity of 0.79 and specificity of 0.90) compared with the UCEIS (sensitivity of 0.95 and specificity of 0.69) and MES (sensitivity of 0.98 and specificity of 0.61). No validation cohort included.

Stidham et al.[57], 2019  CNN vs human reader  UC  Retrospective cohort, 3082 UC patients  Colonoscopy images  Endoscopy severity  The CNN was excellent for distinguishing endoscopic remission from moderate-to-severe disease with an AUC of 0.96 (95%CI: 0.967-0.972); a PPV of 0.87 (95%CI: 0.85-0.88) with a sensitivity of 83.0% (95%CI: 80.8-85.4) and specificity of96.0% (95%CI: 95.1-97.1); and NPV of 0.94 (95%CI: 0.93-0.95). No validation cohort included.

Gottlieb et al.[58], 2021  Neural network vs human central reader  UC  Prospective cohort, 249 UC patients  Colonoscopy images  Endoscopy severity  The model’s agreement metric was excellent, with a quadratic weighted kappa of 0.844 (95%CI: 0.787-0.903) for endoscopic Mayo Score and 0.855 (95%CI: 0.80-0.91) for UCEIS. No validation cohort included.

Table 3 summarizes studies included which applied AI in the prediction of therapy response and clinical outcomes in IBD. There were 9 studies that predicted therapy response, 2 studies that predicted presence of extraintestinal manifestations of IBD, 1 study predicting colonic neoplasia, and 1 study predicting post-surgical complications after colectomy. Data modalities included electronic health records (n = 11), molecular
### Table 3 Artificial intelligence in prediction of therapy response and clinical outcomes in inflammatory bowel disease

| Ref. | AI classifier vs comparator | IBD type | Study design and sample size | Modality | Outcomes | Study results/validation cohort |
|------|-----------------------------|----------|-----------------------------|----------|----------|---------------------------------|
| Waljee et al [59], 2018 | Random forest (RF). No comparator | CD/UC | Post-hoc analysis of prospective clinical trial, 594 CD patients | Veteran’s Health Administration Electronic Health Record (EHR) | Outpatient corticosteroids prescribed for IBD and inpatient hospitalizations associated with a diagnosis of IBD | AUC for the RF longitudinal model was 0.85 [95% confidence interval (CI): 0.84–0.85]. AUC for the RF longitudinal model using previous hospitalization or steroid use was 0.87 (95% CI: 0.87–0.88). Validation cohort included |
| Uttam et al [60], 2019 | Support vector machines (SVM) vs nanoscale nuclear architecture mapping (NanoNAM) | CD/UC | Prospective cohort, 103 IBD patients | 3-dimensional NanoNAM of normal-appearing rectal biopsies | Colonic neoplasia | NanoNAM detects colonic neoplasia with an AUC of 0.87 ± 0.04, sensitivity of 0.81 ± 0.09, and specificity of 0.82 ± 0.07 in the independent validation set. Validation cohort included |
| Waljee et al [61], 2017 | RF. No comparator | CD/UC | Retrospective cohort, 1080 IBD patients | EHR, lab values | Remission and clinical outcomes with thiopurines | AUC for algorithm-predicted remission in the validation set was 0.79 vs 0.49 for 6-TGN. The mean number of clinical events per year in patients with sustained algorithm-predicted remission (APR) was 1.08 vs 3.95 in those that did not have sustained APR (P < 1 × 10^−3). Validation cohort included |
| Popa et al [62], 2020 | Neural network model. No comparator | UC | Prospective cohort, 55 UC patients | Clinical and biological parameters and the endoscopic Mayo score | Disease activity after one year of anti-TNF treatment | The classifier achieved an excellent performance predicting the disease activity at one year with an accuracy of 90% and AUC 0.92 on the test set and an accuracy of 100% and an AUC of 1 on the validation set. Validation cohort included |
| Douglas et al [63], 2018 | RF. No comparator | Peds CD | Cross-sectional, 20 CD patients, 20 healthy controls | Shotgun metagenomics (MGS), 16S rRNA gene sequencing | Response to induction therapy | 16S genera were again the top dataset (accuracy = 77.8%; P = 0.008) for predicting response to therapy. MGS-strain (P = 0.029), genus (P = 0.013), and KEGG pathway (P = 0.018) datasets could also classify patients according to therapy response with accuracy = 72.2% for all three. Validation cohort included |
| Waljee et al [64], 2019 | RF vs boosted trees, RuleFit | CD/UC | Cross-sectional, 774 IBD patients | EHR, lab values (thiopurine metabolites) | Response to thiopurine therapy | A RF algorithm using laboratory values and patient age differentiated clinical response from nonresponse in the model validation data set with an AUC of 0.856 (95% CI: 0.793–0.919). Validation cohort included |
| Mentiu et al [65], 2016 | Naïve bayes vs Bayesian additive regression trees vs Bayesian networks | CD/UC | Retrospective cohort, 152 CD patients | Genomic DNA, genetic polymorphism | Presence of extra-intestinal manifestations in IBD patients | Bayesian networks achieved accuracy of 82% when considering only clinical factors and 89% when considering also genetic information, outperforming the other techniques. Validation cohort included |
| Waljee et al [66], 2017 | RF vs baseline regression model | CD/UC | Retrospective cohort, 20368 IBD patients | EHR, lab values | Corticosteroid-free biologic remission with vedolizumab | The AUC for corticosteroid-free biologic remission at week 52 using baseline data was only 0.65 (95% CI: 0.53–0.77), but was 0.75 (95% CI: 0.64–0.86) with data through week 6 of vedolizumab. Validation cohort included |
| Morilla et al [67], 2019 | Deep neural networks. No comparator | UC | Retrospective cohort, 47 UC patients | Colonic microRNA profiles | Responses to therapy | A deep neural network-based classifier identified 9 microRNAs plus 5 clinical factors, routinely recorded at time of hospital admission, that were associated with responses of patients to treatment. This panel discriminated responders to steroids from non-responders with 93% accuracy (AUC, 0.91). Three algorithms, based on microRNA levels, identified responders to infliximab vs non-responders (84% accuracy, AUC 0.82) and responders to cyclosporine vs non-responders (80% accuracy, AUC 0.79). Validation cohort included |
| Wang et al [68], 2020 | Back-propagation neural network (BPNN), SVM vs logistic regression | CD | Cross-sectional, 446 CD patients | EHR | Medication nonadherence to maintenance therapy | The average classification accuracy and AUC of the three models were 85.9% and 0.912 for BPNN, and 87.7% and 0.930 for SVM, respectively. Validation cohort included |
| Bottiglengo | Bayesian machine | CD/UC | Retrospective cohort, | EHR, genetic | Presence of extra-intestinal manifestations | BMLTs had an AUC of 0.50 for classifying the presence of extra-intestinal manifestations. Validation cohort included |
| Authors | Year | Methodology | Dataset | Response | Description |
|---------|------|-------------|---------|----------|-------------|
| Ghoshal et al. | 2019 | Learning techniques (BMLTs) vs logistic regression | 142 IBD patients | Polymorphisms | Manifestations in IBD patients | Cohort included |
| Sofo et al. [70] | 2020 | Nonlinear artificial neural network (ANN) vs multivariate linear PCA | UC | Prospective cohort, 263 UC patients | EHR | Responses to therapy | Multilayer perceptron neural network was trained by back-propagation algorithm (10 networks retained out of 16 tested). The classification accuracy rate was 73% in correctly classifying response to medical treatment in UC patients. No validation cohort included |
| Kang et al. [71] | 2017 | ANN vs logistic regression | UC | Cross-sectional, 24 UC patients | Gene expression profiles | Response to anti-TNF | Balanced accuracy in cross validation test for predicting response to anti-TNF therapy in ulcerative colitis patient was 82%. Validation cohort included |
| Babic et al. [72] | 1997 | CART vs back propagation neural network (BPNN) | CD/UC | Cross-sectional, 200 IBD patients | EHR | Quality of life | Best reached classification accuracy did not exceed 80% in any case. Other classifiers namely, K-nearest-neighbor, learning vector quantization and BPNN confirmed that outcome. Validation cohort included |
| Dong et al. [73] | 2019 | RF, SVM, ANN vs logistic regression | CD | Retrospective cohort, 239 CD patients | EHR, laboratory tests | Crohn’s related surgery | The results revealed that RF predictive model performed better than LR model in terms of accuracy (93.11% vs 91.15%), precision (53.42% vs 44.81%), F1 score (0.6016 vs 0.5763), TN rate (95.08% vs 92.00%), and the AUC (0.8926 vs 0.8809). The AUCs were excellent at 0.9864 in RF, 0.9538 in LR, 0.8809 in DT, 0.9497 in SVM, and 0.9059 in ANN, respectively. Validation cohort included |
| Lerrigo et al. [74] | 2019 | Latent Dirichlet allocation, unsupervised machine learning algorithm. No comparator | CD/UC | Retrospective cohort, 26023 IBD patients | Online posts from the Crohn’s and colitis foundation community forum | Impact of online community forums on well-being and their emotional content | 10702 (20.8%) posts were identified expressing: gratitude (40%), anxiety/fear (20.8%), empathy (18.2%), anger/frustration (13.4%), hope (13.2%), happiness (10.0%), sadness/depression (8.8%), shame/guilt (2.5%), and/or loneliness (2.5%). A common subtheme was the importance of fostering social support. No validation cohort included |

AI: Artificial intelligence; IBD: Inflammatory bowel disease; CD: Crohn’s disease; UC: Ulcerative colitis; AUC: Area under the curve; TNF: Tumor necrosis factor.

datasets (n = 4), and histologic data (n = 1). Waljee et al. [59,65] and Popa et al. [62] have previously applied RF classifiers to clinical data from electronic health records and laboratory values to predict response to various IBD therapies. In one study using data from a prospective clinical trial consisting of 594 CD patients [59], the AUC for a RF longitudinal model for predicting inpatient hospitalizations in IBD patients prescribed outpatient corticosteroids was 0.85 (95% CI: 0.84-0.85). Using a similar RF approach for predicting remission with thiopurine therapy in a prospective cohort of 55 UC patients yielded an AUC of 0.79 [62]. Applying RF to data from a retrospective cohort of 20368 IBD patients with vedolizumab use yielded an AUC of 0.65 (95% CI: 0.53-0.77) for corticosteroid-free vedolizumab remission at week 52 using baseline data and an AUC of 0.75 (95% CI: 0.64-0.86) with data through week 6 of vedolizumab [65]. Molecular datasets have also been used to differentiate between responders and non-responders to various IBD therapies. For example, Morilla et al. [66] used a deep neural network classifier to construct a predictive panel of colonic microRNAs for IBD therapies in a retrospective cohort of 47 UC patients. Their panel discriminated responders to steroids from non-responders with 93% accuracy (AUC, 0.91). In addition, three
algorithms, based on microRNA levels, identified responders to infliximab vs non-responders (84% accuracy, AUC 0.82) and responders to cyclosporine vs non-responders (80% accuracy, AUC 0.79). A more recent prospective study of 55 UC patients by Popa et al. integrated clinical, laboratory, and endoscopic (Mayo scores) datasets using a neural network classifier to predict disease activity after one year of anti-tumor necrosis factor therapy in patients with UC. This classifier achieved an AUC of 0.92 for predicting the disease activity at one year on the test set and an AUC of 1.00 on the validation set. These studies suggest that AI classifiers may play a role in predicting clinical outcomes and response to specific therapies in patients with IBD. However, future clinical trials are needed to compare the efficacy of AI applications in IBD clinical management vs standard of care before incorporation into real life clinical practice.

Finally, AI algorithms have been previously applied to enhance the detection of colonic polyps and distinguish among subtypes of neoplastic colorectal lesions in the general population. Although patients with IBD who have extensive colitis have a significantly greater risk of colorectal cancer compared to the general population, there have been limited studies applying AI technologies to improve colorectal surveillance or develop prediction risk models in patients with IBD. Most studies evaluating polyp detection have excluded IBD patients. Our literature search yielded only one study applying AI for the detection of colonic neoplasia in IBD. Utam et al. employed support SVM to analyze 3-dimensional nanoscale nuclear architecture mapping (NanoNAM) of normal-appearing rectal biopsies in a prospective cohort of 103 IBD patients. In their study, NanoNAM detected colonic neoplasia with an AUC of 0.87 ± 0.04, sensitivity of 0.81 ± 0.09, and specificity of 0.82 ± 0.07 in the independent validation set. Further studies should focus on determining the clinical utility of incorporating AI methods to enhance standard of cancer surveillance in patients with IBD such as chroendoendoscopy and to develop predictive models for risks of colorectal malignancy in IBD patient populations.

CONCLUSION

In conclusion, our literature review has revealed that the applications of AI in IBD have significantly increased in recent years. Our review also highlighted that various AI classifiers may be applied to analyze and integrate large datasets ranging from clinical data from electronic health records, molecular data including gene expression and protein-based studies to a wide array of datasets consisting of endoscopic and histologic images. The application of AI has the potential to improve the accuracy and precision of predicting risk and diagnosis of IBD, assessing disease severity, and predicting outcomes with various IBD therapies. Currently, the application of AI methods in IBD has been limited to the research setting and has not yet been adopted in real life clinical practice. Furthermore, studies applying AI in the context of colorectal cancer surveillance or prediction in IBD are much needed. Given the current status of the field of AI in IBD, future directions should include: (1) Prospective validation of AI applications in IBD in independent cohorts as there is a risk of bias from internal training cohorts and potential limitations with generalizability; (2) Standardization of AI methods and comparative studies evaluating effect of heterogeneity from using different types of datasets on outcomes of interest; (3) Randomized controlled trials to determine whether application of AI in the clinical management of IBD improves clinical outcomes and could be translated into clinical practice; and (4) Randomized controlled trials to determine whether application of AI leads to greater clinical efficacy and cost-effectiveness compared to standard of care before incorporation into real life clinical practice.

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