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PREDICTING AND CLASSIFYINGTHE INITIAL STAGE CERVICAL CANCER BASED ON DEEP LEARNING APPROACH

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Abstract

Cervical cancer is one of the most prevalent and deadly diseases that affect women. In contrast to other malignancies, it has no symptoms in the early stages, which increases the death rate in women. Transitioning from the precancerous to the severe stage takes 8 to 10 years. The main causes of increased cervical cancer rates in underdeveloped nations include a lack of resources, ineffective screening programmes, and poorly organized health systems designed to identify precancerous conditions before they develop into persistent cancer. As a result, effective cervical cancer screening programmes require a low-cost methodology. Reduced death rates are achieved with early detection and classification of cervical cancer. Images from Pap smears are frequently used for automated cervical cancer detection, resulting in reliable and accurate results. Recently, various image-processing methods have been applied to detect cervical cancer. Colposcopy and the Pap test are the two ways to acquire cells; however, because of their inexpensive cost and painless diagnosis, Pap smear tests are more popular. Both machine learningand deep learning approaches have been used in earlier studies.

Keywords: *Cervical Cancer – Pap smear - Image Segmentation – Classification*

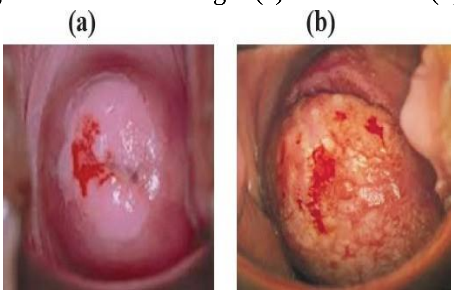
1. Introduction

In the world, especially in developing nations, cervical cancer is the second most hazardous disease for women. Currently, computer assisted automatic methods are employed to detect and diagnose cervical cancer using image processing techniques. Human Papilloma virus (HPV) is the main cause of cervical cancer in female patients. This virus affects the cervix of the human body, causing internal organ damage and the development of cancerous cells. Benign and malignant cancer cells can be distinguished in the cervical picture.

In a Pap smear test, cells in the cervix region are examined, and their nucleus regions are identified. The cervical pictures are employed in the cervigram method to find the cervix's cancerous area. In the current situation, cervical cancer can be found when it is too late and results in a quick death. Patients frequently report no irritations or soreness in the cervix region, which rarely results in symptoms. The patient may be saved if the cancer is found sooner rather than later. This is impossible for locations with a high population density or underdeveloped nations. The detection of cervical cancer in women also requires a large number of qualified doctors or radiologists.

Consequently, a system for automatic detection and diagnosis of cervical cancer is required. This study suggests a classification-based strategy for an automatic cervical cancer detection tool in cervigrams. Cervigrams of the normal patient are shown in Figure 1(a), while those of the abnormal patient are shown in Figure 1(b).

Figure 1: Cervical Images (a) Normal case (b) Abnormal case

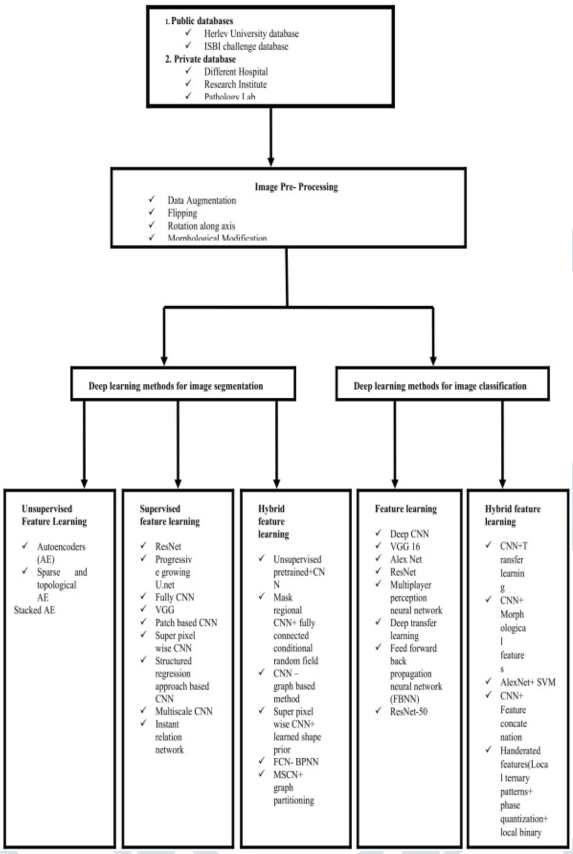


(a) Deep Learning Methods for Analysis

The accuracy of detecting images of disabled people is improved using image classification systems based on deep learning technology. Convolutional neural networks have helped people with physical and mental disabilities to classify images better. In order to identify the hidden characteristics that each disability represents, this study used images of people with various disabilities. The author's technique enhances image prediction for those with visual impairments and enhances image mobility security in cloud systems.

Cervical cancer is becoming less common in developing nations, although it is increasing in prevalence among young women. For accurate early-stage cancer detection, it is therefore essential to make a precise diagnosis and employ tried-and-true methods, which are in high demand. Therefore, accurate and prompt histopathological image analysis is critical for clinical investigation. A doctor who can evaluate histological photos must undergo significant training and focus only on the work at hand for the sample's analysis.

Figure 1: DL methods for the analysis of cervical cancer



2. Related Work

In recent years, research on the automated screening of Pap smears has switched from cytologyto histology. Most countries still practice cytology tests due to its low cost and effectiveness in detecting cervical cancer during routine testing.

Image segmentation is a crucial and challenging task in practically all imaging system analyses. People need help to accurately interpret the segmentation of all cervical cell components (nuclei and cytoplasm) in Pap smears. For cervical cancer screening and diagnosis, precise and automatic computer- assisted segmenting of the entire cervical cell is required. A batch of 50 pictures was tested for cervical cell segmentation and subsequent processing using mean-shift and median filtering.

The cervical cancer dataset from the University of California at Irvine repository is classified using three SVM-based methods. Multi-class SVM classifiers produced 95% accuracy in segmenting and classifying the nucleus and cytoplasm. SVMs have also been employed to segment the nucleus with 95.134% accuracy for the adaptive segmentation of the cervical smear model. With the aid of an SVM, the artifacts from the cytology images' dataset were eliminated to enhance the classification performance. The outcome accurately classified normal and abnormal cells at 85.19% and 88.1%, respectively. Combining SVMs and the block-based segmentation method with extremely large cervical histology digital pictures improves classification accuracy for the diagnosis of cervical intraepithelial neoplasia (CIN) by making use of robust texture feature vectors.

The cell nuclei and cytoplasm are separated using a segmentation technique. The cell nuclei are then classified using the K-Nearest Neighbor (KNN), which produced a classification accuracy of 84.3% without validation and 82.9% with 5-fold cross-validation.

After segmentation step using k-means, a KNN algorithm is utilized to categorize healthy and malignant cells on microscopic biopsy pictures. Pap smear images were segmented using a clustering method that used fuzzy C-means (FCM). FCM clustering has the disadvantage of not detecting all legitimate clusters in color image segmentation.Deep learning has had great success in numerous fields, including cancer research. Digital images of a typical Pap smear were segmented using deep learning toidentify problematic cells.

This article has reviewed many studies on categorizing and segmenting the nucleus.

S.No	Author	Advantages	Disadvantages
1	WEN WU1 and HAO	Parallelism, self-learning, and sensitivity to internal failure are artificial neural network (ANN) characteristics. The suggested paradigm takes advantage of these characteristics.	Although the information processing capabilities of the rough set theory, and the robust, parallel, and vigorous search are characteristics of the GA's. It still faces high computation problems.
2	Ashok, Dr. P. Aruna	various methods of ML, including support vector machines (SVM), gray level concurrence matrix (GLCM), KNN, convolutional neural networks (CNN),	Although it is only best suited for small datasets.
3	Reif	RF is exceptional for detecting high-dimensional data vector characteristics with minimal main effects and low heritability	RF chooses only one attribute at each tree split during construction, strictly epistatic
4	Vidya and Nasira	cancer cervix is evaluated usingpractical data mining algorithms	addressed the imbalanced distribution of data and riskfactors for cervical cancer diagnosis
5	Anuraga	RF to identify tree merger data by combining sample data training	this technique is that it onlyachieves 50% of accuracy
6	Bandyopad hyay and Nasipuri	K-Means clustering to segmentationpre-processed images	contrast is rendered with the other classifiers
7	Alyafeai and Ghouti	detects the cervix area 1,000 timesfaster and identify cervical tumors	trained using two lightweightmodels only
8	William	reduce the probability of mistake by automating the diagnostic process	made low-level features significant for the localization of cervical tumors
9	Wang	solve challenges regarding physical security and over-centralized server problems	outperforms the existing studiesby achieving higher accuracy through minimizing computationis very expensive

Table 1: Review of Literature

3. Dataset

We'll go throughout several popular datasets and method analyses in this section.

Cervical Cytology Datasets

The databases for the Herlev and ISBI challenges were the ones that were used the most frequently. Data separation is the main application of the Herlev and ISBI databases. On the other hand,the Herlev database is mainly used for classification. We found a brand-new classification-useful public database called "SIPAKMED."

Papsmearbenchmarkdatabase(herlevdataset)

A benchmark database for Pap smears was created and reviewed by the team at Herlev Medical University in Denmark. They produced the database by segmenting images using a popular software package called CHAMP (Dimac). They constructed two datasets, one from 2003 and the other from 2005, which had 501 and 917 single-cell photographs, with an overall image size of 158 140 in each. The current collection contains 252 and 665 images of cancerous cells, respectively, as opposed to the old dataset's 140 shots of genuine cells and 340 images of abnormal cells.

ISBIchallengedatabase

The dataset consists of 17 multi-layer cervical cell volumes, of which 8 were used for training and 9 for testing. Four volumes from the training dataset and four from the testing set total eight volumes of annotated multi-layered cytology. The lines indicating each cervical cell's borders are annotated (cytoplasm and nucleus). The most recent nine volumes of multi-layered cytology will be published. Only the training volumes will be manually annotated.

Sipakmeddatabase

After manually cropping 966 cluster cell images from Pap smear slide images, 4049 shots of isolated cells were created and stored in the SIPaKMeD database. These images were captured using a microscope-mounted CCD camera. The cell images divide the types of cells into five groups: normal, aberrant, and benign.

University of California's database

UCI has made the dataset available. The collection included demographic data, patient histories, current practices, and procedures for 858 occurrences, with 32 elements per scenario. Given that privacy and security are prominent concerns in healthcare record frameworks, the dataset includes a number of elements that were overlooked because other examples are incomplete and were selected not to address any privacy concerns. The dataset characteristics and the missed value for each function are shown in Table 2.

Serial number	Features names in dataset	No of missing values
1	"Number of sexual partners"	26
2	"First sexual intercourse"	7
3	"Num of pregnancies"	56
4	"Smokes"	13
5	"Smokes (years)"	13
6	"Smokes (packs/year)"	13
7	"Hormonal Contraceptives"	108
10	"Hormonal Contraceptives (years)"	108
11	"IUD"	117
12	"IUD (years)"	117
13	"STDs"	105
14	"STDs (number)"	105
15	"STDs:condylomatosis"	105
16	"STDs:cervical condylomatosis"	105
17	"STDs:vaginal condylomatosis"	105
18	"STDs:syphilis"	105
20	"STDs:pelvic inflammatory disease"	105
21	"STDs:genital herpes"	105
22	"STDs:molluscum contagiosum"	105
23	"STDs:AIDS"	105
24	"STDs:HIV"	105
25	"STDs:Hepatitis B"	105
26	"STDs:HPV"	105
27	"STDs: Time since first diagnosis"	787
28	"STDs: Time since last diagnosis"	787
29	"Age"	0
30	"STDs: Number of diagnosis"	0
31	"Dx:Cancer"	0
32	"Dx:CIN"	0
33	"Dx:HPV"	0
34	"Dx"	0
35	"Hinselmann"	0
36	"Schiller"	0

Table 2: Dataset Description

The suggested methodology was tested using the Herlev Pap smear dataset. The dataset consists of 1000 pictures that were manually sorted into 7 classifications as shown in Table 3.

Class	Cell Type	Cell Count	Category
1	Superficial squamous epithelial	74	Normal
2	Intermediate squamous epithelial	70	Normal
3	Columnar epithelial	98	Normal
4	Mid squamous non-keratinizing dysplasia	182	Abnormal
5	Moderate squamous non-keratinizing dysplasia	146	Abnormal
6	Severe squamous non-keratinizing dysplasia	197	Abnormal
7	Squamous cell carcinoma insitu intermediate.	150	Abnormal

Table 3: Distributions of 7-classes of HERLEV Pap smear dataset.

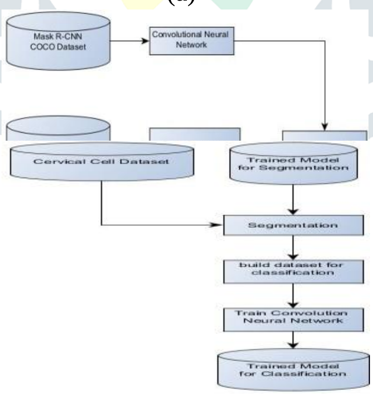
4. Method Analysis

Publicly accessible databases have been used for most of the study's work. The scientist uses the Herlev database entirely for nucleus segmentation. The Zijdenbos similarity index is a well-liked metric for evaluating segmentation outcomes. A higher ZSI number represents more accurate precision. Segmenting the nucleus with a ZSI value of 0.8, the author employs a neural network to extract featureswith C-Means clustering. To partition and obtain a ZSI score of 0:94, the authors advise combining Mask-RCNN with LFCCRF. The technique outlined below is, therefore, more efficient at separating cervical cancer cell nuclei.

In research that segments overlapping cervical cells, private datasets and CPS or ISBI challengedatasets are employed. The nucleus and the cytoplasm are divided into overlapping cell segments. Maximum accuracy, recall, and ZSI value are attained with the overlapped nucleus, and cytoplasm segmentation approach that uses pixel-wise CNN and a learned prior. Additionally, a job is identified forthe CPS database section that uses IR-Net. These are the most effective techniques for separating overlapping cervical cells.

This research aims to create a technique for segmenting complete cervical cells, single and overlapping, from images of a Pap smear taken traditionally and then classifying those segments to distinguish between normal and pathological cells. There are two steps in the suggested procedure. Using Mask R-CNN segmentation, the first stage divides the cell areas. The second stage specifies the entire cell region (nucleus and cytoplasm) by categorizing the segments from the first stage. Figure 3's training and testing phase for the categorization in the second phase.

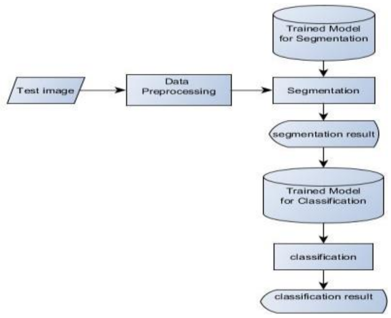
(a)



We use ResNet10 to completely leverage the geographical data and prior knowledge as the foundation of the Mask R-CNN in the proposed segmentation procedure. The main idea behind Mask R- CNN is to segment and construct pixel masks for each image item automatically.

(b)

Segmentation in this proposed strategy separates the cervical cell region from its surroundings. The cervical cell's segmented area covers both the cytoplasm and nucleus. The classification of a cervicalcell may depend on its cytoplasm.



(c)

Figure 3: Proposed method for the automatic detection of cervical cells.

As shown in Figure 4, the classification training algorithm receives the segmentation findings and applies them to the original image dataset (b). The cervical cell (colored black) is the input image (image source) for categorization. The testing procedure used for classification is shown in Figure 2(c). The segmented cervical cell pictures are isolated using Mask R-CNN before being processed by the trained VGG-like network. The system decides which class the cervical image belongs in based on the final score for each category.

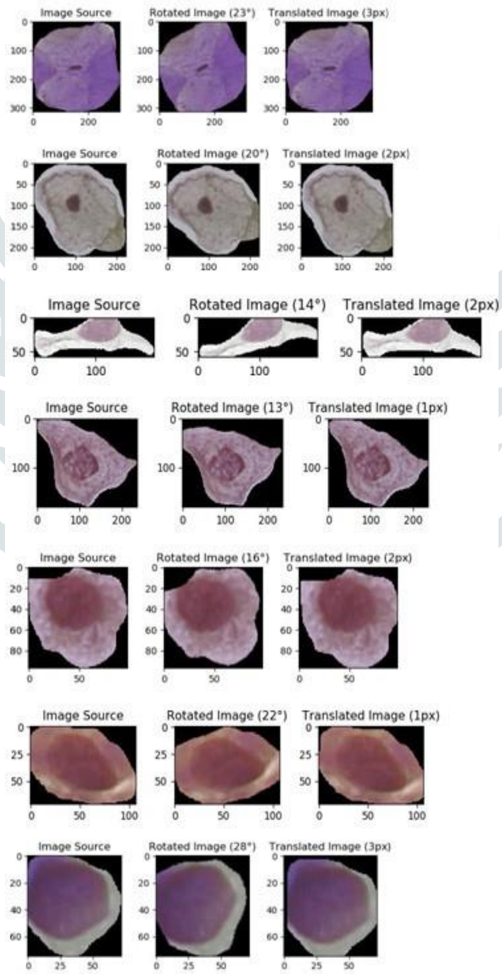


Figure 4. Image rotation and translation

a) Data Preprocessing

A separate preprocessing strategy is used for segmentation and classification training. Preprocessing starts during the segmentation stage by separating the cervical cell's image data from its mask. The original picture and mask data are still combined in one folder, which corresponds to the name of the cancer class, in the Herlev dataset that we use. There are just two different sorts of photos in this collection, the original image of the cervical cell and the mask, which are read based on the file name pattern.

The image will be turned into a binary image, white for pixels that are a part of the cervical cells (a combination of cell nuclei and cytoplasm), and black for the remaining pixels once the preprocessing application determines that what is being read is a mask image. The cervical cell's binary mask image and original picture are then downsized to 200 pixels with lengths that are proportionally changed according to the new width. The two picture groups are prepared for additional processing, specifically network training with Mask R-CNN.

According to the cancer class, the application will read every image in the Herlev dataset in the classification part. The cervical cell areas are the only images used during the categorization stage. Before the image of the cervical cell is copied and grouped by the type of cancer, the binary mask image will be applied to the original image to create a new image that is only made up of the cell portion of the cervix and the background (colored black). The new image is then proportionally adjusted to have a width of 200 pixels. After being scaled the image is copied into each folder corresponding to the classification case we wish to train, i.e., two folders for binary classification cases and seven for class classification instances. The network can then begin training on the dataset.

b)Data Augmentation

The purpose of implementing data augmentation is to improve the model's generalizability, which can expand the dataset size and improve classification accuracy while avoiding overfitting. Both the segmentation training phase and the classification training phase in this study take advantage of data augmentation. On the Herlev dataset, we enhanced the data using various geometric modification techniques, including rotation, top-down translation, left-right translation, horizontal reflection, and vertical reflection. The application will randomly choose the geometric adjustments to apply to each image of training data.

c) Segmentation

The three main objectives of object detection are The three main objectives of object detection are to

1) get a list of bounding boxes for each object in the input image,

2) get a class label for each bounding box, and

3) get the confidence score for each bounding box and class label. Object detection is advanced via instance segmentation. We now want to predict a mask for each object in an image rather than predicting a bounding box, which would give us a fine-grained, possibly even incorrect, segmentation of the object.

d)Algorithms

Support vector machine (SVM), decision tree classifier (DTC), random forest (RF), logistic regression (LR), gradient boosting (GB), XGBoost, adaptive boosting (AB), and K-nearest neighbor are some of the machine learning classification techniques that have been employed in the detection of cervical cancer. The algorithms that have demonstrated satisfactory accuracy on the used research dataset have been highlighted in this section.

The **Selective Search algorithm** replaces sliding windows and picture pyramids, which intelligently examines the input image at numerous scales and locations. As a result, there are far fewer

proposed ROIs that will be forwarded to the network for classification. Selective Search can therefore be compared to an intelligent sliding window and image pyramid technique.The method takes an image as input and extracts around 2000 region proposals from the image.

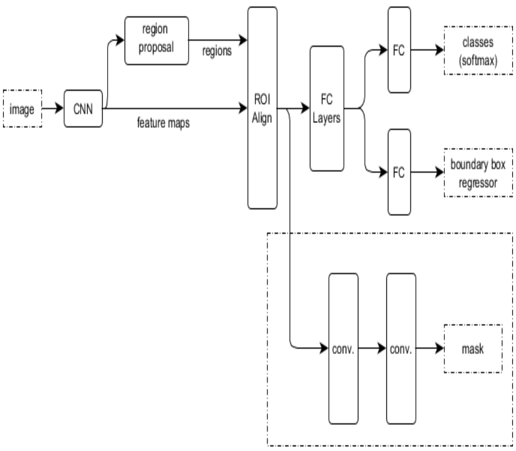
i. Each region proposal is then warped (reshaped) to a fixed size to be passed on as an input toa CNN.

ii. The CNN extracts a fixed-length feature vector for each region proposal.

iii. These features are used to classify region proposals using category-specific linear SVM.

iv. The bounding boxes are refined using bounding box regression so that the object is properlycaptured by the box.

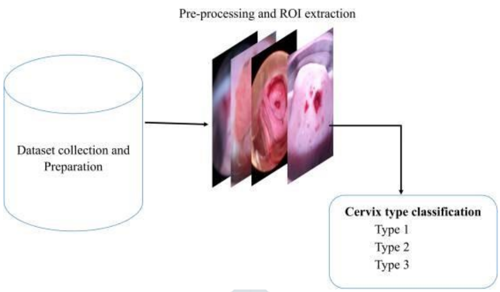
Figure 5: Mask R-CNN architecture.



5. Classification

The principle of this study was to build an integrated and strong system for automatic cervix type and cervical cancer classification using deep learning techniques.Colposcopy and Histopathology images were gathered from several local healthcare facilities and public internet datasets. For classifying cervix types, various pre-trained models were trained and compared. To extract the region of interest (ROI) from cervix pictures prior to classification, a lightweight model that can identify the transformation region was trained and validated. The cervix type classification was then given the retrieved cervix images. The pre-trained model was trained and validated using histogram-matched histopathology pictures for the classification of cervical cancer.

Figure 6:cervix type classification.



The composed images were then labeled into three classes (type 1, type 2 and type 3) by three practiced gynecologists: an integrated emergency surgical officer, and senior medical doctors.

6. Conclusion and Future Work

This study provides ideas for early cervical cancer detection. Recognizing cervical cancer risk factors may help increase the percentage of female cancer cases that survive and the number of survivors.

The use of data mining techniques in the medical sector dramatically facilitates the development of diagnostic and prognosis diagnostic applications that can help in the proper early treatment of life- threatening diseases. It is crucial to improve medical care standards and patient recovery rates using various data mining tools. According to the review, there is an emerging problem with cervical cytopathology image processing. Future study should focus on the use of a deeper network to improve the performance more complex models may be created to improve accuracyresults.

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