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Research Article

Insights into Automated Diagnosis of Cervical Cancer

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ABSTRACT

The cervix is the last part of the uterus where cervical cancer usually develops. Identification of the cervical cells can be very taxing owing to their complexity of morphological changes in the structural parts of the cell. The problem here is that the detection process is tardy and there is not much awareness about it. By means of this study, we attempt to automate this detection process using Computer Vision Techniques like Image Segmentation, Feature Matching, etc. Through this, the patient will be able to get the correct diagnosis of her cancer in a few minutes which otherwise would take a couple of days.

Keywords- Bioinformatics, Life and Medical Sciences, Computer Vision (CV)

Introduction

Cervical cancer is a condition that affects nearly all women and has been the most common cancer among women for at least 30 years (Office on Women's Health, U.S. Department of Health and Human Services, 2018). The best defense against cervical cancer is a monogamous lifestyle, frequent Pap smears and HPV immunization. With 570,000 projected new cases in 2018, cervical cancer ranked fourth among malignancies affecting women and accounted for 6.6% of all cancers affecting women. In nations were the income inferior or moderate, cervical cancer deaths account for almost 90% of all dying women.

Symptoms of cervical cancer include irregular or unusual intermenstrual bleeding after intercourse, back, leg, or vaginal pain, fatigue, weight loss, loss of appetite, foul-smelling vaginal discharge, and one swollen leg. More serious symptoms may occur later. A Pap test is frequently used as a cervical cancer screening tool. A Pap smear is an easy, fast, and nearly painless screening technique for uterine cervix cancer or precancer. The standard biopsy test, cytology, Schiller, and Hinselmann are the screening techniques for cervical cancer. Each test is performed in order to look for cervical cancer.

Worldwide, there has been an increase in patients of all ages of about 15.48%. Given the increased prevalence of the disease, it is advocated that the world has a reliable digital system for detecting cervical cancer. Machine learning algorithms may be the best appropriate for such systems because they are quick to identify cervical cancer in its early phases.

Literature Survey

Previous research papers and other related issues have been considered with the topic of interest in mind. From 2019 to 2022, this study categorizes a number of Cervical Cancer Detection Methods using AI, ML, DL, and image processing (IP).

Youyi Wu et al. in 2022,[1] have examined the behavior of the MRI images of sick people with tumor recurrence and distant metastasis of cervical squamous cell carcinoma both before and after concurrent chemoradiotherapy, using a balloon snake model. This has improved the quality of the MRI images, speed up processing times, and improved diagnostic other models.

Michał Kruczkowski et al. in 2022,[3] employed an optical sensor and a prediction algorithm to create a device to predict cervical cancer. Four algorithms were compared, which were RF, extreme Gradient Boosting, Naïve Bayes, CNN. Saini S.K. et al. in 2020,[4] presented the ColpoNet model, a deep learning approach to colposcopy that is an image-based classification of cervical cancer. Using data collected from the National Cancer Institute, this method was evaluated and compared with other deep learning algorithms, including Alex Net, VGG16, ResNet50, LeNet, and Google Net. It has the highest performance and accuracy of 81.353% compared to ColpoNet with other top depth approaches.

Dhwani Parikh et al. in 2019,[7] used decision tree, KNN and random forest as their classification algorithms. The dataset for K-Nearest Neighbors is evenly distributed. The process of choosing features has finished, and the chosen features have been applied to prediction. The data is split into 25–75 groups for decision trees and random forests. Hill climbing algorithm is used for feature selection. KNN has the highest accuracy of 82.2%, with 52% for decision trees and 53% for random forests. F1 score for KNN is 0.94, 0.88 for decision trees and 0.90 for random forests.

Yuttana Kitjaidure et al. in 2020,[8] used iterative shape- based cell segmentation to detect nuclei. The feature selection process used a random forest algorithm. During the classification phase, a sorter of the bagging set was used. Using the SIPaKMeD dataset, the two-class classification accuracy was 98.27%, while the five-class classification accuracy was 94.09%.

Anjali Goyal et al. in 2020,[9] extracted background, cytoplasm, and nuclear portions from single-cell Pap smears using a hybrid segmentation technique. Out of a total of 25 elements, 20 elements are shape-based. Some techniques such as logistic regression with L1 regularization is 100% accurate, but take too much CPU time compared to other algorithms that achieve 99% accuracy with less CPU time.

Tony George et al. in 2021,[10] introduced for cervical cancer identification, medical image processing using CNN appears to be the most effective. Colposcopy Ensemble Network (CYENET) and the VGG19 (TL) model were the two deep learning approaches used. Cervical tumors were automatically classified using CYENET, and transfer learning was accomplished using VGG19. The classification accuracy for VGG19 was 73.3%. The CYENET model's classification accuracy has increased to 92.3%, which is 19% higher than the VGG19 (TL) model. Lulu Li et al. in 2021,[11] offered a new technique Model of Attention Feature Pyramid Network (AttFPN) for Cervical Cancer Detection. Containing overall sensitivity, specificity, accuracy, and AUC of 95.83%, 94.81%, 95.08%, and 0.991, the result was equivalent to a diagnostician with 10 years of experience that was tested for the dataset with 3970 cervical cytology pictures. The method showed an average diagnostic time of 0.04 seconds per image, which was substantially faster than the typical pathologist's time (14.83s per image).

Swati Shinde et al. in 2022,[12] proposed the study about the classification of cytology images for cervical tumor cells. This paper uses the discrete coefficient transform (DCT) coefficient and the Haar transform coefficients as features. They were utilized as input to seven different machine learning (ML) algorithms that were used to classify normal and bad pap smear images. The DCT transform provided an accuracy of 81.11%, and among all ML algorithms, Random Forest classifiers performed the best.

Methodology

This section covers how to predict that the cell is cancerous or not in general. Figure 1 illustrates a schematic illustration of the process. The following is a discussion of the processing flow:

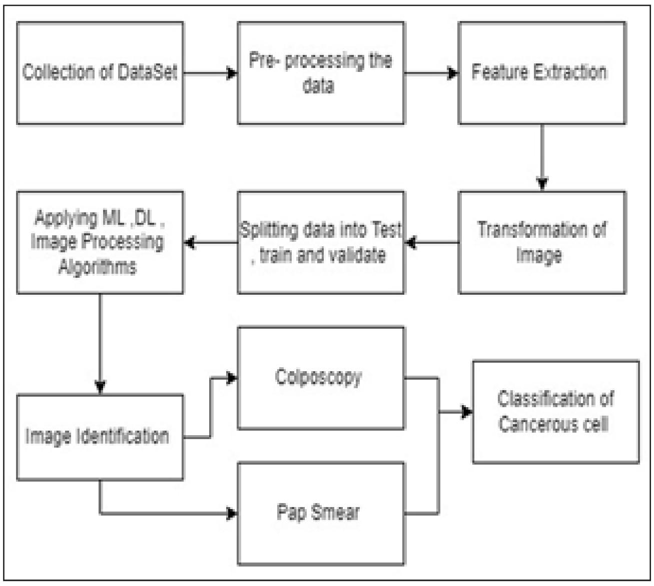


Figure 1.Flowchart of Methodology

Dataset Collection

The data set was collected from various platform such as Herlev dataset, Kaggle, Hospital Dataset, UCI database Colposcopy image, Pap-Smear image. The data set contained the information about the image that are taken during the screening for cervical cancer i.e., pap-smear image which has cell and the various attributes related to it are present like cell size, and the colposcopy image is the direct image of the cervix and the attributes related to it.

Pre-Processing Data

The data is examined for outliers and missing values in this step. Normalization techniques such as min-max normalization are used to put the data in the correct format and visualize the data set to see the same.

Feature Extraction

At this stage, various feature extraction techniques were used to examine the attributes in the dataset to see if they are correlated and if they are important or not to predict the outcome using the graphs generated in the visualization step. Features that are not highly correlated are retained and used in subsequent steps to predict the outcome because they are more relevant than features that are not highly correlated. This step is used in case of only machine learning algorithms because deep learning methods doesn't need explicit feature extraction.

Transformation of Image

Transformation of image involved multiple bands of data that were manipulated from a single multispectral image or from two or more photographs of the same area taken at different times (i.e., multitemporal image data). In each case, image transformations create "new" images from two or more sources that better highlight certain features or properties of interest compared to the original input image and convert the Image Data into a pixel format so that the data can be given the ML model that needs to be trained for classification.

Splitting of Dataset

The dataset is divided into Train and Test data in order to precisely train the model. While 80% of the data, should be utilized to train the model, the remaining 20% of the training set was retained as a validation set. Its performance is assessed using test data that corresponds to 20% of the original data. Because the values of the data in the two sets are entirely distinct when data is split, there is no data redundancy.

Applying ML, DL, and Image Processing Technique

In this phase, we will apply different Machine learning Algorithms like RF, SVM, Decision Tree and Deep learning techniques like CNN, VGG19, and Image processing Algorithms to get the insight of the image and identify the cancerous cell, what the image is about, its type and to get the information about the cell.

Image Identification: In this stage, the image will be identified into Pap-Smear and Colposcopy images, where the pap smear may be categorised into 7 classes and the colposcopy image can be classed into 4 classes. That will be used Further for the Classification of the tumour cell in the respective image class.

Classification

In this phase, we will classify the images into normal and abnormal. An image without cancer cells is considered normal, while an image with cancer cells is considered abnormal and classified whether the cell is cancerous or not.

Techniques

Digital Image Processing

There are six phases to this strategy. In cell segmentation, nuclei are disclosed using an iterative shape-based technique, and overlapping cytoplasm is segregated using a marker- driven watershed approach. During the feature extraction process, three crucial features are gathered from the protoplasm and nucleus of fragmented cells. The random forest algorithm is one method for feature selection. A bagging ensemble classifier, consisting of the outputs of five classifiers (linear discriminant, SVM, KNN, boosted trees, and bagged trees), is utilised in the classification step.

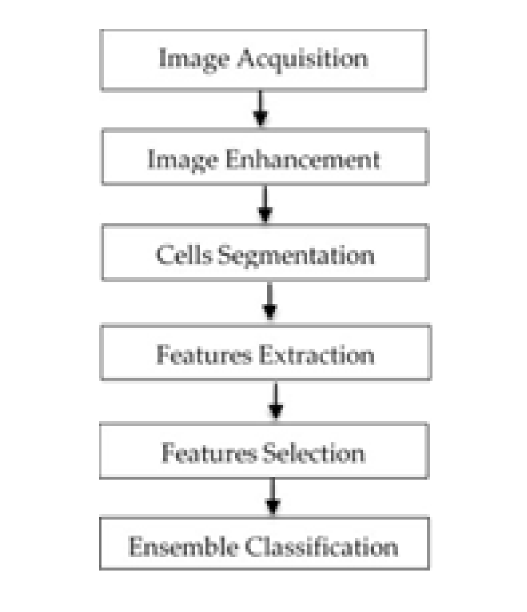


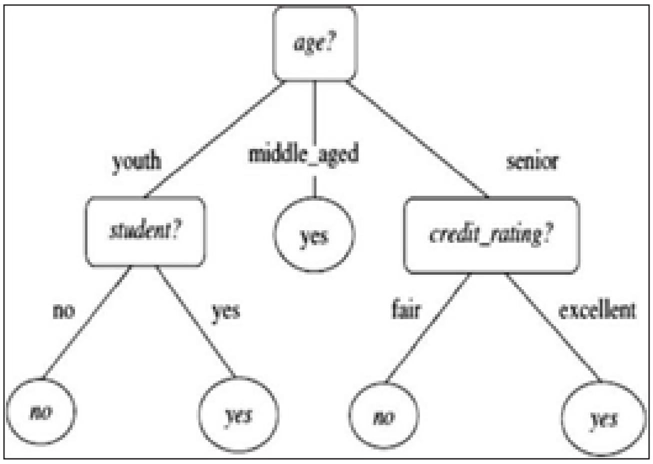
Figure 2. Steps for Digital Image Processing

Decision Tree Algorithm

Supervised machine learning techniques include decision tree algorithms. Problems involving classification and regression are solved with it. The purpose of this strategy is to create a model where the decision tree forecasts the value of the responsive variable that resolves the issue using a tree representation. Leaf nodes represent class labels, and internal nodes reflect attributes.

Probabilistic Neural Network (PNN)

PNN is a type of feed-forward neural network in which the connections between the nodes do not repeat themselves. A given collection of data's probability density function can be estimated via this classifier. It calculates the likelihood that a sample will fall into a learned category. Machine learning engineers use PNN for classification and pattern recognition tasks. PNN uses a statistical memory-based technique that can be supervised or unsupervised to solve classification problems.



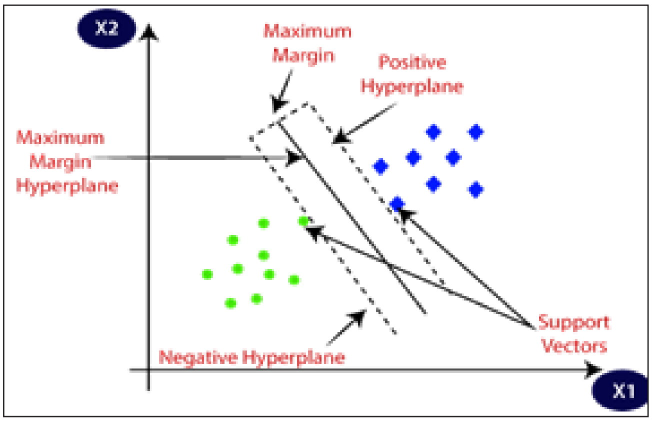


Figure 3.Decision Tree Example

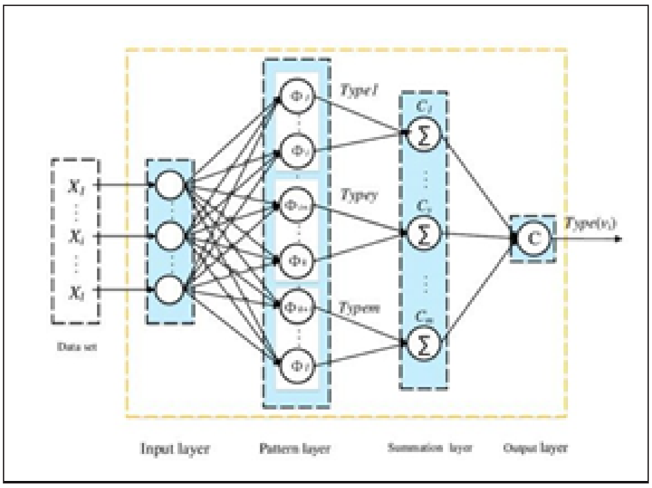


Figure 4.Probabilistic Neural Network

Support Vector Machine (SVM)

Machine learning uses SVM, a type of supervised learning technique, to solve classification problems. In order to quickly categorize new data points in the future, the SVM algorithm aims to determine the optimal line or decision boundary that can divide the n-dimensional space into classes.

Random Forest (RF)

A supervised learning strategy that, rather than relying on just one decision tree, averages the outcomes from numerous decision trees applied to various subsets of a given data set. The predictions of each tree are used by Random Forest, which then calculates the result based on the votes of most of the predictions.

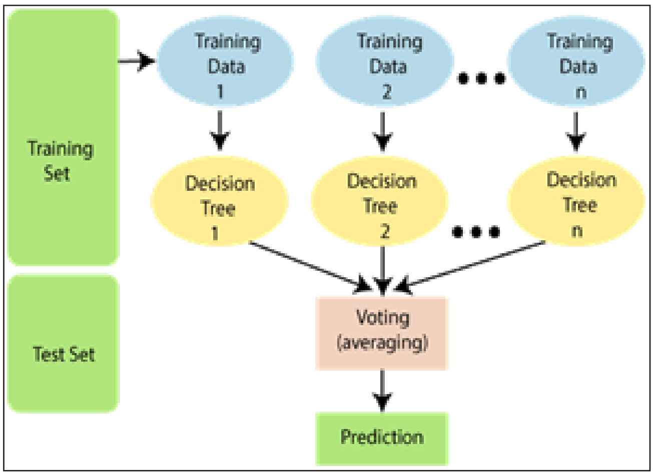


Figure 5.Working of Random Forest

Gradient Boosting Classifier

Gradient Boosting is a gradient function technique that iteratively selects a function that points in the direction of the negative gradient or weak hypothesis to minimize the loss function. It provides a prediction model in the form of a set of weak prediction models like decision trees.

$$F\left(x\right)=\sum_{m=1}^{M}\gamma_m h_m\left(x\right)$$

Here hm(x) represents the fundamental ability of typically underachieving learners. Decision trees of a fixed size are used as weak learners for gradient boosting classifiers.

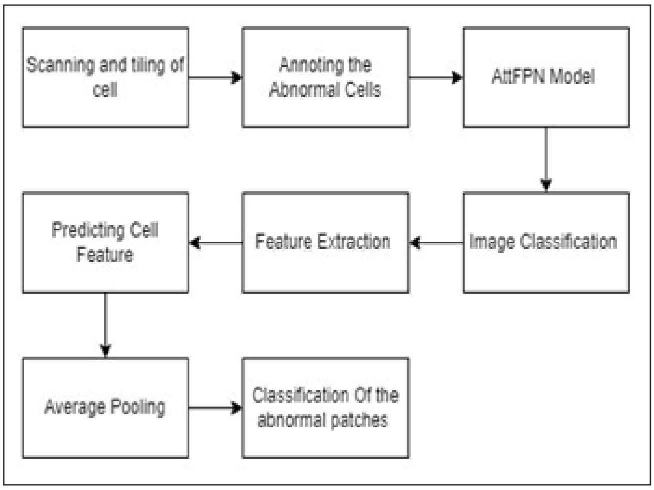


Figure 6.VGG19 Model Architecture

VGG 19

With layers that have already undergone training, advanced CNN VGG19 has a good comprehension of visual properties such as shape, colour, and texture. For difficult classification tasks, the exceptionally deep VGG19 has been trained on a vast array of distinct images. The VGG19 model form has a total of 19 layers.

AttFPN (Attention feature pyramid network)

This strategy had two main parts. The attention module was the first and simulated how pathologists would once read a cervical cytology image. By efficiently refining the extracted data, it then discovers which characteristics to highlight or downplay. Second, to combine better features for identifying aberrant cervical cells at multiple levels, a spatium - based multiscale fusion network based on clinical information was used. Clinical data on the size and morphology of cell distribution of genuine aberrant cervical cells were utilised to develop multiscale network zone recommendations, and cells from abnormal photos of the cancerous cells were used to identify these cells.

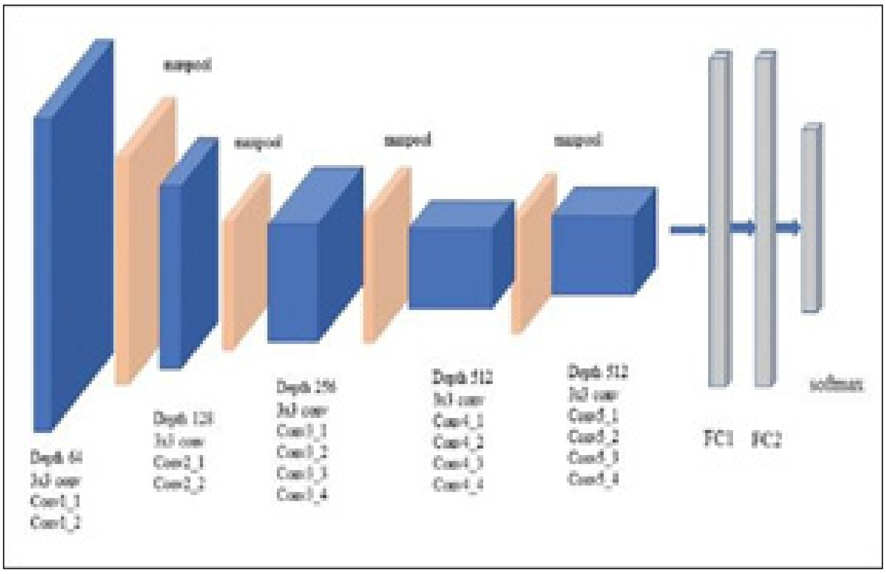


Figure 7.Attention feature pyramid network Flowchart

Table I. Comparison of Results

S.No.	References	Algorithm	Accuracy
1.	Youyi Wu et al.	Balloon snakemodel	-
2.	Davide Chiccoet al.	Probabilistic neural network,Per-ceptron-based neural network, random forest,one rule, anddeci-sion treeclassifier	Random forest MCC=+0.37 and MCC=+0.64
3.	Michał Kruczkowski etal.	RF, XGBoost, Naïve Bayes andCNN	Random Forestand XGBoost provided the highest accracy
4.	Saini S.K., . et al[4]	Colponet	81.353%
5.	Nithya . et al.[5]	SVM and C5.0	97%
6.	Akter L. et al.[6]	Decision Tree, Random Forest, and XGBoost	93.33%
7.	Dhwani Parikh,Vineet Menon[7]	K-Nearest Neighbours, Decsion Trees,and Random	K-Nearest Neighbours hasthe highestaccuracy of

		Forests	82.2%
8.	Kyi Pyar Win et al.[8]	Random forests, bagging ensemble classifier for feature selection	98.27% in two- class classification and 94.09% in five-class classification
9.	Anjali Goyal, Sanjay Kumar Singh[9]	Logistic regression with L1 regularization, SupportVector Machinewith Linear Kernel (svmLK), Gaussian Naïve Bayes Classifier, among others for feature seletion	100% accuracy for logistic regression with L1 regularization, but too much costly in terms of CPU
10.	Tony George et al.,[10]	VGG19(TL) CYENET	VGG19(TL)=7. 3% CYENET =92.3%
11.	Lulu Li et al.[11]	AttFPN	98%
12.	Swati Vijay Shinde, et al.[12]	Simple logistic, BayeNet, Navie Bayes, Random Forest, Random tree, Decision table, Part	Random Forest = + 76%

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