CERVICAL CYTOPATHOLOGY IMAGE ANALYSIS USING DEEP LEARNING

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ABSTRACT

The second most prevalent disease among women in the globe between the ages of 15 and 44 is known as cervical cancer, which is the result of normal cells that were formerly covering the top part of the cervix developing into malignant tumours. One of the deadliest and most frequent malignancies in women is cervical cancer. Yet, if it is discovered at a precancerous stage, this cancer is completely curable. The most common screening procedure for the early diagnosis of cervical cancer is the Pap smear test. This manually operated screening method, however, has a significant percentage of false-positive results due to human error[1]. Countries with little resources account for 85% of cervical cancer mortality. The inability to find qualified medical professionals to perform cervical screenings contributes to a significant portion of these deaths. Additionally, the hospitals in these regions frequently lack the equipment necessary to perform cervical screening tests like pap smear, colposcopy, and biopsy. Hence, for quick identification and treatment, an automated system that can forecast the likelihood of a cervical anomaly can be very helpful[2]. Deep learning-based computer-aided diagnostic techniques are commonly used to automatically segment and categorise cervical cytology pictures, which can increase accuracy and manual screening practises. In this article, we present a thorough examination of the state-of-the-art deep learning-based methods for the processing of cervical cytology pictures[3].

INTRODUCTION

We begin by introducing deep learning and the streamlined versions of its architectures that have been applied to this subject. Second, we go through assessment metrics and the publicly accessible cervical cytopathology datasets for segmentation and classification tasks.The segmentation and classification of cervical cytology pictures are next provided, followed by a full overview of current developments in deep learning. Our investigation of the most effective methods for the examination of pap smear cells is our final step[4].

Throughout the world, cervical cancer ranks fourth among malignancies that affect women behind breast, colorectal, and lung cancers, with 527,624 women being diagnosed with the disease each year and 265,672 losing their lives to it. Cervical cancer can be prevented with the help of efficient screening programmes, which will also lower mortality and morbidity rates[1]. In rural locations, health professionals like nurses frequently lack the training necessary to perform procedures like pap smears and biopsies. There can also be a shortage of specialists qualified to perform a patient's colposcopy. In such circumstances, until the patient visits the closest appropriate specialised hospital, she has no means of knowing if she has a medical issue[2].

Convolutional neural network-based deep learning technology has considerably aided the advancement of CAD in recent years.. Because deep learning can produce high-level feature representation directly from the raw images, it is progressively displacing the conventional machine learning approach[3]. CNNs can perform satisfactorily in cancer detection and diagnosis, according to an increasing number of studies.

A CNN-ELM-based approach was suggested by Ghoneim et al. to categorise cervical cancer cells. This system uses CNN to extract deep-learned features, which are subsequently classified using an extreme learning machine (ELM) based classifier[4].

Two pre-trained deep learning models were utilised by Alyafeai et al. to study cervical cancer. Convolutional neural networks were used by Zhang et al. to classify cervical cancer cells directly, and they achieved 98.3 percent classification accuracy in the Herlev benchmark Pap smear dataset. Deep learning does not require the creation of intricate hand-crafted features or previous segmentation based on deep features[5].

Deep neural networks that have already been trained can be used for many tasks in related domains thanks to transfer learning. We frequently pre-train the first model for detection tasks on ImageNet before refining it on particular datasets[6]

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METHODOLOGY

A colposcopy image is an essential aid in early cancer diagnosis. The transition zone colposcopic examination is necessary for the evaluation and identification of those with irregular cytology who require additional attention or follow-up. Colposcopy is thought to have relatively strong intra- and interobserver heterogeneity in the perception of distinguishing characteristics, but little is known about observer heterogeneity in the evaluation of TZ form and squamous column junction (SCJ) visibility, as well as in the

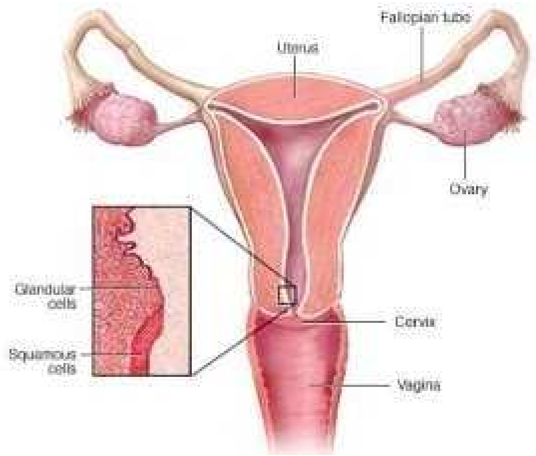


Fig. Schematic diagram of the cervix and the uterus

tracing. Because a TZ is entirely ectocervical (without any endocervical part), it is classified as type 1. Endocervical tissue is still present in Type 2 and Type 3 transition zones. The most recent SCJ was classified as a category 2 when it became fully visible in TZ.

The new SCJ was only partially evident when using external equipment, and it was classified as type 3.The CNN models are widely used in a variety of image processing applications, including the interpretation of medical images. It is clear that finding cervical cancer in colposcopy images is a challenge for computer vision. The neural network, particularly convolutional, is utilised to differentiate between situations of type 1, type 2, and type 3 when comparing deep learning with traditional characteristics. Deep convolutional neural networks are used in the test to identify cervical lesions (moderate). By freezing the top layers, the suggested VGG 19 (TL) model is adjusted to categorise three types of cervical cancer and is then tested using a dataset of cervical images. To improve the extraction of specific cervical cancer features from colposcopy images, we proposed a CYENET architecture that included the key benefits of depth and parallel convolutional filter.

The suggested model comprises of two types of convolution layers, i.e., numerous quantitative calculation of intra- and interobserver similarities of TZ contour

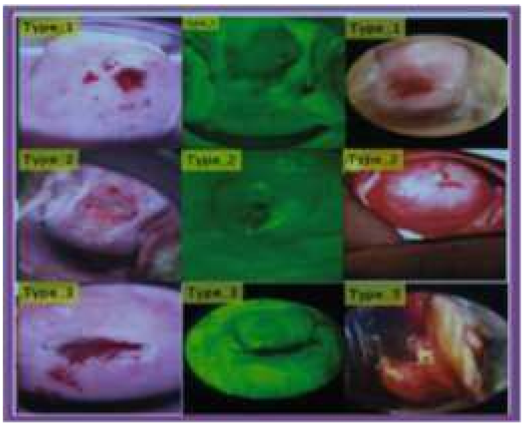


Fig.Dataset example of type 1,type 2, type 3 classes

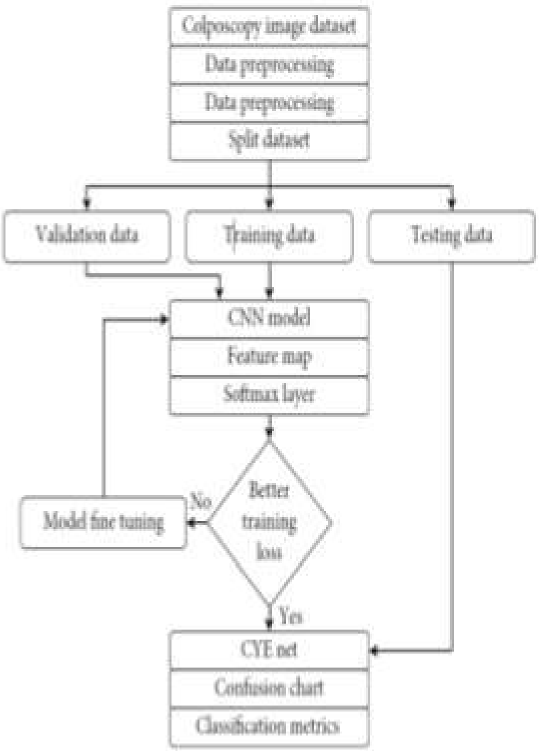
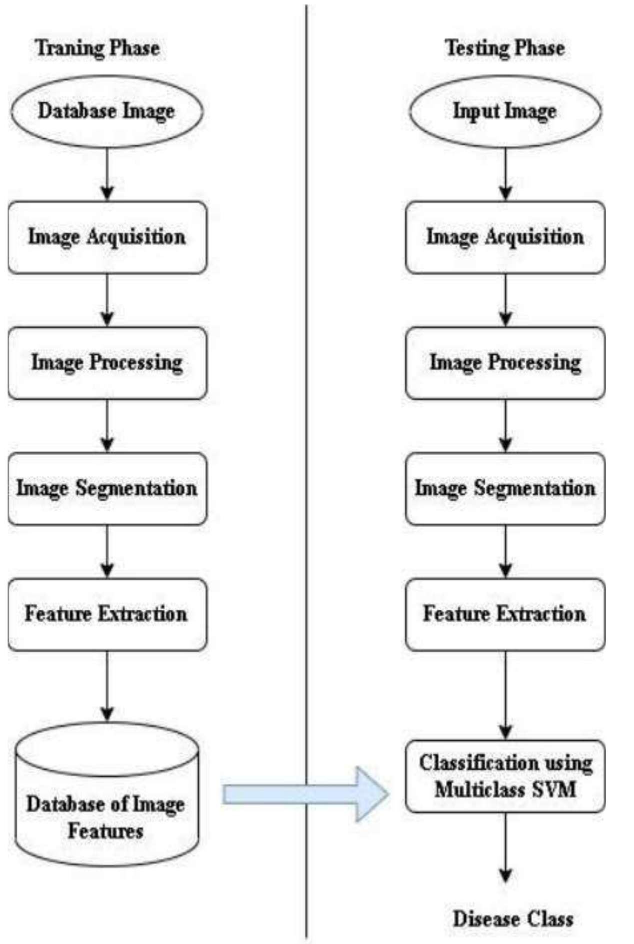


Fig.Proposed CYNET Model

Colposcopy is a frequent method for diagnosis that takes between one and fifteen minutes to complete and gives doctors cervigrams, or pictures of the cervix. Colposcopy is regarded as a potential advancement, especially in areas with limited resources, to a Pap Smear test, because there aren't enough practitioners or tools available. Due to non-standard cervigram data collecting techniques, prior to categorization, segmentation is necessary for accurate outcomes.

convolution layers to extract different features from the same input and classic convolution layers at the beginning of a network followed by a single convolution filter. In order to lessen the overfitting impact, biassed regions are removed using several convolutional filters. Three steps make up this suggested model: data preparation, CNN model training, and classification outcomes. 15 convolutional layers, 12 activation layers, 5 max pooling layers, and 4 cross channel normalisation layers make up the CYENET model. convolutional block.



Numerous applications, including computer vision, natural language processing, forecasting, and battery health monitoring, have benefited greatly from deep learning.

Disease diagnosis depends heavily on medical image processing, which includes classification, identification, segmentation, and registration. The bulk of the picture data processed consists of medical imaging

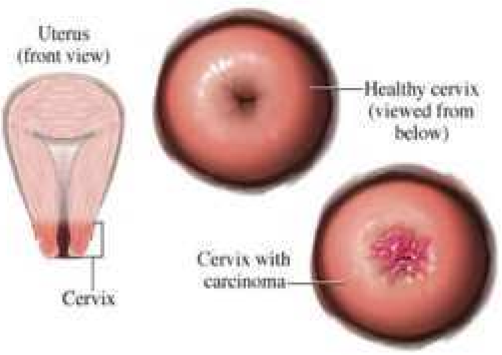


Fig. Healthy vs cancerous cervix

CONCLUSION

According to the findings, characteristics like education level, menstrual history, and menopausal status do have a big impact on predicting cervical abnormality in the patient. One strategy to enhance the outcomes is to collect more patient data in order to lower the large data variation (over fitting). Also, certain novel variables that may have a substantial influence on the outcomes, such as if the patient is experiencing back discomfort or bleeding during sex, might be taken into consideration.

For the purpose of diagnosing the kind of cervical cancer using colposcopic pictures, a new deep learning architecture called CYENET is presented. The oversampling approach balances the picture collection to enhance the classification outcomes. In this study, two models are provided. One is utilising the VGG19 architecture and a transfer learning technique. The other is a specialised brand-new model called CYENET for classifying the cervical cancer type using the dataset of ODT colposcopy images. Classification accuracy, sensitivity, specificity, Cohen's Kappa, and F1-measure are used to compare the two models. With a Cohen's Kappa value of 53.5%, the VGG19 model has a sensitivity and specificity of 33% and 79%, respectively. For VGG19, the classification accuracy was 73.3%. Results for VGG are largely satisfactory.

Comparable results were seen with the planned CYENET, which had high kappa including MRI, CT, ultrasound, and blood smear images.

As a result of the proposed CYENET's improved categorization efficiency, medical experts and trained healthcare practitioners can use it to improve the diagnostic sensitivity and precision of cervical cancer screening via colposcopy. The theoretical deep learning model will eventually be tested on various datasets. To improve the method, some cutting-edge image processing methods and CNN algorithms can be combined to produce a new cervical precancerous data diagnostic system.

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scores of 88%, 96.2%, and 92.4%, respectively. The CYENET model's classification accuracy has increased to 92.3%, which is 19% higher than the VGG19 (TL) model. When compared to previously published outcomes of the work, CYENET's performance as a diagnosis-assistance tool for physicians is successful and promising.

A target population that doesn't require intrusive intervention can benefit from the

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