CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview

Cervical Cancer (CC) is the development of cells that start in the cervix i.e., the bottom portion of the uterus, which is connected to the vagina. CC is one among the cancers that primarily affect women due to various reasons such as long-lasting infections, unavailability of screening facilities, and lack of awareness. Prolonged infection accumulated by high-risk factors facilitates HPV to virtually cause all CC. Nearly all CC cases are related to HPV infection; through sexual contact, an exceedingly common virus is transmitted. However, most HPV-related infections resolve spontaneously without any symptoms, but obstinate infection can lead to CC in women.

Hence, the detection of CC is tremendously required to avoid life-threatening situations. In most cases, non-identifying CC can result in various problems, including death. Thus, recognizing CC plays a substantial role in averting further consequences. In general, different techniques, involving manual approaches, are utilized, that includes Pap smear test, HPV testing, visual inspection with acetic acid (VIA), and histopathology. However, these existing tests help in early intervention and treatment of CC. Despite its advantages, the performance of manual testing is hindered by certain disadvantages, which is showcased in Figure 3.1.

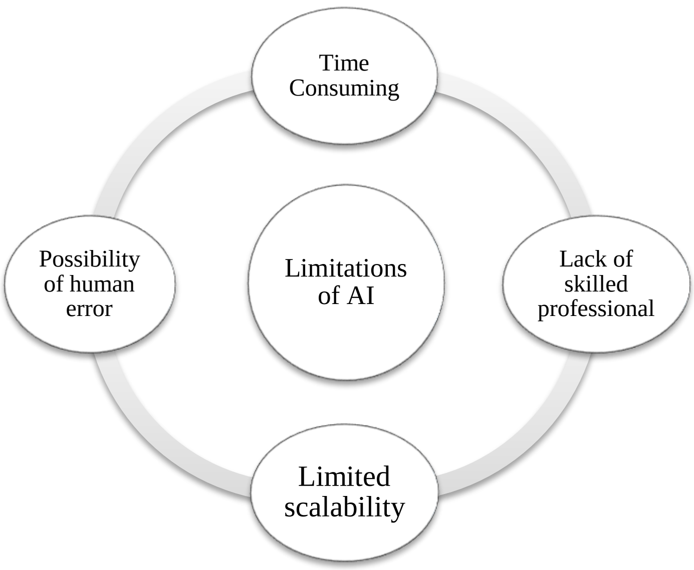

Figure 3.1 Limitations of Manual Techniques

However, these are some of the disadvantages in utilizing manual approaches. Consequently, it can be overcome by considering AI-based techniques, since AI approaches help in combating the drawbacks faced by considering manual techniques for CC detection. Some of the advantages include,

- Magnified and highly illuminated visual evaluation of the cervix
- Analyzing huge amounts of data easily
- Reliable outcome
- Cost-effective

Even though, existing AI-based solution achieves better detection rate, there are certain limitations exist, involving the low accuracy in past state-of-the-art methods, which can shelve the effective performance offered by these algorithms. Thus, the proposed work using enhanced techniques is emphasized to improve the performance of essential models based on effective and precise detection of CC using two different datasets. Therefore, the subsequent section elaborates on model behavior in the proposed mechanism for the effective detection of CC cells.

3.2 Methodology

Research methodology shows the proposed mechanism involving three different proposed models for enhanced CC detection. Figure 3.2 illustrates the involved process in the proposed mechanism for the classification of CC cells.

Pre-processing: This initial step enhances the image quality suitable for subsequent analysis. It incorporates common techniques such as contrast enhancement, noise reduction, and color normalization. The goal is to improve the visibility of important features while suppressing irrelevant information that could interfere with analysis.

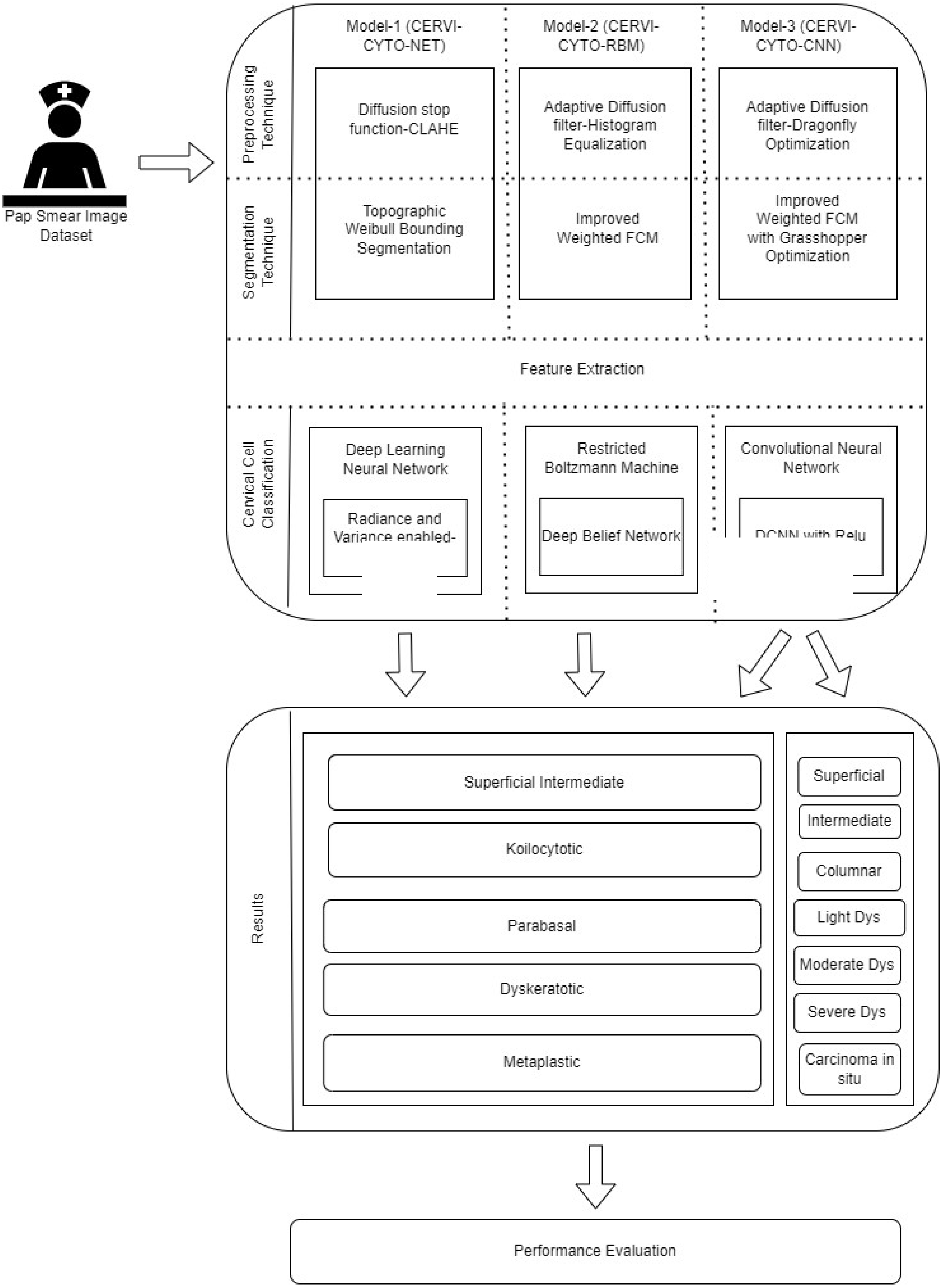

Figure 3.2 Overall flow of all three models

Segmentation: Following pre-processing, segmentation isolates the regions of interest-typically the cervical cells—from the background. Advanced techniques like thresholding, edge detection, or region-based approaches can be employed. The accuracy of segmentation influences the performance of the entire model, as it determines which parts of the image are required to be further analyzed.

Feature Extraction: After segmentation, feature extraction simplifies the representation of the images by reducing their dimensionality. It identifies and quantifies the key characteristics of cells, including shape, size, texture, and color. The extracted features capture the essential information necessary for discerning between different cell types and conditions.

Classification: The final step is the classification of the cells on the basis of the extracted features. ML classifiers like support vector machines (SVM), random forests, or neural networks can be utilized. In the context of deep learning, CNNs are predominantly efficacious as they can automatically learn hierarchical feature representations from the data.

Each of these steps has a very important role in the detection of CC cells and evaluates using the overall performance of the model. Pre-processing assures that the input data is of high quality. Segmentation makes certain that the model focus is on the most pertinent parts of the image. Feature extraction minimizes computational complexity and assists to identify the most discriminative features. Finally, these features influence the classification performance to make predictions about the presence or absence of disease.

By carefully designing and tuning each stage, the model facilitates in achieving high accuracy in classifying cervical cells, which is vital for effective screening and early detection of cervical cancer. It’s also important to note that the choice of algorithms and techniques at each stage necessitates the guidance from specific characteristics of the medical images and the requirements of the task at hand.

The study introduces three distinct models for classifying cervical cells into single cell and multi-cell categories. The single cell category is further divided into seven classes namely Superficial, Intermediate, Columnar, Light_dysplastic, Moderate_dysplastic, Severe_dysplastic, Carcinoma_in_situ. The multi-cell category includes five classes: superficial intermediate, Koilocytotic, Parabasal, Dyskeratotic, and Metaplastic.

3.2.1 Model 1: CERVI-CYTO-NET

The objective of model 1 is to execute the automated diagnosis of cc by using TWBS and RVDLNN.

The steps involved in model 1 are specified below:

Pre-processing: A Diffusion Stop Function-based Contrast Limited Adaptive Histogram Equalization (DSF-CLAHE) is utilized to enhance image contrast while preserving edges.

Segmentation: Employs Topographic Weibull Bounding Segmentation (TWBS) technique that aims to leverage the shape and texture information to isolate individual cells from the background.

Feature Extraction and Selection: After segmentation, feature extraction simplifies the representation of the images by reducing their dimensionality. It identifies and quantifies the key characteristics of cells, including shape, size, texture, and color. The extracted features capture the essential information necessary for discerning between different cell types and conditions. The features are selected using Chaos and Exponential Scale based Butterfly Optimization Algorithm (CES-BOA).

Classification: A Radiance and Variance enabled Deep Learning Neural Network (RVDLNN) is adopted to incorporate radiance and variance features, which could help to distinguish different cell types based on their textural and intensity variations.

The working mechanism of Model 1 is explained below:

Model 1 using TWBS and RVDLNN in PAP SMEAR images are depicted in Figure 3.3 that illustrates the process involved in the classification of cervix cells.

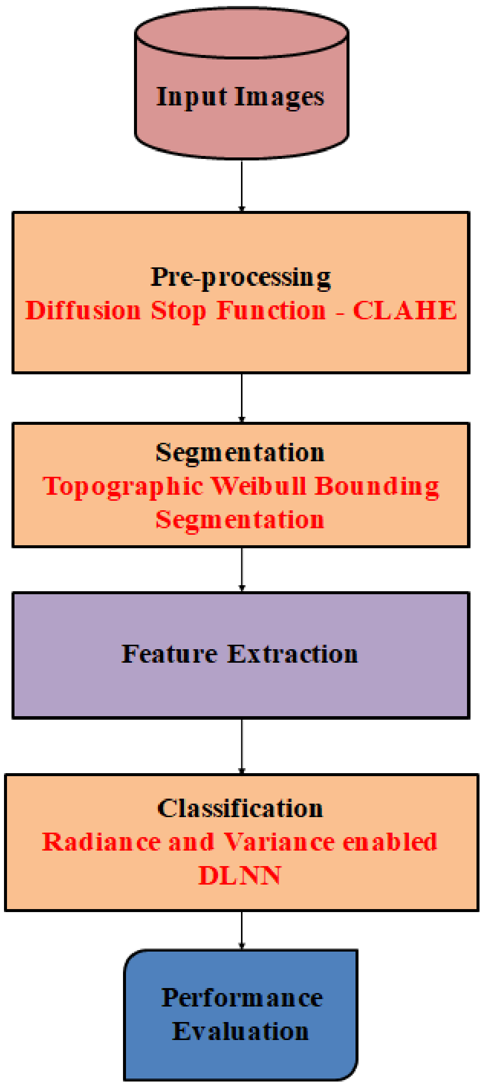

Figure 3.3 Working mechanism of Model 1

Initially, the working model 1 incorporates pre-processing technique to process the images from 2 different datasets. Then, the datasets are pre-processed by using the DSF-CLAHE algorithm in which the image colors are changed, and the input image contrast is improved. It divides the image to numerous sub-sections called tiles, and after applying histogram equalization to each of the split images, by utilizing bilinear interpolation, neighboring tiles are joined, thereby eliminating the artificial border. Subsequently, segmentation using TWBS is proposed to encompass three major steps. In which cell mass is detected from the image using an enhanced Simple Linear Iterative Clustering (SLIC) algorithm in stage 1. Nuclei from the image are identified by using local threshold topography in stage 2, and finally, the cytoplasm is detected and marked using Weibull

Bounding Segmentation in stage 3. These stages play a crucial role in segmenting the images properly. After segmentation, feature extraction is performed to select the significant features. Eventually, the input, the selected features are given to the RVDLNN model for classifying different types of CC cells, and the efficacy of the proposed model is assessed using different metrics.

3.2.2 Model 2: CERVI-CYTO-RBM

The objective of model 2 is a versatile detection of cc with i-WFCM for segmenting the images and deep learning-based RBM for classification.

Model 2 using enhanced weighted Fuzzy C-means (FCM) with RBM-DBN in Pap smear images are depicted in Figure 3.4 to illustrate the process involved in the classification of cervix cells.

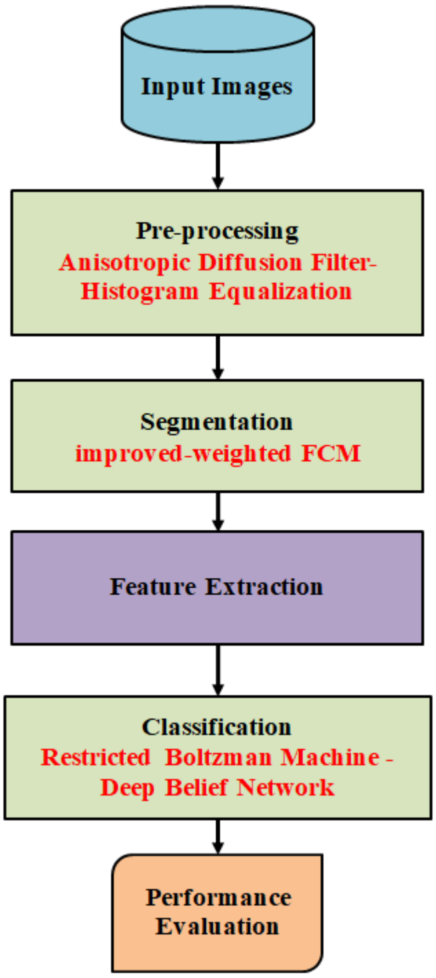

Figure 3.4 Working mechanism of Model 2

The steps involved in Model 2 are specified below:

Pre-processing: An Adaptive Diffusion Filter (ADF) combined with histogram equalization is incorporated to balance the image brightness and enhance details.

Segmentation: An improved Weighted Fuzzy C-Means (i-WFCM) clustering algorithm improves the precise cell segmentation by considering the degree of membership of pixels to clusters.

Feature Extraction: Built-in functions are used to extract the shape, size, textural, and geometrical features.

Classification: A Restricted Boltzmann Machine (RBM) with a Deep Belief Network (DBN) is utilized for feature extraction and classification, providing a probabilistic framework that could capture complex cell characteristics.

The working procedure of model 2 is explained below:

Initially, the dataset containing images are loaded, and pre-processed using ADF and Adaptive Histogram Equalization (AHE). ADF aids in eliminating unwanted noise from the image with the aim of accomplishing high-quality outcomes, and AHE has been incorporated to enhance and to generate the images more efficient. After the pre-processing process, segmentation is proceeded using the i-WFCM approach. i-WFCM is implemented to segment the Region of Interest (RoI) with the purpose of overcoming uneven forms and the composite nature of histology images. After segmentation, feature extraction is applied to extract textural-based features. Finally, classification using the RBM-DBN model is incorporated, and the RBM-DBN model is compared with existing DenseNet201, ResNet50V2, AlexNet, and model 1 RV-DLNN, and the efficacy of the proposed model is defined by using evaluation metrics.

3.2.3 Model 3: CERVI-CYTO-CNN

The objective of MODEL 3 is to detect CC using novel segmentation and Deep Convolutional-based Neural Network with ReLU.

Figure 3.5 depicts Model 3 using Improved weighted FCM with GOA and Deep CNN with ReLU that illustrates the process involved in classifying cervix cells.

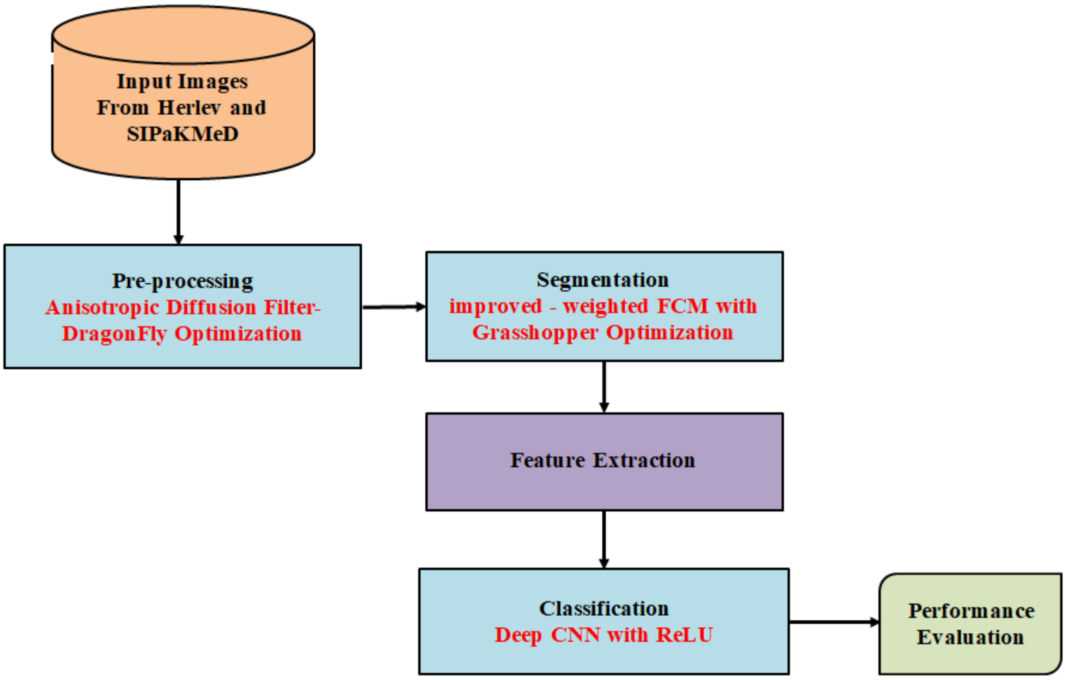

Figure 3.5 Working mechanism of Model 3

The steps involved in Model-3 are specified below:

Pre-processing: ADF with dragonfly optimization is a novel approach that is integrated to optimize the filter parameters for better noise reduction and detail preservation.

Segmentation: i-WFCM is combined with Grasshopper Optimization Algorithm (GOA) that implicitly enhancing the segmentation process by optimizing the clustering parameters.

Feature Extraction: Built-in functions are used to extract shape, size, GLCM and Haralick features.

Classification: A Deep Convolutional Neural Network (DCNN) with Rectified Linear Unit (ReLU) activation functions is employed for their known effectiveness in avoiding the vanishing gradient problem and accelerating the training of deep networks.

The working procedure of Model 3 is explained below:

The steps involved in Model 3 are similar to Model 1 and Model 2. However, pre-processing techniques containing ADF and dragonfly optimization is utilized for optimal decision-making process which can be performed at the end to recognize the ideal edges of the images. Correspondingly, segmentation is done using improved weighted FCM, which is similar to model 2; however, in model 3, improved-weighted FCM is performed using GOA. The integration of GOA has a major objective in tuning the weighted factor for the clustering center without making the computation a tedious process. In the next step, feature extraction is employed, where important features are extracted. Finally, the classification of the model focuses on utilizing Deep CNN with ReLU activation function, where the Deep CNN model employed in the proposed work includes CL (Convolutional Layer), PL (Pooling Layer), FCL (Fully Connected Layer), and softmax layer. The incorporation of these layers, along with ReLU, intended to classify CC cells better. Moreover, the proposed Deep CNN with ReLU model is compared with the existing models like DenseNet201, ResNet50V2, AlexNet, RVDLNN (Model 1), and RDM-DBN (Model 2). Moreover, the efficacy of the proposed work is evaluated by implementing different metrics and evaluated using both datasets for better assessment of the proposed work.

It is crucial for each model to progressively incorporate more sophisticated techniques that can effectively improve the accuracy and reliability of classification, in case of early detection and treatment of cervical cancer. The application of diverse pre-processing, segmentation, and classification methods exhibits a comprehensive approach to combat the challenges encountered by the complex nature of medical images. These three models are used to classify CC cells and effectively prevent life-threatening situations. Eventually, the overall performance of the models is assessed with the use of measures like,

- Accuracy
- Precision
- Recall
- F1 score

3.3. Summary

Chapter 3 details the methodology involved in the automated detection of cervical cancer. Two datasets namely SIPaKMed and Herlev datasets are used. Three distinct models are proposed for the classification of images from Pap smear tests. The pre-processing, segmentation, feature extraction, and classification stages of each model are improved gradually to get the best results for CC classification by evaluating the results using the performance measures.