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ADVANCING CERVICAL CANCER DETECTION AND EARLY DIAGNOSIS WITH RESNEXT-BASED TRANSFER LEARNING

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ABSTRACT

Cervical cancer is the fourth leading cause of cancer-related deaths among women worldwide, with mortality rates projected to rise significantly by 2030. Despite being highly preventable and treatable when detected in early stage. Previous studies have compared DL-based models with conventional screening methods; however, their performance in detecting early-stage cervical cancer has been poor. This work introduces a new DL-based method for cervical cancer detection using a colposcopy dataset, which involves three simple stages: image enhancement, feature selection, and classification. Image enhancement methods are first used to improve the quality of colposcopy images, thus making feature extraction better, followed by feature selection using simulated annealing to identify the most relevant features for classification. The features are then used to train a ResXNet classifier, achieving an accuracy of 98%. The proposed model is compared with state-of-the-art deep learning models, including VGG16 and ResNet-50, the results demonstrate that the proposed model as achieved improved performance in terms of accuracy and efficiency.
Keywords: *Cervical Cancer, ResNeXt, VGG16, ResNet-50, Transfer Learning*

1. INTRODUCTION

Cervical cancer is second most prevalent type of cancer in women, caused by abnormal cell growth in the cervix, an important reproductive anatomical part. Globally, approximately 570,000 females had a cervical cancer diagnosis in 2022, which was responsible for roughly 311,000 female fatalities[1]. It's impossible to overstate significance of early detection, screening methods including Pap smears, colposcopies, as well as Human Papillomavirus (HPV) testing are used to detect any dangers and facilitate prompt intervention. The production of viral oncogenic proteins E6 as well as E7, which deactivate the tumour suppressor proteins p53 along with pRb, is related to development of cervical cancer[2].Proliferation of continuous cells is encouraged by this inactivation, raising the possibility of DNA damage accumulation that may ultimately result in cervical cancer. Examining the cervix for the presence of cancerous cells or abnormal tissues is known as cervical cancer screening. Usually commencing with precancerous alterations among cervix cells, cervical cancer progresses gradually over several years. It is often possible to treat these precancerous alterations before they develop into malignancy[3]. Cervical cancer can be fatal if treatment is not received, and might spread to other areas of body, like lungs, bladder, as well as rectum. Various kinds of cervical cancer each have distinct traits requiring specific diagnostic techniques. Classification includes:

- Normal: Cervical images that exhibit normal characteristics and display no indications of malignancy or precancerous disorders.
- Benign or Non-malignant Changes: Cervical images displaying benign alterations, including inflammation, infections, or cysts.
- Pre-Cancer: Images of the cervix depicting the initial phases of cancer progression, particularly Cervical Intraepithelial Neoplasia (CIN).
- Cancer: Cervical images depicting malignant changes, including squamous cell carcinoma,

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adenocarcinoma, or Aden squamous carcinoma.

The primary therapies for cervical cancer are chemotherapy, radiation therapy, as well as surgery, based on the cancer's location and stage[4]. Cervical cancer patient survival can be considerably increased by early detection and diagnosis. As seen in Figure.1, the various stages indicate the severity of the disease according to their stages, which is dependent on the amount of cancer existing in the body and its location at the time of diagnosis. Abnormal vaginal bleeding, atypical vaginal discharge, early menopause, vaginal narrowing, and lymphoedema are some of the symptoms and indicators of cervical cancer[6]. CIN is an abbreviation that represents "Cervical Intraepithelial Neoplasia." It alludes to anomalous alterations in the cervix's cell surface. These alterations are not cancer, but if left untreated, they may develop into it. When detected by cervical cancer screening, CIN denotes an abnormal alteration in cervix[7].

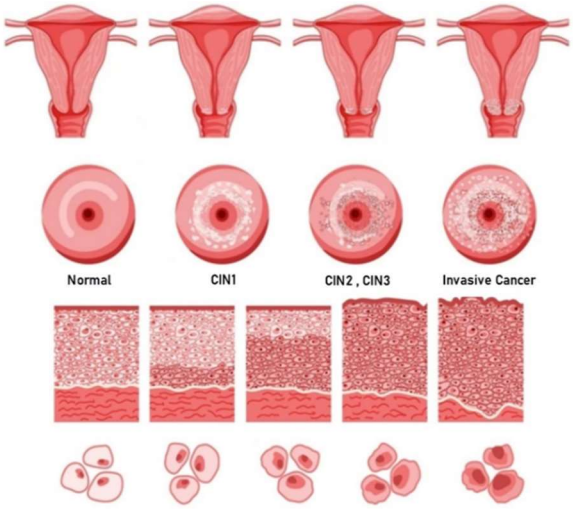

Figure.1. Different Stages of Cervical Cancer

There are three main grades of CIN

- **CIN1 (Mild Dysplasia)**
  This is the mildest form of abnormal cell changes. It indicates a little abnormality of the cells on the cervix's surface. In many cases, CIN1 will go away on its own without treatment. It's monitored closely through Pap smears and may not require immediate intervention.
- **CIN2 (Moderate Dysplasia)**
  CIN2 indicates a moderate degree of abnormal cell changes. It's a more advanced stage than CIN1. While some cases of CIN2 might regress on their own, treatment is often recommended to prevent progression to a more severe stage.
- **CIN3 (Severe Dysplasia or Carcinoma In Situ)**
  CIN3 is the most advanced form of abnormal cell changes before they become cancerous. The cells in CIN3 are highly abnormal and may be close to becoming invasive cancer. Treatment is typically recommended to remove or destroy these abnormal cells. Early identification of cervical cancer has become crucial for effective therapeutic management of patients. Converting biological data into useful knowledge is a critical issue. Considering this, DL has now become a useful technology that uses parallel computing power.

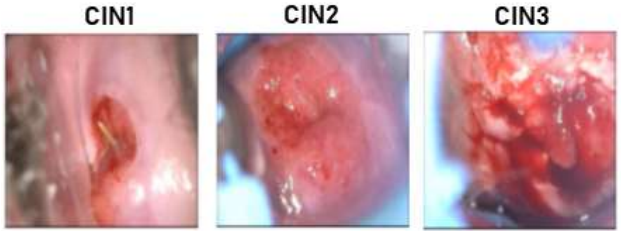

Figure.2. Three main grades of Cervical Intraepithelial Neoplasia (CIN)

For many years, cancer researchers have used a variety of methods, encompassing support vector machines (SVM), Bayesian Networks, Decision Trees, as well as Artificial Neural Networks (ANN), to make precise decisions in accordance with predictive models[8].

The following are the research's main contributions,

- To improve image quality, the Enhanced CLAHE model is used, data augmentation techniques are applied, and images are resized as needed.
- Simulated annealing is used for feature selection to identify the most relevant features for classification.
- These attributes are then to train ResNeXt classifier, which classifies cervical images as either normal or abnormal.

Several experiments were conducted on the Malhari Colposcopy Dataset. The experimental results demonstrate that the proposed framework outperforms all state-of-the-art models in terms of accuracy and efficiency. The remaining sections are organized as follows: Section 2 presents the literature review, while Section 3 discusses the

dataset and initial findings. Section 4 outlines the proposed methodology, followed by Section 5, which examines the results and discussions. Finally, Section 6 concludes the study by summarizing the findings and suggesting directions for future research.

2. RELATED WORK

This section examines few currently employed DL methods for classifying cervical cancer diagnoses.

A notable study by Jhingran et al. [8] offers comprehensive insights into cancers of the cervix, vulva, and vagina. A fundamental resource for comprehending the pathophysiology, epidemiology, and clinical treatment of cervical cancer is this work. Importance of early detection along with precise diagnosis in enhancing patient outcomes is emphasized.

For the categorization of cervical cancer, Alyafeai and Ghouti [9] offer a completely automated DL pipeline. In addition to lowering workload for medical practitioners, their research demonstrates how well DL techniques perform to automate the classification process and increase diagnosis accuracy. Employment of DL models, encompassing convolutional neural networks (CNNs), yields promising outcomes in classification of cervical cancer.

Yang et al. [10] use machine learning (ML) methods to offer a cervical cancer risk prediction model. To forecast a person's probability of acquiring cervical cancer, the authors analyse several risk factors, such as clinical, lifestyle, and demographic characteristics. The promise of ML in individualized risk assessment and prevention is highlighted by this method.

Koh et al. [11] provide guidelines for cervical cancer management, highlighting the importance of comprehensive, multidisciplinary care. Their study emphasizes the need for integrated approaches, including screening, treatment, diagnosis, and supportive care, to enhance patient results along with QoL (quality of life).

CNNs are being studied by Almubarak et al. [12] for localized classification of digital histopathology images of cervical cancer in the uterus. Their research demonstrates how CNNs can reliably identify malignant areas in histological images.

A DL model is put forth by Guo et al. [13] to assess image focus in automated cervical cancer screening. Employing CNNs, they develop a model that assesses image quality and identifies images suitable for screening. This approach enhances the efficiency and streamlines the process of cervical cancer screening programs.

Kudva et al. [14] examine use of CNNs to automate identification of cervical cancer. Their research demonstrates how CNNs can automatically detect malignant areas in cervical images, facilitating early detection and treatment. This technique could improve cervical cancer detection accuracy and lessen reliance on manual screening.

Wojtyla et al. [15] evaluate trends in cervical cancer mortality among European young adult women. Their research highlights necessity of focused treatments and screening initiatives to combat the rising prevalence of cervical cancer in this demographic. By comprehending the epidemiological and demographic causes of these patterns, healthcare systems may create prevention and control strategies that are more efficient.

Adaptive region-based techniques for cellular segmentation in bright-field microscopy images are proposed by Phoulady [16]. With possible uses in cancer research and diagnosis, this work develops image-processing methods for cellular structure analysis.

Ghoneim et al. [17] use extreme learning machines (ELMs) as well as CNNs to study the classification of cervical cancer. Their research paves the way for automated diagnosis tools by demonstrating how well DL algorithms recognize images of cervical cancer.

Dong, N., Zhao et al. [18] presented a cervical cell categorization system based on Inception v3, with intentionally extracted features. Cervical cell detection accuracy increased significantly with the application of artificial features and Inception v3. Additionally, the research addresses the problem of underfitting with insufficient medical data by utilizing the powerful learning capabilities of transfer learning to accomplish accurate as well as efficient classification of cervical cell images. Although suggested algorithm has low complexity, excellent accuracy, and acceptable generalizability, it has problems with some cells' overlapping cytoplasmic parts.

Overall, these studies highlight different strategies as well as methodologies used in cervical cancer detection as well as diagnosis. To enhance precision, effectiveness, along with accessibility of cervical cancer screening as well as diagnosis, researchers are continuously developing new methods, such as DL models, ML algorithms, as well as image processing approaches. Application of artificial intelligence (AI) in cervical cancer treatment presents exciting opportunities to lower

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death rates and enhance patient outcomes as technology develops.

3. PROPOSED WORK

The three fundamental elements of suggested methodology were preprocessing, feature extraction and classification. Preprocessing procedures are employed to further enhance classification efficacy.

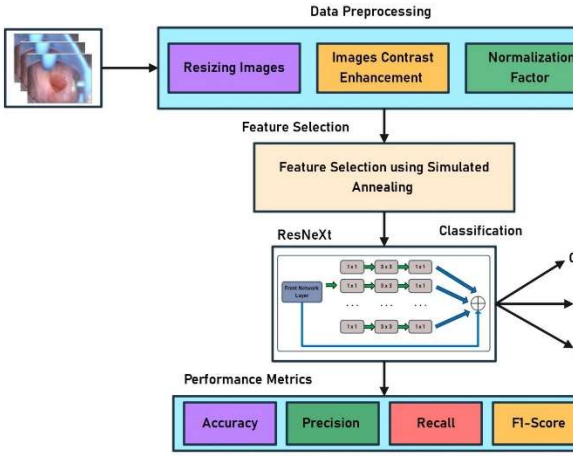

Figure.3. Proposed Framework for Cervical Cancer Detection

3.1. Dataset Description

The Malhari Colposcopy Dataset, which is accessible on Kaggle, is the source of the cervical images. The biggest data science community, Kaggle, provides strong tools along with resources for researchers' databases and data science projects. Additionally, there are 2792 labelled images of 3 stages of CC images in this database, comprising 901 images from CIN1, 931 images from CIN2, and 960 images from CIN3.

3.2. Resizing Images

This procedure entails modifying the pixel values of an image to a designated range, usually between 0-1, to facilitate efficient processing. Original input image is resized to 256 x 256 x 3-pixel dimensions, a size selected to diminish intricacy of the original image while maintaining adequate detail. The resizing utilizes bicubic interpolation, a technique favoured for its capacity to generate smoother and more refined edges than bilinear interpolation. Bicubic interpolation achieves an optimal equilibrium between processing duration and output quality by employing a 4 x 4 grid of 16 neighbouring pixels as samples for estimating pixel values at specified places, as depicted in Figure.4.

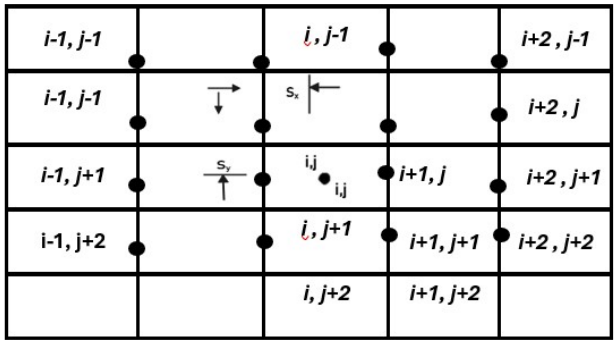

Figure.4.Sampling Bicubic Interpolation at Position (i, j)

Bicubic Interpolation is estimated by

$$f_{i,j} = \left[W_{-1}(S_y)W_0(S_y)W_1(S_y)W_2(S_y)\right] * \begin{pmatrix} f_{i-1,j-1} & f_{i,j-1} & f_{i+1,j-1} & f_{i+2,j-1} \\ f_{i-1,j} & f_{i,j} & f_{i+1,j} & f_{i+2,j} \\ f_{i-1,j+1} & f_{i,j+1} & f_{i+1,j+1} & f_{i+2,j+1} \\ f_{i-1,j+2} & f_{i,j+2} & f_{i+1,j+2} & f_{i+2,j+2} \end{pmatrix} \begin{pmatrix} W_{-1} & (S_x) \\ W_0 & (S_x) \\ W_1 & (S_x) \\ W_2 & (S_x) \end{pmatrix}$$

(1)

where $S_y = j' - j$, $S_x = i' - i$ and $f_{i,j} = pixel\ value\ at\ position\ (i,j)$.

$$W_{-1}(S) = \frac{-S^3 + 2S^2 - S}{2} \quad (2)$$

$$W_0(S) = \frac{-3S^3 - 5S^2 + 2}{2} \quad (3)$$

$$W_1(S) = \frac{-3S^3 + 4S^2 + 2}{2} \quad (4)$$

$$W_2(S) = \frac{S^3 - S^2}{2} \quad (5)$$

Initially," the images underwent uniform resizing to a standard dimension of 110x110 pixels, ensuring consistency in their sizes.

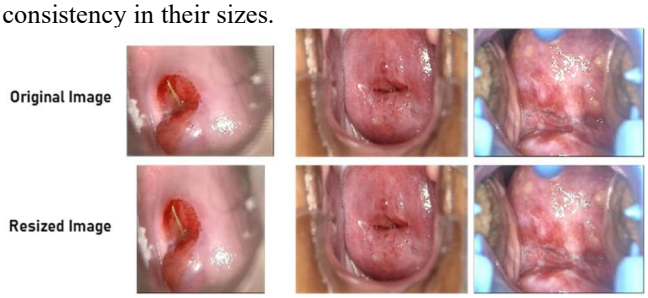

Figure.5. Rows show the sample of original images, and their resized counterparts Columns show; (a) CIN1 (b) CIN2 (c)CIN3

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3.3. Contrast Enhancement Method

Suggested contrast enhancement technique had been subsequently implemented on images across red, blue, as well as green channels. Suggested method utilized "median and standard deviation for global and local data images. Local standard deviation σ_1, local median m_1, global median m_g and global standard deviation σ_g had been evaluated.

Contrast Enhancement technique had been executed according to the subsequent steps:

a. Compute local median as well as standard deviation utilizing 3×3 window size.
b. Compute global median as well as standard deviation.
c. Statistical condition has been formulated as

$$I(x,y)=\begin{cases} R_f(x,y) \text{ if } \sigma_l < \sigma_g \&\& \ m_l > m_g \\ R_p(x,y) \text{ if } \sigma_l < \sigma_g \&\& \ m_l < m_g \\ R_b(x,y) \text{ if } \sigma_l > \sigma_g \end{cases} \quad (6)$$

to identify foreground region, background region, as well as problematic region.

$$where\ R_f(x,y): Foreground\ region,$$
$$R_p(x,y): Problematic\ region,$$
$$R_b(x,y): Background\ region.$$

d. Evaluate optimal threshold $value\ (k)$ by implementing Otsu thresholding on problematic regions to differentiate between nucleus as well as problematic (luminosity, noise, contrast) regions.
e. Apply threshold $value\ (k)$ to obtain $H(x,y)$ is as follows:

$$H(x,y)=\begin{cases} if\ I(x,y) < k = I(x,y) \\ if\ I(x,y) \geq k = \dfrac{I(x,y)+k}{2} \end{cases} \quad (7)$$

$$where\ k: Thershold\ Value$$
$$I(x,y): Problematic\ Image$$
$$H(x,y) = Newly\ Corrected\ Image$$

Using the aforementioned approach, the nucleus remained the same while only a problematic region was improved.

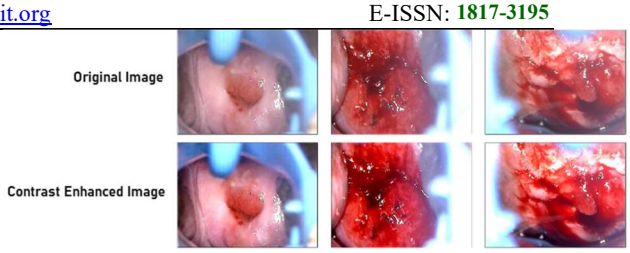

Figure.6. Rows show sample images of original images, and their Contrast-Enhanced Image counterparts Columns show; (a) CIN1 (b) CIN2 (c)CIN3

3.3. Normalization Factor

Normalization is a technique employed to improve contrast in images by altering pixel intensity value range.

3.3.1. Size

- **Area of nucleus and cytoplasm:** Area of cytoplasm as well as nucleus has been evaluated by counting number of pixels in each.
- **N/C ratio:** Degree of malignancy is determined by size of nucleus in relation to the cytoplasm. The small, compact, round nucleus of the benign cells is situated in the middle of cytoplasm. The nucleus of cancer cells is sparser, bigger, as well as shaped differently than normal nucleus. One of the key factors determining the type of cell is the N/C ratio of 8.

$$N/C = Nuclarea/(Nuclarea + cytoarea) \quad (8)$$

- Minor and Major axes length: The roundness of the cytoplasm and nucleus is determined by these measures of the essential image components. Major axis creates biggest diameter, while minor axis creates smallest.

3.3.2. Shape

- Perimeter of cytoplasm and nucleus: Total number of pixels from the perimeter that are located along boundary is calculated.

3.3.3. Location

Cell malignancy is also assessed by measuring the distance between the cytoplasm and nucleus centroids.

3.4. Feature Selection Approach based on Simulated Annealing Algorithm.

Simulated annealing is the main feature selection method used in the suggested framework. In contrast with naive local search algorithms, which employ greedy strategy to get the best solution, simulated annealing uses a probabilistic approach that allows it to avoid local optima in search of superior solutions. Thus, simulated annealing often achieves better results than naive local search techniques. The following is how the simulated annealing-based feature selection algorithm works.

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Initially, a randomly solution is presumed to be the best option. Initial solution's cost is evaluated by employing cost function.

$$\varphi(x)=\begin{cases}1 & if\ p(x)=q(x)\\ 0 & otherwise\end{cases} \quad (9)$$

$\varphi(x)$ is set to 1 if class $p(x)$ determined by K-means clustering algorithm is equal to original class $q(x)$ that a record x belongs to, otherwise, it is set to 0. Cost $C(f)$ for given solution f is evaluated over the training data set.

$$C(v)=\frac{1}{\sum_{i=1}^{N}\varphi(x_i)} \quad (10)$$

An adjacent solution of the present optimal solution is chosen, cost is computed, even though temperature T doesn't fulfill termination requirement. Current optimal solution has been substituted with newly chosen adjacent solution if cost of newly chosen neighboring solution is less than or equal to that of current ideal solution. A random value q between (0,1) is selected if the cost of neighboring solution is higher than the cost of current optimal solution. In this case, replacement of optimal solution is allowed only if random value q is less than $e^{-\frac{\text{Cost}(v_n)-\text{Cost}(v_b)}{T}}$. Similar procedures are carried out again till the termination condition is met. The 544 most important features out of 1024 retrieved features are successfully reduced in this paper by simulated annealing.

Table.1.Some of Features Selected for Analysis

Gray Level Nonuniformity
Entropy
Gray Level Variance
Autocorrelation
Cluster prominence

3.5. Classification based on ResNeXt

The ResNeXt network is a powerful tool for image classification. It continues to employ same block of layers, each of which has a collection of transformation functions to help in classification. These similar blocks are used repeatedly, which results in consistent architecture and fewer hyperparameters. With the inclusion of a new cardinality dimension, ResNeXt design differs significantly from the ResNet network. In Figure 7, ResNeXt's architecture is displayed. These two networks both employ the split–transform–merge technique. This method starts by employing convolutional layer to minimize dimensionality of input, then it uses a specific filter or a filter to change the data, and finally, it concatenates the outputs employing a summing operation. All transformations derive from a singular topology and are collected from that topology, rendering their application straightforward and devoid of specialized design requirements. ResNeXt was developed primarily to augment network accuracy while accommodating substantial inputs, all without necessitating the addition of deeper layers. Rather, ResNeXt aims to enhance cardinality, thereby maintaining manageable complexity. The inputs are provided, modified by the weights, and ultimately aggregated through a summing function.

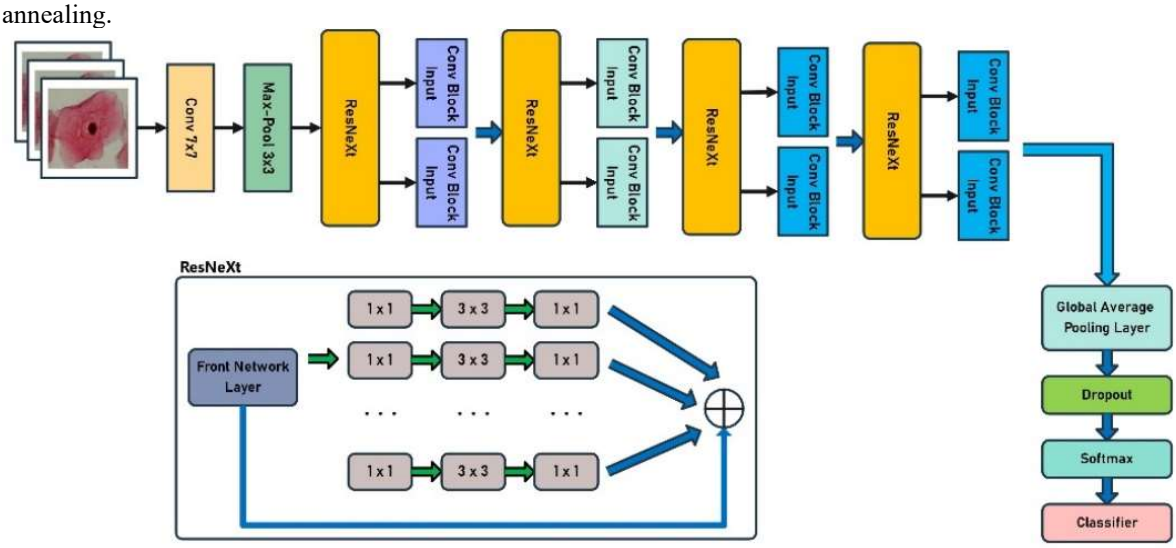

Figure.7. Architecture for ResNeXt Classifier for Cervical Cancer Detection

The same concept is employed by ResNeXt; though, rather than employing weights, function has been employed.

$$F(x) = \sum_{i=1}^{c} T_i(x) \quad (11)$$

Symbol x represents input, and $T_i(x)$ represents generic function that was discussed before, while C represents cardinality of network. Layers employed in architecture are given below:

3.5.1. Convolutional Layer

Convolutional layer executes a convolutional operation on input data by using a filter, also referred to as a kernel. It is therefore possible to extract it as a feature of the image since multiplication results in a rise in the numerical value. This happens when the order of the input image and the filter is the same. Several filters can be applied to an image to create a sequence of filters that capture the characteristics of multiple locations. After applying several different filters, these are applied.

3.5.2. Rectified Linear Unit (ReLU)

As nonlinear activation function, $f(x) = tan(x)$ or $f(x) = (1 + e^{-x})$ was employed; $f(x) = max(0, x)$ learning is enhanced by employing ReLUs. Deep neural networks frequently use ReLUs to solve the problem of vanishing gradients that can occur with conventional activation functions. Because of its efficiency, ReLU is still used even though more sophisticated activation functions have been developed. ReLU was commonly employed after convolution since it sets negative values to 0 and returns positive values unaltered. Since elements with negative values are usually not screened as features, this ensures that only important characteristics are kept. Thus, there are no complications even if a value is reset to 0.

3.5.3. Pooling Layer

Objective is to make characteristics that appear in convolution layer appear blurry and to render them learn if they are like other features of a similar type. It will then be possible to identify the trait even in a completely different image.

3.5.4. Dense Layer

Every neuron in the layer below sends input to this layer. Therefore, this layer is referred to as a dense layer.

3.5.5. Dropout

In dense layers, dropout layer removes any unwanted associations.

3.5.6. SoftMax

SoftMax function provides likelihood of occurrence to each number in vector of integers as well as transforming it into vector of probabilities. Using this built-in feature, a vector of numbers can be converted into probabilities.

4. RESULTS

The objective of the work presented in this study is to overcome the constraint of the available data to identify the optimal model that provides an automatic cervical cancer screening.

4.1. Performance Measures

To evaluate the performance of the proposed ResNeXt, the different performance measures, namely accuracy, precision, recall, and F1-Score, are used. These are the widely used measures, specifically in medical applications. These are briefly defined as

Accuracy (A) is the ratio of the number of correct predictions to all the predictions by the model and is given by

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

where TP is True Positive, TN is True Negative, FP is a False Positive, and FN is False Negative.

Precision (P) is the number of true positives divided by the total number of positive predictions.

$$Precision = \frac{TP}{TP + FP} \quad (13)$$

Recall (R) is the ratio of correctly classified positives to the total number of positives.

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

F1-Score is a measurement that combines recall and precision.

$$F1\text{-}Score = \frac{2' Precision' Recall}{Precision + Recall} \quad (15)$$

AUC: The area under the ROC curve is represented by the AUC (Area under the Curve) value. True Positive Rate (TPR) and False Positive Rate (FPR) are used as the horizontal and vertical coordinates in ROC to characterize the classifier's z

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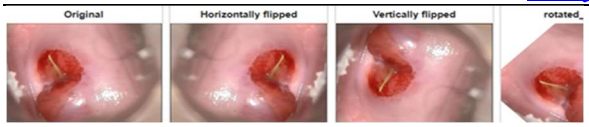
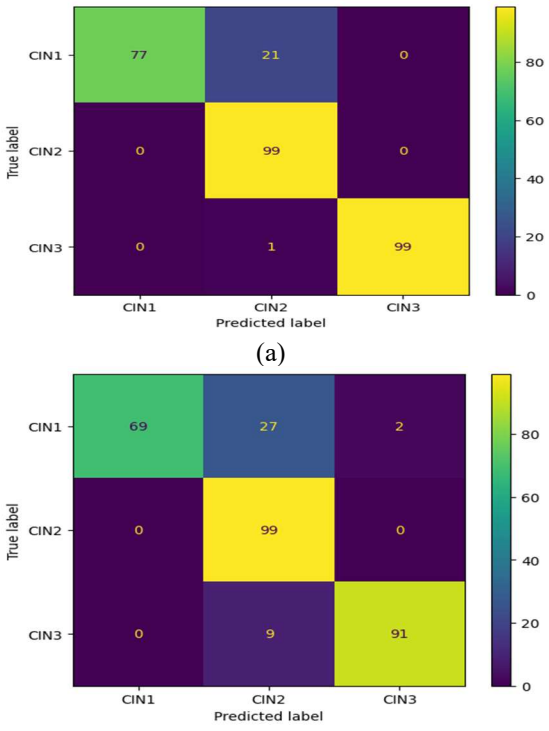


Figure.8. Samples Of Augmented Colposcopy Data. (A) Original, (B) Horizontally Flipped,(C) Vertically Flipped, (D) Rotated 45.

4.3. Classification Results

The dataset for cervical cancer from colposcopy is divided into 20% testing and 80% training. For training and testing, about 1502 testing images and 5998 training images are employed. The model is trained using a constant number of epochs-30. Training of model is conducted in a multi-GPU setting with batch size of 32 along initial learning rate of 0.001. With fixed parameters, the same image dataset has been used to train ResNeXt, RESNET50, and VGG 19 with fine-tuning. The DL model is analyzed by evaluating precision, recall, as well as f1-score. Since it addresses multiclass classification problem, the models are also tested using confusion matrix. Performance of classification model in Figure 10.10, as well as the training accuracy of the RESNET50, VGG_19, and ResNeXt models trained against the training dataset with epoch 30, are examined using the confusion matrix.



(a)

(b)

Figure.9. Confusion Matrix Of Pretrained Models Over Colposcopy Data Classification. (A) Resnext (B) Resnet50

Table 2. Comparative Analysis Of DL Models For Colposcopy Data

Network	Accuracy	Precision	Recall	F1-score
Resnext	99	98	98	97
ResNet50	98	97	97	96
VGG19	89	90	90	91

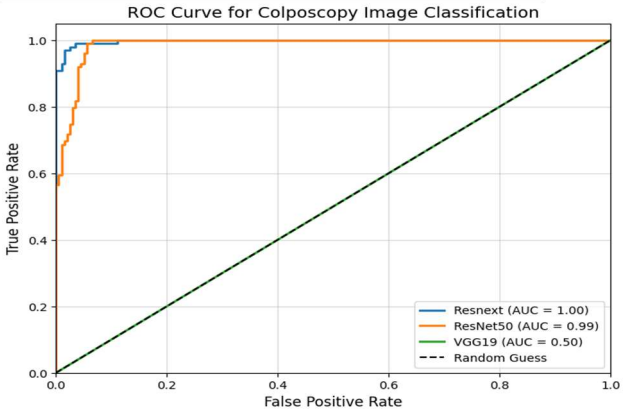


Figure.10. ROC For Pretrained DL Models Over Colposcopy Image Classification.

The performance of classification model has been examined by employing confusion matrix. The AUC values of the VGG_19, ResNet50, and Resnext ResNeXt models trained against the test dataset with epoch 30 were obtained from the confusion matrix and displayed in Figure.9. When compared to the other two models, the Resnext model maintains the best AUC value. However, using the Resnext model, ResNet50 yields a closure result. Visual representations of the model's learning process are provided by training loss vs. epoch validation loss curve and training accuracy vs. epoch curve. The Figure.11, Figure.12 demonstrate the model's reliable operation, strong generalization, and effectiveness in reducing training loss. Overall, these findings highlight our DL model's dependability and efficiency in the context of cervical cancer diagnosis.

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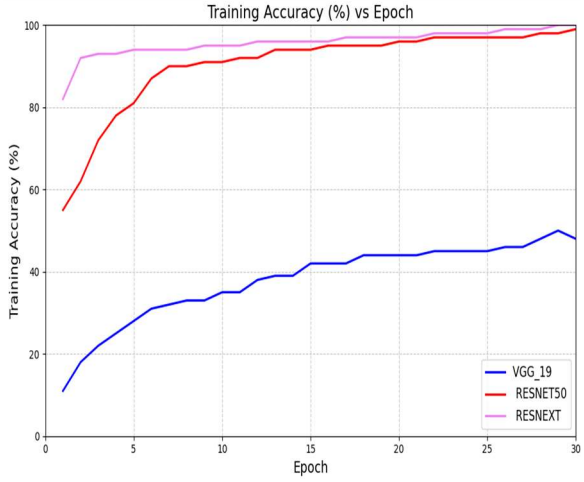

Figure.11. Training Accuracy(%) Vs Epoch For Pretrained DL Models Over Colposcopy Data Classification.

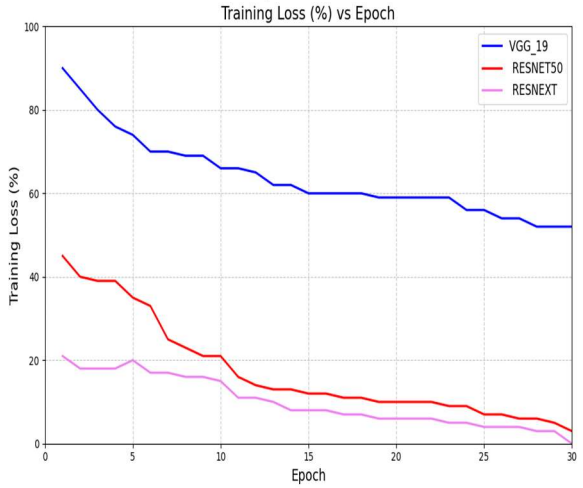

Figure.12. Training Loss (%) Vs Epoch For Pretrained DL Models Over Colposcopy Data Classification.

The significance and potential of DL methods in early detection of cervical cancer are highlighted in the discussion of these findings. Our DL model provides a dependable and automated screening solution, meeting a major healthcare demand with its high level of accuracy. In addition to showcasing the effectiveness of DL in medical image analysis, this highlights the significance of utilizing cutting-edge technologies for prompt disease diagnosis as well as treatment. Together, the findings and discussion confirm that our DL model is successful in automating the identification of cervical cancer. Model's effectiveness has been validated by its high accuracy, strong assessment metrics, and perceptive visual representations, which also highlights its potential for practical clinical applications.

6. CONCLUSION

This study introduces DL methodology for early diagnosis of cervical cancer through cervical images. Suggested methodology involves data preprocessing, feature extraction, as well as classification, attained an exceptional 98% accuracy on a cervical imaging dataset. The ResNeXt CNN architecture, which provides an efficient and precise method to detect cancer early on with significant consequences for screening as well as diagnosis, is at the core of this approach. Building on earlier studies in cancer diagnosis and medical imaging, our work uses CNNs' improved capabilities, especially ResNeXt, to attain higher accuracy, which is in line with the expanding use of DL in medical diagnostics. Expanding the dataset, testing on several imaging modalities, and investigating different CNN architectures or multi-modal data are some future areas that aim to improve performance, robustness, and applicability.

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