Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Layer Selection on Residual Network for Feature Extraction of Pap Smear Images

Alfian Hamam Akbar[1], Imas Sukaesih Sitanggang[1,*], Muhammad Asyhar Agmalaro[1], Toto Haryanto[1], Riries Rulaningtyas[2], Nor Azura Husin[3]

[1] Department of Computer Science, IPB University, Bogor, 16680, Indonesia
[2] Department of Physics, Airlangga University, Surabaya, 60115, Indonesia
[3] Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

ARTICLE INFO

Article history:
Received 21 June 2023
Received in revised form 30 July 2023
Accepted 3 October 2023
Available online 30 December 2023

Keywords:

Cervical cancer; Hierarchical learning; Pap smear; Screening; Support vector network

ABSTRACT

Pap smear screening test is one of the early prevention efforts to detect cervical cancer. Manual screening tests are still prone to observation errors. This study aims to create a convolutional neural network (CNN) model and support vector machine (SVM) model to identify cervical cancer through pap smear images. The data used are 4049 normal and pathological cervical cells in pap smear images sourced from SIPaKMeD, which were divided into 5 classes based on the level of cancer malignancy. The CNN model is used to extract features on the pap smear image, and SVM is used to carry out the classification. The results of this study are four cervical cancer classification models on pap smear images using Resnet50 and Resnet50V2 architecture and SVM algorithms with different scenarios on freeze and unfreeze of the convolution layer. The classification model with the best performance has an accuracy of 97.09%. CNN model with freezing the convolution layer provides much faster in the pre-trained model and the integration of this model with the SVM as the classifier results in the classification model of cervical cells in pap smear images with high accuracy.

1. Introduction

Cervical cancer is a malignant disease that occurs in a woman's cervix. About 99% of all cervical cancer cases are related to infection with high-risk human papillomaviruses (HPV) [1]. The cause of cervical cancer is known to be the oncogenic sub-type of the HPV (Human Papilloma virus). According to data from the World Health Organization (WHO), cervical cancer is the fourth most common cancer in women. In 2018, an estimated 570,000 women were diagnosed with cervical cancer worldwide and around 311,000 women died from the disease [2]. The number of worldwide cervix uteri cases in 2020 is estimated at 604,127 (3.1%) [3]. The Global Cancer Observatory (2021) reports that the number of new cases of Cervix uteri in 2020 in Indonesia reaches 36,633 (17.2%) which is the second position after Breast cancer. The incidence of cervical cancer in Indonesia is 23.4 per

* *Corresponding author.*
E-mail address: imas.sitanggang@apps.ipb.ac.id

https://doi.org/10.37934/araset.36.2.5666

100,000 population with an average death rate of 13.9 per 100,000 population [4]. The case of cervical cancer often occurs in women aged 15-49 years [5].

Cervical cancer is fully treatable if detected at a pre-cancerous stage. WHO emphasizes that once it has been successfully diagnosed, cervical cancer is one form of cancer that has a high success rate for curing, as long as cancer can be detected early and treated effectively. Papanicolaou ("Pap") smear is one of the methods of screening for cervical cancer that is widely used in many countries including Indonesia. Prevention of cervical cancer can be done by detecting it accurately and as early as possible. Over the past 60 years, the Pap smear test has had a significant effect on reducing mortality from cervical cancer [6]. Detection of cervical cancer that is done manually requires a long time and a lot of energy and is prone to errors if the process is carried out intensively. This manual screening process can have high false-positive results due to the higher intensity of the screening process carried out in line with the increase in human error.

The deep learning approach offers automated methods based on specific functions and objectives such as image detection, segmentation, and classification [7]. Convolutional Neural Networks (CNN) is a model architecture that is often used to classify medical images because of its outstanding performance in the field of computer vision [8]. CNN directly extracts features from a series of image data, eliminating the manual feature extraction process. The CNN model is built with several different layers to perform the task of image classification [9]. Over the last few years, CNN have had good achievements to detect the cancerous cells on Pap smear images [10-15]. AlexNet, VGG-16, and RestNet are the architecture of CNN that are most often used to perform segmentation and classification tasks in cervical cancer [16-18]. The combination of CNN and Support Vector Machine (SVM) was implemented to classify pap smear images that results accuracy > 90% [19-22]. Ensemble-based classification models using a fuzzy rank-based fusion and three CNN architectures, namely Inception v3, Xception, and DenseNet-169 pre-trained were implemented on ImageNet dataset for Pap-stained single cell and whole-slide image classification [23]. Deep learning with the architecture InceptionV3, ResNet50, and VGG19 and transfer learning were applied to classify cervix images [24].

The results of previous studies showed that the CNN model has a good performance in extracting features on pap smear images. In this study, the CNN model is implemented to carry out the feature extraction process with the output in the form of a vector of features. The features are then used as input to train the SVM model in the classification process. SVM is one of the best machine learning algorithms for pattern and image classification [25]. The resulting model is expected to assist cytopathologists in making an accurate initial diagnosis of cervical cancer. Instead of using CNN for the classification task of pap smear images, this study focuses on the application of CNN in feature extraction. This aims to evaluate the performance of the feature extraction module in CNN especially on pap smear images. The results will be compared to our other work in developing the classification model of pap smear images using CNN.

2. Methodology

2.1 Data

The data used in this study are the SIPaKMeD image dataset [26]. SIPaKMeD is a new dataset for a feature and image-based classification of normal and pathological cervical cells in pap smear images [26]. The SIPaKMeD dataset consists of 4049 isolated cell images that have been manually cut from 966 groups of pap smear image cells. Cells are grouped into 5 classes. Normal cells are divided into two categories, namely Superficial/intermediate (SI) and Parabasal (PB). Abnormal

but not malignant cells are divided into two, namely Koilocytotics (KC) and Dyskeratotic (DT). One category of cells classified as benign is metaplastic. An illustration of each class is shown in Figure 1.

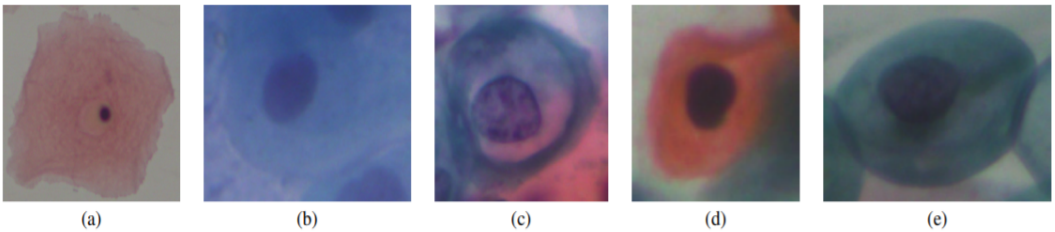

Fig. 1. Image category: (a) Superficial-Intermediate, (b) Parabasal, (c) Koilocytotic, (d) Dyskeratotic, (e) Metaplastic [26]

2.2 Research Steps

There are two main tasks conducted in this study namely the feature extraction from cervical cells in pap smear images and classifiers development using SVM [27]. The steps are data pre-processing, CNN modelling for feature extraction, creating a classifier using SVM, hyperparameter tuning, and model evaluation.

i. Data Pre-processing
In the data pre-processing, we performed resizing images as the input of CNN and splitting a dataset. The size of images is set to 224 × 224. The dataset is divided into three partitions namely training, validation, and testing datasets with the proportion of 80%, 15%, and 5% respectively (Table 1). The training dataset was used to create the model. Hyperparameter tuning was applied to the validation dataset, and model evaluation was done on the testing dataset.

Table 1
Number of images in training, validation and testing datasets

Class	Number of Cell Images	Number of Images in Training Dataset	Number of Images in Validation Dataset	Number of Images in Testing Dataset
Superficial/Intermediate (SI)	831	664	126	41
Parabasal (PB)	787	630	116	41
Koilocytotics (KC)	825	660	124	41
Metaplastic (MP)	793	634	118	41
Dyskeratotic (DT)	813	650	122	41

ii. CNN Modelling for Feature Extraction
This study uses the CNN model with the Resnet50 architecture for feature extraction on pap smear images [26]. There are two Resnet50 models used namely pretrained Resnet50 and pretrained Resnet50V2. Fully connected layers in the two pretrained models are not be used. Freeze and unfreeze processes were implemented on several convolution layers of the two models. This freeze and unfreeze scenario aim to maintain the weight of the convolution layer so that it is not updated as the training progresses. Four scenarios in CNN modelling for feature extraction are as follows
- Scenario 1: CNN Resnet50
- Scenario 2: CNN Resnet50V2

- Scenario 3: CNN Resnet50V2 with freeze
- Scenario 4: CNN Resnet50V2 with pooling layer

The freeze and unfreeze process also aims to reduce the duration required for model training. The output of this model training is a feature map that is used for training data at the classifier development step.

iii. SVM Modelling
There are four SVM models built on the pap smear images dataset. Each SVM model is trained individually using the features extracted from each CNN model. The SVM 1 was trained using the extracted features of scenario 1 (CNN Resnet50). SVM 2 was trained using features from scenario 2 (CNN Resnet50V2). The SVM 3 was trained with features from scenario 3 (CNN Resnet50V2 with freeze) and the SVM 4 was trained using the features extracted from scenario 4 (CNN Resnet50V2 with pooling layer). The method used for multiclass classification in the four SVM models is 'one vs rest'.

iv. Hyperparameter Tuning
Parameter tuning aims to find the most optimal parameter values for the data to be used in the model training process [28]. The SVM parameters to be tuned are C, degree, and kernel. Parameter tuning was performed using the "sklearn" library. A search space is created to obtain parameter pairs that can produce the best model. The search space for tuning parameters can be seen in Table 2. The tuning parameter was carried out once for the four SVM models. After finding the SVM model with the best parameters, the model is retrained using the training data.

Table 2
Search space for hyperparameter tuning

Parameter	Search space
Kernel	[linear, poly, sigmoid, rbf]
C	[0,1 , 1 , 10]
Degree	[1, 2, 3]
Gamma	[0,01 , 0,1 , 1]

v. Model Evaluation
The classification models are evaluated based on accuracy, sensitivity, specificity, and F-measure. The model's performance is calculated based on the number of images that are correctly and incorrectly classified by the models. Those metrics are derived from the confusion matrix.

2.3 CNN Models

We performed four scenarios in CNN modelling. In scenario 1 and scenario 2, the convolution layer in the pretrained model is directly used as feature extraction. In scenarios 3 and 4, the model is trained first with training data, then the convolution layer is used as a feature extractor.

i. Scenario 1 (Resnet50)
The first model uses Resnet50 convolution basis with pretrained Imagenet weights. Before implementing the convolution, a rescaling layer is added which aims to normalize

the value of each pixel in the image into the range 0 – 1. The convoluted features are then entered into a flatten layer to change the feature dimensions to 1 × 100,352. The summary of the CNN model in scenario 1 can be seen in Table 3. The value of training parameters can be changed during the step of the training model, for example, weights. Non-training parameters have value that cannot be changed during the training model, for example, the number of layers.

Table 3
Resnet50 convolution basis model on scenario 1

Layer (type)	Output	Number of parameters
Rescaling (Rescaling)	(None, 224, 224, 3)	0
Resnet50 (Functional)	(None, 7, 7, 2048)	23,587,712
Flatten	(None, 100352)	0
Number of parameters: 23,587,712		
Training parameters: 23,534,592		
Non-training parameters: 53,120		

ii. Scenario 2 (Resnet50V2)
In scenario 2, the convolution base Resnet50V2 is used. The weights used are pretrained Imagenet weights. This model also uses a rescaling layer and a flatten layer as implemented in the model in scenario 1. The summary of the CNN model in scenario 2 can be seen in Table 4.

Table 4
Resnet50V2 convolution basis model on scenario 2

Layer (type)	Output	Number of parameters
Rescaling (Rescaling)	(None, 224, 224, 3)	0
Resnet50 (Functional)	(None, 7, 7, 2048)	23,564,800
Flatten	(None, 100352)	0
Number of parameters: 23,564,800		
Training parameters: 23,519,360		
Non-training parameters: 45,440		

iii. Scenario 3 (Resnet50V2 with freeze)
The Resnet50V2 pre-trained model is used in scenario 3. The pre-trained model is trained first on the training data before the convolution layer of the model is used as a feature extractor. The weights used are pre-trained Imagenet weights. The summary of Resnet50V2 pre-trained model in scenario 3 can be seen in Table 5. Convolution layers 1-4 in the model are frozen, then the model is trained with 20 epochs on the cervical image dataset. After being retrained the model is used as a feature extractor using the convolution layer model section.

Table 5
Resnet50V2 pre-trained model on scenario 3

Layer (type)	Output	Number of parameters
Rescaling (Rescaling)	(None, 224, 224, 3)	0
Resnet50V2 (Functional)	(None, 7, 7, 2048)	23,564,800
Flatten	(None, 100352)	0
Dropout (dropout)	(None, 100352)	0
Fc_layer (dense)	(None, 160)	16,056,480
Classifier (dense)	(None, 5)	805
Number of parameters: 39,622,085		
Training parameters: 31,028,165		
Non-training parameters: 8,593,920		

iv. Scenario 4 (Resnet50V2 with pooling layer)
The Renset50V2 pre-trained model is used in scenario 4. The model is also retrained on the cervical image dataset and the weight used is the pre-trained Imagenet weight. The summary of the Resnet50V2 pre-trained model in scenario 4 can be seen in Table 6. The difference between the pre-trained model used in scenario 3 is that there is a pooling layer that replaces the flatten layer. This scenario is performed because of the limitations of the development environment in this study. The flatten layer function is used to convert the feature dimensions into a one-dimensional array, meanwhile, the pooling layer is utilized to reduce the feature size and also convert the feature dimensions into a one-dimensional array. In scenario 4 the pre-trained models were directly trained on training data of cervical images without going through the freezing process. After the convolution layer model is trained, the model is then used as a feature extractor.

Table 6
Resnet50V2 pre-trained model on scenario 4

Layer (type)	Output	Number of parameters
Rescaling (Rescaling)	(None, 224, 224, 3)	0
Resnet50V2 (Functional)	(None, 7, 7, 2048)	23,564,800
Pooling layer	(None, 2048)	0
Dropout (dropout)	(None, 2048)	0
Fc_layer (dense)	(None, 160)	327,840
Classifier (dense)	(None, 5)	805
Number of parameters: 23,893,445		
Training parameters: 23,848,005		
Non-training parameters: 45,440		

3. Results and Discussion

The basic architecture used to build the CNN model is pre-trained Resnet50 and pre-trained Resnet50V2. The classification performance of each model used in this work was compared using the mean accuracy, specificity, sensitivity, and F-measures. The confusion matrix is also calculated to describe the prediction results for each class, with the 5 existing classes divided into two major classes, namely the positive class and the negative class. Each positive or abnormal cell class is divided into Koilocytotic (KC) and Dyskeratotic (DC) classes. Classes of negative or normal cells and benign cells are divided into superficial-intermediate, parabasal, and metaplastic. Figure 2 shows our model's performance evaluated on the test dataset for each model scenario.

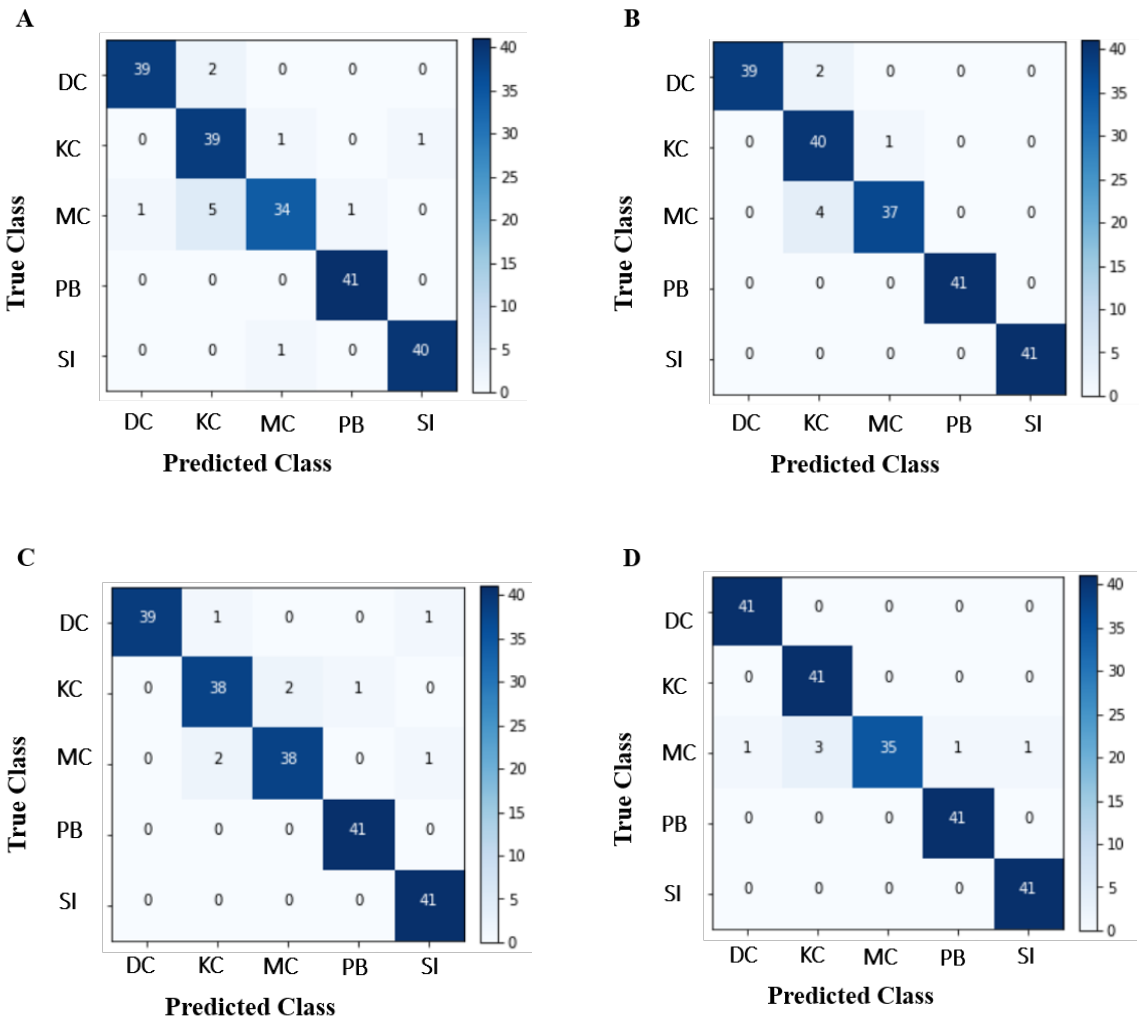

Fig. 2. Confusion matrix of model scenarios: (A) Scenario 1-Resnet50, (B) Scenario 2-Resnet50V2, (C) Scenario 3-Resnet50V2 with freeze, and (D) Scenario 4- Resnet50V2 with pooling layer. DC: Dyskeratotic, KC: Koilocytotic, MC: Metaplastic, PB: Parabasal, and SI: Superficial-intermediate

Sensitivity, specificity, and F-measures were calculated for each existing class of each model. The range of sensitivity, specificity, and F-measure values is 0 to 1. A sensitivity value close to 1 indicates a good model's ability to correctly detect positive labelled data. Then a specificity close to 1 indicates a good model's ability to correctly detect negative labelled data. The F-measure value measures the comparison of precision and recall on the model. The values of sensitivity, specificity, and F-measure can be seen in Table 7.

Table 7
Sensitivity, specificity, and F-measure of models

Model	Class	Sensitivity	Specificity	F-measure
Scenario 1 + SVM 1	DT	0.951	0.993	0.962
	KC	0.951	0.956	0.896
	MC	0.829	0.987	0.883
	PB	1.0	0.993	0.985
	SI	0.975	0.993	0.975
Scenario 2 + SVM 2	DT	0.951	1.0	0.975
	KC	0.975	0.963	0.919
	MC	0.902	0.993	0.936
	PB	1.0	1.0	1.0
	SI	1.0	1.0	1.0
Scenario 3 + SVM 3	DT	0.951	1.0	0.975
	KC	0.927	0.981	0.927
	MC	0.926	0.987	0.938
	PB	1.0	0.993	0.987
	SI	1.0	0.987	0.976
Scenario 4 + SVM 4	DT	1.0	0.993	0.987
	KC	1.0	0.981	0.964
	MC	0.853	1.0	0.921
	PB	1.0	0.993	0.985
	SI	1.0	0.993	0.987

The model in scenario 1 produces a dominant prediction error in the actual class of Metaplastic (MC). There are 6 images that should be non-cancerous cells (MC) predicted as cancer class (False positive) namely 5 KC class and 1 DC class. One image of MC class is incorrectly classified to the normal cell Parabasal (PB). In Scenario 2, the resulting model makes prediction errors which are also dominant in the actual MC class. There are 4 images that should be MC class, predicted as cancer cell class (KC). For scenario 3 the false positive prediction error occurs when the prediction result is a class of cancer cells (KC) but the actual class is non-cancer (MC). While the false-negative prediction error occurs when the prediction result is a non-cancerous class (MC and PB) but the actual class is a cancer cell class (KC). In Scenario 4, the model has the same predictive pattern as scenarios 1 and 2, where the error is dominant when it predicts the actual non-cancer class (MC). There are five prediction errors resulting from scenario 4. A False Positive occurs when 1 image is classified as DC, and the other 2 images are classified as KC. While the other 2 images are predicted as non-cancerous classes Parabasal (PB) and Superficial/intermediate (SI).

The model in scenarios 2, 3, and 4 with the Resnet50V2 architecture has a higher accuracy compared to the model in scenario 1 which uses the Resnet50 architecture. The models in scenarios 2, 3, and 4 have an accuracy of 96.58%, 96.09%, and 97.09%, respectively. While the model with scenario 1 has the less accuracy, although it is not significantly different by 94.14%.

The performance comparison based on sensitivity and specificity and f-measures in Table 7 shows that the models are good in detecting and predicting both the non-cancer cell and cancer cell class label, although there was some false positive prediction in the actual MC class. This shows that the model's ability to predict images into MC class correctly is not as good as the model predicts images with other labels. This can be caused by the image in the MC class, although it is called a normal cell, it is also a transitional cell between normal cells and abnormal cells, so the characteristics and differences are not very clear.

A comparison of scenario 1 with scenarios 2, 3, and 4 shows that the model using the convolution basis of the pre-trained Resnet50V2 model is better than the pre-trained Resnet50 model. Scenarios 3 and 4 also show that the model has a better generalization ability than the model in scenarios 1

and 2. This can be concluded based on the average value of test accuracy during the tuning parameter of the models in scenarios 3 and 4 which is higher than those in scenarios 1 and 2. The use of SVM as a classifier that replaces the fully connected layer which originally served as a classifier on CNN can also work properly. Although there is a decrease in accuracy, the execution time of models using SVM is much faster. This study concludes that the model in scenario 4, namely the CNN model with the convolution basis of pre trained Resnet50V2 combined with SVM is the model with the best performance in classifying cervical cells in pap smear images with an accuracy of 97.09%.

4. Conclusions

This study implemented four scenarios of CNN model to extract features from pap smear images. The results are used to develop a classification model for pap smear images using the SVM algorithm. CNN modelling is divided into 4 scenarios. In scenario 1, the convolution basis of the pretrained Resnet50 model is used directly as a feature extractor. In scenario 2, the convolution basis of the pretrained Resnet50V2 is utilized as feature extraction. In scenario 3, the pretrained Resnet50V2 model goes through a retraining process before the convolution layer, then the model is used as a feature extractor. In scenario 3, a freezing process is also implemented on the convolution layer to reduce the time of the retraining process. In scenario 4, the model is the same as those in scenario 3, the difference is that in scenario 4 there is no freeze process. Comparison of scenario 1 with scenarios 2, 3, and 4 shows that the model using the convolution basis of the pre-trained Resnet50V2 model is better than the pre-trained Resnet50 model. The experimental results on scenario 3 and scenario 4 show that the frozen layer has reduced the time of model retraining compared to the unfreeze model. Scenarios 3 and 4 also show that the model has a better generalization ability than the model in scenarios 1 and 2. This can be concluded based on the average value of test accuracy during the tuning parameter of the models in scenarios 3 and 4 which is higher than those in scenarios 1 and 2. The use of SVM as a classifier that replaces the fully connected layer which originally served as a classifier on CNN can also work properly. Although there is a decrease in accuracy, the execution time of models using SVM is much faster. This study concludes that the model in scenario 4, namely the CNN model with convolution basis of pre-trained Resnet50V2 combined with SVM is the model with the best performance in classifying cervical cells in pap smear images with an accuracy of 97.09%.

Acknowledgment

This research was supported by IPB University through Funding Program for the Establishment of Scientific Groups under Research Assignment of World Class University (No. 9078/IT3.L1/PT.01.03/P/B/2021). We also want to thank Indonesian Collaboration Research-World Class University, Republic of Indonesia for the research grant No. 1763/IT3.L1/PN/2020. The authors would like to thank the committee of International Symposium on Computer Science for Smart Agriculture, Education and Medical (CSSAEM): Perspective from Indonesia and Malaysia for the opportunity to present this research article.

References

[1] World Heatlh Organization. "Human papillomavirus (HPV) and cervical cancer" *Geneva, Switzerland: WHO,* (2020). https://www.who.int/news-room/fact-sheets/detail/human-papillomavirus-(hpv)-and-cervical-cancer

[2] World Heatlh Organization. "Cervical Cancer" *Geneva, Switzerland: WHO*, (2018) https://www.who.int/health-topics/cervical-cancer#tab=tab_1

[3] Ferlay, J., M. Ervik, F. Lam, M. Colombet, L. Mery, M. Piñeros, A. Znaor, I. Soerjomataram, and F. Bray. "Global Cancer Observatory: Cancer Today. Lyon, France: International Agency for Research on Cancer.[Internet]." (2018).
[4] Kemenkes, R. I. "Hari Kanker Sedunia 2019." *Retrieved January* 29 (2019): 2020.
[5] Ministry of Health. "Cervic Cancer Management Guide (in Bahasa)" *Jakarta, Indonesia: Ministry of Health*, (2016). http://kanker.kemkes.go.id/guidelines/PPKServiks.pdf
[6] Layfield, Lester J. "Image Analysis: A Primer for Pathologists." (1996): 482-482. https://doi.org/10.2466/pr0.1996.79.2.482
[7] Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.
[8] Mousser, Wafa, and Salima Ouadfel. "Deep feature extraction for pap-smear image classification: A comparative study." In *Proceedings of the 2019 5th International Conference on Computer and Technology Applications*, pp. 6-10. 2019. https://doi.org/10.1145/3323933.3324060
[9] Krishna, Sajja Tulasi, and Hemantha Kumar Kalluri. "Deep learning and transfer learning approaches for image classification." *International Journal of Recent Technology and Engineering (IJRTE)* 7, no. 5S4 (2019): 427-432.
[10] Abdullah, Azian Azamimi, Aafion Fonetta Dickson Giong, and Nik Adilah Hanin Zahri. "Cervical cancer detection method using an improved cellular neural network (CNN) algorithm." *Indones. J. Electr. Eng. Comput. Sci* 14, no. 1 (2019): 210-218. https://doi.org/10.11591/ijeecs.v14.i1.pp210-218
[11] Haryanto, Toto, Imas Sukaesih Sitanggang, Muhammad Ashyar Agmalaro, and Riries Rulaningtyas. "The utilization of padding scheme on convolutional neural network for cervical cell images classification." In *2020 International conference on computer engineering, network, and intelligent multimedia (CENIM)*, pp. 34-38. IEEE, 2020. https://doi.org/10.1109/CENIM51130.2020.9297895
[12] Wu, Miao, Chuanbo Yan, Huiqiang Liu, Qian Liu, and Yi Yin. "Automatic classification of cervical cancer from cytological images by using convolutional neural network." *Bioscience reports* 38, no. 6 (2018): BSR20181769. https://doi.org/10.1042/BSR20181769
[13] Priyanka, B. Jyothi. "Machine learning approach for prediction of cervical cancer." *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* 12, no. 8 (2021): 3050-3058.
[14] Tan, Xiangyu, Kexin Li, Jiucheng Zhang, Wenzhe Wang, Bian Wu, Jian Wu, Xiaoping Li, and Xiaoyuan Huang. "Automatic model for cervical cancer screening based on convolutional neural network: a retrospective, multicohort, multicenter study." *Cancer cell international* 21, no. 1 (2021): 1-10. https://doi.org/10.1186/s12935-020-01742-6
[15] Li, Xia, Zhenhao Xu, Xi Shen, Yongxia Zhou, Binggang Xiao, and Tie-Qiang Li. "Detection of cervical cancer cells in whole slide images using deformable and global context aware faster RCNN-FPN." *Current Oncology* 28, no. 5 (2021): 3585-3601. https://doi.org/10.3390/curroncol28050307
[16] Rahaman, Md Mamunur, Chen Li, Xiangchen Wu, Yudong Yao, Zhijie Hu, Tao Jiang, Xiaoyan Li, and Shouliang Qi. "A survey for cervical cytopathology image analysis using deep learning." *IEEE Access* 8 (2020): 61687-61710. https://doi.org/10.1109/ACCESS.2020.2983186
[17] Idlahcen, Ferdaous, Mohammed Majid Himmi, and Abdelhak Mahmoudi. "Cnn-based approach for cervical cancer classification in whole-slide histopathology images." *arXiv preprint arXiv:2005.13924* (2020).
[18] Chandran, Venkatesan, M. G. Sumithra, Alagar Karthick, Tony George, M. Deivakani, Balan Elakkiya, Umashankar Subramaniam, and S. Manoharan. "Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images." *BioMed Research International* 2021 (2021). https://doi.org/10.1155/2021/5584004
[19] Bora, Kangkana, Manish Chowdhury, Lipi B. Mahanta, Malay K. Kundu, and Anup K. Das. "Pap smear image classification using convolutional neural network." In *Proceedings of the Tenth Indian Conference on Computer Vision, Graphics and Image Processing*, pp. 1-8. 2016. https://doi.org/10.1145/3009977.3010068
[20] Taha, Bilal, Jorge Dias, and Naoufel Werghi. "Classification of cervical-cancer using pap-smear images: a convolutional neural network approach." In *Medical Image Understanding and Analysis: 21st Annual Conference, MIUA 2017, Edinburgh, UK, July 11–13, 2017, Proceedings 21*, pp. 261-272. Springer International Publishing, 2017. https://doi.org/10.1007/978-3-319-60964-5_23
[21] Aurelia, Jane Eva, Zuherman Rustam, and Ilsya Wirasati. "Cervical cancer classification using convolutional neural network-support vector machine." *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 19, no. 5 (2021): 1605-1611. https://doi.org/10.12928/telkomnika.v19i5.20406
[22] Huong, Audrey KC, Kim Gaik Tay, and Xavier TI Ngu. "Five-Class Classification of Cervical Pap Smear Images: A Study of CNN-Error-Correcting SVM Models." *Healthcare informatics research* 27, no. 4 (2021): 298-306. https://doi.org/10.4258/hir.2021.27.4.298
[23] Manna, Ankur, Rohit Kundu, Dmitrii Kaplun, Aleksandr Sinitca, and Ram Sarkar. "A fuzzy rank-based ensemble of CNN models for classification of cervical cytology." *Scientific Reports* 11, no. 1 (2021): 14538. https://doi.org/10.1038/s41598-021-93783-8

[24] Dhawan, Sanjeev, Kulvinder Singh, and Mamta Arora. "Cervix image classification for prognosis of cervical cancer using deep neural network with transfer learning." *EAI Endorsed Transactions on Pervasive Health and Technology* 7, no. 27 (2021).
[25] Thai, Le Hoang, Tran Son Hai, and Nguyen Thanh Thuy. "Image classification using support vector machine and artificial neural network." *International Journal of Information Technology and Computer Science* 4, no. 5 (2012): 32-38. https://doi.org/10.5815/ijitcs.2012.05.05
[26] Plissiti, Marina E., Panagiotis Dimitrakopoulos, Giorgos Sfikas, Christophoros Nikou, O. Krikoni, and Antonia Charchanti. "SIPAKMED: A new dataset for feature and image based classification of normal and pathological cervical cells in Pap smear images." In *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 3144-3148. IEEE, 2018. https://doi.org/10.1109/ICIP.2018.8451588
[27] Cortes, Corinna, and Vladimir Vapnik. "Support-vector networks." *Machine learning* 20 (1995): 273-297. https://doi.org/10.1007/BF00994018
[28] Probst, Philipp, Bernd Bischl, and Anne-Laure Boulesteix. "Tunability: Importance of hyperparameters of machine learning algorithms." *arXiv preprint arXiv:1802.09596* (2018).