International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Revue d'Intelligence Artificielle
Vol. 37, No. 1, February, 2023, pp. 171-178
Journal homepage: http://iieta.org/journals/ria

Feature Extraction and Classification Techniques for Wireless Endoscopy Images: A Review

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https://doi.org/10.18280/ria.370121

Received: 10 October 2022
Accepted: 19 December 2022

Keywords:
classification, digestive system, detection, feature extraction, feature selection, WCE images

ABSTRACT

Wireless Capsule Endoscopy (WCE) is one of the convenient ways to observe human digestive system, like esophagus, stomach, duodenum, small intestine, large intestine, liver, gallbladder and pancreas which are involved in metabolism. There are no incision-related injuries, no anaesthetic complications, and no negative effects on the patient. The researchers started this investigation because early detection of abnormalities is essential. Through WCE imaging data, polyps, ulcers, and cancers can be identified early. Feature extraction and selection, classification, and image pre-processing are the next three main procedures used to handle the WCE images. One of the crucial phases that can gauge the efficacy of WCE picture classification and, ultimately, the disease, is the feature extraction and selection. This study investigates three feature selection approaches and nine feature extraction methods for classifying WCE photos. It also examines the benefits and drawbacks of each technique. Both of these are taken into account while deciding which approach to use in various situations. A table with a synopsis of each technique is supplied as supporting documentation. This study demonstrates that the suitable feature extraction technique for the civic DVC dataset is Local Binary Pattern combined with GLRLM (Gray Level Run-Length Matrix), ZM (Zero Shot Manipulation Net), PHOG (Pyramid Histogram of Oriented Gradients) and GLCM (Gray-Level Co-Occurrence Matrix), while the best feature selection and extraction techniques for general knowledge bases is CSRN (Cellular Simultaneous Recurrent Networks) and DELM (Deep Extreme Learning Machine) and the classification accuracy achieved is 96.5%.

1. INTRODUCTION

Numerous diseases certainly will have an impact on a person's life. Some diseases, like cancer, can kill us, while the majority only harms our internal organs, including the heart, brain, lungs, kidneys, and liver. According to the study [1] in India, maximum number of mortality is between the age group of 30-39 which is considered as the intellectual resource and upon which economy of India depended. Also, majority of them are males. In the global context, digestive diseases are responsible for 3.8% of male and 3.2% female deaths worldwide [2]. Efficient Feature extraction and Classification methods to detect this critical illness is the need of the hour. A device which gives the clear view of the inside stomach and various organs of the body, is already in use from past decade. The steerable wireless capsule is capable of investigating the upper gastrointestinal (GI) tract including the stomach.

Images captured reviewed post-procedure by the physician. In 2004, Iddan and Swain [3] showed a new avenue to the medical world in the form of a Wireless Capsule Endoscopy. At present, there are several Endoscopies to scan human digestive system such as Gastroscopy or Enteroscopy (mechanical push), Wireless Capsule Endoscopy (WCE) etc. WCE is a method of scanning the digestive system that produces precise photographs of the inside human digestive system. WCE does not use incision or anesthesia. Anesthesia sometimes can be fatal for the human being. The sample dataset image is shown in Figure 1. The Pillcam which captures images is shown in Figure 2.

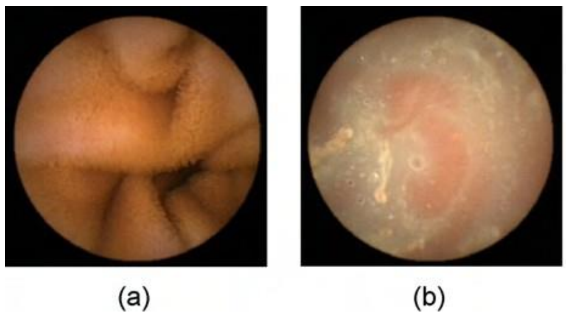

Figure 1. (a) Normal mucosa (b) ulcer

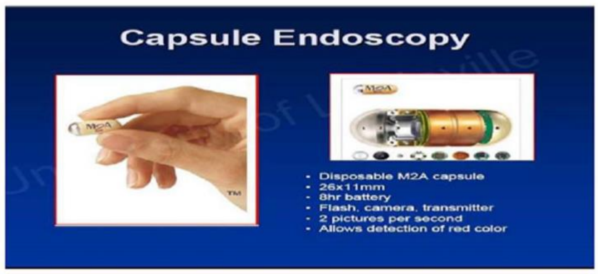

Figure 2. WCE

Through ML and DL, several studies on the prior detection of polyp, ulcer, and tumor have been undertaken. Pre-processing i.e., sizing or altering the quality of the WCE image, then segmentation, later features extraction, and at last classification are typically used to process the WCE images for these researches. Before classification of the WCE image using machine learning methods like deep learning, the study's discussion focuses on several feature extraction and selection methods.

2. RELATED WORK

The first step in WCE image processing is gathering the necessary WCE images as data. Before acquiring the results of categorization of polyp, ulcer, or tumor identification based on the created WCE images, the WCE images will next be processed via a number of phases. The WCE images and the methods used to classify and diagnose diseases using the processed WCE images will be explained in this part.

A. WCE images

Wireless Capsule Endoscopy or popularly called as WCE is a non-invasive diagnostic device which produces images of the complete digestive system using Camera fitted on both sides of the capsule.

B. Classifying WCE images

The process of classifying anything involves dividing it into groups according to its features. Physicians can utilize this classification technique to aid in disease diagnosis and decision-making. When classifying objects, WCE images will be processed in order to determine if they are actually normal or aberrant (indicating any disease). Several tasks need to be completed before the classification procedure can be carried out. The WCE image is processed in this manner to obtain the most precise information possible, assisting the doctors in making correct diagnoses and decisions. As a result, they are able to provide the patient with the proper preventive care.

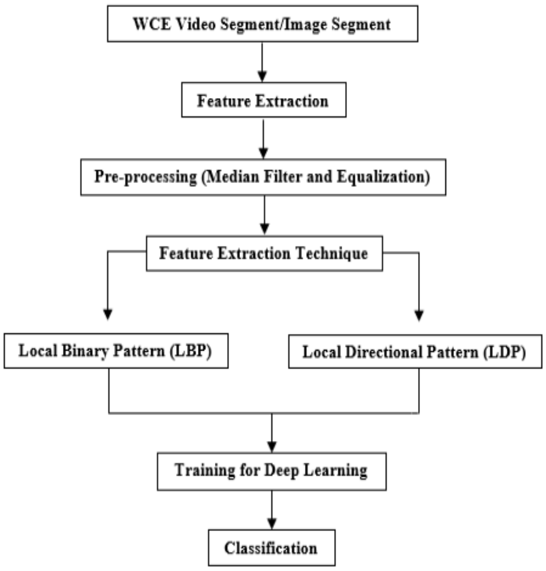

Figure 3. Classification process flow

Figure 3 depicts the procedures/steps used to process WCE photos before classification. Medical WCE photos can be acquired from a variety of online databases that have been made available by numerous institutions. WCE images are available from a variety of sources as training and testing datasets for the classification procedure, including the CVC-ClinicDB and Kvasir databases. Prior to segmenting and finding ROI, images that are being downloaded from some sources should first be analyzed (Region of Interest). Then comes feature extraction. The methodology of extracting features from a definite shape so that they can be processed in the following phase is known as feature extraction. Every point or pixel that is present during every checking procedure is counted in order to extract the features. The digital image that has been studied is traced in many different directions in Cartesian coordinates, including 1) vertical, 2) horizontal, and 3) diagonals [4]. The feature which is then chosen based on how important it is. For the best classifier, the most important attribute is chosen. Datasets that have already been processed are split into training and testing classes throughout the classification phase. To ensure that the categorization procedure is carried out as accurately as feasible, training is used. To assess the effectiveness of the chosen model, testing is used.

A confusion matrix, (sometimes known as error matrix) we are able to observe in the Figure 4 which visualizes obtained precision of classification and errors made by a machine learning model. They are especially useful where multiple categories of classification are present. Every matrix contained different rows signifies at illustrations within an observed category, whereas every feature signifies at illustrations in a real class.

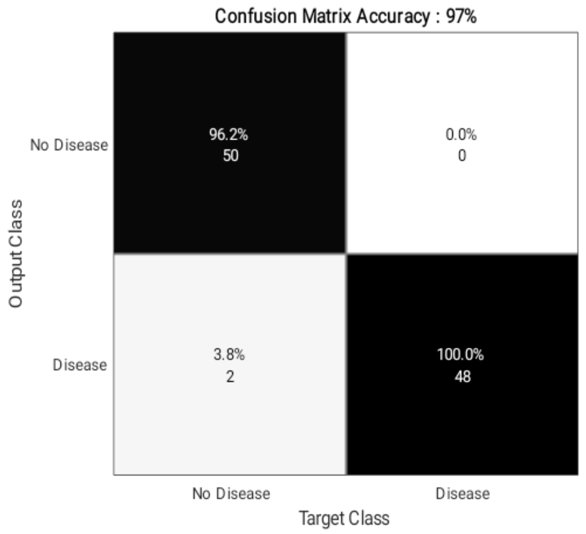

Figure 4. Model classification accuracy and errors by machine learning

3. RECENT ADVANCES IN FEATURE EXTRACTION AND FEATURE SELECTION METHODOLOGIES IN CLASSIFYING WCE IMAGES

In this section, various techniques for extraction and selection of features used to categorize WCE images will be covered. The processes must be addressed because they are crucial to the categorization as early detection of polyps, ulcers, or tumors using WCE images. They must be discussed because they are crucial to the classification's success. We have compiled a list of 12 feature extraction methods and 4 feature selection approaches that have been extensively used in prior research.

3.1 Methodologies for feature extraction

The process of extracting features from images in image processing involves applying mathematical operators to any step of image processing, with the input being either a single image, a collection of images, or even a stream of images. Results of digital image processing can either be a single image or attributes related to that image [5].

1) A system for automatically detecting bleeding in WCE video that uses the CHOBS i.e., Colour Histogram of Block Statistics [6]. For the purpose of obtaining local statistical properties of a single pixel that may be altered due to capsule motion in the GI tract, a block adjacent to the individual pixel in the WCE image is selected. An index value is defined by integrating the local block properties of the three separate RGB colour planes. These index values are used to create a colour histogram, which offers distinct colour texture features. Principal component analysis and colour histogram patterns are used to reduce the dimension of features. On various WCE videos and 2300 pictures, bleeding zone blocks are classified using extracted local features by a KNN classifier. The accuracy for detecting bleeding frames is 97.85%, the sensitivity is 99.47%, the specificity is 99.15%, and the precision for detecting bleeding zones is 95.75 percent.

2) Novel technique enabling GI irregularities in endoscopic video frame sequences to be automatically located and detected [7]. Training is carried out using images that include only minimally detailed pixel-level annotations, utilising solely image-level semantic labels. Abnormal frame detection is a method for analysing huge video endoscopy libraries that is both efficient and capable of suggesting potential sites of GI irregularities visible in the video frames. It is based on attributes of autonomously generated images. Three steps make up its implementation: It first classifies the video images as normal or not using a weakly supervised convolutional neural network (WCNN) architecture; second, a deep saliency detection algorithm is used to detect salient points from deeper WCNN layers; and third, iterative cluster unification (ICU) algorithm is used to localise GI anomalies. ICU relies on a local point-wise cross feature-map (PCFM) descriptor that was obtained from salient sites that were found using information from the WCNN. The knowledge bases utilized, contains different types of GI abnormalities. Both irregularity detection and its localization performance had an Area under Receiver Operating Characteristic (AUC) of >80%. The maximum AUC for irregularity detection was attained on traditional gastroscopy images, attains 96%, where as the maximum AUC for irregularity localization was attained on WCE images, attaining 88%.

3) An area of interest (ROI) separation strategy based on linear discriminant analysis (LDA) is used, followed by a probabilistic model fitting approach, to diagnose numerous GI disorders from WCE videos [8]. A key resource for learning the symptoms of diseases is pixel-level knowledge. An appropriate probability distribution is used to represent the intensity patterns of ROI, and the fitted distribution parameters are used as features in a supervised cascaded classification approach. A series of pixel-labeled images of ulcers, bleeding and tumours are employed to extract the LDA models for the sake of validating the suggested multi-illness detection method, and a sizable WCE dataset is subsequently employed for training and testing. Various supervised multi-class classifiers, such as K-nearest neighbors (KNN), Naive bayes (NB), LDA, artificial neural network (ANN), the error-correcting output codes (ECOC) model, and the ensemble of classifiers for various colour spaces using various PDFs, can achieve a high level of precision even with few pixel-labeled images.

4) Using a proposed least-square saliency transformation (LSST) and a probabilistic model-fitting method, an integrated computer-aided scheme is created for diagnosing numerous GI disorders from WCE videos [9]. Since there are only a few images that have pixel-level annotations, image-level labeling of images is frequently used during the training phase. The prominent points of interest (POI) in a larger Wireless Capsule Endoscopy image dataset without pixel annotations are found using an LSST approach that extracts a collection of ideal prior coefficient-vectors, with the goal of using the knowledge from pixel-level annotated disease ridden images. The intensity distributions of salient POI are represented by a suitable probability density function (PDF), and the fitted PDF parameters are employed as features in the suggested supervised hierarchical classification strategy (supervised SVM). A significant number of WCE images accessed from publicly available Wireless Capsule Endoscopy videos are utilized to evaluate performance. It is discovered that the suggested method produces results that are superior to those of some state-of-the-art methods. Different supervised multi-class classifiers, such as K-nearest neighbors (KNN), LDA, Naive bayes (NB), artificial neural network (ANN), and the ensemble of classifiers for various colour spaces utilizing multiple PDFs, can reach a high degree of precision even with a few numbers of pixel-labeled images.

5) To address the issue of outlier detection in WCE images, a novel deep-structured semi-supervised framework is presented in this research [10]. This model's main idea is to identify the odd graphical patterns that were present in the WCE image by examining the spatial-scale trends of successive image sections. It concludes with three key contributions: 1) Integration of a CNN into a LSTM network to capture the inherent variations among outliers and typical occurrences. Additionally, 2) an assessment model is created using multiple anomalous occurrence indications and the knowledge gained from fake outliers during the learning stage, which considerably improves accuracy of the outlier indicator. In addition, 3) a nest like structure training technique is suggested, which aids in the efficient training of our model. The efficiency of our model is demonstrated by experimental findings using actual WCE images.

6) Because RGB-based approaches for bleeding detection only use colour pixels, their accuracy is negatively impacted by picture and colour distortion [11]. As opposed to that, imaging techniques such as multi-spectral features include a number of distinctive aspects of the targeted content and are thus less likely to inaccuracy. The study develops a bleeding detection sensor mounted on a chip based on the optical characteristics of blood. A 12 optical sensors array, six of which operate in the visible range and six of which operate in the near infrared region, are tested to create this sensor using blood samples (BS) of varying concentrations and blood-free samples, such as food colours and natural consumable foods (digestible and non-digestible). To choose the optimal bandwidth for the maximum detection accuracy, a variety of feature selection and ML techniques being applied. A prototype of capsule is created that uses wavelengths of 450 nanometer, 610 nanometer and 810 nanometer. To confirm the proof of concept, the prototype is put through two in vitro experiments using two intestines from pigs. According to the

results, occult and acute bleeding may be distinguished by the suggested system at 1 centimeter distance and an angle of 45° or 90°. The algorithm of the bagged decision tree yields an F1-score of 99%. By doing away with the necessity for a camera module and significant data transmission, suggested method for detecting GI bleeding uses almost one and a half times lower power than traditional Wireless Capsule Endoscopy systems.

7) GLRLM: In 2020, a study of Shafi and Rahman [12] was carried out to create combination algorithms that are capable of successfully and effectively classify polyps from endoscopic video using Color wavelet, CNN, GLRLM, and SVM. In this study, the colour image frequency domain was decomposed over the Grey Level Run Length Matrix utilising a higher order statistical colour texture features extraction method (GLRLM). With 844 video frames (learning data) and 86 testing data from VCE of 930 patients, the created hybrid technique is capable of classifying VCE polyp and non-polyp pictures with an accuracy of 98.83%, sensitivity of 97.87%, and specificity of 99.13% for SVM linear.

8) Convolutional Neural Networks (CNN): The CNN method is used in a number of researches to extract features. This study uses a deep convolutional neural network (DCNN) framework to investigate the classification problem of the digestive organs in Wireless Capsule Endoscopy (WCE) images [12]. In essence, DCNN has a potent capacity to develop layer-wise hierarchical models from large training sets, mimicking the operation of biological human visual systems. To recognise more complex semantic image features, a powerful deep convolutional neural network based Wireless Capsule Endoscopy classification system (DCNN-WCE-CS) was developed for the classification of digestive organs in WCE images. Extensive experiments are carried out with around 1 million genuine WCE photos to assess its performance by altering network settings. With a classification average accuracy of 95%, hybrid DCNN, WCE and CS is resistant to wide variances of the Wireless Capsule Endoscopy images caused by individual differences and complex digestive tract circumstances, such as rotation and brightness changes.

CNN is employed because it can fast reach convergence without overfitting. The Large Scale Visual Recognition Challenge is one of the significant issues (LSVRC). One of the DL branches, CNN and its variations, demonstrated cutting-edge accuracy on the ImageNet task [13].

9) DWT (Discrete Wavelet Transform): By introducing a novel texture extraction technique for polyp, pathological inflammation, and bleeding regions variances in WCE pictures, you may automate the process of detecting abnormalities in such images [14]. A novel technique based on DWT and LBP variance is suggested. The new technique for textural features has a number of benefits, including the ability to detect multi-directional properties and compensate for illumination fluctuations in WCE images. Two datasets that were created from a number of WCE tests were the subject of extensive experimentation. The provided technique is suited for detection of anomalies in Wireless Capsule Endoscopy images because of promising results. Comparing SVM and MLP Classifiers to discriminant analysis-based classifiers (DAC), better results are obtained [14].

10) GLCM (Gray Level Co- occurrence Matrix): In this study of Constantinescu et al. [15], bleeding WCE images are detected using the Un-decimated – Double – Density - Dual Tree - Discrete Wavelet Transform (UDDDT-DWT). The Gray Level Co-occurrence Matrix (GLCM) of each sub-image acquired after using UDDDT-DWT is used to determine four statistical metrics, including cluster shade, contrast, entropy and cluster prominence. The classification of WCE photos is done using these features. Endoscopic pictures are transformed to HSV (Hue Saturation Value) colour space and a number of classifiers will be taken into account for the purpose of detection of blood in images. When compared to the current methods, experiments demonstrate that suggested methodology offers a whopping accuracy of 99.5%, 99% sensitivity and 100% specificity for the classifier Random Forest and Random Tree.

GLCM is a popular technique for extracting second order statistical features that is utilised in the classification process.

In comparison to other classifiers, the study found that the GLCM and Rand classifiers m Forest and Random Tree may be used to categorise WCE images and determine the degree of bleeding. It is backed by the accuracy average of 95% for the features used, which include contrast, entropy, cluster shade, and prominence.

11) Feature extraction in WCE images that uses the widely used Local Binary Pattern (LBP). LBP technique that is resistant to variations in light [16]. LBP is extracted from Image $I_g(x,y)$ by sliding a window across all slices and using the nearby pixels' values as a threshold to compare them to the centre pixels' values. Next, choose 1 for the nearby intensity if the neighbouring pixels are higher than the centre and 0 otherwise.

$$\mathbf{LBP}_{\mathbf{P,R}} = \sum_{l=0}^{i=p-1} s(gi - gc)2^i$$
$$s(v) = \begin{Bmatrix} 1 & v \geq 0 \\ 0 & v < 0 \end{Bmatrix} \quad (1)$$

In Eq. (1), P represents the neighbor pixels; R represents the radius of neighborhood; g_i is neighboring pixels' intensity; and g_c is center pixel value. The dimension of LBP features is 1 x 59. In the study [16, 17], LBP will be in conjunction with other methods namely LDP. The combination of the two methods is to get accurate classification results.

12) First Order Statistic and Texton Features: The authors [18] study reveals, a novel statistical method was chosen to distinguish pixels with ulcers from pixels without ulcers utilising multiple colour spaces (strictly speaking using relevant colour bands). In order to calculate the performance measures as efficiently as possible, the feature vector chosen was used along with grid search method of SVM. The research and experimental findings demonstrated the suggested algorithm's reliability in identifying ulcers. It is encouraging to see that the accuracy is 97.89%, sensitivity is 96.22%, and specificity 95.09%.

The feature selection process uses the normalised cross correlation (NCC) between the bands I and j, where Di and Dj are the intensity values.

$$NCC_{,\mathrm{j}} = \frac{\sum_{xy}[(Di(x,y) - \underline{Di}) \times (Dj(x,y) - \underline{Dj})]}{\sqrt{\sum_{\mathrm{xy}}(Di(x,y) - \underline{Di})^2} \times \sqrt{\sum_{\mathrm{xy}}(Dj(x,y) - \underline{Dj})^2}} \quad (2)$$

The feature extraction method chosen based on the i) simplicity, ii) stability, iii) accuracy, iii) less computational time and iv) high ability to differ tissues in the WCE images. Out of all these factors the simplicity and high ability to differ tissues in the images score over others and emphasis is given to LBP and combination of LBP with others methods like LDPP or CLEOP or HOG.

Table 1. Summary of feature extraction methods and their advantages

Feature Extraction Techniques	Advantages
Texture features [6, 7, 9, 15]	More stable than intensity and also simple.
WCNN [7]	Having the ability to separate a feature from the spatial and temporal dimensions.
CNN [5, 13]	Fast convergence without over fitting is possible.
GLRLM [12]	Less computational time and more accuracy.
DWT [12, 15]	Able to evaluate signals with various resolutions, translate signals from one domain(time) to other domain(frequency), ability to extract important features from various scales and directions, and circumvent the time domain information loss flaw of the FFT.
GLCM [15]	Less computational time and more accuracy.
Linear Binary Pattern [16, 17, 19]	Simple and highly capable of differentiating tissue images.
Texton features [19]	Able to provide useful details to discriminate any 3D patterns and improve classification precision.
DCNN [20]	Capable of speeding up computation.

Table 2. Summary of works carried by various researchers

Researcher	Application	Feature extraction technique	M L classifier	Classification results in %
Shafi and Rahman [12], 2020	Polyp detection	Automatic polyp classification method using colour wavelets, higher-order statistical texture features, and convolutional neural networks from endoscopic footage (CNN). For higher-order statistical texture features of various directions (ϴ=0 0, 450, 900, 1350), the Gray Level Run Length Matrix (GLRLM) is employed. To train the classifier, the characteristics are loaded into a linear support vector machine (SVM).	SVM:	Acc. 98.3 Sen. 97.87 Spe. 99.13
Sadasivan and Seelamantula [13], 2019	Anomaly detection	Using WCE images of size 320x320, a Convolutional Neural Network was trained on normal and aberrant patches of size 64x64.	CNN:	AUC 95.36
Liu and Yuan [21], 2008	Bleeding detection	Raw colour pixel values.	SVM:	Sensitivity 99.64 Specificity 99.58
Li and Meng [22], 2012	Bleeding detection	LBP and the chrominance moment are computed in HSI colour space.	ANN:	Acc. 92.40 Sen. 93.20 Spe. 91.60
Sainju et al. [23], 2013	Bleeding detection	Histogram Probability.	ANN:	Acc. 89.00
Iakovidis and Koulaouzidis [24], 2014	Lesions detection	Salient points are extracted from WCE images using the speedup robust features (SURF) approach after the images are transformed to CIE-Lab colour space.		Acc. 94.50 Sen. 96.00 Spe. 84.60
Yuan et al. [25], 2018	Polyp detection	KL divergence is used in a sparse auto encoder with a hybrid loss function and an image manifold constraint.	Softmax (CNN):	Acc. 98.17
Kundu et al. [26], 2018	Bleeding detection	Computation of a histogram over normalised green planes.	K-Nearest Neighborhood:	Acc. 97.86 Sen. 95.20 Spe. 98.32
Xiao et al. [27], 2020	Lesions detection	YOLOv3 network-based object detection on the CNN platform.	Softmax (CNN):	MAP 93.50
Khan et al. [28], 2020	Ulcer and bleeding detection	Particle swarm optimization is utilised to choose the pertinent features for Convolutional Neural Network with transfer learning on fused VGG-16 and Gray-Level Co-Occurrence Matrix.	Cubic Support Vector Machine:	Acc. 98.40 Sen. 98.33 Precision 98.36 F1-score 98.34 AUC 100
Jain et al. [29], 2022	Anomaly detection	Activation Maps, 5-layer Convolutional Neural Network.	CNN:	Acc. 89.90 Sen. 90.70 Spe. 88.20
Yuan et al. [30], 2016	Bleeding detection	Histogram utilising K-size colour clusters on a bag of visual words.	SVM:	Acc. 95.75 Sen. 92.00 Spe. 96.50
Karkanis et al. [31], 2002	Lesions detection	2nd-order DWT statistical data.	ANN:	Accuracy 95.50
Naik and Gopalakrishna [32], 2021	Anomaly detection and localization	HOG+LGP.	SOM-FOA (Self Organized Map Fruit Fly Optimization Algorithm	Acc. 94.338 Recall 97.186 Precision 91.82 F1-score 94.427 MCC 88.83

3.2 Feature selection technique

The WCE image being processed will have a variety of features characterising its qualities, as a result of the feature extraction method described above. Because non-dominant traits are used, the quantity of collected features can occasionally lead to erroneous categorization results. One image can be distinguished from another by its dominating features. Additionally, the needed calculation time will increase if there are too many features used. For the sake of disease early detection, this should not occur. The necessary detecting system is a quick-calculating, accurate method. Therefore, to eliminate non-dominant features and increase the efficiency of the produced system, numerous researches included several phases of feature selection to the classifying process. Below are some of the techniques for feature selection used in earlier studies:

1) In a prior study, CNN was also employed for feature selection in addition to feature extraction [5, 10, 13]. In this investigation, 3D-CNN with multi-channel input was used. Data can be collected from several dimensions of time that are present in WCE images because the 3D-Convutional Neural Network can extract characteristics from the temporal and spatial dimensions of each one of its layers. Additionally, it eliminates characteristics that make little difference. Trade-off between computation time and accuracy can be optimized for the refined decision making (shortlisted images).

Table 3. Performance of various feature extraction and selection methods in classification of WCE images

Feature extraction technique	Feature selection technique	Datasets with classification accuracy in %								
		Civic DVC (%)	UIUC database (%)	Jaffe (%)	Kvasir (%)	ETIS-LARIB (%)	MICCAI gastroscopy challenge datasets (%)	PASCAL (%)	KID dataset (%)	Clinical MR images
DWT [4]		86	-	-	-	-	-	-	-	
PCFM [7]	b-CNN 64x64	-	-	-	-	-	83.9	-	84.6	
DCNN [7]	-	-	-	-	98	-	-	-	-	
LDA [8]	SVM	93.0			-	-	-	-	-	
GLCM [9]	-	96.4	-	-	-	-	-	-	-	
CNN [19]	-	-	-	-	94.8	-	-	-	-	
LBP+GLRL+ ZM+ PHOG+ GLCM [23]	-	± 97.1	-	-	-	± 97.8	-	-	-	
First order statistic + Texton features [24]	-	96	-		-	-	86	-	-	
Information theoretic measures + scattering transform + DWT [26]	-	93	-	-	-	-	-	-	-	
Texton features [33]	SIFT descriptors, Naïve Bayes	-	83.09(Mean)	94.25	-	-	-	-	-	
RefineNet + ResNet [34]	-	-	83.4(Mean)	-	-	-	-	-	-	
CNN	CSRN+ RELM [34]	-	96.5	-	-	-	-	-	-	
SVM+ ALEXNET	PCA [35]	93.9	-		-	-	-	-	-	
PSPNet [36]		-	-	-	-	-	-	85.4%	-	
Fast RCNN [37]	ASTN+ ASDN	-	-	-	-	-	-	73.6	-	
CNN [19]	MFE				98				97	
Neural Network [38]	Entropy+ Invariant Moments	-	-	-	-	-	-	-	-	97.77

2) Automatic Tumor Recognition in the Gastrointestinal Tract (GI) tract [19] proposes a candidate colour texture feature to define Wireless Capsule Endoscopy images that fuses a wavelet and a uniform local binary pattern. The suggested attributes characterise the multi-resolution properties of WCE images and are insensitive to changes in illumination. Two support vector machine-based feature selection methods, sequential forward floating selection and recursive feature elimination, are further applied to boost the detection process's suggested features' accuracy. Numerous tests confirm that the suggested computer aided diagnosis approach accomplishes promising tumour recognition with 92.4% accuracy in Wireless Capsule Endoscopy pictures from the accessed data. The encouraging result achieved will assist the physicians in recognizing malignant tumors in Wireless

Capsule Endoscopy images.

3) GLDM (Gray Level Difference Matrix) was employed in a prior study [29] for feature extraction, which serves as an input to the VGG16 for feature selection. One of the often used feature extraction methods, GLDM, can pull out 16 features from medical images.
4) Principle Component Analysis (PCA): PCA, both traditional and nontraditional, has been utilized extensively as a feature selection method. Video endoscopic pictures were subjected to PCA as a feature selection method [25]. In comparison to SVM, the K-nearest neighbourhood technique, which is non-parametric and does not require training, performs better at classifying celiac disease.

Tables 1, Table 2 and Table 3 give the summary of various techniques which acts like an aid to develop an efficient classification model.

4. CONCLUSION

To gather data for the creation of an early detection system for polyps, ulcers, and cancers, a study of feature selection and extraction approaches is essential. The review's findings indicate that the effectiveness of the classification results will depend on the feature extraction technique utilised to extract features from the WCE images. The additional feature selection phases will increase the classification's precision. This analysis demonstrates that the best feature extraction method for the CVC-ClinicDB dataset is Local Binary Pattern combined with CLEOP, with a classification accuracy of 96%, while the best feature selection and extraction method for general knowledge base is CSRN and DELM, with a classification accuracy of 96.5%. By taking into consideration the feature selection and extraction approaches that have been reviewed, the outcome of the above study can be used as a foundation for framing a classifying system of WCE images for the early detection of polyps, ulcers, and tumours in the medical field as well as general object detection like cars and human activity.

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