

# An Improved Mixed Convolutional and Adaptive Residual Network Based Esophageal Cancer Detection and Classification

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**Abstract**— Esophageal adenocarcinoma is the worst cancer that may strike humans. According to the World Health Organization's predictions for 2020, it ranks sixth in global deaths and seventh in illness. Because of this, this effort aims to create a computer system that uses cutting-edge image analysis techniques and algorithms to work on the early identification of esophageal cancer. To lower the fatality rate by assisting qualified medical professionals in spotting it in an early stage. For esophageal cancer detection and classification, such as malignant vs. nonmalignant, the Upgraded Mixed Convolutional and Adaptation Residual Network (IMCARNet) method is presented in this study. The images captured during an Esophageal Endoscopy (EE) procedure are first preprocessed using an Enhanced Kaun Filter to reduce noise and smooth the image (IKF). To improve the expected exactness, particular characteristics are then extracted. IMCARNet has finally been used to classify the tissue. The results of the experiments demonstrate that the anticipated IMCARNet achieves superior execution with a higher degree of deference than the accuracy rate of 98.5%, the sensitivity rate of 97.5%, and the specificity rate of 95.5% when compared to existing algorithms such as the Deep Neural Network (CNN) and quicker Regional Multi-Layer perceptron (R-CNN) schemes.

**Index Terms**— Convolutional neural networks, residual neural networks, dragonfly optimization, endoscopic images, Kaun filters, and esophageal cancer.

## I. INTRODUCTION

Esophageal Adenocarcinoma (EAC), the early stage of carcinoma, is a serious health issue that has been on the rise. Just 18.8% of patients with esophageal cancer survive the disease for five years, according to studies [1]. Particularly BE (Barrett's Esophagus) is the main premalignant factor leading to esophageal malignancy [2, 3], where the metaplastic transformation of healthy tissue in the esophageal facing into columns mucous membrane results in EAC [4]. The likelihood that a patient would survive EAC may be increased with early identification and treatment [5].

Endoscopic examination, using a HD-WLE (high-definition white light endoscope) as the major method for identification [6]; confirmation of cell deformation phases by biopsy illustrations from the esophageal shallow lining [7]. Because of its unpredictable distribution throughout the esophageal tube, the BE or EAC's appearance and physical characteristics obstruct the identification procedure [8]. Moreover, proper identification necessitates a doctor with extensive training, and they are frequently missed during endoscopic surveillance [9]. To prevent the progression of anomalies into more advanced stages, patients must also have routine follow-up endoscopic examinations. CAD systems have become increasingly popular as the percentage of patients continues to rise. Many studies have been conducted and are described in the literature for segmentation, automated detection, and classification using a variety of endoscopies, including narrow-band imaging, confocal laser endomicroscopy, chromoendoscopy and volumetric laser endomicroscopy. These techniques are outlined and addressed in [10, 11]. An overview of earlier research on EAC identification from Hd Quality (HD)-WLE will be included in the following section.

Recent years have seen deep learning's (DL) widespread utility across many fields [12], including NLP, medical image analysis, computer vision, and etc. Detection, classification, segmentation, and other forms of deep learning have become standard in medical image examination [13]. The problem of the precision and quality of images taken with experimental imaging devices is possibly the most pressing problem facing experts in the field of medical image management [14]. As we previously said, the data set employed in this work, which contained more than (11,000) images, requires image-enhancing operations before the suggested system can use for illness diagnosis. Hence, various image optimization techniques, including histogram equalization, median, limit filtering, etc., will be used in the current research. The uneven form of the esophageal cell walls will present another challenge in identifying the region of interest, necessitating the selection of suitable classifiers capable of handling this characteristic and producing reliable findings [15].

Also, correct discoveries need a physician with extensive training, yet they are frequently disregarded during endoscopic surveillance [16]. Moreover, patients must attend regular follow-up appointments for endoscopic evaluation to restrict the progression of abnormalities into later stages [17]. Images of varying quality and color ratios are produced due to the various camera features utilized to take endoscopic test images. The requirement for specific filters to eliminate misrepresentations and normalize the colors of the images seemed to split the region of interest, as seen in the data set utilized in the latest research. This raises the question of how to best deal with this variation and dissimilarity in the images to locate the ROI (Region of Interest) precisely. IMCARNet is offered in this study to help in the diagnosis and categorization of esophageal cancer.

## II. RELATED WORK

Convolutional neural networks were used to produce deep learning by Yoshimasa Horie et al. [18]. (CNNs). To assess the reliability of the diagnostics, we also generated 1118 test images, including 49 cases of esophageal cancer and 50 control cases. With a specificity of 98%, CNN successfully identified instances of esophageal cancer within 27 seconds of analyzing 1118 test images. The seven tiny cancer lesions, each smaller than 10 mm in size, were found by CNN. Although each image showed a 40% positive prediction value, misdiagnosing shadows and regular structures resulted in a 95% negative predictive value. With a 98% accuracy rate, CNN could discriminate between early-stage malignancy and superficial esophageal cancer.

Another PC-aided recognition (CAD) system was developed by Cai et al. [19] using a deep neural structure (DNN). Use multilayer white light imaging for early detection and monitoring of Esophageal Squamous Cancer (ESCC). The engineers independently achieved awareness, particularity, and accuracy percentages (97.8%, 85.4%, and 91.4%). The DNN-CAD architecture increases PPV (positive predictive value) by 86.4% and NPV (negative predictive value) by 97.6%. (NPV).

Ohmori et al. [20] provided a framework for electronic image investigations to recognize and represent ESCC. They used 9,591 non-magnified endoscopic (ME) images, give or take ME. Moreover, 7844 ME were established. As an example of superficial esophageal carcinomas Also, they used 3435 ME images as well as 1692 non-ME images to characterize similar images of the normal throat and non-cancerous tumors. As an illustration, consider a preparation made from a collection of images. 15 board-certified specialists diagnosed the identical acceptance test data (experienced endoscopes).

Ebigbo et al. [21]. 's technique for treating early-stage esophageal adenocarcinoma (EAC) using PC-supported decision-making with deep learning (DL) referred as CAD-DL. Experts used mostly labor-intensive features based on surface and color. The percentage of inclusions between the CAD-DL segment and the experts fortunate enough to obtain and adequately collect the images that CAD-DL had identified as harmful was also

evaluated. Augsburg information had an average gauge of  $D = 72\%$ , similar to WL and NBI images, whereas MICCAI information had  $D$  equal to  $56\%$ .

CNN was used by Liu et al., 2020 [22] to define malignant esophageal development (EC) and differentiate it from precancerous lacerations. Two subnets made up the planned CNN are O-stream and P-stream, in that, the images were used as inputs for the O-stream first, where they were used to distinguish between tonal and global highlights; next, the P-stream used inputs from images of the throat that had already been processed to determine between local and global highlights. After successfully combining the two processes, the improved CNN framework achieved 94.67% explicitness, 85.83% exactness, and 94.23% awareness. The grouping accuracy for a normal throat, the likelihood of malignant development, and European strength were 94.23%, 82.5%, and 77.14% respectively.

Using endoscopic images obtained under normal clinical circumstances, Zhang et al. [23] developed CNN-based innovation representations for distinguishing examination of visible esophageal lesions. The suggested CNN model exhibited AUC assessments of 0.739, squeezing more experienced adults and foot.

Chen et al. [24] showed the enhanced. This research uses 1520 gastrointestinal CT scans from 421 individuals to demonstrate fast R - cnn esophageal cancer diagnosis using OHEM (Online Hard Sample Mining) and next evaluate the three models using the F-1 measure, detection time, and mAP (average percentage precision) to see which performs best overall. The experiment demonstrates that the enhanced Faster RCNN outperforms the other two or more networks regarding overall performance.

### III. PROPOSED METHOD

IMCARNet-based tissue categorization has been discussed according to this section. For improving the accuracy of age detection, preprocessing, effective division, and feature extraction have been given. The subsequent sub-segments have looked at the proposed strategy's well-organized method. The anticipated scheme flow is presented in Fig 1. The input image is first gathered, and after that, IKF is used to preprocess the image. The whole tissue is then segmented from the EE image using IDO clustering. Finally, to increase accuracy, the crucial traits are extracted. Lastly, IMCARNet was utilized to categorize the cancer tissue.

#### A. Dataset

A download of the dataset was made from Kaggle.com. It is the biggest gathering place for students as well as professionals in the disciplines of data science, machine learning, and data analysis. Industry professionals, academics, and Kaggle specialists who assist those in need frequently visit the website. Google owns Kaggle, which was upgraded in the first quarter of 2020. A simulated reinforcement learning method was included after the upgrade. The site may have up to 19,000 essentially identical open-source data sets. In March 2020, a Chinese researcher posted a dataset titled "esophageal Endoscopy Images," which we downloaded. It contains (11564) esophageal endoscopy images, of which we originally implemented the suggested technique using (100) examples.

#### B. Preprocessing

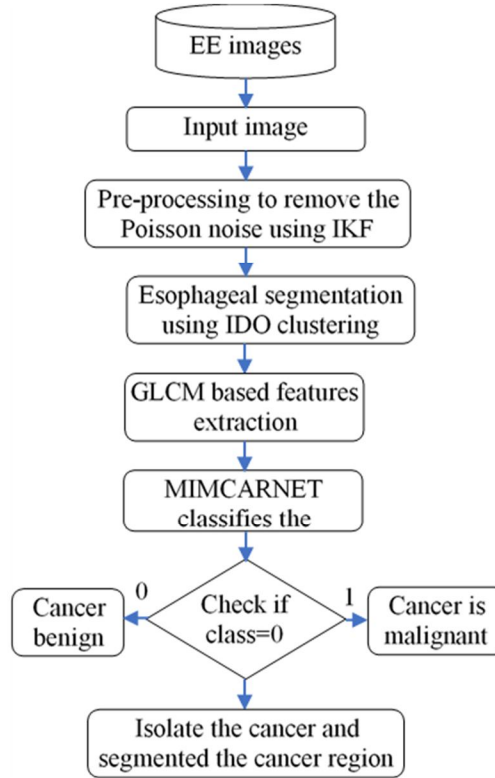
This strategy has improved the visual environment and eliminated noise. This approach proposes using the Enhanced Kuan filter, which may eliminate noises like those mentioned above without compromising the integrity of the underlying image's edges or features. Nevertheless, the noise is changed from a multiplicative to an additive noise model that depends on the image. Following that, the model is subjected to the least Root - mean - square Error (MSE) criterion to estimate the original shape of the image. This is the pre-processing output for grey-level value  $V$ .

(1)

$$V_{i,j} = \sum_{p=1}^{r=3,c=3} \sum_{q=1}^{r=3,c=3} P_{p,q} * Wf_{p,q} + Fw_{p,q} * (1 - Wf_{p,q})$$

Where (r, c) stands for the columns and rows of the pixel value, and (p,q) stands for the image pixels.  $P_{(p,q)}$  is referred to as the center pixel in the filter window  $[[Fw]]_{(p,q)}$ , which is also referred to as the mean intensity

value inside the window, and  $Wf_{-}(p,q)$  is described as the weighting factor. The performance of noise reduction has been anticipated based on this weight. Luus-Jaakola (LJ) has improved the weight factor to enhance image quality and reduce noise [25]. Hence, this function is designated as IKF with KF.



The overall architecture of IMCARNET-based cancer classification

### C. Segmentation using IDO clustering

The processed image is segmented using the IDO clustering technique to increase classification accuracy. Unique to dragonflies is a swarming behavior that serves not one but two distinct purposes [26]: hunting (a static feeding system) and migration. The erratic flight patterns of dragonflies in nature are replicated in the DA using the LFM (Levy Flying Mechanism) that has drawbacks, such as overcrowding the search effort and halting arbitrary aircraft due to its extensive search procedures. Geometric Brownian motion has therefore been incorporated and is known as Improved DO enhance the randomization phase of the DO.

In this case, the highest optimum pixel values serve as the dragonflies' ideal food source (i.e., defect areas). The goal of this procedure is to choose the feature input with the highest value out of all the pixel values. The IDO is mostly used to partition the images' damaged regions. The three distinct behaviors of the swarms, according to Craig and Hart [28], are separation, alignment, and cohesiveness. So, by adjusting the swarming parameters throughout optimization (i.e., the ideal pixel of the image), various exploratory and exploitative features may be achieved. Also, each fake dragonfly is meant to have a specific radius-based neighborhood around it. As the swarm unites to form one cluster during the final optimization stage to reach the global optimum, the surrounding area is also magnified. The mathematical models for these phenomena are as follows [27]: Particles in a liquid (or gas) undergo Geometric Brownian Motion due to collisions with the fluid's fast-moving molecules. In the Markov model, the Average kinetic energy is represented by a Gaussian process that follows a continuous route across time. The afflicted and unaffected areas are successfully segregated using the approaches above.

### D. Future extraction

The suggested system uses the IMCARNET algorithm to identify esophageal cancer early on, using characteristics retrieved by implementing GLCM features. The functions of GLCM and IMCARNET are

explained below, along with how they operate: The virtual variable operator GLCM, which is often employed in sectors including banking, healthcare, and education, was utilized to extract the characteristics for the current study. The GLCM employs pairs of pixels to allow the user to calculate the separation or angle between such pixels accurately. If the distance equals 1, which are physically viewing the association between neighboring pixels; however, if the distance is superior, the correlation occurs on a much larger scale. The parameters of the GLCM material were calculated in the latest research using the grey matrix and greycoprops programs. These characteristics are as follows: contrast, dissimilarity, ASM, energy, homogeneity, and correlation.

#### E. Improved Mixed convolutional and Adaptive residual network (IMCARNet)

In this section, we propose a new architecture, IMCARNet, that combines convolutional layers with adaptive residual layers in a stacked fashion to produce a mixed convolution and residual network, as seen in Fig. 2. The IMCARNet combines one convolutional layer with an adjustable residual layer [30] to reap the benefits of both designs. It should be able to overcome the dominance of the adaptive residual network, which causes CNN's saturation problem, in addition to learning more quickly than CNN (ARN). In this investigation, a three-stacked-layer IMCARNet consisting of three convolution layers and three adaptable residual layers, as well as two Approx layers, one flattening layer, and two Fully Connected layers, was built to cope with the difficulty of eye identification.

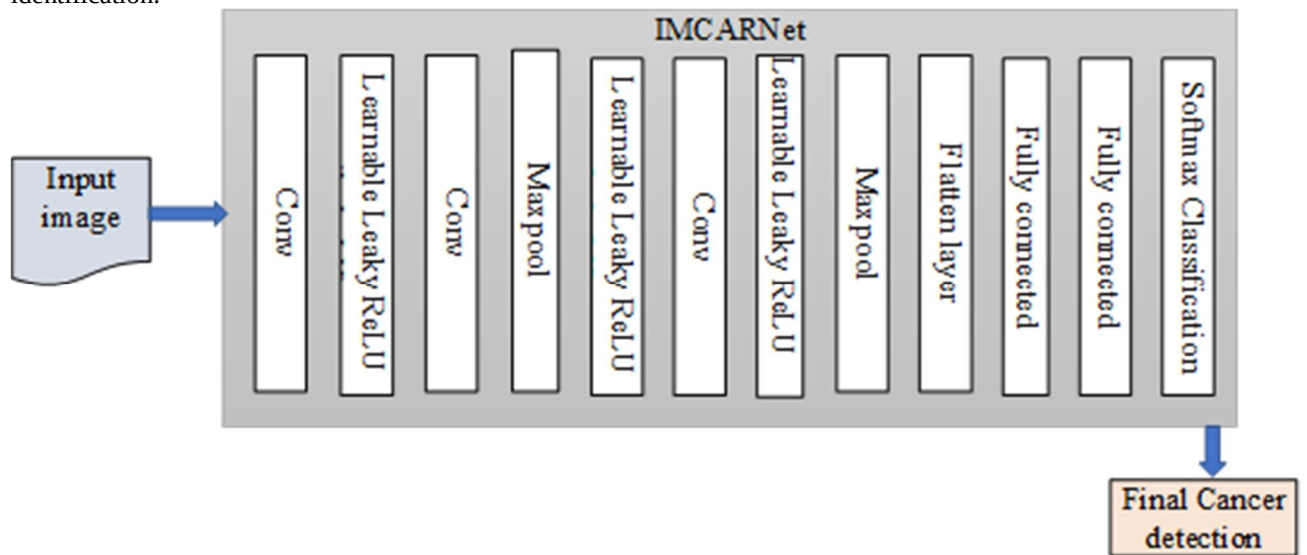


Fig 2. Block diagram of IMCARNet

#### F. Convolutional Neural Networks:

The suggested three-layer CNN uses convolutional kernels of  $5 \times 5$  for the initial two layers of the network, followed by convolutional kernels of  $3 \times 3$  for the last layer. Using two Maxpooling layers, each with two kernels and two pixels, strides are also included. Before feeding the training samples into the initial Convolution layers, the training data are all first bottom to a predefined length of  $70 \times 70$ .

#### G. Learnable Leaky ReLU (LeLeLU):

In this article, we suggest a brand-new activation function that combines the greatest aspects of the ReLU family while being computationally simple and more data-adaptive. The Leaky Learnable ReLU (LeLeLU) is defined by the following equation:

$$y = \delta \max(x, 0) + 0.1\delta \min(0, x) = \begin{cases} 0.1\delta & \text{if } x < 0 \\ \delta x & \text{if } x \geq 0 \end{cases}$$

Where  $\delta$  is a teachable parameter that, like negative inputs, determines the slope of the perceptron, in this case, it also determines the slope for all interventions focused. 0.1 is a consistent multiplier that, like the Leaky ReLU, lowers the slope for negative input values and appears effective in the studies. The following formula may be used to determine the derivative of LeLeLU easily:

$$\frac{dy}{dx} = \begin{cases} 0.1\delta & \text{if } x < 0 \\ \delta & \text{if } x > 0 \\ 0 & \text{if } x = 0 \end{cases}$$

The chain rule may be used to obtain the updated formulas for the parameter  $\alpha$ . The following equation may be used to get the gradient of  $\delta$  for one stage for each neuron  $i$ .

$$\frac{\partial Loss}{\partial \delta_i} = \sum_{y_i} \frac{\partial Loss}{\partial f(y_i)} \cdot \frac{\partial f(y_i)}{\partial \delta_i}$$

where  $y_i$  Denote is the  $i$ -th neuron's output, and  $Loss(\bullet)$  is the loss function of the neural network. One can decide to maintain the parameter  $\delta$  the same for several neurons or a layer to lower the computation complexity in demanding conditions. During testing, we found that the dataset's complexity, the depth-wise position of the relevant filter in the structure of the neural network, and the training phase all affected the learnable parameter  $\delta$ . The learnable parameter's ability to affect positive and negative values makes the suggested activation function powerful. This suggests that when receiving values greater than 1, the adaptation of  $\delta$  can speed up training in specific regions of the circuit during specific training epochs.

In contrast, learning slows down for some network segments when it falls below the value of 1. The neurons' learning stops in the specific scenario when they receive almost zero values, and their output is also nearly zero, indicating that they have been removed from the network. So, by deactivating certain neurons throughout the training process, the network is autonomously regularised in a manner analogous to the well-known dropout method. Network regularisation is achieved by the suggested activation function's adaptation and training, whereas dropout is an additional step that must be taken during network training.

#### H. Flatten Layer:

Two fully connected layers with 512 neurons each are added to the flattening layer during training to perform the categorization job. There are 512 neurons in the new classification layer, and each of them represents a class in the MS training set and is equipped with a softmax-loss feature. With 512 neurons in the layer before it, it lowers the dimensionality of the features.

#### I. Weight optimization:

MS classification study is more precise due to the network's weight being adjusted for the error rate reduction. To determine the rate of Mean Square Error (MSE), one must:

$$MSE_i = \min \left( \frac{\sum_{i=1}^N (DV_i - PV_i)^2}{N} \right)$$

The Desired Value  $DV_i$ , Expected Value  $PV_i$ , and Number of Images  $N$  are all used in this sentence. Moreover, the cross volatility is defined as a loss function using the following formula:

$$\begin{aligned} L(d, y) = & - \sum_{j=1}^N d_j(k) \log y_j(k) \\ & + (1 - d_j(k)) \log (1 \\ & - y_j(k)) \end{aligned} \quad (6)$$

where  $d_j(k)$  denotes the desired raw data value and  $y_j(k)$  Denotes the final result value. Weight optimization in this model was performed using the BLS method [31], and all network bias values were generated randomly from a Gaussian distribution. For optimal classification results, the IMCARNet structure's context unit had its parameter set to 0.21. The network was taught using a 64-batch size, a maximal epoch limit of 40, and a loss function value of no more than 0.002. The aggressive and begin malignantly have been identified using the procedure above.

## IV. RESULT ANALYSIS

This section evaluates the proposed IMCARNet-based classification for esophageal cancer. Comparing the performance of the projected method against the current CNN and RCNN networks. Publicly accessible sets from the Kaggle specialists assessed the categorization accuracy and robustness. The total effectiveness of all cancer categorization and detection methods' graphical representations is shown in Figure 3. It shows that the suggested IMCARNet has outperformed existing R-CNN and CNN in terms of accuracy of 98.5% and specificity rate of 95.5%. The DO process has been enhanced, which has boosted classification accuracy.

IMCARNet's accuracy in Fig. 4 is superior to R and CNN's CNN's. Because of the effective demand reduction and effective tooth location with optimized division with BLS, the accuracy results of the IMCARNet have improved.

Figure 4 visually represents all Carcinoma identification schemes with specificity implementation. It displays the 95.5% specificity of IMCARNet, which is higher than that of R-CNN and CNN. The specificity of the proposed IMCARNet increases due to the significant genuine positive and negative consequences. By segmenting the malignancy, IDO optimization has increased the percentage of true positives.

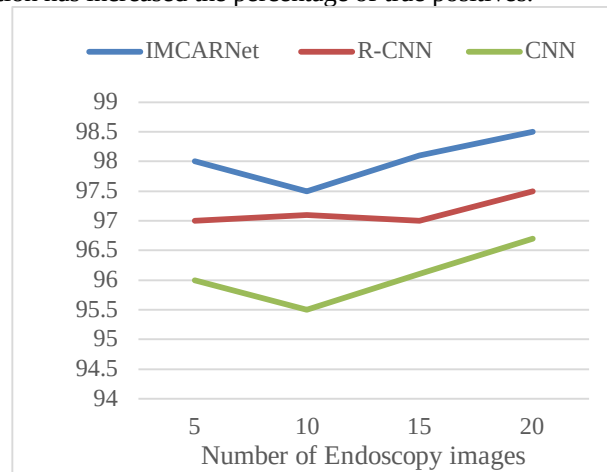


Fig 3. Accuracy among different cancer classification schemes

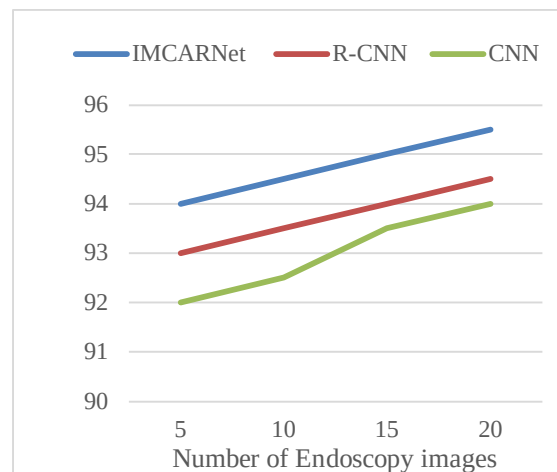


Fig 4. Specificity among different cancer classification schemes

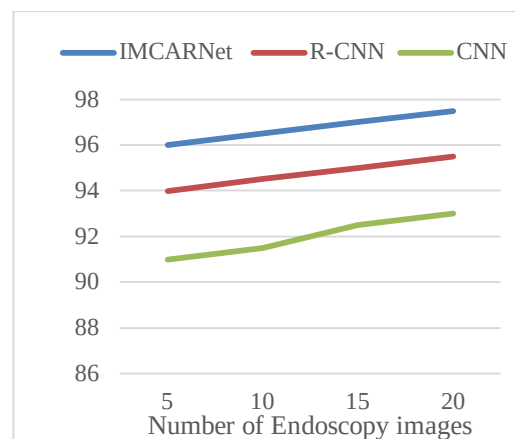


Fig 5. Sensitivity among different cancer classification schemes

Fig. 5 visually represents how all esophageal designs were executed precisely. The real positive rate, or

sensitivity, of the proposed IMCARNet, is 97.5%, larger than R-CNN and CNN. IMCARNet's projected sensitivity is increased due to its high specificity and true positive rate. Compared to machine learning techniques, IMCARNet's computational complexity has been reduced, increasing its accuracy. The graphic representation of the F-measure implementation and operation of all esophageal recognizing plans is shown in figure 6. It shows that IMCARNet's evaluation is 91.23% larger than R and CNN's and CNN's. The suggested EMNN's f-measure has a higher accuracy and review rate than existing plans, contributing to its high regard. The displays of the suggested conspiracy have been improved by the strong positive rate of grouping.

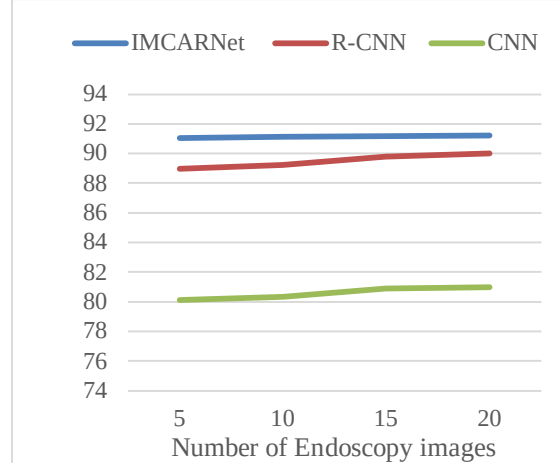


Fig 6. F-measure among different cancer classification schemes

TABLE 1: OVERALL PERFORMANCE NUMERICAL VALUES FOR ALL DA DETECTION METHODS

| Performance of all schemes | Proposed IMCARNet | R-CNN | CNN  |
|----------------------------|-------------------|-------|------|
| Accuracy (%)               | 98.5              | 97.5  | 96.7 |
| Specificity (%)            | 95.5              | 94.5  | 94   |
| Sensitivity (%)            | 97.5              | 95.5  | 93   |
| F-measure (%)              | 91.23             | 90.02 | 81   |

Table 1 predicts OPG images and their numerical evaluation esteems. It indicates that the planned IMCARNet results are superior to the R-CNN and CNN as of right now. Because of the helpful division and highlights, the suggested IMCARNet numerical evaluation results will also grow when the number of images grows.

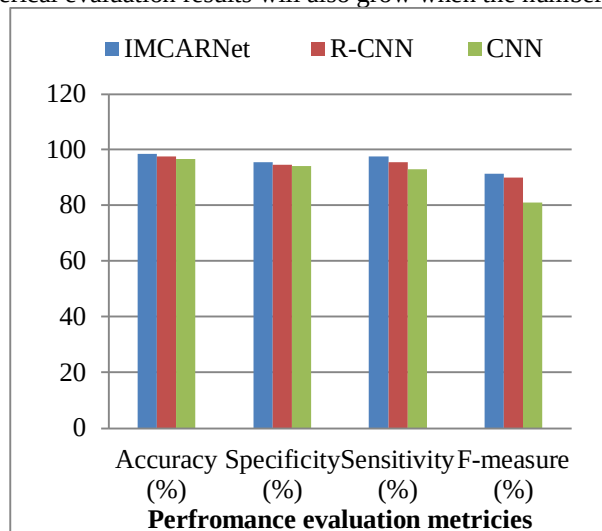


Fig 7. Prediction of overall performances for all detection schemes

Figure 7 shows the overall results of the cancer identification plan's graphical representation. It is demonstrated that the suggested IMCARNet has achieved good performance compared to existing R-CNN and CNN schemes by achieving an accuracy rate of 98.5%, a specific rate of 95.5%, a sensitivity rate of 97.5%, and an f-measure rate of 91.3%. The suggested approach achieved better performance thanks to effective preprocessing and effective optimum segmentation with effective features.

## V. CONCLUSION

This research proposes an IMCARNet-based approach for identifying esophageal cancer. The input endoscopic image is initially preprocessed to reduce motion blur and improve image smoothness. The esophagus is portioned from the preprocessed image using IDO clustering to improve expectation accuracy. This clustering divides the pixels based on the Esophageal area into two groups, one for each. Afterward, the tooth area is removed for useful characteristics. The IMCARNet classifier receives these pixels as input. The BLS technique is used in this IMCARNet to choose the ideal weight. Based on the experimental findings, it is clear that the suggested IMCARNet is quite effective at making predictions, with an accuracy rate of 98.5%, significantly higher than that of existing algorithms such as R-CNN and CNN. Future evaluation of this technique will involve a big collection of esophageal imaging data.

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