Section A-Research paper
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Cervical Cancer Diagnostics Healthcare System Using Hybrid Object Detection Adversarial Networks

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ABSTRACT: Cervical cancer is one of the most frequent diseases in women, and it is a leading cause of death in many underdeveloped nations. Cervical lesions are diagnosed with a pap smear test or acetic acid visual examination (staining). Digital colposcopy, a low-cost screening procedure, produces painless and quick results. As a result, automating cervical cancer screening using colposcopy pictures will be very beneficial in saving many lives. Many automated approaches using computer vision and machine learning in cervical screening have garnered prominence recently, opening the door for cervical cancer diagnosis. However, the majority of the approaches depend exclusively on cervical detection and segmentation annotation. The purpose of this research is to present the Faster Small-Object Detection Neural Networks (FSOD-GAN) to address cervical screening and cancer detection utilising digital colposcopy pictures. The suggested method uses a Faster Region-Based Convolutional Neural Network (FR-CNN) to identify cervical spots and conducts hierarchical multiclass classification of three kinds of cervical cancer lesions. Experimentation was carried out using colposcopy data from publicly accessible sources on 1,993 patients with three cervical classifications, and the suggested technique had 99% accuracy in identifying cervical cancer stages.

Keywords *– Cervical cancer, diagnosis, deep learning, cervical segmentation.*

1. INTRODUCTION

Cervical malignancies are among the most frequent cancers in women. Cervical cancer continues to be the most major health burden for women, demonstrating the effect of global health inequity. Cervical cancer affects around

56 million women each year, with a 90% fatality rate. Four out of every five medical cases are documented, particularly in emerging nations such as India and China. According to the research, there would be over 500 thousand new cases in 2018 and over 300,000 fatalities per year. According to the data, about 85% of the 300,000 fatalities happened in a variety of underdeveloped nations. This is owing to a lack of knowledge about cervical cancer, and the majority of cases were detected only at the latter end. However, cervical cancer growth is a gradual process that results in cervix anomalies. Cervical cancer diagnosis is difficult in the early stages due to the lack of symptoms. Furthermore, patients in poor nations would not comply with frequent screening owing to ignorance. The mortality rate in high-income nations is considerably lowered owing to the appropriate organisation of cervical-screening programmes.

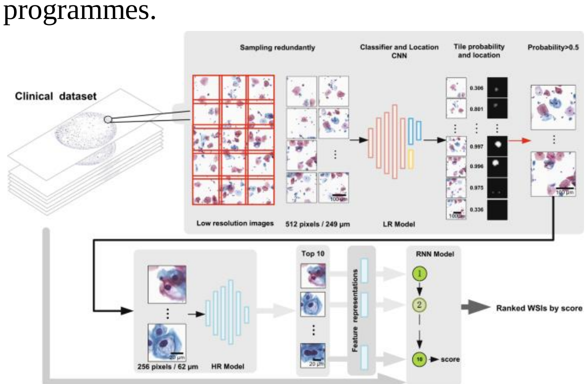

Fig.1: Example figure

Cervical cancer diagnosis will be performed by checking the cervix area for anomalies or lesions. The World Health Organization (WHO) defines cervical abnormalities as Cervical Intraepithelial Neoplasia (CIN) is classified into three types: mild, moderate, and severe (Severe). Cervical screening is often performed with a Pap smear test, liquid cytology, and colposcopic inspection. According to WHO [5,] cervical screening will be performed in large populations using the Pap smear test. However, medical authorities regard colposcopy pictures as the gold standard for assessing cervical cancer. The examination or visual inspection of colposcopy pictures, on the other hand, is a time-consuming operation that needs competent medical specialists.

2. LITERATURE REVIEW

Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries:

This article gives a status update on the global burden of cancer using the International Agency for Research on Cancer's GLOBOCAN 2018 estimates of cancer incidence and death, with an emphasis on regional diversity across 20 geographical regions. In 2018, there will be 18.1 million new cancer cases (17.0 million excluding nonmelanoma skin cancer) and 9.6 million cancer deaths (9.5 million excluding nonmelanoma skin cancer). Lung cancer is the most common cancer diagnosed in both sexes (11.6% of all cases) and the leading cause of cancer death (18.4% of all cancer deaths), closely followed by female breast cancer (11.6%), prostate cancer (7.1%), and colorectal cancer (6.1%) for incidence and colorectal cancer (9.2%), stomach cancer (8.2%), and liver cancer (8.2%) for mortality. Lung cancer is the most common cancer and the main cause of cancer death in men, followed by prostate and colorectal cancer (in terms of incidence) and liver and stomach cancer (in terms of mortality) (for mortality). Breast cancer is the most frequent cancer among females and the main cause of cancer death, followed by colorectal and lung cancer (in incidence) and cervical cancer (in mortality); cervical cancer ranks fourth in both incidence and mortality. The most common cancers and the major causes of cancer mortality, on the other hand, vary significantly among nations and within each country, depending on the level of economic development and related social and lifestyle variables. It is worth noting that most low- and middle-income nations lack access to high-quality cancer registry data, which is the foundation for designing and executing evidence-based cancer control initiatives. The Global Initiative for Cancer Registry Development is an international collaboration that promotes improved estimate, as well as the collecting and utilisation of local data, in order to prioritise and assess national cancer control activities.

Recent advancement in cervical cancer diagnosis for automated screening: A detailed review:

Cervical cancer is one of the most prevalent and deadly illnesses that affect women. The goal of early detection and categorization of cervical cancer is to minimise mortality. The Pap smear pictures are commonly used for the automated identification of cervical cancer, resulting in trustworthy and accurate findings. Various soft computing approaches have recently been utilised to diagnose cervical cancer. This report examines the majority of research papers published between January 2010 and December 2020 in order to get insight into current advances in the disciplines of study. This document provides a graphical and structured overview of current research findings. The study looked at the potential for future research in soft computing approaches for cervical cancer segmentation and classification. The review also performed an analysis of cervical cancer detection by classifying the cited studies into soft computing strategies. This research will help researchers, publishers, and professionals assess developing research trends in the area of cervical cancer diagnosis using pap smear pictures.

Automatic model for cervical cancer screening based on convolutional neural network: A retrospective, multicohort, multicenter study:

Cervical cancer incidence rates have been steadily rising in underdeveloped nations, despite inadequate medical resources for prevention, diagnosis, and treatment. Deep learning approaches based on computers may achieve excellent accuracy and speed in cancer detection. Such procedures may lead to early detection, appropriate treatment, and, ultimately, successful cervical cancer prevention. In this paper, we aim to build a robust deep convolutional neural network (DCNN) model that can help pathologists screen for cervical cancer. ThinPrep cytologic test (TCT) photos were gathered from numerous partnering hospitals in various countries and diagnosed by pathologists. For training and effect assessment of a faster region convolutional neural network (Faster R-CNN) system, the pictures were separated into three datasets: training (13,775 images), validation (2301 photos), and test (408,030 images from 290 scanned copies). A CNN-based TCT cervical-cancer screening model was built in our work using a retrospective analysis of multicenter TCT data. This strategy improves the speed and accuracy of cervical cancer screening while also addressing the scarcity of medical resources necessary for cervical cancer screening.

Carcinogenic human papillomavirus infection:

Human papillomavirus (HPV) infections are widespread and spread by direct contact. Although the vast majority of infections resolve within two years, 13 phylogenetically related, sexually transmitted HPV genotypes, most notably HPV16, cause virtually all cervical cancers worldwide, as well as a large proportion of other anogenital cancers and an increasing proportion of oropharyngeal cancers if not controlled immunologically or through screening. The oncoproteins E6 and E7, which disrupt growth regulatory mechanisms, are principally responsible for the carcinogenicity of certain HPV strains. Persistent high-risk HPVs may go from a productive (virion-producing) infection to an abortive or transforming infection, after which cancer can develop due to the gradual accumulation of host genetic abnormalities. However, it is unknown which precancerous lesions advance and which do not; the majority of precancers discovered during screening are treated, resulting in overtreatment. Following the identification of HPV as a cancer, efficient preventative vaccinations and sensitive HPV DNA and RNA assays were developed. Vaccination programmes (the ultimate long-term preventative method) and HPV testing might significantly change the landscape of HPV-related malignancies. Because HPV testing provides more comfort when the test is negative, it is likely to replace cytology-based cervical screening. However, worldwide adoption of HPV vaccination and screening remains a difficulty.

Artificial intelligence in cancer imaging: Clinical challenges and applications:

One of the key concepts of medicine is the integration of multidimensional data with sophisticated decision making. Cancer presents a unique environment for medical judgements due to not only its many forms with disease progression, but also the necessity to consider the specific state of patients, their capacity to receive therapy, and their reactions to treatment. Despite advances in technology, reliable cancer diagnosis, characterisation, and monitoring remain challenges. The majority of radiographic disease assessment is based on visual assessments, which may be supplemented by sophisticated computer analysis. Artificial intelligence (AI) in particular promises to make significant advances in expert clinicians' qualitative interpretation of cancer imaging, including volumetric delineation of tumours over time, extrapolation of tumour genotype and biological course from radiographic phenotype, prediction of clinical outcome, and assessment of the impact of disease and treatment on adjacent organs. AI may automate image interpretation procedures and change the clinical workflow of radiography identification, management choices on whether or not to deliver an intervention, and subsequent monitoring to an as-yet unimagined paradigm. The authors discuss the present status of AI in medical imaging of cancer and highlight improvements in four tumour types (lung, brain, breast, and prostate) to demonstrate how typical clinical difficulties are being handled. Although the majority of research examining AI applications in oncology to yet have not been rigorously evaluated for repeatability and generalizability, the findings do reflect more focused attempts to bring AI technology to clinical usage and influence future paths in cancer treatment.

3. METHODOLOGY

Fortunately, Artificial-Intelligence-based cervical screening, which uses pap smear and colposcopy pictures to diagnose cervical cancer, is extensively utilised. Several machine learning techniques are utilised to identify cervical cancer and automate colposcopic picture interpretation. Because of its self-learning capabilities in offering automated diagnostic answers, deep learning-based image categorization has been extensively employed in numerous medical image studies. As a result, the advancement of automation in cervical cancer detection using colposcopy pictures may provide future prospects to reduce death rates in many

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developing nations while also improving the performance of the cervical screening procedure.

Disadvantages:

1. Examining or visually inspecting colposcopy photographs is a time-consuming operation that needs competent medical specialists.
2. The majority of the approaches depend exclusively on cervical spotting and segmentation annotation.

This study will now present FSOD-GAN to diagnose cervical cancer and predict the different phases of cervical cancer using colposcopy pictures. The proposed FSOD-GAN deep learning model is a combination of Faster RCNN and GAN. Based on fine-tuned deep features, the proposed FSOD-GAN would automatically conduct cervical spot localization and multiclass categorization of cervical malignant diseases.

Advantages:

1. The suggested FSOD-GAN was created from the ground up, without the use of any pre-trained neural network design or transfer learning ideas.
2. The automated localization and segmentation of cervical spots will eliminate the requirement for human intervention.

To the best of our knowledge, the suggested FSOD-GAN is the only single architecture capable of identifying cervical type, diagnosing cervical cancer, and prognosing the various phases of cervical cancer.

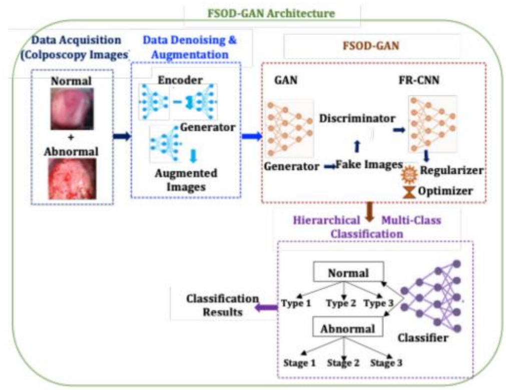

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: We will load data into the system using this module.
- Processing: We will read data for processing using this module.
- Splitting data into train and test: We will divide data into train and test using this module.
- Model generation: We will build the model using FaterRCNN, Adversarial Network Model, FSOD-GAN, Inception V3, MobileNet, DenseNet.
- User register & login: Using this module will obtain registration and login
- User input: Using this module will supply input for prediction
- Prediction: final predicted shown

4. IMPLEMENTATION

ALGORITHMS:

FaterRCNN: Faster R-CNN is a deep convolutional network that appears to the user as a single, end-to-end, unified network. The network can predict the positions of various items correctly and fast.

Adversarial Network Model: A generative adversarial network (GAN) is a machine learning (ML) model in which two neural networks fight to improve their prediction accuracy. GANs often learn unsupervised using a cooperative zero-sum game framework.

FSOD-GAN: Few-shot object detection (FSOD) is a new and fast increasing research field with a wide range of real-world applications. Unlike traditional object detectors, few-shot object detectors may be converted to new domains with just a little amount of annotated data, eliminating the need for expensive data re-collection and re-training anytime the downstream job changes.

Inception V3: The Inception v3 image recognition model has been proven to achieve higher than 78.1% accuracy on the ImageNet dataset. The model represents the result of several concepts explored over time by many academics.

MobileNet: A convolutional neural network (CNN) built for mobile and embedded vision applications. They are based on a simplified design that use depthwise separable convolutions to construct lightweight deep neural networks with reduced latency for mobile and embedded devices.

DenseNet: A DenseNet is a sort of convolutional neural network that makes use of dense connections between layers through Dense Blocks, which link all layers (with matching feature-map sizes) directly with each other.

5. EXPERIMENTAL RESULTS

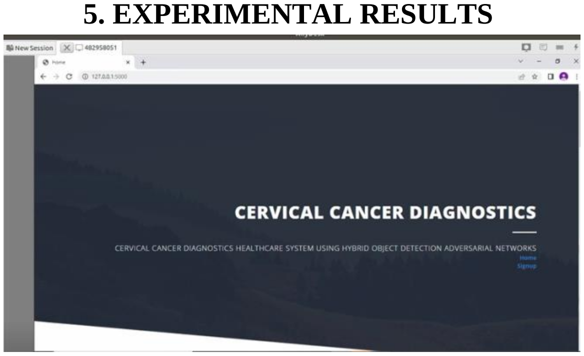

Fig.3: Home screen

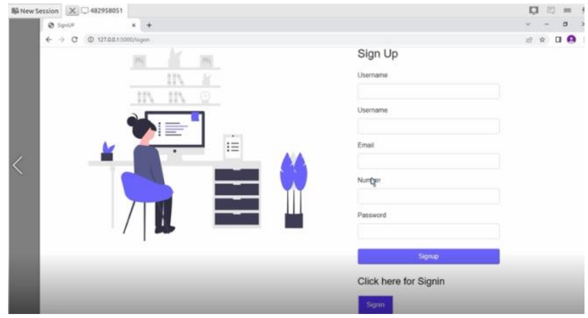

Fig.4: User signup

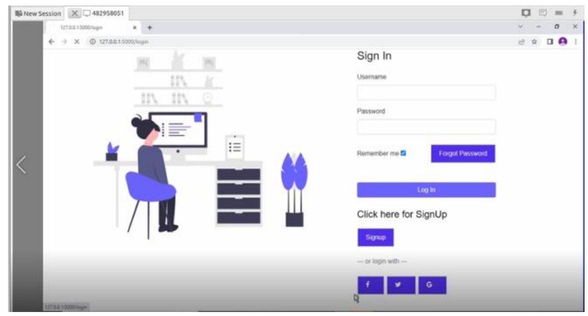

Fig.5: User signin

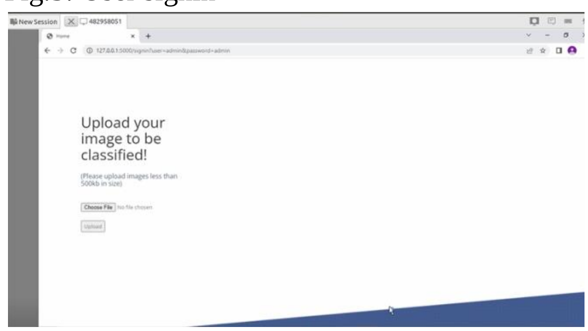

Fig.6: Main screen

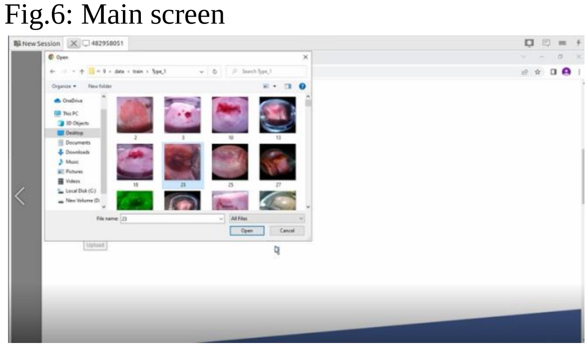

Fig.7: User input

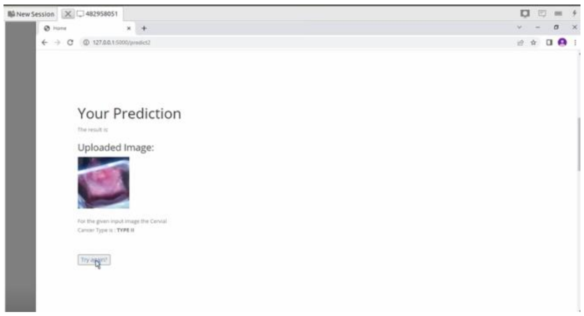

Fig.8: Prediction result

6. CONCLUSION

The hybrid FSOD-GAN approach is introduced in this research by integrating FR-CNN, GAN, and FSDAE techniques. Using cervical colposcopy pictures, this hybrid FSODGAN identifies cervical cancer and separates normal from bad cervical images. To the best of our knowledge, the suggested FSOD-GAN architecture is the first to use hierarchical multiclass classification to categorise normal and abnormal cervical pictures, as well as the kind and stage of infection. The experimental findings also shown that the suggested FSOD-GAN surpasses current cutting-edge approaches for screening and detecting cervical cancer. The suggested FSOD-GAN may now be used in real-time settings for screening, diagnosing, and prognosing cervical cancer utilising colposcopy pictures.

REFERENCES

[1] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries," CA: Cancer J. Clinicians, vol. 68, no. 6, pp. 394–424, 2018.

[2] B. Chitra and S. S. Kumar, "Recent advancement in cervical cancer diagnosis for automated screening: A detailed review," J. Ambient Intell. Humanized Comput., pp. 1–19, 2021.

[3] X. Tan et al., "Automatic model for cervical cancer screening based on convolutional neural network: A retrospective, multicohort, multicenter study," Cancer Cell Int., vol. 21, no. 1, pp. 1–10, 2021.

[4] M. Schiffman et al., "Carcinogenic human papillomavirus infection," Nature Rev. Dis. Primers, vol. 2, no. 1, pp. 1–20, 2016.

[5] [Online]. Available: https://www.who.int/health-topics/cervicalcancer#tab=tab_1

[6] W. L. Bi et al., "Artificial intelligence in cancer imaging: Clinical challenges and applications," CA: Cancer J. Clinicians, vol. 69, no. 2, pp. 127–157, 2019.

[7] T. Torheim et al., "Autodelineation of cervical cancers using multiparametric magnetic resonance imaging and machine learning," Acta Oncologica, vol. 56, no. 6, pp. 806–812, 2017.

[8] W. William, A. Ware, A.H. Basaza-Ejiri, and J. Obungoloch, "A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images," Comput. Methods Programs Biomed., vol. 164, pp. 15–22, 2018.

[9] E. Kim and X. Huang, "A data driven approach to cervigram image analysis and classification," in Color Medical Image Analysis. Dordrecht, The Netherlands: Springer, 2013, pp. 1–13.

[10] S. Gordon, G. Zimmerman, R. Long, S. Antani, J. Jeronimo, and H. Greenspan, "Content analysis of uterine cervix images: Initial steps toward content-based indexing and retrieval of cervigrams," in Proc. Med. Imag. Image, 2006, vol. 6144, Art. no. 61444U.