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Deep ensemble learning model for cervical cancer disease classification on image dataset

Sonam Juneja *
Shikha Atwal †
Department of Computer Science and Engineering
Chandigarh University
Gharuan
Mohali 140413
Punjab
India

Reema Goyal §
Department of Computer Science and Engineering
Chitkara University
Rajpura 140401
Punjab
India

Bhoopesh Singh Bhati ‡
Department of Computer Science and Engineering
Indian Institute of Information Technology
Sonepat 131001
Haryana
India

Abstract

Early detection is the hallmark of ensuring better patient outcomes and successful treatment for most forms of cancer. In our proposed model, we classify the cervical cancer disorders through the developed deep ensemble learning model that was trained on a large dataset of colposcopy photos. It is evident that combining deep learning with an ensemble methodology would make colposcopy data-driven cervical cancer screening more accurate

* *E-mail:* **sonam.december@gmail.com (Corresponding Author)**
† *E-mail:* **shikhaatwal780@gmail.com**
§ *E-mail:* **reemagoyal01@gmail.com**
‡ *E-mail:* **bhoopesh.cse@gmail.com**

and robust. The proposed model was experimented with various known performance measures such as sensitivity, specificity, accuracy, PPV, and NPV. The experimental outcome results find this ensemble deep learning model to perform outstandingly well with remarkable robustness and outstanding accuracy in 'detecting' cervical cancer over individual models. Integrating the Colposcopy Ensemble Network architecture developed to address the problem of cervical cancer detection, this model increases the overall sensitivity and accuracy. Thus, it is highly efficient given other performance standards and fostering the development of ensemble learning models in classifying various diseases based on medical images

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Subject Classification: *68Txx,68Uxx.*

Keywords: *Ensemble, Accuracy, Datasets, Medical, Model, Learning, Disease.*

1. Introduction

Although disease detection and treatment have advanced significantly, a large number of women still continue to lose their lives every year to cervical cancer. Accurate diagnosis allows early identification, which leads to improved patient outcomes. Deep Learning (DL), Machine Learning (ML), Artificial Intelligence (AI). These have proved promising outcomes in the recent years in improving Efficiency and accuracy and speed in diagnosing cervical cancer [2]. Since the conventional screening methods have problems with reliability, specificity, and sensitivity, researchers are looking into alternative diagnostic methods [1].

1.1 *Rise of Deep Learning in Medical Imaging*

Machine learning's deep learning area has transformed medical image processing and disease detection by modeling its architecture and operations after the human brain's neural networks. Among the many medical imaging applications where Convolutional Neural Networks which is a type of deep learning architecture have demonstrated outstanding performance in the detection and categorization of malignant tumors from x-ray imagery [3]. This approach combines more than one independent deep learning models to provide a more reliable model. In that strategy, the range of models available is deemed to decrease the risk of overfitting while the risk of generalization accuracy is increased. The principle underlying ensemble learning is to pool their predictions for making more reliable results.

2. Related Work

[4]The method utilizes DeepCyto+ for imaging in cytology and DeepColpo for colposcopy; together, they provide a comprehensive screening tool. [5] The Automated Visual Examination (AVE) is an AI system with the aim of improving the efficiency of cervical precancer screening. F-1 score was 0.890 and average accuracy 91.6% independently with an independent test dataset of over 30,000 smart phone images. Table 1 shows the comparison of various papers related to proposed work.

Table 1

Comparison of various papers related to our study

Author Name	Year	Objective	Approach Used	Results
Tan, Sher et al. [6]	2023	Develop deep learning models for automated cervical cancer diagnosis	Utilize pre-trained convolutional neural network (CNN) models with transfer learning on pap smear images from the Herlev dataset. Analyze	Encouraging results obtained with little computing load, DenseNet-201 identified as the best model.
Pacal, Ishak and Kılıçarslan, Serhat [7]	2023	Improve computer-aided diagnosis systems for cervical cancer detection	Utilize deep learning- based algorithms from CNN and vision transformers (ViT), employ data augmentation and ensemble learning methods.	Latest ViT-based models outperform predecessors, while CNN models are on par.
Li, Chen & Xue et al. [8]	2019	Develop an ETL framework for classifying cervical histopathology images	Use transfer learning structures with Inception- V3 and VGG-16, fine-tuning technique, and late fusion-based ensemble learning strategy.	Average accuracy of 80% achieved in cervical histopathology image classification.

Contd...

Diniz, Débora and Rezende et al. [9]	2021	Reduce workload of professionals in cervical cancer categorization	Combine three effective designs among ten deep convolutional neural networks trained on cell nuclei. Utilize CRIC dataset. Compare ensemble performance with previous techniques.	Proposed ensemble outperforms previous techniques in sensitivity, recall, accuracy, F1-score, and precision for two- and three-class classification.
Kuko, Mohammed et al. [10]	2020	Develop automated methods to replace pathologists in Pap smear and LBC	Utilize deep learning, ensemble learning, and machine vision to automate Pap smear procedure.	Creation of an automated Pap smear screening test, with deep learning method achieving 91.6% accuracy.

3. Material and Methods

3.1 *Image datasets used*

Incorporating 5679 colposcopy images into the dataset is made possible by utilizing the cervical screening data acquired by Intel and Smartphone ODT In order to detect cancer at an early stage, a colposcopy picture is an invaluable tool. In order to determine if the patient need additional treatment or follow-up, the transition zone (TZ) examination is an essential component of any colposcopic evaluation for abnormal cytology. A TZ is considered type 1 since it lacks an endocervical component. Continuity between Type 2 and Type 3 transition zones includes the endocervical area. The most recent SCJ was given Type 2 rank after it was fully visible in TZ. Even with external instrumentation, the newly discovered SCJ remained partially obscured, earning it a category 3 classification

3.2 *Description of proposed model*

We improved the extraction of key cervical cancer features from colposcopy pictures by using a CYENET architecture that combines the benefits of depth and parallel convolutional filters. As an alternative to using a single convolution filter and the typical convolution layers at the network's foundation, the suggested architecture makes use of several convolution layers to separate individual input features. To reduce the impact of overfitting, we employ a series of convolutional filters to eliminate the biased components. Data priming, CNN model training, and analysis of classification results make up the three stages that make up this suggested process. A total of fifteen convolutional layers, twelve activation layers, four levels of cross-channel normalization, five layers for max- pooling, and six additional layers make up the CYENET model. Figure 1 is a flow diagram depicting the suggested automated method for early cervical cancer diagnosis.

In order to detect cervical lesions in colposcopic images, this research employed a two-deep learning algorithm. An entirely new CYENET

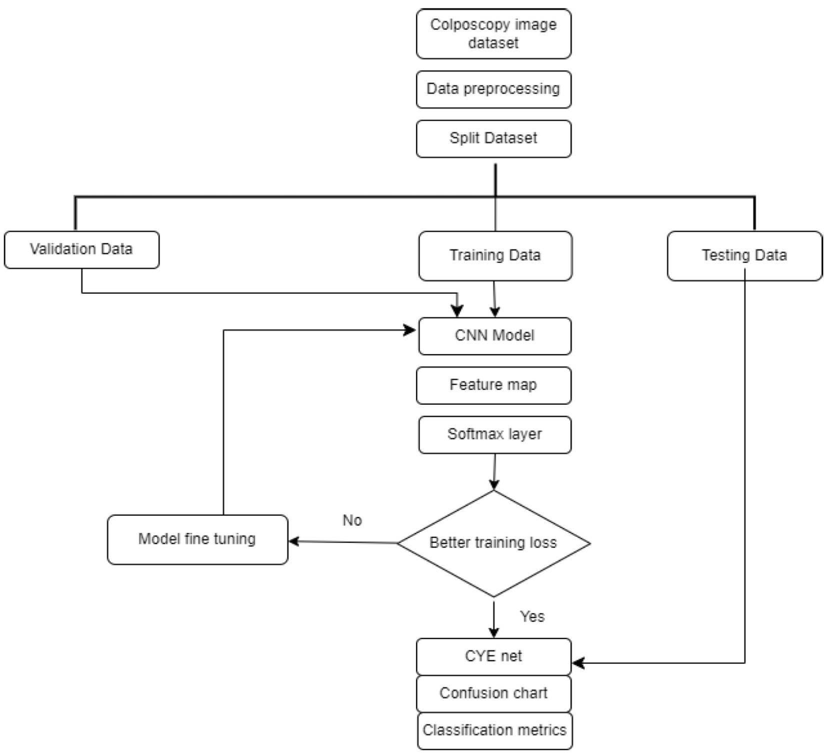

Figure 1

Cervical cancer diagnostic flow diagram based on the proposed CYENET concept

architecture was developed, with the transfer learning VGG_19 fine-tuned to fit the proposed approach. In the traditional neural network architecture, a single CNN filter is used, and the maximum allowable input data size is 5×5. After convolving with the input data, the filter uses a discriminating feature map to transform it into the same data. Combining multiple convolutional filters allows for the extraction of discrimination-based multilayer features, which is a key motivation for designing multilayer convolutional filters.

3.3 *Proposed architecture*

To improve the extraction of targeted cervical cancer characteristics from colposcopy pictures, we presented a CYENET architecture that combines the benefits of depth and parallel convolutional blocks. To get different features out of a single input, the suggested model uses multiple convolution layers. Beginning with a network of traditional convolution layers, the model In order to mitigate the over fitting impact, the biased components are removed using a series of convolutional filters. The three stages of this suggested approach are as follows: (1) preprocessing the data, (2) training the CNN model, and (3) outcomes of classification. Eleven activation layers, fifteen convolutional layers, five max pooling layers, and four cross channel normalization layers make up the CYENET model.

We feed the test data into the trained model and then measure the parameters that come out of it. An architecture reminiscent of Google Nets

Layer No.	Layer type	Filter size	Stride	No. of filters	FC units	Input	Output
1	Convolution 1	5 × 5	2 × 2	64	—	3 × 227 × 227	64 × 112 × 112
2	Max-pool_1	3 × 3	2 × 2	—	—	64 × 112 × 112	64 × 56 × 56
3	Convolution 2	1 × 1	1 × 1	64	—	64 × 56 × 56	64 × 56 × 56
4	Convolution 3	3 × 3	1 × 1	128	—	64 × 56 × 56	128 × 56 × 56
5	Max-pool_2	3 × 3	2 × 2	—	—	128 × 56 × 56	128 × 28 × 28
6	Parallel convolution 1	1 × 1, 3 × 3, 5 × 5	1 × 1	32 ⊕ 64 ⊕ 128	—	128 × 28 × 28	224 × 28 × 28
7	Max-pool_3	3 × 3	2 × 2	—	—	224 × 28 × 28	224 × 14 × 14
8	Parallel convolution 2	1 × 1, 3 × 3, 5 × 5	1 × 1	32 ⊕ 64 ⊕ 128	—	224 × 14 × 14	224 × 14 × 14
9	Parallel convolution 3	1 × 1, 3 × 3, 5 × 5	1 × 1	32 ⊕ 64 ⊕ 128	—	224 × 14 × 14	224 × 14 × 14
10	Max-pool_4	3 × 3	2 × 2	—	—	224 × 14 × 14	224 × 7 × 7
11	Parallel convolution 4	1 × 1, 3 × 3, 5 × 5	1 × 1	32 ⊕ 64 ⊕ 128	—	224 × 7 × 7	224 × 7 × 7
12	Max-pool_5	5 × 5	1 × 1	—	—	224 × 7 × 7	224 × 2 × 2
13	Fully connected 1	—	—	—	512		
14	Fully connected 2	—	—	—	3		

Figure 2

An explanation of the CYENET model's network architecture progresses to a single convolution filter at its conclusion

serves as an inspiration for the first few levels, which include multiple functionality- manipulating layers and two completely connected layers that incorporate Softmax classification layers. Figure 2 below shows the CYENET model's network description, which includes the max-pooling layer and the convolution layer, with the filter size in the parallel convolutional block varied.

4. Result and Discussion

The dataset for cervical cancer colposcopy is split as follows: eighty percent for training, ten percent for validation, and 10 percent for testing. The optimizer, momentum value, L2 regularization value, layer depth, and layer depth are all computed using Bayesian optimization. In order to train the model, fifty epochs will be utilized. With a batch size of 64 GPUs and an initial learning rate of 0.0001, we trained the model. We have previously demonstrated that the parameters of CYENET and VGG 19 are fixed, and that they are trained using the identical picture dataset. The CYENET model's training accuracy hit 97.1% and the VGG_19 (TL) model's reached 87% as the number of epochs grew. The proposed CYENET and the fine-tuned VGG 19 are displayed in a validation plot against the epoch. As the number of training epochs increases, the model's accuracy will surely rise. A validation accuracy value of 91.3% is achieved after 23 rounds of iterations by the suggested CYENET model. At the same time, when trained with a learning rate of 0.0001, the advanced VGG-19 model initially displayed an accuracy fluctuation. With a validation accuracy of 68.8 percent, the VGG 19 model accomplished the task at hand. The results show that the proposed CYENET model is better than the VGG19 model for cervical screening using colposcopic pictures. This is likely because the CYE- NET model is simpler and more trustworthy.

The test's sensitivity is the percentage of infected people that test positive. The proportion of healthy people who respond negatively describes a test's specificity. Positive test results increase the likelihood of a diagnosis, known as the positive predictive value (PPV). The negative predictive value (NPV) is the likelihood of not becoming infected after a negative test. Table 2 shows the suggested model's 1884 test image assessment results. The experimental findings show that the CYENET model outperformed all colposcopic image-trained model.

Table 2

Experimental findings comparing the proposed design to several models

Model name	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
DenseNet-121	72.39	59.91	76.79	48.41	84.48
DenseNet-169	69.83	65.00	71.52	44.79	85.28
Colponet	81.0	—	—	—	—
SVM	63.22	38.45	71.84	32.39	76.91
Inception-Resnet-v2	69.3	66.66	70.6	47.18	84.00
CYENET	92.26	92.39	96.18	92.00	95.00
VGG19 (TL)	73.25	33.00	79.00	70.00	88.00

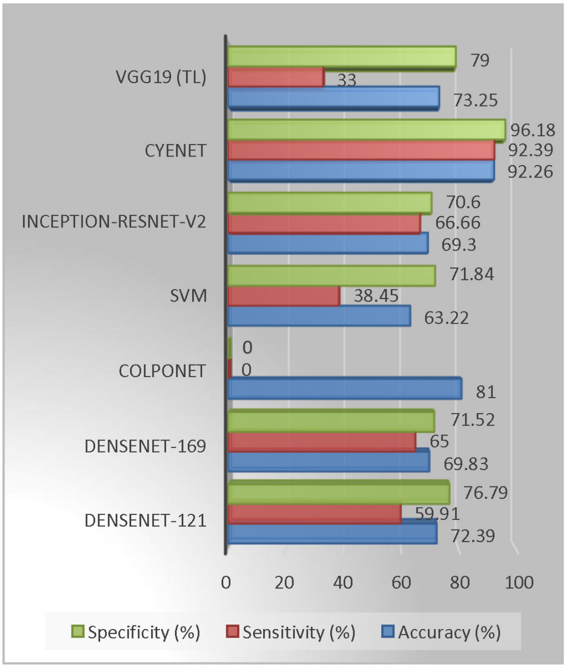

Figure 3

Evaluation of the suggested design in comparison to alternative models

The table 2 and figure 3 display the experimental results of various models within the proposed architecture compared to one another; it is likely utilized for illness categorization or diagnosis. There are a number of performance metrics used to assess the models, including PPV, NPV, Specificity, Accuracy, and Sensitivity.The accuracy measure is the percentage of cases that are correctly categorized out of all instances. The term “sensitivity” can refer to either the true positive rate or the percentage of real positive events that a model accurately detects. The positive predictive value, expressed as a percentage, is the ratio of the number of instances that were positively identified to the total number of casesthat were favorably predicted. The specificity of DenseNet-121 is marginally greater than that of DenseNet-169, although both networks attain modest accuracy and sensitivity.Among the models mentioned, Colponet has the best accuracy, suggesting that it performs better overall. But we don’t have any sensitivity, specificity, PPV, or NPV numbers.Support vector machines (SVMs) have poor sensitivity and PPV and are less accurate than other models. Inception- Resnet-v2 performs comparably to DenseNet-169, displaying a modest level of accuracy while maintaining a balanced sensitivity and specificity.

Overall, the given metrics suggest that CYENET is the most promising model, while Colponet does exhibit comparable performance as well.

5. Conclusion

Finally, a technique to improve cervical cancer detection and diagnosis is to use ensemble deep learning networks. Applying ensemble learning algorithms to colposcopy images improves cervical cancer diagnosis in several significant ways. The proposed method of cervical cancer classification can help a group of people who do not need invasive procedures performed on them. That colposcopy screening for cervical cancer may be made more sensitive and accurate by the proposed CYENET is excellent news for doctors and other trained healthcare providers

Ensemble deep learning networks offer interpretability and transparency that is very helpful for clinical decision-making in cervical cancer diagnosis. Because of their scalability and flexibility, ensemble deep learning networks are perfect for integrating with the healthcare system as it is. There is significant potential for ensemble deep learning networks to improve healthcare delivery and cervical cancer screening when applied to colposcopy pictures for cancer diagnosis. Improvements in the detection, diagnosis, and treatment of cervical cancer are anticipated to result from ongoing research into ensemble learning approaches and colposcopy imaging technology.

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