Cervical Cancer Diagnostics Healthcare System Using CNN

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Abstract

Cervical cancer is one of the common cancers among women and it causes significant mortality in many developing countries. Diagnosis of cervical lesions is done using pap smear test or visual inspection using acetic acid (staining). Digital colposcopy, an inexpensive methodology, provides painless and efficient screening results. Therefore, automating cervical cancer screening using colposcopy images will be highly useful in saving many lives. Nowadays, many automation techniques using computer vision and machine learning in cervical screening gained attention, paving the way for diagnosing cervical cancer. However, most of the methods rely entirely on the annotation of cervical spotting and segmentation. This paper aims to introduce the Faster Small-Object Detection Neural Networks-Generative adversarial network (FSOD-GAN) to address the cervical screening and diagnosis of cervical cancer and the type of cancer using digital colposcopy images. The proposed approach automatically detects the cervical spot using Faster Region-Based Convolutional Neural Network (FR-CNN) and performs the hierarchical multiclass classification of three types of cervical cancer lesions. Experimentation was done with colposcopy data collected from available open sources consisting of 1,993 patients with three cervical categories, and the proposed approach shows 99% accuracy in diagnosing the stages of cervical cancer.

1. INTRODUCTION

Cervical cancers are one of the most common cancers diagnosed in women. Cervical cancer remains the most significant burden for women's health and shows the impact of global health inequality [1]. Every year, cervical cancer is diagnosed with around 56 million women, with a mortality rate of 90% [2]. Especially in developing countries like India and China [3], four out of five medical cases are reported. The report estimates more than 500 thousand new cases in 2018 and more than 300 thousand deaths annually. And the report indicates that out of 300 thousand deaths, almost 85% of the deaths occurred in many of the developing countries. This is due to the lack of awareness about cervical cancer and most of the cases were diagnosed only at the final stage. However, the cervical cancer development is generally slow process leads to abnormalities in cervix. Diagnosing cervical cancer is very tedious in early stages because of absence of symptoms. And also, in developing countries patients will not adhere regular screening due to unawareness. In high-income countries [4], the death rate is sarcastically reduced due to proper organization of cervical-screening programs. Cervical cancer diagnosis will be done to find abnormalities or lesions by examining the cervix region. According to World Health Organization (WHO), the abnormalities in the cervix Cervical Intraepithelial Neoplasia (CIN) is characterized into three categories: CIN1(Mild), CIN2(Moderate) and CIN3(Severe). Generally, the screening of cervix will be done using Pap smear test, liquid cytology and colposcopic examination. According to WHO [5], cervical screening will be done using the Pap smear test in large populations. But colposcopy images are considered a gold standard practice by medical experts to assess cervical cancer. However, the examination or visual inspection of colposcopy images is generally a time-consuming process, and it requires skilled medical experts.

1.2 Scope of the Project:

The project aims to design an efficient fair payment scheme based on blockchain, referred to as EFPB, to facilitate the outsourcing of computational tasks. EFPB is intended to ensure robust fairness without relying on zero-knowledge proof (ZKP) or trusted third parties (TTPs). Specifically, EFPB incorporates one-way accumulator (RSA-based construction), stealth address, and symmetric encryption. The fair payment process is executed using smart contracts, acting as a communication bridge between the outsourcer and the worker. This approach minimizes communication overhead compared to TTP-based solutions. Additionally, EFPB reduces computational costs and transaction fees, making it more efficient and cost-effective than existing blockchain-based solutions. The project's scope includes designing, implementing, and evaluating the EFPB scheme for practical application in outsourcing computational tasks.

2. LITERATURE SURVEY

The literature survey encompasses a comprehensive exploration of studies and reviews addressing various aspects of cervical cancer diagnosis, screening, and the role of artificial intelligence in medical imaging. Firstly, the Global Cancer Statistics report [1] furnishes crucial estimates regarding cancer incidence and mortality worldwide, emphasizing the substantial burden of cervical cancer, particularly in developing nations. This foundational data underscores the urgency of implementing effective screening and diagnostic strategies to mitigate the impact of cervical cancer on women's health globally. Moreover, the Recent Advancement in Cervical Cancer Diagnosis for Automated Screening: A Detailed Review [2] delves into an extensive analysis of research papers spanning from 2010 to 2020. By scrutinizing recent advancements in soft computing techniques for cervical cancer detection, this review provides valuable insights into emerging trends and identifies avenues for further investigation, particularly in the realm of segmentation and classification methodologies.

In the pursuit of enhancing screening accuracy and efficiency, the Automatic Model for Cervical Cancer Screening Based on Convolutional Neural Network [3] presents a significant advancement. Through the development of a deep convolutional neural network (DCNN) model trained on ThinPrep cytologic test (TCT) images, this study achieves notable sensitivity and specificity in cervical cancer screening, underscoring the potential of AI-driven approaches in clinical settings. Furthermore, the Carcinogenic Human Papillomavirus Infection study [4] sheds light on the pivotal role of human papillomavirus (HPV) infections in cervical cancer etiology. By elucidating the carcinogenicity of specific HPV genotypes and their association with cervical and other anogenital cancers, this research underscores the importance of HPV testing and vaccination as preventive measures against cervical cancer. In the realm of medical imaging, the Artificial Intelligence in Cancer Imaging: Clinical Challenges and Applications review [5] provides a comprehensive overview of AI's potential in qualitative interpretation of cancer imaging. By discussing advancements in AI applications across various tumor types, this review elucidates the transformative impact of AI on clinical workflows and patient outcomes in oncology. Lastly, the Auto delineation of Cervical Cancers Using Multiparametric Magnetic Resonance Imaging and Machine Learning study [6] introduces an automatic method for tumor delineation using machine learning approaches. By leveraging multiparametric magnetic resonance imaging (MRI) coupled with machine learning, this study demonstrates significant progress in tumor segmentation, showcasing the potential of AI-driven methodologies in improving diagnostic accuracy and efficiency in cervical cancer management.

Collectively, these studies underscore the critical need for innovative approaches in cervical cancer diagnosis and screening, with AI-driven methodologies presenting promising avenues for enhancing early detection, treatment efficacy, and ultimately, improving patient outcomes.

3. OVERVIEW OF THE SYSTEM

3.1 Existing System

Cervical cancer diagnosis typically involves identifying abnormalities or lesions within the cervix region. According to the World Health Organization (WHO), these abnormalities, known as Cervical Intraepithelial Neoplasia (CIN), are categorized into three levels of severity: CIN1 (Mild), CIN2 (Moderate), and CIN3 (Severe). Common screening methods include the Pap smear test, liquid cytology, and colposcopic examination. While the Pap smear test is widely used for large-scale cervical screening, colposcopy images are considered the gold standard by medical experts for assessing cervical cancer. However, the visual inspection of colposcopy images is a time-consuming process that necessitates skilled medical professionals.

3.1.1 Disadvantages of Existing System

Time-Consuming Process: The visual inspection of colposcopy images is inherently time-consuming. Skilled medical professionals need to meticulously examine each image, which can lead to delays in diagnosis and treatment initiation. This prolonged process contributes to inefficiencies in healthcare delivery, potentially delaying patient care and increasing the burden on medical resources.

Dependency on Skilled Experts: The interpretation of colposcopy images requires expertise and experience. The reliance on skilled medical professionals for accurate diagnosis introduces a bottleneck in the healthcare system. Limited availability of experts, especially in resource-constrained settings, can lead to delays in diagnosis and disparities in access to timely healthcare services.

Subjectivity and Variability: Interpretation of colposcopy images may vary among different medical professionals due to subjective judgment and interobserver variability. This variability can impact the consistency and reliability of diagnoses, leading to discrepancies in patient management and treatment decisions. Moreover, inexperienced or less-trained professionals may struggle with accurately identifying abnormalities, potentially leading to misdiagnosis or underdiagnosis.

Training and Education Requirements: Becoming proficient in interpreting colposcopy images requires extensive training and education. Medical professionals need to undergo specialized courses and practical training to develop the necessary skills for accurate diagnosis. This poses challenges in regions with limited access to training resources and can hinder the scalability of cervical cancer screening programs.

Cost Implications: The reliance on skilled experts and the time-intensive nature of visual inspection using colposcopy images incur significant costs. Healthcare facilities need to allocate resources for training, equipment maintenance, and personnel expenses. These costs may pose financial barriers to widespread adoption of colposcopy-based screening programs, particularly in low-resource settings where healthcare budgets are limited.

3.2 Proposed System

The proposed system aims to leverage deep learning-based image classification to automate cervical cancer diagnosis using colposcopy images. Automation in cervical cancer diagnosis has the potential to reduce mortality rates in developing countries and enhance the efficiency of the screening process. The paper introduces FSOD-GAN, a hybrid deep learning model combining Faster RCNN and GAN. FSOD-GAN automates the localization of cervical spots and performs multiclass classification of cervical malignant conditions based on fine-tuned deep features.

3.2.1 Advantages of Proposed System

Automation: The proposed FSOD-GAN automates the localization of cervical spots without the need for manual intervention. This automation reduces reliance on skilled medical professionals, streamlines the diagnostic process, and increases efficiency.

Enhanced Diagnostic Accuracy: By leveraging deep learning techniques, the proposed system can analyze colposcopy images with high precision and accuracy. It utilizes fine-tuned deep features for multiclass classification of cervical malignant conditions, leading to more reliable diagnoses compared to traditional manual methods.

Time Efficiency: Automation of cervical spot localization and classification significantly reduces the time required for diagnosis. By eliminating manual inspection and speeding up the analysis process, the proposed system enables quicker turnaround times for patient results, facilitating prompt treatment initiation and improving patient outcomes.

Scalability: Once developed and implemented, the proposed system can be scaled up to serve larger populations without significant increases in resource requirements. It can be deployed across various healthcare settings, including remote or underserved areas, thereby increasing access to timely cervical cancer screening and diagnosis.

Reduction in Healthcare Costs: Automating cervical cancer screening with FSOD-GAN can potentially lower healthcare costs by reducing the need for skilled personnel and minimizing the time and resources required for diagnosis. This cost-effectiveness makes the proposed system particularly valuable for healthcare systems with limited budgets or resources.

Standardization: By employing a standardized deep learning model, the proposed system ensures consistency and uniformity in cervical cancer diagnosis. It reduces interobserver variability and subjective interpretation biases, leading to more reliable and reproducible results across different healthcare settings and practitioners.

3.3 Proposed System Design

In this project work, these are the modules and each module has specific functions, they are:

1. Data Exploration Module
2. Processing Module
3. Splitting Data into Train & Test Module
4. Model Generation Module
5. User Signup & Login
6. User Input
7. Prediction

3.3.1 Data Exploration Module

The data exploration module involves loading data into the system. During this phase, we analyze the data, check for missing values, and explore its characteristics. Various data sources, such as databases, files, or APIs, can be used to populate the system.

3.3.2 Processing Module

In the processing module, we read the loaded data for further manipulation. This step includes data cleaning, transformation, and feature engineering. By preparing the data, we ensure that it is ready for model training and analysis.

3.3.3 Splitting Data into Train & Test Module

The splitting module divides the data into two subsets: training data and testing data. The training data is used to build machine learning models, while the testing data evaluates the model's performance. Proper data partitioning ensures unbiased model assessment.

3.3.4 Model Generation Module

The model generation module focuses on building machine learning models. Algorithms like Faster RCNN, Adversarial network model, FSOD-GAN, InceptionV3, Mobilenet, and Densenet are considered. Model accuracy is calculated to assess their effectiveness in predicting relevant outcomes.

3.3.5 User Signup & Login Module

Users interact with the system through the signup and login module. Secure authentication mechanisms allow users to register and log in. User data is stored safely, ensuring privacy and access control.

3.3.6 User Input Module

The user input module captures input from users. Whether it's an image upload, text entry, or other forms of input, this step prepares the data for prediction by the machine learning models.

3.3.7 Prediction Module

Finally, the prediction module displays the system's predictions to users. For instance, if a user uploads an image, the system predicts relevant information, such as object detection or classification results.

3.4 Architecture

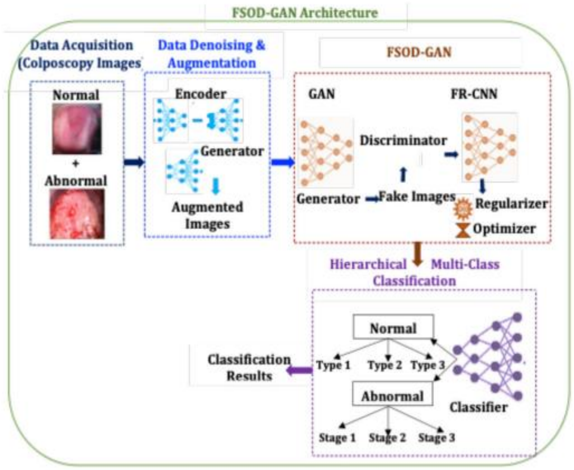

Fig 1: System Architecture

4. RESULT SCREEN SHOTS

Fig 2 : Home page

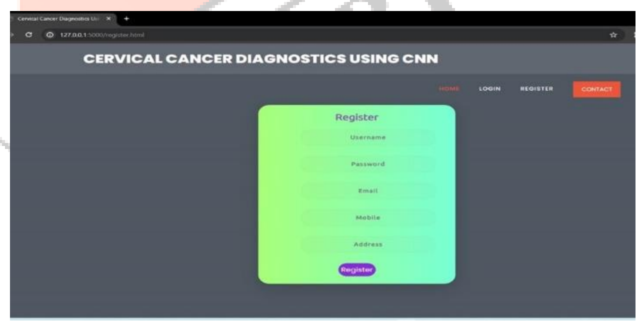

Fig 3 : Register Page

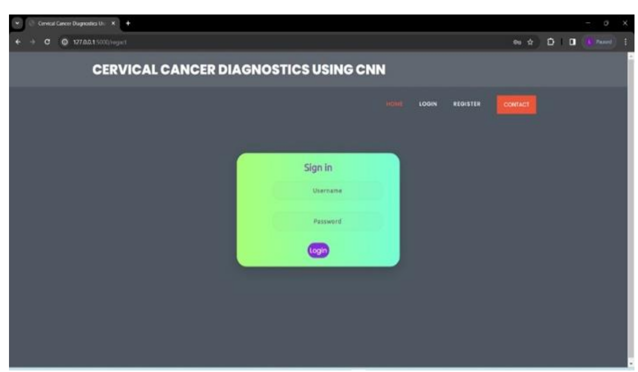

Fig 4 : Login Page

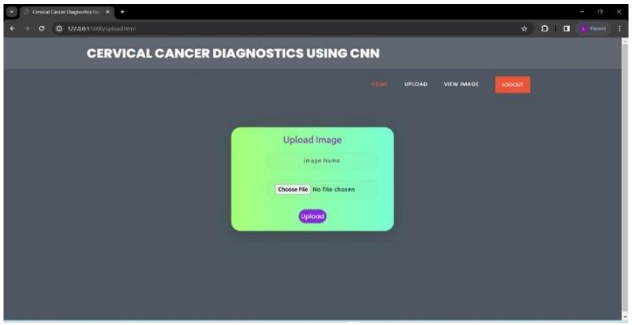

Fig 5 : Image Upload Page

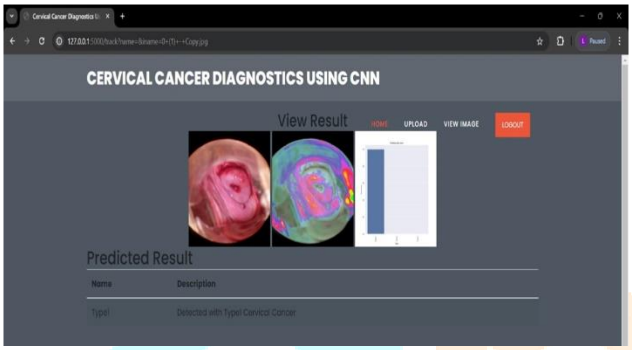

Fig 6 : Type1 Cancer

Fig 7 : Type2 Cancer

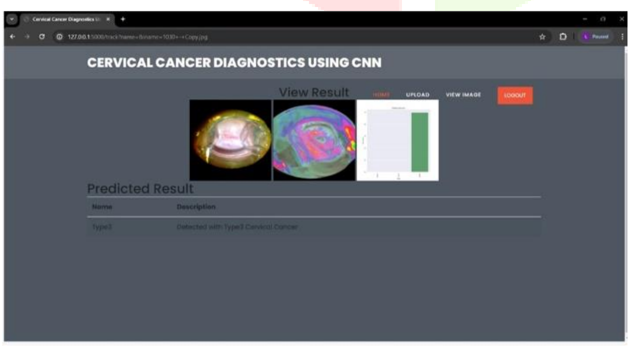

Fig 8 : Type3 Cancer

5. CONCLUSION

This paper introduces the hybrid FSOD-GAN by combining FR-CNN, GAN techniques. This hybrid FSODGAN diagnoses cervical cancer and screens the normal cervical images from the abnormal images using cervical colposcopy images. To the best of our knowledge, the proposed FSOD-GAN is the first architecture that performs hierarchical multiclass classification to classify the normal and abnormal cervical images along with the type and stage of infection, respectively. Experimental results also proved that the proposed FSOD-GAN outperforms the other state-of-the-art techniques in screening and diagnosing cervical cancer. Henceforth, it is proved that the proposed FSOD-GAN can be adopted in real-time scenarios in screening, diagnosing, and prognosing cervical cancer using colposcopy images.

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