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Abstract within 300 words:

Cervical cancer (CC) is the most significant contagious disease possessing women's health by infecting Human PapillomaVirus (HPV) in cervix. Considering, the life daring outcomes of cervical cancer in later stage, early detection is considered crucial. However, past studies employed manual methods like Manual Liquid-based Cytology (MLBC) and Visual Inspection with Acetic acid (VIA) to identify cancerous cells. Meanwhile, the promising limitations including a high error rate, labor-intensive processes, and the need for specialized expertise have been witnessed in existing studies.

Furthermore, Artificial Intelligence (AI)-based solutions are explored in this study to overcome the above mentioned shortcomings. Since, AI models are capable of analysing huge volume of datasets to achieve precise results, it showcase more accurate detection and classification of cervical cancer cells. At present, the AI-based solution for cervical cancer detection and classification has reported suboptimal accuracy in their models. The major aim of this research is to enhance the accuracy of AI-based solution for CC detection using enhanced Deep Learning (DL) models. Three DL models have been enhanced using dissimilar pre-processing and segmentation technique with three distinct mechanisms for accurate classification of cervical cancer cells. These models are evaluated using two datasets: the Herlev dataset used for classification of single-cell images and SIPaKMeD for multi-cell classification in cervical cancer. The methodology encompasses four key stages in three models for detection and classification of cervical cancer: pre-processing, segmentation, feature extraction, and classification. The three models for CC detection and classification are described below. In Model-1, pre-processing based on diffusion stop function using Contrast Limited Adaptive Histogram Equalization (CLAHE) is utilized along with Topographic Weibull bounding-based segmentation, and segmented image is trained using radiance and variance enabled Deep Learning Neural Network for detection and classification. Model-2 pre-processes by employing the combination of Anisotropic Diffusion Filter (ADF) – histogram-based pre-processing and improved-Weighted Fuzzy C-Means (i-WFCM) - based segmentation; the CC is detected and classified using Restricted Boltzmann machine –Deep Belief Network (RBM-DBN). Model-3 performs ADFDragon Fly Optimization-based pre-processing along i-WFCM with Grasshopper Optimization Algorithm (GOA) -based segmentation

techniques; Further, Deep Convolutional Neural Network with Rectified Linear Unit (DCNN with ReLU) is incorporated for classification. These models classify the single cell images from Herlev dataset into 7 classes; superficial, intermediate, columnar, light, moderate, severe, and carcinoma. Whereas multi-cell images from SiPaKMed dataset into 5 classes; superficial, koliocytotic, parabasal, dyskeratotic, and metaplastic. In addition, the proposed three models are evaluated using different performance measures namely accuracy, precision, recall and F1-measure. Out of the three models Model-3 achieves better performance than other models with 97.2% accuracy, 91.3 % precison, 96.9 % recall, and 94.02 % Fmeasue for multi-cell Classification; in contrast, model-3 achieved 96.7% accuracy, 85.1 % precision, 95.2 % recall, and 89.8 % F-measure for single cell classification in cervical cancer detection. However, evaluating the present research work using real images in a software application could aid the medical professionals in real-time for identifying the cancerous cells with the aim of saving patients' lives lynching in cervical cancer disease.

i) Major objectives :

- To enhance the identification and classification of cervical cancer in pap smear images using Deep Convolutional Neural Network Deep Learning techniques that are capable of categorizing cell samples from pap smear tests into normal or abnormal consisting of various classes by integrating image pre-processing, image segmentation, and feature-based classification methods, and evaluate the performance in terms of accuracy, precision, recall, and F-measure.
- To preprocess and segment the image datasets using Contrast Limited Adaptive Histogram Equalization based Diffusion Stop Function and Topographic Weibull Bounding Segmentation for further multi-class classification using Radiance and Variance enabled Deep Learning Neural Networks for CC cell detection.
- To combine Anisotropic Diffusion Filter –Histogram Equalization based pre-processing technique and improved - Weighted Fuzzy C-Means based segmentation for further CC cell detection and classification using Restricted Boltzmann Machine in pap smear images.
- To combine Anisotropic Diffusion Filter –Dragonfly Optimization based pre-processing technique and improved - Weighted Fuzzy - C Means –Grasshopper Optimization Algorithm based segmentation in image dataset for further CC cell

detection and classification using Deep-Convolutional Neural Network with Rectified Liner Unit.

- To compare the performance of all three models with other state-of-the-art methods to find the best among them for cervical cancer cell detection with a higher performance.

ii) Methodology :

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.

Initially, the working model 1 incorporates pre-processing technique to process the images from 2 different datasets. Different datasets helps the models to understand the features more thus improving the accuracy. Training the models on variable datasets helps the models to perform better during test phase as it have already learned from various classes of images. Variations in datasets can reduce overfitting also. 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.

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.

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.

iii) Findings:

In the First model, an automatic identification of cervical cancer through TWBS with RVDLNN in Pap smear images was proposed. The method included numerous processes, such as pre-processing, fragment removal, tramped cytoplasm separation, the partition of the nucleus, extraction and selection of features, and classification. Subsequently, the investigation exploration was achieved wherein the efficiency exploration with the absolute examination of the projected methods were completed regards with certain performance measures so as to authenticate the efficacy of the projected procedure. The advanced method could control several indecisions with condensed further promising outcomes. The openly available datasets, named Herlev dataset and SIPaKMeD dataset, were utilized in this study, wherein the projected technique achieved an accuracy of 92.73%, precision of 71.15%, recall of 88.10% and F-measure of 78.72% for single cell and accuracy of 93.08%, precision of 82.61%, recall of 97.69%, and F-measure of 85.07% for multi-cell classification. Generally, the proposed cervical cancer recognition outperformed the prevailing advanced approaches and also remained further dependable and forceful.

Correspondingly, in the second model, DL-based RBM classification was incorporated for identification of cervical cancer through the Pap smear Test. Besides, an Anisotropic Diffusion Filter by means of Histogram Equalization utilized for reduction of the disorder by reducing the boundaries that influences the improvement of dissimilar images which aimed at improved segmentation. Hence, an i-WFCM was implemented to define the optimum cluster center of an image in the segmentation that has led towards the extraction of the features proficiently. In addition, the RBM classifier was employed for classification. While associated with additional classifiers such as DenseNet201, ResNet50V2, AlexNet, RVDLNN, and DBN, the outcome for proposed RBM-DBN attained 95.27% accuracy, 95.86% precision, 79.59% recall, and 85.71% F-measure for single cell and 95.5% accuracy, 87.14% precision, 93.85% recall, and 90.37% F-measure for multi-cell.

In the third model, the proposed work essentially concentrated on the finding of cervical cancer in the former phase. The noise in the cervical image was pre-processed by an Anisotropic Diffusion filter. Where, the filter weights were enhanced using Dragonfly optimization (DA). Consequently, the edges were conserved, and correspondingly, the noise became compact. Besides, depending on the pre-processed image, improved - Weighted FCM with Grasshopper optimization algorithm was employed for segmentation. The desired portions of the segmented cervical cancer image were extracted and selected for further analysis. Through the support of Deep CNN with ReLU as an activation function, the features were classified and the classification label of cervical cancer was identified efficiently. Here, the projected Deep CNN with ReLU accomplished an accuracy of 96.73%, precision of 95.24%, recall of 85.11%, and F-measure of 89.89% for single cell and an accuracy of 97.23%, precision of 91.30%, recall of 96.92%, and recall of 94.03% for multi-cell and compared with further prevailing classifiers aimed at cervical cancer classification.

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