Cancer Diagnosis in Endoscopic Images using Discrete Wavelet Transform

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ABSTRACT:
Stomach cancer destroys the tissues of the digestive system. This cancer is one of the deadliest diseases. Endoscopic imaging is used to diagnose cancer. In endoscopy, the diagnosis of gastric cancer is difficult due to the similarity of the tissues, the low contrast of the image and the background. In order to overcome these problems, discrete wavelet transform has been used to detect stomach cancer. In the proposed method, there are data registration, data preprocessing, feature extraction, dimensionality reduction, and classification. The features are extracted with the help of discrete wavelet transform and then dimension reduction is done with the help of principal component analysis. The proposed approach was evaluated on datasets collected from five classes, including gastritis, ulcer, esophagitis, bleeding, and healthy. random forest has a value above 99% in all evaluation criteria, which represents the advantages of this category. RF is ensemble classifier that can perform well in cancer detection The results of this research show that this method is accurate and reliable in diagnosis.

KEYWORDS: Diagnosis, Destroyed tissues, Endoscopic Images, Based Stomach.

1. INTRODUCTION

Perishability from esophageal cancer remains high against advances in medical treatment. Although the propagation of esophageal squamous cell carcinoma stays unchanged, the propagation of esophageal adenocarcinoma has incremented over time. Gastroesophageal reflux disease (GERD) and obesity are factors in the development of Barrett's esophagus and subsequent adenocarcinoma . Early detection of this disease can lead to the removal of esophageal cancer before lymphatic vascular invasion occurs[1-3]. Various methods have been performed for correction. Precancerous lesions and esophageal cancer Primary[4]. Chromondoscopy, narrow-band imaging, and endoscopic ultrasound examination are commonly used to evaluate primary lesions of the esophagus and stomach. Video endoscopy is a standard gastrointestinal screening method[5]. It is a less aggressive procedure used for early detection of gastric diseases. Manual search of large numbers of gastric frames is a comprehensive and time-consuming task and requires expertise. Conversely, several computer-aided detection systems have been suggested by researchers to deal with the problem of manual inspection of large volumes of frames[6-12]. Artificial intelligence (AI) is considered as a potential solution to reduce detection challenges. In recent years, artificial intelligence has made significant progress in endoscopic image diagnosis, including colorectal polyp detection, detection of Helicobacter pylori infection [13-16], and upper gastrointestinal cancer diagnosis [۱۴]. In the method based on machine learning, pattern recognition processes are used. In this category of methods, after applying pre-processing on the image, numerous features including textural, spectral, geometric and statistical features are extracted from the desired image[10, 17-19]. These features are reduced in another step with the help of methods based on principal component analysis (PCA), independent component analysis (ICA). At this stage, feature selection methods can be used to select the most effective features [۱۶-۱۹]. Several researches have been presented in order to diagnose breast

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cancer. Rodriguez-Diaz and Singh [۲۰]proposed a method based on good criteria for diagnostic purposes. Veronese et al [17] suggested a computer-aided research for gastric cancer diagnosis based on the use of apparent features in co focal images. In [۲۱] suggested a method based on HD endoscopic images for automatic detection of esophageal lesions. In [۲۲] suggested a new method that computes local texture and color features based on Gabor-filtered original images for automatic early cancer detection in high-resolution endoscopic images. In [۲۳] illustrated a real-time and computationally efficient bleeding detection technique using wireless capsule endoscopy (WCE) technology. In [۲۴]conducted a study to test the possibility of classifying Adenocarcinoma in endoscopic images. In [۲۵]used Endoscopic ultra sonography (EUS) to diagnose esophageal cancer. In [۲۶] used computer vision techniques to correctly predict the presence of dysplastic tissue in VLE images. In [۲۴] presented deep learning on adenocarcinoma and BE disease images applied to the given dataset. In [۲۷] introduced restricted Boltzmann machines in the field of classification of the "MICCAI 2015" dataset. Using a convolutional neural network (CNN), Liu et al. proposed to automatically classify esophageal cancer (EC) and distinguish it from premalignant lesions [۲۸]Chen et al. have used deep learning to detect esophageal cancer [۲۹]. In the last decade, there are many tendencies towards feature extraction with thin representation. Because in this representation, there are almost only a small number of non-zero coefficients, or they have been thinned after applying transformations on the image. This trend seems to be due to the potential to reconstruct a signal or image from a smaller number of measurements than conventional methods to reconstruct an entire signal. The features extracted in thin transformations are more unique. One of the notable thin transforms is the use of wavelet transform. The purpose of wavelet transform is a desirable strategy to establish an optimal balance between time accuracy and frequency accuracy[36]. At higher frequencies, the wavelet transform gains temporal information at the cost of losing frequency information. While at lower frequencies, it gains frequency information at the cost of losing temporal information. This favorable approach to information exchange is useful for digital signal processing and music applications. Because events that happen at high frequencies and events that happen at high frequency usually need high frequency accuracy. Early detection of gastric cancer is important to improve patient survival, but accurate diagnosis of superficial neoplasms in the stomach is difficult even for experienced doscopists. It is believed that the computer-aided diagnostic system is an important method to provide accurate and rapid assistance to endoscopists in the diagnosis of gastric cancer. In this research, a new method based on thinning transformations using multiple classifications will be developed to detect gastric cancer using endoscopic images, and the purpose of our study will be to evaluate the system's ability. In the following, this article is divided as follows. In the second part, the wavelet transform will be introduced as a thinning transform. In the third part, the proposed method is presented. In the fourth part, the evaluation of the proposed method will be done. Finally, in section 5, the conclusion of the article will be presented.

1.1. Discrete Wavelet Transform

Wavelet transform is a desirable strategy to establish an optimal balance between time accuracy and frequency accuracy. At higher frequencies, the wavelet transform gains time-domain information at the cost of losing frequency-related information. While at lower frequencies, it gains frequency information at the cost of losing temporal information [36]. This favorable approach to information exchange is useful for digital signal processing and music applications. Also, events that occur at high frequency usually require high frequency accuracy. As the Fourier transform is defined based on an integral, the wavelet transform can also be defined based on an integral as follows(1)

$$W_{X(S,U)} = \int_{-\infty}^{+\infty} X(t)\Psi_{s,u}(t)dt \tag{1}$$

In the above integral, the input signal x(t) is related to the wavelet by means of the transfer parameter u and the coherence parameter s. This transform transforms a signal into coefficients that represent time-frequency information. These coefficients have more time accuracy at high frequencies and more frequency accuracy at low frequencies. The homogeneity parameter enables the wavelet to exchange information in frequency events. One of the fast ways to calculate the wavelet transform is to use filters. The input signal is passed to two filters, H and G: these filters produce two sets of coefficients, both of which are sampled by a factor of two. As seen in Figure 1, this method is successively applied to a set of coefficients that come out of the H filter [37].

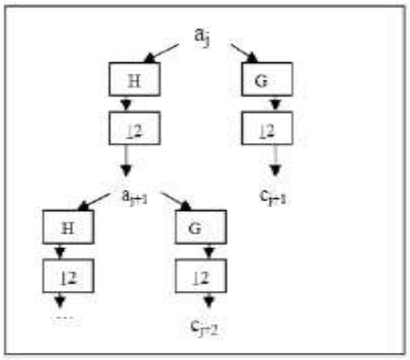

Fig. 1. Fast Wavelet Transformation using Filters[٣٠].

The DWT method overcomes the drawbacks and weaknesses of the fast Fourier transform (FFT). Signal analysis based on FFT works well when its frequency spectrum is not dependent on time, in other words, it is statistically stationary, but many signals are non-stationary in nature[38]. Time-frequency representation of time series signals is an attractive way to capture frequency information at low frequencies and time information at high frequencies. The DWT method is one of the techniques based on multi-resolution analysis [39]. For the X(t) signal, the wavelet transform is defined as follows: [٣١].

$$WT_X\left(j,k\right)=\frac{1}{\sqrt{a_0^j}}\int x(t)\Psi^*\left(\frac{t-ka_0^jb_0}{a_0^j}\right)dt \qquad (2)$$

In equation (2), x(t) and Ψ are the initial signal and the wavelet transform function, respectively, and also the transmission parameter and a_0^j is the scale parameter. where j represents the wavelength. Usually $a_0 = 2$, so scales are sampled during a binary sequence. The sample time domain is specified using kb_0.

At each level of analysis, approximation coefficients CA and detail coefficients CD are created by passing the X(n) signal through the high-pass H and low-pass L filters [40]. Approximation coefficients and detail coefficients are obtained by the following equations:

$$CA_j=\sum_{n=-\infty}^{\infty}X_{j-1}(n)l(n-2k) \qquad (3)$$

$$CD_j(k)=\sum_{n=-\infty}^{\infty}X(n)l(n-2k) \qquad (4)$$

After separating the signal into high and low frequencies in the first level, only the low frequency part of the wavelet transform is taken in the next steps. By putting together the coefficient of approximation of the last level and the detail coefficients of all levels, it is reconstructed [٣٠].

2. PROPOSED METHOD

Machine learning-based methods should distinguish healthy from unhealthy tissues, including gastritis, ulcers, esophagitis, and bleeding. In machine learning, there are stages of image preprocessing, feature extraction, feature selection and finally classification. In this article, filter-based methods are used for the pre-processing of stomach images obtained from endoscopy. Then the features based on discrete wavelet transform will be extracted. It is suggested in the reduction after PCA. Finally, the selected features will be classified with the help of support vector machine, K nearest neighbor and random forest classifiers. Figure 2 depicts the proposed method. In the following, the proposed method will be explained in detail. A two-way filter is used for the pre-processing of endoscopic images. This filter is used as an edge preservation tool in image enhancement applications [42]. Along with a low-pass spatial kernel (which helps with smoothing), it uses a kernel to prevent smoothing near edges. As a result, the filter is able to smooth homogeneous areas and preserve sharp edges at the same time. In feature extraction, useful information is drawn in the space of low-dimensional features. In other words, the unique characteristics of an event such as an endoscopic image are calculated during different processes[41]. Usually, the extracted segments have smaller dimensions than the signal. Image thinning features are based on multi-resolution transformations called discrete wavelet transformation. Wavelet bases are efficient in wavelet transformation for non-stationary endoscopic image analysis. Many researchers have used DWT to analyze endoscopic images. Basically, the Dubichse basis creates orthogonal wavelet filters. It has been used to analyze endoscopic images. Several classes of wavelet filters have been used to analyze non-stationary signals. The choice of a particular wavelet filter depends on the given application and the type of signal to be analyzed. Daubechies orthogonal wavelet filters are considered as a suitable choice for analyzing pre-processed endoscopic images in this research. This wavelet filter base has maximum smoothness or regularity. Daubechies wavelet filter banks are optimally designed for accurate signal analysis. Figure 3 shows a wavelet transform of an image at a level. As can be seen from Figure 3, with the increase in the number of wavelet conversion levels, the signal information in the high frequency (detail) and low frequency (approximation) sections decreases[44]. In this research, high frequency and low frequency information is used at level one.

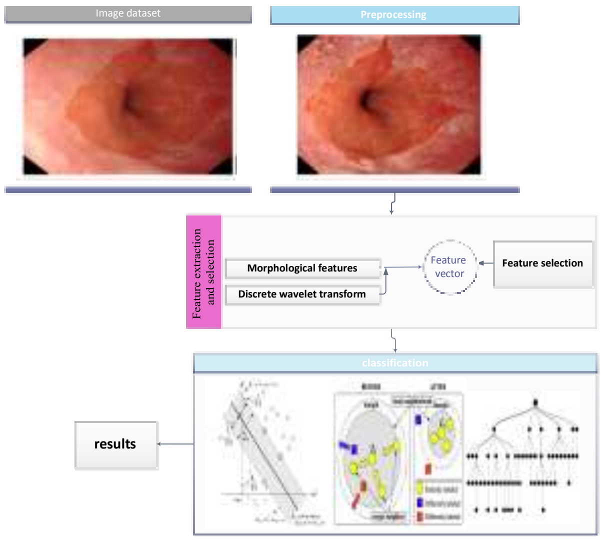

Fig. 2. Block diagram of the proposed method.

It has been used for reduction after principal opponents analysis. For a data matrix with zero empirical mean, where each row is a set of observations and each column is data corresponding to an index [45].

Fig. 3. Wavelet transform at a level on stomach image.

In order to reduce the dimension and remove duplicate information, principal component analysis has been used in this research. Finally, the features of the given dimension cache will be classified by three classes of support vector machine, K nearest neighbor and random forest.

3. EVALUATION

In this article, four classes of stomach disease are diagnosed along with the healthy class. In the proposed method, after pre-processing, the features of the multi-day field were extracted based on the discrete wavelet transform. Then dimension reduction was done using PCA method. In the end, classification is done with support vector machine, random forest and k nearest neighbor. In this research, the identification rate criterion was used to evaluate the proposed method. The measures used are recall rate (Equation 5), precision (Equation 6), accuracy (Equation 7), and f-criterion (Equation 8)[43].

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad (5) \qquad \mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \quad (6)$$

$$ACC = \frac{TN + TP}{TN + FN + FP + TP} \quad (7)$$

$$F\_Measure = \frac{2 \times TN}{T2 \times TP + FP + FN} \quad (8)$$

In these equationships, true positive is shown by TP, true negative is shown by TN, false positive is FP and false negative is FN. A standard dataset for esophageal carcinoma pathology reporting was developed based on International Collaboration on Cancer Reporting (ICCR) approach with the aim of improving cancer patient outcomes and international benchmarking in cancer management. The ICCR convened an international multidisciplinary expert panel to identify the best evidence-based clinical and pathological parameters for inclusion in the gastric cancer [۳۲]. In order to evaluate the proposed method, the relevant features are extracted and then with the help of the desired classification types in the mode without feature selection and with the feature selection, the classification and diagnosis of the disease type is done. At first, each feature will be applied to the category input without selecting the feature. Then, these features are combined in series by applying feature selection. In the following, these evaluations have been made in the criteria presented in the research. To evaluate the absolute value of the size of the features of high frequency details and approximation in low frequency, the discrete wavelet transform has been extracted based on the Daubechies filter bank. The number of extracted features is 300 in the second level wavelet transform. The parameters of recall rate, precision, accuracy, specificity and f-criterion are evaluated in three categories: SVM, KNN and RF. Figure 4 shows the detection results of the detection results for the ICCR database on the wavelet transform features at the first level. Similar to what happened in the morphological features, this time the RF classification has shown the best result in the diagnosis of the disease in the endoscopic image. This superiority in the criteria of recall rate, accuracy, specificity and f-criterion is established as an approximation. This time, in wavelet features as well as morphological features, the evaluation criteria of diagnosis has reached 90% in the best case. It should be noted that the results obtained in the multi-resolution features of wavelet transform were much better than the morphological features. The much larger number of features and also the use of Daubechies filter bank in the disease in the endoscopic image is the cause of this difference in the result. In the feature criterion and F criterion, the measured value in the RF category, which has the best result, has reached 95%. Although the desired result is acceptable, due to the large number of features, there is a possibility of over-training and over-fitting.

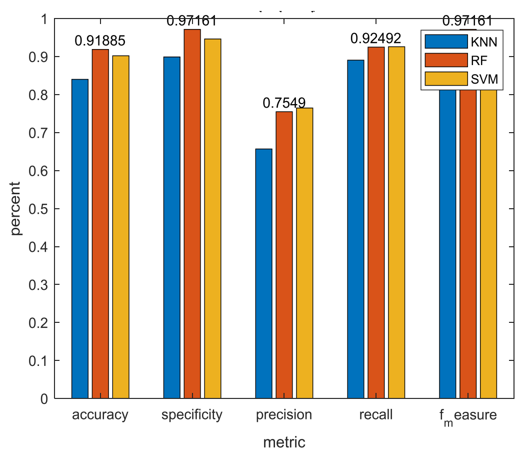

Fig. 4. Detection results for ICCR database in wavelet transform features.

3.1. The Vector of the Series of Features

In this evaluation, the extracted morphological features and wavelet transformation are placed next to each other in series and the corresponding feature vector is made. The length of the feature vector is 325. The parameters of recall rate, precision, accuracy, specificity and f-criterion are evaluated in three categories: SVM, KNN and RF. Figure 5 shows the results of disease diagnosis in the endoscopic image in the ICCR database in the feature series vector. As shown in the results in Figure 5, similar to what happened in the morphological characteristics and discrete wavelet transform, the RF classification has shown the best result in the diagnosis of the disease in the endoscopic image, as in the previous three cases. This superiority in the criteria of recall rate, accuracy, specificity and f-criterion is established as an approximation.This time, like the morphological characteristics, the diagnostic evaluation criteria has reached 90% in the best case. It should be noted that the results obtained in the multi-resolution features of wavelet transform were much better than the morphological features. The much larger number of features and also the use of Daubechies filter bank in the disease in the endoscopic image is the cause of this difference in the result. In the feature criterion and F criterion, the measured value in the RF category, which has the best result, has reached 99%. Although the desired result is acceptable, due to the large number of features, there is a possibility of over-training and over-fitting. For this purpose and to avoid over fitting in this research, a dimension reduction based on PCA is presented.

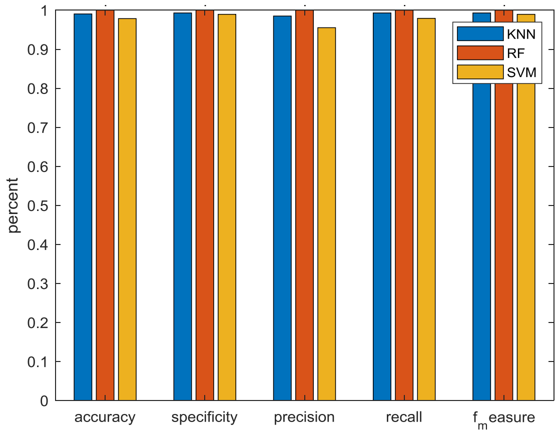

Fig.5. Recognition results for the ICCR database in the reduction after the feature series vector.

3.2. Comparison of Detection Time

By selecting the feature, the speed of diagnosing the disease in the endoscopic image will increase. While the feature vector length is 325 numbers in the series mode, only 65 features are selected in the feature selection mode. Choosing a smaller number of features, in addition to preventing over fitting of the classifications, also improves the evaluation criteria proposed in the research for diagnosis. Also, less number of features can improve the detection speed. In order to evaluate the detection time, the ric-toc command is used. This order is placed before and after the categories. Table 1 shows the comparison of classification and diagnosis time in different categories. The detection time is measured with the system used for simulation. Based on the results obtained in this table, the SVM classifier has a higher speed in diagnosis. Although the RF classifier has shown a better result from the point of view of other evaluation criteria, but because it is in the group classifiers, it has a weaker performance in response and recognition time.

Table 1. Samples of times roman type sizes and styles used for formatting a technical work.

Database	**Class type**	**Before feature (selection seconds)**	**After selecting the (feature seconds)**
ICCR Database	SVM	0.1902	0.1500
	KNN	0.2314	0.1803
	RF	0.2996	0.2408

3.3. Comparison with Other Researchers

The best result obtained in this research belongs to the RF category. Therefore, the results obtained in this research will be compared with other studies that have used a similar database (ICCR database). In these articles, some criteria are reported and others are not reported. The results and criteria reported in these articles will be presented. As can be seen from Table 2, the proposed method shows superior results compared to the presented methods.

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Table 2. Comparison with other researches.

Reference	Methodology/WL	Performance
[33]	Hybrid Deep Learning Model	Sen:94%
[34]	Texture and Color Enhancement Imaging	Spec:91% Sen: 94.45%
[35]	Deep Learning Model for Disease Prediction Using Gastrointestinal-Endoscopic Images	Spec:93.8% Acc:96/2% Sen: 94.1%

4. CONCLUSION

In this article, the proposed method was evaluated in the diagnosis of gastric cancer in the endoscopic image. Multi-resolution features based on wavelet transform were extracted with Daubechies filter bank. The parameters of recall rate, precision, accuracy, specificity and f-criterion are evaluated in three categories: SVM, KNN and RF. RF classifier has the best result with numerical values higher than 99% in the proposed method in feature selection based on PCA algorithm, the result in disease diagnosis in endoscopic image in ICCR database. The detection speed was also checked in the proposed method in the detection in all three databases. The SVM classifier has classified the disease in the endoscopic image in the shortest time compared to other classifiers in the database.

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