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Multi-Class Segmentation with Deep Learning based Pap Smear Image Analysis for Cervical Cancer Detection and Classification Model

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Abstract: Cervical cancer (CC) is a significant global health issue, but earlier diagnosis and accurate detection could considerably enhance treatment outcomes and reduce mortality rates. Pap smear test is a popular screening technique for CC. But the manual interpretation of Pap smear images can be subjective and error-prone. Deep learning (DL) technique assists to automate and enhance the performance of CC detection on Pap smear images. DL model continuously enhances with more diverse and larger datasets, potentially resulting in even more reliable and more accurate diagnoses. In this aspect, this study introduces an Automated Deep Learning based Pap Smear Image Analysis for Cervical Cancer Detection and Classification (ADLPSIA-CCD) method. The objective of the ADLPSIA-CCD technique is to utilize DL models for the segmentation and classification of Pap smear images for CC diagnosis. In the presented ADLPSIA-CCD method, the initial stage of image preprocessing takes place in two levels such as image sharpening using Gaussian blur and contrast enhancement. In addition, the ADLPSIA-CCD technique exploits U-Net based image segmentation process with EfficientNetB3 as a backbone network. Next, radiomics feature extraction process takes place where the features in every segmented class are extracted separately. Finally,Conv-Recurrent Hopfield Neural Network (CRHNN) model is exploited for the classification of CC. Notably, the CRHNN model trains the segmented class features separately. The simulation outcome of the ADLPSIA-CCD algorithm is tested against a benchmark dataset. The comprehensive result analysis showed the superior performance of the ADLPSIA-CCD technique on CC detection.
Keywords: Cervical cancer; Pap Smear Images; Computer-assisted diagnoses; Deep learning; Image segmentation

1. Introduction

Globally, cervical cancer (CC) is the foremost cause of cancer-associated mortality in women with 80% of the cases happening in growing countries. The human papilloma virus (HPV) data centres reported the approximately 6294 latest CC cases detected yearly in Ethiopia [1]. In remote regions, which have inadequate medicinal treatments with lack of medical availability and incompetent healthcare staff, CC occurrences and deaths are predicted to be high. Image classification is an important field where deep neural networks are more proficient in the analysis of clinical images [2]. If a disease occurred, it can be computed by the use of image classification, which can take images as data to produce classification output [3]. Several unique concepts of the classification have been suggested to recognize CC diagnosis.

The advanced techniques of CC screening incorporate the visual investigation afterwards the applications of the Papanicolaou test (Pap test), the Human Papilloma Virus (HPV) test and Acetic acid (VIA) [4]. The category of CC is affirmed by the visual analysis of histopathological images (HSI) under a microscopic process. This manual approach was generally difficult, laborious, and prone to error because of variability in inter-observer and intra-observer [5]. Computer-assisted diagnoses (CAD) methods can computerize the diagnostic procedures, and manual screening and support healthcare experts in a broad range of decision-making, involving disease diagnosis, cancer grading, treatment arrangement, and localization of the cervix [6]. Medical image examination requires the methods and processes to acquire comprehensive data from clinical images for medical analysis and healthcare interventions. Machine learning (ML) approaches are a subject area of artificial intelligence (AI) that is associated with the problems of learning from information samples [7]. ML applies several types of probabilistic, statistical, and optimization methods that can enable the computers to "learn" from previous instances and to determine hard-to-identify patterns from huge-amount, complex or noisy databases [8].

The concepts of Deep learning (DL) have created important advances in various application areas namely Natural Language Processing (NLP), battery condition observing, Computer Vision (CV) and prediction [9]. Clinical image processing comprises segmentation, identification, registration and classification plays a crucial role in disease detection. Medical images like ultrasound images, CT and MRI, and blood smear images generate massive amounts of image data. DL models can learn many abstract feature images and are supposed to address the problems in traditional healthcare CAD systems [10].

This study introduces an Automated Deep Learning-based Pap Smear Image Analysis for Cervical Cancer Detection and Classification (ADLPSIA-CCD) technique. In the presented ADLPSIA-CCD method, the initial stage of image pre-processing takes place in two levels such as image sharpening using Gaussian blur and contrast enhancement. In addition, the ADLPSIA-CCD technique exploits U-Net based image segmentation process with EfficientNetB3 as a backbone network. Next, radiomics feature extraction process takes place where the features in every segmented class are extracted separately. Finally, Conv-Recurrent HopField Neural Network (CRHNN) model is exploited for the classification of CC. Notably, the CRHNN model trains the segmented class features separately. The simulation result analysis of the ADLPSIA-CCD method is tested against a benchmark dataset.

2. Related works

The authors in [11], a fully automated pipeline for the recognition and classification of CC from cervigram images. The presented method comprises two pretrained DL algorithms for the automated detection and classification of CC. Khamparia et al. [12] study aims to automate cancer detection and classification via DL methods to timely ensure patient health condition progress. The fusion of the convolution network with VAE was adopted for the data classification. Further, the use of CAE decreases the data dimensionality for processing with the involvement of softmax layer for training. In [13], an approach for the retrieval of CC images using hash coding with CNN was implemented. A sensitive deep hashing technique that combines rotation invariance and interpretable mask generation is developed for CC recognition. The distinct characteristics of CC cells with complicated morphological feature were concentrated on the hybrid dilated convolution spatial attention model and irrelevant feature was removed.

Al Masri and Mokayed [14] introduce an intelligent ML-based CAD (IML-CAD) method for classifying CC. The proposed method includes dissimilar phases of operation to identify and classify the CC cells. Furthermore, the study includes histogram-based segmentation to define the infected region. Additionally, LBP-based feature extractors and LS-SVM-based classifiers are developed for the classification of CC. Kalbhor et al. [15] present the method for CC prediction based on Pap smear images. Pre-trained DNN model was utilized for feature extraction and dissimilar ML algorithms are trained on extracted features. In this work, four pretrained approaches namely GoogLeNet, AlexNet, Resnet18 and Resnet50 are fine tuned for feature extraction followed by the ML approaches.

Waly et al. [16] introduce an intelligent deep CNN for CC detection and classification (IDCNN-CDC) algorithm through biomedical Pap smear images. At first, the Gaussian filter (GF) module is used for enhancing data via the noise elimination method in the Pap smear images. The Tsallis entropy method with the dragonfly optimization (TE-DFO) technique defines the image segmentation to properly recognize the diseased portion. The cell image was given into the DL-based SqueezeNet architecture for extracting deep features. Lastly, the extracted feature from SqueezeNet is exploited to the weighted ELM classification method for detecting and classifying the CC. Sellamuthu Palanisamy et al. [17] presented work comprises of data augmentation, DTCWT and CNN models for the automated classification of Pap smear images. The CNN model needed large amount of cell images to obtain the highest classification rate.

3. The Proposed Model

In this study, a new ADLPSIA-CCD method was introduced for the automatic diagnosis of CC on Pap smear images. The major intention of the ADLPSIA-CCD algorithm is to utilize DL models for the segmentation and classification of Pap smear images for CC diagnosis. In the presented ADLPSIA-CCD technique, different processes are involved namely pre-processing, U-Net-based multi-class segmentation, radiomics feature extraction, and CRHNN-based classification. Fig. 1 represents the workflow of ADLPSIA-CCD methodology.

3.1. Image Pre-processing

Image sharpening is a process of enhancing the edges and details in an image, which makes it appear clearer and sharper. One conventional method to image sharpening includes the usage of Gaussian blur. The Gaussian blur method works by convolving the image with Gaussian filter. This filter exploits a weighted average of the nearby pixel to all the pixels in the image. The amount of blurring can be controlled by the standard deviation parameter of the Gaussian filter. The objective of Contrast enhancement technique is to enhance the visual quality and enhance the details in an image by increasing the contrast between the intensity values. CLAHE is a more commonly used contrast enhancement technique which adapts histogram equalization to local image regions, thus avoiding over-amplification of noise. CLAHE is very effective in improving image contrast with localized intensity variation. By adaptively adjusting the contrast within local region, it avoids the common problem of global contrast enhancement technique that tends to amplify noise and leads to unnatural-looking images. These two images sharpening with Gaussian blur and contrast enhancement using CLAHE are effective ways of enhancing the details and contrast and enhancing the visual quality of images. They are applied individually or combined as part of large image processing pipeline, depending on the particular characteristics and requirements of the images.

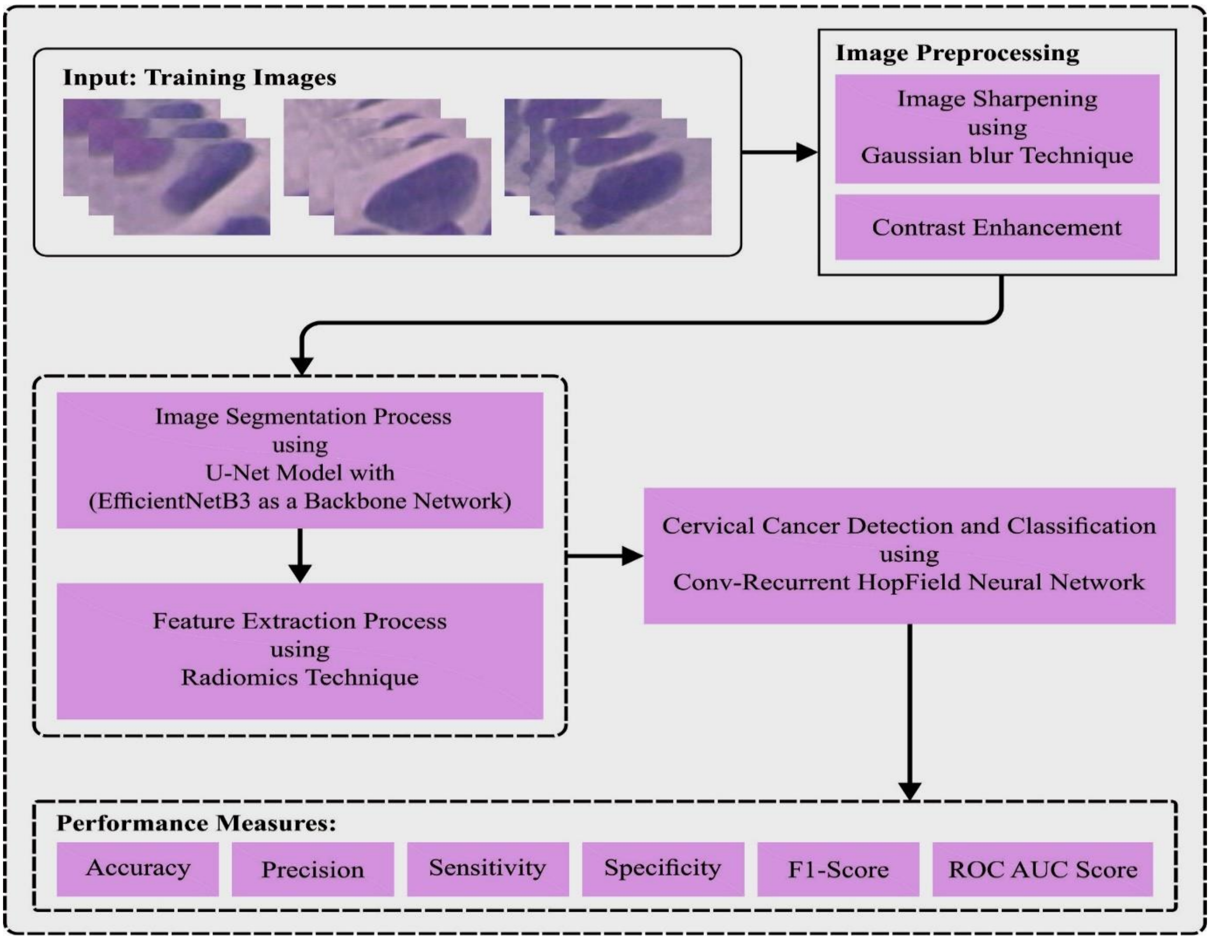

Fig. 1: Workflow of ADLPSIA-CCD method

3.2. Multi-Class Segmentation using U-Net

In this work, the U-Net model is used to segment the multi-class images. U-Net is usually trained from scratch, beginning at a randomly initialized weight [18]. Training from scratch can be a tedious process as it requires a large amount of data and is mathematically expensive. The network has an overall 23 layers, and while ensuring accuracy, the amount of layers is considerably lesser than the other networks. The UNet model primarily consists of two parts, up-sampling and down-sampling. Downsampling is named as feature extraction part that exploits the pooling and convolutional layers for extracting features of the input images. Upsampling exploits a deconvolution function to upsample the feature maps. This upsampling and downsampling structure is named an encoder-decoder structure. During downsampling, the input image passed over the pooling and convolutional layers for obtaining feature map of dissimilar levels. This feature map contains image features with dissimilar levels of abstraction. During upsampling, the deconvolution layer progressively restores the size of feature maps, and the downsampling feature map is combined to improve the segmentation accuracy of the network and repair the lesser abstract details lost in the training process.

A pretrained model was previously trained on the larger benchmark dataset to offer an effective basis to resolve a new task. Thus, we leverage the deep CNN (DCNN) model that is pretrained on the ImageNet datasets as a backbone for the work rather than convolution block to extract features during the encoding. The backbone represents the base network structure that extracts the feature maps and takes the image as input.

Furthermore, the EfficientNetB3 is used as a backbone network of the UNet architecture. The EfficientNetB3 Convolutional Network is a network structure where it gives a new scaling technique that uniformly scales each dimension of depth, width and resolution of the network [19]. This structure exploits the grid search technique to find the relationships between the fundamental network scaling dimensions under the fixed resource constraints. This could find the proper scaling coefficient for all the dimensions to be scaled by using these strategies. Using this coefficient, the fundamental network was scaled to the desired size. By comparing EfficientNet with other present CNNs on ImageNet. Generally, the parameter size and FLOPS are reduced by the order of magnitude, the EfficientNet model could accomplish better efficiency and accuracy than the presented CNN models.

3.3. Radiomics Feature Extraction

At this stage, radiomics feature extraction process takes place where the features in every segmented class are extracted separately. Radiomics feature extraction is a process in medical image analysis that aim is to extract and quantify a massive amount of quantitative features from medical images [20]. This feature provides relevant data regarding the tumor phenotype, heterogeneity, and other features that might be complex to be visually measured. Radiomics has drawn considerable interest in cancer research and personalized medicine as it allows non-invasive and objective analysis of medical images. A broad range of quantitative features is extracted from the segmented ROI. This feature was classified into different groups' namely shape-based features, first-order statistics, intensity-based features, wavelet-based features, and texture features. Example of radiomics feature includes gray-level run-length matrices (GLRLM), statistical measures (mean, median, standard deviation), shape descriptors (volume, surface area), and texture features (entropy, homogeneity, contrast) derived from GLCM, or other texture analysis.

3.4. Image Classification using CRHNN Model

Lastly, the CRHNN model is exploited for the accurate and automated recognition of CC. The CRHNN is a NN structure which integrates CNN with recurrent Hopfield network[21]. It is intended to overcome the problems of modeling long-term dependencies and capturing spatial information in sequential data, namely time series or images. Fig. 2 displays the structure of RHNN.

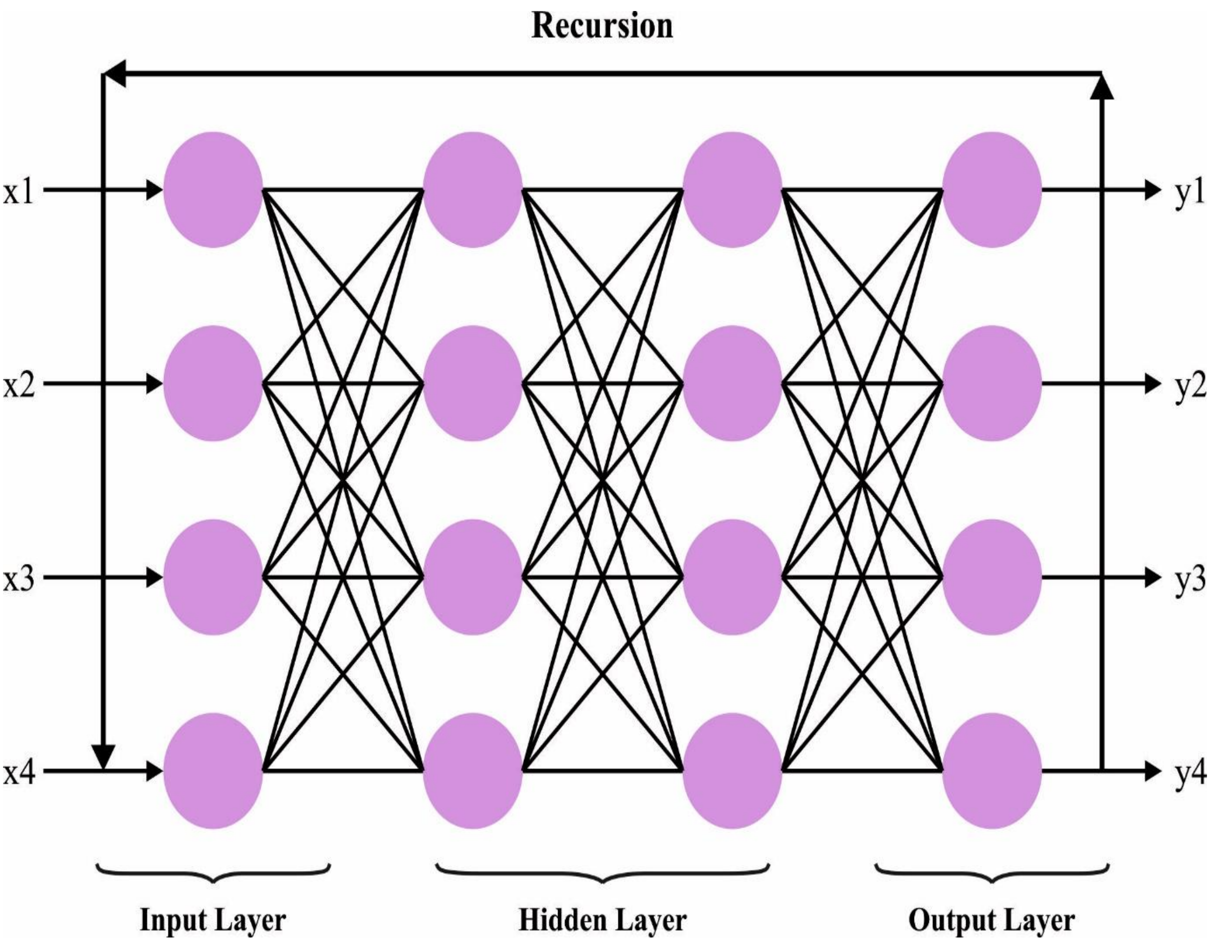

Fig. 2: Framework of RHNN

The CRHNN structure leverages the strength of recurrent Hopfield networks and CNNs to accomplish relevant data processing abilities. The outline of working principles and key components of CRHNN: CNN is extensively applied for image processing tasks because of the capability of capturing local spatial patterns. The CNN components of the CRHNN extract applicable features from the input dataset using convolution layer, pooling layer, and nonlinear activation function. This layer enables the network to learn hierarchical representation of the input dataset. The CNN is primarily comprised of pooling and convolutional layers that basically encode the input data and lastly realize the function of dimensionality reduction and feature extraction. Meanwhile, a multi-channel signal serves as input to the network, and the dimension of each pooling and convolution layer is set to 2D.

The time step concept was integrated with the CNN to decrease the insensitivity of local receptive fields to time series feature. Then, the signal of all the time steps is fed to the network in the sequence form to accomplish the impact of the time step. In l^{th} layer, convolution layer at t^{th} time steps, dissimilar convolution kernels k convolved with output dataset $f_i^{(l-1)}$ of l-1 layers, and the outcomes attained are utilized as input to the following layer:

$$f_j^{(l)} = f\left(\sum_{i\in M_j} \omega_{i,j}^{(l)} \cdot f_i^{(l-1)} + b_j^{(l)}\right) \tag{1}$$

In Eq. (1), $f_i^{(l-1)}$ denotes the i^{th} input dataset of l^{th} layers, $f_i^{(l)}$ indicates the j^{th} output features of the convolutional layer, M_j is the input for computing the j^{th} features, $\omega_{i,j}^{(l)}$ and $b_i^{(l)}$ shows the weights and biases of the convolutional layer, correspondingly, and $f(\bullet)$ represents the activation function.

The pooling layer decreases the feature dimension by subsampling that decreases the sensitivity of feature outputs to distortion and, simultaneously, introduces invariance, viz., keeps the major features in the signal while decreasing the dimensionality:

$$p_{t,i}(l) = \text{pool}_{p\in S_p}\left\{f_{t,i}^{(l)}, p\right\} \tag{2}$$

In Eq. (2), p denotes the size of pooling window, $p_{t,i}^{(1)}$ characterizes the i^{th} features of the t time step in the l^{th} layers, $pool(\cdot)$ shows the subsampling function, and S_p represent the size of input dataset.

Hopfield network is a recurrent neural network that stores and retrieves patterns from the connection weight. They are mainly effective to model associative memory and perform content-addressable pattern retrieval. In the CRHNN structure, recurrent Hopfield network was used for capturing the long-term dependency and temporal relationship within the sequential data. The CRHNN structure incorporates the output of the CNN layer with the recurrent Hopfield networks. The CNN layer extracts spatial features from the input dataset that is given into the recurrent Hopfield networks. The Hopfield network implements recurrent computation using connection weight, which enables the network for capturing dependency and refine the representation of the input dataset. The CRHNN is trained through BP through time (BPTT), a method which enables the training of RNN. The training model includes adjusting the weight of the Hopfield network and CNN components to minimalize a specified loss function, generally using gradient descent optimization algorithm.

4. Experimental Validation

In this study, the CC detection outcomes of the ADLPSIA-CCD method are tested on the Herlev dataset [22], comprising 917 samples with 7 classes. The amount of images per class is demonstrated in Table 1. There exist 675 images for abnormal and 242 images for normal. Fig. 3 showcases the segmented images.

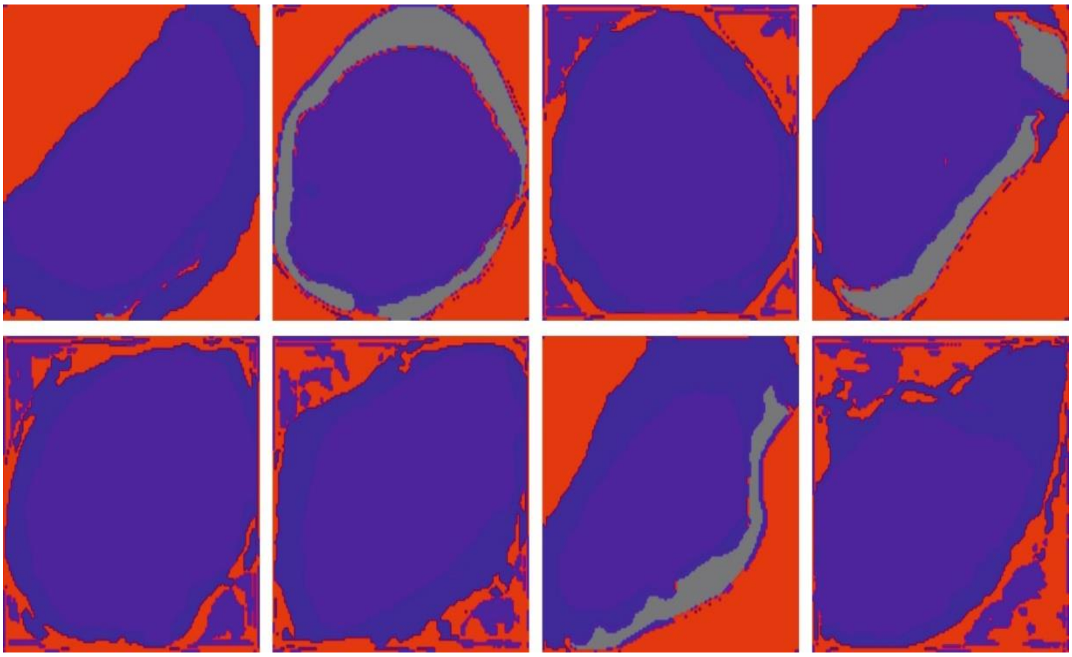

Fig. 3: Segmented Images

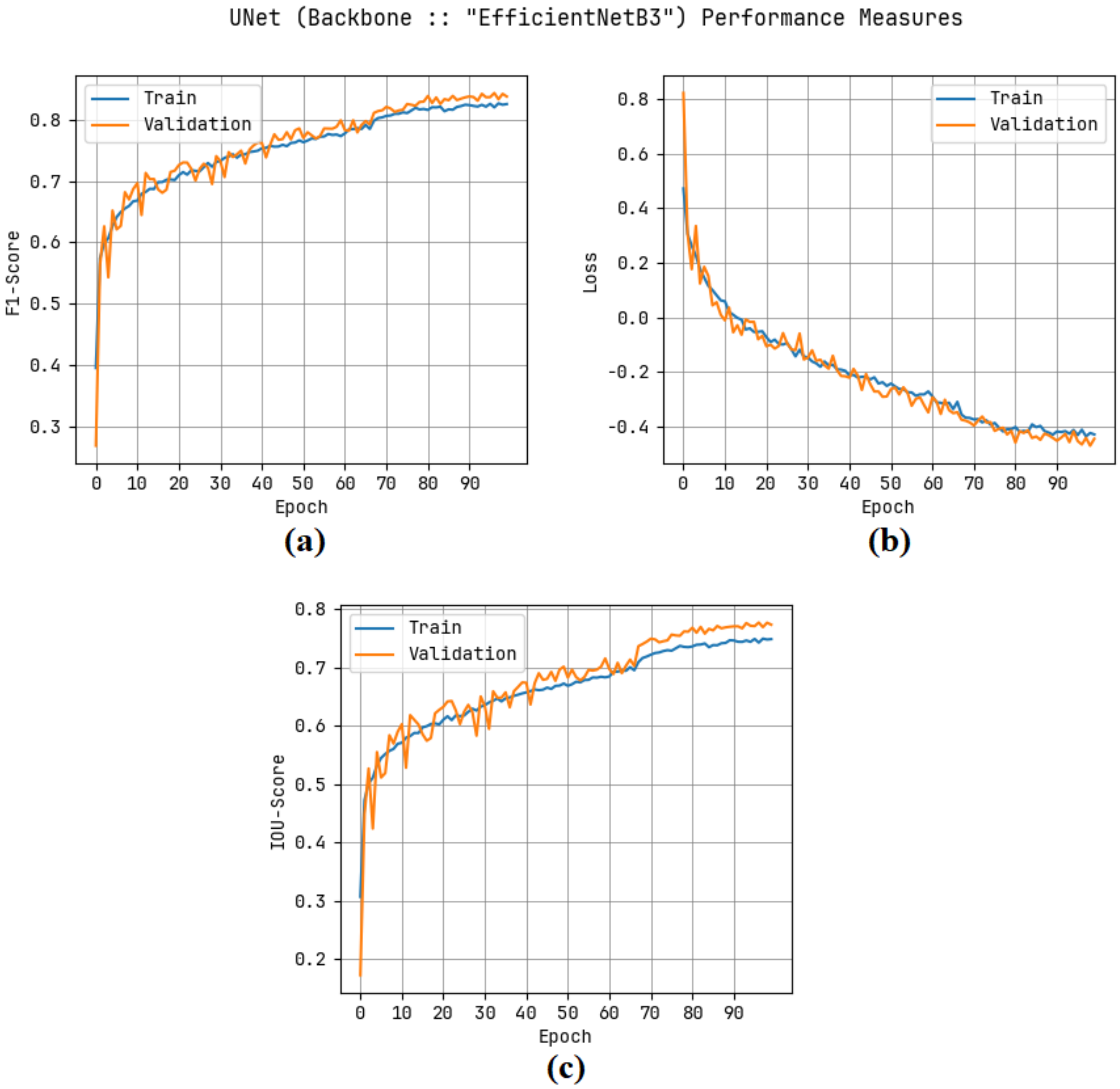

Fig. 4. Segmentation Performance in terms of a) F1-Score b) Loss Graph c) IoU-Score

In Fig. 4, the segmentation outcomes of the ADLPSIA-CCD method are demonstrated. The results indicated that the ADLPSIA-CCD technique attains higher accuracy and IoU values with a rise in epochs. At the same time, the ADLPSIA-CCD approach attains decreasing loss values over an increase in epochs.

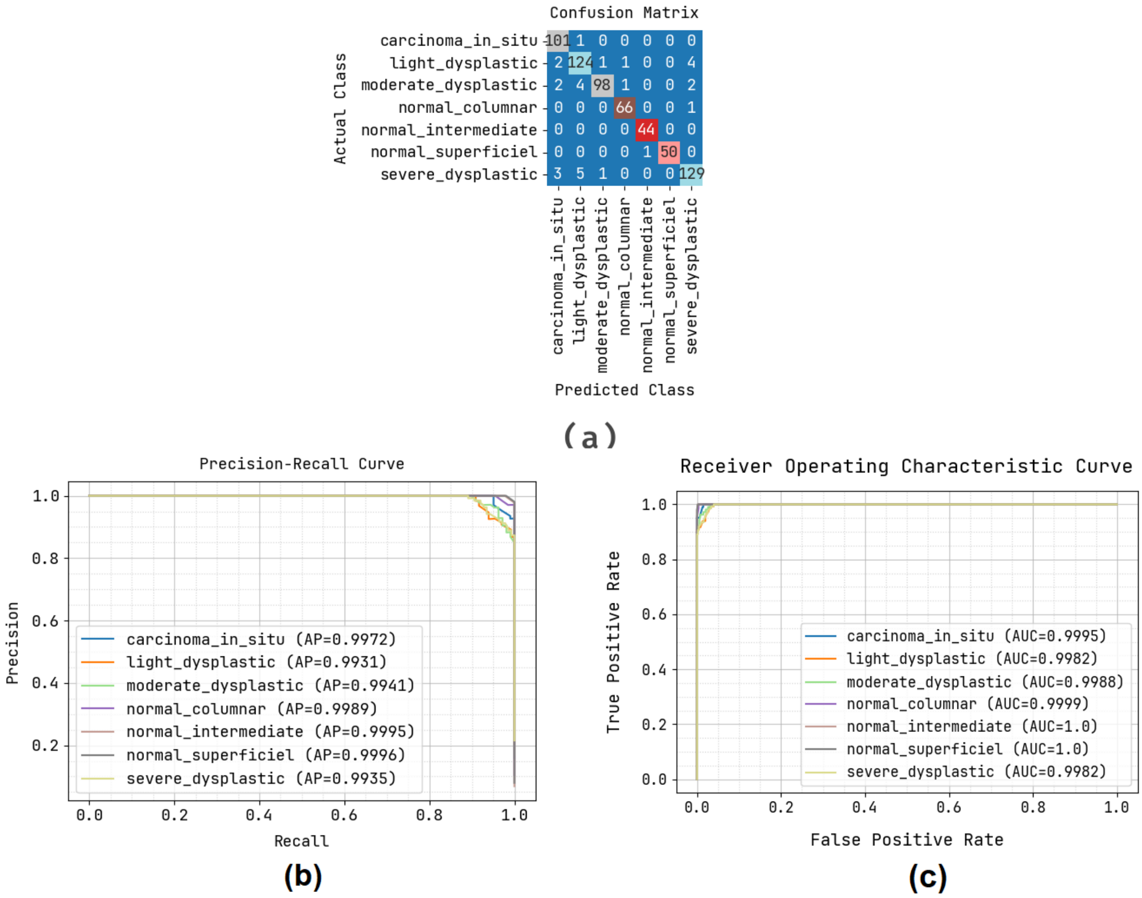

Fig. 5: Result Analysis of Training Set a) Confusion Matrix b) PR-Curve c) ROC

Fig. 5 exemplifies the classifier outcomes of the ADLPSIA-CCD method under training set. Figs. 5a depicts the confusion matrix offered by the ADLPSIA-CCD technique. The figure denoted that the ADLPSIA-CCD technique has detected and classified all 7 class labels accurately. Similarly, Fig. 5b illustrates the PR analysis of the ADLPSIA-CCD technique. The figures demonstrated that the ADLPSIA-CCD method has attained highest PR performance under 7 classes. Lastly, Fig. 5c exemplifies the ROC investigation of the ADLPSIA-CCD model. The figure depicted that the ADLPSIA-CCD technique has resulted in proficient outcomes with high ROC values under 7 class labels.

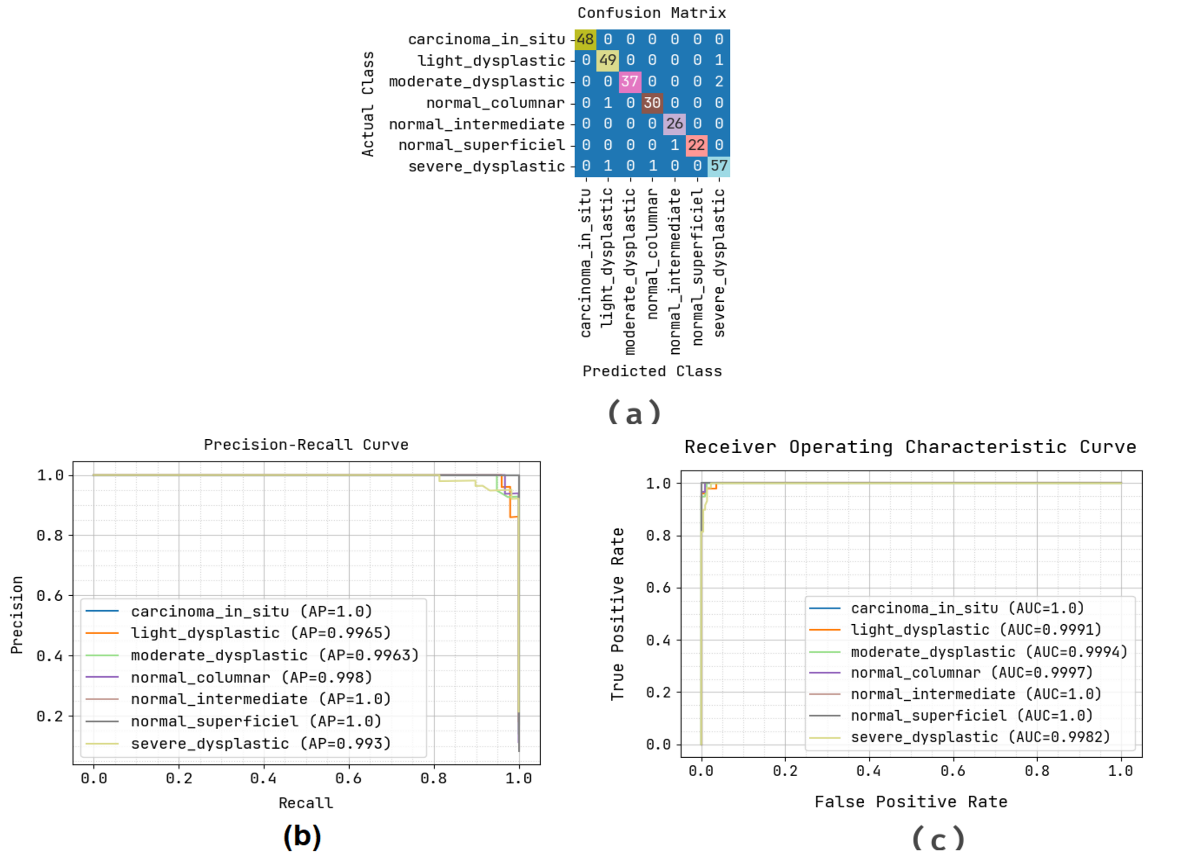

Fig. 6: Result Analysis of Testing Set a) Confusion Matrix b) PR-Curve c) ROC

Fig. 6 exhibits the classifier outcomes of the ADLPSIA-CCD method under the testing set. Figs. 6a depicts the confusion matrix offered by the ADLPSIA-CCD approach. The figure denoted that the ADLPSIA-CCD technique has recognized and classified all 7 class labels accurately. Similarly, Fig. 6b illustrates the PR analysis of the ADLPSIA-CCD technique. The figures reported that the ADLPSIA-CCD method has accomplished the highest PR performance under 7 classes. Finally, Fig. 6c depicts the ROC investigation of the ADLPSIA-CCD model. The figure portrayed that the ADLPSIA-CCD technique has resulted in proficient outcomes with the highest ROC values under 7 class labels.

The cervical cancer recognition outcomes of the ADLPSIA-CCD technique are represented under TRS and TSS in Table 1 and Fig. 7. The obtained values stated that the ADLPSIA-CCD method has effectually recognized the samples. On TRS, the ADLPSIA-CCD technique offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, $F1_{score}$, and ROC AUC score of 95.48%, 96.25%, 96.37%, 99.21%, 96.28%, and 99.92% respectively. On the other hand, on TSS, the ADLPSIA-CCD technique offers $accu_y$, $prec_n$, $sens_y$, $spec_y$, $F1_{score}$, and ROC AUC score of 97.46%, 97.74%, 97.42%, 99.56%, 97.55%, and 99.95% respectively.

Table 1: CC detection outcome of ADLPSIA-CCD system on TRS and TSS

Measures	**Training Set**	**Testing Set**
Accuracy	95.48	97.46
Precision	96.25	97.74
Sensitivity	96.37	97.42
Specificity	99.21	99.56
F1-Score	96.28	97.55
ROC AUC Score	99.92	99.95

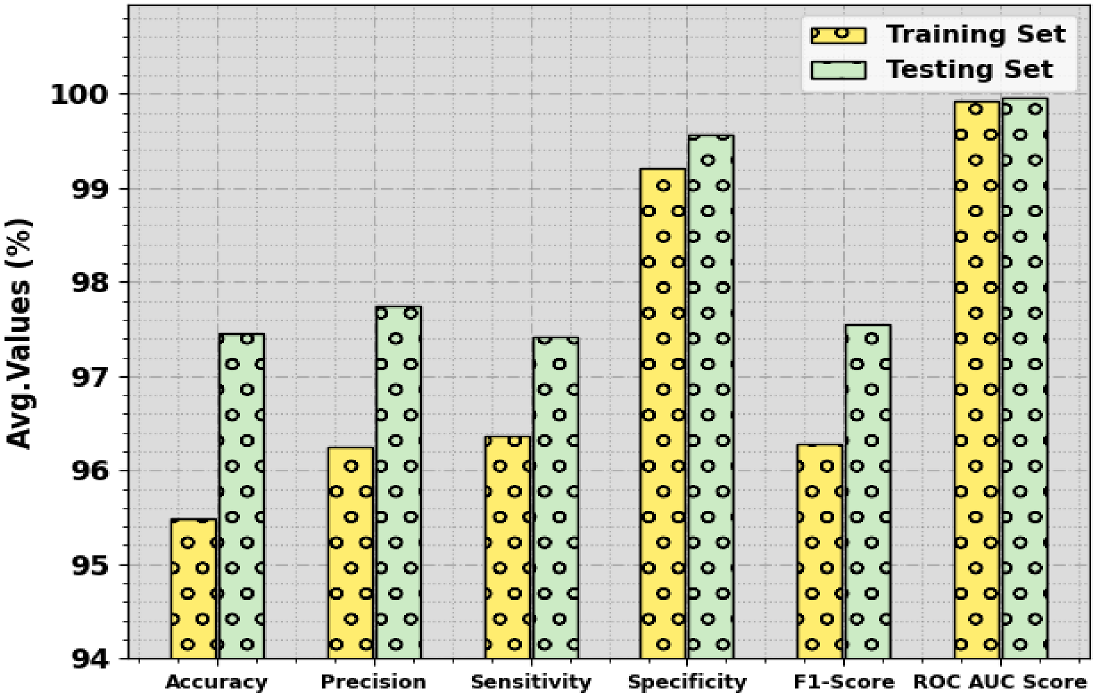

Fig. 7: Average outcome of ADLPSIA-CCD system on TRS and TSS

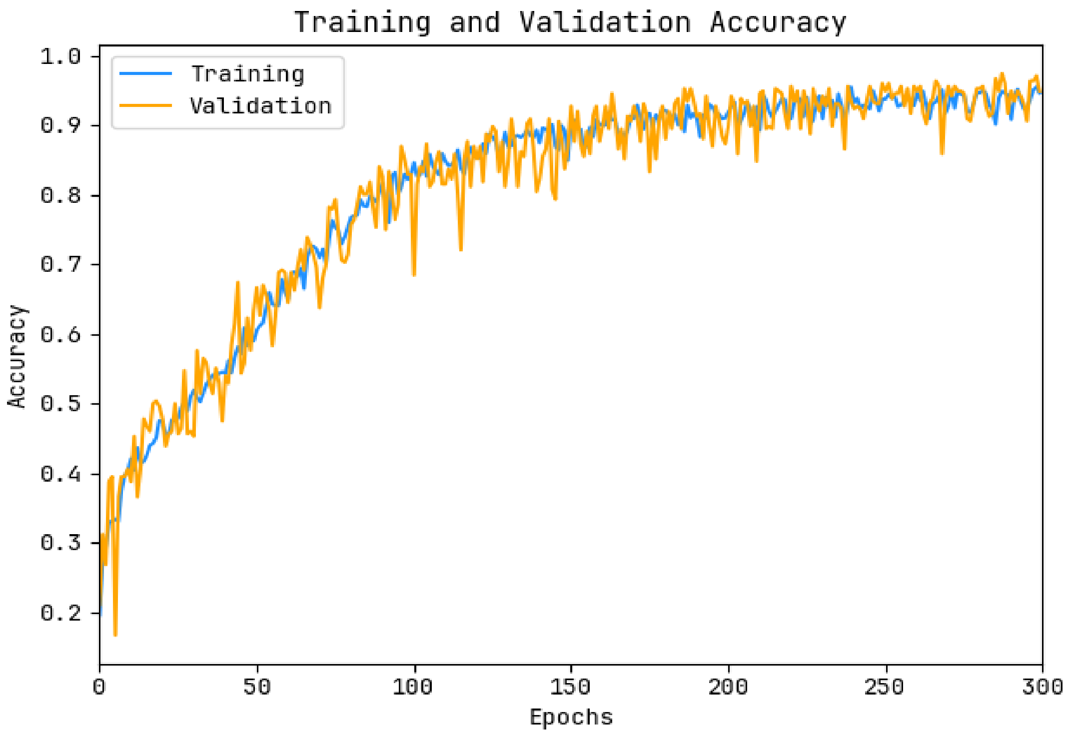

Fig. 8: $Accu_y$ curve of ADLPSIA-CCD methodology

Fig. 8 investigates the $accu_y$ of the ADLPSIA-CCD method in the training and validation process on the test database. The figure shows that the ADLPSIA-CCD system obtains maximum $accu_y$ values over the highest epochs. Furthermore, the maximum validation $accu_y$overtraining $accu_y$ demonstrates that the ADLPSIA-CCD technique efficiently learns on the test database.

The loss analysis of the ADLPSIA-CCD approach in training and validation is depicted on the test database in Fig. 9. The outcomes show that the ADLPSIA-CCD method attains closer values of training and validation loss. The ADLPSIA-CCD method efficiently learns on the test database.

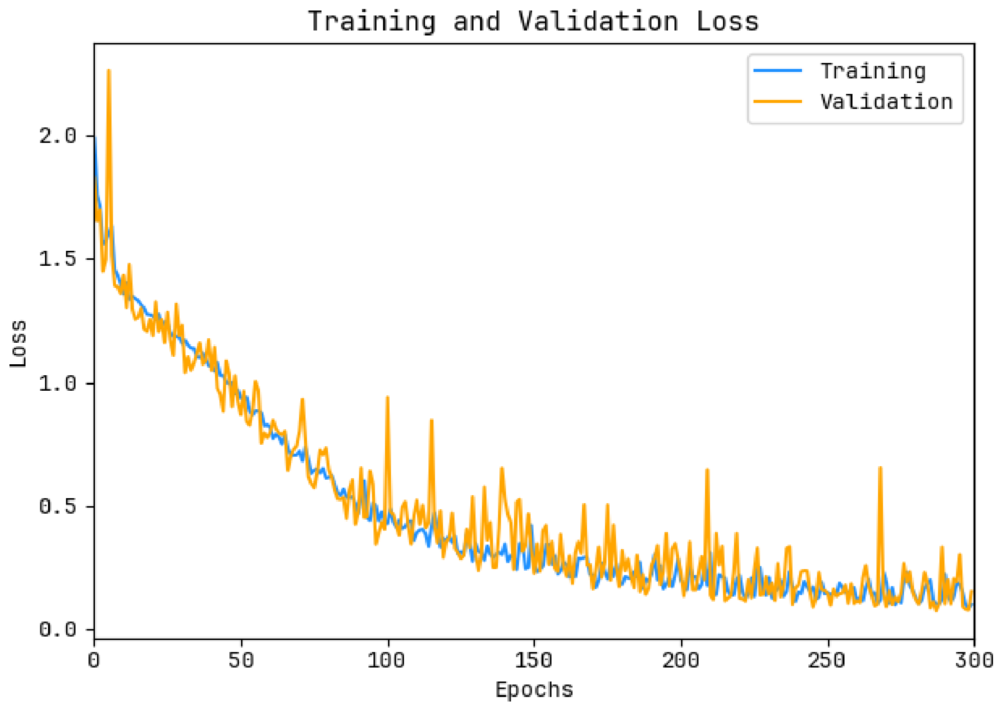

Fig. 9: Loss curve of ADLPSIA-CCD methodology

Finally, the comparative results of the ADLPSIA-CCD method with existing approaches are made in Table 2 and Fig. 10 [11, 23, 24]. The results indicate that HRBF (MKM) and HRBF (AFKM) models reached worse results than other ones. Simultaneously, the DLP-CCC, DT, SVM, KNN, and HMLP (GA) techniques have obtained slightly improved performance. Meanwhile, the LR, MLP, and MLCCD-EA models have reported moderately greater results. Furthermore, the ADLPSIA-CCD technique exhibited its supremacy with maximum $prec_y$, $reca_l$, $accu_y$, and $F1_{score}$ of 97.74%, 97.42%, 97.46%, and 97.55% respectively. Therefore, the ADLPSIA-CCD technique can be exploited for accurate and automated cervical cancer detection.

Table 2 Comparative outcome of ADLPSIA-CCD method with other techniques

Methods	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{Accu_y}$	$\boldsymbol{F1_{score}}$
ADLPSIA-CCD	97.74	97.42	97.46	97.55
DLP-CCC	78.00	75.20	77.10	78.09
Logistic Regression	45.90	21.40	82.80	26.10
Decision Tree	31.50	30.20	78.00	30.30
SVM	34.50	7.40	79.30	10.60
MLP	48.00	24.60	82.90	28.60
KNN	22.00	8.70	77.70	11.10
MLCCD-EA	51.70	28.40	83.20	32.80
HRBF (MKM)	84.20	35.00	64.60	8.45
HRBF (AFKM)	84.70	36.00	65.30	80.76
HMLP (GA)	86.80	72.50	74.80	82.64

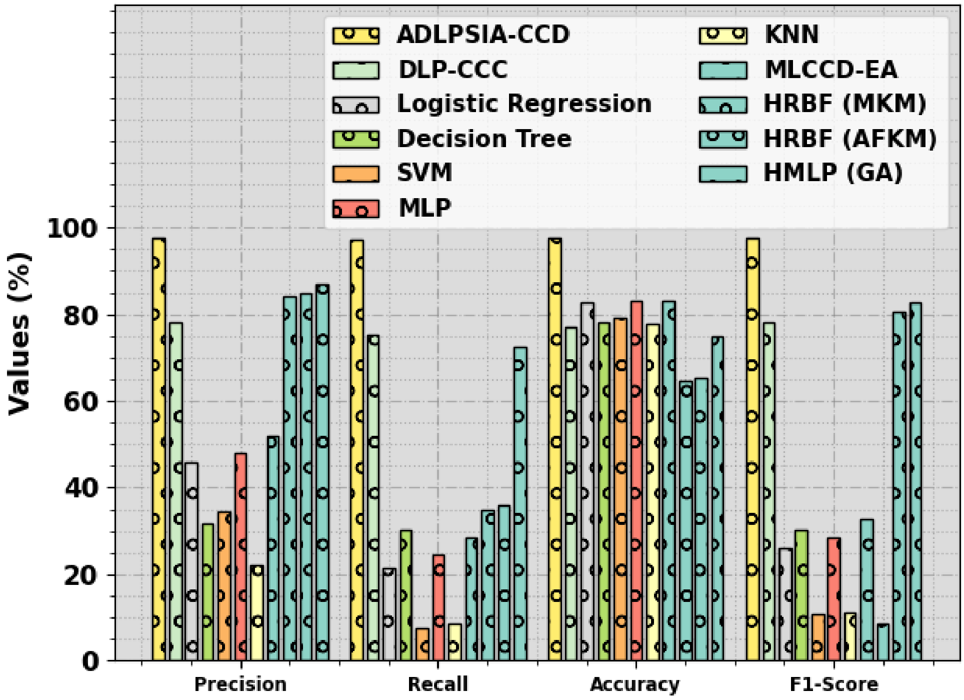

Fig. 10: Comparative outcome of ADLPSIA-CCD method with other systems

5. Conclusion

In this study, a new ADLPSIA-CCD algorithm was introduced for the automated recognition of CC on Pap smear images. The major intention of the ADLPSIA-CCD algorithm is to utilize DL models for the segmentation and classification of Pap smear images for CC diagnosis. In the presented ADLPSIA-CCD technique, different processes are involved namely pre-processing, U-Net based multi-class segmentation, radiomics feature extraction, and CRHNN based classification. Notably, the CRHNN model trains the segmented class features separately. The simulation outcome of the ADLPSIA-CCD method is tested against benchmark dataset. The comprehensive result analysis showed the superior performance of the ADLPSIA-CCD technique on CC diagnosis.

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