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Automated diagnosis of celiac disease using DWT and nonlinear features with video capsule endoscopy images

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HIGHLIGHTS

- Automated detection of celiac disease using video capsule images.
- Employed DWT and nonlinear features techniques.
- Accuracy of 86.47% was achieved with the 10-fold cross-validation strategy.
- Accuracy of 85.91% was attained with LOOCV technique.

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ABSTRACT

Celiac disease is a common immune response when gluten is ingested. Over time, this response will impair the lining of the small intestine and result in malabsorption. This could bring about critical health complications. However, the symptoms of celiac disease vary and hence, it is relatively challenging to make an accurate diagnosis. This results in a high percentage of misdiagnoses. Therefore, a computer-aided detection (CAD) system is proposed to overcome the challenges. Hence, this study employed the discrete wavelet transform (DWT) to decompose the video images, after which textural and nonlinear features were extracted. Thereafter, the particle swarm optimization (PSO) was performed to choose 30 optimal features for classification. An accuracy level of 86.47%, and sensitivity and specificity of 88.43% and 84.60%, respectively, was achieved with the 10-fold cross-validation strategy. Moreover, an accuracy of 85.91% was attained with the leave-one-out cross-validation (LOOCV) technique. This methodology demonstrates potential for accurately identifying celiac disease. It can therefore be noted that the developed CAD system may improve the diagnostic performance in the detection of celiac disease, and thus reduce the number of misdiagnoses.

1. Introduction

Celiac disease is a critical lifelong autoimmune condition, whereby the consumption of gluten (protein that is present in barley, rye, and wheat) will damage the small intestine of genetically vulnerable individuals [1]. The disease is due to the inflammatory reaction in the mucosa of the small intestine that is resulted from a dysregulated immune response, stimulated by ingested gluten [2]. Fig. 1 shows some examples of healthy and damaged villi. Intestinal villi consist of millions of finger-like projections extending from the lining of the small intestine, that enable the efficient absorption of nutrients from digested food. When the villi are damaged or inflamed, they become flattened and are unable to absorb nutrients, leading to malabsorption.

This disease affects roughly 1% of the human population globally, although the majority with celiac disease are undiagnosed [3]. Furthermore, the prevalence of this disease is multiplying at a fast rate. Thus, there is a need to develop a proper diagnostic technique to accurately diagnose celiac disease [4]. This is also because it is difficult to diagnose celiac disease, and it is often misdiagnosed. However, if the disease is left untreated, there will be long-term health effects; celiac disease is correlated with having

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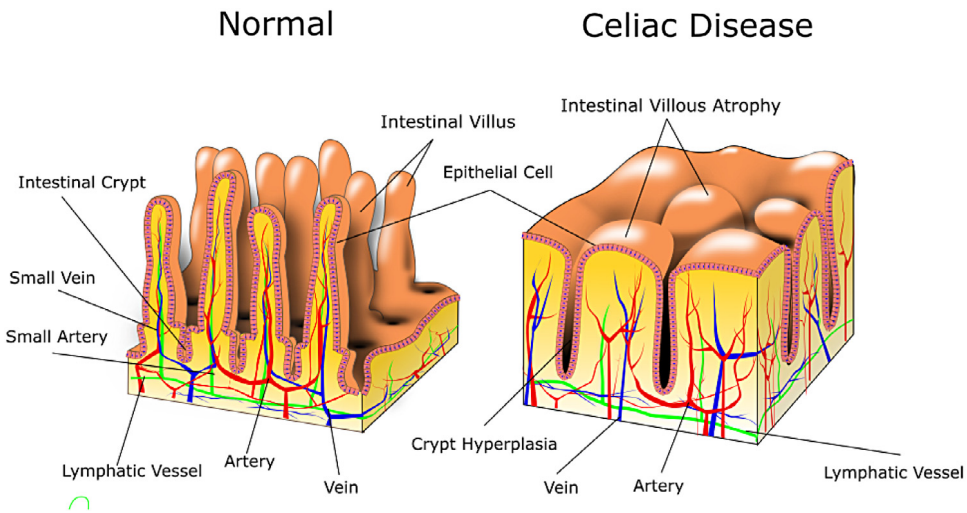

Fig. 1. A representation of (a) healthy and (b) damaged villi.
Source: Adapted from: https://www.dreamstime.com/stock-illustration-celiac-disease-medical-illustration-modification-intestinal-mucosa-subject-image41508355.

a higher probability of developing cancer and it might possibly also contribute to the onset of other autoimmune diseases.

Celiac disease may be divided into classical, non-classical, or silent, as stated by the World Gastroenterology Organization [5].

Classical: This group presents clear signs and symptoms of malabsorption which includes weight loss and diarrhea.

Non-classical: This group experiences slight gastrointestinal symptoms without explicit indications of malabsorption or are present with unassociated symptoms.

Silent: This group is also termed as having asymptomatic celiac disease. No clear symptoms are exhibited but the patients experience villous atrophy within their small intestine.

Presently, endoscopy with biopsy is the gold standard to confirm the diagnosis of celiac disease [6]. Typically, the healthcare professional inspects the duodenum, as it is the entrance to the small intestine, and is considered the area that is often the most affected. However, the procedure is invasive, time-consuming, and costly. By comparison, video capsule endoscopy is a pain-free, noninvasive, and more economical alternative to standard endoscopy [7]. Furthermore, it has portrayed its sensitivity toward the detection of celiac disease, and it can capture images of the entire small intestine. The pill-shaped device, which contains a video camera, is swallowed and subsequently travels through the gastrointestinal tract. A data recorder will be attached to the patient's body and then is removed after eight hours. The pill will be expelled from the body in the stool after one or two days.

Following data acquisition, images obtained from the data recorder are characterized according to Marsh's criterion [8]. Nevertheless, the grading of the endoscopic images is somewhat subjective and is susceptible to inter-operator variabilities. Therefore, it can be relatively challenging to manually diagnose the patients. Moreover, the lack of physician awareness of celiac disease plays a part in the underdiagnosis of the disease. Thus, a computer-aided detection (CAD) system for celiac disease using video capsule endoscopy images is proposed to aid doctors in the diagnosis of the disease. Also, in this study, previous work conducted using video capsule endoscopy are summarized and discussed.

2. Data used

The video capsule images utilized in this work were acquired from 13 control subjects and 13 celiac patients. They were obtained from the Columbia University Medical Center, New York. These subjects swallowed a PillCam that could acquire images of the duodenal mucosa through the passage of the small intestine. Two samples of normal and damaged villi can be observed in Fig. 2.

In this work, two different PillCam devices—the PillCam SB2 (older data) and SB3 (new data) were used. The image acquisition rate is approximately 2 frames per second (constant for SB2 but variable for SB3) and these video clips vary in length (either 100, 200, or 1000 images). These videos have a resolution of 576 x 576 pixels.

Old data: five video clips were obtained from five levels in the small intestine. The levels were approximately the duodenal bulb, duodenum, distal duodenum/proximal jejunum, distal jejunum, and proximal ileum.

New data: three video clips were obtained from three levels—duodenum, jejunum, and ileum.

3. Methodology

Different types of feature extractors were employed in this study to obtain characteristic features to characterize the *two* classes. The proposed CAD algorithm is illustrated in Fig. 3. The input data were first masked and subjected to the discrete wavelet transform (DWT) [9]. After which, various features were employed to extract significant features from the decomposed coefficients. Then, an optimizer technique, the particle swarm optimization (PSO) [10] was implemented to select a set of features for classification. Lastly, two different cross-validation strategies (10-fold and leave-one-out) were employed to validate the detection capability of the proposed technique.

3.1. Pre-processing

Firstly, the border of the video images obtained was masked to remove the wording bordering the image, prior to converting to a grayscale, and then the discrete wavelet transform (DWT) is applied to the images. The masking is done to ensure that the words on the video capsule images will not introduce any bias in the automated decision-making.

Subsequently, DWT was applied to the grayscale images [11–13]. In this study, the mother wavelet bio-orthogonal 3.1 is used to decompose the images up to 3 levels of decompositions with

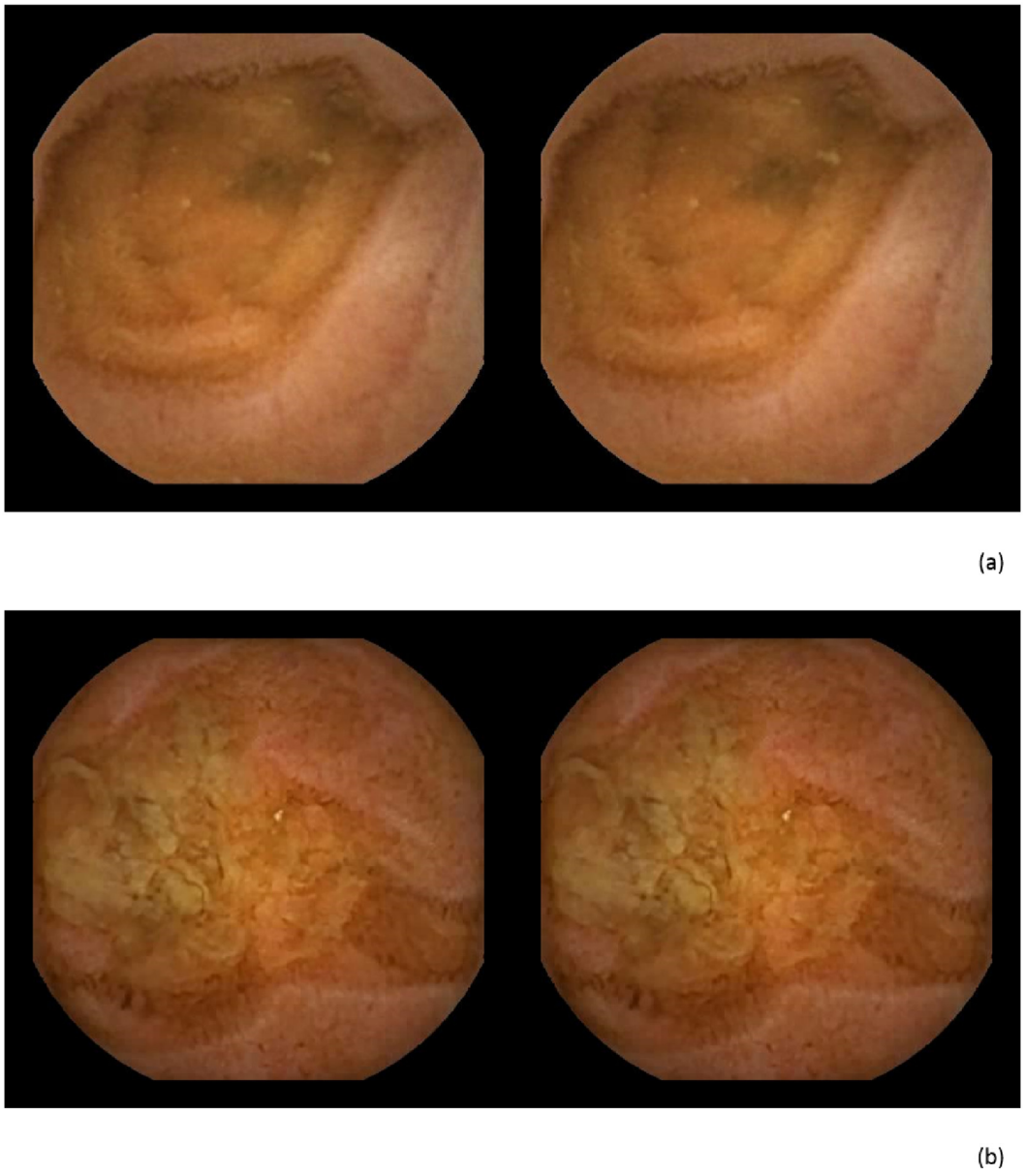

Fig. 2. Samples of (a) healthy and (b) damaged villi acquired with video capsule endoscopy.

Fig. 3. A schematic diagram of the proposed CAD algorithm.

low and high-pass filters [9]. All 3 levels of approximate, diagonal, horizontal, and vertical coefficients were generated. Fig. 4 depicts an example of a level 3 DWT decomposition of a control and celiac disease image. The features are extracted from all three levels of the approximate and detail coefficients. During the high-pass filtering of DWT, subtraction of the image pixels is performed, and the edges of the celiac images are detected [11]. As a result, the edges of the healthy and damaged villi are detected accurately. The ability to detect the villi is important because healthy villi have finger-like projections whereas damaged villi are flattened. Therefore, an accurate detection of the villi edges will ensure better diagnostic accuracy.

3.2. Features extraction

Several nonlinear and textural features were extracted from the decomposed DWT coefficients. The proposed feature extraction techniques can detect subtle pixel changes in the celiac images of the *two* classes efficiently, yielding high classification performance.

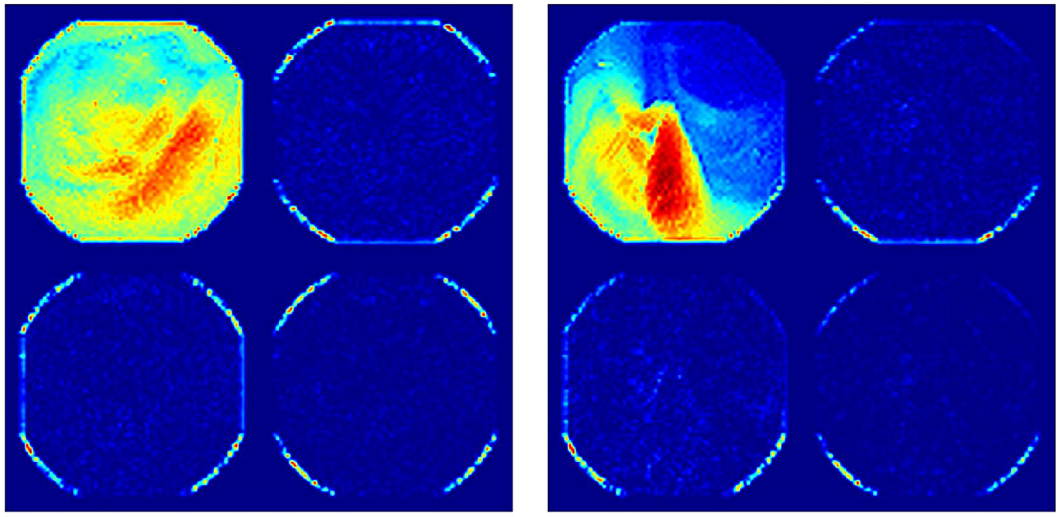

Fig. 4. Level 3 of the DWT decomposition for (a) control and (b) celiac disease.

Texture: the gray-level co-occurrence matrix (GLCM) [14] and the gray-level run-length matrix (GLRLM) [15] are employed for feature extraction.

Nonlinear: The following methods: energy, Fourier energy, fractal dimension [16], Hurst's exponent [17], Hu's moments [18], higher order spectra (HOS)-based parameters such as the skewness, kurtosis, and variance [19], fuzzy entropy [20], Kapur entropy [21], max entropy, Renyi entropy [22], Shannon entropy [23], Vajda entropy [24], and Yager entropy [25] are used to extract the features. Furthermore, the Radon transform (at 1° increment) was performed to transform the 2-dimensional images into 1-dimensional signals [26,27]. Then, the transformed 1-dimensional signals were subjected to HOS bispectrum entropy features; namely the normalized bispectrum (HOS entropy1), normalized bispectrum squared (HOS entropy2), normalized bispectrum cubic (HOS entropy3), HOS entropy phase, and magnitude [28] were extracted [29–33].

A representation of HOS bispectrum plots obtained from the DWT is illustrated in Fig. 5. It can be noted that the two categories (normal and celiac disease) of plots are clearly distinguishable. These plots in four directions (approximate, horizontal, vertical, and diagonal) are distinct and unique.

3.3. Feature selection

After the feature extraction process, the particle swarm optimization (PSO) [10] technique was employed to choose a set of optimal features for classification. The PSO is an evolutionary computation that uses swarm intelligence to search for the best set of features. This algorithm looked for features in the search space that are complementary to each other. In this study, the PSO technique is employed to select 30 highly distinguishing features for the classification. The PSO was done on each fold of the 10-folds.

3.4. Classification

The old and new video images were combined in this study. 20% of the middle part of the video is randomly selected for training and testing (total number of frames divide by 3 to get the middle frame) of the classifiers.

The following classifiers namely the decision tree (DT) [34], k-nearest neighbor (KNN) with a neighbor of 10 [35], probabilistic neural network (PNN) [36], and support vector machine (SVM) [37] were adopted in this work. The SVM classifier with the radial basis function (RBF) and polynomial 1, 2, 3, kernel functions were used in this study. The performances of the proposed CAD system were validated with 10-fold cross-validation [38] and leave-one-out cross-validation (LOOCV) [39] strategies. The performance parameters include accuracy (ACC), specificity (SPE), sensitivity (SEN), and positive predictive value (PPV). The PSO was performed on each fold out of the 10-folds.

4. Results

A total of 10 iterations were run and the average performances (ACC, PPV, SEN, and SPE) were recorded and shown in Table 1. Table 2 lists the average performance obtained using the LOOCV strategy. It can be noted that the SVM RBF classifier with a parameter of 2.4 and 2.5 exhibits the highest ACC of 86.47% and 85.91% for 10-fold and LOOCV strategy respectively. The accuracies obtained for each fold using 10-fold for KNN, PNN, and SVM RBF classifiers can be observed in Fig. 6. It can be noticed that the accuracies fluctuate in each fold using different sets of features obtained from PSO. However, the fluctuation of the accuracy for different folds is less for the SVM RBF classifier.

Furthermore, Fig. 7 shows the SPE, SEN, and ACC achieved in each fold using the SVM classifier with RBF kernel function. It can be observed that the performances in each fold differ slightly, using 30 features.

5. Discussion

In this paper, a novel combination of the various features was extracted to classify normal and celiac disease. The DWT can reveal multiresolution salient features from the video capsule images that are effective in differentiating control images versus celiac disease images with villous atrophy. Furthermore, the features (nonlinear and textural) can capture the characteristic features for the characterization of the classes [40].

The various research efforts using data collected from identical PillCam video capsule images are presented in Table 3. It is evident that the majority of the studies used statistical approaches such as comparing the mean and standard deviation (SD) of the brightness and intensities of the pixels between the images. In the proposed algorithm, we have subjected the images up to 3 levels of DWT, and then extracted nonlinear and textural features. Moreover, PSO

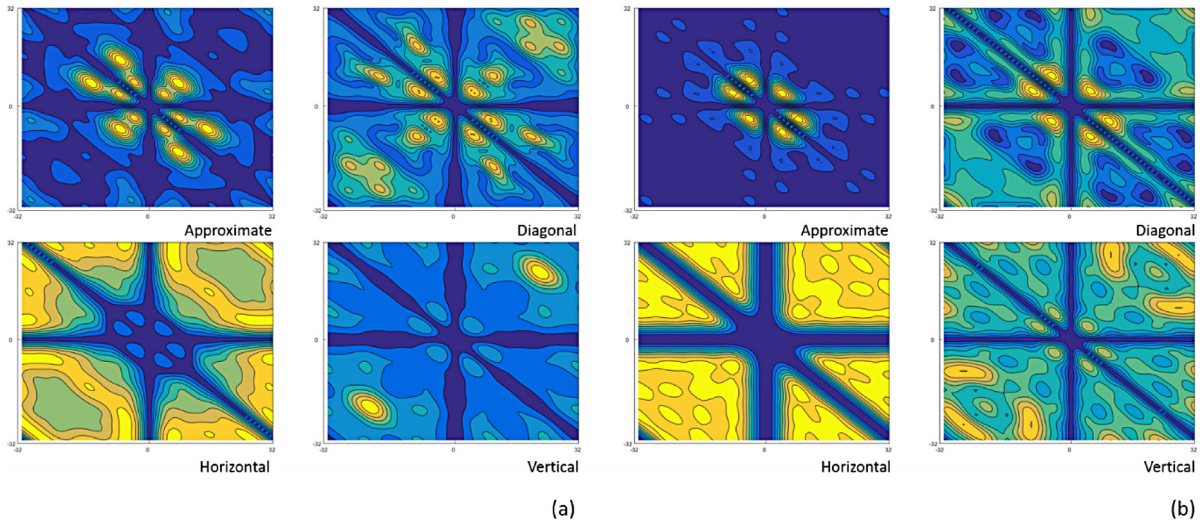

Fig. 5. The level 1 of DWT HOS bispectrum plots for (a) control and (b) celiac disease.

Table 1
Performances of various classifiers using the 10-fold cross-validation strategy.

Classifiers	Parameter	P_{TP}	P_{TN}	P_{FP}	P_{FN}	ACC (%)	PPV (%)	SEN (%)	SPE (%)
DT		379	427	125	148	74.70	75.29	71.92	77.35
KNN	10	421	489	63	106	84.34	86.96	79.93	88.60
PNN	0.1	427	499	53	100	85.82	89.01	81.06	90.40
SVM, Poly 1		333	401	151	194	68.02	68.99	63.20	72.64
SVM, Poly 2		380	441	111	147	76.08	77.30	72.10	79.88
SVM, Poly 3		412	445	107	115	79.43	79.56	78.22	80.63
SVM, RBF	2.4	466	467	85	61	86.47	84.61	88.43	84.60

P_{TP}: true positive, P_{TN}: true negative, P_{FP}: false positive, P_{FN}: false negative.

Table 2
Performances of various classifiers using the LOOCV strategy.

Classifiers	Parameter	P_{TP}	P_{TN}	P_{FP}	P_{FN}	ACC (%)	PPV (%)	SEN (%)	SPE (%)
Decision Tree		387	438	114	140	76.46	77.25	73.43	79.35
KNN	5	408	486	66	119	82.85	86.08	77.42	88.04
PNN	0.08	432	475	77	95	84.06	84.87	81.97	86.05
SVM, Poly 1		326	396	156	201	66.91	67.63	61.86	71.74
SVM, Poly 2		393	449	103	134	78.04	79.23	74.57	81.34
SVM, Poly 3		408	455	97	119	79.98	80.79	77.42	82.43
SVM, RBF	2.5	473	454	98	54	85.91	82.84	89.75	82.25

P_{TP}: true positive, P_{TN}: true negative, P_{FP}: false positive, P_{FN}: false negative.

is introduced in the proposed algorithm to enable faster and more efficient selection of features for classification. Further, PSO is easy to implement and requires lesser computational complexity.

Nevertheless, Zhou et al. [41] developed a CAD system using the state-of-the-art algorithm. They have designed a 22-layer deep convolutional neural network (CNN) that could distinguish normal and celiac disease video images with 100% accuracy. The CNN model is a group of deep learning (DL) technique that does not involve a feature extraction or selection process [42,43]. The model automatically learns to single out the significant features through the data training process. Consequently, no human-engineered features are required for the CAD system. However, implementing DL requires big data. Hence, due to the limited availability of data in this study, the DL technique was not employed. Therefore, as part of the future development, the authors aim to collect more images and improve the proposed CAD system by adopting DL techniques to automatically characterize the *two* classes (normal and celiac disease). Also, we aim to achieve a real-time diagnosis in our future work. We intend to extend this study by classifying the abnormal class into its various sub-classes as part of the future work.

Additionally, various CAD systems were developed by different researchers using the images obtained with duodenoscopy [44–47]. Yet, these diagnostic techniques are invasive, and they may introduce discomfort to the patients. Therefore, we used data collected from the video capsule endoscopy in this study.

Fig. 8 illustrates the use of a celiac diagnosis CAD system in the clinical setting. The developed machine-learning model is placed in the cloud. The captured celiac image was input through the web server to our trained model placed in the cloud. Then the diagnosis is sent from cloud to web server immediately for clinicians to crosscheck their diagnosis.

Overall, the advantages of the proposed technique are:

i. The integration of DWT with nonlinear and textural features can detect distinctive and subtle pixel variations in the *two* classes.
ii. Two different cross-validation strategies (ten-fold and LOOCV) were implemented.
iii. Feature selection is implemented on the training data of each fold. Thus, the system is more robust.

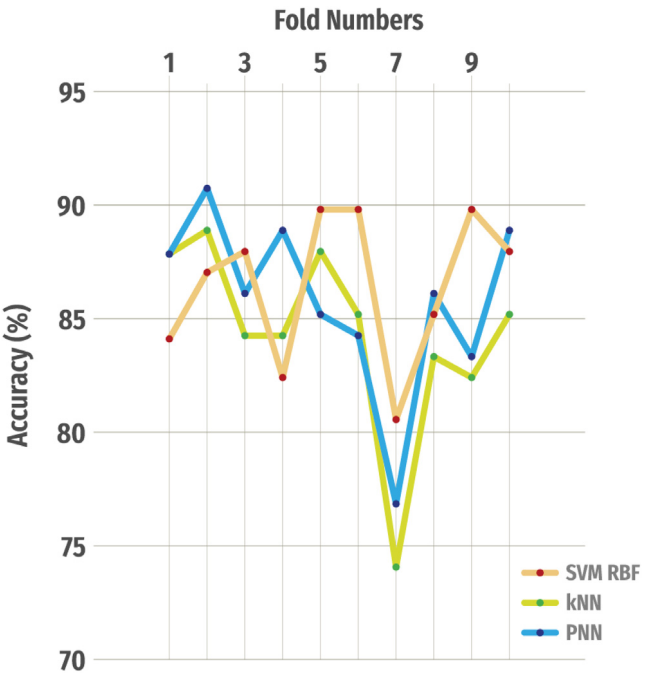

Fig. 6. The accuracy plot of SVM RBF, PNN, and KNN classifiers in each fold using 10-fold cross-validation.

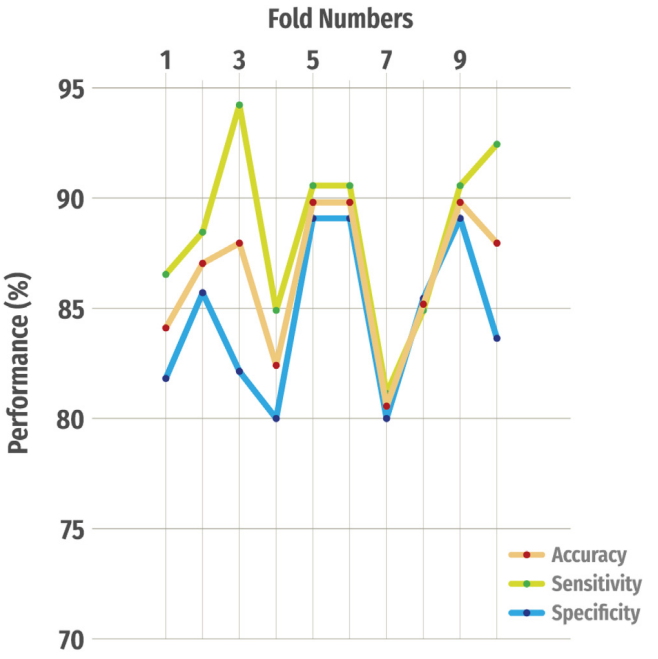

Fig. 7. The ACC, SEN, and SPE of SVM RBF in each fold using 10-fold cross-validation.

iv. It can be deployed in a mass-screening session and hence, create awareness of celiac disease in the region.

On the other hand, the disadvantages of the proposed technique are:

i. A large number of video clip images are needed.
ii. The current system cannot be used in real-time.
iii. The classification performance must be enhanced by employing advanced DL techniques.

6. Summary and conclusions

All in all, celiac disease is a persistent auto immune disease that is often underdiagnosed and may cause severe health conditions if the disease is undiscovered. Therefore, this paper proposed an algorithm to automatically distinguish celiac disease from the video capsule images. An accuracy of 86.47% and 85.91% was achieved using the 10-fold and LOOCV technique respectively. Based on the experimental results, we have demonstrated that the proposed methodology possesses the capability to be installed in clinics to

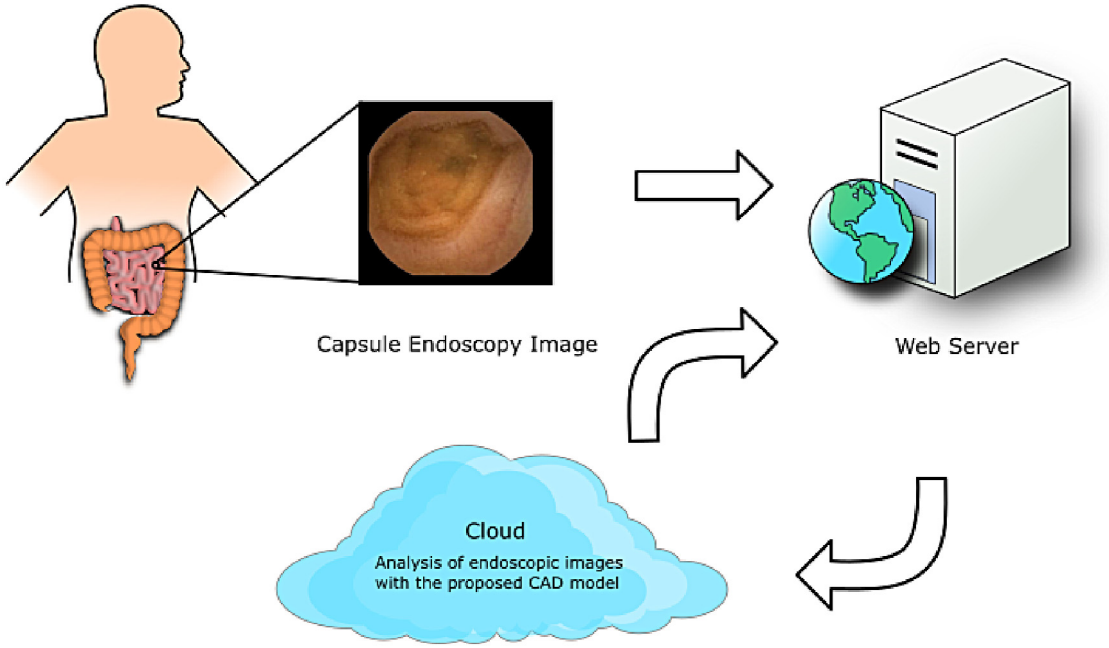

Fig. 8. Use of the celiac diagnosis system in a clinical diagnosis setting.

Table 3
A list of literature review on the development of CAD systems for celiac disease.

Authors	Year	Techniques	Conclusion
Ciaccio et al. [48]	2010a	• Mean and SD in brightness	Threshold classifier: SEN: 80% SPE: 96% Incremental classifier: SEN: 88% SPE: 80%
Ciaccio et al. [49]	2010b	• Mean and SD in brightness	SEN: 92.7% SPE: 93.5%
Ciaccio et al. [50]	2011	• Dominant frequency analysis	–
Ciaccio et al. [51]	2014	• Histogram level	SEN: 76.9%–84.6% SPE: 69.2%–92.3%
Zhou et al. [41]	2017	• CNN (22-layer GoogLeNet)	SEN: 100% SPE: 100%
Present work	2018	• DWT • Nonlinear, textural features • PSO • SVM classifier	10-fold: SEN: 88.43% SPE: 84.60% ACC: 86.47% LOOCV: SEN: 89.75% SPE: 82.25% ACC: 85.91%

assist clinicians in the diagnosis of celiac disease. With a robust diagnosis system, it will enable clinicians to improve the rate of diagnosis and to administer appropriate and timely treatment to the patients.

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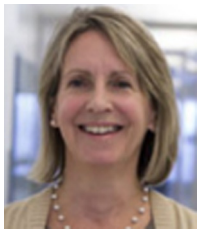

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