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Computer Vision Based Diagnostic System For Cervical Cancer Using Colposcopy Images

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ABSTRACT

Cervical cancer is common and preventable disease that poses a significant threat to women's health and well-being. It is the fourth most prevalent cancer among women worldwide, with approximately 604,000 new cases and 342,000 deaths in 2020, according to the World Health Organization.

This project aims to develop a computer vision–based diagnostic system for cervical cancer using a colposcopy images . Early detection plays a pivotal role in improving patient treatment by timely intervention and effective treatment. This paper explores two distinct strategies for enhancing cancer detection. The dataset contains 350 to 500 images 80% images are kept in train and 20 % images are kept in test set. This data is use to classify the core of cancer.

Firstly ,Convolution Neutral Network Consists of Customized CNN model ,not a pre-trained architecture. CNN layers contains Dense layer, flatten layer,conv2D layer, pooling layer, batch normalization, Dropout layer, fully connected layer. Secondly ,Region base Convolution Neutral Network it uses the CNN layers as a backbone for feature extraction. Through this the accuracy of the model is increased to the 0.95 to 0.98 in all three classifications they are severe, moderate ,mild. Finally, the confusion matrix is shown between CNN and partial RCNN.

KEYWORDS: ***Deep learning, CNN, RCNN, Classification ,Flask, cervical images.***

INTRODUCTION

Medical imaging plays a vital role in the early detection and diagnosis of various cancers. Techniques such as colonoscopy, Pap smear, and liquid-based cytology (LBC) are widely used for identifying abnormalities in different parts of the body. Colonoscopy images help in detecting polyps and colorectal cancer, while Pap smear and LBC techniques are used for cervical cancer screening by analizing cell structures. However, manual analysis of these medical images by experts can be time-consuming and may lead to human error. To overcome these challenges, automated systems based on deep learning have been introduced. Among these, Convolutional Neural Networks (CNNs) are highly effective due to their ability to automatically extract important features such as edges, textures, and shapes from images. In this project, a CNN-based model is developed to analize and classify medical images obtained from colonoscopy, Pap smear, and liquid-based cytology techniques. The model uses convolutional layers for feature extraction and provide better performance.

RELATED WORK

In recent advancements in cervical cancer detection, deep learning models based on layered architectures have shown significant improvement in accuracy and reliability when applied to Pap smear and colposcopy images. The process begins with the input layer, where pre-processed images are fed into the network, often after resizing and normalization. The images then pass through multiple convolutional layers, which play a crucial role in extracting low-level features such as edges, colour gradients, and texture patterns that represent the structure of cervical cells. Each convolutional layer is followed by an activation function, typically (Rectified Linear Unit), which introduces non-linearity and enables the model to learn complex and non-linear relationships present in abnormal cell formations. To further enhance performance and reduce computational complexity POOLING layers such as max pooling are applied, which down-sample the feature maps while preserving the most important information. As the network deepens, higher-level features such as nucleus enlargement, irregular cell shapes, and abnormal tissue patterns are captured more effectively.

To improve training efficiency and model stability, batch normalization layers are incorporated, which normalize the outputs of previous layers and accelerate convergence. A key component in preventing overfitting is the DROPOUT, where a fraction of neurons is randomly deactivated during training. This ensures that the model does not rely too heavily on specific neurons and instead learns more generalized features, which is especially important in medical imaging where datasets are often limited. After sufficient feature extraction, a flatten layer is used to convert the multi-dimensional feature maps into a one-dimensional feature vector. This vector is then passed through one or more fully connected (dense) layers, which act as a classifier by learning relationships between extracted features and target classes. Finally, the model uses a soft- max layer to produce probability distributions across different classes such as mild, moderate, and severe stages of cervical cancer. This layered architecture enables automatic feature learning, reduces manual intervention, and significantly enhances diagnostic performance compared to traditional approaches.

LITERATURE SURVEY

In recent years, cervical cancer detection has gained significant attention due to the need for early diagnosis and reduced mortality rates. Traditional screening methods such as Pap smear analysis relied heavily on manual observation by medical experts, which is time-consuming and prone to human error. To overcome these limitations, researchers have explored automated approaches using image processing and machine learning techniques. Early methods focused on segmentation of cervical cells and extraction of handcrafted features like shape, size, and texture, followed by classification using algorithms such as Support Vector Machines (SVM) and Random Forest. However, these approaches showed limited accuracy due to their dependency on manually designed features. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for cervical cancer detection. CNN-based models automatically learn hierarchical features directly from Pap smear and colposcopy images, eliminating the need for manual feature extraction. In these approaches, images are passed through multiple layers such as convolutional layers for feature extraction, activation layers like Re LU for non-linearity, and pooling layers for dimensionality reduction. Deeper layers capture complex patterns such as abnormal nucleus structure and irregular cell boundaries, which are critical indicators of cervical cancer. To improve model performance and stability, researchers have incorporated additional layers such as batch normalization to accelerate training and dropout layers to prevent overfitting by randomly deactivating neurons during training. After feature extraction, the data is flattened and passed through fully connected layers for classification. Finally, a softmax layer is used to categorize the images into different classes such as normal, mild, moderate, or severe stages of cancer. Some studies also explored region-based approaches like RCNN for detection. In addition to classification-based approaches, some researchers have explored region-based detection techniques such as RCNN to identify specific abnormal regions within cervical images. These methods involve region proposal and object localization, which provide more detailed analysis. However, they require higher computational resources and are more complex to implement. As a result, many recent studies prefer CNN-based classification models due to their simplicity, efficiency, and strong performance in real-world applications. Overall, the integration of deep learning techniques in cervical cancer detection has greatly improved diagnostic accuracy, reduced human effort, and enabled faster analysis. These advancements highlight the potential of automated systems in supporting medical professionals and improving early detection, which is critical for effective treatment and patient survival.

EXISTING METHOD

In the existing paper investigates cervical cancer detection using a diverse set of deep learning models, including Efficient- NetB0, DenseNet, Xception, and ResNet50. The study begins by evaluating these models on the low-resolution SkipMed dataset. To enhance classification accuracy, the ViT-Cerv model is introduced. Despite this achievement, performance variations across different classes are observed, leading to the development of the fusion-based HV iT Cerv model. This model combines CNN and ViT architectures to address limitations and enhance classification performance. The research aims to contribute to the advancement of cervical cancer detection methodologies and provide insights with potential implications for clinical diagnostic procedures. The main contributions of this paper are summarized as follows: We conducted an in-depth comparative analysis of four CNN architectures—EfficientNetB0, DenseNet121, Xception, and ResNet50—specifically for cervical cancer detection on the challenging low-resolution SkipMed dataset. This analysis highlights the strengths and weaknesses of each model in the context of medical image classification. We introduced a novel vision transformer-based model, ViT-Cerv, specifically designed for cervical cancer clas sification. Trained from scratch on the SkipMed dataset, ViT-Cerv demonstrated a significant improvement in classification accuracy, achieving an accuracy of 0.94, thus showcasing the potential of transformer-based models in medical image analysis. To further enhance the classification performance, we developed the HViT-Cerv model, which inte- grates the capabilities of CNN architectures with the ViT through a fusion-based approach. This hybrid model achieved state-of-the-art accuracy ranging from 0.97 to 0.99, significantly surpassing the performance of individual models. Our study also identified and addressed performance. The main disadvantage of this project is that they use pap smear images which is very difficult to take single cell from the microscope .It is time consuming and having less accuracy comparing with the our project.

PROPOSED METHOD

The proposed system aims to develop an automated and efficient method for detecting cervical cancer using deep learning techniques on colposcopy images. The system is designed to classify cervical cell images into different categories such as mild, moderate, and severe, thereby assisting in early diagnosis and reducing manual effort.Initially, the input images are collected from standard medical datasets and undergo pre-processing steps such as resizing, normalization, and noise removal to improve image quality. These pre-processed images are then fed into a deep learning model based on a layered Convolutional Neural Network (CNN) architecture. The model consists of multiple convolutional layers that extract important features like edges, textures, and cell structures, followed by activation functions such as Re LU to introduce non-linearity.

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To enhance performance and reduce computational complexity, pooling layers are used to down sample the feature maps while preserving essential information. Batch normalization is applied to stabilize and speed up the training process. A dropout layer is incorporated to prevent overfitting by randomly deactivating neurons during training, ensuring better generalization of the model.

After feature extraction, the data is passed through a flatten layer and fully connected layers, which perform the classification task. Finally, a soft max layer is used to generate probability scores for each class, and the image is classified into one of the categories: mild, moderate, or severe.

The trained model is then integrated into a web-based application using a framework like Flask, allowing users to upload medical images and receive predictions in real time. This system aims to provide a fast, accurate, and user-friendly solution for cervical cancer detection, supporting healthcare professionals in decision-making and improving early diagnosis. Input Image Colposcopy image is given to the system. Pre-processing resize, normalize, remove noise. Feature extraction Convolution + layers extract features .Dimensionality reduction pooling layers reduce size. Regularization dropout layer avoids overfitting. Classification

Fully connected layer classifies

Output .Soft max gives result: mild / moderate / severe.

Algorithm:

Collect labelled image dataset (severe, moderate, mild) .

Pre-process dataset (resize, normalize)

RCNN Feature Extraction Generate region proposals from images Extract features using RCNN (pre-trained CNN backbone) **Train CNN Classifier** Use extracted features as input .Train CNN model for classification Save trained model Initialize

Flask application .Load trained CNN model User registration and login Upload image uploaded image Extract features using RCNN Predict class using CNN display predicted class, confidence, and suggestions and end the process.

ARCHITECTURE

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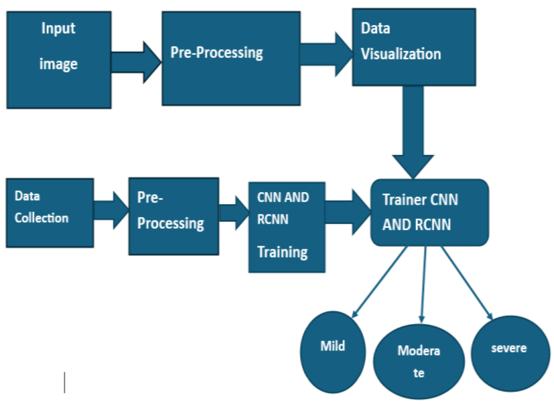

Figure 1: proposed method architecture

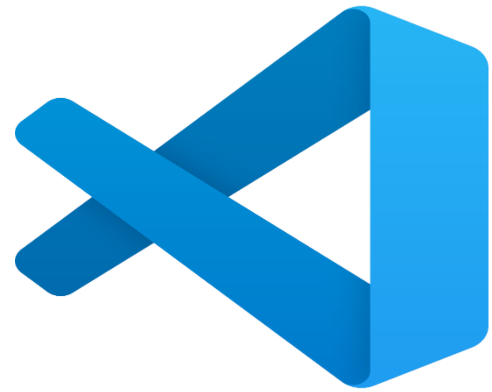

Figure 2.1: - Visual Studio

METHODOLOGY DESCRIPTION

Data Collection**:** The system uses RCNN for feature extraction and CNN for classification to detect disease severity (severe, moderate, mild) from colposcopy images**.** First, a dataset of labelled colposcopy images is collected, then pre-processed by resizing and normalizing. RCNN is applied to extract important features from regions of interest, which are then used to train the CNN classifier. A flask web application allows users to upload colposcopy images, where RCNN extracts features and CNN predicts the severity with a confidence score.

SOFTWARE AND HARDWARE REQUIREMENTS

Visual Studio

Visual Studio provides a complete environment to develop Python-based cervical cancer detection systems. It allows coding, debugging, and running machine learning models like CNNs for image classification.

Colposcope:

Figure 2.2: - colposcope used in Hospitals

A **colposcope** is a medical imaging device used to examine the cervix in detail and the dataset is collected from this device images. It provides magnified, high-resolution images of the cervix, which can help in detecting abnormal changes, precancerous

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lesions, or cervical cancer. These images, called colposcopy images, are commonly used in cervical cancer detection systems for training machine, deep learning models like CNNs.

RESULTS AND DISCUSSION

A **confusion matrix** evaluates a classification model by comparing predicted and actual labels. It shows True Positives, True Negatives, False Positives, and False Negatives, or their multi-class equivalents. It helps calculate accuracy, precision, recall, and F1-score, highlighting model performance and misclassifications.

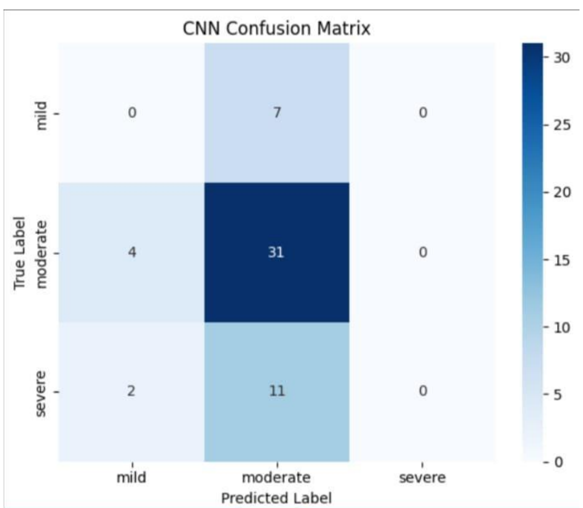

Figure 3.1: - confusion matrix for CNN

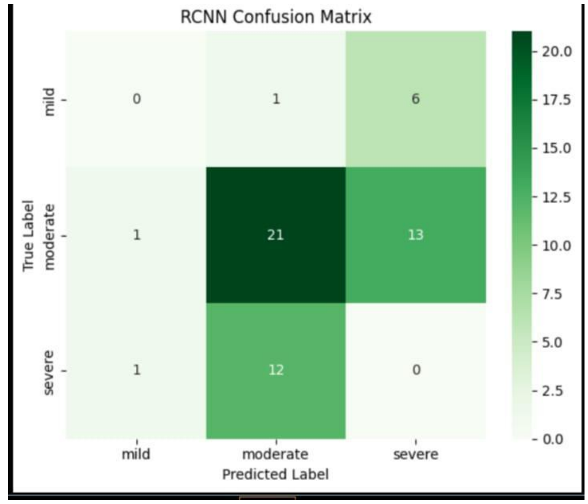

Figure 3.2: - confusion matrix For RCNN

Accuracy measures how often a model predicts correctly. It is calculated as the number of correct predictions divided by the total predictions. In cervical cancer detection, high accuracy shows the model reliably classifies normal and abnormal cases.

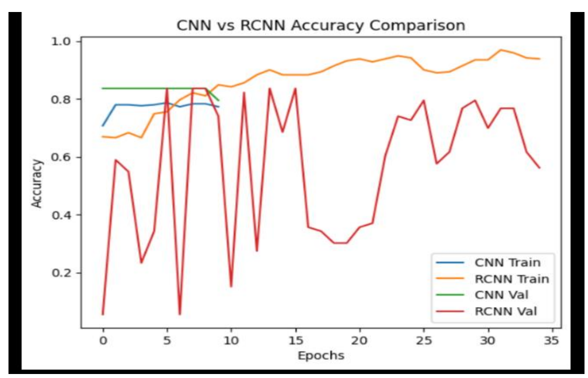

Figure 3.3: -accuracy plot

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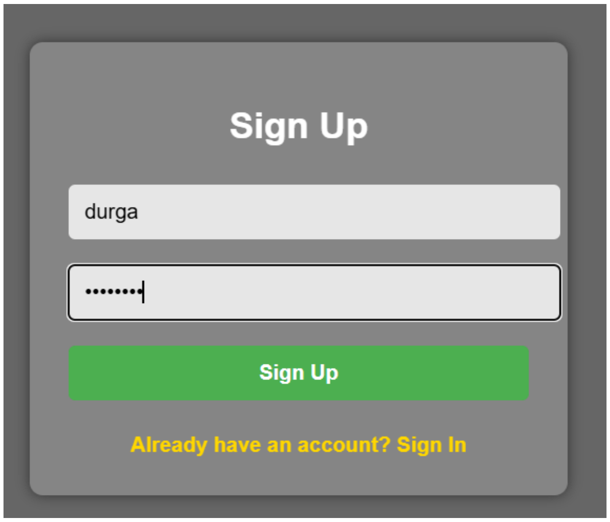

Figure 3.4: -Home page

Accuracy is the most significant things in any deep learning models .If accuracy is more than 90 percentage it will show how the model is efficient. This below and above images represents the output interface of computer vision to classify cervical cancer in women.

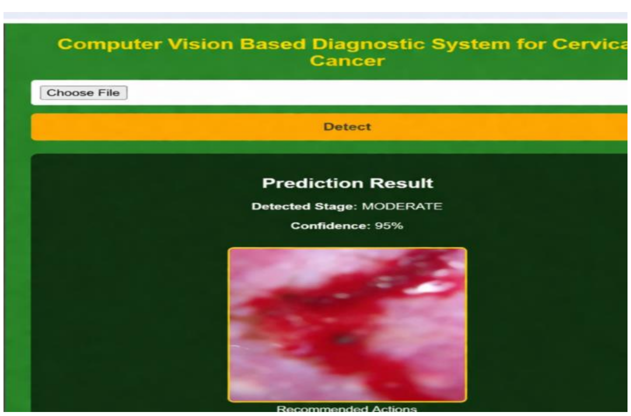

Figure 3.5: -Prediction page

CONCLSUION

The computer vision-based diagnostic system for cervical cancer using colposcopy images offers a reliable, automated, and non-invasive solution for early detection. By leveraging RCNN for precise feature extraction and CNN for accurate classification**,** the system effectively distinguishes between normal, mild, moderate, and severe cervical conditions, reducing dependency on manual evaluation and minimizing diagnostic errors. The integration of the model into a user-friendly web application enables healthcare professionals and patients to easily upload colposcopy images and obtain real-time predictions along with confidence scores and medical suggestions. This not only speeds up the screening process but also facilitates timely interventions, which are critical for preventing the progression of cervical cancer. Moreover, the system's use of deep learning and advanced image analysis ensures scalability and adaptability, allowing it to be enhanced with larger datasets or integrated with other diagnostic tools in the future. Overall, this approach improves the accessibility, efficiency, and accuracy of cervical cancer screening, contributing significantly to public health and early cancer management initiatives.

FUTURE ENHANCEMENT

Future enhancements for cervical cancer detection systems can make them more accurate, efficient, and widely accessible. One key improvement is the integration of larger and more diverse datasets, including multi colposcopy images, which can help the model generalize better across different populations and imaging conditions. Advanced deep learning architectures like EfficientNet, ResNet, or transformer-based vision models can be explored to improve feature extraction and classification accuracy. Combining RCNN or other region-based methods with attention mechanisms can focus more effectively on suspicious regions of the cervix. In addition, the system can be enhanced with real-time mobile or cloud deployment, allowing doctors in remote areas to upload images and receive instant analysis. Integration with patient history, demographic data, or genomic information could further personalize predictions and improve early diagnosis. Finally, incorporating explainable AI (XAI) methods can make the predictions more transparent, showing which regions contributed to a classification, thus increasing clinician trust and adoption in real-world screening programs.

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