

CER-XNET: CERVICAL CANCER CLASSIFICATION VIA DEEP LEARNING BASED XCEPTION NETWORK WITH MRI IMAGES

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Abstract – Cervical cancer (CC) is the fourth most frequent form of cancer in women. The HPV-related condition most usually associated with HPV infection is CC in general. One of the often-used methods to find CC is the pap smear. However, some drawbacks include a long wait for findings, a reduction in sensitivity, and a reduction in laboratory quality control. In this research, a novel CER-XNET approach to identifying CC and reducing death rates has been proposed to address these drawbacks. Images from the dataset are initially acquired for MRI cervical scans. The classification of several MRI scans of CC is then done utilizing the deep learning (DL) network. Next, feature extraction is performed on the pre-processed images using capsule network. Using an Xception network, the images are then divided into normal and abnormal classes. The suggested based on its F1score, precision, recall, specificity, and accuracy. The accuracy of the suggested CER-XNET method is 99.24%. The accuracy of the L1reg CNN network strategy outperformed the majority of the reported existing methods, which suggests successful outcomes.

Keywords – Cervical cancer, Deep learning, Xception, Capsule network.

1. INTRODUCTION

Cervical cancer, often known as cancer of the cervix, first manifests symptoms on the surface of the cervix. It occurs when the cervix begins to produce precancerous cells. There are usually two types of CC. Adenocarcinomas and squamous cell carcinomas. Squamous cells make up the lining of the cervix's exterior. Adenocarcinomas [1-2]. The bulk of cervical malignancies begin in the column-shaped gland cells that line the cervical canal. The main factor causing CC is HPV. For most people, the infection rarely results in problems. Typically, it leaves on its own. But in certain individuals, the virus changes the cells in a way that leads to cancer. CC risk factors include cigarette smoking, an increase in sexual activity, a weakened immune system, and others [3].

CC is the fourth most prevalent type of cancer in women. According to estimates of the 570 000 new cases of CC in 2018, 311 000 women died from the disease globally [4]. For to monitor and assess a country's progress, effective surveillance and monitoring mechanisms are essential There were 4,820,000 and 2,370,000 new cases of cancer, as well as 3,210,000 and 640,000 cancer-related deaths, in China and the USA, respectively.

One of the methods is an automated CC system that extracts the features and chooses which ones are most important using a state-of-the-art DL [5] framework. DL structure surpasses current machine learning (ML) [6] models for diagnosing CC from cardiography images with few changes to the recovered features. However, this method does not make it simple, dependable, or quick. By combining the KNN methodology with other methods including Support Vector Machines (SVMs), pixel-level classifications, and statistical shape models, the performance of the KNN technique was enhanced. even though it has been recognized that the KNN technique is a very good cervical image classifier [7]. However, adding many datasets does not make it process more thoroughly. The ELM-based classifier or the AE-based classifier was employed when the CNN [8] model was added to the system [9]. This system doesn't be enhanced by the addition of particular handmade features. This paper introduced the DL Xception for classification to address these challenges. The contribution of this paper is

- Initially MRI cervical scan images are scanned and pre-processed using normalization and augmentation.
- The pre-processed images are fed to capsule network for feature extraction
- Extracted feature is process under the classification by using xception.

- The proposed CER-XNET network was modified to analysis the range of accuracy, F1score, recall, specificity and precision respectively.

The setup of the research in this paper is as follows. The literature study is briefly presented in Section 2, and the proposed CER-XNET model is described in Section 3. Sections 4 and 5 of the report, which include a conclusion and suggestions for future work, contain the performance outcomes and a comparison analysis of them.

2. LITERATURE SURVEY

Numerous techniques have been developed over time to detect CC using blood cells. and some of these inquiries provided an answer to the question of how to address the identifying defect. Only image data categorization is offered by some of the demonstration systems.

In 2020 Alyafeai, Z. and Ghouti, L., was developed a fully-automated pipeline for CC classification and cervix recognition from cervigram images. Two pre-trained DL models are used in the suggested pipeline to automatically detect cervixes and classify cervical tumors. while attaining an intersection of union (IoU) measure detection accuracy of 0.68.

In 2022 Shinde, S., et al., is recommended for DeepCyto, a hybrid DL-based method used to categorize pap smear cytology images. Two techniques receive the feature fusion vectors that the DeepCyto builds from pre-trained models. Principal component analysis and ML are used in Workflow-1 to classify the pap smear images. When categorizing data using an ANN using feature fusion vectors as input, Workflow 2 achieves a 97% accuracy rate.

In 2022 Alquran, H., et al., has been created the first technique that categorize pap smear images into seven different problems. A computer-aided diagnosis method is created using Pap smear images to categorize the irregularity in cervical imaging cells. Support Vector Machine (SVM)

classifier uses automated characteristics that ResNet101-extracted to distinguish between seven image classes. In the exam phase, the overall accuracy is 97.3%, with an average test score of around 92% across all seven classes.

In 2022 Mulmule, P.V. and Kanphade, R.D., recently published work intends to apply the most advanced pretrained networks, AlexNet, ImageNet, and Places365, on photos of the cervix to identify malignancy. Using the publicly available benchmark CERVIX93 dataset, these pre-trained networks are augmented and retrained for data enhanced for CC. With a 99.03% accuracy rate and a 0.98 kappa coefficient exhibiting perfect agreement, the results show that the AlexNet model is the most reliable for predicting CC.

In 2022 Chen, W., et al., suggested combines a hybrid loss function with label smoothing to enhance the discriminating power of light-weight CNNs for cervical cell categorization. The results provide hybrid loss-constrained lightweight CNNs for the SIPakMeD dataset achieve acceptable accuracy at a fraction of the computational cost, more confidence. GhostNet increased the accuracy of its categorization to 96.39%.

In 2022 Sentürk, Z.K. and Süleyman, U.Z.U.N., et al., implemented a transfer learning-based method for early CC detection. To increase classification accuracy, Pap smear image noise was reduced before training the DL model. Pre-trained networks can distinguish between cervical malignant and non-cancerous cells. SqueezeNet outperformed all other unsupervised approaches in the literature with a validation accuracy of 96.90% for the diagnosis of CC.

3. PROPOSED METHOD

The classification of several MRI scans of CC is then done using the DL network. Next, feature extraction is performed on the pre-processed images using capsule network. Using a Xception network, the images are then divided into normal and abnormal categories. Figure 1 shows the proposed CER-XNET methodology.

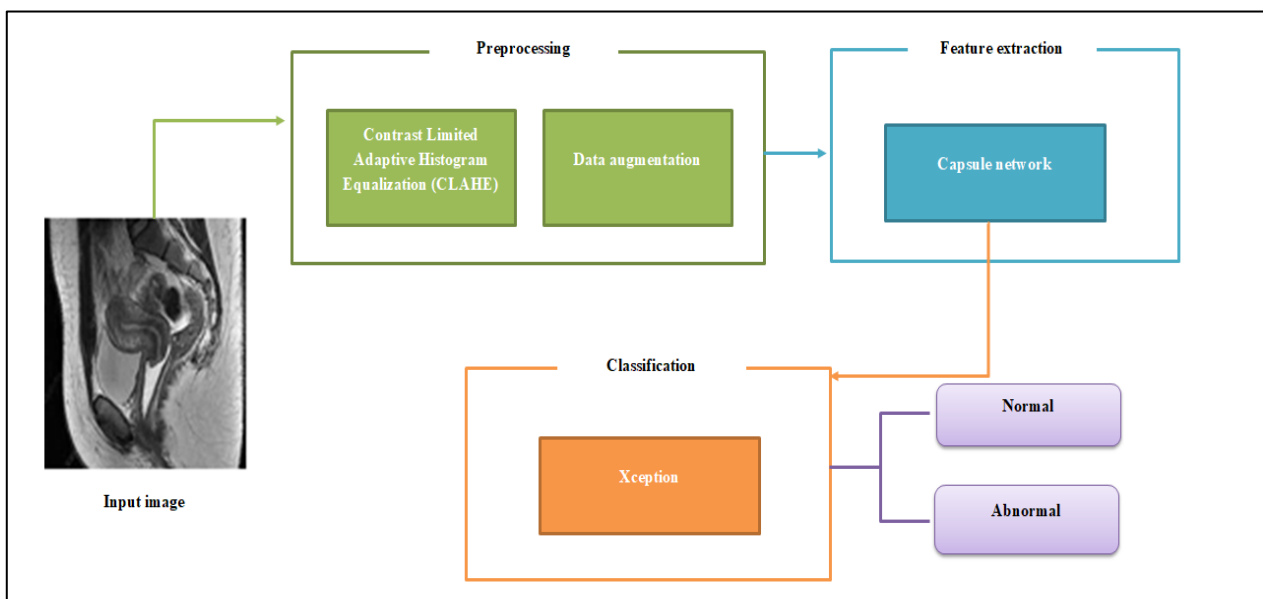


Figure 1. Proposed CER-XNET methodology

3.1 Dataset description

The cervix, or bottom part of the uterus, is where CC manifests itself. Among the methods utilized to achieve this goal are Pap tests, biopsies, CT scans, MRIs, PET scans, cystoscopies, laparoscopies, and other diagnostic procedures. The investigation's diagnostic method is MRI. The dataset comprises of 24 magnetic resonance scans of CC patients who had the disease locally progressed. The three datasets that are considered include axial T1- and T2-weighted images as well as sagittal T2-weighted images.

3.2 Image pre-processing

Many image pre-processing approaches were applied to enhance the image quality and make images suitable for learning the features using the CNN model.

3.2.1. Contrast Limited Adaptive Histogram Equalization (CLAHE)

The CLAHE technique seeks to improve image contrast by employing histogram-based techniques. By first transforming the RGB fundus image into the LAB color space, where "L" stands for Lightness and "A" and "B" indicate different color dimensions, this method improves contrast. Next, with a tile grid size of 50 and a clip limit of 2, the CLAHE function is only used on the "L" channel. The image is then converted back into the RGB color space after this improvement process.

3.2.3. Data augmentation

Data augmentation is a crucial pre-processing step that entails creating fake data so the model can learn features. The ideal way to support the network's learning of the desired features is to use data augmentation. Using the hundreds of images in the datasets to train the CNN model is insufficient. Thus, during training, data augmentation is done online.

3.3. Feature extraction with capsule network

Convolutional layers are used by the capsule network for extraction the images, while the capsule layers are in charge of learning the features. The capsule network differs from the neural network in general. The capsule network is intended for images containing two or more dimensions of data.

The low-level semantic data collected by the Inria dispersed into a quantity of flow-level capsules represented by $h \in P^{d_u}$ for the relation extraction task. K low-level capsules express the representation of each word token. Through the entire vector, a nonlinear squash function called e is applied to each low-level capsule.

$$g_t = [h'_{t1} \dots \dots; h'_{tk}] \quad (1)$$

$$h_{tk} = e(h'_{tk}) = \frac{\|h'_{tk}\|^2}{1 + \|h'_{tk}\|^2} \frac{h'_{tk}}{\|h'_{tk}\|} \quad (2)$$

Where $[c, d]$ denotes the vertical concentration of c and d . High-level related features represented by groups of low-level capsules. Therefore, the following formulae are used to calculate high-level capsules $q \in P^{d_q}$.

$$q_j = e(\sum_i d_{ij} D_j u_i), \quad (3)$$

Where $D_j \in P^{d_q \times d_u}$ are weight matrices for each high-level capsule and d_{ij} are coupling coefficients generated via a dynamic routing process that is iterative.

3.4. Classification using xception

The Oval Exception model receives the pre-processed images. The CNN's Inception approach serves as a bridge between standard convolution and in-depth, depthwise separable convolution operation. The depthwise separable convolution is a multi-tower Inception Module. Consequently, the observational results point to a deep CNN that was influenced by Inception.

To enhance performance, Depthwise Separable Convolutions, specifically Xception, were employed as a substitute for the inception module, outperforming Inception V3 on ImageNet. The efficacy of the model is heightened due to more efficient parameterization, maintaining an equivalent number of parameters between the Xception architecture and Inception V3. In the convolution layer, analysis of three-dimensional filters involves two spatial dimensions, width and height, in addition to channel dimensions. This design ensures that each convolutional kernel addresses both spatial and cross-channel correlations. The Inception module strives to refine and simplify this process by decomposing it into a series of steps, each dedicated to determining cross-channel and spatial correlations independently. Inception's foundational principle posits that there is no imperative need to concurrently map spatial and cross-channel correlations. The "Extreme Inception" architecture of Xception employs a 36-layer convolution as the feature extraction network. The 14-module Xception architecture is structured as a linear stack of convolution layers with residual connections and depth-based separability. These 14 modules are further categorized into three groups: the entry flow (comprising 4 modules), middle flow (repeated 8 times), and exit flow. The data progression follows the sequence of the entry flow, the mid flow and the exit flow. Notably, every layer in both the Separable Convolution and Convolution models undergoes batch normalization.

Each channel exhibits variation in the three Xception convolution block results, which was offer a comprehensive feature representation for the tracked object. Channels from three Xception convolutional blocks were combined to generate a tracked object representing a rich and diverse feature representation. The average layer is the last layer and the input of the Xception module is (299, 299, 3). The performance of the new model was improved by leveraging useful features that the pre-trained model already had from the large dataset. The ability to extract features effectively likewise steadily gets better with the addition of increasingly deep feature layers. Multiple convolution layers, each with multiple convolutions that are provide unique feature descriptions from the original image, enable deep features to learn various feature descriptions from the image. Deep features are the Oval Xception's output

4. RESULTS AND DISCUSSION

In this section, the effectiveness of the CER-XNET method for detecting CC is assessed. The MRI scan images are initially pre-processed into the appropriate frames in

order to get them ready for additional processing. For the examination of CC scan images, estimations of recall, specificity, accuracy, F1 score, and precision have been established. Additionally, CER-XNET is compared to traditional DL models. The system is evaluated using the selected method by taking scan images in order to obtain the evaluation results.

4.1 Performance metrics

Accuracy: The percentage of accurately predicted samples compared to all samples can be easily computed.

$$Accuracy = \frac{(TP+FP)}{(TP+TN+FN+FP)} \quad (4)$$

Precision: It evaluates how effectively the model categorizes favourable events. By dividing the sum of the expected positive values by the actual positive values, the accuracy ratio is determined.

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Specificity: To determine this, divide the actual negative number by the negative sum,

$$Specifity = \frac{TN}{TN+FP} \quad (6)$$

Recall: The ratio of true positive values to all true positive values is known as recall.

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

F1score: It incorporates a model's recall and precision ratings.

$$F1\ score = 2 \left(\frac{Precision*Recall}{Precision+Recall} \right) \quad (8)$$

Table 1. Performance evaluation of the L1reg CNN network

Data	Accura cy	Precisi on	Specifici ty	Reca ll	F1 Scor e
Normal	99.46	98.11	97.07	98.35	97.18
Abnor mal	99.02	97.67	98.94	96.96	98.35
Overall	99.24	97.89	98.05	97.65	97.76

An example of the input images for identifying the CC with the particular constraints is given in Table 1. The proposed CER-XNET network's average accuracy, F1score, precision, recall, and specificity are 99.24%, 97.89%, 98.05%, 97.65% and 97.76% respectively.

Figure 2 shows the chart-based cervical scan images for detecting the cancer input images. The suggested has average recall, accuracy, specificity, F1score and precision of 99.24%, 97.89%, 98.05%, 97.65% and 97.76% respectively.

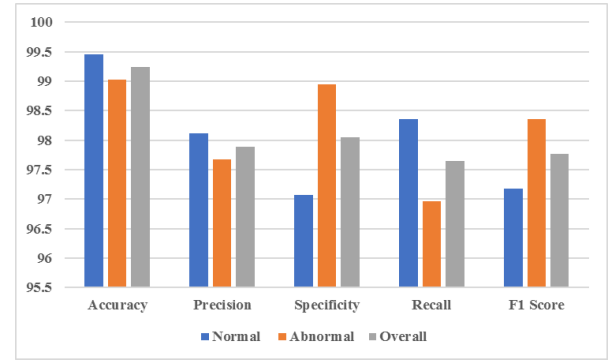


Figure 2. Graphical representation of performance analysis

4.2 Comparative analysis

This section comparisons and contrasts the proposed CER-XNET model with the current model using comparative analysis. Four DL classifiers CNN, Light weight CNN and Squeeze net as well as the L1reg CNN were put to the test. F1 Score and accuracy were used to assess the presentation of existing techniques and demonstrate the superiority of the suggested L1reg CNN network strategy.

Table 3. Comparison of different conventional network

Author	Networks	Accuracy	F1 score
Alyafeai, Z.	CNN	68	65.45
Chen, W	Light weight CNN	96.39	95.03
ŞENTÜRK, Z.K	Squeeze net	96.90	94.60
Proposed	Clust-L1reg CNN	99.24	97.76

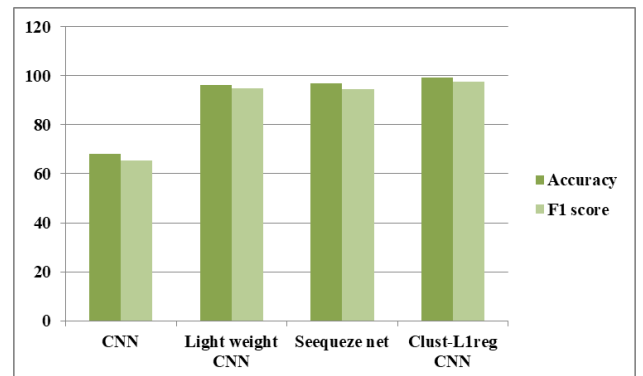


Figure 3. Comparison of existing network with CNN

5.CONCLUSION

This proposed CER-XNET method is utilized to detecting and classifying the CC to prevent the deathrate. the CC process is classified into normal and abnormal images. The classification of several MRI scans of CC is then done utilizing the DL network. Next, feature extraction is performed on the pre-processed images using Probabilistic Shape Priors and SegNet (PSP-SEG). Using a clustering-based L1 regulation-CNN, the images are then divided into normal and abnormal classes. The results were positive, and

the accuracy of the L1reg CNN network method outperformed the majority of the reported existing methods. The proposed CER-XNET network approach has a 99.24% accuracy in detecting cervical cancer. The CER-XNET forecast improves the accuracy and efficiency of the system.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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