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A COMPARATIVE ANALYSIS FOR DETECTION OF CERVICAL CANCER USING COMPUTER VISION METHODS

J Stella Mary,Assistant Professor, Department of Electronics and Communication Engineering, BhojReddy Engineering College for Women, Hyderabad, Telangana, India.

[1] stellavijay14@gmail.com

Sravya Reddy Soodini, Ganji Sowmya Lakshmi Students, Department of Electronics and Communication Engineering, BhojReddy Engineering College for Women, Hyderabad, Telangana, India.

[2] *sravya672001@gmail.com* , [3] *gsowmyalakshmisss@gmail.com*

Abstract

Most whole-slide picture classification systems now rely on manual pixel-level annotations, which are delicate and time-consuming, and necessitate the annotation of specialized topic expertise. We propose employing self-supervised learning and multiple instances learning tohandle large WSI datasets with only the reported diagnoses as labels to address this issue. Here weuse a machine learning technique i.e. K-Nearest Neighbors (KNN), Support Vector Machine (SVM) and the deep neural network i.e., Convolutional Neural Network, Alexnet that showed better performance when compared to KNN, SVM, and the features learned by CNN and Alexnet are better for classification applications.

Currently, most whole slide images classification models rely on manual pixel-level annotations, which requires specific domain experts to annotate that is delicate and time- consuming. To overcome this problem, we propose to combine self-supervised learning with multiple instance learning to deal with large WSI's datasets only with the reported diagnosis as labels. In WSI's classification task, it's a key challenge to learn good image representation, whereself-supervised learning has held tremendous potential. In our study, we propose to use self-supervised learning network Bootstrap Your Own Latent as the pre-trained network, which can be trained using unlabeled data and learn the deep domain-specific features. We evaluated our proposed framework at scale on a uterine cervical dataset of 3,063 whole slide images. Our resultshave shown that the combination of self-supervised learning model and multiple instance learningmodel can match and exceed the performance of former methods.

I.INTRODUCTION

The emergence of digital pathology has opened new horizons in medical image analysis for diagnostic purposes. Histopathology images, also known as whole slide images (WSIs), are generally accompanied with information about the site and type of diseases and malignancies. The recent advances in digital technology enable the fast digital scanning of tissue slides to generate high-quality WSIs. As a result, the volume of WSI archives in hospitals and clinics has been drastically increasing. Consequently, the necessity of timely analysis of WSIs has become apparent to address urgent needs in daily workflow of modern pathology. Hence, the digital scanning of slides, alongside the other benefits of pathology, has made computerized technique a favorite approach for image analysis and diagnosis. The field of digital pathology has been drastically changing due to the recent success of artificial neural networks in the field of AI.

Deep learning can facilitate various pathology tasks such as segmentation, classification of regions and nuclei, and searching among WSIs to find similar morphology. However, the representation of digitized pathology slides has proven to be rather challenging due to the large data size of WSIs (generally larger than 50 000 × 50 000 pixels). Besides, the morphological characteristics that discriminate different diagnoses may be microscopically small which causesa fundamental challenge for WSI representation. Creating a single vector representation directly from a WSI is subject to research with current convolutional neural networks (CNNs). A common approach is to break a WSI into many small patches, feed each patch to a CNN, and aggregate the output features to develop a single WSI representation for search and classification. Nonetheless, developing patch-based feature extraction may not be efficient due to its multi-stage architecture. Also, in aggregation stage, information about patch importance and spatial patch knowledge is often ignored. In this paper, we propose an end-to-end architecture that has two main contributions. Firstly, an end-to-end self-supervised, attention-based multiple instance learning (SS-CAMIL) method, that exploits the primary site information of each WSI

which is almost always available during the tissue preparation and subsequent digitization. Furthermore, we show that employing a supervised contrastive learning approach can improve the quality of model embeddings both in WSI classification and search tasks.

Currently, most whole slide images classification models rely on manual pixel-level annotations, which requires specific domain experts to annotate that is delicate and time- consuming. To overcome this problem, we propose to combine self-supervised learning with multiple instance learning to deal with large WSI's datasets only with the reported diagnosis as labels. In WSI's classification task, it's a key challenge to learn good image representation, where self-supervised learning has held tremendous potential. In our study, we propose to use self-supervised learning network Bootstrap Your Own Latent as the pre-trained network, which can be trained using unlabeled data and learn the deep domain-specific features. We evaluated our proposed framework at scale on a uterine cervical dataset of 3,063 whole slide images. Our results have shown that the combination of self-supervised learning model and multiple instance learning models can match and exceed the performance of former methods.

Cervical cancer develops in a woman's cervix (the entrance to the uterus from the vagina). Almost all cervical cancer cases (99%) are linked to infection with high-risk human papillomaviruses (HPV), an extremely common virus transmitted through sexual contact. Although most infections with HPV resolve spontaneously and cause no symptoms, persistent infection can cause cervical cancer in women.

Cervical cancer is the fourth most common cancer in women. In 2018, an estimated 570 000 women were diagnosed with cervical cancer worldwide and about 311 000 women died from the disease. Effective primary (HPV vaccination) and secondary prevention approaches (screening for, and treating precancerous lesions) will prevent most cervical cancer cases.

When diagnosed, cervical cancer is one of the most successfully treatable forms of cancer, as long as it is detected early and managed effectively. Cancers diagnosed in late stages can also be controlled with appropriate treatment and palliative care. With a comprehensive approach to prevent, screen and treat, cervical cancer can be eliminated as a public health problem within a generation.

II.LITERATURE SURVEY

J. Yao, X. Zhu, J. Jonnagaddala, N. Hawkins, and J. Huang, "Whole slide images-based cancer survival prediction using attention guided deep multiple instance learningnetworks," Medical Image Analysis, vol. 65, p. 101789, 2021.

Thresholding and filtering are to reduce the noise by making use of the pixel intensities. In threshold, the intensity histogram of an image is employed to determine the threshold value where the pixels are considered to be noise. For example, the Otsu method determines an optimal threshold which minimizes the within-class variance. This method yields satisfactory results when the numbers of pixels in each class are close to each other. One weakness of threshold is that all pixels under the threshold value can be noise even the pixel information which is important. Conversely, the pixels over the threshold value can be information even the pixels which are noise. In filtering, the value of a pixel is transformed to a new value which is computed as a function of the values of pixels located in a selected neighbourhood around this particular pixel. This is an improvement over the threshold method.

Another method for noise reduction which reduces the noise-based shape characteristics of the input image is to use mathematical morphology. The basic morphological operators are the erosion and dilation of the set with a structuring element. These two basic transformations give two other transformations known as opening and closing. Opening is the erosion of an image followed by the dilation; it breaks narrow isthmuses and eliminates small objects and sharp peaksin the image.

We extract patches from all WSIs belong to the same patient and then cluster them into different phenotypes. To capture detailed information of the images, those patches are extracted from 20X (0.5 microns per pixel) objective magnifications and then fixed to 500 ×500 ×3size. In one whole slide image, usually about 50%of areas are background and it is easy to select regions to contain tissues rather than background or irregular regions according to pixel values. Even we only extract tissue patches and ignore background regions, it can still get tens of thousands of patches per WSI which will result in a huge number of images from the whole dataset. Different from recent segmentation and detection task in whole slide image analysis, our task is for patient-level decision aggregated from patch-level results. As pointed out in [40], training patch- based CNNs for weakly supervised learning is very time costly (several weeks) and we propose to use features from pre-trained models instead of using CNNs to learn features from the scratch. We use the pre-trained model (e.g., VGG) from ImageNet [41] to extract features for each image patch which have more representation power than smaller size (50 ×50) thumbnail images to represent their phenotypes will result in tens of millions of annotated images organized by the semantic hierarchy of WordNet. This paper offers a detailed analysis of ImageNet in its current state: 12 subtrees with 5247 synsets and 3.2 million images in total. We show that ImageNet is much larger in scale and diversity and much more accurate than the current image datasets. Constructing such a large- scale database is a challenging task. We describe the data collection scheme with Amazon Mechanical Turk. Lastly, we illustrate the usefulness of ImageNet through three simple applications in object recognition, image classification and automatic object clustering. We hope that the scale, accuracy, diversity and hierarchical structure of ImageNet can offer unparalleled opportunities to researchers in the computer vision community and beyond.

III.PROBLEM STAEMENT

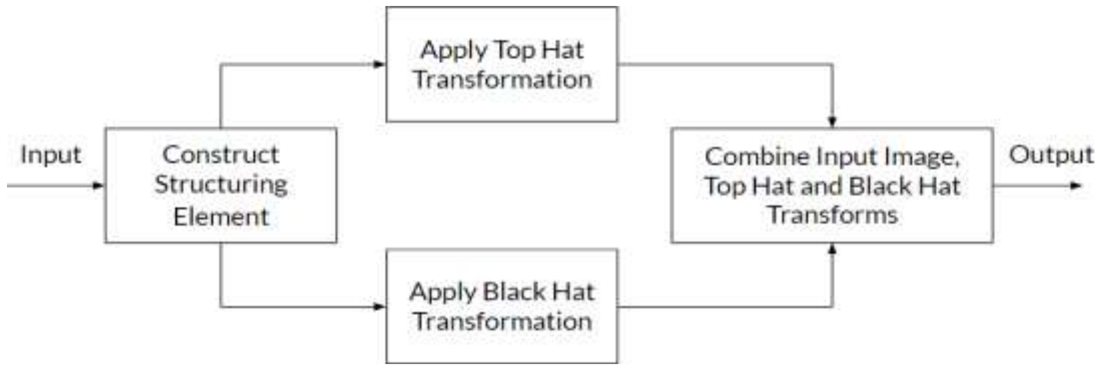
To compare the machine learning and deep learning algorithms in cervical cancer detection Deep learning methods will have the greater efficiency in detecting the type of cancers Classification of images is the primary domain in which deep neural networks are most effective in medical image analysis. Our project mainly discuss about the comparison analysis between the machine learning and deep learning methods. With this project, we can easily detect the cervical cancer with the help of deep learning methods which will give the accurate readings.

3.1Motivation

Image analysis in digital pathology has proven to be one of the most challenging fields in medical imaging for AI-driven classification and search tasks. Cervical cancer is the most common and deadly malignancy affecting women worldwide. The prediction and treatment of this malignancy are necessary in order to avoid serious complications. In recent days, deep learning has enhanced the accuracy of cervical cancer prediction in its early stages. Cervical cancer is one of the leading causes of premature mortality among women worldwide and more than 85% of these deaths are in developing countries. There are several risk factors associated with cervical cancer.

Deep learning can facilitate various pathology tasks such as segmentation, classification of regions and nuclei, and searching among WSIs to find similar morphology. However, the representation of digitized pathology slides has proven to be rather challenging due to the large data size of WSIs. A motivation for exploitation of anatomic site for self-supervision is to enhance and encourage unsupervised learning in pathology, since the annotations are expensive to acquire. We have also utilized a supervised contrastive learning loss to create a more robust representation at the WSI level

IV EXISTIING METHOD



4.1Disadvantages

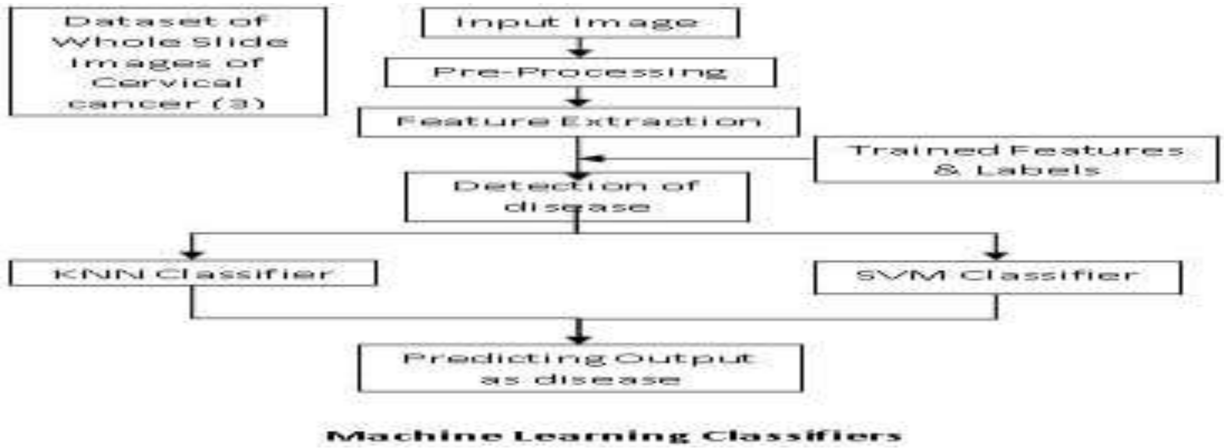
- Manual process
- Takes a lot of computational time
- Images contain noise cannot process well
- There may be a chance of human error
- Not suitable for larger datasets

V.PROPOSED SYSTEM

The proposed system consists of machine learning techniques KNN and SVM. Machine learning helps computer systems learn and improve by developing computer programs that can automatically access data and perform tasks via predictions and detections. Machine learning is the ability to adapt to new data independently and through iterations. Machine learning is an important component of the growing field of data science. Through the use of statistical methods, algorithms are trained to make classifications or predictions, and to uncover key insights in data mining projects. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so.

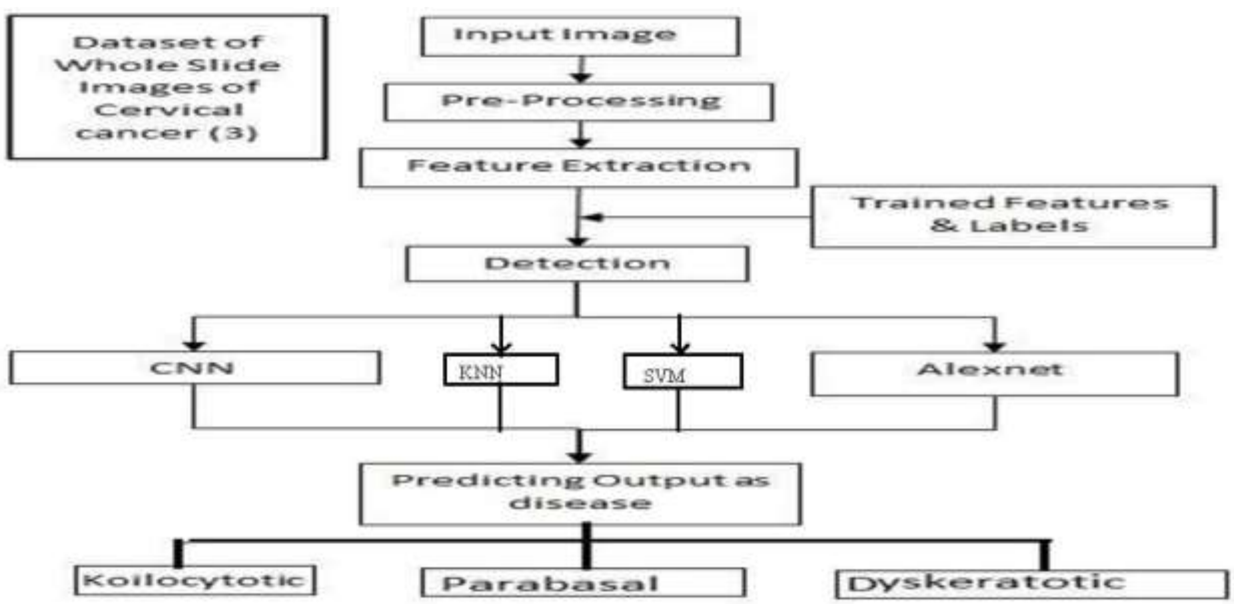
It completes the task of learning from data with specific inputs to the machine. The machine learning process starts with inputting training data into the selected algorithm. New input data is fed into the machine learning algorithm to test whether the algorithm works correctly the prediction and results are then checked against each other. This enables the machine learning algorithm to continually learn on its own and produce the optimal result, gradually increasing in accuracy over time.

5.1Block Diagram of Proposed System



Block diagram of proposed system

In supervised learning, we use known or labeled data for the training data. Since the data is known, the learning is, therefore, supervised, i.e, directed into successful execution. The input data goes through the machine learning algorithm and is used to train the model. Once the model is trained based on the known data, you can see unknown data into the model and get a new response. In this case, the model tries to figure out whether the data is the required result. Once the model has been trained well, it will identify the data is a desired result and give the desired response. In the proposed system we are using machine learning algorithm that is KNN and SVM. The input image is taken from the human body secretion which is examined under the microscope, this input image is pre-processed to eliminate noise or the disturbances from the image and the features are extracted to compare with the trained data to get the desired output.



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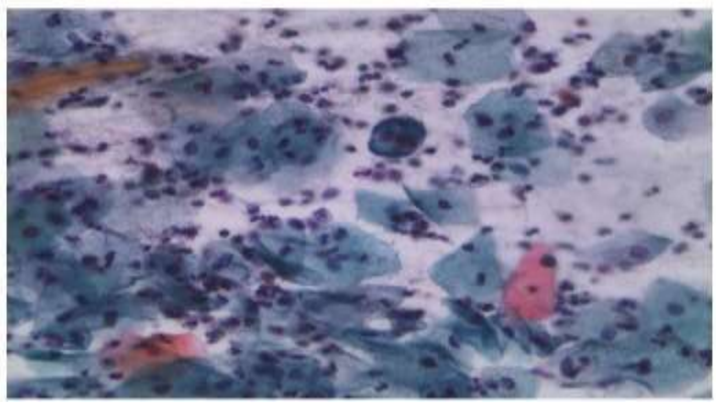
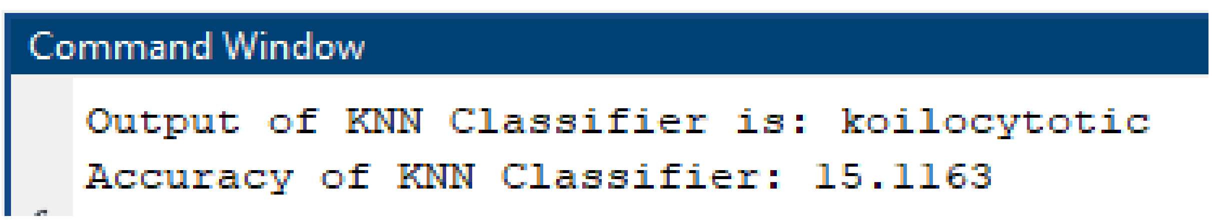
VI RESULTS



Original Image

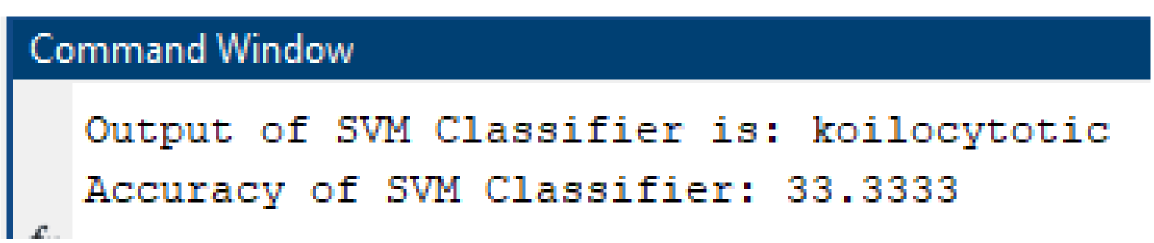
The above image is an input image which will consists of Cancerous Cells present in it. Through, which we can detect the cervical cancer with the help of machine learning algorithms that are KNN and SVM.

The corresponding efficiencies of these classifiers can also be determined using input image.



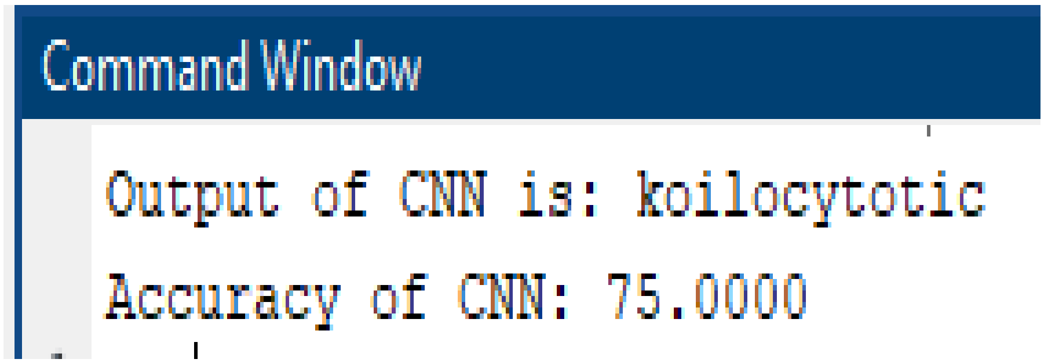
Accuracy of KNN

Koilocytotic is a cell if it is present in human body then the detected disease will be cervical cancer. Here, when we are using KNN classifier for the input image taken koilocytotic detect it means cervical cancer is present in human body. The Accuracy of KNN Classifier for the input image is15.1163



Accuracy of SVM

Koilocytotic is a cell if it is present in human body then the detected disease will be cervical cancer. Here, when we are using SVM classifier for the input image taken koilocytotic detect it means cervical cancer is present in human body. The Accuracy of SVMClassifier for the input image is 33.333.

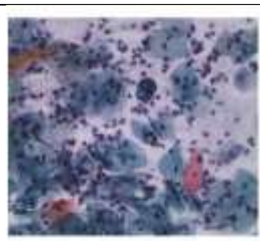


Accuracy of CNN

Koilocytotic is a cell if it is present in human body then the detected disease will be cervical cancer. Here, when we are using CNN classifier for the input image taken koilocytotic detect it means

Koilocytotic is a cell if it is present in human body then the detected disease will be cervical cancer. Here, when we are using Alexnet classifier for the input image takenkoilocytotic detect it means cervical cancer is present in human body. The Accuracy of Alexnet Classifier for the input image is 99.999451

Comparison Table

Original Image	KNN	SVM	CNN	Alexnet
	Accuracy is: 15.1163	Accuracy is: 33.3333	Accuracy is: 75.0000	Accuracy is: 99.999451

VIII CONCLUSION

Combination of Self supervised learning methods and Multi instance learning methodsare done to deal with larger WSI's datasets. The Deep neural network ie Alexnet and CNN shows better performance when compared to Machine learning techniques ie KNN and SVM. The proposed network is suitable for larger datasets in which we can detect the cervical cancer and also other types of diseases.

REFERENCES

[1] J. Yao, X. Zhu, J. Jonnagaddala, N. Hawkins, and J. Huang, "Whole slide images-based cancer survival prediction using attention guided deep multiple instance learning networks," Medical Image Analysis, vol. 65, p. 101789, 2021.

[2] M. Mostavi, Y.-C. Chiu, Y. Huang, and Y. Chen, "Convolutional neural network models for cancer type prediction based on gene expression," BMC medical genomics, vol. 13, pp. 1-13, 2020.

[3] F. Idlahcen, M. M. Himmi, and A. Mahmoudi, "Cnn-based approach for cervical cancer classification in whole-slide histopathology images," arXiv preprint arXiv:2005.13924, 2020.

[4] J.-B. Grill, F. Strub, F. Altche', C. Tallec, P. H. Richemond, E. Buchatskaya, C. Doersch, B. A. Pires, Z. D. Guo, M. G. Azar et al., "Bootstrap your own latent: A new approach to self- supervised learning," arXiv preprint arXiv:2006.07733, 2020.

[5] V. Iglovikov and A. Shvets, "Ternausnet: U-net with vgg11 en- coder pretrained on imagenetfor image segmentation," arXiv preprint arXiv: 1801.05746, 2018.

[6] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A simple framework for contrastive learning of visual representations," in international conference on machine learning. PMLR, 2020, pp. 1597-1607.

[7]K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick, "Momentum contrast for unsupervised visual representation learning," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9729-9738.M. Noroozi, A. Vinjimoor, P. Favaro, and H. Pirsiavash, "Boosting self-supervised learning via knowledge transfer," in Proceedings of the IEEE Conference on Computer Vision andPattern Recognition, 2018, pp. 9359-9367.