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ENHANCEMENT OF CERVICAL CANCER DIAGNOSIS USING RESNET-BASED DEEP LEARNING MODELS

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Abstract - The primary method of preventing cancer is screening the transition zones. There are three types of cervical precancerous phases, and they can all progress to cancer. In order to determine whether a cervix is in a normal (healthy) or precancerous stage, it is imperative to carefully screen for cervical abnormalities and have a reliable method in place. When applied to biological challenges, such as medical image analysis, disease prediction, and picture segmentation, deep learning demonstrated remarkable potential. Therefore, very deep residual learning based networks are built for cervical cancer detection in this paper. Furthermore, we emphasize in this work the significance of the activation functions on the performance of a residual network (ResNet). As a result, three residual networks with various activation functions are constructed using the same topology. The models in use undergo training and testing on a collection of cervical colposcopy pictures. The latest advancements in deep learning for the segmentation and classification of cervical cytology pictures are then thoroughly reviewed. Lastly, we look into the best practices for the analysis of cervical cancer as well as the current approach. Deep convolutional neural networks (DCNNs) have demonstrated impressive results recently in a number of medical applications, including cancer detection and diagnosis, medical picture categorization, and medical image interpretation and comprehension [6]. Over time, these networks have experienced substantial enhancements and modifications. The primary focus of this upgrade was on depth and performance, and it was discovered that CNN performance varies in direct proportion to matching depth.

Keywords- Cervical Cancer, ResNet, colposcopy dataset.

I. INTRODUCTION

Scientists and healthcare professionals who treat patients with cervical disease face a great challenge because cancers, and cervical cancer in particular, are among the world's leading causes of mortality. Because of their limitations and the kind of medical detection tests they employ, none of the current methods can reliably identify cervical illnesses in their early stages. The cervix, the tiny opening to the uterus, is where cervical cancer begins to grow. Women in their 30s to 45s who are sexually active are most susceptible to this cancer. 13800 women are predicted to receive a cervical cancer diagnosis. The primary cause of this cancer is the sexually transmitted virus known as the human papillomavirus, or HPV. Often known as the "smear test," cervical cytology is the most widely used test for cervical cancer detection. This test can assist in early cancer detection, which lowers the death toll from the disease. There are five distinct stages of this cancer, and the chance of survival increases if it is discovered early on. This paper uses deep learning to address cervical cancer screening.

There aren't many studies on cervical cancer diagnosis with deep learning. Therefore, deep networks must be used to identify precancerous cervical colposcopy cases in order to stop them from developing into cancer. In this case, a network inspired by the ResNet18 structure is used to classify colposcopy cervical images into pre-cancerous and healthy colposcopy images. The network is designed from the ground up to identify patients at high risk of developing cervical cancer. It is trained on precancerous and healthy images. Since this network is brand-new, we looked into finding the optimal activation function to match our model..

With particular applications in health monitoring, recent deep learning-based solutions show remarkable efficacy in object detection and classification speed and accuracy. Despite the fact that a number of earlier research had documented the use of deep learning-based algorithms in conjunction with common cervical disease screening procedures like colposcopy. Furthermore, in order to support the necessary prompt treatments and supports, the accuracy of any appropriate solutions must reach a high and accepted level in all stages of cervical pre-cancer and cancer. In order to prevent morbidity and mortality, particularly in low-income countries, there is a pressing need to further enhance the current deep learning-based digital solutions for the timely and accurate diagnosis and detection of cervical diseases in all stages, especially in the early stages.

It is true that the majority of prior research on cervical cancer risk prediction has focused on applying machine learning techniques to create models that are more accurate. On the other hand, improving these models' clinical credibility also depends on the choice of objective variable. Pre-existing target variables have been used in a number of previous studies. which takes into account elements like age, race, sexual orientation, and smoking status? These studies, however, have adopted a comprehensive viewpoint and have not adequately given weight to the significant variables.

II. Related Works

Deep networks have recently begun to reach deeper levels, or multiple hidden layers. This "very" depth appeared to be linked to a few optimization issues that arose when networks were learning. When a network is trained using a stochastic gradient descent algorithm, an issue known as the vanishing gradients appears. According to the theory, the loss function's computed gradient starts to drop exponentially as a network descends farther and eventually returns to its starting layers. It may therefore get close to zero at some layers, which makes it challenging to train the network. A small or zero gradient indicates that weights and biases might not be sufficiently adjusted for each training pass, which would result in a high error value and less convergence.

Cervical cancer diagnosis is achieved by using three deep residual networks with three distinct activation functions. Our network architecture, which has 50 layers and four residual and convolution blocks, is modeled after the ResNet18 structure. Repaired linear unit functions (ReLU) and 1 × 1 and 3 × 3 convolution operations (Conv) are contained in each residual and convolution block. Additionally, dropout layers and batch normalization (BN) are employed to enhance model generalization and create more workable designs. Keep in mind that the figure's simplicity prevents some layers from being displayed. After a 3x3 max-pooling operation, the entire output of the residual blocks from each of these layers is forwarded to the global averaging pooling layer. Every feature map is converted into a value by this layer, which takes the place of the fully connected layer. We then feed the computed values into a sigmoid function because our task involves binary classification.

In order to address the activation functions of a convolutional network on a specific medical classification task, three ResNets—each with a distinct activation function—are constructed. Only the ReLU-based ResNet architecture is used; two other, comparable networks—one with Leaky-ReLU and the other with PReLU—are constructed using the same architecture but distinct activation functions. It should be noted that these functions are used in the residual blocks, while the fully connected layer uses a Sigmoid function because our cervical classification task is binary—that is, it determines whether a cervical cervix is precancerous or healthy.

III. Proposed System

Investigated research on deep learning-based image segmentation and classification for cervical cytopathology. Major deep learning concepts are also explained, along with popular architectures for them. The review demonstrated the growing interest in the field of deep learning for image analysis related to cervical cytopathology. The majority of cutting-edge techniques for classification and segmentation have been suggested, and they are all used on the same dataset. It is believed that CNN has performed exceptionally well in the segmentation and classification task, which will benefit the patient by assisting with the early diagnosis, treatment, and detection of cervical cancer. Still, there's space for development. To begin with, the texture feature is an important low-level feature that does a great job of describing the content or area of an image.

After a 3x3 max-pooling operation, the entire output of the residual blocks from each of these layers is forwarded to the global averaging pooling layer. Every feature map is converted into a value by this layer, which takes the place of the fully connected layer. We then feed the computed values into a Sigmoid function because our task involves binary classification. Because there are no parameters to optimize in this layer, global average pooling has been shown in multiple studies to reduce overfitting. Additionally, this method sums the spatial information of the input data and is more resilient and effective in spatial translation.

Convolutional network on a specific medical classification task; as a result, three ResNets—each with a distinct activation function—are constructed. only the ReLU-based ResNet architecture; nevertheless, two additional networks that are comparable to it are also constructed using the same architecture, albeit with two distinct activation functions: Leaky-ReLU and PReLU. It should be noted that these functions are used in the residual blocks, while the fully connected layer uses a sigmoid function because our cervical classification task is binary—that is, it determines whether a cervical cervix is precancerous or healthy. To choose the best optimizer, those networks were all trained and tested using images of cancerous and healthy cervical tissue. According to the authors, the CNN built on Adam had the best classification accuracy (90%) between cancerous and normal cervical tissue.

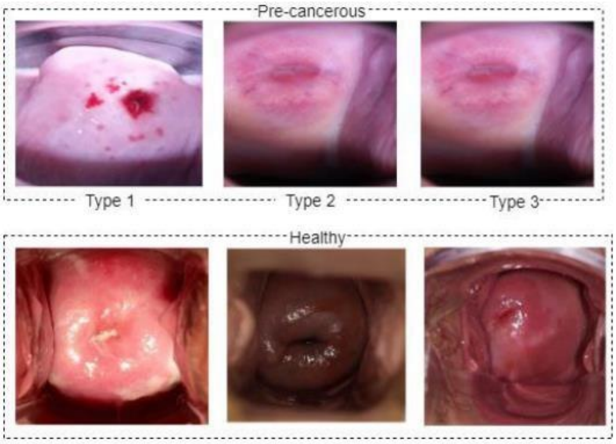

FIG 1

Figure 1 shows a healthy colposcopy image and an image of cervicle cancer.

Overall, this study demonstrates that difficult medical classification tasks, such as cervical screening, can be accomplished by a deep learning system. Medical professionals can diagnose this disease and identify its precursor before it develops into cervical cancer with the aid of such systems.

IV. ADVANTAGES OF PROPOSED SYSTEM

This consequently affects how well the organizations execute their learning processes because, as ReLU-ResNet demonstrates, it is by all means incapable of identifying the appropriate highlights of cervical images that aid in determining whether the cervix is sound or pre-destructive. This is undoubtedly the explanation for why this organization performed with less accuracy and more errors than other organizations.

There are a few advantages to using a ResNet (Remaining Organization) design for cervical malignant growth discovery in terms of clinical picture analysis and PC supported determination. ResNet is a deep neural network architecture that has been successfully used for various PC vision tasks, such as clinical image analysis. It is renowned for its ability to handle extraordinarily deep networks.

Better Feature Learning: ResNet's skip connections help to avoid the vanishing gradient problem when training very deep networks. This makes it possible for the model to extract abstract and hierarchical features from cervical images, which can be very useful in detecting minute patterns linked to precancerous or cancerous lesions.

Increased Accuracy: In image classification tasks, deep neural networks such as ResNet have shown state-of-the-art performance. When properly trained and fine-tuned, ResNet models can achieve high accuracy in distinguishing between normal and abnormal cervical images.

Transfer Learning: Pre-trained ResNet models on large datasets like ImageNet can be fine-tuned for cervical cancer detection tasks. Transfer learning leverages the knowledge gained from one dataset to another, often leading to faster convergence and better generalization on smaller medical image datasets.

Reduced Overfitting: ResNet's skip connections and batch normalization layers help mitigate overfitting, which is crucial in medical image analysis where limited labeled data is available.

Interpretable Features: While deep learning models are often considered as "black boxes," the hierarchical feature learning in ResNet can allow for some degree of interpretability. Researchers can examine the learned features to gain insights into what the model is capturing in cervical images.

Scalability: ResNet architectures can be adapted to different input image resolutions and sizes, making them adaptable to various imaging equipment and datasets commonly used in cervical cancer detection.

V. SYSTEM ARCHITECTURE

An "identity shortcut connection" was introduced by the artificial neural network ResNet, enabling the model to bypass one or more layers. With this method, thousands of layers of network training can be done without degrading performance. It has emerged as one of the most widely used architectures for a range of computer vision applications.

High Accuracy: ResNet architectures have a reputation for being able to train neural networks with a great depth without running into the vanishing gradient issue. This improves the accuracy of cancer detection by enabling them to identify complex patterns and features in medical images.

Speed and Efficiency**:** ResNet architectures are designed to be computationally efficient. Once trained, they can make predictions quickly, which is essential in real-time medical applications or when processing a large number of images.

ResNet is designed to train very deep neural networks, often consisting of hundreds or even thousands of layers. Deep networks have the potential to learn complex features but are challenging to train due to the vanishing gradient problem. ResNet addresses this issue using skip connections.

Numerous computer vision tasks, such as semantic segmentation, object detection, image classification, and facial recognition, have been effectively tackled by ResNet. It is especially useful for tasks that need modeling complex visual features because it can handle deep networks with skip connections.

Detecting cervical cancer using a ResNet (Residual Neural Network) involves training a deep learning model to analyze medical images, such as cervical smear or biopsy images, to identify signs of cancerous cells.

Upload Image:

Gathering an image and upload the image in this system to find out the cervicle cancer.

Data Collection and Preprocessing:

Collect a dataset of cervical smear or colposcopy images. Ensure that the dataset is labeled with information about whether or not each image has cancerous cells.

Make training, validation, and test sets out of the dataset.

Training: Apply the chosen loss function and optimizer to the modified ResNet model during training on the training dataset.

To prevent overfitting, keep an eye on the model's performance on the validation set. To avoid overfitting, you could employ strategies like early stopping. Place a new layer in place of the final classification layer after loading the pre-trained ResNet model.

that has the appropriate number of output units (typically 2 for binary classification: cancerous or non-cancerous). Freeze the weights of the convolutional layers in the ResNet backbone to retain the knowledge learned from a large dataset (e.g., Image Net).Medical applications require rigorous validation and regulatory compliance. Consult with healthcare professionals, data privacy experts, and legal authorities to ensure that your cervical cancer detection system meets all necessary standards and regulations.

VI. MODULES

Upload Image: user interface for users to select and send images to your server for processing.

Data Preprocessing: Data Collection: Gather a dataset of cervical images, which may include colposcopy images.Data Augmentation: Increase the diversity of the dataset by applying transformations such as rotation, flipping, and cropping to improve model generalization.ResNet Model Architecture: Base ResNet Model: Choose a pre-trained ResNet variant (e.g., ResNet-50, ResNet-101) as the backbone for feature extraction. Fine-tuning: Modify the last few layers of the pre-trained ResNet model for transfer learning on the cervical cancer dataset. Feature Extraction: Image Input: Input the cervical images into the ResNet model. Feature Extraction Layers: Utilize the convolutional layers of ResNet to extract hierarchical features from the images. Classification:

Add more layers by connecting dense, fully connected layers to the ResNet backbone's output. Activation Function: Give each dense layer's output an activation function (such as ReLU). Add an output layer (usually benign and malignant) with the number of units equal to the number of classes. Instruction: Define a suitable loss function to quantify the difference between the predicted and actual class labels. A common choice is the cross-entropy loss. Optimizer: To update the model weights during training, use an optimizer such as Adam or SGD. Training Loop: Use the training dataset to train the model while keeping an eye on its performance on the validation set. Regularization: To avoid overfitting, use strategies like dropout or L2 regularization. Analysis: Measures: Evaluation metrics like accuracy, precision, recall, F1-score, and ROC-AUC are used to evaluate the model's performance. Confusion Matrix: Examine the confusion matrix to determine how well the model performs in terms of classification. Hyperparameter tuning: To maximize the performance of the model, play around with hyperparameters such as learning rate, batch size, and network architecture. Conclusion: Testing: Make predictions on the test dataset or fresh cervical images using the trained model.

Post-processing: Additional post-processing steps, such as clustering or ROI analysis, may be required for further refinement, depending on the application. Your cervical cancer detection model's performance will be influenced by a number of variables, including the size and caliber of your dataset, the ResNet architecture you choose, and the fine-tuning procedure. To adjust to changing clinical needs, the model may also need to be updated and maintained on a regular basis.It might also be necessary to update and maintain the model in order to accommodate changing clinical requirements.

(a) ReLU-ResNet features at ReLU-7 layer

Fig: 2 ReSnet Pre-processing Stage

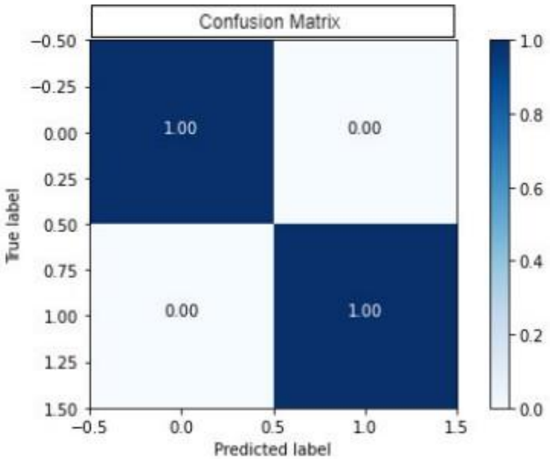

Fig: 3 Confusion Matrix

VII. Results and Discussion

We conducted an exploratory trial of the excess cervical data that had not previously been seen by the organizations, such as grouping exactnesses and assessment measurements, in order to evaluate the viability of the three ResNet models in classifying cervical disease. In terms of minimal order exactness, responsiveness, particularity, and region under bend (AUC), the ReLU-ResNet performed the best individually.

This may be due to its ReLU initiation capability, which, when compared to other used enactments like ReLU and ReLU, drives a terrible showing and, as examined, makes "biting the dust ReLU" during preparation. It is evident that ReLU and ReLU contributed to the organizations' increased capacity for speculation by causing the slope to be slightly but not completely zero, which activates neurons and allows loads to be altered.

The PReLU-ResNet's ROC diagram and disarray lattice. The organization, PReLU-ResNet, outwitted any surviving organizations with its learned actions. The learned actuations at the maxpooling and principal convolution layers are displayed. Though learning is still occurring in the primary layers, it is evident that the organization learned angles and levels of reflections in these two layers. Nevertheless, those elements are limited to variety, directions, and edges.

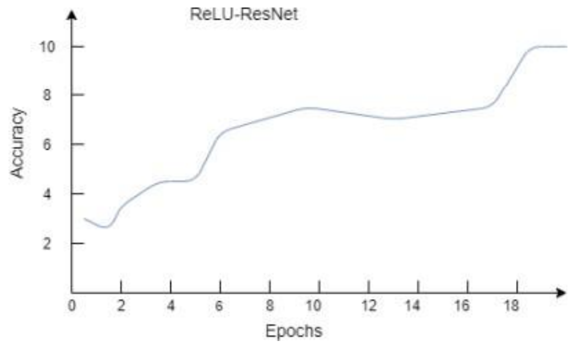

Fig 4 ResNet

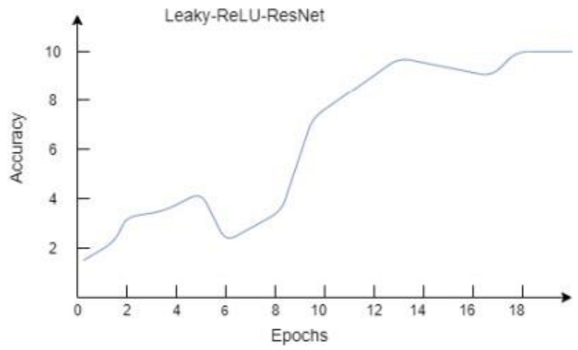

Fig 5 Leaky-ResNet

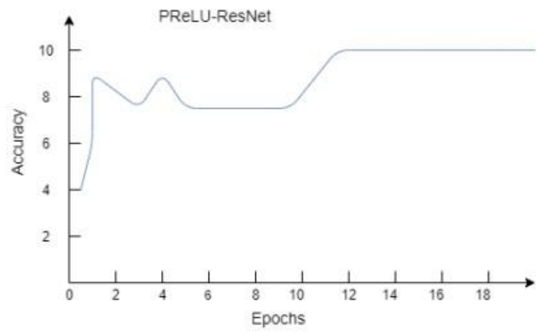

Fig 6 PReLU ResNet

As we progress, networks seem to pick up increasingly complex and important elements over time, such as objects and whole segments of crevices; in deeper layers, newly acquired highlights are created by combining highlights from earlier layers. We have chosen to display both the layer of enactments of each organization and the learned elements at a deeper level in Fig. 8.

Next, we select each organization's seventh enactment capability layer and envision its inclined highlights. As can be seen in the figure, in comparison to other organizations with defective PReLU and ReLU capabilities, which seem to learn more dynamic and confused highlights, the organization with

ReLU actuation capability appears to gain proficiency with nosignificant elements.

This consequently affects how well the organizations execute their learning processes because, as ReLU-ResNet demonstrates, it is by all means incapable of identifying the appropriate highlights of cervical images that aid in determining whether the cervix is sound or pre-destructive. This is undoubtedly the explanation for why this organization performed with less accuracy and more errors than other organizations.

VIII. CONCLUSION

In this paper, a very deep structure is created to use colposcopy images for the analysis of cervical malignant growth. The intended organization is a residual ResNet (learning-based network) that has been revitalized by the ResNet18 architecture. Three distinct enactment capabilities are used to investigate the impact of enactment capability on the ResNet's presentation, and the drawbacks of actuators capabilities are also explored in this work. Three distinct organizations were then planned as a result of this. Every organization was ready and made an effort to use a dataset of unpolished cervical images. Overall, this analysis shows how a deep learning framework can handle challenging clinical grouping tasks such as cervical screening. Clinical specialists can find useful frameworks for analyzing this illness and locating its precursor before it develops into a cervical malignant growth.

IX. FUTURE WORK

It is also possible to expand this system to diagnose the three distinct forms of cervical cancer. An advanced system like this could be very important since it can stage cervical cancer, which aids in creating a personalized treatment plan for each patient based on their particular cancer type.

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