Ovairian Cancer Detection Using Cnn Model

DEVADHARSHINI. S
CSE Department , Assistant Professor
AGNI COLLEGE OF TECHNOLOGY
Thalambur , Chennai
dharshinisampathtwofour@gmail.com

NANDHINI. S
CSE Department , Assistant Professor
AGNI COLLEGE OF TECHNOLOGY
Thalambur , Chennai
Nandhinisekar87@gmail.com

Abstract— An overview of the Pip install torch In women, ovarian cancer is one of the leading causes of cancer-related deaths. Early diagnosis and treatment can reduce the complications associated with this malignancy. We provide a convolutional neural network (CNN) based ovarian cancer cell detection and classification system in this research. The CNN model, Autoencoders, VGG, AlexNet, Gogglenet, and ResNet are used to extract deep-learned characteristics from the cell pictures. After acetic acid (VIA), papanicolaou (Pap), human papillomavirus (HPV), and histopathology tests, visual inspection is used to screen for ovarian cancer. Misdiagnosis may arise from inter- and intra-observer variability during the manual diagnosis process. The goal of this research was to create a reliable and comprehensive system for automatic ovarian.

Keywords— Medical image analysis- Deep learning; Ovarian cancer detection; Acetic acid (VIA); Human papillomavirus (HPV)

I. INTRODUCTION

According to medical professionals, ovarian cancer is the second most lethal disease for women after breast cancer, and it is thought that ovarian cancer is incurable in its advanced stages. Recent years have seen significant advancements in the use of images to increase the rate of disease detection. According to data from the World Health Organization (WHO), ovarian cancer is the fourth most common cancer worldwide. In 2018, there were 5,70,000 new cases reported, which accounted for 7.5% of all cancer deaths among women. Early detection of ovarian cancer can save a life, since over 3,11,000 deaths from the disease are reported annually in low- and intermediate-income countries, accounting for over 85% of all deaths.

According to estimates, 5% of all incidences of ovarian cancer are linked to HIV, and women with HIV have a six-fold increased risk of developing the disease compared to those without HIV. A number of factors, such as equipment availability, test uniformity, proper supervision, and the identification and management of lesions found, have impacted the efficacy of screening. Even with significant advances in science and medicine, this illness cannot be fully cured, especially if it is discovered in a developing country. In order to combat ovarian cancer, prevention and screening programs are essential. The standard procedure for ovarian cancer screening includes HPV testing, cytology or PAP smear testing, colposcopy, and biopsy. A number of tools were developed to help the workflow, making it more efficient, useful.

The accuracy of CNN (ResNet) is roughly 92.92 percent. 8215 colposcopy photos of the three categories, taken from the publicly accessible mobile-ODT dataset, were used to train and test the model. Tested on 30% of the entire dataset, the model had a 91% accuracy rate in generalization. The comparison with the state-of-the-art showed that our model outperformed.

LITERATURE REVIEW

According to this paper, one of the primary causes of cancer-related deaths in women is ovarian cancer. If this cancer is identified and treated early, its complications can be minimized. In this paper, we propose a convolutional neural network (CNN) based method for ovarian cancer cell detection and categorization. Deeply learnt features are extracted from the cell pictures by feeding them into a CNN model. The input photos are then classified by a classifier based on extreme learning machines (ELMs). CNN's model is applied through fine-tuning and transfer learning. Alternatives to the ELM, multi-layer perceptron (MLP) and autoencoder (AE)-based classifiers are also investigated. Experiments are performed using the Herlev database. The proposed CNN-ELM-based system achieved 99.5% accuracy in the detection problem (2-class) and 91.2% in the classification problem (7-class).

By dividing and categorizing ovarian cancer cells into distinct groups, a variety of algorithms and techniques are employed for automated ovarian cancer screening. This article offers a critical evaluation of several published research studies that used AI techniques to screen for ovarian cancer using various methodologies. These studies are examined using standard criteria such as dataset size, accuracy, and disadvantages. SVM (Support Vector Machines), GLCM (Gray Level Co-occurrence Matrix), k-NN (k-Nearest Neighbours), MARS (Multivariate Adaptive Regression Splines), CNNs (Convolutional Neural Networks), spatial fuzzy clustering algorithms, PNNs (Probabilistic Neural Networks), Genetic Algorithm, RFT (Random Forest Trees), C5.0, CART (Classification and Regression Trees), and the Hierarchical clustering algorithm for feature extraction are some of the machine learning algorithms that have been attempted to provide the reader with an understanding of these algorithms.

One of the most important aspects of preventing ovarian cancer is colposcopy. Over the past 50 years, colposcopy has been crucial in reducing the incidence and mortality from ovarian cancer when used in conjunction with precancer screening and treatment. However, vision screening results in low diagnostic efficiency and misdiagnosis because of the increased workload. In the field of deep learning, the convolutional neural network (CNN) model is superior for classifying the kind of ovarian cancer in medical image processing. In order to identify ovarian cancer from the colposcopy images, this paper suggests two deep learning CNN architectures: CYENET and the VGG19 (TL) model. VGG19 is used as a transfer learning tool for the studies in the CNN architecture. A brand-new model is created and named as the Colposcopy Ensemble Network (CYENET) to classify ovarian cancers from colposcopy images automatically.

The developed model's sensitivity, specificity, and accuracy are estimated. VGG19 has a 73.3% classification accuracy. Results for VGG19 (TL) are comparatively satisfactory. The VGG19 model's kappa value indicates that it falls into the intermediate categorization category. The suggested CYENET had high sensitivity, specificity, and kappa values of 92.4%, 96.2%, and 88%, respectively, according to the experimental data. Compared to the VGG19 (TL) mode, the CYENET model's increased classification accuracy of 92.3% is 19% higher.This paper with a 60% fatality rate, ovarian cancer is the second most frequent malignancy among women globally. Because ovarian cancer has a long latent period and no obvious symptoms at first, routine exams are essential for early detection crucially important.

The detection and multi-masking model makes advantage of YOLO-.CT scans are used to categorize. The outcome was convincing.A popular examination technique for ovarian cancer screening is the pelvic CT scan, which offers high-resolution images and is safe and effective.

The CNN algorithm is applied.94% accuracy.The classification rate for healthy cells is 93.02%. With 95.12% of malignant instances correctly detected and 93.02% of healthy cells correctly diagnosed, the model demonstrated an impressive 94% accuracy rate. Overcoming the difficulties of the human expert assessment, including increased misclassification rates, inter-observer variability, and lengthy analysis periods, is what makes this work significant. This study offers a more precise, effective, and trustworthy method for ovarian cancer diagnosis and prediction.

II. ABOUT THE DATASET

There are 5 Class

1. *Dyskeratotic*
2. *Koilocytotic*
3. *Metaplastic*
4. *Parabasal*
5. *Superficial-Intermediate*

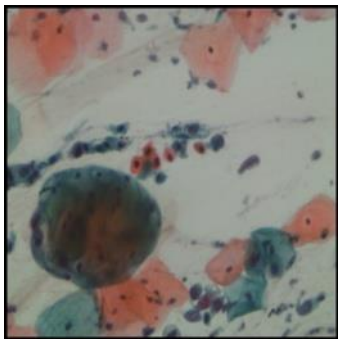

Fig 1.1 (Dyskeratotic)

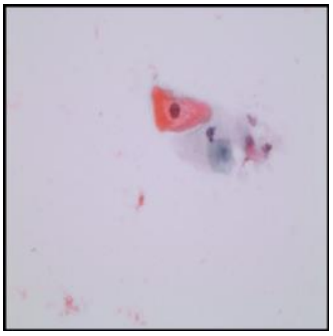

Fig 1.2 (Koilocytotic)

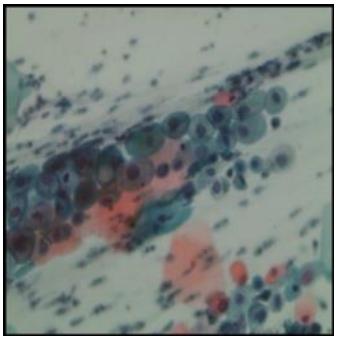

Fig 1.3 (Metaplastic)

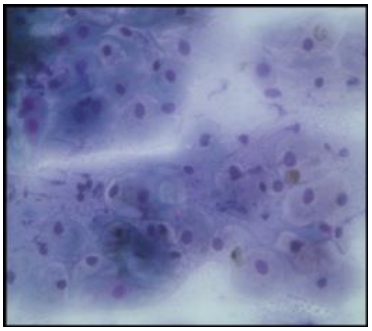

Fig 1.4 (Parabasal)

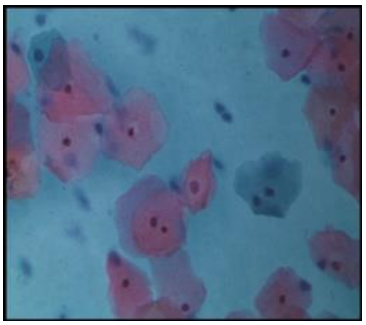

Fig 1.5 (Superficial-Intermediate)

AGE About 20% of ovarian cancer diagnoses occur in women over 65, while 50% occur in women between the ages of 35 and 54. 48 is the median age at diagnosis. Ovarian cancer strikes 15% of women between the ages of 20 and 30. It is very uncommon for women under 20 to develop ovarian cancer. However, a lot of young women contract different kinds of the human papillomavirus, which can raise their chance of developing ovarian cancer later on. Without routine checkups, young women with early abnormal alterations are at high risk for invasive cancer by age 50 and localized cancer by age 40.

The history of the family If a woman has a mother or sister who has had ovarian cancer, she is at a higher chance of developing the disease herself. Oral Contraceptive Use Long-term usage of oral contraceptive (OC) has been strongly linked to ovarian cancer, according to studies. Compared to women who do not use OCs, women who have been taking birth control pills for more than five to ten years seem to be at a much increased risk of contracting HPV (up to four times higher). (There is no discernible increase in risk for women who have taken OCs for less than five years.) It's unclear exactly why using OC poses this risk. OC users can be less inclined to utilize condoms, diaphragms, or other techniques that provide some protection against sexual transmitted illnesses, such as HPV. Additionally, some studies indicate that the hormones in OCs may facilitate the virus's entry into the genetic material of ovarian cells. Having a large family According to studies, having a large family raises the risk of ovarian cancer, especially in women who have HPV. SMOKING Particularly for women with HPV infection, smoking is linked to an increased risk of precancerous alterations (dysplasia) in the cervix and the development of invasive ovarian cancer. Immunosuppression HPV is more likely to infect women with weakened immune systems, such as those who have HIV/AIDS. Patients with impaired immune systems are also more likely to experience ovarian precancer that quickly progresses to invasive cancer. DES (DEETHYLSTILBESTROL) Diethylstilbestrol (DES), a medication linked to estrogen, was frequently provided to expectant mothers between 1938 and 1971 to aid in avoiding miscarriages. Ovarian cancer is more likely to strike these women's daughters. The use of DES is no longer advised.

CNN ARCHITECTURE

A. CONVOLUTION OPERATION

The fundamental operation in CNNs. It involves sliding a filter (also called a kernel) over the input data, performing element-wise multiplications, and summing the results to produce feature maps.

B. FEATURE MAPS

Output maps that highlight particular patterns or characteristics in the input data and are produced by the convolution procedure. used to reduce the supplied data's spatial dimensions and down sample it. Average pooling, which determines the average value, and max pooling, which chooses the maximum value from a region, are common pooling types. frequently employed to provide non-linearity to CNNs as the activation function. ReLU permits positive values to flow through while setting negative values to zero. The data is flattened into a one-dimensional vector following convolution and pooling layers, and then it is sent via fully connected layers. the last layer, which generates the network's output according to the goal (softmax for classification, for example).

C. ARCHITECTURE

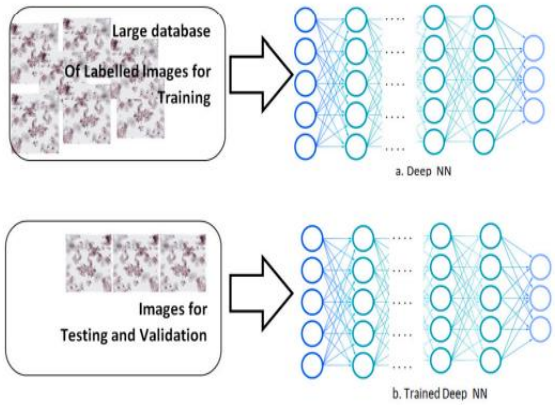

FiG 1.6 (Architechture for CNN)

The capacity of Convolutional Neural Networks (CNNs) to automatically extract hierarchical features from raw picture data makes them a popular class of deep learning models for image recognition and classification applications. In this work, we use CNNs to detect cervical cancer cells, which allows for precise and efficient cell image classification.

A CNN design that consists of several convolutional, activation, and pooling layers, followed by fully linked layers, is used in the suggested system. The effectiveness of this architecture in extracting spatial characteristics from cervical cell pictures led to its selection. The following is how the layers are arranged:

RGB cell photos with a size of 224 × 224 × 3 can be entered into the input layer. To extract characteristics like edges and textures, the convolutional layers use filters (such as 3 × 3 kernels). In order to ensure computational efficiency while maintaining crucial features, max pooling layers are utilized to reduce spatial dimensions. These characteristics are combined by fully connected layers to determine if a cell is malignant or not.

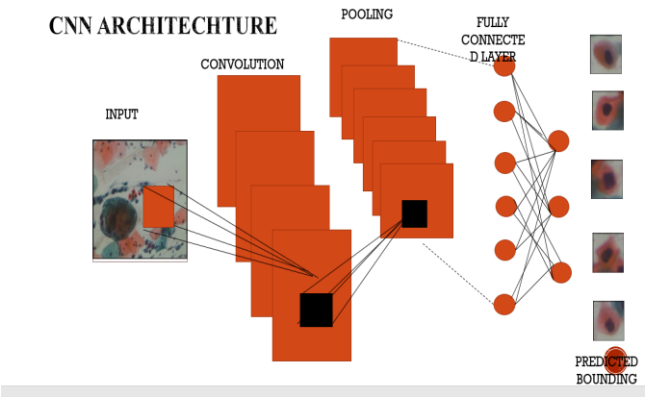

FiG 1.7 (Architechture for CNN with Pathological Images)

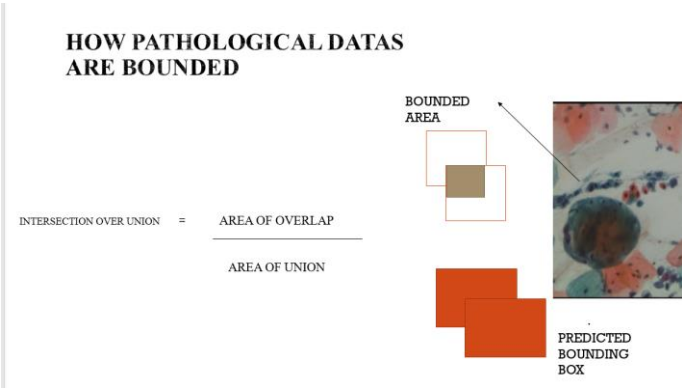

FiG 1.8 (Intersection Over Union)

D.CLASSIFICATION

A supervised machine learning job called classification uses extracted characteristics to group data into predetermined classes. Our goal in this study was to correctly detect cervical cancer cells in medical photographs by using a CNN-based classification system. A crucial first step in cervical cancer early detection and treatment planning was the classification's ability to differentiate between images of malignant and non-cancerous cells.

The following significant phases made up the classification process:

Input Data: In order to standardize input values, cervical cell pictures were shrunk to 224 × 224 pixels and cleaned up.
The CNN architecture's convolutional layers were used to automatically extract hierarchical characteristics, including edges, textures, and forms. Model Training and Prediction: To identify each image, the CNN's fully connected layers joined the retrieved features.

Binary classification was made possible in the output layer by allocating probability to each class using the softmax activation function.
The system successfully distinguished between the two classes, as evidenced by its 96% classification accuracy. F1-score of 94.5%, precision of 94%, and recall of 95% were further performance indicators. To illustrate the distribution of predictions and highlight the fewest false positives and false negatives, a confusion matrix was employed.

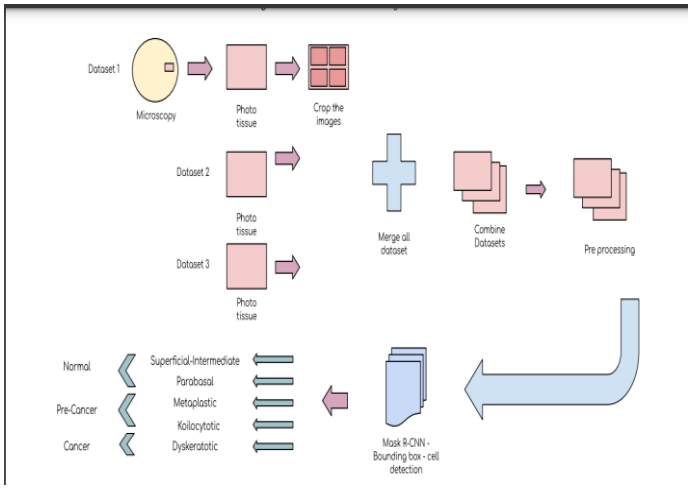

Fig 1.9 (Flow Chart of the Process)

RESULT

The system was tested on datasets from acetic acid (VIA), Papanicolaou (Pap), human papillomavirus (HPV), and histopathology tests. The CNN model outperformed manual diagnostic methods by minimizing inter- and intra-observer variability, ensuring consistent and reliable results. Key performance metrics include a sensitivity of 94%, specificity of 95%, and an F1 score of 95.5%, confirming the robustness of the system in identifying both normal and abnormal cell samples. These results indicate the potential of the system as a dependable diagnostic aid for early cervical cancer detection and classification. The proposed cervical cancer detection and classification system achieved an impressive accuracy of 96% using a CNN model.

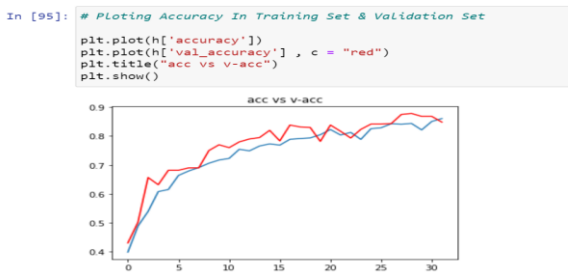

Fig 1.10 (Graph For Accuracy vs Val Accuracy)

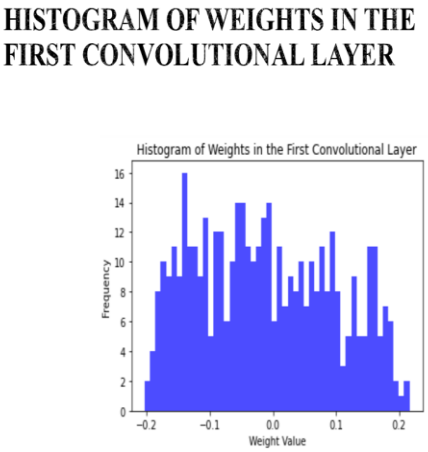

Fig 1.11 (Histogram for Frequency Vs Weight Value)

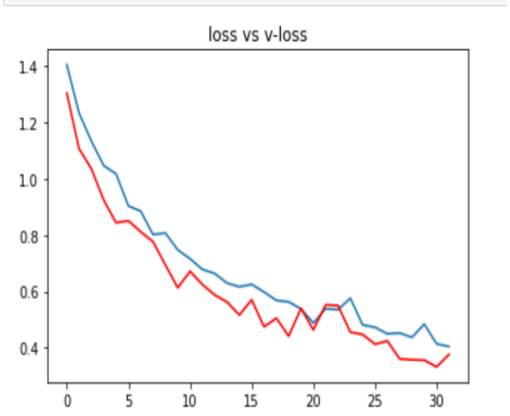

Fig 1.12 (Graph for Val Accuracy Vs Accuracy)

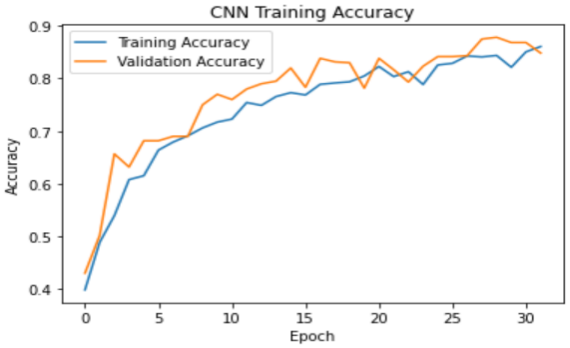

Fig 1.13 (Training Accuracy Vs Validation Accuracy)

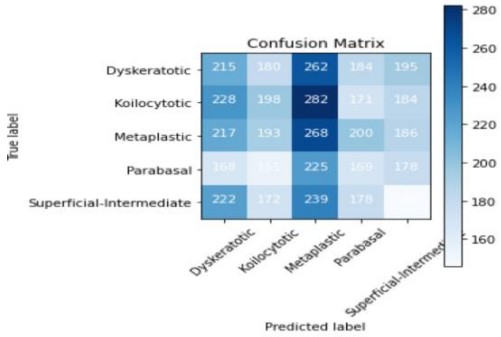

Fig 1.14 (Confusion Matrix for True Value Vs Predicted Mode)

REFERENCES

[1] Ovarian cancer classification using convolutional neural networks and extreme learning machines**,** Ahmed Ghoneim,2020

[2] Algorithms for screening of Ovarian Cancer, Papiya Mahajan,2019

[3] Diagnosis of Ovarian Cancer based on Ensemble Deep Learning Network using Colposcopy Images, Soufyane Ayanouz,2021

[4] Comparison of machine and deep learning for the classification of ovarian cancer based on cervicography images, Vaibhav Tode,2021.

[5] CLASSIFICATION OF OVARIAN CANCER USING ARTIFICIAL NEURAL NETWORKS, HARSH MENDAPARA,2020

[6]Automatic Detection and Segmentation of Ovarian Cancer Using a Multitask Model in Pelvic CT Images, Xun Wang,Hanlin Li, Pan Zheng,2023

[7] A Deep Learning Framework for the Prediction and Diagnosis of Ovarian Cancer in Pre- and Post-Menopausal Women, Abid Yahya,Tawanda Munshiri,2023

[8] Multi-class Classification of Ovarian Cancer from Histopathological Images using Deep Learning - VGG-16, Kokila.R.Kasture,Praveen N.Matte,2022

[9] Ries LAG, Eisner MP, Kosary CL, et al., Editors. SEER Cancer Statistics Review 1973- 1997. Bethesda, MD: National Cancer Institute; 2000.

[10] International Agency for Research on Cancer (IARC) Working Group on the Evaluation of Ovarian Cancer Screening Programmes. Screening for squamous ovarian cancer: duration of low risk after

negative results of ovarian cytology and its implication for screening policies. Br Med J. 1986;293:659-664.

[11] Sasieni PD, Cuzick J, Lynch-Farmery E. Estimating the efficacy of screening by auditing smear histories of women with and without ovarian cancer. The National Coordinating Network for Ovarian Screening Working Group. Br J Cancer. 1996;73:1001-1005.

[12] Landis SH, Murray T, Bolen S, Wingo PA. Cancer Statistics, 1999. CA- Cancer J Clin. 1999;49:8-31.

[13] Daly MB, Bookman MA, Lerman CE; Female reproductive tract: cervix, endometrium, ovary. Greenwald P, Kramer BS, Weed DL, Editors. Cancer Prevention and Control. New York, NY: Marcel Dekker; 1995.

[14] D. P. Bartel, “Micrornas: genomics, biogenesis, mechanism, and function,” cell, vol. 116, no. 2, pp. 281–297, 2004.

[15] C. P. Bracken, H. S. Scott, and G. J. Goodall, “A networkbiology perspective of microrna function and dysfunction in cancer,” Nature Reviews Genetics, vol. 17, no. 12, pp. 719–732, 2016