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Systematic Review

Health Information Technology and Celiac Disease Diagnosis: A Scoping Review of Methods and Applications

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ABSTRACT

Background:
In recent years, health information technology methods have been increasingly used to diagnose celiac disease (CD). In order to improve diagnosis, image analysis, deep learning, and machine learning methods have been used to improve the accuracy of diagnosis in the shortest time while requiring the least human resources. This article summarizes these techniques and discusses the latest advances in the diagnosis of CD.

Materials and Methods:
All articles that use patient data for diagnosis are presented in this article, and systems designed for follow-up were excluded. EMBASE, PubMed, Web of Science, and Scopus databases have been searched in this inquiry. After searching different databases to eliminate duplicate and review articles, 2266 articles were evaluated in the first stage, and then the titles, abstracts, and concepts were reviewed, and 33 articles were finally selected.

Results:
The results showed that 14 studies were conducted in children (42.42%), eight studies were conducted in adults (27.58%), and 10 studies were conducted in two populations (roughly 30.30%). 14 studies were completed in the United States, 16 studies were completed in Europe, and two studies were completed in Asia. 12 articles (37.93%) used the integration of image processing and artificial intelligence methods. 23 articles (69.69%) used endoscopy images, and nine articles (27.27%) used patient information in their research.

Conclusion:
The results express a general acceptance of using information technology to improve the diagnosis of CD, but further research is needed to improve and optimize the method of diagnosis. Recent artificial intelligence techniques using deep learning (DL), machine learning methods such as convolutional neural network, support vector machines, and K-nearest neighbors, and also image processing have emerged as the breakthrough computer technology that can be used for computer-aided diagnosis of CD. The current review summarizes methods used in clinical studies to diagnose CD, from feature extraction methods to artificial intelligence and machine learning techniques.

Keywords: Clinical Decision Support System, CD, Health information technology, Diagnosis

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INTRODUCTION

Celiac disease (CD) is considered a multifactorial chronic immune-mediated disease of the intestinal tract (1-3) accompanied by small bowel inflammation, crypt hyperplasia, and eventually villi atrophy (4). CD is a multi-system disease that affects almost every system of the human body but most often involves the skin, blood, nerve, musculoskeletal, endocrine, reproductive, and digestive systems (5). Although the prevalence of

CD is increasing, most cases are undiagnosed (6). In addition, some health complications increase the morbidity and mortality of untreated CD, which may place a significant burden on the healthcare system and reduce the patient's quality of life (QOL) (2). Since the various clinical manifestations and symptoms of CD are also shared with other diseases, its diagnosis is still difficult (7).

Health information technology (HIT) alone includes a wide range of health care technologies, and it also plays a vital role in all aspects of disease diagnosis. Electronic health records (EHR), clinical decision support, laboratory, and medical imaging information systems, health information exchange, and medical equipment are examples of HIT applications in healthcare and diagnosis (6). In Clinical Decision Support System (CDSS), each electrical system is designed to directly assist clinical decision-making (7), and enhance medical help in different ways. Reducing medical errors, ensuring extensive treatment of diseases and conditions, promoting compliance with guidelines, reducing hospital stays, and reducing costs are the advantages of using these systems (8). In parallel, CDSS, by integrating healthcare professionals' knowledge and evidence-based data, plays an important role in improving the quality of patient care (9).

Therefore, finding an accurate diagnosis of CD in society is an urgent need to develop such a system (6). Today, in order to assist in the diagnosis and clinical monitoring of CD, the development of health information systems is a workable strategy (7). Since many tools and technologies are involved in the process of disease diagnosis, this article discusses the application of health information technology in disease diagnosis. We have conducted research on the latest developments in information technology for CD. The purpose of this comprehensive review is to answer two questions:

- What HIT systems have been developed for the diagnosis of CD?
- How do these systems affect the diagnosis of CD?

MATERIALA AND METHODS

In this scoping review, as far as possible, we pursued the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (8). The health information system is considered as any technology that helps specialists in the diagnosis of CD. Our assessment is based on articles published between 1972 and 2020. We have investigated studies of information technology systems in the diagnosis of CD. All articles that used patient data for diagnosis are presented in this article and systems designed for follow-up were excluded.

Here, a comprehensive search was conducted on the application and effect of HIT in the diagnosis of CD. EMBASE (Ovid), PubMed (NLM), Web of Science and Scopus databases were searched in this survey. For background information, systematic reviews and related narrative reviews were evaluated, but they are not presented here. All published studies from 2007 to 2020 are included.

The concepts of information technology and CD are described in PubMed's medical topic title (Mesh) terminology. Search strategies were developed for each database. In the initial evaluation, the title and abstract of the articles were reviewed, and, where appropriate, the text of the articles was reviewed.

Related review articles were used to identify additional publications not included in the last articles. Two first authors assessed the titles and abstracts of publications found through this search for consistency with the topic. In the event of a conflict arising from independent data extraction based on inclusion or exclusion criteria, a consensus was reached to resolve it. Inclusion criteria for our review were as follows: (i) full-text paper available in English, (ii) original papers describing techniques for computer-aided diagnosis of CD. We excluded case reports, reviews, and descriptive papers. One article was excluded because of inaccessibility. The following keywords were searched: CD (Mesh) and terms referring to computer-aided diagnosis, neural network, medial and clinical decision support system, decision support system, expert system, artificial intelligence, decision making, medical electronics, text mining, automation decision making, and information technology. There were no limitations set on the search regarding article type, text availability, or publication date. Publications showed through this search were evaluated by the first author according to the subjects, their titles, and abstracts. For example, the search strategy in the

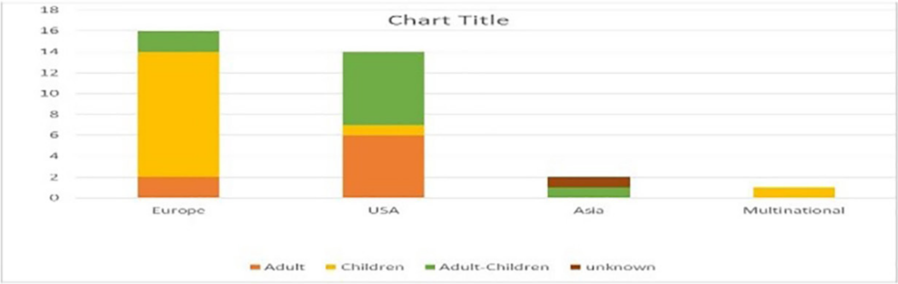

Chart 1: comparison of the populations of studies

PubMed database was executed in the appendix.

Data gathering was performed through data abstraction form in the full text of the final articles. For each study included in the article, we recorded the following data: first author, year of publication and country in which the study was conducted, overall study objective, study population (CD & control cases), target group (children & adult), tested method and diagnostic performance (sensitivity, specificity, diagnostic accuracy).

RESULTS

As a result of searching the different databases, 2266 articles were evaluated in the initial phase after eliminating duplicate and review articles. Moreover, 1600 and 624 papers were excluded at the title and abstract stages, respectively. In addition, 45 full-text papers were further evaluated, of which 16 did not meet the inclusion criteria. Finally, 33 studies were examined in this review, and all included studies were retrospective (figure 1).

The results showed that 14 studies (approximately 41.37%) were conducted in children, eight studies (approximately 27.58%) were conducted in adults, and 10 studies (approximately 27.58%) were conducted in two populations. 14 studies were completed in the United States, 16 studies were completed in Europe, and two studies were completed in Asia. As shown in chart 1, a comparison of the populations studied on the continents is presented.

11 articles (about 37.93%) used a combination of image processing and artificial intelligence. The k-nearest neighbor algorithm is one of the artificial

intelligence methods and has been used in seven articles (9-15). Support vector machine (SVM) is a supervised machine learning model. Eight articles studied the application of SVM in the diagnosis of CD (13-20).

23 articles (about 69.69%) used endoscopic images, and nine articles (about 27.27%) used patient information for research. Nine studies (nearly 31%) stated that the sample size was limited when evaluating their results and emphasized that implementing these concepts requires a broad population. 18 of the 33 CD diagnostic studies were performed automatically and semi-automatically through endoscopic images, which is the largest number of studies. Finally, in the eight articles, the applicability and implementation ability of the research in the clinical setting were clearly mentioned, and promising progress was made in the application of information technology in the diagnosis of CD. According to the findings of table 1, the most common information technology methods used in the diagnosis of CD in the articles are listed below. All results are detailed in table 2.

Deep learning method:

Deep learning term is defined as computer empowerment that uses a set of techniques and algorithms to discover complex patterns in large data sets(21). These techniques commonly have achieved notable success over machine learning algorithms in several fields. The advances mentioned in recent articles show that deep learning techniques are valuable tools for accelerating or assisting human research(22). 8 of the articles (about 27.58%) are about using the deep learning method in diagnosing CD. One of the first subjects to be influenced by deep learning is an image-based medical diagnosis, expected to provide a more accurate diagnosis using

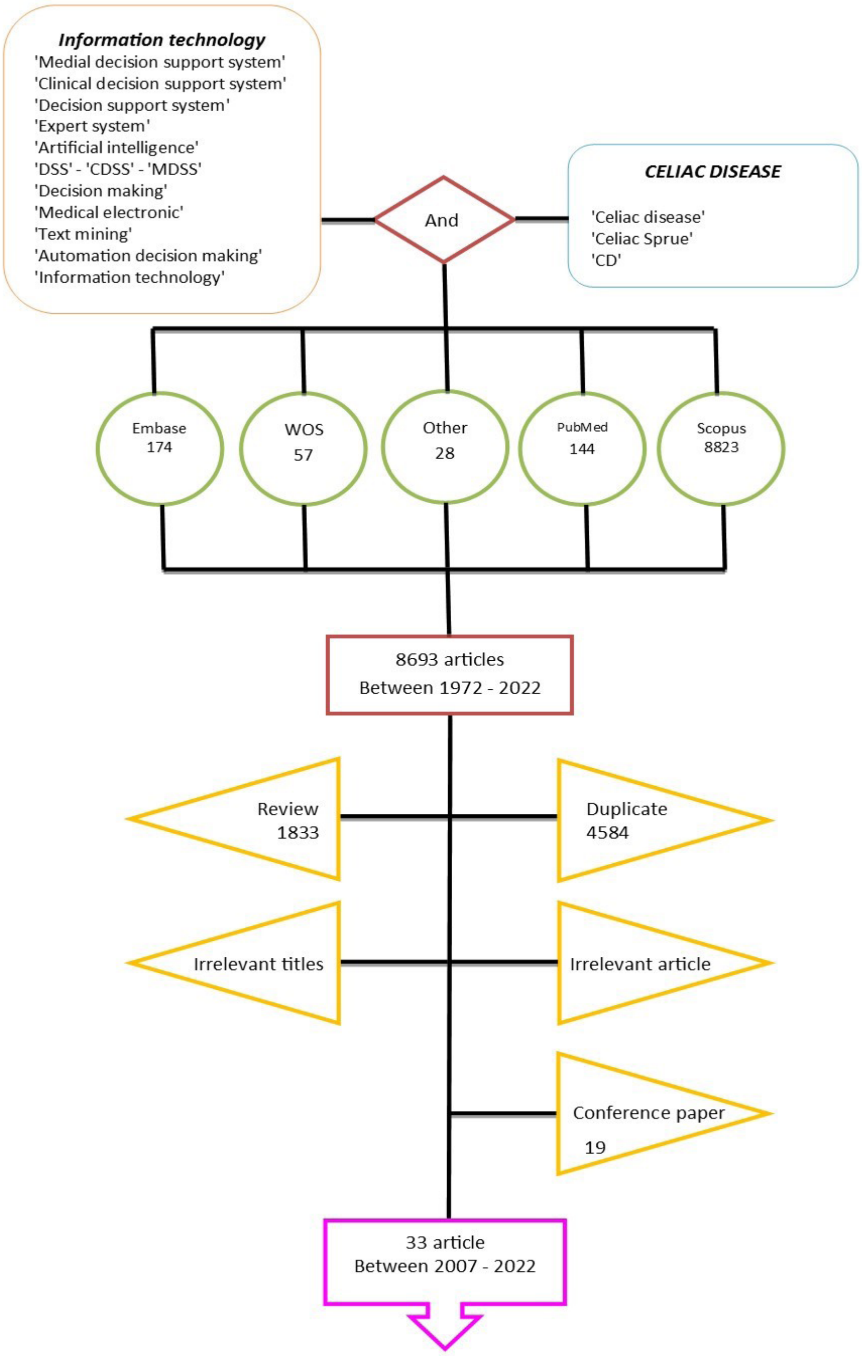

Figure 1: **Literature flow of Health Information Technology in Celiac Disease Diagnosis studies**

Table 1: Summary of Health Information Technology application in Celiac Disease Diagnosis

numb	Author (year)	country	Objective(s)	Sample size	Study method	Target group	Study result OCR	Study setting
1	Stoleru.et al (36) 2022	Europe	Assist the diagnosis of CD	45 healthy patients and 65 CD patients	Machin learning image processing K-NN Weighted KNN SVM	Adult-children	SVM ACC: 94.1% W-KNN ACC:92.2% KNN ACC: 84.3%	Iuliu Hatieganu, University of Medicine and Pharmacy, Romania
2	Giuseppe Magazzù.et al (37) 2022	Europe	Multidisciplinary health project about CD	Not clear.	Machine learning neural network fuzzy five-point Likert-like scale	Children	ACC:99% Sens 86% Spec:99%	Physics and Chemistry Department "E. Segre" at the University of Palermo and AcrossLimits Ltd. in Malta respectively, Italy
3	Francesco Piccialli.et al (38) 2021	Europe	categorize potential CD patients by machine learning methods	340 potential CD patient	Machine learning Random Forests Extremely Randomized Trees, Boosted Trees, Logistic Regression k-fold cross validation	Children	Best result for boosted trees: ACC :80%, Sens: 58% Spec: 84%.	University of Naples , Italy
4	Or Shemesh.et al (31) 2021	Asia	CD diagnosis by B cell receptor encoding genes	52 individuals with CD 48 healthy controls 80% for test 20% for train	Machin learning Random Forest (RF) 10-fold cross-validation	Adult-children	F1 score : 85% ACC :71.6%	Bar Ilan University, Ramat Gan, Israel
5	Wang, X,et al (15) 2019	United States	Assist the diagnosis of CD	8 celiac patient (1040 images) 13 healthy individuals(1100 images)	deep learning image processing (BSCE learning module ResNet50 Inception-v3 SVM, KNN, and LDA classifiers) 10-fold cross-validation	Adult-children	ACC:95.94% Sens:97.20% Spec: 95.63%	Columbia University Medical Center, New York
6	Syed, S et al (39) 2019	Asia Africa United States	Distinguished pathological from healthy tissue in gastrointestinal biopsy images.	102 individuals 42 healthy, 26 with EE 34 with CD) 3118 images	deep learning image processing (CNN, R coding language 10-fold cross-validation	children	ACC: 93.4%	Aga Khan University Hospital, Karachi, Pakistan; University Teaching Hospital, Lusaka, Zambia; and University of Virginia, Charlottesville
7	Wei, J. W, et al (24) 2019	United States	identified CD, normal tissue, and nonspecific duodenitis	1018 duodenal biopsy images 681 patients	deep learning (deep residual network (ResNet))	Adult-children	CD ACC:95.3%, normal ACC:91.0% Nonspecific ACC:89.2%	Dartmouth-Hitchcock Medical Center (DHMC) 2016 to 2018
8	Vicnesh, J, et al (14) 2019	United States	classifying CD	702 healthy, 1027 celiac images 16 healthy individuals and 21 celiac patients	machine learning image processing (Daisy descriptors PSO Decision Tree, KNN, PNN, SVM classifier) 10-fold cross-validation	Adult-children	Acc:89.82%, Sens:94.35% Spec: 83.20%	Columbia University Medical Center in New York
9	Koh, J. E. W, et al. (17) 2019	United States	automatically distinguish CD	13 control subjects and 13 celiac patients.	machine learning image processing (DWT Nonlinear, textural features PSO SVM classifier)	Adult-children	10-fold: SEN: 88.43% SPE: 84.60% ACC: 86.47% LOOCV: SEN: 89.75% SPE: 82.25% ACC: 85.91%	Columbia University Medical Center, New York 2018

numb	Author (year)	country	Objective(s)	Sample size	Study method	Target group	Study result OCR	Study setting
10	Robert L. Pastore, et al(27) 2019	United States	educational model, combining the accurate language of signs, symptomatology, and other associated diseases,	13 experts	Expert system (Exsys Corvid Mayo Clinic CD testing algorithm and ACG SPSS)	Adult-children	100% of experts agreed with this systems	School of Health Professions, Rutgers University, Newark, New Jersey, USA 2018
11	Caetano dos Santos, F. L. , et al (16) 2019	Europe	automatic assessment and classification of the EmA test	2597 EmA images 70% for training and 30% for testing	machine learning Image Processing (SVM Descriptor: multiscale MATLAB)	Adult-children	Sens: 82.84% Spec :99.40% Acc: 96.80%	Tampere University, Tampere, Finland 2017-2018
12	Amirkhani, A , et al(40) 2018	Iran	classifying CD	7 features	fuzzy based deep learning (Clustering : FCM - PFCM weighing: nonlinear Hebbian learning algorithm)	-	combining the FCM with the PFCM clustering algorithm: A, B1, and B2 accuracies as 88, 90, and 91%	Iran
13	Wimmer, G, et al. (20) 2018	Europe	endoscopic image classification	986 control image patches 675 celiac image patches 353 patient	deep learning machine learning (CNN Fisher Encoding SVMs) Fivefold cross-validation	children	Acc : 92.5%	Austria, Vienna, Anna Children's hospital
14	Escudié, J.-B, et al. (41) 2017	Europe	identifying relevant autoimmune comorbidities in CD	741 patient 6340 document	Text mining (browser-accessible software, FASTVISU UMLS mapping Text mining)	Adult	ease the extraction of relevant information from EHR	Georges Pompidou European Hospital 2000-2014
15	Zhou, T, et al (23) 2017	United States	evaluation of CD-associated villous atrophy	200 images 12 celiac patients 10 healthy individuals (1/2 for training 1/2 for testing))	deep learning (CNN)	Adults	Sens: 100% Spec: 100%	Columbia University Medical Center May 1, 2008, to July 31, 2009
16	Gadermayr, M, et al. (42) 2016	Europe	improve the endoscopic detection of intestinal mucosa alterations due to CD	Control: 679 image patches from 215 patients (children) Celiac: 479 image patches from 75 patients (children) (80% training and 20% validation)	Image processing (Expert knowledge acquisition Feature extraction(LBP-MFS-IFV) Hybrid classification)	children	Acc : 92.8% hybrid system with expert increased acc to 98.9%	Austria, Vienna, Anna Children's hospital August 2008 and December 2014
17	Ciaccio, E. J, et al. (29) 2016	United States	methods to extract and process video capsule endoscopy data	200 control images 200 patient images	image processing programming (Feature extraction techniques MATLAB)	Adult	celiac patients tended to have a rougher small intestinal texture as compared with control patients	Columbia University Medical Center
18	Gadermayr, M , et al (30) 2015	Europe	fully automatize decision support systems for CD diagnosis	Training: image patches (306 celiac, 306 control) Testing: 172 images from 72 patients	deep learning image processing (Feature extraction techniques(LBP ELBP, SCH) k-nearest neighbor classifier)	children	Acc: 86%	Austria, Vienna, Anna Children's hospital

numb	Author (year)	country	Objective(s)	Sample size	Study method	Target group	Study result OCR	Study setting
19	Gadermayr, M, et al (43) 2014	Europe	showing a high degree of similarity with reference to destruction by dividing images into smaller collections	300 image	Image processing machine learning (Feature extraction(RDF-HOG-SCH-FF-ELBP-LBP-ECM) (NNC) linear (Bayes normal) classier (SVC) McNemar's test)	children	Best ACC in DcM:cL measure (LBP-LDC):86%	Austria, Vienna, Anna Children's hospital
20	Ciaccio, E. J, et al. (44) 2014	United States	improve the image-based detection of villous atrophy and other abnormality in video capsule endoscopy by means of incorporating basis images.	13 control patients 104 basis images 13 celiac patients 104 basis images	Image processing Programming (ImageJ software Matlab)	adult	Sens : 84.6% spec : 100.0%	Columbia University Medical Center, New York, May 1, 2008, to July 31, 2009
21	Kwitt, R, et al (18) 2014	Europe	we can circumvent the requirement for expert annotations by using a substantially larger corpus of training data labeled by non-experts	Control: 592 images patches from 240 patients Celiac: 458 images from 80 patients	Programming Machine learning (MATLAB SVM Fisher vector encoding local-binary pattern (Multiscale LBP) transform-domain based approach to statistical texture characterization) cross-validation	children	ACC : 86%	Austria, Vienna, Anna Children's hospital
22	Hegenbart, S, et al (45) 2013	Europe	Focus on Invariant texture classification approaches being applied in the computer-assisted diagnosis of CD.	312 image 87 patient	Programming Machine learning (Java Matlab k-NN classifier)	children	Results imply that scale invariance is not a key feature required for the successful classification of our CD dataset.	Austria, Vienna, Anna Children's hospital
23	Shirts, B. H, et al.,(25) 2013	United States	Illustrate the relationship between tTG IgA test results and duodenal biopsy for CD in a local diagnostic context.	1000 case	Machine learning programming (Nearest-neighbor algorithms R statistical programming language)	Adult - children	Near-neighbor analysis can yield accurate probability estimates and can illustrate pertinent patient-specific and institution-specific information.	17 hospitals or over 70 clinics associated with Intermountain Healthcare (Salt Lake City, UT) any tTG IgA testing and a duodenal biopsy Jan 2008 and Oct 2011
24	Ludvigsson, J. F, et al (46) 2013	United States	developed two electronic medical record (EMR)-based algorithms to identify patients at high risk of CD and in need of CD screening	NLP : 146 patient-181 control ICD : 132 patient-350 control)	text mining (NLP SAS)	Adult - children	ACC : 23.3% for ICD9 vs 78.0% for NLP	Mayo Clinic's EMR systems Between 1995 and 2012
25	Gadermayr, M, et al. (10) 2013	Europe	Investigate the impact of methods used to correct such distortions in images on the classification accuracy in the context of automated CD classification	Control: 163 image patches from 100 images from 59 patients Celiac: 124 image patches from 67 images from 23 patients	Image processing Machine learning (Feature extraction methods KNN SCH ECM Haralick features SSD LBP LTP) LOPO-CV	children	ACC: SCH: 86.1% ECM: 86.1% Haralick features: 86.8% SSD: 90.2% LBP: 88.2% LTP: 86.8%	Austria, Vienna, Anna Children's hospital

numb	Author (year)	country	Objective(s)	Sample size	Study method	Target group	Study result OCR	Study setting
26	Ciaccio, E. J, et al. (9) 2013	United States	Increasing classification accuracy by three-dimensional modeling using shape-from-shading principles	10 patients 10 control	Image processing Machine learning (Matlab ImageJ software program map3d KNN)	Adult	overall, significant differences between celiac and controls were found in most parameters, as would be expected due to the presence of villous atrophy in celiac patients	Columbia University Medical Center, New York, from May 1, 2008, to July 31, 2009
27	Vécsei, A, et al (12) 2011	Europe	describe for the first time a system aimed at performing automated classification of duodenal texture patches according to a reduced 4-class Marsh-like classification system	Control: 306 image patches from 131 patients Celiac: 306 image patches from 40 patients	Image processing Machine learning (Feature Extraction Techniques(local binary pattern LBP LTP LBP/C ELBP WT-LBP) KNN classifier)	children	LBP: sens 87.3%, spec 79.5%, acc 83.3% LTP: sens 94.0%, spec 75.5%, acc 84.7% LBP/C: sens 92.6%, spec 82.1%, acc 87.3% ELBP: sens 92.6%, spec 79.5%, acc 86.0% WT-LBP: sens 90.6%, spec 85.4%, acc 88.0%	Austria, Vienna, Anna Children's hospital
28	Ciaccio, E. J, et al. (47) 2011	United States	determine whether synthesized periodicity could be accurately detected	200 images 11 celiac patients	signal processing (Dominant frequency analysis)	Adult	With > degree of random noise, mean absolute error between anticipated and actual dominant frequency increased.	Columbia University Medical Center, New York May 1, 2008, to July 31, 2009
29	Tenório, J. M, et al (19) 2011	United States	develop a clinical decision–support system (CDSS) integrated with an automated classifier to recognize CD cases	178 clinical cases for training 270 for test	Machine learning Deep learning (web-based decision trees, Bayesian inference, k-nn algorithm, SVM and artificial neural networks)	children	ACC : 84.2% Sens : 92.9% Spec : 79.2 %	Department of Pediatrics, in Hospital São Paulo, the university's teaching hospital.
30	Hegenbart, S, et al (11) 2011	Europe	assess how well cross-validation techniques are suited to predict the outcome of a preferred setup of distinct test- and training data sets	Control: 306 images patches from 131 patients Celiac: 306 images patches from 40 patients	Image processing Machine learning (Feature Extraction Techniques KNN classifier LBP ELBP ELTP) LOPO-CV	children	LBP: sens 94.2%, spec 93.6%, acc 93.9% ELBP: sens 93.6%, spec 94.3%, acc 93.9% ELTP: sens 93.6%, spec 94.3%, acc 93.9%	Austria, Vienna, Anna Children's hospital
31	Ciaccio, E. J, et al. (48) 2010	United States	Determining Quantitative CD markers	10 patients 10 controls	Programming (Matlab Rapid5 software nonlinear boundary used for classification)	Adult	Sens: 92.7% spec: 93.5%	Columbia University Medical Center, New York, from February 1, 2009, to December 31, 2009
32	Vécsei, A, et al , (13) 2009	Europe	Detection of the villous atrophy and classification with respect to its extent (no villous atrophy, partial, or total villous atrophy).	391 images	machine learning (Fourier domain features kNN, SVM, Bayes classifiers) LOPO-CV	Children	Bayes classifier(bulb images): Acc: 94%	Austria, Vienna, Anna's Children Hospital in Vienna during 2006 and 2007
33	Hopper, A. D, et al ,(28) 2007	Europe	Evaluating a Decision Making Tool Using Patient Information	1464 patients - 2000 consecutive adult patients	DSS tools (SPSS)	Adult	Sens: 100% Spec: 60.8%	Teaching hospital in Sheffield. January 2003 to January 2004 - January 2004 to April 2006

Table 2: **Detailed of information technology methods used in the diagnosis of CD in studies**

population	N	References
children	14	(10, 12, 13, 18-20, 30, 37-39, 42, 45, 49, 50)
adult	8	(23, 29, 41, 44, 48, 51-53)
Children-adults	10	(14-17, 25, 27, 31, 36, 46, 54)
Not mentioned	1	(40)
Country		
Asia (Iran, Israel)	2	(31, 40)
Europe (Austria- Finland-Italy)	16	(10, 12, 13, 16, 18, 20, 30, 36-38, 41, 42, 45, 49-51)
United States (Dartmouth - New York - Salt Lake City- São Paulo-America)	14	(14, 15, 17, 19, 23, 25, 27, 29, 44, 46, 48, 52-54)
Multinational (Pakistan, Zambia, Charlottesville)	1	(39)
Study design		
Image processing - Machine learning	9	(10, 12, 14, 16, 17, 36, 49, 50, 53)
Deep learning - Machine learning	2	(19, 20)
Machine learning	4	(13, 31, 37, 38)
Deep learning - Image processing	3	(15, 30, 39)
Deep learning	2	(23, 54)
DSS tools	1	(51)
signal processing	1	(52)
Image processing	1	(42)
Expert system	1	(27)
fuzzy based - deep learning	1	(40)
text mining	2	(41, 46)
Programming- Machine learning	3	(18, 25, 45)
Programming	1	(48)
Programming- Image processing	2	(29, 44)
Data type		
Endoscopy image	23	(10, 12-15, 17, 18, 20, 23, 29, 30, 36, 39, 40, 42, 44, 45, 48-50, 52-54)
Patient data and information	9	(16, 25, 27, 31, 37, 38, 41, 46, 51)
CD symptom and sign	1	(19)
Data gathering tools		
One Endoscopy devise	4	(13, 23, 30, 54)
Two Endoscopy device	6	(12, 15, 20, 45, 49, 50)
Three Endoscopy device	2	(10, 42)
One Video capsule endoscopy	6	(29, 36, 44, 48, 52, 53)
two Video capsule endoscopy	2	(14, 17)
Patient information	10	(16, 19, 25, 27, 31, 37, 38, 41, 46, 51)
Not mentioned	3	(18, 39, 40)
Sample limitation	9	(14, 17, 23, 25, 42, 46, 52-54)
Applicability	8	(16, 17, 19, 27, 29, 48, 53, 54)

automation of detection and classification of lesions. These images come from standard and video capsule endoscopy. Some articles have mentioned people as a sample (CD & control cases), while some other articles have mentioned the number of images.

Zhou et al. have the best results with 100% sensitivity and specificity in the diagnosis of CD and marshes. In this paper, computer-aided clinical techniques were discussed to improve the evaluation of real-time mucosal atrophy in video-capsule endoscopic images. A deep convolutional neural network was presented using images of 11 patients with CD and 10 controls. For learning and operation, computer-aided analysis without manual scoring is not only user-friendly, fast, and low-cost but also free from the subjective results of user bias. Insufficient data is the limitation of this article. It is best to check on the large population (23).

In 2019, Wei et al. used biopsy images to detect CD and developed an automated analysis system with excellent performance. A deep learning network for CD identification on duodenal biopsy images from 1048 patients was developed. The accuracy of ResNet as a convolutional neural network in CD diagnoses was 95.3%, and in normal tissue was 91.0%. This study provided a tool that can be integrated with laboratory information systems (LIS) (24).

A tool clinical decision-support system (CDSS) was developed in the study by Tenório and colleagues for uncomplicated, reliable, efficacious clinical decision making and integrated with an automated classifier to recognize CD cases in three phases. System Usability Scale score showed users' acceptance of the tool. In the first phase, they developed a web-based system for obtaining and retrieving clinical data in an outpatient clinic and to advance their research. They created a database with 178 training data and 28 test data. In the second phase, the collected data were coded, and the training database was tested with a set of automated classification algorithms such as Bayesian, decision trees, k-nearest neighbors, ANN (Artificial neural network), and SVM in Weka software. The model was integrated with the most accurate parameters (accuracy, sensitivity, specificity, and area under the curve) in the web-based system. Finally, in the third phase, the system was evaluated by comparing the diagnoses proposed by the clinical decision-making system. Physicians made the findings during the patient's consultation. The accuracy of this system was described as 84% (19).

Machine learning:

The development of methods that enable computers to solve problems by learning from experience is called machine learning. The primary purpose of these models is to generalize their learned expertise and provide accurate predictions for new and unseen data (21). Machine learning has entered the medical field in recent years and many successes have been achieved in this field. Recognizing the learning of those things that physicians can already do well and learning things that physicians have only had limited success with is one application of this method. With these points in mind, 17 articles (approximately 51.51%) used machine learning methods, and we could review some medical categories that have or may benefit from machine learning methods.

Caetano dos Santos FL and colleagues (16) developed a system for evaluating and automatically classifying EMA (Endomysial antibodies) test results, using ESPGHAN (The European Society for Pediatric Gastroenterology Hepatology and Nutrition) standard as the diagnostic criterion. This tool is suitable for areas where the prevalence of diseases is low, and the data type is IgA images.

Computer-based methods have acceptable performance in the diagnosis of CD. The accuracy of image classification depends on the expert's annotation of the training data, which is too time-consuming and costly in practice. Therefore, the amount of training data can be limited, leading to fuzzy comments on the generalization ability of the system. Many of these studies are not generalizable to other institutions and require a larger population, different endoscopic devices, and images of different parts of the small intestine in endoscopy images. Kwitt and others concluded that by using a considerably larger training database labeled by non-experts, needing for expert people was diminished (18).

In another study, Hegenbart and co-workers evaluated the impact of validation techniques on predicting the outcome of a preferred setup of test and training data sets. They concluded that the leave-one-patient-out (LOPO) cross-validation technique

Table 3: The top 13 most productive authors

Author	Count
Uhl, a	10
Vécsei A	10
Ciaccio EJ	9
Green PH	9
Lewis SK	8
Bhagat G	7
Gadermayr M	4
Tennyson, Christina A	4
Hegenbart, S	4
Liedlgruber, M	3
Wimmer, G	2
Murray, J. A	2
Oh, S. L	2

combined with inner-optimization implies to be the most sufficient approach if no distinct sets for training and evaluation can be created. (11).

Since the treatment of CD requires many lifestyle changes, the accuracy of the diagnosis is crucial. Internists and pediatricians usually feel comfortable when diagnosing simple cases. It is important to know when to refer patients to specialists for invasive diagnostic procedures. Shirts and colleagues developed a tool to help physicians know when to offer invasive diagnostic procedures. They suggested that local analysis could lead to the identification of opportunities to improve the clinical system and quality control, but this local usefulness might come at the expense of external validity and generalizability (25).

Other methods

Other methods used in the articles include image processing, expert systems, and decision-making systems.

According to Castillo, the purpose of CDSS is to improve care safety, quality, treatments, and outcomes. In addition, it will reduce the dependence on memory, response time, and error rate (26). In a study about CD, using an expert system method based on the Mayo Clinic algorithm using Exsys Corvid software. Factors and indicators involved in CD were extracted through related articles, and finally, its evaluation was done using 13 experts in gastrointestinal and CD as a questionnaire, including 10 questions. In total, 100% of experts concluded that the designed system was appropriate for diagnosing the disease. It is necessary to mention that the purpose of the study was to estimate the risk of CD and create an expert decision-making system as an educational diagnostic tool for inexperienced physicians (27).

Hooper and colleagues have developed an effective method for diagnosing all cases of CD with no duodenal biopsy. The combination of serology refers to the measurement of tissue transglutaminase antibodies, and stratification of patients according to their referral symptoms are the methods used in the article. In addition, they also mentioned improving the quality of life of patients with CD through early diagnosis. According to our review, this study is the first decision support system for CD (28).

The video capsule endoscopy is one of the imaging tools. If the existence and villous atrophy can be determined, the more invasive method of the standard endoscope is not needed. Owing to the computation method and its very little cost, results would be available in real time. Images from these capsules convert to gray-scale for simplicity, reduced storage requirements, and ease of use. In the next step, the Portable Gray Map specification (PGM) is

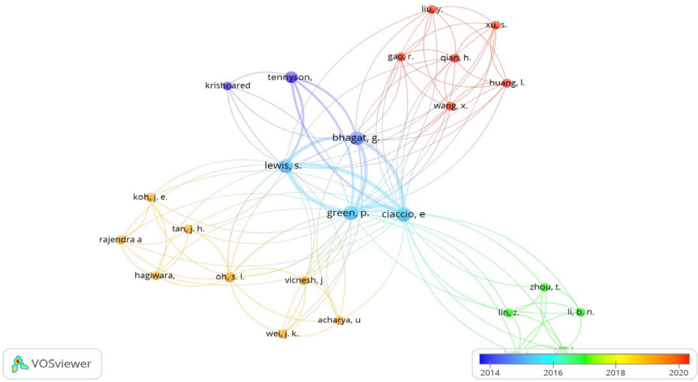

Figure 2: Network Visualization of co-authorship

Table 4: Most frequent words in the article

words	Occurrences
Celiac disease	12
Endoscopy	6
Sensitivity and specificity	3
Humans	3
Deep learning	2
Particle swarm optimization	2
Duodenum-small intestine	2

used to encrypt the gray-scale images, which is one of the simplest methods. Images information was displayed by the Image J application. In this article, In this article, Ciaccio and others showed computer methods for extracting and processing data from capsule endoscopic images.(29)

According to the review results of the final article, 13 authors have done the most research on the use of information technology to diagnose CD (table 3). Figure 2 also shows the authors who have collaborated the most in this field. Table 4 shows the most repeated words in the article, and figure 3 shows the network of co-occurring keywords.

DISCUSSION

We conducted a rapid study of information technology applications in the diagnosis of CD. This review study evaluates the effectiveness of IT-based interventions in the diagnosis of CD. Information technology tools can often improve the diagnosis of CD. Increasing the number and quality of tests and studies in the automatic diagnosis of CD is encouraging. Various training sets and test sets have been used to evaluate the proposed methods. In this article, we have three data models that have been used to diagnose CD, which are endoscopic images, patient data and information, and signs and symptoms of CD, but due to the lack of uniformity and standardization of articles, it is almost impossible to make fair comparisons.

Video capsules or standard endoscopy images are used for feature extraction. In some studies, training

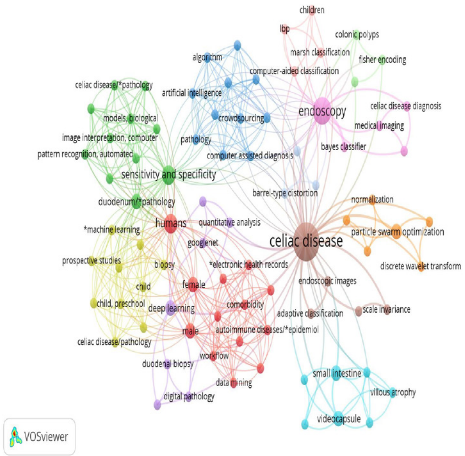

Figure 2:Network of co-occurring keywords

and testing samples that were used in image processing techniques included the number of full images and the number of sub-images obtained as patches from the full image, but others included the number of subjects analyzed (healthy and with CD).

However, some factors, such as the accurate description of the research, the design of automatic and semi-automatic systems, the evaluation of the effectiveness and acceptability of the system, and the efforts to implement the system in the clinic, have made progress in this field. Also, the use of different IT methods maximizes accuracy, reduces detection time, and minimizes the need for human resources. In 2015, Gadermayr conducted preliminary studies on various techniques for fully automated diagnosis of CD (30), and in 2018, Wimmer made acceptable advances in this field by combining deep learning and machine learning that recognized CD with an accuracy of 92.5% (20). As the studies progressed, another best result was the use of machine learning and image processing methods in the Caetano study, which established a system for automatic evaluation and classification of EmA test results. The accuracy of the diagnosis was 96.80%. In this study, the ESPGHAN standard criterion was used. The results showed that standard information and data might lead to a better result for creating a system (16).

The ability to detect individuals at risk of CD will be essential if measures to prevent CD become a reality. A risk assessment may include analyzing B-Cell Receptor as presented in Or Shemesh study. It is possible that BCR-encoding genes play an important role in CD genetics (31).

Authors have pointed out that using technology will determine pathology across the small intestine and the same patient change or improvement in a visual appearance at different times, evaluation of the gluten-free diet or medication effect on the patient, and prospective CD screening. Ciaccio was the first introducer of the real-time diagnosis of CD systems using image processing and machine learning tools (9). In previous studies, the detection of CD was carried out through delayed images. This research provided a new idea for the automatic diagnosis of CD.

Studies have shown that recent efforts to use different deep learning methods are more effective and have achieved excellent results in the diagnosis of CD, so the use of this method has been more popular in recent years. The creation of the first deep learning network for disease diagnosis has achieved good results, with a diagnostic accuracy rate of 95.3%, providing one of the acceptable results in this field. In addition, Local Binary Pattern is a feature extraction technique in image processing. In most studies of endoscopic images, compared with other techniques, LBP usually has the best operation in the diagnosis of CD. Vécsei, for the first time, described a system aimed to perform an automated classification of duodenal texture patches according to a reduced 4-class Marsh-like classification system, and the results showed that the LBP-operator family exhibited better result accuracy compared with a wide range of other feature extraction techniques (12).

Similar review studies have been conducted on the diagnosis of CD using computers (32,33). Our article differs from others in that we have investigated artificial intelligence techniques (such as image processing techniques, machine learning, and deep learning) and also other methods to diagnose CD, a unique approach from other studies. This review incorporated a variety of data, including endoscopic images, patient information, signs, and symptoms of CD. This multifaceted review is not seen in other review studies and mostly has been concerned with the diagnosis of CD using images and not discussing other data sources.

The use of endoscopy in the diagnosis of CD has been an invasive procedure that most people do not want to undergo. On the other hand, using video capsules in imaging is costly and produces low-quality images (34). Moreover, noise and bubbles are also present in the captured images, and their blurring is another limitation in image processing (35). The developed system may not be able to fully automate the selection of images in many cases because the researcher chose endoscopic images without bubbles or blurs.

The possibility of creating a large and accessible database of endoscopic images, and on the other hand, the computing power of artificial intelligence, has led researchers to use this technology to diagnose CD.

Conclusion

The results express that there is a general acceptance of using information technology to improve the diagnosis of CD, but further research is needed to improve and optimize the method of diagnosis. Moreover, artificial intelligence has the capability to analyze images and make primary classifications in its current state. Recent artificial intelligence techniques using deep learning, machine learning methods such as convolutional neural networks, SVM, K-nearest neighbors, and image processing have emerged as the breakthrough computer technology that can be used for computer-aided diagnosis of CD. The current review summarizes methods used in clinical studies to diagnose CD, from feature extraction methods to artificial intelligence and machine learning techniques. Information technology has the potential to play a prominent role in the diagnosing of CD and screening at the lowest cost using computer algorithms.

Ethics approval and consent to participate

All sections of the methodology are in accordance with ethical principles. The study was approved by the Ethics Committee of Tabriz University of Medical Sciences (IR.TBZMED.REC.1398.516). Written informed consent was obtained from all the participants involved in our study.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and Material

Data are available from the corresponding author upon reasonable request.

Consent for publication

Not applicable.

Authors' contributions

Nafiseh Naseri: Design research, gathering data, analysis, and interpretation of data

Zeinab Mohammadzadeh: Design research, analysis, and interpretation of data

Elham Masert: Design research, gathering data, analysis, and interpretation of data

Mohammad Rostami-Nejad: Design research, analysis, and interpretation of data

Alireza Khoshsirat: Design research, Analysis, and interpretation of data

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