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Automatic Classification of Cervical Cells Using Deep Learning Methods

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Abstract: *Cervical cancer, second only to breast cancer, is one of the cancers leading to cause death among women. Cervical cancer is a cancer that forms in the cells of the cervix, which is the lower section of the uterus that connects the uterus to the pelvis to the vaginal area. Various forms of the papilloma virus (HPV), a sexually transmitted infection that plays a role in cervical cancer and plays a critical part in most cases. The risk of cervical cancer developing can be reduced by undergoing screenings and receiving a vaccination that protects against HPV infection Cancer prevention is important. Most of the time, this is accomplished by checking the transformation zones. Cervical pre-cancerous stages can be observed in three different types, and all can transfigure into cancer. As a result, it's crucial to screen cervical anomalies sensibly and have a reliable process to determine if a cervix is normal (healthy) or pre-cancerous. Presently, the test being carried is a Pap smear test, commonly referred as a Pap test, which is a cervical screening procedure. It examines the cervix for the presence of pre - cancerous or cancerous cells. At present times deep learning is becoming more important alternative for cancer screening. A cervical cancer detection and classification system based on CNN has been proposed. Deep-learned features are acquired using the CNNs mode*

Keywords: Deep Learning

I. INTRODUCTION

Cervical cancer is the second most common type of cancer that affects women, ranked after the breast cancer. The acceptability of increased cervical cancer risk and cause of cancer death projected. Cervical screening program has minimize the rate of death in developed countries. Cervical cancer is the one of the deadliest disease, it can be cured if detected in early stage. Pap Smear Test this was introduced as a screening test for cervical cancer in the year of 1943 by Dr. George Papani was the scientist who proposed a method where a spoon like wooden instrument is used to take out a smear and used to see them in the microscope. Our technique first segments each independent cells in the microscopic image. One or more cells may be cancerous cells or non of the cells may be cancerous or only one out of the many cells may be cancerous or all the cells present in the microscopic image may be cancerous. Therefore regression based technique can' t separate the cancers cells from the normal cells therefore our technique should effectively separate every cell present in the image and then extract the features. And the morphology descriptor for each of the cell presents that information to a machine learning system which farther classifies the normal or the presence of cancer from each of the cells if one or more cells present in the cervical smear sample has cancer then we say the presence of the cervical cancer.

II. EXISTING SYSTEM

Current cervical cancer screening methods heavily rely on manual techniques like Pap smear tests and HPV testing, where trained medical professionals examine cell samples under a microscope to identify abnormalities. However, the interpretation of results is subjective and prone to human error, leading to potential inaccuracies. These manual approaches have limited scalability and efficiency due to their dependence on the availability of skilled experts, making it challenging to ensure consistent quality and timely analysis as screening demand increases. Furthermore, the process is highly time-consuming, delaying diagnosis and treatment, which is especially detrimental for early-stage cervical cancer cases where prompt detection is crucial. Manual screening may sometimes fail to accurately detect precancerous or early-stage cancerous changes, resulting in missed opportunities for timely intervention and allowing the disease to progress further. Consequently, there is a need for automated, accurate, and scalable methods to improve cervical cancer screening and diagnosis

III. LITERATURE SURVEY

Ensemble classification method based on majority voting for an accurate diagnosis addressing the patient' s medical conditions or symptoms has been proposed. The study experiments a wide range of available classifiers, namely Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbour (KNN), Naive Bayes (NB), Multiple Perceptron (MP), J48 Trees, and Logistic Regression (LR) classifiers. The proposed model bestows a second opinion to health practitioners for disease identification and timely treatment.

A deep learning framework for the accurate identification of LSIL (including CIN and cervical cancer) using time-lapsed colposcopic images has been proposed. The framework involves two main components, i.e., key-frame feature encoding networks and feature fusion network. The features of the original (pre-acetic acid) image and the colposcopy images captured at around 60s, 90s, 120s and 150s during the acetic acid test are encoded by the feature encoding networks. Several fusion approaches are compared, all of which outperform the existing automated cervical cancer diagnosis systems using a single time slot. A graph convolutional network with edge features (E-GCN) is found to be the most suitable fusion approach in our study, due to its excellent explain ability consistent with the clinical practice.

In this study, diffusion-weighted images (DWI) of 98 patients with cervical cancer were acquired. We trained an automatic tumor contour segmentation model using 2D U-Net and 3D U-Net to investigate the possibility of applying such a model to clinical practice. A total of 98 cases were employed for the training, and they were then predicted by swapping the training and test images. To predict tumor contours, six prediction images were obtained after six training sessions for one case. The six images were then summed and binarized to output a final image through automatic contour segmentation.

A deep learning-based algorithm for automatic visual evaluation (AVE) of aceto-whitened cervical images is shown to be effective in detecting confirmed precancer (i.e. direct precursor to invasive cervical cancer). The images were selected from a large longitudinal study conducted by the National Cancer Institute in the Guanacaste province of Costa Rica. The training of AVE used annotation for cervix boundary, and the data scarcity challenge was dealt with manually optimized data augmentation. In contrast, a novel approach for cervical precancer detection using a deep metric learning based (DML) framework is presented which does not incorporate any effort for cervix boundary marking.

It is crucial to intelligently screen cervical abnormality and have a robust system for detecting whether a cervix is in normal (healthy) or at a pre-cancerous stage. Deep learning showed great potentials when applied to biomedical problems, including medical image analysis, disease prediction, and image segmentation. Deep residual learning based networks are designed to perform cervical cancer screening. The importance of the activation functions on a residual network (ResNet)'s performance. Three residual networks of the same structure are built with different activation functions. The employed models are trained and tested using a dataset of colposcopy cervical images.

IV. PROBLEM STATEMENT

The implementation of an automated cervical cancer detection system leveraging machine learning and digital image processing techniques is proposed to address the major limitations of current manual screening methods like Pap smear tests. An in-depth study of existing literature highlights the crucial problems of subjectivity, human error proneness, limited scalability due to dependence on expert availability, and time-consuming analysis processes - which can lead to delays in diagnosis and missed opportunities for early intervention when cancerous cells are present. By investigating these drawbacks thoroughly, researchers aim to develop an automated system where machine learning models are trained on vast datasets of labelled cervical cell images to objectively learn intricate patterns that differentiate normal from abnormal/cancerous cells. Digital image processing techniques preprocess the cell images, enhancing discriminative features for efficient analysis by the machine learning algorithms. Such an automated approach eliminates subjective human interpretation errors, expedites the screening process for prompt diagnosis and treatment to

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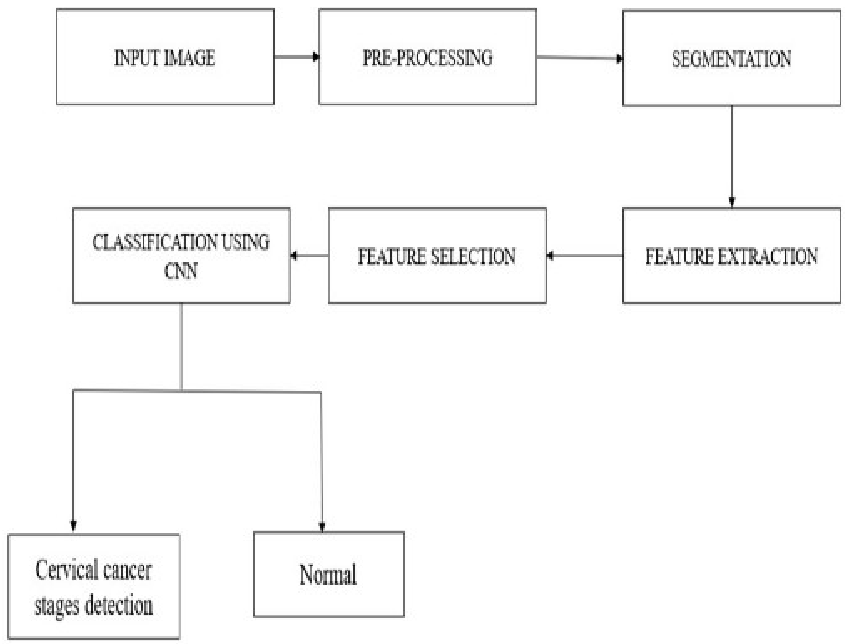
improve patient outcomes, especially for early-stage cases, and enables scalable cervical cancer screening unbounded by expert workforce constraints. Rigorously proposing this automated system's development based on systematically identified flaws in manual methods paves the way for a more accurate, efficient, and high-throughput cervical cancer screening solution with life-saving potential through early detection and timely clinical intervention.

V. METHODOLOGY



Input Image: The dataset that we have used in this project is available publicly on the internet (https://www.kaggle.com/datasets/obulisainaren/ multi-cancer). The website has images of various types of cancer while we use cervical cancer dataset.

Input to proposed system is Classification of CT scan, PET scan, MRI scan.

Preprocessing: Goal of pre-processing is an improvement of image data that reduces unwanted distortions and enhances some image features important for further image processing. Image pre-processing involves three main things

- Gray scale conversion
- Noise removal

Image enhancement

Grayscale conversion: Grayscale image contains only brightness information. Each pixel value in grayscale image corresponds to an amount or quantity of light. The brightness graduation can be differentiated in grayscale image. Grayscale image measures only light intensity 8-bit image will have brightness variation from 0 to 255 where '0' represents black and '255' represent white. In grayscale conversion color image is converted into grayscale image shows. Grayscale images are easier and faster to process than colored images. All image processing technique are applied on grayscale image.

Noise Removal: The objective of noise removal is to detect and remove unwanted noise from digital image. The difficulty is in deciding which features of an image are real and which are caused by noise. Noise is random variations in pixel values.We are using median filter to remove unwanted noise. Median filter is nonlinear filter, it leaves edges invariant. Median filter is implemented by sliding window of odd length. Each sample value is sorted by magnitude, the centermost value is median of sample within the window, is a filter output.

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Image Enhancement: The objective of image enhancement is to process an image to increase visibility of feature of interest. Here contrast enhancement is used to get better quality result.

Segmentation: The next step after image pre-processing was to segment the cervical tumor area from the surrounding CT Images. A black and white image was produced with its contrast adjusted to provide better segmentation.

Feature Extraction: The purpose of feature extraction (GLCM) is to suppress the original image data set by measuring certain values or features that helps to classify different images from one another. Feature extraction is the process which involves for clarifying the amount of resources required from a large set of data accurately. Once features are selected then it need to be extracted. Image features Extraction stage is an important stage that uses algorithms and techniques to detect various desired portions or shapes. The selected features (affected part) must be extracted. The GLCM is a tabulation which shows how often various combinations of pixel values (grey levels) occur in an image. Firstly, create gray-level co-occurrence matrix from image using matrix function in CNN. A GLCM denote the second order conditional joint probability densities of each of the pixels, which is the probability of occurrence of grey level I and grey level j within a given distance ‘ d’ and along the direction ‘ θ’ .

Features are considered for proposed method.

- Area: It shows the actual number of pixels in the ROI.
- Convex Area: It shows the number of pixels in convex image of the ROI.
- Equivalent Diameter: It is defined as the diameter of a circle with the same area as the ROI.
- Solidity: It is defined as the proportion of the pixels in the ROI.
- Energy: It describes that the summation of squared elements in the GLCM and its value ranges between 0 and 1.
- Contrast: It is defined as the measure of contrast between an intensity of pixel and its neighboring pixels over the whole ROI.
- Homogeneity: The homogeneity is the measure of closeness of the distribution of elements in the GLCM to the GLCM of each ROI and its Value ranges between 0 and 1.
- Correlation: It is the measure of correlation of pixel to its neighbor over the ROI
- Eccentricity: The eccentricity is defined as the ratio of the distance between the focus of the ellipse and its major axis length.

Feature Selection: Feature Selection also called variable selection. It is the process which is used for selecting a small set of relevant features for future use. After preprocessing have to select the features or region from the preprocessed image using genetic algorithm which is best in selecting the feature for biomedical images.

Classification using CNN:

The binary classifier which makes use of the hyper-plane which is also called as the decision boundary between two of the classes is called as Convolution Neural Network. Some of the problems are pattern recognition like texture classification makes use of CNN. Mapping of non- linear input data to the linear data provides good classification in high dimensional space in CNN. The marginal distance is maximized between different classes by CNN. Different Kernels are usedto divide the classes. CNN is basically binary classifier which determines hyper plane in dividing two classes. The boundary is maximized between the hyper plane and two classes. The samples that are nearest to the margin will be selected in determining the hyper plane is called support vectors.

VI. CONCLUSION

We conclude that expert-level diagnosis of cervical cancer can be achieved using a relatively simple, efficient, and explainable technique with limited training data. By integrating domain knowledge and other techniques, the proposed approach could potentially aid in medical image segmentation and detection tasks. To automate the detection of cervical pre-cancerous lesions, we developed algorithms trained on colposcope images, aiming to improve overall sensitivity and specificity. Unlike previous methods, our system uses pathology-confirmed labels for training and automatically detects regions of interest across the entire cervix, without requiring manual pre-selection. The preprocessing techniques reduce specular reflection and automatically segment the relevant areas.

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VII. FUTURE SCOPE

The proposed cervical cancer detection system holds significant potential for further advancement. Future work could involve developing a real-time system for immediate analysis during colposcopy, incorporating advanced imaging techniques for enhanced lesion detection and characterization, and exploring applications in other gynecological cancers. Additionally, creating a mobile or web-based application, integrating with electronic health records, and leveraging transfer learning techniques could expand the system's accessibility and robustness. Ultimately, the development of comprehensive decision support systems that combine the cervical cancer detection system with patient data and risk factors could provide personalized recommendations for improved cervical cancer management.

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