A Comprehensive Review on Analysis of Cervical Cancer Diagnostic Techniques

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Abstract
Cervical cancer (CC) in women among the ages of 18 and 60. Cervical cancer refers to the unrestrainedexpansion of abnormal cells in the cervix area. It is very problematic to detect and classify the CC. Because it occurs without any symptoms in the early stages. However, early detection of CC/pre-cancer can improve patient survival rates. This disease was diagnosed, using both manual and automatic detection methods. Compared with manual detection approachessuch as the pap-smear test and the LCB test, classification of normal, precancerous and cancer cells using a Convolutional Neural Network (which combines feature classification) with Deep Learning algorithms produces more accurate results. This paper examines the application of various algorithms indiagnosis of CC as well as their accuracy and performance measurement.

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1. Introduction

World Health Organization (WHO) reported that CC is the 4th malignant cancer midst women in emergent countries. Uncontrolled growth of cells is termed as cancer, which can easily spread to nearby cells and organs. Cervix region is the lower part in uterus of female and cancer which originates from cervix region is known as CC. It is a slowly growing cancer without any symptoms at an initial stage. Vaginal bleeding and pelvic pain are the most common symptoms realized by CC patients. It is a slowly growing cancer .Before getting into cancer ,abnormal cells appear in cervix region. This stage is known as dysplasia. Abnormal cells turns into cancer and spread to nearby cells and regions.

CC can be diagnosed using manual screening approaches. Recent advancements in bio-medical field enables automatic detection and classification of CC and also increases survival rate of patients. Early detection of CC can be treated and cured .This is the only way of reducing mortality rate[1].

According to GLOBOCAN 2018 report, assessed the five types of common cancer in Indian females as lung , cervix , ovary, breast and oral cavity cancers. Breast cancer is leading CC in the second position. GLOBOCAN 2018 report states that the new cancer incidence cases per year is 1.1 million and mortality rate is 0.78 million. In 2008 ,CC mortality rate was 73,000 among 134,000 and in 2018.It was 60,000 among 96,000. This shows a reduction in mortality rate through effective screening and early diagnosis of abnormality cells [2].

Numerousmethod of machine and deep learning (DL) employed in diagnosis and prognosis process. Machine learning (ML) and (DL) techniques are subset of AI.Machine learning algorithms (ML) requires small amount of input data and it training time also small. Here feature selection should be done manually. Deep learning techniques, requires large amount of data as input .Here feature selection is done automatically. Associated to ML algorithms ,Deep learning algorithms provides improved accuracy.

2. Manual Screening methods

2.1 Pap smear test

In a test, cells are composed manually from the cervix region of the uterus by using a brush or spatula. Samples are collected by a doctor or physician. These collected cervical cell samples are stored in a vessel and sent to the classification of normal and up to normal cells. Manual screening is done by an experienced physician and it has a rate in the classification of cells due to human errors. Sometimes, the nucleus of cells may be overlapped with neighboring cells at that time it is difficult to find the boundary of cells by the physician. Therefore, it takes more time for manual classification. The manual screening method is a cost-effective and tedious method.

2.2Liquid cytology-based (LCB) test

The second common manual screening method. Cervical samples are immersed in the liquid o alcohol-based solution, which is viewed under a microscope of classifying cells into normal or abnormal cells. Changes in color were observed for abnormal cells. A cells with the nucleus are shown in Figure.1. This method also fails to produce accurate results in classification. Manual screening methods produce less accuracy in the classification of cervical cells because it fully depends on the physician's experience.

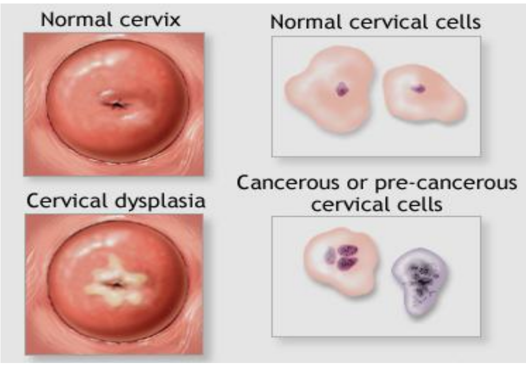


Figure1Normal and cancerous cervical cell.

3. Automatic Screening methods

CC can be cured if it is identified in the early stage. Therefore a need for fully automated and reliable cancer detection and classification technique for CC to reduce the mortality rate.

Developing and underdeveloped countries are in need of high accuracy with automated techniques for the detection ata low cost.

To progress the accuracy in the detection of CC Convolutional Neural Network(CNN) ,Inception V3,SqueezNet,VGG16, VGG19 are used with classifiers like Random Forest Classifier, SVM,CVM, Fuzzy C-means algorithm-Nearest neighbor and decision tree.ANN and CNN have mostly used networks

3.1Artificial Neural Network (ANN)

ANN works like a human brain. It performs the operations in a serial manner. The architecture of ANN is shown in figure.2.Hidden, input, and output layers form the core of an artificial neural network. As the sum of input photos increases, the sum of layers in an ANN increases as well. The hidden layer is used to pass processed input images. ANN-trained datasets as well as untrained datasets are employed in the training process.

ANN operates in both feed-forward and back propagation methods and it produces the highest accuracy. One of the drawbacks is computational time is more when compared to Convolutional neural network because ANN works in a series fashion i.e. one instance can be trained at a time [4].

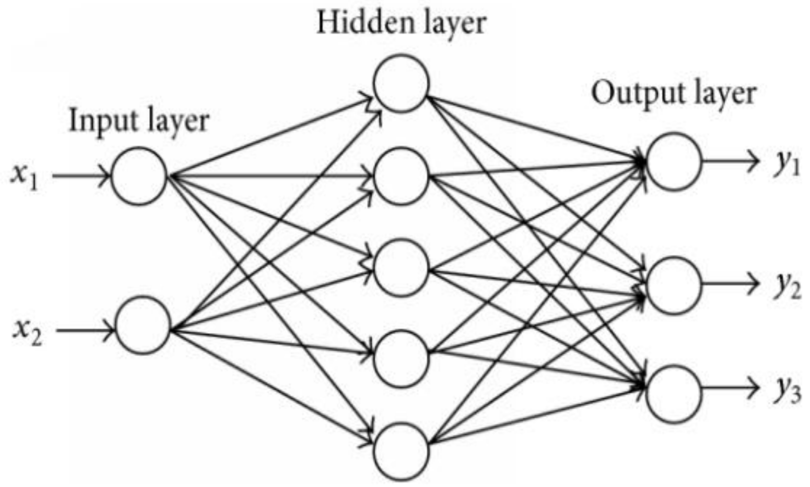


Figure2Architecture of artificial neural network.

3.2Convolutional Neural Network (CNN)

CNN work based on the DL technique. Input data are processed in a parallel manner. It converts input images into a suitable form of easy processing. By using filters it produces good prediction without loss of features and by capturing the spatial and temporal characteristics in an image. Convolutional Neural Network has some basic layers.Figure.3 shows layers in CNN.

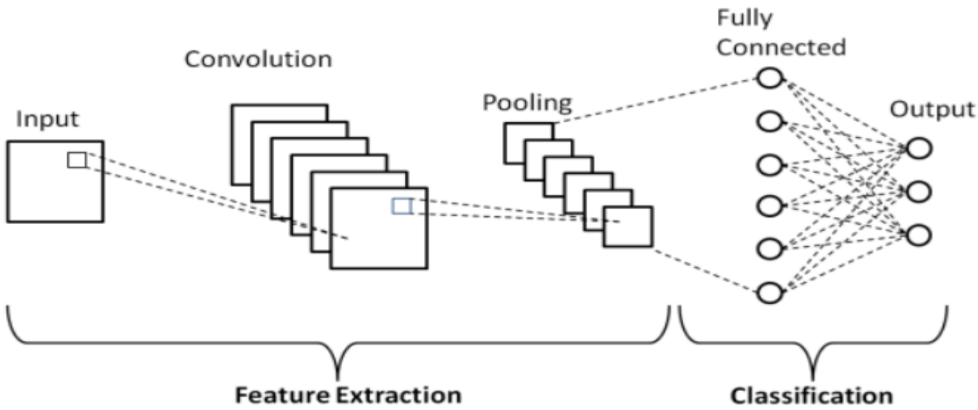


Figure3Basic architecture of Convolutional Neural Network**.**

Real-time images or Images from datasets are given as input, which is converted into matrix form. Then, the input layer reads each pixel value for further processing. The role of the convolution layer is to lessen the size of the images.i.e. for dimension reduction. With the usage of Convolutional filters, CNN obtains features of images without any loss. Filters also help with the isolation and mapping of images for analysis. The next layer is the pooling layer. The function of the pooling layer is to reduce the size of features obtained. From the Convolutional layer. Reduction in feature size reduces the computational power of data processing.

The fully connected layer contains of three layers i.e. Flatten Layer, Dense Layer, and Soft max Layer. It is also known as a linear layer or feed-forward neural network[4].GoogleNet,SqueezNet and ResNet50 are some of the familiar CNN architecture used in medical field applications.

3.2.1 GoogleN**et**

GoogleNet is also known as InceptionV3. It is an advanced version of the CNN.InceptionV3 is capable of handling a large amount of input data. It uses 48 deep layers for the recognition and classification process.

3.2.2 VGG19

VGG19 is a pre-trained deep CNN with 19 layers. It classifies images into different categories based on the image source.VGG19 uses bounding box architecture for classification purposes. This model uses stacked architecture in the convolutional layer which causes an increase in weight. This increases training time.

3.2.3 SqueezNet

Fire modules of SqueezNet consist of two phases namely the squeeze phase and expansion phase. The Convolutional filter size used by the squeeze phase is 1*1 and expand phase uses 1*1 and 3*3 filter sizes. For the same feature size squeeze phase decreases depth whereas expanding phase increases depth. So that information can be represented at an abstract level. SqueezNet reduces the total number of features by using deep compression. The accuracy provided by SqueezNet and AlexNet is the same for the image dataset.

3.2.4 ResNet50

ResNet50 is a influential network consisting of 50 layers. In one iteration ResNet50capable of classifying up to 1000 objects. Increasing network depth leads to accuracy degradation problems. ResNet50 solves this problem by utilizing residual function with layers Validation error rate of ResNet50 is 3.57%.

The residual block model is combined with GoogleNet which forms an advanced Inception-Residual V2 model. In ResNet50, input is added to the output of convolution blocks, which helps to achieve high accuracy when compared to other networks.

4. Dataset

CC cell classification using automatic detection methods needs a benchmark dataset for training neural network models. For research purposes, datasets available in the public forum and individually obtained datasets are considered. Publically available dataset details are explained below

4.1Herlev dataset

Herlev dataset contains seven classes of CC images. 247 normal images and 675 abnormal images are used. Totally, 917 Pap smear images are uploaded by Herlev University Hospital (Denmark). Images of normal, as well as cancer cells, were captured at a magnification of 0.2m/pixel. Then pathologists physically classified the captured cells into seven classesis categorized in table.1.Row1 represents Pap smear images and Row2 represents segmented cell images.

4.2Herlev dataset

Haceptte dataset consists of 198 pap smear images. Pap smear images are collected from 18 different patients. Images are taken from 40x, 80x, and 100x magnification. Out of 198 Pap smear images,82 images are with 40x magnification, 84 images are with 80x magnification, and 32 images are with 100x magnification. This dataset was prepared by the computer department of Bilkent University and the pathology department of Haceptte university.

4.3Risk factor dataset

The risk factor dataset can be downloaded from UCI Repository. This dataset was uploaded by Hospital Universitariode Caracas. Images from 858 patients are available. Due to some privacy issues, some values are missed in this dataset.

5. Flow diagram

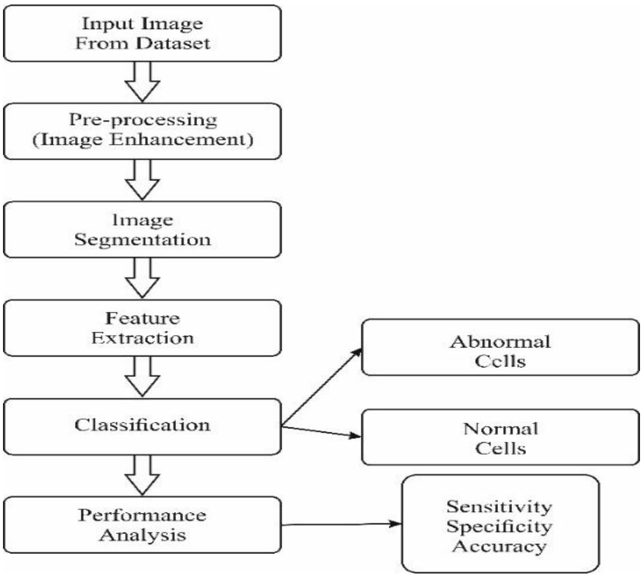
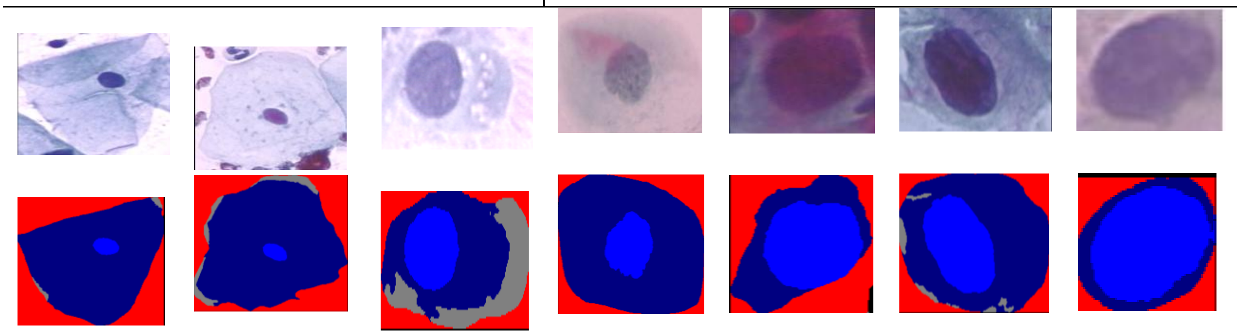


Figure4Process flow in cervical cancer diagnosis.

Table 1Herlev dataset –images of 7 class.

Herlev dataset seven classes With cell count						
Normal Squamous (74)	Intermediate squamous Samples (70)	Columnar (98)	Mild dysplasia (182)	Moderate dysplasia (146)	Severe dysplasia (197)	Carcinoma in situ (150)
Normal cells			**Abnormal cells**			



5.1Input Image

Automatic detection and classification of CC require a considerable amount of input data to produce an accurate classification result. Research studies are based on both publically available datasets and individually collected datasets. Most researchers used the Herlev Public data set of 917 single cell pap-smear images. A large amount of data or images can be easily analyzed using various Machine Learning algorithms. Computational approaches make it easy of handling a large number of samples.

5.2Image enhancement / preprocessing

Pre-processing or enhancing images is the first and essential step in image analysis. It involves increasing the resolution of images using different filters. Several data augmentation approaches can be applied to suppress the images and enhance their quality. Augmentation includes scaling or resizing, rotation, and shearing of images[6].

Enhancement of image quality plays a major role in Image quality focus on brightness, removal of noise, and resolution. Pre-processing removes unwanted features like the presence of bacteria, overlapped cells, crumpled cells, and blood samples from dataset images[7]. The presence of noise (mostly Gaussian and Poisson) degrades the quality of an image. Usage of filtering methods like Gaussian, Median, and min-max filter enhances the quality of pap-smear images[8]. Image enhancement can also be done with the help of histograms and fuzzy-based algorithms. Adaptive wiener filter performs well in the removal of Poisson noise in microscopic pap smear images proposed by Deepa et al[9]. For effective medical image enhancement or pre-processing authors, suggest a histogram equalization algorithm. It works better in areas of de-blurring of images and preserving image feature quality[10]

5.3Image segmentation

In medical imaging analysis, segmentation results in the severity of the disease. Image segmentation is demanding work. Poor segmentation leads to poor classification results. SVM Classifier, K-means Nearest Neighbour(KNN), and Fuzzy C-means algorithm can be used for segmenting pap-smear images. Pap smear images are single-cell images [11]. The author used the Herlev dataset, patch-based Fuzzy C-means clustering is used for segmenting cell features [12]. Here, Deep learning techniques are used to segment pap-smear images. The author used Mask-R-CNN in segmented the input image into the background and cell region(combination of nucleus and cytoplasm).Implementation of mask R-CNN is easier and it requires small computational overload.Kurnianingsih et al [13] classify the segmentation problem into2 types. There are two types of problems in the first: normal and aberrant. 7th-class difficulty is the second one.This segmentation uses the Herlev dataset with VGG like NET. In medical imaging, the Edge-based model and active contour model play a major role in the segmentation point of view. Edge-based model performance is not better compared to the active contour model [14]. It produces good results by specifying clear curves. For controlling the progress of the curve, quantitative methods are used in the region-based active contour model[15]

5.4Feature extraction

Feature extractions are an optimization process, which selects a minimum number of effective features. It plays an important role in classification results. A drastic change in Color, the texture of cells, topology, and morphological features can be considered during the classification of normal and abnormal cervical images. Features should be selected by considering, the reduction of the computational difficulty of algorithms. Feature selection algorithms are confidential into 3 types.

They namely filter, wrapped, and embedded method. Filter methods are faster, scalable, and easy to interpret. Filter methods fail to find the subset of features in any situation. Wrapped and embedded methods use a machine-learning algorithm for feature selection. Achieves greater performance results compared to filter methods[22]. Filter methods are based on a self-regulating evaluation of the classification algorithm and it evaluates feature subsets by mutual information, information content, and interclass distance. The wrapper method evaluates feature subsets by predictive accuracy by cross-validation. Embedded methods are specific methods.

a) color features and Morphological

When the nucleus grows rapidly in relation to the cytoplasm or changes its shape or structure, this suggests a problem in the cells. Area, radius, and perimeter are used to describe cell size-based properties.. Aside from circularity, the main axis length of the cell, and minor axis length of the cell [23,24], other shape-based criteria include: It is the axis length that determines the nucleus and cytoplasm's roundness and form. Threshold approaches, fuzzy, clustering, and wavelets are utilised to locate the size and shape-based features[25]. In order to differentiate among normal and pathological cervical pictures, the author uses GLCM, wavelet, features.

b) Gray level co-occurrence matrix (GLCM)

Second-order texture characteristics can be extracted using the feature extraction technique GLCM. It is possible to build a GLCM matrix for any single channel picture The GLCM matrix is square. An input image's grey levels determine the number of rows and columns. Comparing the abnormal and normal cervical images using GLCM features such as energy, contrast, entropy, and correlation is possible.

c) Wavelet features

Compared with contourlet and curvelet transforms, wavelets are useful and fast. Discrete Wavelet Transform (DWT) was utilised by Elayaraja et al[25] to break down the image. There are four sub-bands generated by the first level decomposition: LL, HL, LH, and HH sub-bands. Low frequency is denoted by L, while high frequency is denoted by H. Second level decomposition of DWT is performed using the LL sub-band, which again creates four sub-bands. In the classification of cervical images, subbands are used as feature patterns.

c) Moment invariant features

Features from input images are extracted using Moment Invariant features. Geometric, Legendre, Complex, and Zernike are the types of Moment Invariant features.For cervical image pattern recognition, most of the authors chose Legendre moment invariant feature by comparing the performance of the Legendre moment with other moment features. Geometric and complex moment invariants are used for the normalization process.

d) Local binary pattern (LBP) features

The local binary pattern method was found by Ojala. It is an effective method for texture description.LBP operator generates binary output for the corresponding pixel in the cervical image. Pixels are labeled, then value zero is set to neighborhood pixels, or else the value is set as 1. This process is repeated until no more pixels in the cervical image.Then the histogram of the labels can be used as a texture descriptor[26].

e) Deep CNN features

Deep Convolutionalneural networks automatically extract or learns needed features from the input cervical image and it also reduces the computational complexity [27]. The author used deep learning for image analysis and the proposed diverse deep learning techniques with multi-layer neural networks to extract image features [28]. Deep neural networks are also used to extract features from colposcopy images in computer-aided cervical detection. The author used an ensemble approach to extract necessary features from colposcopy images without doing segmentation and feature extraction stages. Performance of Deep learning network found to be efficient recognition of patterns and features in huge datasets [29] DNN is able to quickly and accurately identify features that are difficult for the human eye to discern from images because of its ability to extract correlations between the images' various complicated aspects. [28,29]. Region-Based X Lia et al. proposed the CNN-Feature Pyramid Network. Input, feature pyramid network, and feature map creation with classifier block are all part of the architecture. It demonstrates the pyramid network's capacity to detect malformed cells of varied sizes while also increasing its scalability.

5.5Classification

Random Forest Classifier, KNN (K-means Nearest Neighbor),SVM classifier, Decision tree, and Naive bays Classifier are some of the machine learning algorithms. SVM – classifier is one of the common and most widely used methods for the classification of medical images. Zhang et al. projected a Naive SVM-based screening method for the classification of multispectral pap smear images. This method achieves considerable improvement in the pixel-level [30].Semi-automatic CC classification was proposed by Chen et al. Here SVM classifier is used with texture and morphological features for the classification of normal and abnormal images with an accuracy of 96.12%[31].

Ashmita et al used HOG feature extraction with SVM,KNN, and ANN. Among these, ANN achieves the highest accuracy of 95.5%[32]. Pap smear images are classified into seven classes using texture features.SVM produces a classification accuracy of87.33% for mild dysplasia,58.52% for severe dysplasia, and 84.72% for carcinoma in situ.

Using K-means clustering, you may learn without any supervision. Clusters are formed by placing maximum points in close proximity to one another. Each iteration adds a new data point to the cluster. K clusters are generated from N data points using this approach. The cluster's data points all share the same characteristics. K stands for a clustering algorithm that is used to classify CC photos into several groups [33].

Multi-layered perceptron method was proposed by Devi et al[34].Here ANN (Artificial Neural Network) is used for the detection of CC. ANN is a feed-forward neural network is a faster rate[35].

Artificial intelligence-based techniques work better in the detection of CC than computer-assisted tools. The authors evaluated that ANN with limited clinical parameters is best for forecasting skeletal metastasis. The proposed method constructs a model for a particular patient's medical condition. By using Multiple back propagations neural network algorithm author-produced 78% efficiency[36].

The author tried eight machine learning algorithms to identify the best CC screening method.AmongKNN,MLP,RandomForest,DecisionTree,SVM,LogisticRegression,Adaboost, and Gradient method, Multilayer perceptron(MLP) is identified as best with an accuracy of 98% and Decision tree achieved the lowest accuracy of 86%.

DL is a branch of ML algorithms with flexibility.CNN is the most widely used deep learning network.CNN performs parallel processing of input data with three major layers of input, convolution, and fully connected layer.CNN found their major application in image analysis and recognition, video processing, and speech data processing.CNN extracts features effectively, which is most helpful in recognition-related applications.

Almubarak et al[37] proposed CNN with a fusion-based algorithm to classify the CIN(Cervical Intraepithelial Neoplasia)images. The author used a dataset with 65 images and achieves an accuracy of 77.25%.HOG features are used for the detection and classification of CC using pap-smear images. Ashmita Bhargava et al[38] perform classification with SVM,KNN, and ANN. 66(25 normal and 41 abnormal).ANN achieves an accuracy of 95.5% compared to SVM(62.12%) and KNN(65.15%).

Author [39]classifies the cells using a fuzzy C-Means algorithm with scene segmentation. Tool analyses the input pap-smear full images with 3mins.A new novel was proposed by Aditya Khamparia for the detection and classification of cervical cells. He used a transfer learning approach with IoHT(Internet of health things with multi classifier. The minimum training and testing time is 0.032 and 0.006s for CNN. For feature extraction inception V3,SqueezNet, ResNet and VGG19 are used. With this ResNet50 achieves the highest accuracy of 97.89%.For automatic detection of abnormal cells X Li et.al. Experiments new novel based on Faster RCNN-FPN for pap smear images. Pyramid CNN network is used for feature extraction and efficient detection of abnormal cells[40].

In the classification process,80% of images from the dataset are used for training purposes, and the remaining are used for testing. Testing images results are taken for validation.[41]proposed deep ensemble method with CNN and Efficient Neural Network achieves accuracy of 97 % in classification of pap-smear cervical images.

CNN with variational auto encoder proposed for classification. Herlev Dataset of 917 images used. Variational Auto Encoder reduces the size or dimensionality of incoming data so that next-level processing is made easier. Here 70% of images are used for training and 30%images are used for testing. The projected method achieves accuracy of 99.2% and 99.4% for different filter sizes(2*2,3*3)[42].

6. Analysis of segmentation and classification in cervical cancer

The following table shows collection of work done by various researchers with performance.

Table 2Comparison table of work done by various researchers.

Dataset	Approach	Results	Ref.
Hacettepe dataset	Cervical cells are segmented and classified using an unsupervised approach. Segmentation is done using a binary classifier and a hierarchical classifier.	-	[43]
Real-time images	Deep learning-based Convolutional Neural Network utilized for nucleus cell segmentation	Accuracy 94.5% Precision 0.914 Recall 0.8726±0.0008	[44]
MRI - real time images	A fuzzy C-Means Algorithm(FCM) is used for segmentation,SVM, and ANN is used for the classification of MRI Images.	SVM classifier accuracy 92% ANN accuracy 84%	[45]
MRI- real time images 3 data sets are used	SVM Classifier is used based on second-order texture features and transform features of tumors	Accuracy of axial T1-weighted MR images 81%. T2-weighted MR images 82%,T2 weighted sagital accuracy 83%.	[46]
Real time images	ANN with different architectures are used for classification.	-	[34]
Realtime images	15 machine learning algorithms are used for screening for cervical cancer.	Among 15 algorithms, the back propagation neural network provides an accuracy of 78%.	[35]
Realtime images	Fusion-based algorithm with CNN used for classification of cervical cell images.	Achieves 77.25% accuracy.	[47]
Data set collected from Air Force Hospital,Bengaluru.	Feature extraction HOG used and SVM, KNN, and ANN used for classification.	The accuracy of SVM is 62.12, KNN is 65.15, and95.5% for ANN.	[38]
Realtime images	CNN was used for segmentation, CapsNet Cervix	Training set accuracy 99% and test set accuracy 80.1%.	[48]

Dataset	Approach	Results	Ref.
	model used for classification.		
Guanacaste dataset	Oriented Wavelet,GLCM,LBp features are extracted from the multi-resolution image using OLHT, DT-CWT, and the Local Histogram Technique (OLHT) for image enhancement. classification is performed using a feedforward back propagation neural network.	Sensitivity 97.42% specificity 99.36% , accuracy 98.29%.	[25]
MDE lab	CNN used for image classification	89% accuracy obtained	[4]
Herlev dataset	ELM classifier with CNN used	For 2 class problem 99.5% accuracy was obtained and 91.2% for 7-class problem.	[49]
A single cell, multiple cells, and pap smear images collected from the pathology lab	Trainable Weka Segmentation and FCM algorithm classification are used	The overall accuracy of a single cell, multiple cells, and pap smear images are 98.88%,99.28%,97.47% was achieved	[50]
Real-time pap smear images	Selective-Edge Enhancement-based Nuclei Segmentation (SEENS) method used for nucleus segmentation.	For low contrast images, SEENS achieves a precision value of 0.9785.	[51]
Herlev dataset	Cervical image categorization with CNN and variational autoencoder	For 2*2 filter size, 99.2% accuracy and 99.4% with 3*3 filter size were obtained	[6]
Herlev dataset	The Internet of Health Things and transfer learning are coupled. Cervical image recognition and classification using deep learning	97.89 %of accuracy was obtained.	[42]
Colposcopy realtime images	Hybrid Deep learning with SOD-GAN with fine tunes stacked encoder used.	Small-Object Detection Generative Adversarial Networks achieved an accuracy of 97 percent (SOD-GAN).	[52]

6.1Evaluation parameters

Different parameters are used for evaluating or diagnosing CC. These parameters decide the performance or efficiency of the adopted model for authors. Commonly used matrices are Accuracy, Sensitivity, Specificity, andF1 score. Four basic scores used in performance measures are,

Definition1: Sum of positive samples correctly classified as positive is called TP as True positive.

Definition2: Sum of negative samples correctly classified as negative asTN True negative.

Definition3: Sum of negative samples incorrectly classified as positive asFP False positive.

Definition4: Sum of positive samples incorrectly classified as negative as FN False negative.

$$True\ Positive\ Rate\ (Sensitivity) TPR \quad = \quad TP\ /\ (TP + FN) \text{--------------(1)}$$
$$True\ Negative\ Rate\ (Specificity) TNR \quad = \quad TN\ /\ (TN + FP) \text{--------------(2)}$$
$$False\ Positive\ Rate \quad FPR \quad = \quad FP\ /\ (FP + TN) \text{---------------------------(3)}$$
$$False\ Negative\ Rate \quad FNR \quad = \quad FN\ /\ (FN + TP) \text{---------------------------(4)}$$
$$Accuracy \ = \ (TP + TN)\ /\ (TP + TN\ + FP + FN) \text{--------------------------------(5)}$$

7. Conclusion

CC diagnosis using pap-smear images plays a dynamic role in plummeting the mortality rate. More cancer screening ML and DL algorithms contribute more, to increasing the effectiveness of the process. Developing countries struggle to screen for cancer at the initial stages because of lagging in the usage of cost-effective techniques and low awareness about the disease. This leads to an increase in the mortality rate. Automatic detection and classification systems help to save the lives of cancer patients. The process efficiency depends on image acquisition, digitization of images, noise removal from images, segmentation, and classification. From the literature review, it is noted that poor classification results are due to poor segmentation and ineffective pre-processing. To get good classification results, more concentration is needed in pre-processing and segmentation part. This paper summarizes the introduction of CC, screening methods i.e both existing and emerging techniques for pap smear image processing, methods used for enhancement, segmentation, and classification process up to performance evaluation parameters

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