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AN IMPROVED CLASSIFICATION OF MR IMAGES FOR CERVICAL CANCER USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract
Cervical cancer is the biggest cause of death in the field of women gynaecology. Patient treatment outcomes are influenced by the stage and nodal status of their cancers as well as their tumour size and histological classes. In this paper, we develop a classification model using a state-of-art heuristic mechanism that enables the use of deep learning algorithm to classify the MRI image from the input cervical images. The classification is conducted with highly dense network that helps to reduce the errors during the testing process. The simulation is conducted in matlab to test the efficacy of the model and the results of simulation shows that the proposed method achieves higher grade of classification accuracy than the other existing methods.

Keywords:
Classification, MR Image, Cervical Cancer, CNN

1. INTRODUCTION

Cervical cancer is the second leading cause of death among women worldwide. Doctors presumed that cervical cancer would be treaTable.no matter how far it had progressed. Recent advances in using images to increase disease detection rates [1] have been developed. Early detection of cervical cancer can save lives, as low- and middle-income countries account for nearly 85% of all cervical cancer deaths.

Cervical cancer is six times more common in HIV-positive women than in HIV-negative women, and HIV is responsible for approximately 5% of all cervical cancer cases. Many factors, including access to equipment, consistency of screening tests, sufficient supervision, and identification and treatment of lesions discovered [1]-[3], have redefined screening effectiveness. Despite significant advances in medicine and science, this condition is not treaTable.unless detected in an early stage. As a result, cervical cancer prevention and screening programmes play a critical role in the battle against the disease. Cervical cancer screening often includes HPV testing, cytology or PAP smear testing, colposcopy, and biopsies. These tests include the standard screening process. The process is supported by many tools developed to improve its efficacy, practicality, and affordability.

While the PAP smear image screening is most commonly used to diagnose cervical cancer and rule out other conditions, it is time-consuming and requires the expertise of trained professionals. Additionally, the conventional screening method can miss cancerous lesions that would otherwise be detected. The PAP smear and HPV testing are pricey and ineffective therapy options. On the other hand, Colposcopy treatment is frequently used in developing nations. The limitations of the PAP smear and the HPV test are overcome using colposcopy screening. Treatment is more likely in the early stages of cervical and other cancers, but the absence of signs and symptoms prevents early diagnosis. Effective screening programmes can help prevent cervical cancer deaths and lead to reduced disease and impermanence. Cervical cancer screening centres are hard to come by in low and middle-income countries due to a lack of trained medical personnel and inadequate healthcare financing [4].

In order to examine closely for signs of cervical cancer, an instrument called a colposcope is used. When this type of cancer is diagnosed early, it can substantially impact the treatment of the patient and the outcomes. Several studies have used various methods to get information from digital colposcopy images. The primary goal of these studies is to provide healthcare providers, regardless of their degree of expertise, with alternate tools. Previous works have used computer-aided methods to improve and evaluate image quality, regional segmentation, image identification, unstable regions and patterns identification, transition zone type classification (TZ), and cancer risk categorization [5]. Cervical colposcopy images are enhanced with CAD tools, allowing doctors to see any abnormalities that may be present more clearly. Clinicians can use these tools to aid in diagnosing, but only those with sufficient training and experience should use them. The discovery of diseased regions in a colposcopy analysis may be necessary for this reason. Acetowhite, aberrant vascularization, mosaic regions, and punctures are abnormalities found here [6]-[9]. A method to spot irregularities in standard colposcopy images is adopted in most studies.

Advances in computer vision, natural language processing, forecasting, and battery health monitoring have all been made possible because of deep learning [10]. Analysis of medical images is critical to disease diagnosis. The most processed image data comes from medical images such as MRIs, CTs, ultrasounds, and blood smears [11]. With the multilayer neural network perception mechanism of deep learning, images can learn more abstract features to overcome the difficulties plaguing conventional CAD systems in medicine. On the other hand, deep learning needs to be backed up by an extensive database, especially for successful examples.

Many ensemble learning approaches are mentioned in the prior work to tackle this problem. An effective CAD system for urban healthcare in smart cities uses a convolution neural network (CNN) to identify MI signals [12]. To detect arrhythmia, a new feature extraction methodology, followed by a genetic algorithm, has been proposed [13].

This study aims to construct a deep Convolutional Neural Network (CNN) to automatically detect cervical cancer from colposcopy images. This strategy eliminates the need for segmentation and feature engineering for the first time, allowing the discriminative features to be extracted using ensemble approaches instead. The VGG19 model, extensively used in medical image processing, is fine-tuned using the transfer learning approach to forecast accuracy.

Colposcopy images are augmented with additional data to prevent an overfitting problem with a trained model. In order to learn the specific features and improve accuracy, this method is an effective strategy. The use of occlusion sensitivity maps to depict the image properties of cervical tumors for classification purposes is another noteworthy contribution to this paper.

2. RELATED WORK

When it comes to machine learning, various algorithms were used, with the most remarkable results coming from random forests [14], a segmentation refinement approach. Adaboost detectors [15], SVM supports [16], and Gaussian mixture models [17] are just a few of the unattended learning approaches to the various image or superpixel patches that have been extracted using robust refinement methods. The use of superpixels as a new Markov random field segmentation method for non-overlapping cells has been proposed and implemented [18].

In order to identify cervical cells, a multifilter SVM was used, and the parameters have been chosen accordingly. Artificial Neural networks (ANN) have been shown to classify cervical cells with 78% accuracy [10]. Using an unsupervised method, the issue of unbalanced medical evidence for various cervical cancers was addressed [11].

The Particle Swarm Optimization (PSO) with KNN membership values is one of the best classification models. Segmentation and classification approaches and Gabor features are used to classify the cervical cancer cell. The accuracy of normal and cancer cell classification was found to be 89% [13]. It was found that classifying the collected CNN features with LSSVM (the least square support vector machine) yielded the most impressive results [14]. RBF SVM also had a strong outcome and outperformed logistic regression and random forests [10]. Depending on the features, accuracy ranged from 90 to 95%.

Many applications have shown promising results with new deep architectures, including ResNet, Inception, and tree models [16]. CNN, one of the deep learning approaches, are extensively used to detect and recognize cervical cancer [17]. A CNN-based technique for early cervical cancer cell identification and classification extracted deep learning characteristics from cervical images [15]. In order to classify the images, an extreme learning machine (ELM) was deployed. Using the CNN paradigm, we could fine-tune and transfer our learning. The ELM, MLP, and AE-based classifiers were also used as alternatives to the ELM, MLP, and AE.

The stacked soft-max autoencoder claimed to have a precision of 97.25% on the cervical cancer dataset [9]. It was decided that a preliminary attempt be made to use machine learning applications to increase cervical cancer risk. Cervical screening with machine learning software was utilized to address the issue of predicting the patient risk. In order to anticipate a patient risk, they focused on the movement of information from linear classifiers to linked activities.

Methods for lowering dimensionality can increase the predictive power of machine learning models [11] since the population-associated risk factors are highly sparsely impacted. While some methods gain from employing sub-optimal means to reduce dimensionality and classify them, many others benefit from this approach [12] to efficiently collect and classify cell characteristics in smeared cervical images [13].

An early cervical cancer prediction model (CCPM) has been proposed to incorporate risk factors [14]. CCPM initially eliminates outliers by balancing the number of cases in the dataset, outlier identification methods. This new approach may now predict cervical cancer risk with better precision. The intelligent diagnostic component received data from the cervical cell images with features extracted. An artificial neural network was used to predict pre-cancerous stages.

Better screening techniques are also out of reach in developing nations because of the difficulties and time involved in manually screening a cervical cytology specimen for abnormal cells. For the automatic categorization of cervical images to assess CIN2 or higher-level lesions in cervical imaging, this system relies on transfer learning and densely linked convolutional networks that have been pretrained.

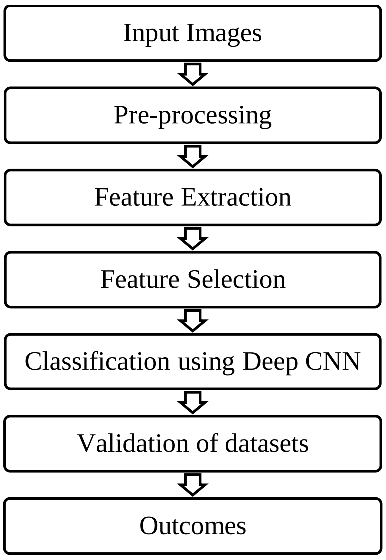
Pathologists needed more time to analyze Pap smear screening samples since there were so many cells to look at. The Pap smear image was screened using deep learning models, which were utilized to identify all of the cells and other elements present. In the system, two cells overlap, making it difficult to categorize. This challenge needs precisely labeled data, but producing this medical sector dataset is quite challenging. A new deep learning model for cervical cancer screening by colposcopy is proposed in light of the challenges outlined above. Because it is a quick and painless way to screen for cervical cancer, colposcopy images are an excellent option for this type of screening (no need to introduce instruments into the body). The array of colposcopy datasets is sparse in comparison to the other tests. In order to speed up the screening process for medical professionals, automatic classification of cervical cancer from colposcopy images has been developed. This research presents a computerized approach for predicting cervical cancer based on colposcopy images.

3. PROPOSED METHOD

One of the best ways to detect cancer early is with the help of a colposcopy image. The Transition Zone (TZ) colposcopic examination is required to evaluate and identify patients with irregular cytology who require additional care or monitoring. The TZ is also an essential part of this investigation. Observer heterogeneity of the TZ form and squamous column junction (SCJ) visibility evaluation and quantitative calculations of the intra-and interobserver similarities of TZ contour tracing are all considered to be relatively robust in colposcopy perception of distinctive properties.

In TZ, the most recent SCJ was classified as a type 2 when it was clearly visible. The New SCJ could only be seen with external instruments and was listed as a type 3. Even though it is not a definitive diagnostic test, this test can be used to evaluate someone who has been diagnosed with abnormal cytology. The same or different colposcopies can produce different results. As a diagnostic tool, employing colposcopy relies heavily on the clinician knowledge and experience. Colposcopy is accurate in detecting both pre-invasive and invasive cervix tumors.

For the automated identification of hepatocellular carcinoma, an ensemble learning strategy employing seven machine learning algorithms is used. A collaborative representation classification with a boosting technique is used to categorize hyperspectral images.



3.1 DATASET AND PRE-PROCESSING

Intel and Smartphone ODT collected 5679 colposcopy images for their cervical screening data collection. The diagnostic study-specific image is used in order to classify the data. Data is pre-processed to remove all ethical aspects from each case. Initially, the data is classified into type 1, type 2, and type 3.

MATLAB image labeller apps help identify the region of interest (ROI) in the cervical images by referencing a pre-trained dataset. The ROI area in which the lesion is located is known as the transition zone of the clinic. Annotations, markings, and ROI are added to the original image first.

Because of the uneven distribution of images in the dataset, it is concluded that the dataset is unbalanced. The model may become overfit due to imbalances in the dataset. Oversampling is used to address this problem. With the oversampling method, type 1 and type 3 images are repeated indiscriminately and equal to the type 2 image count. After the oversampling process, the total number of images in the data collection is 9378.

Second, strategies for improving the quality of the training data are employed. Overfitting is reduced by using the data augmentation method, which increases the robustness of the model. Rotation, brightness adjustment, cropping, and a random dataset increase are all applied to the original image. Image augmentation increases the overall image size to 11266 pixels. Ultimately, the altered image data must be re-sized to fit the CNN model.

4. DEEP CONVOLUTIONAL NEURAL NETWORK MODEL

Many images processing applications, including medical image analysis, have relied on CNN models. Cervical cancer detection with computer vision is an obvious challenge. Using CNN, it is possible to discriminate between types 1, 2, and 3.

The test uses deep convolutional neural networks to detect cervical lesions (moderate). This model has been fine-tuned to classify three cervical cancer classes by freezing the top layers and testing them with cervical imaging data. Using the advantages of depth and parallel convolutional filtering, a CNN architecture is designed that can better identify certain cervical cancer signals in colposcopy images. The proposed model uses two types of convolution layers: classic convolution layers at the beginning of a network and multiple convolution layers to extract different features from a single dataset.

Overfitting can be reduced by using multiple convolutional filters to eliminate the biased bits. The three phases of this proposed model are data pre-processing, CNN model training, and classification outcomes. The CNN model has 15 convolutional layers, 12 activation and 5 pooling layers, and 4 cross-channel normalisation levels. The trained model is fed the test data, and the output parameters are measured.

4.1 FITNESS FUNCTION

The greater the distance between a person and the solution, the greater the individual's fitness value; the greater the distance between an individual and the solution, the better the solution it contains. When developing an objective function in this topic, the data of cervical cancer patients and their parameters is employed as a starting point. This is what the fitness function looks like represented graphically:

$$F(i,j)=\sum_{i,j=1}^{N} NC-D_{j-i}+V_{j-i} \tag{1}$$

5. RESULTS AND DISCUSSION

The Kaggle dataset is used as a source of experimental data. There is an 80/20 ratio between training, validation, and testing in the cervical cancer dataset.

Table.1. Training and Testing Accuracy

Classifier	Train Loss	Test Loss	Train Accuracy	Test Accuracy
DBN	0.157	0.157	0.185	0.208
MLP	0.156	0.210	0.157	0.256
RNN	0.126	0.124	0.551	0.531
CNN	0.125	0.121	0.549	0.565

When assessing the completeness of a classifier (Table.1), the most reliable metrics are sensitivity (Table.2) and specificity (Table.3), which are obtained from the confusion matrix in medical images.

Table.2. Sensitivity

Images	DBN	MLP	RNN	CNN
100	41.98	45.27	49.29	52.54
200	42.55	48.08	52.36	56.68
300	45.27	54.82	59.74	67.79
400	78.99	82.14	84.21	87.26

Table.3. Sensitivity

Images	DBN	MLP	RNN	CNN
100	56.22	61.04	66	71.47
200	59.11	63.06	67.8	73.86
300	59.87	64.89	68.45	74.06
400	79.72	82.77	84.81	88.44

The harmonic mean of the accuracy and reminder is used to compute the model F1 score (Table.4). Cohen Kappa metrics are deemed to have the correct measure to solve various class concerns and class imbalances with the statistical standards to identify agreement between two parties. However, the dataset still has class imbalances that influence the f1 score.

Table.4. F-measure

Images	DBN	MLP	RNN	CNN
100	51.53	54.98	61.46	78.14
200	58.59	62.67	72.54	78.18
300	60.88	64.11	73.52	78.84
400	60.94	66.67	74.79	79.15

Further in Table.6, the proposed method is compared with other existing methods in terms of accuracy, precision, recall, F-measure, Matthews Correlation Coefficient (MCC) and Jaccard Index (JI).

Table.6. Datasets Validation

Accuracy	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	76.14	85.45	89	90.13
SIPaKMed	70.26	73.62	81.11	83.84
Intel ODT	79.71	87.3	88.82	92.34
DHB	88.9	89.88	90.06	97.91
Precision	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	76.95	84.39	89.06	91.41
SIPaKMed	69.29	81.16	81.42	84.15
Intel ODT	81.29	88.9	89.08	94.77
DHB	86.58	88.97	89.97	98.6
Recall	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	82.17	74.67	88.94	90.98
SIPaKMed	69.17	69.56	81.06	83.72
Intel ODT	80.95	86.31	88.78	91.09
DHB	88.3	88.86	89.83	94.57
F-measure	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	75.79	83.27	89	91.19
SIPaKMed	69.23	74.91	83.93	81.23
Intel ODT	81.12	87.67	88.84	92.89
DHB	87.43	88.91	89.9	96.54
MCC	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	71.69	83.4	83.59	88.86
SIPaKMed	70.02	73.13	81.14	83.15
Intel ODT	78.95	86.3	88.73	90.17
DHB	86.43	88.65	88.75	96.6
JI	**DBN**	**MLP**	**RNN**	**CNN**
Herlev	0.7126	0.8297	0.8331	0.8848
SIPaKMed	0.6973	0.7271	0.8093	0.8289
Intel ODT	0.7858	0.8616	0.8856	0.8913
DHB	0.8631	0.8785	0.8868	0.8964

The results of simulation show that with entire datasets, the proposed method achieves higher degree of classification accuracy with higher accuracy, precision, recall, F-measure, MCC and JI.

6. CONCLUSION

Cervical cancer types can be identified using colposcopy images and CNN novel deep learning architecture. In order to enhance the accuracy of the categorization, the image dataset is balanced using the oversampling technique. In this study, two different models are discussed. With the VGG-19 architecture, one can employ a transfer learning strategy. The other is a novel CNN algorithm that uses the ODT colposcopy image dataset to classify cervical cancer types. Medical experts and trained healthcare practitioners can benefit from the proposed CNN improved classification efficiency in their efforts to detect cervical cancer through colposcopy screening. Different datasets will be tested against the theoretical deep learning model in the future. Additionally, modern image processing and CNN algorithms can be used to construct a cervical precancerous new data diagnostic system.

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