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Based on MRI Classification of Cervical Cancer using Pre-Trained Convolutional Neural Networks Model

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***Abstract*— Cervical cancer is still a major global health concern. By taking some step we can reduce the number of cervical cancer patients like an early and valid diagnosis is very essential to improve patient outcome. By using pre-trained algorithms on MRI (Magnetic Resonance Imaging) scans the survey shows the classification of cervical cancer stages. About 25,000 MRI image dataset which are Utilized. Those are acquired form Kaggle. By using cutting-edge machine learning methods Our objective is to improve the diagnostic procedure. The dataset underwent large-scale preprocessing, as well as scaling, normalization, and augmentation, to make sure high-quality inputs for the models. Pre trained convolution neural networks(CNN) were very much advance to maximize on this dataset with a strong feature extraction capability, focus on essential features like difference of texture and intensity patterns. Our goal is to classify the cervical cancer accurately by using pre-trained MRI models, and suggest doctor that could be useful tool for early recognition and treatment planning. The result show how good deep learning works in terms of explain medical images, which could help to enhance patient care and give correct result of cervical cancer identification.**

Keywords— Cervical Cancer, CNN, VGG16, RestNet50, MRI

I. INTRODUCTION

Diabetic In the whole world, the fourth ranks cancer that affect women is cervical cancer. In a reach about 2000000 cases of uterine body cancer, 200000 cases of other cancers, and half million cases of cervical cancer. In Gynecological cancer like affecting the ovaries, vagina, and vulva that occur every year. Around 85% of cervical cancer death happens in middle- and low-income countries, that shows that early detection can save lives. Magnetic resonance imaging (MRI) is now become a vital method for taking the high- resolution imaging capabilities and that also non harmful for nature. Using a dataset of 25,000 cervical cancer stages, this survey shows the application of pre-trained convolutional neural network (CNN) models for the classification of cervical cancer stages. The dataset have five definite classes those represent cervical cancer: cervix-dyk, cervix-koc, cervix-pab, Cervix-mep, Cervix-koc. By using pixel normalization and image scaling method we try to improve the data for model training. Our aim is to make a reliable classifier by using pre-trained CNN models that can identify between different stages of cervical cancer based on MRI scans.

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II. LITERATURE REVIEW

The paper Ichrak Khoulqi and Najlae Idrissi, Proposes traditional image processing relevant for bilateral filtering, DRLSE, Region Growing used for segmentation and feature extraction by classifier training. Pre-trained DCNNS with transfer Learning, data augmentation and stacking generalization leverages for classification improvement. Both methods increase accuracy in detecting and classifying cervical cancer. [1] The paper proposes a CNN-based model with a dense architecture used to improve classification accuracy for cervical cancer detection from MIRS, focused for "Improved classification of MR Images for Cervical caner using Convolutional Neural Network". Data augmentation is used for balancing and preventing overfitting, with better accuracy and significantly reduced errors compared to previous methods. [2]A cervical cancer detection system engages CNNs (VGG-16, CaffeNet) with extreme learning machines (ELM) for classification. The model detected high accuracy about 99.5% for binary and 91.2% for seven-class classification, using transfer learning and fine-tuning the model and demonstrates effectiveness in cercvical cancer detection [3].

The paper "SIPAKMED"; proposes a new dataset for classifying normal and pathological cervical cells in Pap smear images. The SIPakMeD database contains 4049 annotated images and is valuable for evaluating various cell classification techniques by addressing the lack of extensive publicly available datasets. [4].

The paper proposes learning model for lymph node metastasis (LNM) detection in cervical cancer MRIs. This model focuses radiomics, identifying characteristics like shape, texture, and intensity, to noninvasively predict LNM and improve treatment planning and patient outcomes [5].

"MRI-Based Radiomics approach with Deep Learning for Predicting Vessel Invasion in Early-Stage Cervical Cancer" discusses the potential of combining deep learning and radiomics to predict vessel invasion. It discusses critical factor in cervical cancer prognosis. The process proposes the value of multi-parametric MRI techniques for improving diagnostic precision. In [6].

The review highlights the evolution of cervical cancer detection, from traditional machine learning In [7]

algorithms (Random Forests, SVM) to advanced deep learning techniques (CNNs). Recent deep architectures, like ResNet and Inception, obtains superior accuracy and reliability in detecting cervical cancer.

"Transfer Learning with Partial Observability Applied to Cervical Cancer screening that focuses on improving cervical cancer diagnosis in low-income countries. The study accentuates transfer learning to optimize screening strategies and individual risk prediction in resource-limited settings. In [8].

"Cervical Cancer Classification Using Combined Machine Learning and Deep Learning Approach" assembles ResNet101 with Polynomial Component Analysis (PCA) for feature extraction and performance enhancement. The system

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accomplishes 100% accuracy in distinguishing normal from abnormal cases and 92% in classifying varying levels of abnormality. In [9].

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III. METHODOLOGY

The study for Cervical cancer detection is structured into main stages like data collection, preprocessing, model selection, training, evaluation, etc for a powerful classification system. As illustrated in Figure 1, shows the process of preprocessing dataset and fit to model. The dataset categorized into five classes: cervix-dyk, cervix-koc, cervix-pab, Cervix-mep, Cervix-koc. Images were sourced from public databases and online repositories from Kaggle.

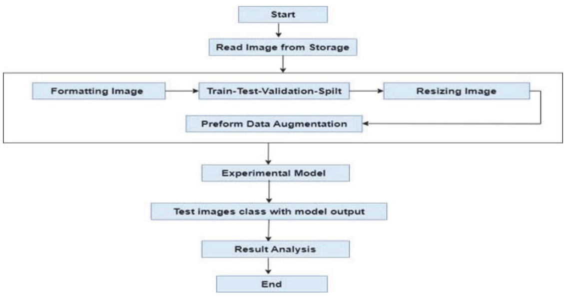

Figure 1 System Workflow

The datasets image illustrated in Figure 2. It resulted in an initial set of 25,000 images. Different prepared techniques were applied to the dataset, prior to training. All images were resized to 224×224 pixels to ensure uniformity over models. Pixel values were normalized to the range [0, 1] for efficient training. Data increment tech niques with random rotations flips, and brightness adjustments were used to reduce class imbalance and increase model generalization.

A. *Dataset Description :*

The dataset for this project focuses on cervical cancer classification utilizing MRI (Magnetic Resonance Imaging) scans. For each class, we have taken 5,000 pre trained MRI images. That contains 5 classes (cervix-koc, cervix-dyk, cervix-pab, cervix-mep, cervix-sfi) with 25,000 MRI images were gathered, capturing different stages and types of cervical cancer. The images are taken from Kaggle. We have taken colored images to feed the model after pre-processing for this project. Key features extracted from these MRI images include intensity patterns and texture characteristics, which are crucial for distinguishing between different stages of cervical cancer. The pretrained MRI models utilize these features to accurately classify the images.

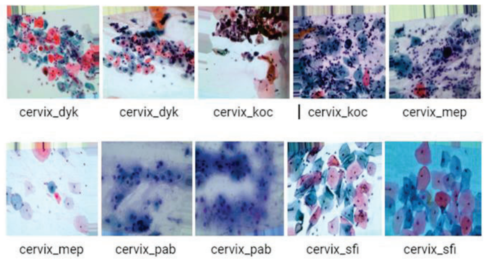

Figure 2 Sample images of the dataset

B. *Dataset Preprocessing*

Before The training, validation, and testing datasets are preprocessed using TensorFlow's ImageDataGenerator in the notebook that is provided. The preparation stages include applying data augmentation methods to the training data, such as shearing, zooming, and horizontal flipping, and normalizing pixel values to the range [0, 1]. Twenty percent of the training data in the dataset is set aside for validation. 'Train' is the directory for testing, 'Validation' is for validation, and 'Cervical Cancer' is for training. Data generators are then used to input the preprocessed data, producing batches of images with the predetermined dimensions (150 x 150), and classifying them for testing, validation, and training.

C. *Model Training*

The Three models have been utilized for categorization in order to identify the 'Cervical Cancer from Cervical Cancer affected pictures. Utilizing two built in pre-trained models, such as mobilenetv2 and VGG19, in addition to the yolov8n model. This allowed us to assess the models' correctness and determine their kind. Using our own set of setups, we have examined and tested the CNN model. In addition, we have enhanced the data in order to comprehend the impact on the models' correctness. After layer configuration and data augmentations, we employed the untrained VGG19 pre-trained model. For both the yolov8n and the moblienetv2 model We have followed the same.

D. *VGG19*

In our project the first model that we have use is VGG19. The Visual Geometry Group (VGG) family of neural network architectures includes the deep convolutional neural network design VGG19 in Figure 3. Fully connected layers are known as dense layers, and the ReLU activation function gives the model non-linearity. By adding a Dropout layer, which randomly sets a portion (in this case, 50%) of the input units to 0 at each update during training, overfitting is less likely to occur. This layer is frequently applied to enhance the model's capacity for generalization. The number of units added to the final Dense layer is the same as the number of classes in training set

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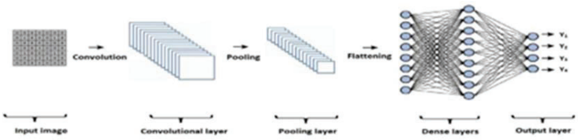

Figure 3 VGG19 System Architecture

E. YoloV8n

In our project we use another model is YoloV8n in Figure 4. We imported the model using the Ultralytics library. This deep learning toolkit, called Ultralytics, is being utilized for YOLO-based object detection. It offers implementations and utilities for a variety of computer vision tasks. We trained YoloV8n for object classification from our given input Image. And in our three models YoloV8 performs the best in terms of prediction and accuracy.

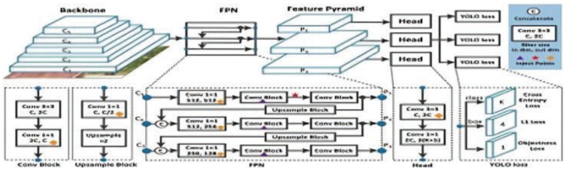

Figure 4 YoloV8n System Architecture

F. MobileNetV2

Another model is MobileNetV2 as a feature extractor in Figure 5. The model is then customized with additional layers for classification, and it is designed to work on input images of size (224, 224, 3) for a task with four classes. MobileNetV2 is the second performer after the Yolov8n in terms of accuracy and prediction. Global Average Pooling 2D layer is added in this model. This layer takes the average of all values in each feature map, reducing the height and width of each spatial dimension of the input to 1.

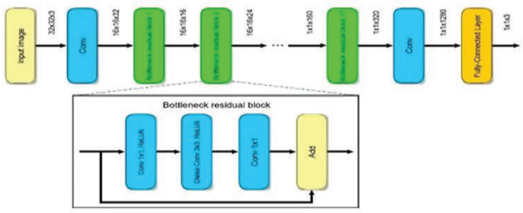

Figure 5 MobileNetV2 System Architecture

IV. Result and Discussion

Here we use three model in our data set 1. VGG19 2. MobileNetV2 3. yolov8n. For fitting our model, we run 10 epochs in our VGG19 and MobileNetV2.

Table 1 Result Analysis

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Vgg19	0.5948	0.60	2.4489	1.1931
Mobilenetv2	0.8227	0.4922	1.085	11.171
yolov8n	0.95	0.949	0.949	1.533

From Table 1 here we can see that best accuracy we got from VGG19 is 0.5771428346633911 and from MobileNetV2 we got 0.8926. Best validation accuracy in VGG19 is 0.5813 and from MobileNetV2 we got 0.6641. And at last, we got best accuracy from yolov8n is 0.99. So, we saved the yolov8n model for predict for this paper.

Table 2 A comparison between the proposed structure and popular architecture currently in use.

Model	Accuracy	Pertained
CNN Model [3]	89.8%	NO
VGG16 [4]	82.54%	YES
RF [7]	91.02%	YES
YoloV8	0.95%	Yes

In Table 2 shows the comparison between the related work and our saved model that we haved Used in our porject for E.C.G image classification. Our model is a pre trained model of Convunential neural network cnn. Here we can see that it performs better than all the models Of our realted works, and also it is much helpful for calssify the images and it's accuracy is 0.99%.

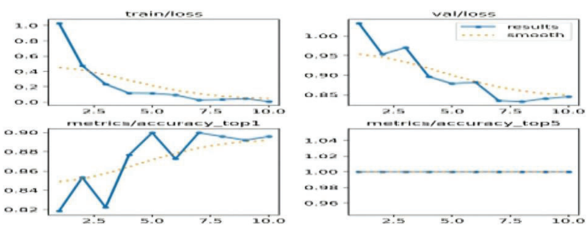

Figure 6 train/loss, val/loss, metrics/accuracy of model yolov8

This figure 6 shows us the train/loss, Val/loss, metrics/accuracy_top1 and metrices/accuracy_top5 of model yolov8 model. Here we can see that the train/loss value from the actual value is very slight. And the validation/loss value which we uses for prediction is also showing the accurate result graph and it will helps us to image classification. And the trics/accuracy_top1 metrics helps us to check the model accuracy of yoloV8

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and from that model we got the peak value of 0.9, And the metrics/accuracy_top5 is linearly separable with the results and smooth value

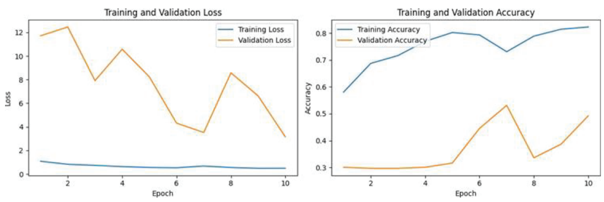

Fig. 7 Training and validation loss and accuracy of VGG19

In Figure 7 is the ROC curve demonstrates how well our model distinguishes between classes. Class 4 achieves the greatest AUC of 0.96 with 113 samples. Class-0 has an ROC curve of 0.71. The micro and macro averages also illustrate the model's overall performance. As an example, the micro-average ROC sums up each individual true positive, false positive, and false negative and then maps a value on a graph. Where macro-average calculates the average of precision and recall and plots it on a graph. When the dataset is substantially skewed, the micro-average ROC is used.

V. Conclusion

Lastly, we can say, that this study estimates the performance of VGG19, MobileNetV2, and YOLOv8n for cervical cancer classification while using MRI images. From all of these, YOLOv8n shows good performance with training and validation accuracies of 0.95 and 0.949, respectively, and low losses, indicating its strong generalization capabilities. By its computational intensity, VGG19 delivers consistent but modest results with accuracies of 0.60. MobileNetV2 has a high training accuracy of 0.8227 but struggles with generalization with a high validation loss it shows a validation accuracy of 0.4922 which could show overfitting or sensitivity to data variations.The results show the potential of YOLOv8n. Because it is an efficient, reliable and useful tool for cervical cancer diagnosis through MRI imaging. It is a suitable model for real-time clinical applications because it has some capabilities like accuracy and computational efficiency. MobileNetV2's performance advised that in lightweight architectures it may need more optimization and regularization techniques to better generalization on medical datasets. In terms of VGG19, though it is stable, it may benefit from minimizing complexity to increase its practicality for deployment. To increase model potential, future research should be focused on solving dataset imbalances and expanding the variation of training data.

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