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Automatic Abnormality Detection System for Capsule Endoscopy

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One-third of the world population suffers from diseases related to gastrointestinal (GI) tract. Capsule endoscopy (CE) is a non-sedative, hygienic, non-invasive and patient-friendly and particularly child-friendly technology to scan the entire GI tract. How- ever, CE generates nearly 60000 images, which make the diagnosis process time consuming and tiresome for physicians. Also, the diagnosis is highly subjective and varies from person to person. Thus, a computer-aided diagnosis (CAD) system is a must. This study addresses a multi-class medical image analysis problem using image processing and machine learning techniques. It presents a CAD system based on the hybrid confluence of transfer learning and conventional machine learning technique for automatic abnormality detection in the GI tract. The system performs with an accuracy of 96.89%. The rigorous performance evaluation shows that the system is capable of fast and accurate diagnosis of GI tract abnormalities. Such a system can be beneficial to physicians and with the advancement of smart devices and IoT, such a system can prove to be a handy remote diagnosis tool for geographically distant locations where an expert of the subject may not be available.

Keywords: CAD, capsule endoscopy, medical image analysis, deep learning, transfer learning

1. INTRODUCTION

Capsule endoscopy (CE) is the latest technology capable of scanning the entire gastrointestinal (GI) tract to diagnose GI tract diseases. It is a nonsedative, noninvasive and a patient-friendly alternative to conventional endoscopy. Since its introduction by Given imaging in the year 2000 and approval by U.S. FDA in the year 2015, over 1,000,000 Pillcam small bowel (SB) capsules have already been swallowed [1]. The capsule is a swallowable endoscopic device with 11×26 mm dimensions and 3.7g weight [2]. Once taken, the capsule is propelled by natural peristalsis transmitting images of the GI tract at a frame rate of 2 fps. An RF receiver tied on the waist of the patient receives this transmitted data. This process continues until the battery of capsule lasts or till the capsule disposes naturally from the GI tract. Since there is no need to retrieve the capsule, concerns related to sterilization and patient hygiene is automatically addressed, unlike other

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endoscopic procedures. However, CE generates approximately 55000 to 60000 images during the 6 to 8 hrs long video. Depending upon the individual expertise of physicians, the examination and analysis of CE videos will take 45 minutes to 2 hrs of time. For the entire duration of examination, experts need to concentrate continuously. Hence, the manual analysis is tedious and time-consuming. Also, decision making is a subjective process, and so a decision may change from person to person. Thus, a computer-aided diagnosis (CAD) system is a must for a fast and accurate diagnosis. CAD systems play an essential role in training inexperienced clinicians and assisting the medical experts in improving the accuracy of medical diagnosis [3]. A CAD system capable of analyzing and understanding the visual scene will undoubtedly help the doctor with a precise, fast, and accurate diagnosis. After the manual analysis of CE video, CAD can also provide a second opinion to a gastroenterologist [1]. In medical imaging, CAD is a prominent research area capable of delivering precise diagnosis [2]. The ultimate goal of CAD is to reduce interpretation errors, reduce search errors and, reduce variation among observers [3]. In particularly a computer-aided medical diagnostic system for CE can consist of the following units: (1) a data capturing and transmitting unit – the capsule (2) a data receiver and storage unit – the waist belt (3) a data processing unit for pre-processing and feature extraction (4) a machine learning-based classification unit or decision support system (5) a user interaction unit for final diagnostic report. Fig. 1 shows a capsule endoscopy system. It shows how a capsule comprising different components captures and transmits the data to the external receiver. Further, the data is transferred to a computer for diagnosis.

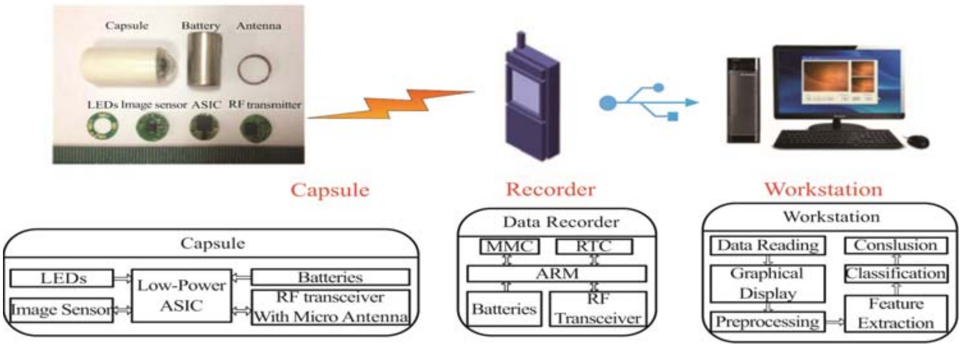

Fig. 1. CAD system for capsule endoscopy [4].

CAD in CE is a multi-class classifier problem. A general drawback for CAD system in CE is lack of annotated dataset in public domain. Due to this reason, a common comparison between proposed and existing system is a challenge. In the recent past, a few CAD systems for disease detection in CE is proposed; however, only two systems are found capable of detecting multiple abnormalities. Both these systems have been implemented on different datasets-not available in public domain and different abnormalities. Nawarathna *et al.* [5] proposed a system with 130 texton histogram features from Leung and Malik (LM) and local binary pattern (LBP) to detect bleeding, erythema, erosion, ulcer and, polyp using k-nearest neighbor (KNN). The system performed with a recall of 92% and specificity of 91.8% on a dataset of 1750 images. The method is found computationally intense due to convolution of image blocks with LM-LBP filter bank. Also, it focuses on the textural information while ignoring other features such as shape from spatial domain and completely ignores the wavelet domain features. Yanagawa *et al.* [6] proposed a system with Kanade-Lucas-Tomasi (KLT) feature points to detect red spot, phlebectasi, angiodysplasia, lymphangiectasia, erosion, erythematous, ulcer, and white-tipped villi using affine transform. Their system showed 114 correct predictions, and 06 predictions were lost out of 120 images. The prior art shows four major disadvantages of the existing systems. Firstly, the important information is ignored as wavelet domain features and shape features are ignored. Secondly, the systems do not explore full potential of computer vision and machine learning techniques as the learning process is compromised by skewed data, insufficient data and lack of validation of proposed systems. Thirdly, the performance in terms of accuracy and finally the limited size of the dataset. Also, other important performance criterion such as f-measure and Matthew's correlation coefficient (MCC) are not discussed.

2. MATERIAL AND METHODS

This study presents automated abnormality detection for CE images using a hybrid approach of conventional machine learning and deep learning. Fig. 2 gives an overview of how both these approaches differ functionally.

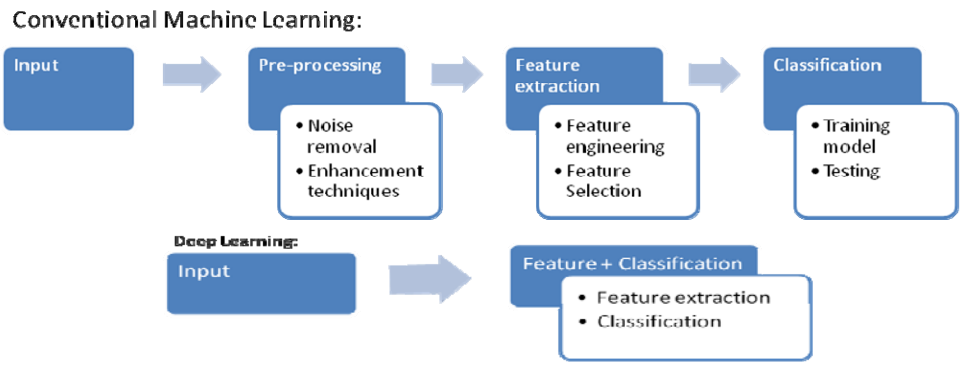

Fig. 2. The workflow of conventional system and deep learning system.

As seen in Fig. 2, the conventional machine learning approach broadly includes pre-processing, feature extraction, and classification. Depending upon the input quality of the image, noise removal and enhancements techniques such as Adaptive contrast diffusion [7], Contrast-Limited Adaptive Histogram Equalization (CLAHE) [8], Total variation (TV) minimization [9] and many more are used. Feature extraction phase aims to derive most discriminative features. A few such features are gray-level co-occurrence matrix (GLCM) and local binary pattern (LBP), color moments, shape features, and wavelet-based features. Subsequently, the classification phase classifies between abnormalities using techniques such as support vector machine (SVM), K-nearest neighbor (kNN), ensemble, and many more. Every stage is equally important to achieve successful results in the final stage. On the other hand, the deep learning-based approach is more kind of a black box. One can fine-tune various parameters, and then the model does the feature learning and classification part. Jani *et al.* [10] presented both these systems individually for CE image analysis. The proposed system is a hybrid of both these approaches, and the results section will show how the proposed method outperforms both approaches individually. The core contribution of this study is as follows:

- The acceptable solution even with the limitation of the size of data
- Discriminative and robust feature set to classify between CE images
- Reduced false alarm rate

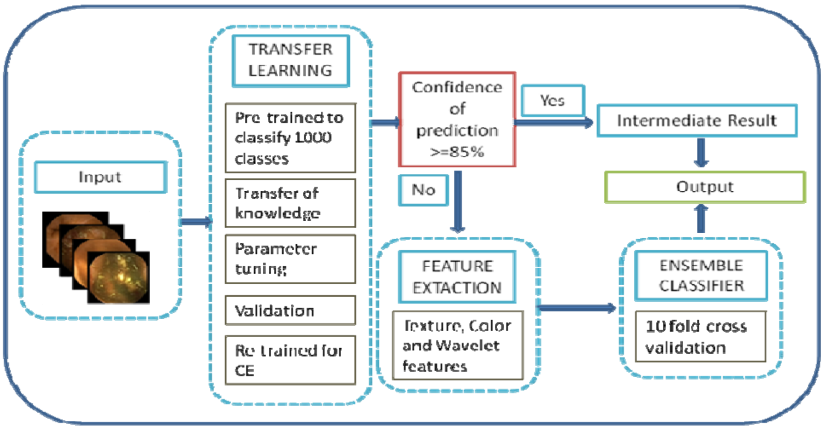

Fig. 3. Overview of the proposed system.

Fig. 3 shows the overview of the proposed solution for automatic abnormality detection in CE and the details of each component of the system is explained subsequently.

Steps involved in the proposed system:

1. Extract images from CE videos
2. Segregate CE images as per defined class namely angeostecia, bleeding, ulcer and normal
3. Create separate training and testing data
4. Set various parameters for transfer learning such as learning rate, batch size, training, testing, and validation percentage and many more
5. Input CE image training date to re-train transfer learning model
6. Collect intermediate results by considering all samples with the confidence of prediction $\geq 85\%$
7. Refer samples with the confidence of prediction $<85\%$ to the conventional system
8. Extract features CE image data
9. Train the classification algorithm on training data
10. Classify the referred samples let out from transfer learning technique
11. Merge the results with intermediate results to get the final result
12. Derive various performance metrics of the system

The proposed hybrid system takes into accounts the threshold for confidence of prediction as 85%. This value is obtained by performing experiment on four different threshold values namely 80%, 85%, 90% and 95%. The total misclassifications and overall system accuracy at different threshold values indicate that the lower value tends to over fitting while higher value tends to poor results. Thus, to balance between both the threshold value is chosen as 85%.

2.1 Deep Learning

Amongst various deep learning techniques, the transfer learning technique is employed in this study to classify GI tract abnormalities. Deep learning has shown commendable progress in the field of computer vision in general and classification task in particularly. Most of the deep learning techniques work with an assumption that the training and testing data belong to the same feature space and follow an identical distribution. However, in all real-world applications, this assumption may not always hold. It is challenging to obtain training data. Under such situations, transfer learning is desirable [11]. In transfer learning, a model is trained on base dataset and base task, and then the learned features are transferred to train the target dataset and target task [12]. Two popular approaches to transfer learning are (a) develop a model approach and (b) pre-trained model approach. We have selected the second approach with MobileNets model. MobileNets are low-latency, low-power, and small models parameterized to meet the resource constraints of a variety of use cases. They can be built upon for classification, detection, embeddings, and segmentation tasks [13]. This study has adopted a pretrained model approach to transfer learning with the following steps:

- Select a source model
- Re-use the model
- Tune the model

We reused a model MobileNet_v1_1.0_224 using TensorFlow libraries, which was trained on a similar task to design a multiclass CAD system. This architecture-MobileNet was pre-trained on ImageNet dataset. MobileNet has proven effectiveness in various applications such as object detection, face recognition, and many more [14]. Essentially, we transferred the pre-learned values of the model and added our dataset parameters to the model to re-train the model according to our use. This is effective in our case because the dataset is comparatively small, so we used our dataset to train only last layer, and utilized pre-learned parameters on ImageNet dataset. In our case the following simulation parameters are used: MobileNet version = 1.0, learning rate = 0.005, number of training steps = 5000, training batch size = 20, training, testing and validation percentages as 60, 20 and 20 respectively. As seen in Fig. 4, the feature extraction part is done by pre-trained model, and classification task is performed for CE images. Essentially it is called transfer learning.

2.2 Conventional Machine Learning

A CAD system for medical image analysis consists of pre-processing for image enhancement, feature extraction to discriminate between classes, feature selection for re-

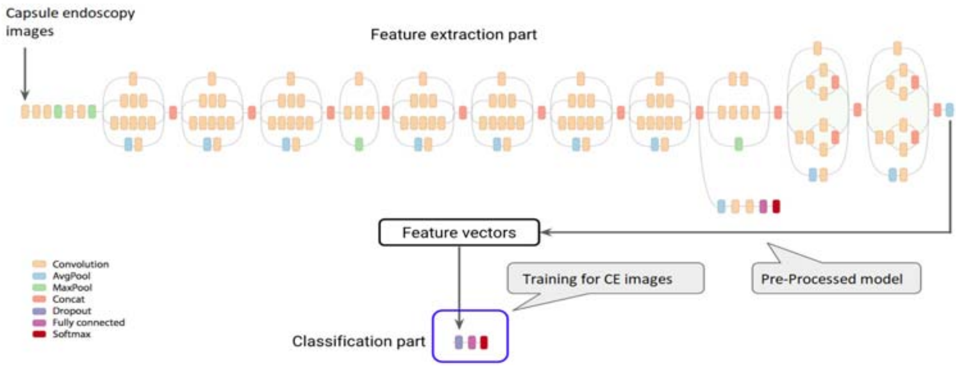

Fig. 4. Workflow of deep learning-based system.

duced and relevant search space and classification to reach a diagnosis. The CE images of GI tract diseases exhibit a wide range of color and texture. To address all the diseases under this study, the proposed feature set comprises features from the wavelet domain and color and texture features from the spatial domain. Texture features include a gray-level co-occurrence matrix (GLCM) and local binary pattern (LBP). The GLCM features are very close to human inference from texture and describe image texture well [15]. After obtaining GLCM matrices for every pixel with offset [0 1], statistical features namely contrast, correlation, energy and homogeneity are calculated. Also, the mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness, inverse difference moment (IDM) is extracted from the image. Uniform local binary patterns are fundamental properties of the texture of an image, and their occurrence histogram is a compelling textural feature [16]. It is learned that LBP performs robustly to illumination variations. A 3×3 neighborhood would produce up to 2^8 = 256 local texture patterns. Texture feature descriptor is the LBP histogram of 256 bin occurrence calculated over the region. Eq. (1) defines the LBP number of p members on the circle of radius r.

$$LBP_{p,r} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \tag{1}$$

Where $s(x)$ is the sign function, the obtained LBP number as per Eq. (1) contains transitions from 0 to 1. Color moments for HSI and RGB color space are computed as it provides a measurement for the color similarity between images [17]. Statistical features namely mean, standard deviation, kurtosis and, skewness for each of the color channels are computed. Color coherence vector (CCV) shows coherent pixels versus incoherent pixels for each color [18]. CCV consist of 27 different colors and thus, it will create a feature of 54 values indicating coherent and non-coherent pixels for each color. An auto-correlogram captures the spatial correlation between identical colors [19]. Gabor features have been successful in many image processing and computer vision applications. It extracts local pieces of information which are then combined to recognize an object or region of interest [20]. Here we have utilized two features from Gabor response: mean-squared energy and mean amplitude. DWT is a high-level feature extraction technique [21]. In this study, we have considered the first two moments of DWT coefficients as features. The feature vector is then obtained by combining all features. This feature vector is then fed to the classifier to get results. GI tract disease detection in CE is a multiclass classification problem. To perform classification, we have deployed an ensemble classifier: subspace discriminant. An ensemble of classifiers is a set of classifiers, whose individual classification decisions are combined typically by a weighted or non-weighted voting system to classify new samples [22]. The performance is compared with various other classifiers.

2.3 Dataset

Total of 900 images from CE videos [23] is extracted out of which 100 images are of angioectasia, 200 images are of ulcers, 200 images are of bleeding, and 400 images are normal. The dimension of each image is 576×576 pixels. All the images were manually diagnosed and annotated by experts providing the ground truth.

2.4 Performance Metrics

Performance metrics used are accuracy, precision, sensitivity, specificity, *F* measure, and MCC. Accuracy is the ability of a classifier to classify instances correctly. Precision is the probability that an object is classified correctly as per the actual value. Sensitivity is the percentage of abnormal samples correctly classified. Specificity is the percentage of normal samples correctly classified. The *F* measure is the harmonic average of precision and sensitivity. *F* measure at 100 indicates perfect precision and sensitivity and worst at 0. MCC is a balanced measure which is used even if the classes are of very different sizes [24]. MCC in machine learning is used as a measure of the quality of binary classifiers.

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \tag{2}$$

$$Precision = TP/(TP+FP) \tag{3}$$

$$Sensitivity = TP/(TP+FN) \tag{4}$$

$$Specificity = FP/(FP+TN) \tag{5}$$

$$F\ measure = 2\left(\frac{precision * sensitivity}{precision + sensitivity}\right) \tag{6}$$

$$MCC = \frac{TP*TN - FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{7}$$

Where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative. The system is implemented on the Dell Optiplex 9010 machine with an intel core i7 processor and 6GB RAM using Matlab 2017a for conventional approach and python for deep learning.

3. RESULTS

The ultimate objective of the CAD system is to provide a timely and accurate diagnosis with a negligible or no false prediction rate. Both these objectives are nicely met by the proposed system. This experiment with transfer learning shows that how knowledge obtained from a different domain can be transferred altogether to another field and does wonders. Despite different statistical properties, features, and objectives, the knowledge turns out to be very consistent. The marvelous ability of MobileNet model to classify 1000 different classes gives us an edge over other models. The re-training of the pre-trained model on four class CE image dataset triggered the idea to reach a highly accurate CAD system. This confluence of transfer learning and conventional machine learning overcomes the limitations of both these approaches individually. This proposed model works in two phases; one for coarse tuning and other for fine-tuning. The transfer learning approach is capable to produce the intermediate results with reasonably acceptable accuracy and time at a prediction probability confidence level of 85%. The average evaluation time per image is 0.192 seconds. This first phase left only 18 out of 225 samples to be re-evaluated by the second phase. In the fine-tuning process, the second phase produced results by utilizing the discriminative feature set to classify the left out images. This approach employs an ensemble classifier with 10-fold cross-validation to predict the unknown samples. The average prediction time per image for this phase is 0.001 seconds. The final result is obtained by merging both these results. Fig. 5 shows the final confusion matrix of the proposed approach.

		Predicted			
		A	B	C	D
Actual	A	24	0	1	0
	B	0	49	1	0
	C	0	0	50	0
	D	2	0	3	95

Fig. 5. Confusion matrix of the proposed system.

The performance of the proposed system is compared with six other approaches on six different criterions as discussed in Section 2.4. Jani and Srivastava [25] discussed these approaches in designing CAD system for CE by reviewing the previous works. Table 1 shows the statistical comparison and Fig. 6 shows the graphical representation of the obtained results. It is observed that the system outperforms other approaches in all aspects.

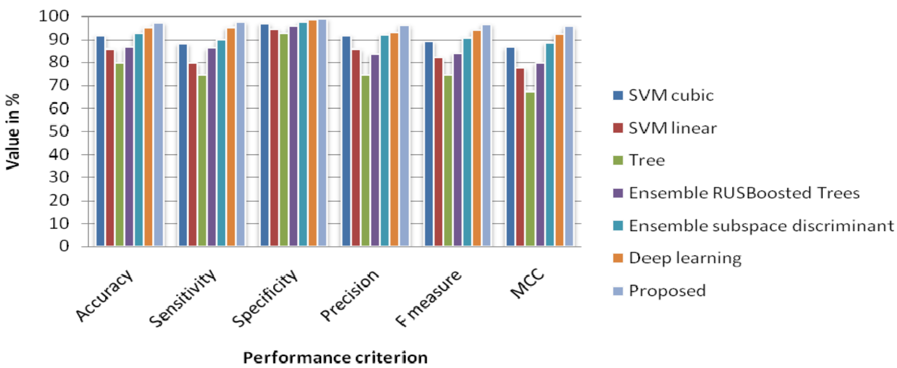

Fig. 6. Graphical representation of results.

Table 1. Comparative analysis of the system with other approaches.

Classifier	Accuracy	Sensitivity	Specificity	Precision	F measure	MCC
SVM cubic	91.33	88	96.74	91.35	89.31	86.41
SVM linear	85.89	79.69	94.46	85.88	82.03	77.42
Tree	79.56	74.37	92.66	74.57	74.43	67.16
Ensemble RUSBoosted Trees	86.33	86.06	95.48	83.38	84.01	79.74
Ensemble subspace discriminant	92.67	89.87	97.31	91.83	90.75	88.26
Deep learning [10]	95.11	95.25	98.42	92.83	93.9	92.26
Proposed	96.89	97.25	99.04	95.80	96.45	95.41

Table 2. Evaluation time analysis of the system with other approaches.

Classifier	Observations evaluated per second
SVM cubic	1200
SVM linear	2700
Tree	3000
Ensemble	3300
Ensemble subspace	1200
Deep learning [10]	5.2
Proposed	5.18

In addition to above results, this study also observes evaluation time taken by each method. Table 2 presents the evaluation time in terms of observations per second.

4. CONCLUSION

The proposed system is a hybrid system of transfer learning and conventional machine learning technique. It performs with an accuracy of 96.89% and F measure of 96.45%. The system outperforms not only in accuracy but also MCC, which is a balanced measure and Kappa coefficient, which is a more robust measure than simple percentage agreement measures. Kappa coefficient of the proposed system is 0.917, while amongst the rest of the systems, the best kappa co-efficient value is 0.804. Notably, the false positive is drastically reduced, and most importantly, none of the abnormal images, *i.e.*, angioectasia, ulcer, or bleeding, are misclassified as normal. The total time of evaluation of each sample is approximately 0.193 seconds empowering the system to provide a fast and accurate diagnosis of GI tract abnormalities from CE images.

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