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Deep Learning-Based Classification of Cervical Cancer Variants

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Abstract: Cervical Cancer (CC) arises in the lower, narrow end of the uterus, called the cervix. It is the second deadliest disease amongst women, just after breast cancer. It is curable if detected in early stages. A popular screening technique that assesses abnormalities in cervical cells is the Pap Smear test, it involves microscopic detection of cervical cells. The basic technology used for classifying the stages of cervical cancer is Convolutional Neural Network (CNN) algorithm, which is one of the deep learning methods. By using CNNs, learnt features we can improve accuracy and provide a powerful tool for medical settings to fight cervical cancer.

Index Terms: Deep Learning, Cervical Cancer, Classification, Machine learning algorithms, CNN algorithm

I. Introduction

Computer science has brought an influence in the rapidly changing health industry. It has enabled unprecedented possibilities of detecting the diseases and their treatment through revolutionized technological innovations. Deep Learning is capable enough to bring wide range of opportunities in this domain.

A. Deep Learning (DL)

The DL method was chosen due to its multiple layers of data processing computational models that enable learning by presenting input data through various levels. In the clinical fields cancer diagnoses and type identification the DL approaches are most effective.

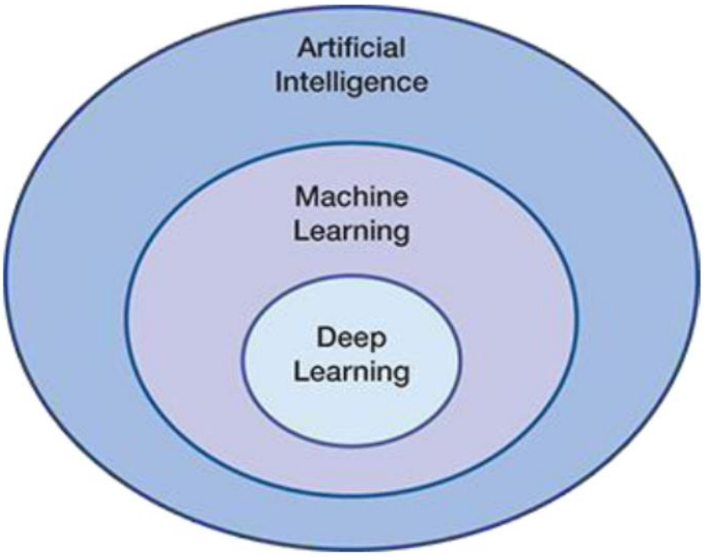


Figure 1:Deep Learning

B. Cervical Cancer (CC)

CC is the cancer that arises in the women's cervix region. Around 350000 deaths are recorded, making the cervical cancer disease the fourth frequent disease amongst women. 94% of deaths occurred in the low and middle-income countries.

The cancer can be treated if caught early. Certain tests, such as Pap smear and cervical biopsy, are often used for diagnosis. Building on this, it allows us to use deep learning tools to detect and treat cancer early.

C. Problem Statement

CC is becoming challenging for the doctors and scientists to detect the cancer in early stages and provide with necessary precautions to lower mortality. The foremost goal is to construct the efficient and effective data driven model techniques for classifying the distinct stages of cervical cancer and put into practice data-driven framework for accurate staging by using comprehensive clinical and diagnostic information, leveraging real-world datasets.

II. Related Works

In [1] the realm of cervical cancer research, the fusion of IoT and AI technologies is employed for predicting gene recurrence, by utilizing LASSO regression for enhanced accuracy in feature selection. This study integrates advanced data handling techniques and adopts the ENSCF framework to analyze patient survival. Leveraging real-time patient data through IoT, the LASSO model identifies key genetic markers, contributing to more precise prognostic assessments. The ENSCF framework further employs network-based approaches, providing a comprehensive understanding of the disease's complexity and enhancing our ability to stratify patients based on molecular characteristics. This interdisciplinary approach showcases the potential of combining IoT and AI for improved insights into recurrent cervical cancer.

In this study, the residual network (ResNets) methoddescribed in [2] was used and showed the best performance in identifying healthy and the detection of pre-cancerous colposcopy cervical cancer images and accurately performing pain diagnosis. However, a notable limitation is the lack of discussion regarding the diagnosis of the three distinct stages of cervical cancer. Despite its success in distinguishing pre-cancerous conditions and healthy states, the ResNet approach may require further refinement to address the specific challenges associated.

Employing Deep Metric Learning (DML) as the method in [3], this study rigorously assesses feature quality and classification performance. The merits lie in the quantitative evaluation of these aspects within a consistent dataset, enhancing the trustworthiness of the results. The occurrence of some misclassifications raises concerns, potentially attributed to absence of proper generalizability.

Utilizing 2D U-Net and 3D U-Net as the educational frameworks in [4], this study leverages automatic segmentation of tumor contours. The merits lie in the application of these advanced models for accurate and automated tumor delineation. However, a notable limitation is the lower quantity of instances used for training, this may occur more frequently when the training and test images are separated. This potential scarcity of training data raises concerns about the generalizability of the models, emphasizing the need for cautious interpretation of results and potential avenues for augmenting the dataset to improve the ability of the segmentation models.

Employing Decision Tree (DT), Support Vector Machine (SVM), and Random Forest (RF) as classification methods in [5], this study observes a notable improvement in terms of the final output. The merits of this approach are reflected in the enhanced accuracy achieved through the combined use of these algorithms. However, a notable limitation arises from the performance variations among individual classification methods when identifying cervical cancer. To overcome this obstacle, it may need further investigation into optimizing the synergy between these classifiers or exploring alternative approaches to ensure consistent and reliable performance across the spectrum of cervical cancer identification tasks.

The [6] research paper focuses on the advancement of synthetic CT imaging for pelvic assessment in cervical cancer patients, with the overarching goal of improving precision in treatment planning and ultimately enhancing patient outcomes. The innovation is present in creating synthetic CT images, offering a non-invasive alternative that not only mitigates radiation exposure for patients but also provides accurate anatomical information crucial for treatment planning. This work represents a significant stride toward optimizing the balance between treatment efficacy and patient safety in the realm of cervical cancer management.

The [7] study utilizes E-GCN, a Convolutional Network with Edge Features, achieving a notable 78.33% classification accuracy. However, its dependency on a large dataset of time- lapsed colposcope images presents a resource-intensive challenge.

III. Methodology

CNN, also known as Convolutional Neural Network, is a technique, in learning that is commonly applied to analyze data like images. It utilizes layers such as convolution neural network layers for sorting data feature extraction layers pooling layers to retain details and fully connected layers for tasks related to classification. These components play a role, in recognizing and organizing phases of cancer.

The key factors used to identify cancer include the intensity of color, the cell boundaries, and the texture. Any alterations in these characteristics will be detected by the DL model, which then determines the cancer stage and assigns a probability score.

In this model, the CNN algorithm is used to classify the stage of cancer with the decent accuracy.

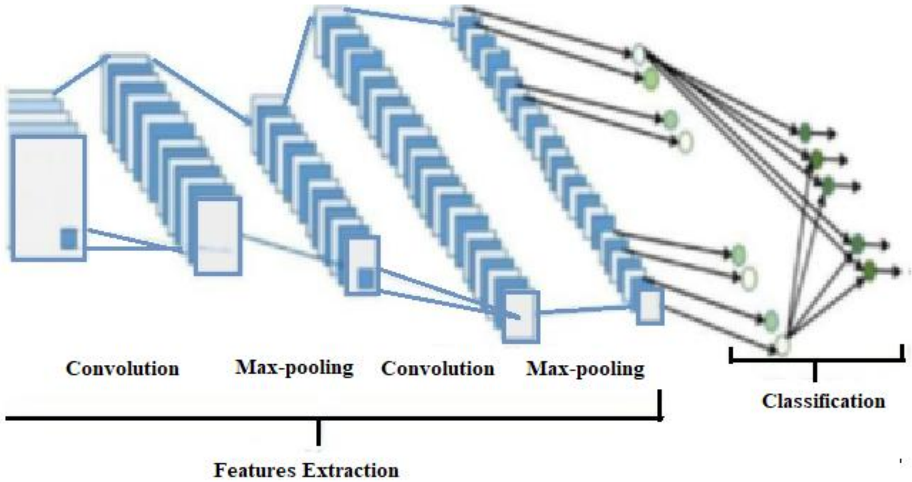


Figure 2.: Convolutional Neural Network Layers

A. Dataset

The dataset contains 500 CT scan images which was collected from a PhD student. It has been broadly divided into two categories: normal and abnormal.

B. Data-Preprocessing

Image pre-processing main idea is an enhancement of the image data by removing the unnecessary distortions and featuring some more features of the image, which possibly important to the subsequent image processing. Its main elements include these three things: a) elimination of noise; b) sharpening of image details; c) visual quality enhancement.

a) Grayscale conversion: Grayscale images contain brightness information, with each pixel value images corresponding to the amount of light. The range is 0 to 255; here "0" represents black and "255" represents white. It simplifies image processing by processing images faster when converting to grayscale. The disadvantage of grayscale conversion is that the color information contained in the original image is lost. However, this can be done, depending on the nature of the job. There are wide variety of ways to achieve transition change: one of the ways is to weight the RGB (red, green, and blue) values with the pixels.

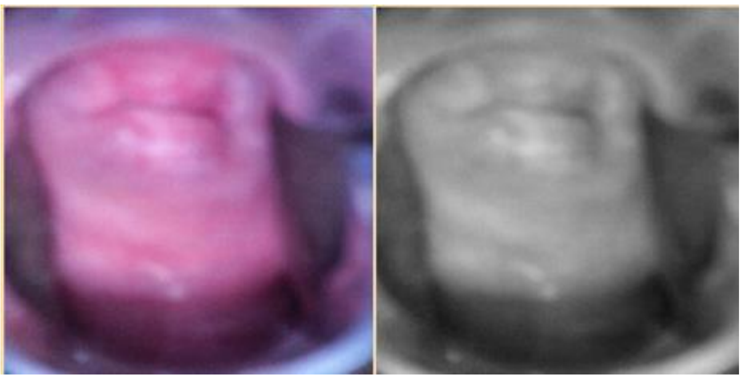
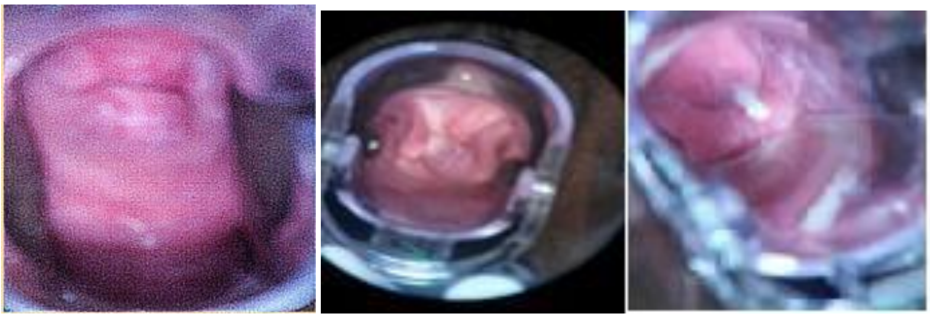


Figure 3.: Grayscale Conversion of CT scanned Cervical Cancer Image

b) Noise Removal: The agenda of noise elimination is to identify and eliminate noise from an image. The challenge lies in distinguishing between image features and those introduced by noise. Noise comprises fluctuations in values. To address this, we employ a filter for noise removal. This filter, which is nonlinear in nature, preserves image edges. It operates by moving a window of length over the image, sorting sample values by magnitude, and outputting the value at the center of the window.



(a) (b)

Figure 4.: (a) Noise Removal and (b) Data Augmentation of CT scanned Cervical Cancer Image

We see here in (c) that in addition, the data augmentation techniques as, rotation, and flipping were also put to the image.

c) Image Enhancement: The purpose of imaging upgrade is to facilitate the visibility of features captured in the image to facilitate image analysis. 'Contrast increase (or statistically enhanced outcome)' is the aim of contrast enhancement.

C. Data Segmentation

After completing the image processing stage, the following task involved isolating the region of the cervical tumor from the surrounding CT images. A grayscale image was generated with its contrast fine-tuned to ensure segmentation.

$$\Sigma_i \Sigma_j (i-j)^2 C(i,j)$$

$$\Sigma_i \Sigma_j C^2(i,j)$$

D. Feature Extraction

Feature extraction is of primary importance, this is when subtle information, maybe hidden within a picture, emerges candidly. We undertake GLCM in documenting the texture of the images. GLCM further brings out the relationship loop between pixels in an image. The grey level co-occurrence matrix (GLCM) imputes significant features by use of the co-occurrence matrix for multi-dimensional characters, e. g. contrast, entropy, energy, homogeneity, correlation, ASM,Cluster-Shade Contrast

a) Energy

$$\Sigma_i \Sigma_j \frac{C(i,j)}{1+|i-j|}$$

b) Homogeneity

Feature extraction (GLCM) aims to simplify the complexity of the image dataset by evaluating values or characteristics that aid, in distinguishing between various images.

c) Training

Forming a dataset with images depicting all the cancer stages was a big part of this work. With the classifiers, the dataset was used for training. The directory had the dataset for the testing procedure stored. In the context of test scenario, the outcome prediction results were used to come up with the chart for classifiers and the test file was worked on with the purpose of enhancing the feature sets in order to give accuracy to the models of image processing.

d) Classification

The hyper-plane which is frequently known as decision border is mainly used by the Convolution Neural Network, a classifier of binary form. The admission standards are considered one of the prime issues. In the high frequency domain CNN carries out the precise classification by proper matching of the non-linear input with that of the output data. The CNN maximizes the minimal distance between distinct classes and kernels are used for the division of classes. In essence, CNN being the classifier uses hyper plane to divide two classes and along with this the border is made maximum between these two. The samples that are nearest to the margin will be selected.

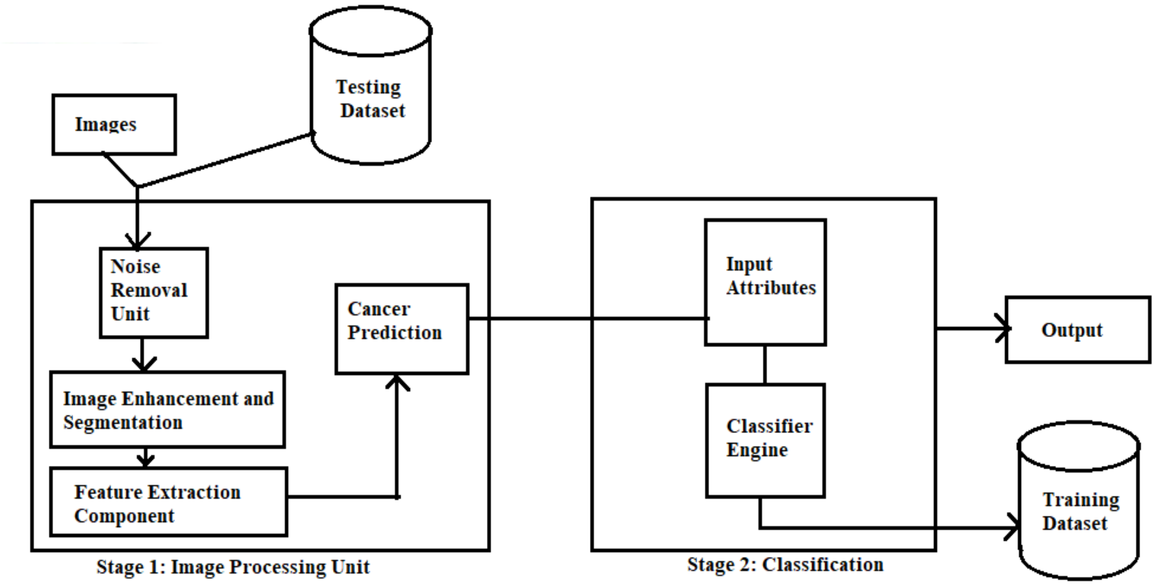


Figure 5.: Architecture diagram of image processing

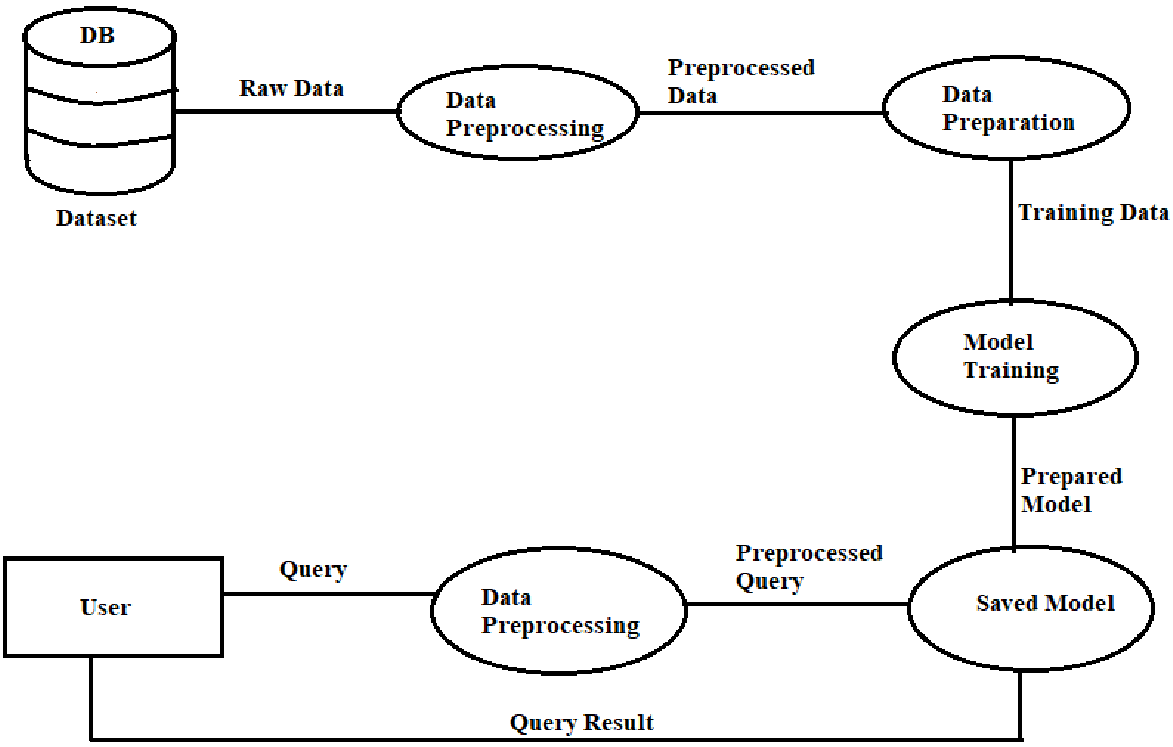
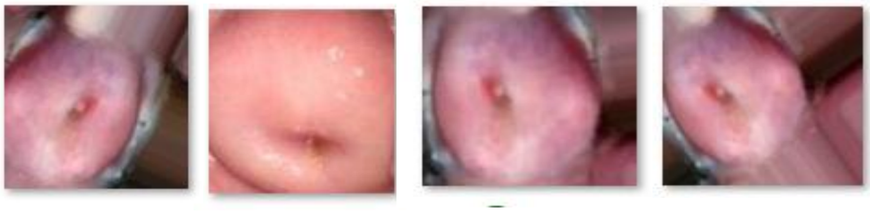
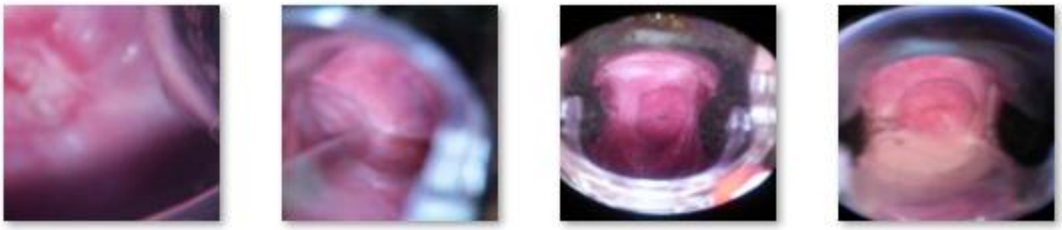


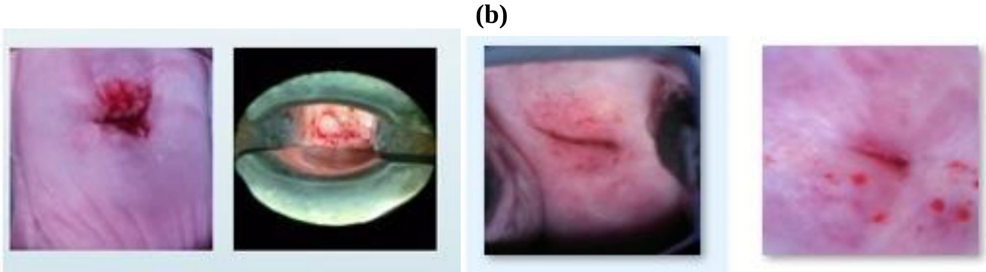
Figure 6.: Data Flow Diagram



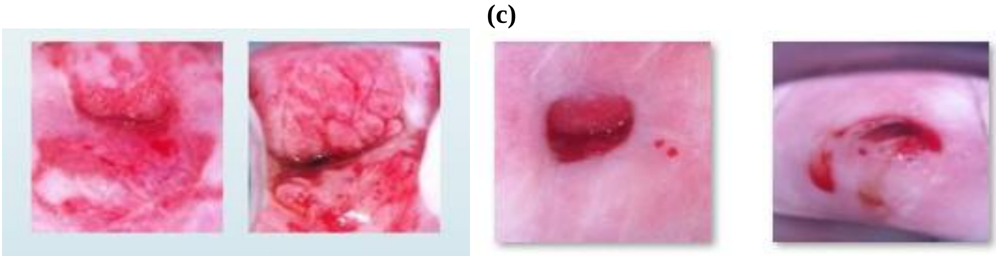
(a)



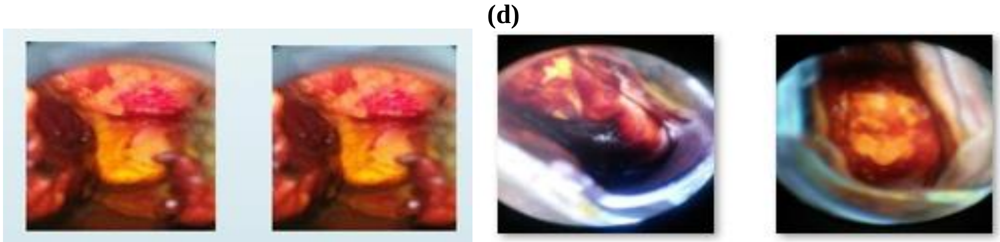
(b)



(c)



(d)



(e)

Figure 7.:(a) Normal Cervix (b) Stage 1 of cancer (c) Stage 2 of cancer (d) Stage 3 of cancer (e) Stage 4 of cancer

III. Implementation

The deep learning method to detect cancer is considered a reliable method. Tkinter a standard Python library is imported for creating GUI (Graphical User Interface) applications, offering a toolkit for building windows, buttons, menus, and other interactive elements. The OpenCV-Python library is used for analyzing the computer applications that provide tools and functions such as image and video processing, target detection and feature extraction. tqdm creates complete tutorials for loops and functions, improving code readability and providing recommendations to improve and work on long term performance. Tflearn a deep learning library built on TensorFlow, offers high-level abstractions and utilities to simplify the work of neural networks for classification, regression, and clustering. Pandas' library of python is imported to handle data manipulation due to its powerful and expressive data structure. Matplotlib is a plotting library used for python programming and hence imported. Label encoders converts the strings to tokens.

Later the path for training and testing is provided to import the dataset. The data. head () function considers the specific dataset and read them. The dataset is checked for null values and specific actions are taken to replace the values.

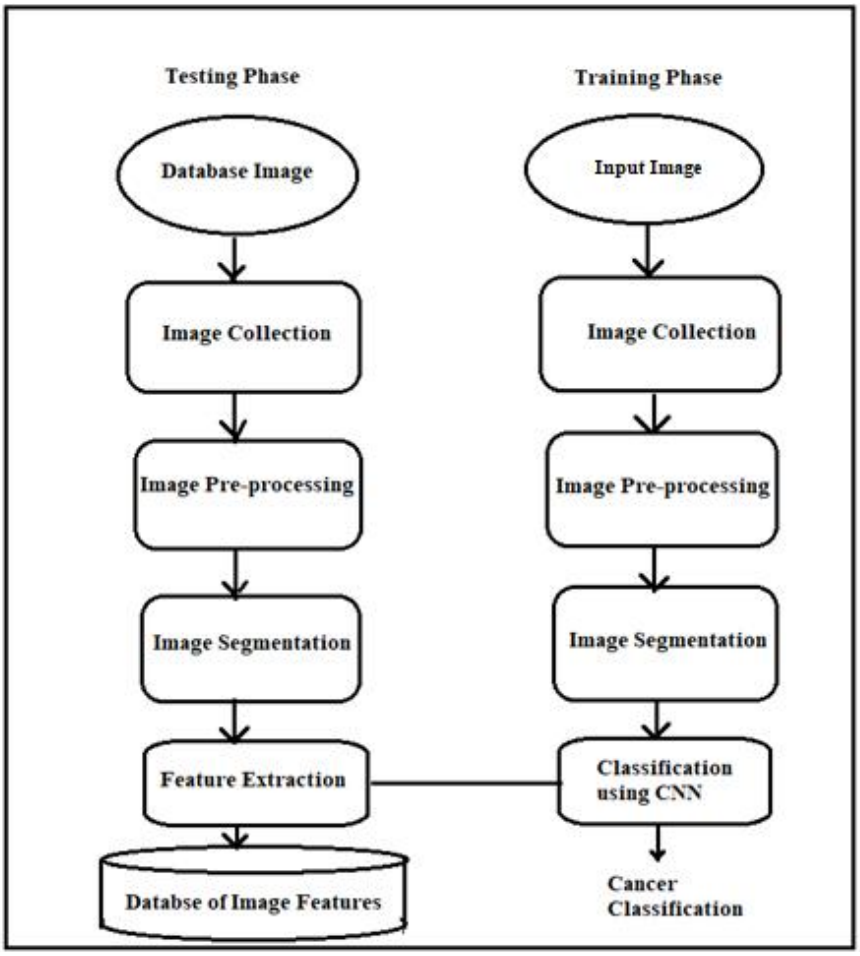
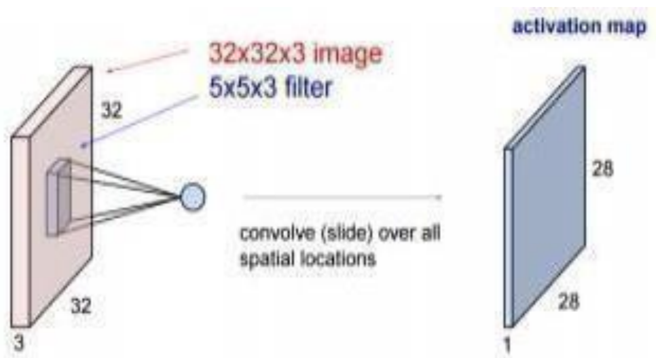


Figure 8.: Data flow Diagram of Training and Testing Phase

The project, Cervical Cancer Classification model uses the three layers of CNN which include convolutional layer, pooling layer, fully connected layer, and activation layer.

A. Convolution Layer

This includes examination of all the images for the model and their representation in the form of a 3x3 matrix. This convolutional feature matrix of an image is called the kernel. Each value in the kernel is called a weight vector.



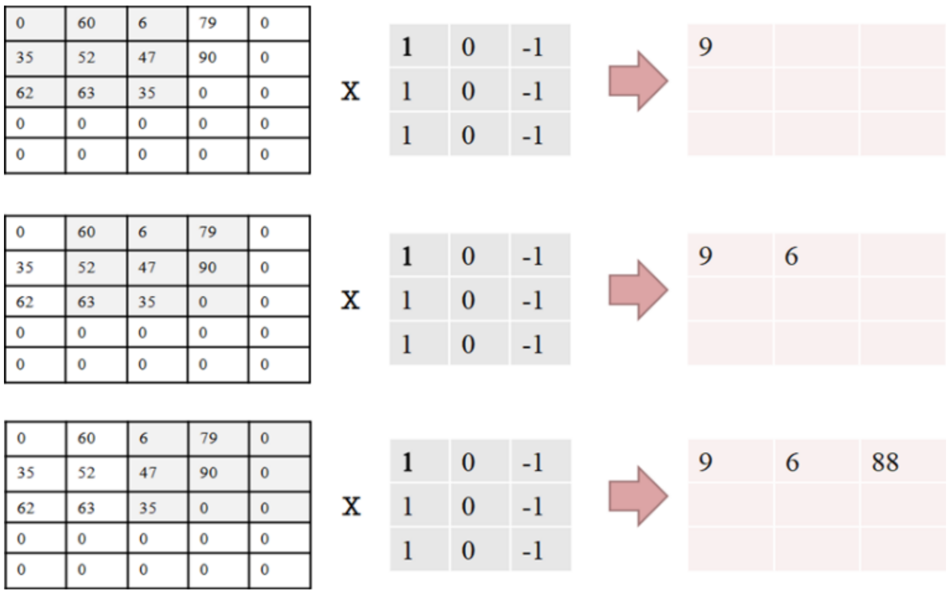


Figure 9.: Matrix images of Convolution Layer

B. Pooling Layer

Here, when the convolution reaches the pooling stage, the picture matrix is divided into four non-overlapping parts. Maximum pooling and average pooling are two variant pooling. Use maximum pooling to maximize the relative matrix field. Use mean pooling for obtaining the mean value in the correlation matrix field. The main advantage of layer pooling makes the computer faster and reduces the effectiveness of overfitting.

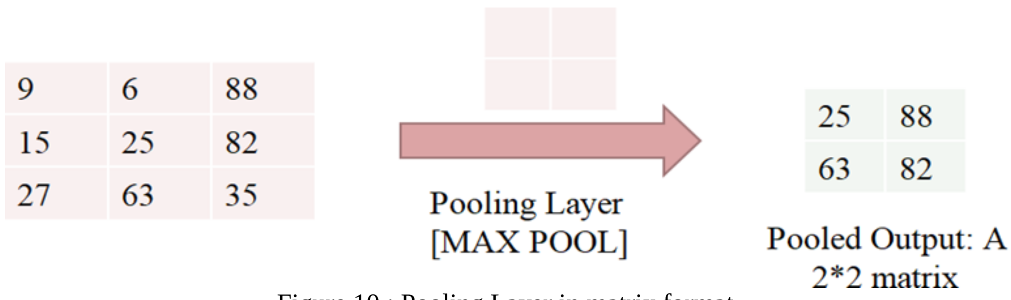


Figure 10.: Pooling Layer in matrix format

C. **Fully Connected Layer**

This set of layer takes the result of previous layer and later flattens them and turns it into single vector for input of further layer.

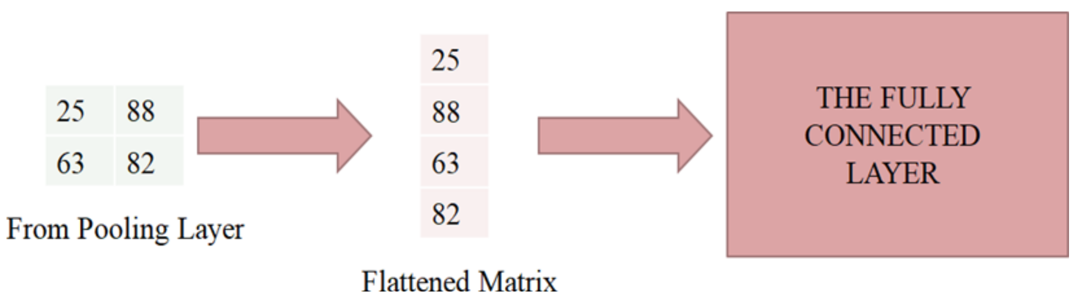


Figure 11.: Fully Connected Layer in matrix format

IV. Conclusion

On analysis it was found that expert-level diagnosis may be achieved with limited training data using a simple, computationally effective, and technique. When appropriately integrated, as done here, with domain knowledge and other more generic techniques, particular the prototypes learned from the recommended methodological involvement could potentially aid supplementary medical appearance fractionation and concealing appeals. To summarize skillful colposcopies enactment, we used characteristic uprooting and elementary contraption algorithms that were acquired with a colposcope for self- operating recognition of cervical pre-malignant. This system, unlike prior approaches, employs morphology gold caliber labels for concealing and does not require fettle care to pre- sorting an area of scrutiny, instead of evaluating the whole cervix to discover areas of attention robotically. The methods diminish specular reflection by preprocessing photos and automatically segmenting a scene's overall sensitivity and specificity.

V. Results

In the realm of cervical cancer classification on the basis of stages, the accuracy rates achieved by Convolutional Neural Networks (CNN) surpassed those of traditional methods such as K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN). The use of CNN has enhanced some essential factors like those of sensitivity and specificity. It is one of the crucial factors for the detection of cancerous and non-cancerous cells, the parameters used for classification was mainly based on cell boundary and diameter.

By using CNN model, we achieved the accuracy rate of 93.5 percent with 2000 iterations. This thus provided the accurate probability score by reducing the risk of misclassification and false positives.

ACRONYMS

AI	Artificial Intelligence
ML	Machine Learning
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
NN	Neural Network
ReLU	Rectified Linear Unit

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