Early Esophageal Cancer detection using Deep learning Techniques. (Review Article)

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Abstract. Esophageal cancer is one of the deadliest diseases for humans, since it is discovered in very advanced stages. As result, pathologists are increasingly relying in image recognition and artificial intelligence tools to aid in the early identification and evaluation of this lesion. We examined a number of papers that dealt with this issue during the time span in order to shed light on the studies that were performed in this area (2017 and 2020). We have looked at experiments that used Convolutional Neural Network (CNN) technologies in the study of endoscopic images to help with early detection or diagnosis of esophageal cancer and its various forms. More research on esophageal malignant growth is required, as well as improving the disease's indicative existence and employing more proven techniques for feature selection/extraction of endoscopic images. The aim of this review is to highlight the research conducted on endoscopic images of the esophagus using deep learning algorithms, including CNN, Support Vector Machine (SVM), Random Forests (RF) and other techniques that were used to design the Computer-Aided Detection (CAD) system. In this review we covered some but not all articles that was of great contact with our master's thesis research in this regard.

Keywords: Esophageal Cancer, Endoscopic images, Computer-Aided Detection, Deep Learning, Convolutional Neural Network.

1. Introduction
Esophageal Cancer (EC) is one of the principle ten driving dominating malignancies around the globe, situating the seventh in the scene and the sixth in mortality in 2018 [1]. Esophageal malignant development is a sickness wherein unsafe (illness) cells from the tissue of the Esophageal [2]. There are three kinds of esophageal harmful development: Esophageal Squamous Cell Carcinoma (ESCC), Esophageal Adenocarcinoma (EAC), and Barrett's Esophagus (BE). EC is astoundingly destructive, and the 5-years survival rate-stage EC is under 25% [1]. Measurements demonstrate that squamous cell carcinoma is pervasive on the planet, while Esophageal adenocarcinoma is normal in the Caucasus [7]. The Esophageal Pre-Cancerous (Barrett's Esophageal) study maintain study has started obtaining thought actually on account of the speed of rate increase over a few years. Early discovering is critical for early intervention and a high treat rate. In any case, the examination is ordinarily irksome due to the more unobtrusive changes in cells during the change stages and the subjective zones in which they appear. [10].

The malignancy of the Esophagus can be identified using three types of tools: - Positron Emission Tomography (PET) scan, Computerized Tomography (CT) scan, and attractive reflexology (X-rays) by giving the patient a barium solution that is taken through the mouth and which it helps to detect normal or abnormal tissue in the patient [16], but it does not give information whether there is a
malignant disease or not. Moreover, another tool used to detect and diagnose malignant tumors in the esophagus is endoscopy which is the focus of our current review, and this tool is the most widely used tool for diagnosing this disease. Additionally, the Magnetic Resonance imaging (MRI) scan machine can be used to detect malignant and benign Esophageal cancer or Barrett's cancer, as this field has been poorly studied in previous research, and if studies were focused in this area, it would achieve a qualitative leap in early detection of Esophageal cancer and thus reduce the percentage of Death due to this disease (Table 1). In this review we focused on studying papers that specifically address the possibility of using deep learning techniques (CNN) algorithm to detect esophageal cancer in endoscopic images.

Table 1: - Imaging systems used to detect and diagnose precancerous and non-cancerous lesions in the esophagus. [12]

| Usage                     | Device          | X-ray | Endoscopy | CT-Scan | PET-Scan | MRI-Scan |
|---------------------------|-----------------|-------|-----------|---------|----------|----------|
| Diagnosis                 |                 | ✓     | ✓         |         |          | ✓        |
| T-Staging                 |                 | ✓     | ✓         |         |          |          |
| N-Staging                 |                 | ✓     | ✓         |         |          |          |
| M-Staging                 |                 | ✓     | ✓         |         |          |          |
| Tumor delineation for RT  |                 |       | ✓         | ✓       | ✓        |          |
| Evaluation of response    |                 | ✓     | ✓         | ✓       |          |          |

1.1 Endoscopic Devise:
- **The Program**: - Endoscopy and biopsy are useful for diagnosing esophageal cancer. [12]
- **Advantage**: - Allows immediate examination and biopsy of the esophageal mucosa for histologic diagnosis. [12]
- **Disadvantage**: - It is an invasive mechanism [19] and operator dependent [17], [18], [19].

Table 2: - TNM staging for esophageal cancer [20],[21].

| Symbol | characterization                                                                 |
|--------|---------------------------------------------------------------------------------|
| **T- Staging** |                                                                                   |
| 0a     | Large-level dysplasia.                                                           |
| 1a     | Tumour pervades platelet own or muscularity mucosae.                             |
| 1b     | Tumour pervades submucosal.                                                      |
| 2      | Tumour pervades their muscularity.                                               |
| 3      | Tumour pervades adventitia.                                                       |
| 4a     | Re-sectable tumour pervading pleura, pericardium, midriff or close peritoneum.  |
| 4b     | Un-resectable tumour pervading other near structures, like the aorta, trachea, vertebral body. |
| **N- Staging** |                                                                                   |
| 0      | There are no provincial lymph node metastases.                                   |
| 1      | 1-2 provincial lymph node metastases.                                            |
| 2      | 3-6 provincial lymph node metastases.                                            |
| 3      | ≥7 provincial lymph node metastases.                                             |
| **M-Staging** |                                                                                   |
| 0      | There are no far metastases                                                      |
| 1      | Far metastases                                                                  |

Artificial Intelligence (AI) advances were created in this way to advance the reliability of stability to clear clinical options. One of the main functions of AI is to recognize critical injuries. Machine learning (ML) and also Deep Learning (DL) can be called a sub-topic form the artificial intelligence. Artificial intelligence is the use of numerical technology to capture the frame in information [3]. Thus, accounts evolve and improve with experience and should not be unambiguously allocated. [4]. The last frame set can be used to produce an esophageal spotting prediction.
ML and CNN algorithms have been worked out to prepare projects to identify normal and foreign regions in the lumen of the gut (esophagus in particular in our present paper). To define benign tumours, ML uses a fixed number of characteristics, for example, the shape of the polyps, examples of the mucosa, and the size of the tumour. A variety of developments in the neural regulation of deep learning are related to DL-based systems that subsequently identify critical imaging highlights without human perceptual biases. [5] Figure 1.

Figure 1: - Diagram showing how deep learning algorithms analyze endoscopic images [8].

2. Computer-Aided Detection / Diagnosis system (CAD-system).

Since Malignant is a significant reason for death around the world [13]. The need to create Computer-Aided Detection (CAD) have arisen to assist clinicians with improving the effectiveness of deciphering clinical images. The Computer-Aided Detection (CAD) analysis was initially evolved to screen for breast disease from mammograms during the 1960s [22, 23]. These days, it is quite possibly the main territories of exploration in the field of clinical picture examination and radiological.

There are two important parts of computer-aided flow research: Computer Aided Diagnosis (CADx), which gives a specific output to describe a disease or lesion. And computer-assisted detection (CADe) that actively contributes to the identification of suspicious lesions [24].

The mechanism of action of the common CAD systems (shown in Fig. 3) in examining the clinical picture can be divided into four stages: image pre-processing, segmentation, feature extraction and selection, and finally disease classification.

Numerous CNN-based frameworks had been introduced as LeNet-5 [25], for example, AlexNet [26], VGG G-N e t (VGG G-16 and VGG G-19) [27], GoogLeNet [28], ResNet [29], as well SPP-Net [30], which centre around expanding the organization profundities and planning more adaptable designs. Profound convolutional neural organization (DCNN), as a recently arising type of clinical picture examination, permits the programmed extraction of highlights and managed to learn of enormous scope datasets, prompting quantitative clinical choices. The use of CNN-based strategies for clinical images is very not the same as those for characteristic images [31].

From one viewpoint, a huge scope marked dataset, for instance, the Image Net is needed to the preparation and testing for C N Ns. Then again, clinical images are typically grayscale as opposed to containing RGB channels. Notwithstanding, enormous scope clinical picture datasets are not generally accessible because of the escalated marking work and expert experience requirement [32].
Deep learning is another method that is overwhelming the conventional AI strategies and is progressively being utilized in CAD systems [33]. Usually, features are extracted manually in ML, while in DL, it is a totally programmed measure. Likewise, simple features, for example, edges, textures, colors, and could be acquired in AI, while in DL, several graded or architectural features could be reached by the training set.

3. Convolutional Neural Network. (CNN)

CNN is an automatic forward neural network as shown in Fig 4. Here, the signal is handled directly without turns or circuits. Thus, the signal is handled straightforwardly with no circle or cycles. That can be addressed by the following equation [13]:

$$G(X) = g_N(g_{N-1}(\ldots(g_1(X))))$$

Where:
- \(N\) = number of hidden layers.
- \(X\) = the input signal.
- \(g_N\) = the corresponding function to the layer \(N\).

A fundamental CNN frame holds a convolutional layer, that include a function is \(g\) for many convolutional kernels \((h_1, h_2, h_3, \ldots h_{k-1}, h_k)\). Each \(h_k\) indicated to a linear function in \(k\)th kernel, as the following role: [13]:

$$h_k(x, y) = \sum_{s=-m}^{m} \sum_{t=-n}^{n} \sum_{v=-w}^{w} v_k(s, t, v) X(x - s, y - t, z - v)$$

Where:
- \((x, y, z)\) is pixel position of input \(X\).
- \(m\) is height.
- \(n\) is width.
- \(w\) is depth of the filter.
- \(V_k\) is weight of \(k\)th kernel.
Essential reason for Pooling during CNN does the errand of sub-sampling for where it sums up close-by neighborhood pixels and exchange them with the yield by an area by summed up qualities. Pooling lessens the dimensionality and plays out the in-variance of rotating changes and interpretation changes.

Around several Pooling capacities [34]; perhaps the most acclaimed is maximum Pooling, where the yields are the greatest estimation of the quadrangular pixel area. at normal Pooling capacity, the yield turns into the normal of the quadrangular area. the other sort comprises from the weighted normal dependent at the separation of the focal pixel. Hence pooling assists with making the portrayal in variant to little variation into the interpretation at the info.

Atrous Convolution happens depending on the following equation:

\[ y[i] = \sum_{k=1}^{k} [i + r.k] w[k] \]

Where:
- \( x[i] \) is the 1D input signal.
- \( w[k] \) is the filter of length of \( k \).
- \( r \) is the stride rate with which the input signal is sampled.
- \( y[i] \) is the output of the atrous convolution.

The atrial convolution is applied to the info \( x \) of every area to the yield \( y \) and the w-channel with the atrial rate \( r \), which compares to the progression rate.

Deep learning is utilized to face the issue of debasement, which shows up as the deep association joins, i.e., immersing exactness and defilement with expanding profundity. The lingering association unambiguously permits the stacked layers to fit the leftover proof as opposed to the ideal base catalogue. As demonstrated in the investigation results, the disentanglement of the excess associations is less complex, and exactness can be achieved with a great extension all around. Skipping joins help in information crossing in profound neural associations. Bypassing through numerous layers, the point information might be lost, which is known as the dissipation inclination issue. The Skip Link featured on the top side of looking over object information to drop layers, which makes it simpler to portray fine subtleties existing apart from everything else. A piece of the spatial information is lost because of the most extreme total action, while skip joins to make it possible to have more information on the last layer so the game plan precision is expanded [13].

4. Literature review

Robert Mendel et al. [9] in 2017, proposed a programmed an automated way to detection of adenocarcinoma in the esophagus earlier. This study dependent on an image dataset collection given via the Endoscopic Vision Challenge MICCAI 2015. Which have 100 high-definition (1600x1200 pixels) endoscopic images from 39 patients. Where (22) sufferer offer malignant tumours and (17) were diagnosed as non-cancerous Barrett. They utilized CNN to plan the system, where the last classification of an image was certain by completely one spot, for which the likelihood element a malignancy spot passes a given threshold. The model was assessed with Leave One Patient Out Cross-Validation (LOPO-CV). They achieve specificity of 88% and sensitivity of 94%.
In 2018, Yoshimasa Horie et al. [3] developed technique using DL through CNN, to facilitate early prognosis of esophageal cancer. These researchers using dataset from (8428) images for training of esophageal cancer of (384) sufferer in the centre of Cancer Institute Hospital, Japan. They reach sensitivity of 98% and 98% of accuracy.

In 2018, Sjors van Riel et. al. [4], They proposed a technique for early detection of esophageal cancer using CNN Transfer Learning Technology. They used the Endo Vis MICCAI 2015 dataset, consisting of 100 high-resolution (1600x1200) pixel endoscope images of 39 patients, interpreted by five major European human medicine institutions. The authors used an intermediate result for CNNs such as features tried in the process such as learning transfer by CNN codes. In this paper, they used a support vector machine (SVM) and random forests (RF) as the classifier, and this technique achieves results of an area under the ROC curve (AUC) of 0.92.

In 2019, Noha Gatwary et al. [1], They presented strategies to naturally recognize esophageal cancer (EAC) regions by studying high-resolution white light endoscopy (HD-WLE) images. In view of the CNN techniques and the following features extracted: local binary patterns (LBP), histogram-directed gradient (HOG), gray-plane co-event network (GLCM), Fourier features, tissue spectrum, and dominant neighbor structure (DNS) Gabor highlights. The segmentation and classification were carried out using CNN techniques, namely: Regional Convolutional Neural Network (R-CNN), Fast R-CNN, Faster R-CNN, and Single-Shot Multibox Detector (SSD). The SSD was found to have a susceptibility of about 0.96, a ratio of 0.92 and an F-ratio of 0.94, so the average recovery rate for the fastest R-CNN in the accurate discrimination of the EAC is 0.83. Whereas, R-CNN and Faster R-CNN are not quite the same.

In 2019, Noha Gatwary et al. [11], They proposed a new deep learning model based on a faster region-dependent convolutional neural network (Faster R-CNN). This strategy has been introduced to diagnose abnormalities that are naturally detected in the esophagus from endoscopic images. They took advantage of a large number of handcrafted Gabor features as well as extracted by design (DenseNets) CNN features. They relied in this study on two sets of data (Kvasir and MICCAI 2015). Regarding Kvasir, the results show exceptional exposure with 90.2% recall and 92.1% accuracy with an average normal accuracy (mAP) of 75.9%. As for the MICCAI 2015 dataset, the model can outperform the latest performance with 95% recall and 91% accuracy with a mAP value of 84%.

In 2019, Shi-Lun Cai et al. [5], They developed a new computer-aided detection (CAD) system using a deep neural network (DNN). To restrict and quantify early esophageal squamous cell carcinoma (ESCC) proliferation by convolutional white light imaging. They collected 2,428 endoscopic images from (740 patients), which were classified (1332 abnormal images and 1096 normal images). These images were used to create a new system (DNN-CAD) in two centers and a data set was prepared for the purpose of verifying the results consisting of 187 images taken of 52 patients. The developers achieved specificity, sensitivity and accuracy ratios (97.8%, 85.4%, 91.4%) respectively. The DNN-CAD system gains 86.4% for positive predictive value (PPV) and 97.6% for negative predictive value (NPV).

Masayasu Aomori et al. [6] In 2019, they introduced a computerized image analysis system to detect and describe ESCC. They used approximately 9,591 non-magnified endoscopic images (ME) and 7844 (ME) that were confirmed as superficial esophageal carcinomas, and they used 1692 non-ME and 3435 ME images to be characterized as images of normal esophagus or non-cancerous lesions as a training set of images. For validation, they used 255 non-white light (WLI) images, 268 non-ME / BLI narrowband images (NBI / BLI) and also 204 ME-NBI / BLI images from 135 patients. The same validation test data were diagnosed by 15 board-certified professionals (experienced endoscopes). This experiment verifies the results that will be shown in a file (Table 3).

Table 3: Results of Masayau Ohmori paper [6].

| Seq. | System type | Metrics | Sensitivity | specificity | Accuracy |
|------|-------------|---------|-------------|-------------|----------|
|      |             |         |             |             |          |


|   | non-ME with NBI/BLI | AI system | Non-ME with WLI | AI system | ME | AI system |
|---|-------------------|-----------|-----------------|-----------|---|-----------|
| 1 | 100%              | 63%       | 77%             | 92%       | 69% | 78%       |
| 2 |                   |           |                 |           | 87% | 67%       |
| 3 |                   |           |                 |           | 98% | 56%       |

There were no noticeable differences in diagnostic performance between the AI systems and the experienced endoscopy specialists.

In 2020, Alanna Ebigbo et al. [2] They proposed a strategy with early location of esophageal adenocarcinoma (EAC) in light of computer-aided diagnosis using deep learning CAD-DL. Professionals used mainly manual features based on texture and color. They relied on two databases, with EAC detection by CAD-DL reaching a sensitivity of 97% and a specificity of 88% for Augsburg data, 92% for sensitivity, and 100% specificity (Medical Image Computing and Computer Aided Intervention Data [MICCAI]) for WL white light images and 94% for sensitivity and 80% for narrowband images (NBI). They also evaluated the adoption of the dice coefficient D as the ratio of coverage between the CAD-DL section and that of the professionals who had been treated to effectively obtain the images requested by CAD-DL as being cancerous. A mean estimate of D = 72% was recorded for Augsburg data, likewise for WL and NBI images, while in MICCAI data D was equivalent to 56%.

In 2020, Gaoshuang Liu et al. [14], they used CNN to classify esophageal cancer (EC) to identify it from precancerous lesions. The proposed CNN consisted of two subnets (O-stream and P-stream). The original images were exploited as inputs for the O-stream to extract color and general features, and they made use of pre-processed esophagus images as inputs for the P stream to determine texture and detail features. The developers then took a dataset of 1,272 white-light photos of 748 patients from Nanjing Medical University's first hospital, including normal conditions, precancerous lesions and precancerous lesions. In the algorithm training phase, they trained 1,017 images, and another 255 images were analyzed to evaluate the CNN design. The improved CNN system achieved a specificity of 94.67%, an accuracy of 85.83%, and a sensitivity of 94.23% after achieving the fusion of the two currents. The classification accuracy for normal esophagus, potential incidence of cancer and European strength was 94.23%, 82.5%, and 77.14% separately.

In 2020, Min Zhang et al. [15], CNN-based technology models were created for contrasting diagnosis of prominent esophageal lesions through endoscopic images obtained throughout practical clinical environments. They used a dataset collected from 1,217 patients who experienced WLI and endoscopic ultrasound (EUS) during (Jan. 2015 and Apr. 2020). The creators' planned model consisted of 3 deep-CNN designs created for fulfilling accompanying duties: First, clearly controlled evidence of Sound esophageal ulcer favorable using WLI images; second, separating three sub-types of expected esophagus ulcers (like esophagus leiomyoma (EL), esophagus cyst (EC), and esophagus papillomatosis (EP)) utilizing WLE images; And finally the third separation of EL and EC by EUS images. The clinical endoscopy specialists had selected patients to independently decode all images. Finally, they achieved these results to the first task, complete the CNN AUC model 0.751 (95% CI, 0.652 - 0.850) in mild metal esophagus injuries. For the second task, the proposed model using WLI images to separate the esophageal twisted lesions achieved an AUC of 0.907 (95% CI, 0.835 - 0.979), and 897 (95% CI, 0.841 - 0.953) and 0.868 (95% CI, 0.769 - 0.968) For EP, EL and EC separately. The CNN model achieved the same discrimination proof accuracy or higher resolution for both the differentiated EL and EC and the endoscope. while the task separating EL from the EC (task 3), the proposed CNN model had AUC estimation of 0.739 (EL, 95% CI, 0.600 - 0.878) and 0.724 (EC, 95% CI, 0.567 - 0.881), cramping older adults and feet.

5. Discussion and Conclusion

The field of medical image processing and deep learning is one of the most important fields for several reasons, including helping doctors diagnose diseases, speed and accuracy in performance, and the most important thing is to reduce deaths due to esophageal cancer. One of the challenges we noticed
by studying scientific papers in this regard is the difficulty in obtaining the data set for the endoscopy examination. The current global data sets are two on the borders of our knowledge, Kvasir and MICCAI 2015, and the studies conducted on them are limited. All factors contribute to the reluctance of researchers to delve into the development of a system that works to detect early esophageal cancer. In addition to the above, the irregular shape of the esophageal tissue poses a major challenge to developers of medical image processing systems, and this is a complicating factor in designing a system that fits variable specifications. In addition to the above, the stage during which the patient is examined is also important. Another challenge is the type and accuracy of the camera used in an endoscopy to examine the esophagus. All of the above factors directly contribute to the development of an efficient and accurate CAD system. We had great difficulty in obtaining a local data set from hospitals and government or private centers, as we wanted to work on real data and accurate and realistic numbers, which forced us to resort to global data sets. We also note that most papers discuss static image analysis, which means that there are complications in real-time fluoroscopy video analysis. So hopefully, in the future, we will be able to create a model that processes video images for endoscopic examination in real time.

Table 4: Summarization of the works considered in this review.

| NO. | Author | Goal | Dataset | Testing Device | Classifier | Validation Protocol | evaluation method | Name of technique | performance Metric |
|----|--------|------|---------|---------------|------------|---------------------|------------------|-------------------|------------------|
| 1  | Robert Mendel et al. [9] 2017 | Developed an automated way for early detection of adenocarcinoma in the esophagus. | MICCAI 2015 | Endoscopy CNN using Transfer learning | CNN | LOPO-CV | Proposed a programmed way for early detection of adenocarcinoma in the esophagus. They convolutional neural network (CNN) to plan the system, where the last classification of an image was specified by fully one spot, to the probability entity a malignant spot passes an assumed threshold. | CNN | 94 % | 88 % | \ |
| 2  | Yoshimasa Horie et al. [3] 2018 | Illustrate diagnosis of AI to expose EC containing adenocarcinoma and squamous cell carcinoma. | 8428 images from 384 patients. | Endoscopy CNN | CNN | \ | Industrialized technique using DL through CNN, to facilitate early prognosis of esophageal cancer. | CNN | 98 % | 79 % | 98 % |
| NO. | Author | Goal | Dataset | Testing Device | Classifier | Validation Protocol | Evaluation Method | Name of Technique | Performance Metric |
|-----|--------|------|---------|----------------|------------|---------------------|------------------|------------------|-------------------|
| 3   | Sjors van Riel et al. | Focus on achieving real-time performance for clinical application | MICCAI 2015 | Endoscopy | SVM | LOPO-CV | Suggested a novel technique to early detection of esophageal cancer, using CNN by Transfer Learning. | SVM, RF | 92.9% 93.1% 83.50% |
| 4   | Noha Gatwary et al. | Automatically identify esophageal adenocarcinoma (EAC) regions using CNN techniques. | MICCAI 2015 | Endoscopy | SVM | LOPO-CV | Strategies presented to naturally recognize esophageal cancer (EAC) regions from high-resolution white light endoscopy (HD-WLE) images. | R-CNN, Fast R-CNN, Faster R-CNN, SSD | 60% 65% 88% 96% |
| 5   | Noha Gatwary et al. | Automatically detect abnormalities in esophagus from endoscopic images. | Kvasir | Endoscopy | Faster R-CNN | LOPO-CV | Proposed a novel DL model based on a Faster R-CNN. | Faster R-CNN | \ \ \ |
| 6   | Shi-Lun Cai, MD | Localization and determination of early ESCC under conventional endoscopic white light imaging. | (1332 abnormal and 1096 normal) esophagogastroduodenoscopy images of 746 patients (671 patients from Zhongshan Hospital and 75 of Kiang Wu Hospital) during January 2016 to April 2018 | Endoscopy | DNN | Berkeley Vision and Learning Centre | An advanced and proven computer-aided detection (CAD) system using a DNN; for restrict and categorize early esophageal squamous cell carcinoma (ESCC) under white light convolutional imaging. | DNN | 97.8% 85.40% 91.4% |
| No | Author | Goal | Dataset | Testing Device | Classifier | Validation Protocol | Name of technique | Performance Metric |
|----|--------|------|---------|----------------|------------|---------------------|-------------------|--------------------|
| 7  | Masayasu Ohmori et al. [6], 2019 | Detecting and diagnosing esophageal Squamous Cell Carcinoma (ESCC) | Osaka International Cancer Institute. | Endoscopy | SVM | A set of 255, 268, and 204 non-ME WLI and non-ME NBI-BLI and ME NBI-BLI images, respectively, were selected for 135 patients. | An advanced digital image analysis system for detecting and distinguishing ESCC so this AI systems displayed high sensitivity to ESCC diagnosing in non-ME and high accuracy to distinguishing ESCC in non-cancerous lesions for ME images. | Non-ME with BBI/BLI | SE: 100%, SP: 63%, AC: 77% |
| 8  | Alanna Ebigbo et al. [2], 2020 | Optimizing endoscopic evaluation for Barrett's esophagus (BE) and adenocarcinoma (EAC) in an early stage | Augsburg data | Endoscopy | CAD-DL | Learning a strategy with EAC early location of esophageal adenocarcinoma in light of CAD-DL. | CAD-DL | SE: 97%, SP: 88% |

Note: The performance metrics SE, SP, and AC stand for Sensitivity, Specificity, and Accuracy, respectively.
| No. | Author | Goal | Dataset | Testing Device | Validation Protocol | Evaluation Method | Name of Technique | Performance Metric |
|-----|--------|------|---------|----------------|---------------------|------------------|-------------------|--------------------|
| 9   | Gaoshuang Liu et al. [14], 2020 | Using a CNN, a deep educational method, for spontaneous classifying EC and recognize it of precancerous lesions. | 1,272 endoscopic images of esophagus had collected of 748 patients in the first hospital affiliated with Nanjing Medical University between 2010 and 2018. | Endoscopy SVM | Five-Fold Cross-Validation | Utilized convolutional neural network (CNN) to consequently classifying the EC and recognize it since precancerous injuries | SVM | SE: 85.8% | SP: 94.23% | AC: 94.67% |
| NO. | Author | Goal | Dataset | Testing Device | Validation Protocol | evaluation method | Name of technique | performance Metric |
|-----|--------|------|---------|----------------|---------------------|-------------------|------------------|-------------------|
| 1   | Min Zhang et al. [15], 2020 | Development of models for CNN-based methods for diagnosing prominent esophagus lesions in the beginning stage using an endoscopic image obtained through actual clinical settings. | 1,217 patients experienced (WLI) and endoscopic ultrasound (EUS) were collected during Jan. 2015 and Apr. 2020. | Endoscopy | Devised frames of CNN-based techniques for the differencing the diagnosing of palpable esophagus lesions through endoscopic images obtained in actual clinical settings. Three CNN profound models were established to achieve associated tasks: (1) Clear evidence of favorable esophageal ulcers from voice controlling utilizing WLI images; (2) Separating 3 sub-types form expected esophagus ulcers (EL count: esophagus leiomyoma, EC: esophagus cyst, and EP: esophageal papillomatosis) via WLE images; although (3) separation of EL and EC using EUS images. | CNN | \ | \ | \ | \ | \ | \ | \ | \ |

6. References

[1] G. Zhang et al., ‘Reinforced concrete deep beam shear strength capacity modelling using an integrative bio-inspired algorithm with an artificial intelligence model’, Eng Comput, pp. 1–14, 2020.
[2] R. M. A. F. J. M. L. A. d. S. J. J. P. C. F. H. M. Alanna Ebibgo, "Computer-aided diagnosis using deep learning in the evaluation of early oesophageal adenocarcinoma," https://gut.bmj.com/, no. doi:10.1136/gutjnl-2018-317573, pp. 1143–1145, 3, september, 2020.
[3] Yoshimasa Horie, MD,1,2 Toshiyuki Yoshio, MD,1,3 Kazuharu Aoyama, MM,4 Shoichi Yoshimizu, MD, Yusuke Horiiuchi, MD,1 Akiyoshi Ishiyama, MD,1 Toshiaki Hirasawa, MD,1,3 Tomohiro Tsuchida, MD,1 Tsuyoshi Ozawa, MD,3,5 Soichi Ichihara, MD,3,5 Youichi Kumagai,1, "Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks," www.giejournal.org, no. https://doi.org/10.1016/j.gie.2018.07.037, pp. 1 - 8, 2018.
[4] S. v. R. F. v. d. S. S. Z. E. J. S. P. H. d. With, "AUTOMATIC DETECTION OF EARLY ESOPHAGEAL CANCER WITH CNNS USING TRANSFER LEARNING," https://ieeexplore.ieee.org/abstract/document/8451771/, no. 978-1-4799-7061-2/18/$31.00 ©2018 IEEE, pp. 1383 - 1387, 2018.

[5] M. B. L. M. W.-M. T. P. X.-J. N. H.-H. M. Shi-Lun Cai, "Using a deep learning system in endoscopy for screening of early esophageal squamous cell carcinoma (with video)," www.giejournal.org, pp. 1 - 11, 2019.

[6] M. R. I. M. P. K. A. K. e. a. Masayasu Ohmori, "Endoscopic detection and differentiation of esophageal lesions using a deep neural network," the American Society for Gastrointestinal Endoscopy GIE, no. https://doi.org/10.1016/j.gie.2019.09.034, pp. 1 - 47, 21 september 2019.

[7] Y.-H. Z. e. al, "Artificial intelligence-assisted esophageal cancer management: Now and Future," World Journal of Gastroenterology WJG, vol. 26, no. 35, pp. 1 - 25, 21 september 2020.

[8] G. C. M. e. al, "Emerging artificial intelligence applications in gastroenterology: A review of the literature," Artificial Intelligence in Gastrointestinal Endoscopy, vol. 1, no. 1, pp. 1 - 18, 28 July 2020.

[9] R. M. e. al, "Barrett’s Esophagus Analysis Using Convolutional Neural Networks," Springer-Verlag GmbH Deutschland, no. DOI 10.1007/978-3-662-54345-0_23, pp. 80 - 85, 2017.

[10] 2. A. a. X. Y. Noha Ghatwary1, "Automated Detection of Barrett’s Esophagus Using Endoscopic Images: A Survey," Springer International Publishing AG , no. DOI: 10.1007/978-3-319-60964-5_78, pp. 897 - 908, 2017.

[11] 2. X. Y. I. A. M. Z. NOHA GHATWARY 1, "Esophageal Abnormality Detection Using DenseNet Based Faster R-CNN With Gabor Features," IEEE Access , vol. 7, no. http://creativecommons.org/licenses/by/3.0/, pp. 84374 - 84385, 30 May , 2019.

[12] I. D. e. al, "Computer Vision in Esophageal Cancer: A Literature Review," IEEE Access , vol. 7, no. http://creativecommons.org/licenses/by/4.0, pp. 103080 - 103094, 7 July 2019.

[13] K. M. e. al, "Cancer Diagnosis Using Deep Learning: A Bibliographic Review," www.mdpi.com/journal/cancers, vol. 11, no. doi:10.3390/cancers11091235, pp. 1 - 36, 2019.

[14] G. L. e. al, "Automatic classification of esophageal lesions in endoscopic images using a convolutional neural network.,” Annals of Translational Medicine. , vol. 8, no. doi: 10.21037/atm.2020.03.24, pp. 1 - 10 , Feb 21, 2020.

[15] M. Z. e. al, "Differential diagnosis for esophageal protruded lesions using a deep convolution neural network in endoscopic images,” American Society for Gastrointestinal Endoscopy GIE , no. https://doi.org/10.1016/j.gie.2020.10.005, pp. 1 - 14, 1 October 2020.

[16] F. Y. e. al, "Feature Extraction and Classification on Esophageal X-Ray Images of Xinjiang Kazak Nationality,” Journal of Healthcare Engineering, vol. 2017 , no. https://doi.org/10.1155/2017/4620732, pp. 1 - 12 , 4 April 2017.

[17] J. F. a. V. G. Kieran Foley1, "Novel imaging techniques in staging oesophageal cancer," Best Practice and Research: Clinical Gastroenterology, Vols. 36 - 37, no. http://dx.doi.org/10.1016/j.bpg.2018.11.009, pp. 17 - 25 , 2018.

[18] H. O. Y. S. a. T. M. Ryuji Ohura, "Computer-aided diagnosis method for detecting early esophageal cancer from endoscopic image by using dyadic wavelet transform and fractal dimension,” Springer International Publishing Switzerland, no. DOI: 10.1007/978-3-319-32467-8_80, 2016 .

[19] P. S. N. v. Rossum, "Towards individualized treatment for esophageal cancer,” PhD thesis, Utrecht University, The Netherlands, 2016 .

[20] M. Thomas W. Rice, M. Valerie W. Rusch, P. Hemant Ishwaran and M. and Eugene H. Blackstone, “Cancer of the Esophagus and Esophagogastric Junction,” https://pubmed.ncbi.nlm.nih.gov/20564099/ , no. DOI: 10.1002/cncr.25146, August 15, 2010.

[21] M. E. S. G. F. B. D. B. R. W. M. G. J. C. H. K. S. D. J. J. B. J. G. L. S. R. B. C. W. D. A. E. M. Amin, AJCC Cancer Staging Manual, 2016 .
[22] H. S. •. K. H. •. C. P. •. I. K. •. M. K. •. M. Reiser, "Computerunterstützte Auswertung von Mammographien," https://pubmed.ncbi.nlm.nih.gov/28347448/, no. DOI: 10.1016/j.ijmedinf.2017.02.004, pp. 610 - 616, 2017 Feb 17.

[23] Y. K. Ryohi Takahashi *, "Computer-aided diagnosis: A survey with bibliometric analysis," International Journal of Medical Informatics, no. http://dx.doi.org/10.1016/j.ijmedinf.2017.02.004, pp. 58 - 76, 4 February 2017.

[24] U. B. 1. B. F. 1. Z. X. 1. G. Z. P. 1. L. R. F. 1. J. K. U. 1. D. J. M. 1. Awais Mansoor 1, "Segmentation and Image Analysis of Abnormal Lungs at CT: Current Approaches, Challenges, and Future Trends," https://pubmed.ncbi.nlm.nih.gov/26172351/, no. DOI: 10.1148/rg.2015140232, Jul-Aug 2015.

[25] L. B. Y. B. A. P. H. YANN LECUN, "Gradient-Based Learning Applied to Document Recognition," IEEE, vol. 86, no. 11, 1998.

[26] A. K. e. al, "ImageNet Classification with Deep Convolutional Neural Network," International Conference on Neural Information Processing Systems, Curran Associates Inc, no. Available from: https://dl.acm.org/citation.cfm?id=2999257., pp. 1097 - 1105 , 2012.

[27] "Error-Driven Incremental Learning in Deep Convolutional Neural Network for Large-Scale Image Classification," the ACM International Conference on Multimedia - MM ’14 Orlando, Florida, USA., no. http://dx.doi.org/10.1145/2647688.2654926., November 3 – 7, 2014.

[28] W. L. Y. J. P. S. S. R. D. A. D. E. V. A. R. Christian Szegedy, "Going Deeper with Convolutions," https://www.semanticscholar.org/ , no. DOI:10.1109/CVPR.2015.7298594, 2015.

[29] S. W. ·. S. Z. ·. Y. L Liu2, "Deep residual learning for image steganalysis," Springer Science+Business Media New York 2017, no. https://doi.org/10.1007/s11042-017-4440-4, 23 January 2017.

[30] "Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition," https://arxiv.org/abs/1406.4729, no. 10.1007/978-3-319-10578-9_23, 23 Apr 2015.

[31] B. V. G. a. R. M. S. H. Greenspan, "Guest Editorial Deep Learning in Medical Imaging: Overview and Future Promise of an Exciting New Technique," http://ieeexplore.ieee.org/document/7463094, vol. 35, no. 5, MAY 2016.

[32] * Q. J. B. Z. a. D. C. Jun Gao1, "Convolutional neural networks for computer-aided detection or diagnosis in medical image analysis: An overview," Mathematical Biosciences and Engineering, vol. 16, no. 6, 15 July 2019.

[33] I. G. W. a. H.-I. S. Dinggang Shen, "Deep Learning in Medical Image Analysis," https://pubmed.ncbi.nlm.nih.gov/28301734/, no. doi: 10.1146/annurev-bioeng-071516-044442. Epub 2017 Mar 9., 2017 Jun 21.

[34] C.-Y. L. e. al, "Appearing in the Proceedings of the 19th Generalizing Pooling Functions in Convolutional Neural Networks: Mixed, Gated, and Tree," International Conference on Artificial Intelligence and Statistics (AISTATS) 2016, Cadiz, Spain. JMLR: W&CP, vol. 51, no. arXiv.org > stat > arXiv:1509.08985, pp. 9 - 11, 2016.

[35] *: https://datasets.simula.no/kvasir/"