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ORIGINAL ARTICLE

# Radiomics prediction of surgery in ulcerative colitis refractory to medical treatment

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## Abstract

**Background** The surgeries in drug-resistant ulcerative colitis are determined by complex factors. This study evaluated the predictive performance of radiomics analysis on the basis of whether patients with ulcerative colitis in hospital were in the surgical or medical treatment group by discharge from hospital.

**Methods** This single-center retrospective cohort study used CT at admission of patients with US admitted from 2015 to 2022. The target of prediction was whether the patient would undergo surgery by the time of discharge. Radiomics features were extracted using the rectal wall at the level of the tailbone tip of the CT as the region of interest. CT data were randomly classified into a training cohort and a validation cohort, and LASSO regression was performed using the training cohort to create a formula for calculating the radiomics score.

**Results** A total of 147 patients were selected, and data from 184 CT scans were collected. Data from 157 CT scans matched the selection criteria and were included. Five features were used for the radiomics score. Univariate logistic regression analysis of clinical information detected a significant influence of severity ($p < 0.001$), number of drugs used until surgery ($p < 0.001$), Lichtiger score ($p = 0.024$), and hemoglobin ($p = 0.010$). Using a nomogram combining these items, we found that the discriminatory power in the surgery and medical treatment groups was AUC 0.822 (95% confidence interval (CI) 0.841–0.951) for the training cohort and AUC 0.868 (95% CI 0.729–1.000) for the validation cohort, indicating a good ability to discriminate the outcomes.

**Conclusions** Radiomics analysis of CT images of patients with US at the time of admission, combined with clinical data, showed high predictive ability regarding a treatment strategy of surgery or medical treatment.

**Keywords** Ulcerative colitis · Radiomics · Ulcerative colitis surgery · Machine learning · Prediction

## Introduction

Ulcerative colitis (UC) is an inflammatory bowel disease (IBD) that causes autoimmune inflammation of the colon, with a prevalence of 156–291 cases per 100,000 people per year and that is increasing worldwide [1, 2]. Patients with UC have chronic and recurrent inflammation of the colon and experience repeated relapse and remission despite drug therapy. Drug therapy for UC has evolved rapidly in recent years, with new molecular-targeted agents being approved [3–5]. Endoscopic diagnosis has also evolved, and screening tests after the onset of disease allow for early response to relapse [6]. However, 8–24% of patients with UC still undergo surgery [4, 5].

The indication for surgery in patients with UC can be difficult to determine at the time of relapse. The rate at which patients admitted for UC relapse undergo surgery has changed significantly over time, from 5% in 2007 to 2.7% in 2016, according to previous reports [7]. Perforation, life-threatening intestinal bleeding, and toxic megacolon are conditions that require emergency surgery [8]. On the other hand, when a patient is hospitalized for relapse with nonemergent states, the first step in many cases is to induce remission with drug therapy [9]. Surgical treatment is considered if the patient is refractory to drug therapy, but the indication for surgery is determined on an individual

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basis based on laboratory data, drug treatment history, and patient preference [10].

Radiomics has been studied in recent years to predict treatment outcomes. Radiomics is an image analysis method that extracts a large number of high-dimensional features from medical images [11, 12]. Features obtained by radiomics are phenotypic of the lesion and are associated with clinical and genetic information [11–15]. Studies in cancer and cerebrovascular disease have shown good outcome prediction from data obtained by radiomics [16–19]. In some IBD studies, scholars have reported that machine learning, involving extraction of radiomics data from computed tomography (CT) images of the rectum, was useful for differential diagnosis between Crohn's disease and UC [20, 21]. Whether CT findings are useful in predicting outcomes in UC is controversial [22, 23]. Radiomics, which can extract high-dimensional image information, could improve the accuracy of predicting treatment selection from CT images of patients with UC.

The purpose of this study was to perform machine learning using the radiomics features obtained from admission CT images of patients with UC to predict two optional outcomes: surgery or medical treatment alone before discharge.

## Methods

### Subjects

This study was approved by the Institutional Review Board of Keio University School of Medicine (no. 20221035). CT images of patients with UC at the time of hospitalization for relapse were included in the radiomics analysis. The CT data of patients were collected for study enrollment according to the inclusion and exclusion criteria below. The inclusion criteria were as follows: (1) patients were endoscopically diagnosed with UC by IBD specialists at Keio University Hospital (Tokyo, Japan); (2) patients were admitted to Keio University Hospital between 2015 and 2022 with relapse of UC, where relapse is defined as a subjective or objective worsening of symptoms such as diarrhea, bloody stools, or abdominal pain compared to when the patient was stable and indications for hospitalization were determined by IBD specialists; and (3) patients had a noncontrast CT of the pelvic region performed between 3 days prior to admission and the day after admission. The exclusion criteria were as follows: (1) mild UC states on admission; and (2) treatment with induction therapy prior to CT imaging. Supplementary Fig. 1 summarizes the data recruitment process. If the same patient satisfied the criteria and had been hospitalized multiple times, each hospitalization was treated as a separate CT image on admission.

Clinical data on the date of CT imaging for the radiomics analysis were collected from the medical records. The clinical data collected were as follows: age, sex, body mass index (BMI), duration of UC, UC severity [24], Lichtiger score, extent of colorectal inflammation, number of hospital admissions to date, medication, and blood test results. Medication is the number of drug types used to date, including calcineurin inhibitors (FK506 or cyclosporin), anti-tumor necrosis factor (TNFα) antigen (infliximab or adalimumab or golimumab), vedolizumab, and ustekinumab. The decision regarding choice of medication, dosage, and method of administration was made by a physician specializing in IBD. The primary endpoint was defined as whether the patient underwent surgery during the same hospitalization. UC surgery in this paper includes total or subtotal colorectal resection.

### Segmentation on CT images

Detailed CT protocols are described in Supplementary Method 2. Manual segmentation was performed on noncontrast axial CT images using 3D Slicer (version 5.2.1, https://www.slicer.org/). The region of interest (ROI) was the rectal wall at the level of the tip of the tailbone. A gastrointestinal surgeon with more than 5 years of experience in UC surgery annotated regions as shown in Fig. 1, Supplementary Fig. 2; this work was then checked by another gastrointestinal surgeon with 10 years of experience.

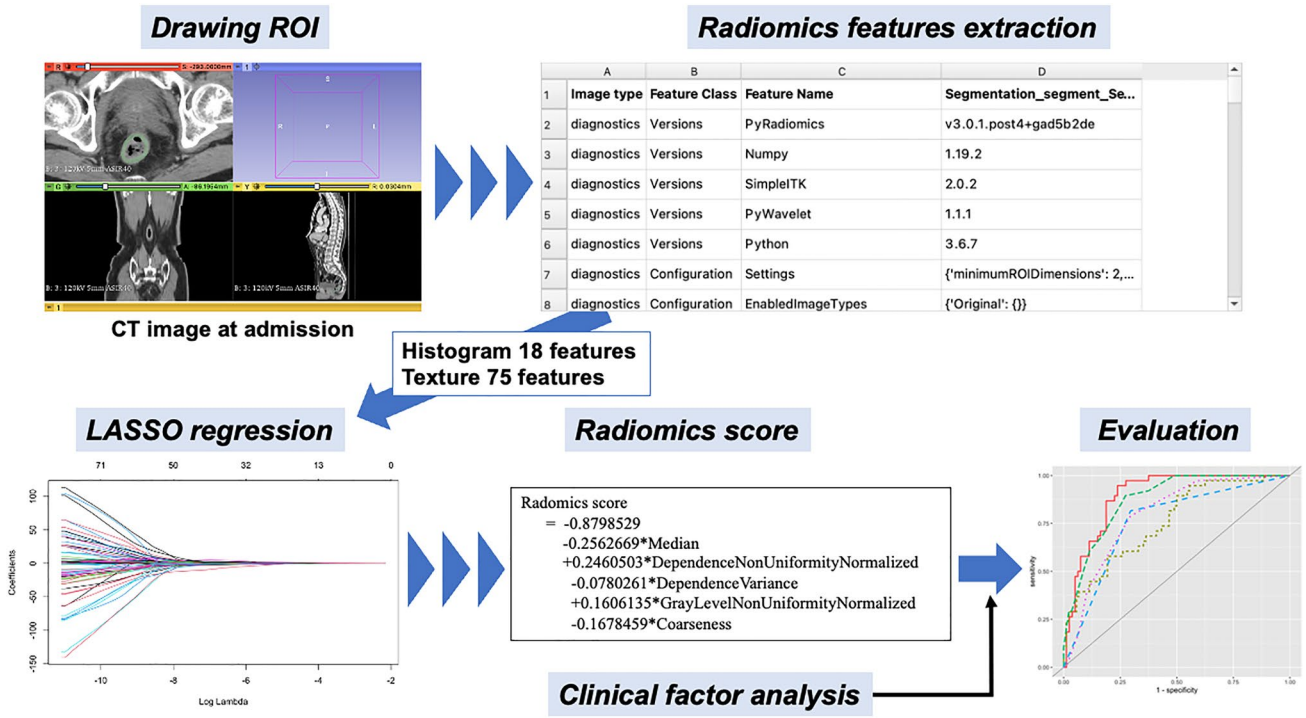
### Radiomic feature extraction and selection

The extracted radiographic features consist of three main groups: shape features, primary features, and texture features. Algorithms were provided in PyRadiomics (version 3.0) and implemented in SlicerRadiomics, which is an extension for 3D slicer. Feature normalization was performed using the $z$ score. Shape features were not used for analysis because only one slice was segmented. In all, 93 features were used in the analysis.

In this study, 157 CT scan data were allocated to a training cohort and a validation cohort at an 8:2 ratio using random numbers. We applied the least absolute shrinkage and selection operator (LASSO) method with tenfold cross-validation for training data, which is commonly used in feature selection. Radiomics scores were constructed from the main features, and their coefficients were obtained through LASSO.

### Creating the nomogram and evaluating the predictive model

Significant factors were extracted in the training cohort by statistical tests on clinical information (Table 1). Then, the




| | A | B | C | D |
|---|---|---|---|---|
| 1 | Image type | Feature Class | Feature Name | Segmentation_segment_Se... |
| 2 | diagnostics | Versions | PyRadiomics | v3.0.1.post4+gad5b2de |
| 3 | diagnostics | Versions | Numpy | 1.19.2 |
| 4 | diagnostics | Versions | SimpleITK | 2.0.2 |
| 5 | diagnostics | Versions | PyWavelet | 1.1.1 |
| 6 | diagnostics | Versions | Python | 3.6.7 |
| 7 | diagnostics | Configuration | Settings | {'minimumROIDimensions': 2,... |
| 8 | diagnostics | Configuration | EnabledImageTypes | {'Original': {}} |

**Fig. 1** Experimental design flowchart. *ROI* region of interest, *LASSO* least absolute shrinkage and selection operator, *CT* computed tomography

**Table 1** Clinical characteristics of patients with ulcerative colitis in the training and validation cohorts

| Clinical characteristics | Training cohort ($n=126$) | | | Validation cohort ($n=31$) | | |
|---|---|---|---|---|---|---|
| | Medical therapy ($n=88$) | Surgery ($n=38$) | $p$ value | Medical therapy ($n=20$) | Surgery ($n=11$) | $p$ value |
| Age (years)* | 37.0 [26.0–56.0] | 36.5 [27.3–52.3] | 0.854 | 48.5 [26.8–61.5] | 42.0 [26.5–42.5] | 0.283 |
| Sex (male/female) | 47/41 | 23/15 | 0.587 | 12/8 | 2/9 | 0.063 |
| BMI (kg/m$^2$)* | 19.9 [18.30–21.9] | 19.3 [17.4–22.1] | 0.359 | 19.7 [17.8–21.8] | 21.2 [19.7–24.2] | 0.150 |
| Duration of UC (months)* | 49.0 [11.8–112.3] | 68.0 [16.8–132.0] | 0.316 | 41.0 [2.0–116.0] | 116.0 [66.5–159.5] | 0.154 |
| Severity (moderate/severe) | 62/26 | 7/31 | <0.001** | 13/7 | 5/6 | 0.500 |
| Lichtiger score* | 12.0 [10.0–15.0] | 14.0 [12.0–15.8] | 0.032** | 12.0 [9.5–14.0] | 13.0 [11.0–15.0] | 0.449 |
| Location of inflammation | | | 0.456 | | | 0.207 |
| Total colon (%) | 43 (48.9) | 17 (44.7) | | 17 (85.0) | 7 (63.6) | |
| Left side of colon (%) | 27 (30.7) | 6 (15.8) | | 2 (10.0) | 1 (9.1) | |
| Rectum (%) | 13 (14.8) | 6 (15.8) | | 1 (5.0) | 3 (27.3) | |
| Hospital admission (times)* | 2.0 [1.0–2.0] | 2.0 [1.0–3.0] | 0.145 | 1.0 [1.0–3.0] | 2.0 [1.0–4.5] | 0.134 |
| Medication (number of drug types)* | 1.0 [0.0–2.0] | 2.0 [2.0–3.0] | <0.001** | 1.0 [0.0–2.25] | 2.0 [2.0–3.0] | 0.014** |
| Albumin (g/dl)* | 3.3 [2.9–3.7] | 3.1 [2.7–3.5] | 0.166 | 3.2 [3.0–3.7] | 3.3 [2.6–3.6] | 0.376 |
| WBC (×1000/μl)* | 9.1 [6.6–12.6] | 8.0 [5.5–12.1] | 0.291 | 8.6 [5.3–9.6] | 7.8 [6.5, 11.8] | 0.605 |
| Hemoglobin (g/dl)* | 12.1 [10.3–13.6] | 10.4 [8.9–12.5] | 0.005** | 10.9 [10.3–13.7] | 9.9 [9.2–12.1] | 0.102 |
| Platelet (×1000/μl)* | 359.0 [271.3–481.0] | 319.5 [245.5–419.0] | 0.244 | 290.0 [209.0, 381.0] | 327.0 [299.5–408.0] | 0.197 |
| CRP (mg/dl)* | 3.54 [1.35–7.78] | 4.01 [2.09–6.80] | 0.705 | 2.84 [1.27–5.81] | 5.17 [0.85–6.46] | 0.846 |

*BMI* body mass index, *UC* ulcerative colitis, *CRP* C-reactive protein

$p$ values were calculated from the Mann−Whitney $U$ test and Fisher's exact test

*Continuous variables are presented as mean [IQR]

radiomics score and selected clinical factors were integrated by linear model estimation using ordinary least squares to obtain a potential formula for the nomogram.

The performance of each model was evaluated with receiver operating characteristic (ROC) curves in both the training and testing cohorts, yielding metrics including the area under the receiver operating characteristic curve (AUC), sensitivity, and specificity. The ROC of the two models was compared using the Delong test.

For comparison, significant predictors were selected by multivariate analysis using the extracted clinical factors. A linear equation with significant clinical predictors and regression coefficients was created as a clinical model.

### Statistical analysis

Differences between the surgery and medication groups were compared using the Mann−Whitney *U* test for continuous clinical factors and Fisher's exact test for categorical clinical factors. A two-tailed $p$ value $< 0.05$ represented statistical significance. Logistic regression analysis was used to select clinical factors influencing the choice of surgical treatment. Factors with a $p$ value $< 0.1$ in the univariate analysis were used in the multivariate analysis. All statistical analyses were performed using R software (version 4.2.1; https://www.r-project.org), and the R packages used in our work are summarized in Supplementary Method 3.

## Results

### Clinical characteristics

A total of 147 patients were selected, and data from 184 CT scans were collected. Finally, data from 157 CT scans matched the selection criteria and were included. As obtained by splitting using random numbers, the number of data points in the training cohort was 126, and the number of data points in the validation cohort was 31. The patient characteristics of the training cohort and the validation cohort are summarized in Table 1. The ratio of the medication to surgery group was 88:38 (69.8%/30.2%) in the training cohort and 20:11 (64.5%/35.5%) in the validation cohort. The allocation of each group was not significantly different between the two cohorts ($p = 0.567$, chi-square test). The factor for which significant differences were detected between the surgery and drug treatment groups in both the training and validation cohorts was the number of drugs used before surgery ($p < 0.001$, $p = 0.014$), indicating that the frequency of surgery increased as the number of drugs used increased. Significant differences were also detected in UC severity ($p < 0.001$), Lichtiger score ($p = 0.032$), and hemoglobin level ($p = 0.005$) in the training cohort. Logistic regression analysis was performed in the training cohort (Table 2). Univariate analysis showed that UC severity ($p < 0.001$), Lichtiger score ($p = 0.024$), number of drugs used until surgery ($p < 0.001$), and hemoglobin level ($p = 0.010$) had $p$ values $< 0.1$, and they were used as variables in the multivariate analysis. In the multivariate analysis, a significant influence was detected in UC severity ($p < 0.001$) and the number of drugs used until surgery ($p < 0.001$).

### Radiomics score building

From the ROI on each CT image, 14 shape features, 18 histogram features, and 75 texture features, i.e., a total of 107 features, were extracted. A total of 93 features were used in the analysis. LASSO regression was performed using the training cohort, and five features (median, dependence nonuniformity normalized, dependence variance, gray level nonuniformity normalized, coarseness) were obtained by removing the features with zero coefficients. Using the obtained features and coefficients, we created the following linear formula to calculate the radiomics score:

Radiomics score
= −0.8798529
−0.2562669 ∗ Median
+0.2460503 ∗ Dependence Non - uniformity Normalized
−0.0780261 ∗ Dependence Variance
+0.1606135 ∗ Gray Level Non - uniformity Normalized
−0.1678459 ∗ Coarseness

**Table 2** Univariate and multivariate logistic regression analysis in the training cohort

| Variables | Univariate analysis | | Multivariate analysis | |
|---|---|---|---|---|
| | Odds ratio | *p* value | Odds ratio | *p* value |
| Age* | 0.999 | 0.923 | – | – |
| Sex | | | | |
| Male | 1 | – | – | – |
| Female | 0.748 | 0.461 | – | – |
| Severity | | | | |
| Severe | 1 | – | 1 | – |
| Moderate | 0.095 | < 0.001** | 0.057 | < 0.001*** |
| Lichitiger score* | 1.177 | 0.024** | 1.013 | 0.894 |
| Medication* | 2.293 | < 0.001** | 2.480 | < 0.001*** |
| Hemoglobin* | 0.798 | 0.010** | 0.896 | 0.345 |

Medication means the number of drug types used to date, including calcineurin inhibitors (FK506 or cyclosporin), anti-TNFα antigen (infliximab or adalimumab or golimumab), vedolizumab, and ustekinumab

*Continuous variables, **$p < 0.1$, ***$p < 0.05$

A detailed description of each feature used in the radiomics score is provided in Supplementary Method 4.

## Development of the risk model and nomogram

Based on the logistic regression analysis results using UC severity and medication, a regression equation was created and defined as the clinical model score. The formula for calculating the clinical model score is as follows:

Clinical model score
$= -1.4203 - 2.7724 * \text{severity (severe} = 0,\ \text{moderate} = 1)$
$+0.9855 * \text{medication (number of drug types used until surgery)}$

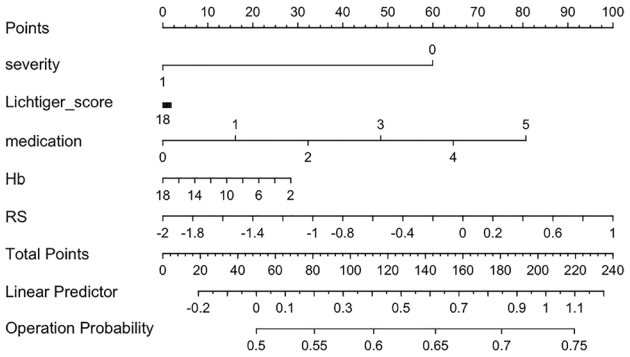



**Fig. 2** Nomogram created by combining four clinical factors identified in univariate analysis in the training cohort (ulcerative colitis severity, Lichtiger score, medication, and hemoglobin level) with the radiomics score, generated by regression analysis from radiomics features. *Hb* hemoglobin, *RS* radiomics score

A nomogram was created by combining four clinical factors identified in univariate analysis in the training cohort (UC severity, Lichtiger score, medication, and hemoglobin level) with the radiomics score (Fig. 2). The formula for calculating the nomogram score is as follows:

Nomogram
$= -0.3882300 * \text{severity (severe} = 0,\ \text{moderate} = 1)$
$-0.0036895 * \text{Lichtiger score}$
$+0.2090000 * \text{medication (number of drug types used until surgery)}$
$-0.0385640 * \text{Hemoglobulin (g/dl)}$
$+0.1026800 * \text{Radiomics score}$

## Performance evaluation of each predictive model

ROC curves were created using UC severity, number of drugs used until surgery, radiomics score, clinical model score, and nomogram (Fig. 3). The nomogram achieved excellent discrimination performance, with an AUC of 0.822 (95% confidence interval (CI) 0.841–0.951) in the training cohort and an AUC of 0.868 (95% CI 0.729–1.000) in the validation cohort (Table 3). The AUC was 0.874 (95% CI 0.815–0.933) for the training cohort and 0.818 (95% CI 0.658–0.978) for the validation cohort in the clinical model score, while the nomogram performed well on average in terms of accuracy, specificity, and sensitivity. In particular, the best ability to predict the patients that could be discharged without surgery, i.e., sensitivity, was achieved by the nomogram, with values of 0.947 and 0.889 in the training cohort and validation cohorts, respectively. The DeLong test

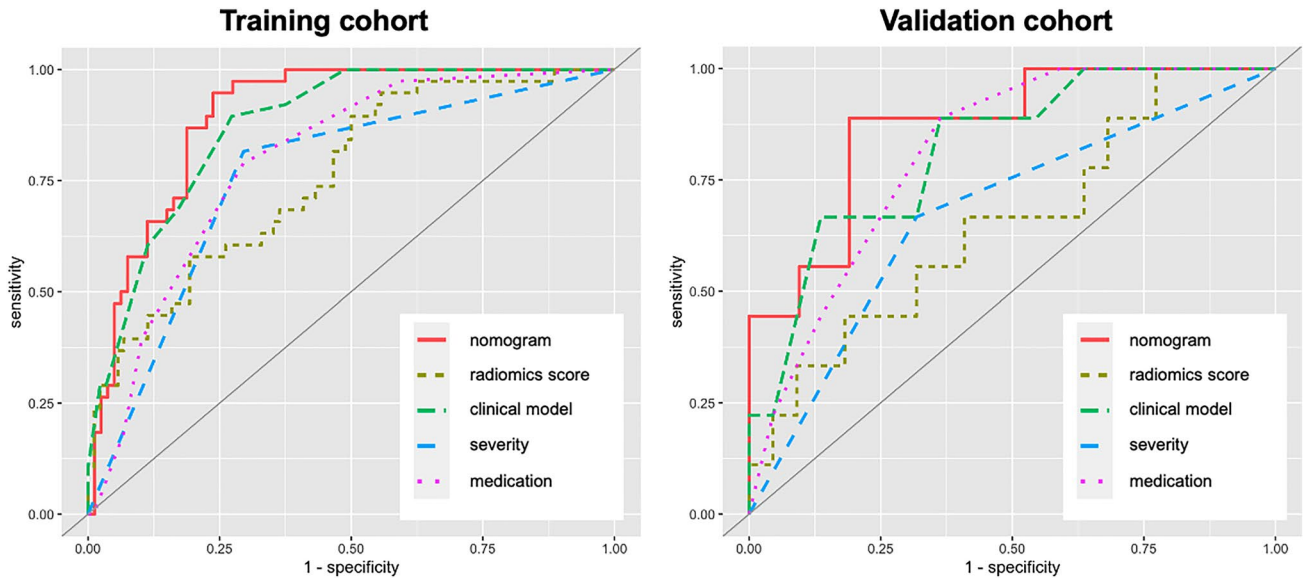



**Fig. 3** Receiver operating characteristic curves of three predictive models and two factors in the training and validation cohorts. Severity means ulcerative colitis severity; medication means the number of drug types used until surgery

**Table 3** Comparison of the predictive ability of nomograms combining clinical data and radiomics score with other models and factors

| Models | Training cohort | | | | Validation cohort | | | |
|---|---|---|---|---|---|---|---|---|
| | AUC (95% CI) | ACC | SPE | SEN | AUC (95% CI) | ACC | SPE | SEN |
| Nomogram | 0.896 (0.841–0.951) | 0.822 | 0.763 | 0.947 | 0.868 (0.729–1.000) | 0.833 | 0.810 | 0.889 |
| RS | 0.759 (0.670–0.848) | 0.619 | 0.500 | 0.895 | 0.652 (0.429–0.874) | 0.710 | 0.818 | 0.444 |
| CMS | 0.874 (0.815–0.933) | 0.778 | 0.727 | 0.895 | 0.818 (0.658–0.978) | 0.867 | 0.864 | 0.667 |
| Severity | 0.760 (0.681–0.839) | 0.738 | 0.816 | 0.705 | 0.674 (0.483–0.866) | 0.677 | 0.864 | 0.667 |
| Medication | 0.794 (0.717–0.871) | 0.730 | 0.705 | 0.790 | 0.811 (0.665–0.957) | 0.710 | 0.636 | 0.889 |

*AUC* area under the curve, *ACC* accuracy, *SPE* specificity, *SEN* sensitivity, *RS* radiomics score, *CMS* clinical model score

confirmed that the nomogram had significantly better discriminative power than the radiomics score and UC severity in both cohorts (Supplementary Fig. 4).

## Discussion

This is the first study to use radiomics from CT images of patients with UC at admission to predict indications for surgery. Combining radiomics data with clinical information at admission yielded a predictive power of approximately 90% (AUC 0.896 (95% CI 0.841–0.951) in the training cohort). This predictive model was also robust in the validation cohort, with an AUC of 0.868 (95% CI 0.729–1.000). This study suggests that radiomics may be able to predict discharge outcomes for patients with UC from CT at admission.

Although CT scans are frequently performed in the practical treatment of patients with UC, the usefulness of these scans is not clear. The percentage of patients with UC who undergo a CT scan at the time of their outpatient visit has been reported to range from 8% to 89% [25–28]. The more recent the report, the higher the percentage of CT scans performed. The probability of significant findings on CT in symptomatic patients with UC is low, and some are skeptical about performing CT routinely because of the associated radiation exposure [23–26]. On the other hand, some reports indicate that mural stratification on CT at admission can be used to predict surgical intervention [22]. In this study, the use of radiomics to extract high-dimensional information from noncontrast CT images improved the accuracy of predicting indications for surgery. Non-contrast CT is quicker and easier to perform in emergency situations and is expected to develop analytical methods.

The development of radiomics-based disease classification and prognostic models has been attempted for various diseases [16–19, 29–31]. Radiomics has been shown to contain microscopic information such as pathological findings and genetic information and is expected to be useful as a digital biopsy [13, 14]. Previous IBD studies have suggested that radiomics can differentiate CD from UC, predict disease stage, and predict treatment response [20, 21, 32–37]. Radiomics alone provides good discrimination (AUC 0.630–0.846) but combining it with clinical data further improves discrimination (AUC 0.723–0.880) [20, 21, 36, 37]. Studies have also been conducted using other imaging modalities, such as MRI and CT enterography (CTE) [32–37]. Establishment of optimal image analysis methods in IBD will enable more accurate medical care.

Timely determination of surgical indications in UC is essential to optimize surgical outcomes and patient safety. Previous radiomics treatment prediction studies in IBD have reported the prediction of infliximab (IFX) efficacy in Crohn's disease [33, 36, 37]. Radiomics analysis of CTE and MRI before IFX administration could predict mucosal healing or secondary invalidity in IBD. The Simple Endoscopic Score for CD (SES-CD) has been used to assess mucosal healing in the prediction of mucosal healing in CD [37]. In the assessment of IFX secondary invalidity for CD, the evaluation criteria include clinical symptoms, which may lead to inconsistent assessment due to patient tolerability and clinician experience [33, 37]. Therefore, it is not possible to determine from these studies whether a change in treatment was necessary for life expectancy. Essentially, it is important to identify patients with UC who can achieve remission without surgery. This requires prospective randomized controlled trials with long-term observation. On the other hand, medical treatment of UC is characterized by rapid change and the standard of care is likely to change during observation. The development of flexible mathematical models that can incorporate various conditions is a challenge.

This study is affected by several limitations. First, ROI selection was performed manually only. There are no established methods for automatic or semiautomatic segmentation of nonpretreated intestinal tracts, and the development of these methods could lead to more accurate predictive models. Second, this was a retrospective cohort study, and there were many selection biases. In general, patients who undergo CT are relatively severely ill, and the selection of

patients depended on whether CT imaging was performed. However, given considerations of radiation exposure, it is ethically difficult to perform CT on all hospitalized patients with UC; prospective studies should be conducted to establish certain criteria for CT imaging.

## Conclusion

Radiomics analysis of CT images of patients with UC at the time of admission, combined with clinical data, showed high predictive ability regarding a treatment strategy of surgery or medical treatment.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s10151-025-03139-x.

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**Author contributions** Kyoko Sakamoto and Koji Okabayashi collected all data. Kyoko Sakamoto designed and performed statistical analysis and edited the manuscript. Koji Okabayashi, Ryo Seishima, Kohei Shigeta, Hiroki Kiyohara, Yohei Mikami, Takanori Kanai, and Yuko Kitagawa supervised this study and interpreted the data. All co-authors approved the submission of the final version of the manuscript.

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**Data availability** No datasets were generated or analysed during the current study.

## Declarations

**Conflict of interest** The authors declare no competing interests.

**Ethics statements (human ethics approval declaration)** This study was approved by the Institutional Review Board of Keio University School of Medicine (no. 20221035).

**Informed consent** Informed consent was obtained from all individual participants included in this study.



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