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Advancements in cervical cancer risk prediction using ResNet50

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Abstract: It underlines the rather important role that cervical cancer plays in being a major cause of deaths from cancer among women around the world, not necessarily because of other reasons it progresses slowly and often unpredictably. Early detection through screening forms the basic steps involved in the prevention of cervical cancer and this involves identification and monitoring of precancerous zones within the cervix, which again can be categorized into three different types namely, type 1, type 2, and type 3. Proper identification and analysis of every one of these stages can effectively check their progression into invasive cancer. Such appeals for accurate classification of cervical pre- cancerous images into these categories through highly advanced automated systems. The intelligent system through artificial intelligence as well as machine learning is designed to improve efficiency and precision in the cervical cancer screening so that timely intervention is facilitated. Systems focused on the more individualized and targeted approach tend to prevent the precancerous cells from being transformed into cancerous cells. Automated tools provide a reliable alternative in resource constraint settings whereby the screening process done through manual tools is not in place, and such a screening becomes possible with fewer rates of error in diagnosing it, which also happens to be accessible since a deep model like ResNet-50 generates notable performance in the colposcopy image classification that improves the cervical cancer screening as well as the preventive measures in place. Such discoveries promise a new direction in the treatment of cervical cancer and significantly fewer deaths from that disease, therefore ensuring improved overall results for women's health worldwide.

Keywords: Cervical cancer screening, Colposcopy images, Deep learning, Diagnostic accuracy, Early detection, Machine learning, Pre-cancerous zones, ResNet-50, Screening.

I. INTRODUCTION

Cervical cancer is one of the leading cancer death burdens worldwide and predominantly affects women. The cells producing this disease are located on the cervix, being the part of the uterus that connects to the vagina. This disease is often attributed to chronic infection by high-risk strains of human papillomavirus, also known as HPV, which is a common sexually transmitted infection. Despite its potential fatality, advancements but because in treatment, early detection, and prevention have greatly improved the prognosis of cervical cancer. Routine screening practices, including that help in the identification of precancerous changes and early malignancies, thereby facilitating timely intervention. Understanding and awareness of cervical cancer is an important tool to arm individuals with the opportunity to take control of their health. Heavy, irregular, or abnormal menstruations and spotting could be early signs of cervical cancer. Pap smear is one of the easiest, fastest, and almost painless methods for screening cervical cancer. It involves pelvic examination where cells from the cervix are taken in by clinicians and viewed under a microscope. Due to the Pap smear, cervical cancer incidence has decreased by 60-90%, and mortality has declined by 90%. For example, Pap smears have adverse effects, such as poor patient compliance, low repeatability, and poor aftercare, primarily because they are lengthy tests. The prediction algorithms based on risks have received momentum in the last few years as even more promising tools to increase accuracy in the cervical cancer screening and diagnosis process. Such algorithms estimate the risk of cervical cancer in a person based on multiple parameters. These include clinical and demographic information such as age, number of sexual partners, age when first sexual experience occurred, presence of HPV infection, conditions of immune deficiency (for example, HIV infection), and smoking history. Utilize algorithms with information like these to be able to tailor cervical cancer detection and prevention even more according to individual risk profiles, likely increasing their precision and timing.

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II. LITERATURE REVIEW

1. Abdul Samad et al. (2022)
Introduce an automated system using ResNet-50 in classifying cervical precancerous stages based on accuracy with 77 % and F1- score of 79 %. This might be a potential early diagnosis and prevention in cervical cancer by finding high-risk individuals. [1]

2. Adhikary et al. (2021)
proposed a novel approach that combines DIC imaging and support vector machine, multi-layer perceptron, and k-nearest
neighbour algorithms for cervical cancer screening. SVM turned out to be the one that performed the best with an accuracy of 97% in classification accuracy providing a fast, label- free diagnostic tool. [2]

3. Al Mudawi and Alazeb. (2022)
investigated the use of machine learning algorithms, such as Gradient Boosting and XGBoost, for predictive aims in cervical cancer at 100% accuracy with Random Forest while discovering ensemble methods to have potential power for clinical early diagnosis. [3]

4. Fekri-Ershad and Ramakrishnan (2022)
introduces a two-stage classification approach using Modified Uniform Local Ternary Patterns (MULTP) and a feedforward neural network optimized by a genetic algorithm for cervical cancer diagnosis in Pap smear images. Their model is accurate as well as computationally efficient. [4].

5. Liu et al., 2022,
introduced CVM-Cervix which is a hybrid model involving Convolutional Neural Networks and Visual Transformers in cervical cancer. The current study further applied the mentioned above model in detailed feature extraction for complete analysis and high classification accuracy which would lead to real-time diagnostics. [5]

6. Mohammed et al. (2022)
applied WSIs and combined deep learning with traditional features like LBP and GLCM in order to have a high classification accuracy rate of 99.4%. Such hybrid approaches not only prove the contribution of hand-crafted features along with deep learning but are also worth every combination towards medical diagnostics. [6]

7. Alquran et al. 2022:
the authors designed Cervical Net, implementing a deep learning architecture that incorporates Shuffle Net with PCA, achieving an accuracy of 99.1% from the five classes of cervical cell images. This work introduces the boost in classification accuracy based on the dimensionality reduction techniques. [7]

III. RESEARCH GAP

Despite significant advancements in deep learning for cervical cancer detection, several research gaps remain. A major challenge is the limited availability of large, diverse datasets, leading to overfitting and reduced model generalizability. There is also a lack of standardization in preprocessing techniques, making model comparisons difficult. The black-box nature of deep learning models raises concerns about interpretability, necessitating explainable AI approaches for clinical trust. Additionally, class imbalance in datasets affects predictive performance, requiring better augmentation techniques. While many models show high accuracy in research settings, their real- world deployment remains limited due to regulatory and computational constraints. Furthermore, most studies rely solely on imaging data, overlooking the potential of multi-modal fusion with clinical records for improved diagnosis. Addressing these gaps can enhance model reliability, efficiency, and real- world applicability in cervical cancer detection.

IV. METHODOLOGY

The methodology for cervical cancer risk prediction using ResNet-50 consists of four key stages: data collection, data preprocessing, feature extraction, and model selection. Each stage is crucial for the accurate classification of cervical cancer risk types, enabling the model to differentiate between varying levels of cancer severity effectively.

1. Data Collection
The process begins with data collection, utilizing the Malahari dataset, which contains a range of medical images labeled

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across three risk categories: Type 1 (mild), Type 2 (moderate), and Type 3 (severe). This dataset is carefully curated to represent diverse stages and levels of severity in cervical cancer, ensuring that the model has sufficient variability to learn from. To further guarantee the accuracy and reliability of the data, images are reviewed by experts. This validation step ensures that the data fed into the model is of high quality, providing the necessary foundation for accurate model training. The diversity in the dataset is essential as it exposes the model to various forms and stages of cancerous lesions, which helps in learning distinct features that can differentiate between the three risk categories. This robust dataset enables the model to effectively classify new images by identifying subtle features that correlate with each cancer risk type.

2. Data Preprocessing

Once the dataset is assembled, preprocessing is carried out to prepare the images for training. Each image is resized to 224x224 pixels, which is the standard input size for ResNet-50. This resizing ensures consistency across all images, which is essential for the model's efficiency during both training and inference stages. Furthermore, pixel values are normalized to a range between [0, 1], which helps in standardizing the data distribution, thereby speeding up the model's convergence during training.

To avoid overfitting and enhance model generalizability, data augmentation techniques are applied. These techniques include rotating images, adjusting brightness, and performing random flips and zooms, all of which artificially increase the variety of the training data. This augmentation makes the model more robust to variations and distortions that may be present in real- world images. Depending on computational resources and the model's requirements, images may be kept in RGB or converted to grayscale, which reduces computational complexity while preserving essential structural information.

3. Feature Extraction

Feature extraction is the next vital step, where ResNet- 50's deep convolutional neural network architecture autonomously identifies crucial features from the input images. ResNet-50, a model pre-trained on large datasets like ImageNet, leverages transfer learning to build upon its existing knowledge of generic features such as edges and textures. As the images progress through deeper layers of the network, the model begins to capture more complex patterns and high-level features, including those that are critical to classifying cervical cancer, like tissue structure or abnormalities. By the end of the convolutional layers, a global average pooling layer condenses these feature maps into a feature vector, summarizing the image's key characteristics. This automated feature extraction process minimizes the need for manual intervention, making it efficient and highly adaptable to specific domains like cervical cancer risk classification. For further optimization, dimensionality reduction techniques like Principal Component Analysis (PCA) may be applied to simplify the feature space without sacrificing critical information. This step ultimately enhances the model's predictive accuracy and enables more precise classification of cervical cancer risk types.

1. Model Selection

The selection of ResNet-50 for this task is based on its proven effectiveness in handling complex image classification problems. With a 50-layer architecture that includes residual blocks, ResNet-50 overcomes issues like vanishing gradients that commonly occur in deep networks. These residual blocks include skip connections, which allow the model to maintain strong gradient flows during backpropagation, thus enabling effective training of deep networks without accuracy loss. As the preprocessed images pass through ResNet- 50, the network extracts essential spatial features such as edges, textures, and patterns that indicate varying levels of cervical cancer risk. In the final fully connected layers, these features are aggregated, and a softmax function produces a probability distribution for each risk category. This setup allows the model to classify each image accurately, providing a prediction for the most likely risk type (mild, moderate, or severe). The combination of deep layers, residual connections, and fully connected layers enables ResNet-50 to achieve precise and reliable classification, making it a suitable choice for cervical cancer risk prediction.

The development begins with **Data Collection and Preprocessing**, where raw data is gathered and cleaned to prepare it for model training. After this, the data is split into **Training**, **Validation**, and **Testing** sets. This helps the model learn effectively, allows performance tuning, and ensures unbiased evaluation.

Following this, **Model Selection** takes place based on task- specific needs. Once chosen, the model is trained using the training data. During training, **Hyperparameter Tuning** is done to improve performance. The model's effectiveness is then measured using the **Validation set**, and necessary adjustments are made. Once it performs well on validation data, the model is finally assessed using the **Test set** for a fair performance estimate. If results are satisfactory, the model is **Deployed** to operate in real-time environments and make predictions on new data. This entire process is iterative to ensure consistent improvement and reliability. For cervical cancer risk prediction, ResNet-50 is chosen due to its strong performance in image classification tasks. It's a deep convolutional neural network with 50 layers, designed to tackle issues like the vanishing gradient problem common in deep networks.

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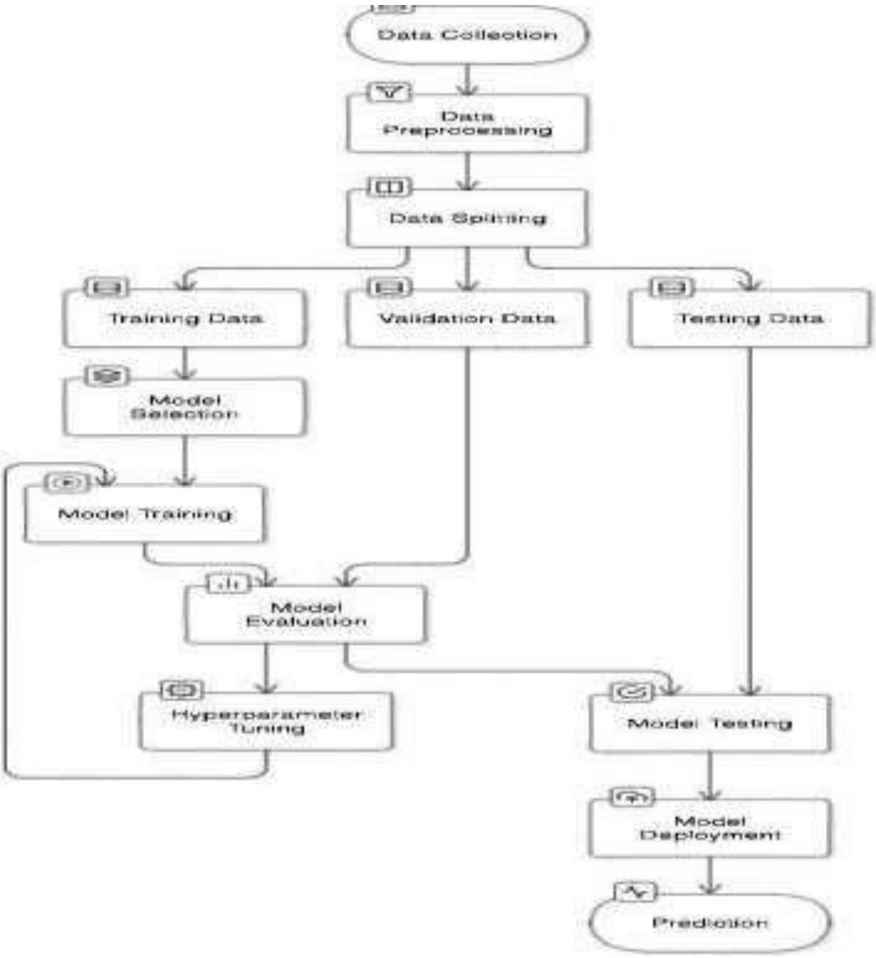

Fig. 1 – Methodology flow- chart

The key feature of ResNet-50 is its residual (skip) connections. These connections allow certain layers to be bypassed during training, helping maintain strong gradient flow. As a result, the model can learn complex patterns without losing accuracy.

There are two main types of blocks in ResNet-50: Identity Block: Passes the input through multiple layers and adds it back to the output.

Convolutional Block: Reduces the number of filters using a 1x1 convolution before applying a 3x3 convolution, then merges the original input.

These skip connections enable deeper and more effective learning by avoiding training slowdowns caused by vanishing gradients.

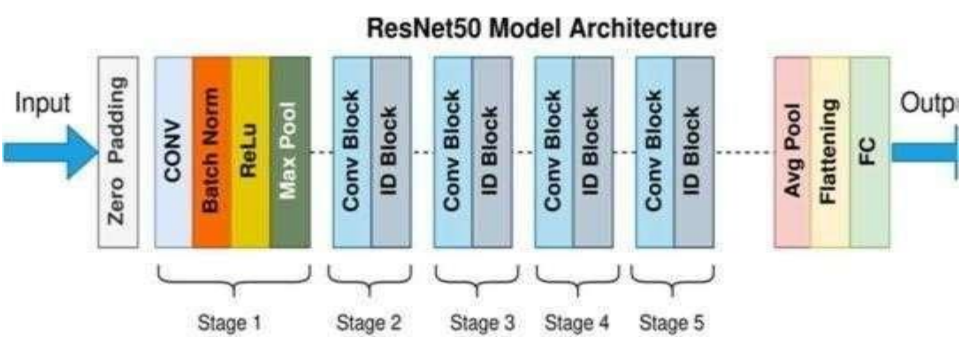

Fig. 2 – ResNet50 Model Architecture

Figure 2 illustrates the architecture of a ResNet model used for image processing. It starts with Zero Padding to maintain spatial dimensions, followed by a Convolutional Layer for initial feature extraction. This is succeeded by Batch

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Normalization to stabilize training and a ReLU activation to introduce non-linearity. A Max Pooling layer then reduces spatial dimensions while retaining essential features.

The core of ResNet includes multiple Convolutional Blocks and Identity Blocks. Convolutional Blocks continue extracting complex features, while Identity Blocks allow information to bypass certain layers, preserving important details and addressing the vanishing gradient problem.

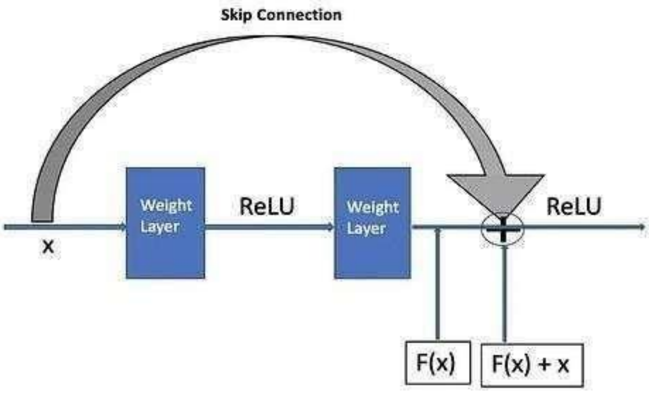

Fig.2.1 Skip Connections in Residual Learning

Figure 2.1 depicts a skip connection in ResNet. In a residual block, the input x passes through two sequential weight layers, each followed by ReLU activation. The transformed output is denoted as F(x). A skip connection adds the original input x directly to this output, resulting in F(x) + x. This addition helps preserve information from earlier layers and supports learning of identity mappings. A final ReLU activation follows this addition.
These skip connections help maintain strong gradient flow, enabling ResNet to train very deep networks efficiently and improving overall convergence and performance.

2. Model Training

After defining the ResNet-50 architecture, the model was trained on the Malahari cervical cancer dataset using transfer learning. Pre-trained weights from ImageNet were leveraged, allowing the model to adapt existing learned features to our specific task. To fine-tune for cervical cancer classification, the final layers were replaced with custom layers suited for multi-class output.
The training used the categorical cross-entropy loss function, which is ideal for multi-class classification, as it evaluates the difference between true labels and predicted probabilities. Adam optimizer was applied for efficient weight adjustment during backpropagation. The dataset was divided into training and validation sets to monitor performance during training. Early stopping was also implemented to prevent overfitting by halting training when validation accuracy stopped improving.

3. Evaluation and Validation

The model's performance was evaluated using **categorical cross-entropy loss** and a **confusion matrix**, which offered a clear view of prediction accuracy across different risk levels. This matrix helped identify where the model struggled—especially between closely related risk types.
Further improvements were achieved by fine-tuning **hyperparameters** such as learning rate, batch size, and the number of trainable layers. Techniques like **learning rate scheduling** and **batch normalization** helped stabilize and speed up training.
Key performance metrics:

- **Accuracy**: Measures the overall correctness of predictions.

Accuracy=TP+TNTP+FP+FN+TN\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}Accuracy=TP+FP+FN+TNTP+TN
Precision: Indicates the proportion of correct positive predictions.
Precision=TPTP+FP\text{Precision} = \frac{TP}{TP + FP}Precision=TP+FPTP

- **Recall**: Reflects how well the model identifies actual positive cases.

Recall=TPTP+FN\text{Recall}=\frac{TP}{TP + FN}Recall=TP+FNTP

- **F1-Score**: Harmonic mean of Precision and Recall, especially useful for imbalanced datasets.

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F1-Score=2×(Precision×Recall)Precision+Recall\text{F1- Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision}+\text{Recall}}F1- Score=Precision+Recall2×(Precision×Recall)

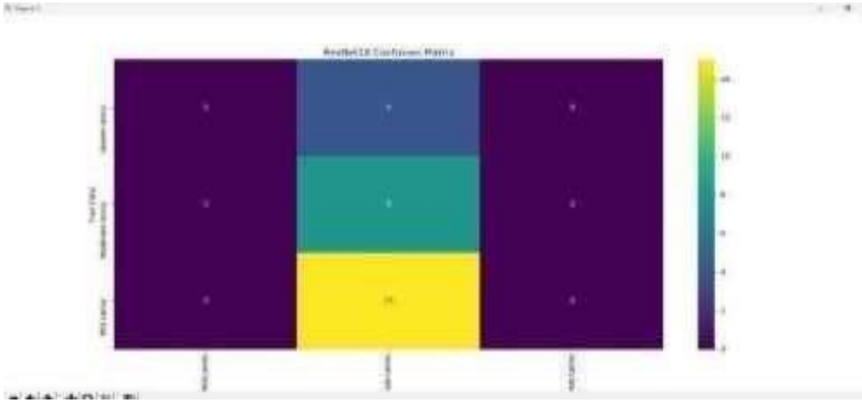


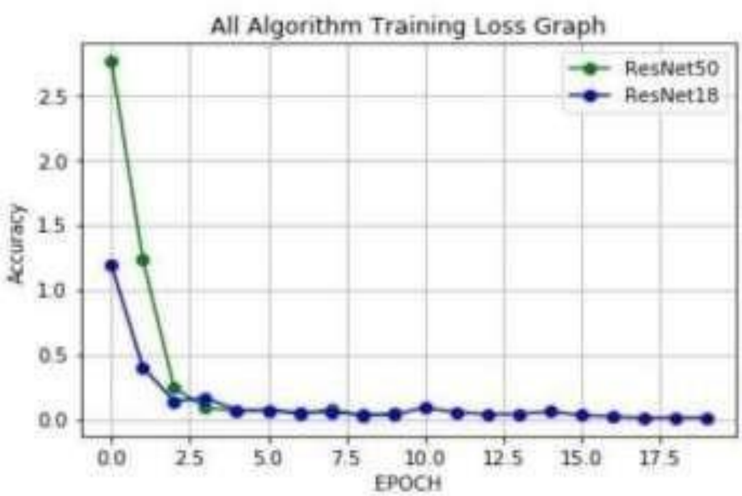
Fig.3 Confusion Matrix – ResNet50

The confusion matrix visualization shows the model's performance across three classes: Severe, Mild, and Normal. It reveals that:

All 4 Severe cases were misclassified as Mild. 4 Mild cases were correctly predicted.
For Normal cases, 13 out of 16 were correctly classified, with 3 misclassified as Mild.
The color gradient indicates frequency, from purple (0) to yellow (14), emphasizing strong performance for Normal cases but limited accuracy for Severe cases.

V. RESULT & DISCUSSION

To validate our integrated framework for insider threat detection in cervical cancer diagnosis, experiments were conducted using real-world clinical data. A large dataset of cervical cancer images is essential to develop accurate, automated diagnostic tools that can aid in early detection and treatment.



We compared two transfer learning models—ResNet-50 and ResNet-18—based on accuracy, computational efficiency, and scalability across dataset sizes.

ResNet-50 achieved over 90% accuracy, proving highly effective even with medium-sized datasets (100–500 images). Its deeper architecture allows it to capture complex features and reduces overfitting through residual connections.

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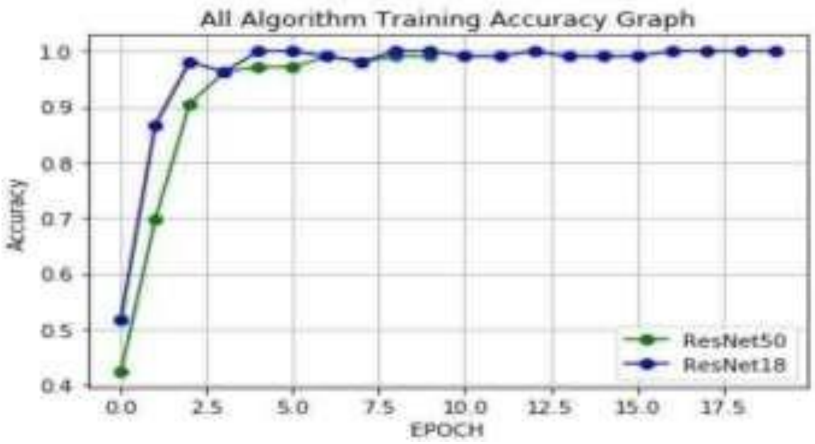

ResNet-18, while more computationally efficient, performs better with larger datasets and is more prone to overfitting when data is limited.

Overall, ResNet-50 offers a better balance of accuracy and generalization for small to moderate datasets, making it the preferred choice for medical imaging tasks like cervical cancer classification.

Fig. 6 - Predicted as 'Mild Cervical cancer'

It appears to be a type of medical image of a cervix. It can be made during the cervical checkup. There is an area of redness and slight inflammation marked in the region, which probably points to some irregularities. Meanwhile, the center has a white or yellowish structure, probably representing tissue or an instrument in the checkup.

The words at the top of the photo read "Predicted Cervical Cancer is: Mild cervix." This means that the photo really should be a part of a diagnostic output and has been created with some sort of machine learning or medical imaging system.

The system predicts a mild stage of cervical cancer according to the visual data used, which may involve some image processing and AI algorithms. Pixel dimensions are indicated by the axials at the edges; this image is a high- resolution resolution and can, therefore, be analyzed. This entire setup brings in clinical or AI-assisted diagnostic context to the possible early detection of cervical cancer.

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Fig. 7 - Moderate Cervical Cancer detected

In the picture, it is a medical image of the cervix with significant redness and much worse than the one in the previous picture. The tissue seems inflamed, and the surface looks coarser and contains all sorts of irregularities that may indicate an advanced abnormality or lesion. The accompanying text with the image reads "Predicted Cervical Cancer is: Moderate cervix," which indicates a diagnostic tool, most probably reliant on some version of machine learning or artificial This appears to have a number of darkspots, possibly areas of dead or necrotic tissue, and theoverall appearance is that of inflammation, which goesalong with the system's opinion that this is mildly affected. On the left and right sides of the image are axes representing pixel dimensions that may be usefulin additional image processing. These probably form part of an automatic or AI- driven diagnostic tool to classify cervical cancer as mild, moderate or another stage based on the appearance within images taken as part of medical examination procedure

VI. CONCLUSION

The developed model for diagnosing cervical cancer using deep learning represents a milestone achievement in the application of the ResNet-50 architecture through transfer learning to classify pre- cancerous colposcopy images. Despite visual similarity and artifacts in the dataset, the approach succeeded in achieving outstanding accuracy. This research adds to how deep learning technologies can enhance the diagnosis of medical imaging, hence assisting medical professionals in clinical decision-making. However, the study reveals several areas in which more work is needed. First, an expanded dataset with images of patients from other demographics, with different clinical conditions and acquired by other imaging modalities might make the model more robust and generalizable.

Therefore, a larger dataset could possibly improve recognition capability for more subtle differences clinically relevant. Second, optimization of the model could be done by seeking alternative architectures, appropriate hyperparameter values, and some of the techniques enhanced, including ensemble methods or attention mechanisms, which would probably reduce misclassifications and could eventually increase accuracy levels. Real-world validation would also be essential for showing how valid the model is in practical utilization of results. Perhaps, the expert evaluation compared with the predictions given by the model would become necessary to validate how the model works when put into practical application within a real healthcare environment.

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International Journal of Advanced Research in Computer and Communication Engineering

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