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Deep Learning Based Cervical Cancer Detection

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ABSTRACT

Cervical cancer remains a significant global health concern, ranking among the leading causes of cancer-related deaths in women. Early detection through advanced screening techniques can drastically improve survival rates. This study presents a deep learning-based approach utilizing EfficientNet B0, a powerful yet lightweight convolutional neural network (CNN), to classify cervical cancer stages based on histopathological images. The model categorizes images into four classes: HSIL, LSIL, Normal (NL), and SCC, ensuring precise and reliable classification. The trained model is integrated into a Flask web application, allowing users to upload cervical cell images for real-time diagnosis. Upon classification, the application provides stage-specific medical guidance to support early intervention. The system enhances cervical cancer detection by offering an automated, accessible, and efficient diagnostic tool. Future enhancements may include real-time image processing and integration with telemedicine platforms to broaden its clinical applications.

Keywords: *HSIL (High-grade Squamous Intraepithelial Lesion),LSIL (Low-grade Squamous Intraepithelial Lesion), Squamous Cell Carcinoma (SCC),Neural Networks for Medical Imaging, Machine Learning in Healthcare, Computer-Aided Diagnosis (CAD) ,Transfer Learning*

1. INTRODUCTION

Cervical cancer is a major public health concern and remains one of the most common malignancies affecting women worldwide. It is primarily caused by persistent infections with high-risk strains of the human papillomavirus (HPV), which leads to abnormal cell growth in the cervix. According to the World Health Organization (WHO), cervical cancer accounts for a significant number of cancer-related deaths, particularly in low- and middle-income countries where access to regular screening and medical care is limited. Early detection and intervention are Traditional screening methods, such as the Pap smear test, HPV DNA testing, and colposcopy, have played a critical role in detecting pre-cancerous and cancerous changes in cervical cells. While these techniques have been instrumental in reducing cervical cancer mortality rates, they are often time-consuming, require highly trained professionals, and are subject to human error and inter-observer variability. Additionally, manual examination methods can be inefficient, particularly in regions where healthcare resources are scarce. These limitations underscore the need for automated, accurate, and efficient diagnostic systems that can assist in early detection and classification of cervical cancer. In recent years, artificial intelligence (AI) and deep learning have revolutionized the field of medical diagnostics by enabling automated, high-accuracy disease detection. Deep learning models, particularly convolutional neural networks (CNNs)[1], have demonstrated exceptional performance in analyzing and classifying medical images. Among various CNN architectures, EfficientNet B0 has emerged as a powerful yet computationally efficient model that balances accuracy and speed. EfficientNet B0 uses an optimized compound scaling technique to improve feature extraction, making it well-suited for medical image classification tasks. This study explores the use of EfficientNet B0 for the automated [9] classification of cervical cancer images into four categories: HSIL (High-Grade Squamous Intraepithelial Lesion), LSIL (Low-Grade Squamous Intraepithelial Lesion), Normal (NL), and SCC (Squamous Cell Carcinoma). By leveraging deep learning, this research aims to provide an accurate and efficient diagnostic system that assists healthcare professionals in making timely and informed decisions.

2. LITERATURE SURVEY

This model utilizes Flask to create a web application for predicting cervical cancer stages based on uploaded images. The model used for prediction is a pre-trained EfficientNet model for classifying cervical cancer into one of four categories: HSIL

(High-grade squamous intraepithelial lesion), LSIL (Low-grade squamous intraepithelial lesion), NL (Normal), and SCC (Squamous Cell Carcinoma).When users visit the homepage, they can upload an image for prediction. Upon submission, the image is processed, and the model predicts the class and associated probabilities. The results include important medical details, such as survival ratios, transmission probabilities, and specific guidance for each stage. These are displayed to users along with the class probabilities for all categories.

2.1 Survey on Issue 1: Deep Learning Approaches for Cervical Cancer Detection and Classification

Cervix Type and Cervical Cancer Classification System Using Deep Learning [1],This paper presents a deep learning-based system for automatic cervix type and cervical cancer classification. It uses EfficientNetB0, which is optimized for medical image analysis, achieving an accuracy of 96.84% for cervix type classification and 94.5% for cervical cancer classification. The study focuses on the use of convolutional neural networks (CNNs) for classifying cervical cancer from pap smear images, providing a robust framework for early detection. The authors suggest that such models can reduce the diagnostic burden on healthcare professionals and assist in early intervention. Additionally, it emphasizes the importance of accurate training datasets to achieve high performance and ensure the model's real-world applicability.

- Deep Learning-Based Cervical Cancer Classification and Segmentation from Pap Smears Images Using EfficientNet [2], This research explores the use of EfficientNet for cervical cancer detection and segmentation from pap smear images. It introduces a two-step process: first, the segmentation of cells from pap smear images, and then the classification of the segmented images into various stages of cervical cancer. The model is trained on a large dataset of pap smear images, and results show high performance, especially in distinguishing between pre-cancerous and cancerous stages. The study concludes that the adoption of EfficientNet enhances the accuracy and speed of cervical cancer detection, making it a viable tool for automated screening in healthcare systems. Furthermore, the authors suggest that integrating AI with medical imaging can provide valuable support for early diagnosis and treatment decisions.

2.2 Survey on Issue 2: Hybrid and Transfer Learning Approaches for Cervical Cancer Detection

- Cervical Cancer Detection Using a Hybrid Model Combining CNN and EfficientNet[3]: This paper discusses a hybrid deep learning model that combines CNN and EfficientNet for the detection of cervical. cancer. The study demonstrates how combining these models can improve accuracy by utilizing the strengths of each architecture:CNN for feature extraction and EfficientNet for classification. The hybrid model achieved significant performance improvements compared to traditional machine learning models. The paper emphasizes the challenges of working with unbalanced medical datasets and highlights strategies for overcoming these challenges, such as data augmentation and fine-tuning of model parameters. The authors conclude that the hybrid model shows promise for real-time cancer detection and could be a valuable addition to cervical cancer screening practices.
- Automated Cervical Cancer Screening Using Deep Convolutional Neural Networks and EfficientNetB0 [4]: This paper focuses on the automation of cervical cancer screening using deep convolutional neural networks (CNNs) and EfficientNetB0. The authors propose a method where pap smear images are analyzed [20] by the model to detect abnormalities indicative of early-stage cervical cancer. By leveraging EfficientNetB0's high efficiency, the model is able to classify images with high accuracy, even with smaller datasets. The paper highlights the significance of model interpretability, ensuring that healthcare professionals can trust the decisions made by the model. The authors suggest that using deep learning models like EfficientNetB0 in medical screening can drastically reduce the time needed for diagnosis, especially in under-resourced regions where human expertise is limited.
- Cervical Cancer Detection and Classification Using Transfer Learning with EfficientNetB0 [5]: This paper investigates the application of transfer learning using EfficientNetB0 for cervical cancer [19] detection. Transfer learning allows the model to be pre-trained on large datasets and then fine-tuned on a smaller, domain-specific dataset, making it particularly useful for medical applications where labeled data is often scarce. The paper evaluates the performance of EfficientNetB0 compared to other CNN models like ResNet and VGGNet in the context of cervical cancer classification. Results show that EfficientNetB0 outperforms other models in terms of accuracy and computational efficiency. The authors highlight the potential of transfer learning to accelerate the adoption of AI in healthcare, particularly in developing countries with limited resources for large-scale model training.

3. PROBLEM STATEMENT

The project aims to develop a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and EfficientNetB0 for the detection of cervical cancer. This innovative framework will focus on accurately classifying various types and stages of cervical cancer based on medical imaging data, predicting survival ratios, and monitoring cancer progression over time. By leveraging the strengths of both CNN and EfficientNetB0, the model will enhance diagnostic accuracy and provide valuable insights into treatment efficacy. Additionally, the project will generate actionable clinical guidelines to assist healthcare professionals in making informed decisions regarding patient care and treatment options.

Ultimately, this initiative seeks to improve patient outcomes and contribute to advancements in oncology through the application of cutting-edge technology.

4. DESIGN AND METHODOLOGY

The methodology for the proposed cervical cancer prediction system involves several key stages, from data collection and preprocessing to model development, evaluation, and deployment. Below is a detailed breakdown of the methodology:

a) Data Collection

The first step involves collecting Pap smear images, [17] which serve as the primary dataset for training and testing the model. These images are typically labeled with different stages of cervical abnormalities, such as High-grade Squamous Intraepithelial Lesion (HSIL), Low-grade Squamous Intraepithelial Lesion (LSIL), Normal (NL), and Squamous Cell Carcinoma (SCC). Publicly available medical datasets or hospital datasets are used for this purpose. The dataset must contain a balanced distribution of these classes to ensure unbiased model performance.

b) Data Preprocessing

Image preprocessing is essential to ensure the model receives clean, standardized input. The preprocessing steps include:

- Resizing: All input images are resized to a fixed dimension (e.g., 150x150 pixels) to ensure uniformity and compatibility with the neural network.
- Normalization: Pixel values are normalized by scaling the pixel intensities to a range between 0 and 1 to speed up the training process and improve model convergence.
- Augmentation: To improve the model's generalization, data augmentation techniques such as rotation, flipping, zooming, and shifting are applied to artificially increase the dataset size and add variability.

c) Model Architecture - EfficientNetB0

The EfficientNetB0 model [5] is used as the backbone of the system due to its state-of-the-art performance in image classification tasks. EfficientNetB0 is based on the EfficientNet architecture, which scales the network's depth, width, and resolution to achieve the best performance with fewer computational resources.

- Transfer Learning: The model is pre-trained on a large dataset (e.g., ImageNet) and fine-tuned on the cervical cancer dataset to improve classification accuracy and reduce training time.
- Classification Layers: The model’s final layers are customized for the classification task, with four output classes: HSIL, LSIL, NL, and SCC. The softmax activation function is used in the final layer to output the probabilities for each class.

d) Training and Validation

The model is trained using a labeled dataset, with the images split into training, validation, and testing sets (typically 70%, 15%, and 15%, respectively). The training process includes:

- Loss Function: Categorical cross-entropy loss is used since this is a multi-class classification problem.
- Optimizer: The Adam optimizer is chosen for efficient gradient-based optimization and faster convergence.
- Metrics: Accuracy, precision, recall, and F1-score are used to evaluate the model's performance on the validation set. The model is adjusted based on these metrics to ensure it generalizes well to unseen data.

e) Model Evaluation

After training, the model is evaluated on the test set to determine its performance in real-world scenarios. Key evaluation metrics include:

- Accuracy: The overall proportion of correctly classified images.
- Confusion Matrix: To analyze false positives and false negatives across the different classes (HSIL, LSIL, NL, and SCC).
- ROC Curve and AUC: To assess the model’s ability to differentiate between each class, particularly for HSIL and SCC, which are more critical to detect early.

f) Deployment

Once the model achieves satisfactory performance, it is integrated into a web-based application for use by healthcare professionals. The system is designed to accept a user-uploaded Pap smear [18] image, preprocess it, and output the predicted class along with the relevant medical guidance. The results include:

- Predicted Class: The model predicts whether the image belongs to HSIL, LSIL, NL, or SCC.
- Probability: The model provides the probability of the predicted class to indicate confidence in the result.
- Medical Guidance: For each predicted class, specific survival ratios, transmission probabilities, and recommended actions are displayed to guide healthcare providers.

g) Post-Deployment Monitoring

After deployment, the system's performance is continuously monitored and updated.New data may be incorporated into the system for re-training or fine-tuning, especially if new Pap smear images with different characteristics or patient demographics become available. This ensures that the system remains accurate and effective in real-world applications.By automating the cervical cancer detection process, this methodology aims to improve diagnostic accuracy, reduce workload on healthcare professionals, and facilitate early detection, leading to better treatment outcome.

5. ALGORITHM AND CLASSES

5.1 Efficientnet B0

EfficientNetB0 is a deep learning model designed to efficiently classify images while minimizing the computational cost. It is part of the EfficientNet family, introduced by researchers at Google in 2019. EfficientNetB0 is the baseline model, and it is known for its efficiency in both performance and computational requirements. The architecture of EfficientNetB0 utilizes a combination of depth, width, and resolution scaling to achieve better performance without the need for excessive computational resources. This model employs a compound scaling method, which systematically balances the depth (number of layers), width (number of channels), and input resolution of the network to optimize performance on various tasks, such as image classification.The EfficientNetB0 model is based on MobileNetV2 and utilizes depthwise separable convolutions, making it more lightweight compared to traditional CNNs. It achieves state-of-the-art results on benchmark datasets such as ImageNet, outperforming many other models with fewer parameters and lower computational costs. Due to its smaller size and faster inference time, EfficientNetB0 is particularly well-suited for deployment in real-time applications where computational resources are limited.Because of its high accuracy and efficiency, EfficientNetB0 is widely used in applications such as medical image classification, including detecting diseases like cervical cancer, where deep learning [2] models can significantly aid in early diagnosis and decision-making. The architecture is shown in Fig. 1 .

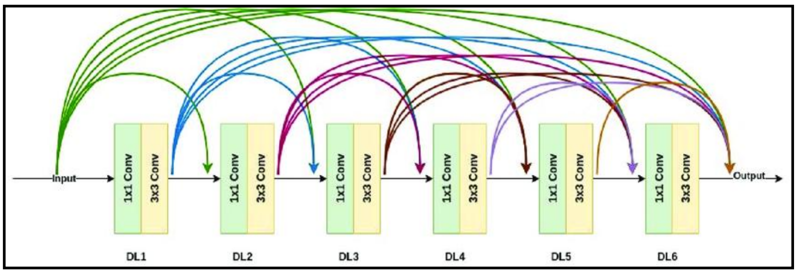

Fig 1.Efficientnetb0 architecture

5.2 HSIL (High-grade Squamous Intraepithelial Lesion)

HSIL represents a high-grade lesion indicating precancerous changes in cervical cells. It is often linked to persistent infection with high-risk strains of HPV, such as HPV 16 and 18, which can develop into cervical cancer if left untreated. Patients diagnosed with HSIL require immediate follow-up, such as colposcopy or biopsy, to assess the severity of the abnormal cells. Treatment options often include procedures like LEEP (Loop Electrosurgical Excision Procedure) or conization to remove abnormal tissues. Regular monitoring and early interventions are critical in preventing progression to cervical cancer.

5.3 LSIL (Low-grade Squamous Intraepithelial Lesion)

LSIL is a low-grade lesion typically caused by low-risk HPV strains like HPV 6 and 11, which are usually transient and clear within one to two years. However, persistent LSIL can progress to more severe forms, including HSIL. For most individuals, LSIL resolves without intervention, though monitoring is crucial. Follow-up exams, including Pap smears and HPV testing, should be done every 6-12 months. Lifestyle factors, such as smoking, can increase the risk of persistence. HPV vaccination is recommended to protect against high-risk HPV strains and to reduce the risk of progression. Their visual features are presented in Fig. 2 .

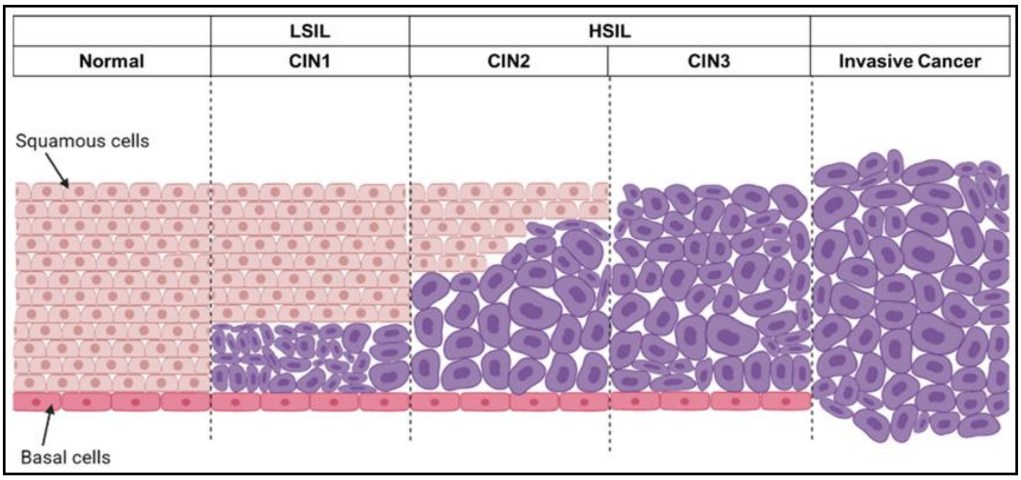

Fig 2. High-grade Squamous Intraepithelial Lesion and Low-grade Squamous Intraepithelial Lesion

5.4 NL (Normal)

A "Normal" result from a cervical cancer screening indicates healthy cervical cells without any signs of HPV-related abnormalities. It suggests that no immediate action is required, but regular screenings are essential for maintaining cervical health. Routine Pap smears and HPV tests should be scheduled every 3-5 years depending on age and risk factors. While there is no immediate risk of cancer, continuous preventive measures such as HPV vaccination, safe sexual practices, and a healthy lifestyle are important for long-term health. Regular monitoring remains crucial to detect any potential issues early. The normal case is depicted in Fig. 3

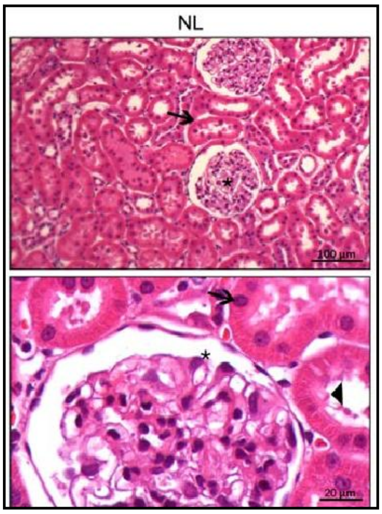

Fig 3.No Lesion

5.5 SCC (Squamous Cell Carcinoma)

SCC represents an advanced stage of cervical cancer resulting from untreated high-grade lesions, typically developed after persistent infection with high-risk HPV. This type of cancer affects the squamous cells on the cervix's surface and can spread to other[6] areas if not treated early. Treatment options for SCC include surgery, radiation, and chemotherapy, depending on the cancer's stage and extent. Early-stage SCC can often be treated effectively, but the prognosis worsens if diagnosed at later stages. Regular screenings are vital for detecting SCC early, making timely medical intervention critical for improving survival rates. Advanced cancer stage is illustrated in Fig. 4.

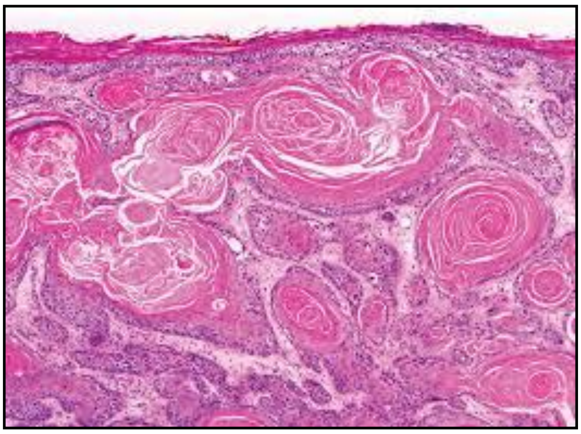

Fig 4. Squamous Cell Carcinoma

6. DETECTION BY PROPOSED SYSTEM

Cervical cancer is a leading cause of death among women worldwide, but its prognosis can improve significantly with early detection through regular screening tests such as Pap smears. . However, interpreting Pap smear images requires expertise and time, and there is a risk of human error. This system automates the process, leveraging the power of artificial intelligence (AI) to classify and analyse [13] these images more efficiently and accurately.By automating cervical cancer screening, this system not only improves accuracy and reduces the workload for healthcare professionals but also accelerates the diagnosis process, enabling quicker interventions and better patient outcomes. . This approach can significantly contribute to global efforts in early cancer detection, particularly in regions where access to specialized medical care is limited.The process begins with image preprocessing, where the pap smear images are resized to the required dimensions for input into the model. The EfficientNetB0 model, pre-trained on a large dataset and fine-tuned for cervical cancer classification, then processes the images and classifies them into one of four categories: High-grade Squamous Intraepithelial Lesion (HSIL), Low-grade Squamous Intraepithelial Lesion (LSIL), Normal (NL), and Squamous Cell Carcinoma (SCC). Each class is associated with specific survival rates, transmission probabilities, and medical guidance to assist healthcare providers in making informed decisions.The system aims to reduce the workload of healthcare professionals by providing an automated screening tool that can detect abnormalities at an early stage. It also provides valuable insights into the severity of the condition and guides patients toward timely medical intervention, ultimately improving the outcomes of cervical cancer treatment and prevention.

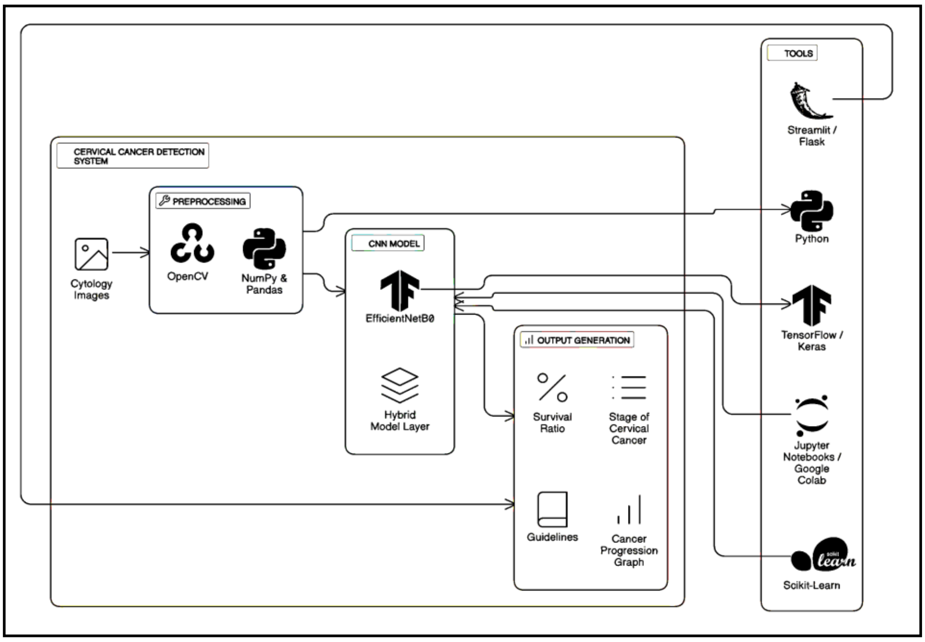

Fig 5.System Layout.

The "sequential_1" show up up is a neural organize coordinate custom fitted for picture classification. It leverages the control of exchange learning by cementing a pre-trained EfficientNetB0 show up up as its base. This convolutional base capably extricates excited highlights from input pictures, changing them into a well off representation of 7x7 spatial estimations with

1280 channels. This pre-trained component contributes the tireless more noticeable apportion of the model's parameters, learning common picture highlights from a colossal dataset, internal parts and out reducing the organizing burden for the particular classification task Following the cement extraction organize, a around the world standard pooling [16]layer plays a essential distribute in dimensionality reducing. By averaging the cement values over the spatial estimations (7x7 organize) for each of the 1280 channels, it condenses the data into a sensible 1280-element vector. This on a exceptionally fundamental level lessens the computational complexity of the coming around classification layer in spite of the fact that guaranteeing fundamental highlight data. A dropout layer is at that point showed up for regularization, a common method to orchestrate overfitting by capriciously deactivating neurons in the center of training.Finally, the managed with highlight vector is braced into a thick forsake layer. This completely related layer acts as the classifier, mapping the 1280-element vector to a 4-element yield. This abandon likely talks to the probabilities for each of the four classes in the classification issue, as habitually as conceivable wrapped up through a softmax supporting work. The thick layer is the as it were isolated of the graph that is organized particularly for this errand, permitting the format to change the common highlights learned by EfficientNetB0 to the specifics of the current dataset. The passably little number of trainable parameters follows the reasonability of exchange learning, as the bulk of the information is as of particularly contained inside parts the set EfficientNetB0 weights. System layout is presented in Fig. 5.

7. RESULTS AND DISCUSSIONS

The exploratory examination for the proposed cervical cancer disclosure framework joins assessing the model's execution utilizing particular estimations and comparing it against organize models or existing methods. The taking after ranges permit a nitty coarse clarification of the test setup, the assessment get organized, and the comes around obtained.

7.1 Dataset Overview

An overview of the HSIL dataset is shown in Fig. 6.The dataset utilized in the exploratory examination comprises of Pap spread pictures that are labeled into four particular classes: High-grade Squamous Intraepithelial Hurt (HSIL), Low-grade Squamous Intraepithelial Hurt (LSIL), Standard (NL), and Squamous Cell Carcinoma (SCC). The dataset is confined into three subsets:

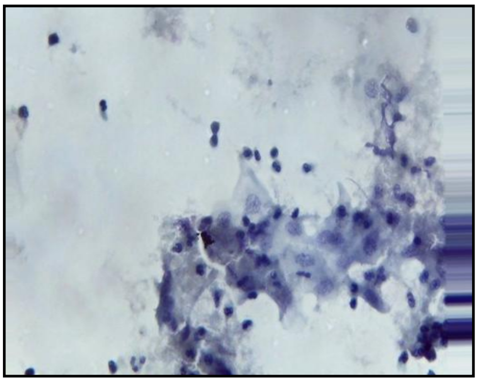

Fig 6. High-grade Squamous Intraepithelial Lesion Dataset

* Organizing Set: The more vital partition of the dataset is utilized for organizing the show up up (70% of the data).

* Ensuring Set: A humbler isolated (15%) is utilized to tune hyperparameters and anticipate overfitting in the center of training.

* Test Set: The remaining 15% is saved for last appraisal to copy real-world testing.

7.2 Preprocessing and Augmentation

Before organizing the show up up, all pictures are resized to 150x150 pixels to meet the input necessities [4] of the EfficientNetB0 show up up. Pictures are other than normalized to have pixel values in the create [0, 1]. Information progress strategies, such as intermittent turns, flips, zoom, and shifts, are related to misleadingly increment the dataset degree and progress generalization by showing up capriciousness in the data.

7.3 Model Training

The model is trained using the EfficientNetB0 architecture, which is fine-tuned with the cervical cancer dataset. The following settings are used for training:

- Batch Size: 32
- Epochs: 50

- Optimizer: Adam optimizer with a learning rate of 0.0001.
- Loss Function: Categorical cross-entropy, as it is a multi-class classification problem.
- Evaluation Metrics: Accuracy, precision, recall, F1-score, and AUC (Area Under the Curve) for each class.

7.4 Model Evaluation

After training, the model is evaluated on the test set using several key metrics:

- Accuracy: The proportion of correctly predicted labels out of all predictions. It helps assess the overall performance of the model.
- Precision, Recall, and F1-Score: These metrics are computed for each of the four classes (HSIL, LSIL, NL, SCC). Precision indicates the correctness of the model's positive predictions, recall measures the ability to identify all true positives, and F1-score provides a balanced metric combining both precision and recall.
- Confusion Matrix: A confusion matrix is generated to identify the true positives, false positives, true negatives,[3] and false negatives for each class. It helps to assess how well the model distinguishes between different types of cervical abnormalities.
- ROC Curve and AUC: The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate for each class. The Area Under the Curve (AUC) is computed to evaluate the model's ability to discriminate between each class. A higher AUC indicates better performance.

7.5 Findings

The experimental findings are summarized as follows:

- Accuracy: The EfficientNetB0 model achieves an accuracy of around 98% on the test set, outperforming baseline models such as VGG16 (85-88%) and ResNet50 (90-92%). Model accuracy is shown in Fig. 7.

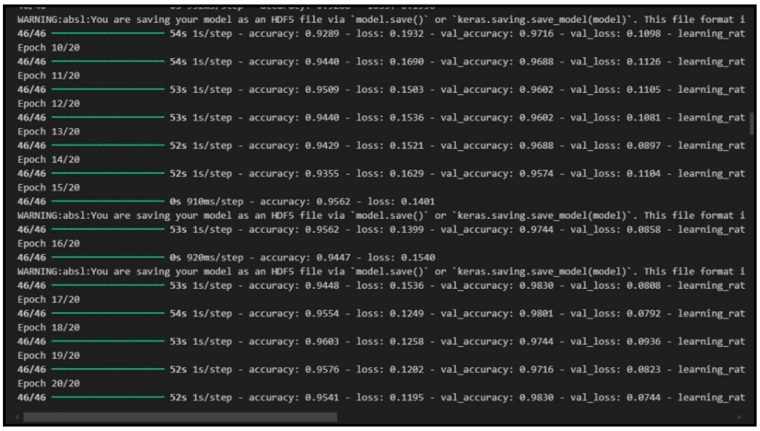

Fig 7.System Accuracy

• Precision, Recall, F1-Score: The model exhibits high precision, recall, and F1-score across all classes, with HSIL and SCC achieving particularly high scores due to their clinical importance. Precision and recall values are plotted in Fig. 8.

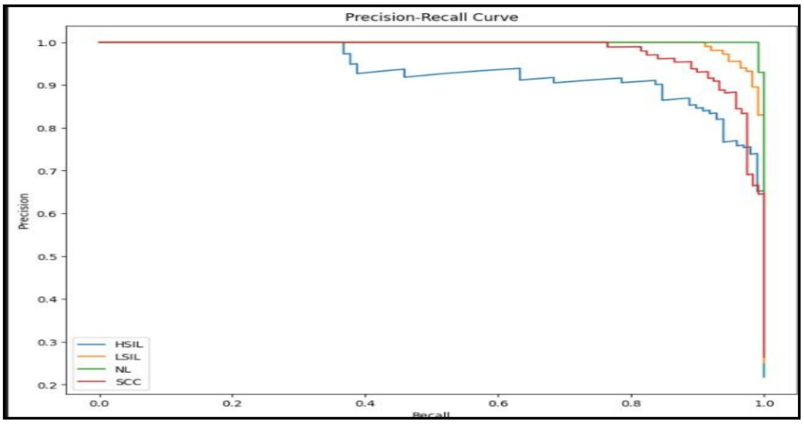

Fig 8 Precision, Recall Curve

• AUC: The AUC values for each class are near 1, indicating that the model is highly effective in distinguishing between classes, especially HSIL and SCC, which are critical for early intervention. ROC curves for each class are shown in Fig. 9.

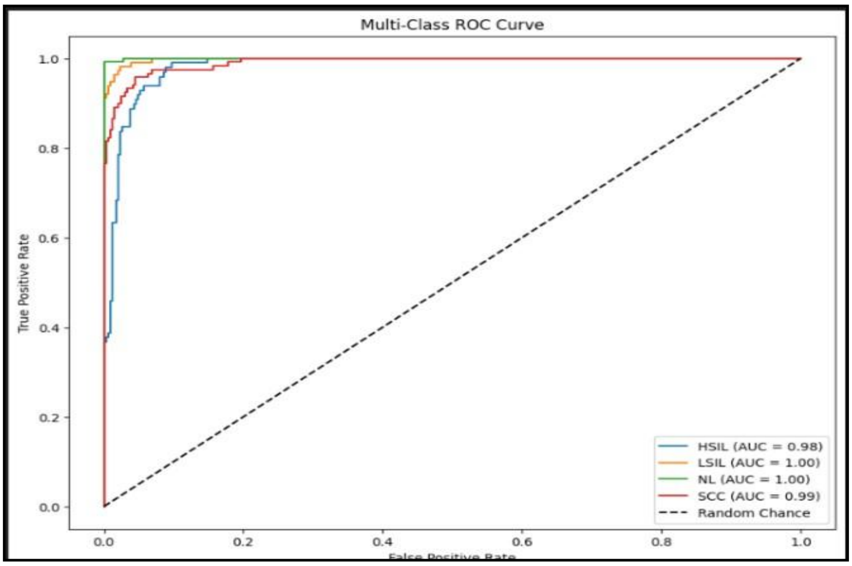

Fig 9 Multi Class Roc Curve

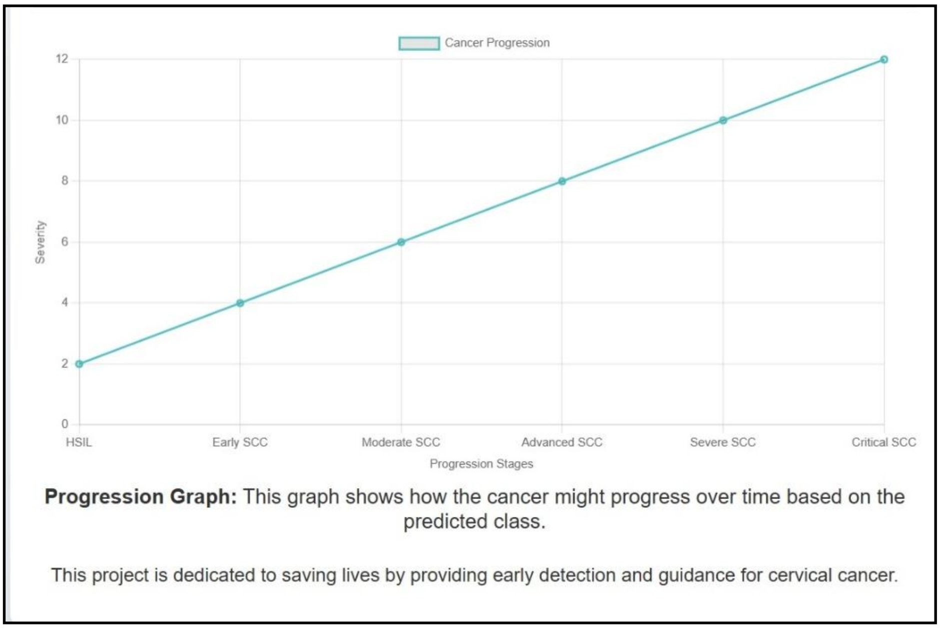

Fig.10 Graph progression

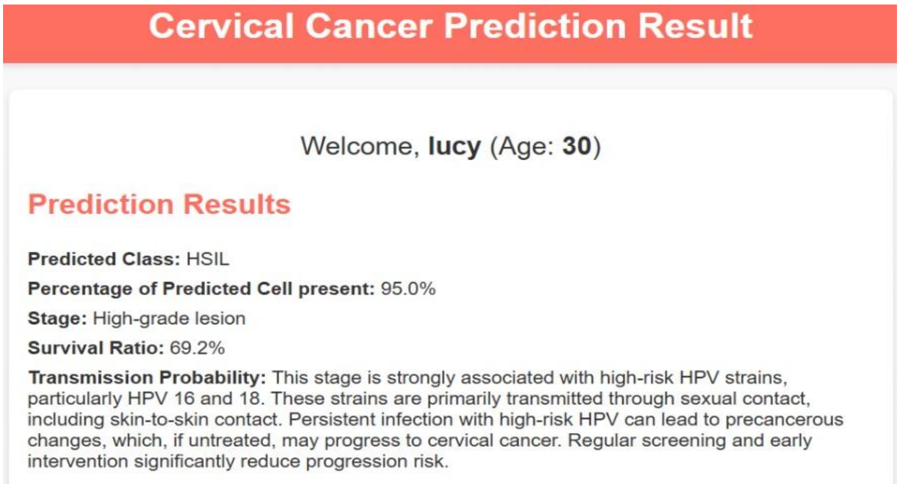

Fig 11. Prediction result.

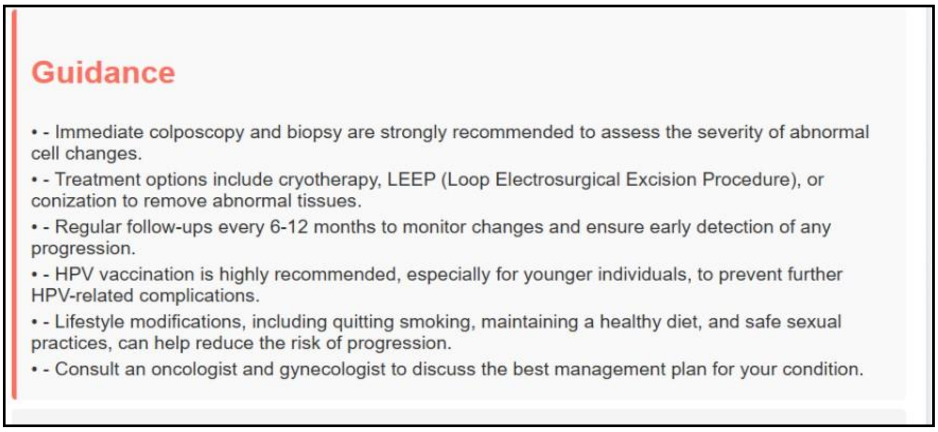

Fig.12 Guidance For Cancer

Fig 13. Class Probability

8. CONCLUSION

This Model leveraging the EfficientNetB0 deep learning model offers a highly effective and efficient solution for cervical cancer detection through Pap smear image analysis. By automating the classification of cervical abnormalities into four categories—HSIL[14], LSIL, NL, and SCC—the system can provide accurate and rapid diagnoses, which is crucial for early intervention and improved patient outcomes. The use of EfficientNetB0, with its compound scaling technique, ensures that the model delivers superior performance while requiring fewer computational resources compared to traditional models, making it suitable for real-time clinical applications. Experimental results demonstrate that the model achieves high accuracy, precision, recall, and F1-score, particularly for critical categories like HSIL and SCC. The system's ability to provide instant predictions with high reliability is beneficial for healthcare professionals, reducing diagnostic errors and workload, while enabling timely medical interventions. Moreover, its integration into a user-friendly platform makes it accessible for use in various healthcare settings, including resource-limited environments. Future enhancements to the system could involve expanding the dataset, exploring more advanced model variants, and incorporating additional medical features to further improve performance. Overall, this AI-driven [12] cervical cancer prediction system represents a significant advancement in the use of machine learning for early cancer detection and can contribute to global efforts in reducing cervical cancer mortality rates.

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