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Detection and Classification of Cervical Cancer using Deep learning and SVM – An overview

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***Abstract*— According to the World Health Organization, cervical cancer is the second most common cancer in females. The lack of adequate early treatment has been one of the leading causes of this. As a result, early detection of cervical cancer is of utmost importance. The asymptomatic presence of cervical cancer poses a significant obstacle in early detection. SVM has proved to be useful in a number of medical applications, and it can be used as a classifier in the early detection of cancerous cells in the uterus's cervix area. The aim of this paper is to conduct a survey and review of the various methods that have been used to diagnose cervical cancer. The survey paper compares and contrasts the various current strategies for cervical cancer prediction using medical evidence, highlighting their benefits and drawbacks.**

Keywords*— Magnetic Resonance Imaging(MRI), Support Vector Machine(SVM), cervical cancer.

I. INTRODUCTION

In the developing world, cervical cancer is the most common cancer among women. Near to 370,000 (80 percent) of the total 470,000 new cases per year arise in developed countries. It is the leading cause of death, with nearly 190,000 people dying each year. Many procedures, such as the Pap smear test, colposcopy, and diagnostic biopsies, are used to restrict and mitigate the growth of this cancer. HPV (Human papillomavirus) infection has been related to almost all cervical cancers, according to reports.

A. Cervical Cancer

The cervix is split into two categories:

- The ectocervix canal is lined by stratified squamous non-keratinized epithelium and is the part of the cervix that projects via the vagina. The transition from the ectocervix to the endocervical canal is marked by the external os, a gap in the ectocervix.
- The endocervical canal (or endocervix) is a mucus-secreting simple columnar epithelium that lines the more proximal and "inner" section of the cervix. At a narrowing called the internal os, the endocervical canal ends and the uterine cavity starts.

The growth of abnormal cells in the cervix can invade and damage normal tissue, triggering cervical cancer. Most cervical cancers begin in the cells that line the cervix and do not transform into cancer overnight. Instead, normal cervix cells eventually undergo pre-cancerous changes that may lead to cancer; these changes can be identified using the medical test and treated to prevent cancer from growing. Cancers affect people between the ages of 45 and 55. Cervical cancer incidence rises with age and plateaus around the age of 55. However, only a small percentage of HPV-positive women can develop a tumor. Most women are able to get rid of the virus on their own. Cervical cancer is a multifactorial disease caused by a number of field-related cofactors such as immune deficiency, tobacco, and other sexually transmitted diseases, among others.

B. Cervix Magnetic Resonance Imaging (MRI) images processing

Magnetic Resonance Imaging (MRI) is a procedure that allows doctors to see the inside of the body in two or three dimensions. The most advanced medical imaging technique uses a powerful magnetic field and radio waves to generate high-quality photographs of each part of the body in detail by visualizing its finer details of internal structure. While treating cervical cancer or other cancers, MRI is sometimes used. It assesses tumors morphology and local magnitude, as well as tumors features with prognostic value, such as endocervical growth size, parametrial infiltration, and involvement of the pelvic side wall or adjacent organs (bladder, rectum). For determining tumor level, recorded MRI accuracy values range from 75% to 96%. This technique, which is far superior to computed tomography (CT) for tracking the size of a cervical lesion, primarily detects variations between tissues and structures. Lesions cells that aren't apparent on normal X-rays, ultrasounds, or CT scans may be correctly identified with MRI. Organs that are difficult to explore such as the brain, spine, pelvic section, soft tissue joints. MRI is used by doctors to see if cancer has spread to nearby organs and tissues in the pelvis, the brain or spinal cord, or lymph nodes.

Cervical lesions require the use of MRI imaging to be diagnosed. On MRI images, the signal amplitude or configuration of the lesion represents a pathological finding.

II. LITERATURE REVIEW

Xiran Jiang [1] has proposed a study using multi-parametric MRI data to develop deep learning-based radiomic approaches for differentiating vessel invasion from non-vessel invasion in cervical cancer. To train and justify deep learning models, researchers used a set of 1,070 dynamic T1 contrast-enhanced (DCE-T1) and 986 T2 weighted imaging (T2WI) MRI images from 167 early-stage cervical cancer patients (January 2014 - August 2018). The DCE-T1 showed more discriminative results than the T2WI MRI in terms of predictive efficiency, as calculated by the receiver operating characteristic (ROC) curve and uncertainty matrix analysis. The highest average area under the ROC curve (AUC) of 0.911 (Sensitivity = 0.881 and Specificity = 0.752) was obtained by using an attention ensemble learning technique that incorporates all MRI sequences. The study's superior findings when compared to current radiomic methods demonstrate that a plethora of deep learning-based radiomics may be developed to assist radiologists in predicting vessel invasion in cervical cancer patients prior to surgery.

Ichrak Khoulqi [2] provide a work centered on the analysis of MRI images of the cervix, has proposed work that is involved in creating a method to assist in the diagnosis and early detection of cervical cancer, the proposed framework takes place in three stages: 1- Pretreatment of the image to remove noise in general; they used the K-means method; 2- Segmentation using the rising regions method; 3- The classification or decision phase, in which inference rules derived from the FIGO classification were used to decide which stage it was. The results are promising, demonstrating the effectiveness of their system for detecting cervical cancer level.

Remya V, [3] provide a work Centered on Hierarchical Adaptive Local Affine Registration, this type of registration determines the boundary of an organ of interest. It combines all local affine component transformations at each stage to form an overall smooth transformation. The proposed method could outperform current registration algorithms like Rigid Registration and Non-Rigid Registration in terms of accuracy.

Shipra Roy, [4] presents an experimental study that aims to establish an automated image classification method for medical images by using the proposed framework to identify Regions of Interest (ROI). Using only the shape, scale, and gray-level details of a patient's cervix, recognising anomalies and quantifying cervical tumour grading is difficult. The heart of our proposed approach is multi-resolution wavelet image analysis using wavelet transform. Wavelet transformations of the images are used in the experiments, and the results are compared and analysed.

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Turid Torheim, [5] proposed a method where Dynamic Contrast Enhanced MRI (DCE-MRI) has been suggested as a tool for determining tissue's vascular properties. Pharmacokinetic models may be used to analyse DCE-MRI absorption patterns, allowing for biologically meaningful interpretations. The researchers wanted to see whether Brix pharmacokinetic model parameters derived from pre-chemoradiotherapy DCE-MRI could predict treatment outcomes in 81 patients with locally advanced cervical cancer. The mean, variance, and percentiles were used as first-order statistical features of the Brix parameters. In addition, texture analysis of Brix parameter maps was carried out by generating grey level co-occurrence matrices (GLCM) from the maps, resulting in second-order statistical features that captured spatial variations within the tumours. Clinical causes, first and second order characteristics, and treatment outcome were used as explanatory variables, with treatment outcome as the answer, for support vector machine (SVM) classification. Leave-one-out cross-model validation was used to test classification models, which is a more stringent version of leave-one-out cross-validation. In addition, the model's statistical significance was evaluated using a random value permutation test.

Wen Wu et al, [6] have analyzed data using SVM, SVM-RFE and SVM-PCA approaches. The dataset was obtained from the Hospital Universitario de Caracas in Caracas and stored in the University of California at Irvine's (UCI) repository. During the classification process, the following factors were considered: sensitivity, precision, positive predictive accuracy, and negative predictive accuracy. In their conclusion, the authors note that SVM is efficient, but that SVM-RFE and SVM-PCA are more effective when the number of features is reduced. They also mentioned that the SVM method has a high computational cost as one of its drawbacks.

MD Mamunur Rahaman, [7] provided a systematic review of state-of-the-art deep learning-based methods for the study of cervical cytology photos. To begin, discuss about deep learning and the various simplified architectures that have been used. Second, examine the publicly available cervical cytopathology databases, as well as the metrics used to evaluate segmentation and classification tasks. The following section provides a detailed overview of deep learning's recent developments in the segmentation and classification of cervical cytology images. Finally, they look at the most up-to-date techniques as well as the most effective approaches for researching pap smear cells.

Zhi Lu, [8] introduce and evaluate the systems that competed in the first Overlapping Cervical Cytology Image Segmentation Challenge, which took place in conjunction with the IEEE International Symposium on Biomedical Imaging (ISBI) 2014. This challenge was created to promote the development and testing of techniques for segmenting individual cells from overlapping cellular clumps in cervical cytology images, which is needed for the development of the next generation of cervical cancer computer-aided diagnosis systems. Even if the nucleus and cytoplasm of each cell are clumped together and thus partially occluded, these automated systems must detect and segment them. Due to poor cytoplasm boundary contrast, a broad range of cell sizes and forms, debris, and a high degree of cellular overlap, this remains an unresolved issue. The task used a database of 16 high-resolution (40 magnification) images of complex cellular fields-of-view, with the separated actual cells used to create a database of 945 cervical cytology images with varying numbers of cells and degrees of overlap to provide full access to the segmentation real data. The results show that all of the methods submitted are capable of segmenting clumps of at most three cells with overlap coefficients of up to 0.3. This highlights the challenge's inherent difficulty and acts as motivation for positive change.

Peng Guo, [9] introduces a method to quantify the relative increase in nuclei numbers as the CIN grade increases, new acellular and atypical cell concentration features were computed from vertical segment partitions of the epithelium area within digitized histology images. Image-dependent epithelium classification is investigated using support vector machine (SVM) and linear discriminant analysis (LDA) methods, with vertical segment voting fusion based on two expert pathologists' CIN grade assessments. Leave-one-out is used in CIN classification training and testing because it has a precision of up to 88.5 percent when labelling grades.

Mercy Nyamewaa Asiedu, [10] In this work, They suggest methods for improved results by integrating features/diagnosis of different contrasts in cervigrams, and even some automated feature extraction and classification for acetic acid and lugol's iodine cervigrams. Methods: They created algorithms to extract basic yet useful colour and textural features from pathology-labeled cervigrams before processing them. The features were used to train a support vector machine model to distinguish cervigrams for visual inspection with acetic acid, visual inspection with Lugol's iodine, and a combination of the two contrasts based on corresponding anatomy. Results: The proposed method had sensitivity, precision, and accuracy of 81.3 percent, 78.6 percent, and 80.0 percent, respectively, when used to distinguish cervical intraepithelial neoplasia (CIN+) from natural and benign tissues. On the same data set, this outperformed three expert physicians' average values for separating normal/benign cases from CIN+ cases(77 percent sensitivity, 51 percent specificity, 63 percent accuracy). Conclusion: The findings indicate that by integrating consistent color-and texture-based features from visual inspection with Lugol's iodine images, unbiased automated, expert-level diagnosis of cervical pre-cancer could be achieved at the point-of-care.

Yiming Liu,[11] propose a method for segmenting cervical nuclei in which pixel-level prior knowledge is used to offer supervisory information for the training of a mask regional convolutional neural network (Mask-RCNN), which is then used to retrieve the nuclei's multi-scale features, and the nuclei's coarse segmentation and bounding box are obtained by forward propagation of the Mask-RCNN. A local completely connected conditional random field (LFCCRF) with unary and pairwise energy terms is used to refine the segmentation. The unary energy is calculated using the nuclear region's coarse segmentation, and the pairwise energy is calculated using the location and intensity information of all pixels in the nuclear region. The final segmentation is accomplished by lowering the energy of the LFCCRF. They tested the device using cervical nuclei from the Herlev Pap smear dataset, and found that accuracy, recall, and the Zijdenbos similarity index were all greater than 0.95 with low standard deviations, suggesting that the process is more accurate and robust than current state-of-the-art methods.

III. PROPOSED SYSTEM

Problem Statement: The proposed system is works based on Deep Learning and it deals with implantation of an system which helps us to detect the cervical cancer at the cell level using Image Processing technique.

Color conversion for RGB to Gray scale, enhancement and scaling, segmentation, detecting the cell boundary and overlapping cytoplasm and nuclei, feature extraction, and classification of cells based on features are all part of the initial process.

The proposed detection method is depicted in Figure 1 as a five-step procedure.

1) Obtaining an image
2) The preprocessing phase improves the efficiency of the cervical MRI images by removing noise and improving structure and tissue borders.
3) The segmentation stage involves extracting the ROI region and the cancer spread region.
4) Extraction of features.
5) Classification of stages.

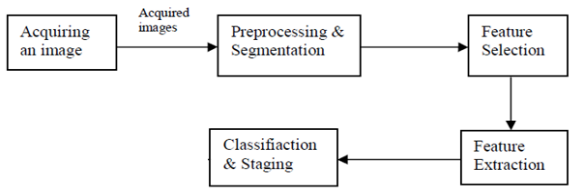

Fig1: Block Diagram of Cervical Cancer Detection and Classification

Preprocessing

The aim of pre-processing is to improve image data by reducing unnecessary distortions and enhancing some essential image features for subsequent image processing. There are two key stages in image pre-processing. a) Resizing and Gray scale conversion b) Contrast enhancement

a) Resizing and Gray scale conversion

The only detail in a grayscale picture is brightness. In a grayscale image, each pixel represents an amount or quantity of light. In a grayscale picture, the brightness gradient can be distinguished. Only light intensity is measured in a grayscale image. The brightness of an 8 bit image will range from 0 to 255, with 0 representing black and 255 representing white.

Figure 2 illustrates how a colour image is transformed into a grayscale image during grayscale conversion. Colored images are more difficult and time consuming to process than grayscale images. On a grayscale image, all image processing techniques are used.

The coloured or RBG picture is transformed to grayscale in our proposed method.

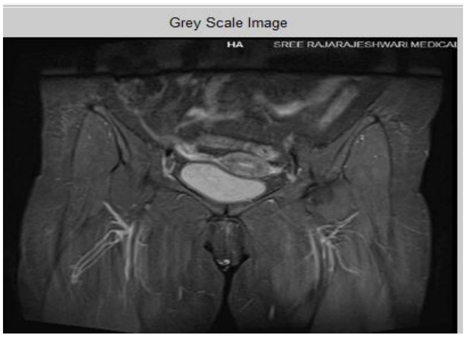

Fig2: RGB to Grey-scale Converted Image

b) Contrast enhancement

The aim of contrast enhancement is to enhance the brightness of a feature of interest in an image. To achieve a higher quality performance, contrast enhancement is used.

When the data in the picture is represented by near contrast values, histogram equalisation normally increases the global contrast. This modification could improve the distribution of intensities on the histogram. The majority of the details would be lost due to excessive lighting. This is due to the fact that each histogram is not limited to a single area. For Histogram equalisation, the image's global contrast will be taken into account.

The above problem can be solved using adaptive histogram equalisation. The picture is divided into small blocks called "tiles" in this case (8x8 will be the tile size by default in OpenCV. The histograms for each of these blocks are then normalised. The histogram will be limited to a small area within a small area. Noise would be intensified if it exists. Contrast limiting is used to prevent this.

In our proposed system we are using Contrast-limited adaptive histogram equalization (CLAHE) to remove unwanted noise.

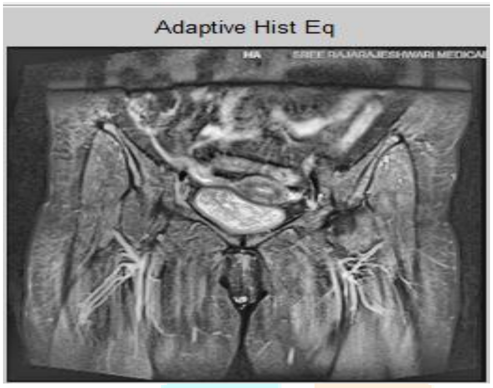

Fig3: Adaptive Histogram Image

Image Segmentation

The lesion was segmented from the surrounding skin after image pre-processing. Thresholding was perfect for the job because there was a clear colour difference between the lesion and the skin. To improve segmentation, a black-and-white picture was created and the contrast was changed.

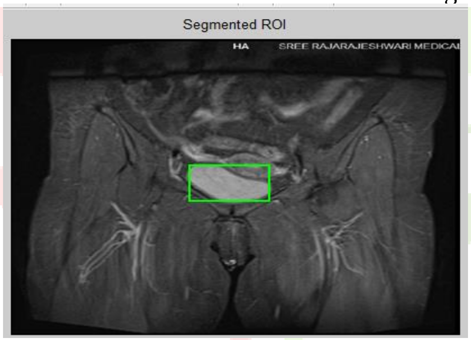

Fig4: Segmented Image

Feature Selection and Extraction

Variable selection is another name for feature selection. It is the method for selecting a limited number of useful features for potential use.

The process of accurately determining the amount of resources needed from a wide collection of data is known as feature extraction. The Extraction stage, which uses Cervical Cancer Detection, is a critical stage, Detecting different desired portions or forms using CNN algorithms and techniques. It is necessary to extract the selected features (affected part). In an image, the GLCM shows how often different pixel values appear. Begin by using CNN's graycomatrix function to generate a gray-level co-occurrence matrix from an image. The second order conditional joint probability densities of each of the pixels are denoted by a GLCM, which is the probability of grey levels I and j occurring within a given distance 'd' and in a given direction 'ɵ'.

Classification

In addition to linear classification, SVMs can perform non-linear classification efficiently using the kernel trick. SVM is a commonly used clustering algorithm that uses support vector statistics to categorize unlabeled data.

IV. CONCLUSION

In this paper we have studied the basic mechanism for tumor detection. In this review article we have specifically focused on the Cervical Cancer detection using Grey-scale conversion, K-means for segmentation, GLCM for feature extraction , CNN for training and SVM for classification.

We propose a system which is of less cost and could be checked in during regular checkup which increases efficiency of detecting tumor in early stage. Thus our proposed system provides a different way for detecting the cervical cancer with high accuracy.

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