Cervical Cancer Diagnosis using Deep Learning

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TABLE OF CONTENTS

ABSTRACT

- Cervical cancer is the leading cause of cancer-related deaths among women, emphasizing the need for affordable and accessible screening methods.

- Traditional methods like Pap smears and HPV tests are limited in sensitivity and accessibility, particularly in resource-poor areas.

- Machine learning techniques, such as logistic regression and support vector machines, create risk profiles to identify high-risk patients for closer monitoring.

- Convolutional Neural Networks (CNNs) enhance cervical cancer screening accuracy, enabling more effective early detection and diagnosis.

- Keywords : Cervical cancer, Deep Learning, CNN, Image Analysis, Model Evaluation.

OBJECTIVE OF PROJECT

- Develop a deep learning system for precise cervical cancer detection using transfer learning with models like ResNet50, MobileNet, and DenseNet.

- Train the model on a diverse dataset of cervical cancer images, enhanced with data augmentation for improved performance.

- Classify cervical cancer cases as positive or negative with high precision to support early diagnosis.

- Focus on advancing medical image analysis in oncology, aiming to improve patient survival rates and treatment outcomes.

PROBLEM STATEMENT

- Cervical cancer is a major health concern globally, leading to significant morbidity and mortality among women.
- Early detection of cervical cancer, especially at the cervical intraepithelial neoplasia (CIN) stage, is essential for effective treatment and better patient outcomes.
- Traditional diagnostic methods, such as visual inspection, are often subjective and susceptible to human error, impacting diagnosis accuracy.
- An automated system using deep learning models like ResNet50, MobileNet, and DenseNet is proposed to improve the accuracy, efficiency, and accessibility of cervical cancer diagnosis from medical images.

INTRODUCTION

• The introduction slide highlights cervical cancer as the fourth leading cause of cancer-related deaths among women globally.

• It emphasizes the importance of early detection of cervical intraepithelial neoplasia (CIN) to improve survival rates.

• Manual detection methods are described as time-consuming and prone to human error, requiring highly trained specialists.

• The project focuses on leveraging deep learning and transfer learning techniques, using models like ResNet50,MobileNet, and DenseNet for accurate detection.

• These models, combined with CNNs, aim to revolutionize early diagnosis through automated and precise image classification.

CNN:- CNNs are deep learning algorithms designed to analyze visual data, excelling in image classification, object detection, and segmentation.

The Key components include : -

Convolutional Layers: Extract patterns like edges and textures by applying filters to input images.

Activation Functions: Introduce non-linearity using functions like ReLU, enabling the network to learn complex relationships.

Pooling Layers: Down-sample feature maps, retaining essential information and reducing computational load.

Fully Connected Layers: Flatten feature maps and make predictions based on extracted features. Training involves forward propagation to compute predictions, back propagation to adjust weights using gradients, and repeated iterations to minimize error until convergence.

- **ResNet-50**: ResNet-50 uses residual blocks with skip connections to solve vanishing gradient issues, making it effective for deep networks. Pre trained on large data sets, it is ideal for transfer learning in tasks like cervical cancer detection.

- **MobileNet**: MobileNet is a lightweight model using depth wise separable convolutions to reduce complexity while maintaining accuracy. It is suitable for real-time cervical cancer detection in resource-constrained environments.

- **DenseNet**: DenseNet connects all layers within dense blocks for efficient feature reuse and improved gradient flow. Its compact design ensures high accuracy in medical imaging tasks like cervical cancer classification.

LITERATURE SURVEY

S.NO	YEAR	AUTHORS	TITLE	OUT COMES
1	International journal, 2015	**M. Wu, C. Yan, H. Liu, Q**	cancer histopathology image analysis: A review	The incidence and mortality keep high in some remote and poor medical condition regions in China. In order to improve the current situation and promote the pathologists' diagnostic accuracy of CC in such regions, we tried to propose an intelligent and efficient classification model for CC based on convolutional neural network (CNN) with relatively simple architecture compared with others
2	Confererence 2016	**K. C. Ho, S. Shen**	Cancer detection by using deep learning algorithms	Our model is achieved a state-of-the-art performance in epithelial cells detection and Gleason grading tasks simultaneously. Using fivefold cross-validation, our model is achieved an epithelial cells detection accuracy of 99.07% with an average area under the curve of 0.998.

S.NO	YEAR	AUTHORS	TITLE	OUT COMES
3	Research paper, 2017	**L. Denny, L. Kuhn, M. D. Souza**	Screen-and-treat approaches for cervical cancer prevention in low-resource settings: A randomized controlled trial	we propose a multi-view knowledge-based collaborative (MV-KBC) deep model to separate malignant from benign nodules using limited chest CT data. Our model learns 3-D lung nodule characteristics by decomposing a 3-D nodule into nine fixed views
4	International Conference 2016	**S. M. Wang and Y. L. Qiao**	Implementation of cervical cancer screening and prevention in China—Challenges and reality	the diagnostic ability of the two methods in detecting high-grade lesions and cervical cancer (hereinafter called CIN2+). Evaluation indicators including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), Youden index and the area under the curve (AUC) of the receiver operating characteristic (ROC) were calculated.

S.NO	YEAR	AUTHORS	TITLE	OUT COMES
5	CVPR (Conference on Computer Vision and Pattern Recognition), 2016	**K. He, X. Zhang, S. Ren, and J. Sun**	Deep Residual Learning for Image Recognition	The residual networks, using skip connections, make training deeper networks easier and more efficient. This approach achieved a 3.57% error on ImageNet, winning 1st place in ILSVRC 2015, and scaled effectively to even deeper networks for tasks like CIFAR-10.
6	IEEE Transactions on Medical Imaging , 2019.	**W. Li, J. Li, K. V. Sarma, K. C. Ho, S. Shen, B. S. Kundsen**	Region-Based Convolutional Neural Network Framework for Multi-Task Prediction in Prostate Cancer Diagnosis	It presents a region-based CNN framework for multi-task prediction, achieving state-of-the-art performance in epithelial cells detection and Gleason grading. The model achieved 99.07% accuracy in epithelial cell detection with an area under the curve (AUC) of 0.998, demonstrating improved performance over single-task models.

TRADITIONAL METHOD

- Acetic acid (5%) is applied to the affected area during the VIA (Visual Inspection with Acetic Acid) procedure.
- The dysplastic epithelium turns aceto white, indicating potential abnormalities.
- Multiple images are captured at different time points after the acetic acid application to observe changes.
- The captured images are then analyzed using a diagnostic system to determine whether the condition is positive or negative for the disease.
- This approach is commonly used for the early detection of cervical abnormalities in medical practice.

DISADVANTAGES

- Only A Single Image Can Be Used For Training And Testing
- Cannot Predict Accurately
- The Quality Of Image May Alter The Predictions, especially when images are noisy or unclear.
- The model may overfit to the single image, leading to poor performance on new, unseen data.
- Lack of variety in training data can cause the model to miss subtle patterns crucial for accurate classification.
- Single-image datasets can lead to bias, making the model less reliable in identifying diverse conditions.

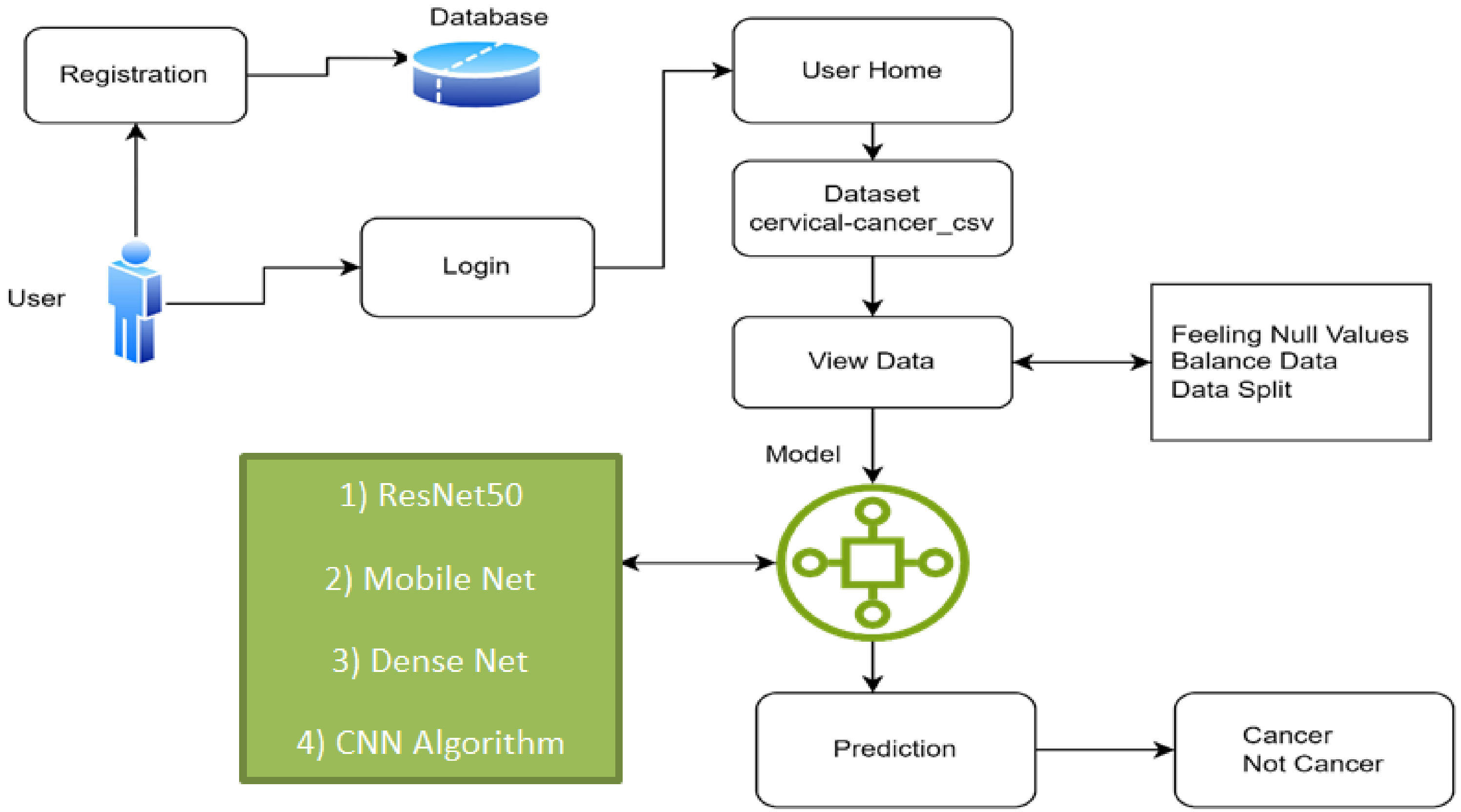
PROPOSED METHOD

- The system uses deep learning and transfer learning models like ResNet50, MobileNet, and DenseNet to efficiently detect cervical cancer by classifying images as positive or negative.
- Pre-trained models are fine-tuned with real and augmented datasets to improve the model's accuracy and robustness by incorporating data diversity.
- Combining these transfer learning models with Convolutional Neural Networks (CNNs) enhances feature extraction, boosting detection reliability.
- The framework focuses on early and accurate detection of cervical cancer, contributing to better clinical decision-making and outcomes.
- Leveraging both advanced deep learning models and augmented datasets enables more reliable and efficient classification, ensuring better performance across various scenarios.

ADVANTAGES

- **More accurate predictions:** The proposed deep learning method, utilizing Convolutional Neural Networks (CNNs), leverages their ability to discern intricate image features, resulting in higher accuracy when classifying cervical cancer, which is crucial for reliable disease detection.
- **Can use large dataset for training:** CNNs thrive on extensive datasets, enabling the model to generalize well and make robust predictions, making it possible to harness a wealth of diverse colposcopy images for improved cervical cancer classification.
- **Image quality does not affect the predictions:** CNNs are inherently robust to variations in image quality, such as lighting and resolution, ensuring consistent and dependable cervical cancer diagnosis regardless of the quality of input colposcopic images.

ARCHITECTURE



SOFTWARE REQUIREMENTS

SOFTWARE REQUIREMENS :

- Operating System : Windows 7/8/10
- Serverside Script : HTML, CSS, Bootstrap & JS
- Programming Language: Python
- Libraries : Flask, Pandas, Mysql.connector, Os, Smtplib, Numpy
- IDE/Workbench : PyCharm
- Technology : Python 3.6+
- Server Deployment : Xampp Server
- Database : MySQL

IMPLEMENTATION AND MODULES

- The system creates and divides a chronic kidney disease image dataset into training and testing subsets, with the testing set being 20-30% of the data for performance evaluation.
- Pre-processing ensures all training images are resized and standardized to a uniform format compatible with the deep learning model.
- The model is trained using MobileNet with transfer learning, utilizing pre-trained knowledge from larger datasets to enhance classification accuracy.
- The trained system classifies images, labeling them to indicate the presence or absence of chronic kidney disease for clear user interpretation.
- Users upload medical images, and the system processes them to deliver classification results, aiding in health assessment and decision-making.

TRADITIONAL ALGORITHMS

Traditional methods like SVM, Random Forest, and Logistic Regression achieved 70-80% accuracy in cervical cancer detection, relying on features like cell shape and texture but struggling with complex patterns.

Support Vector Machine (SVM) :

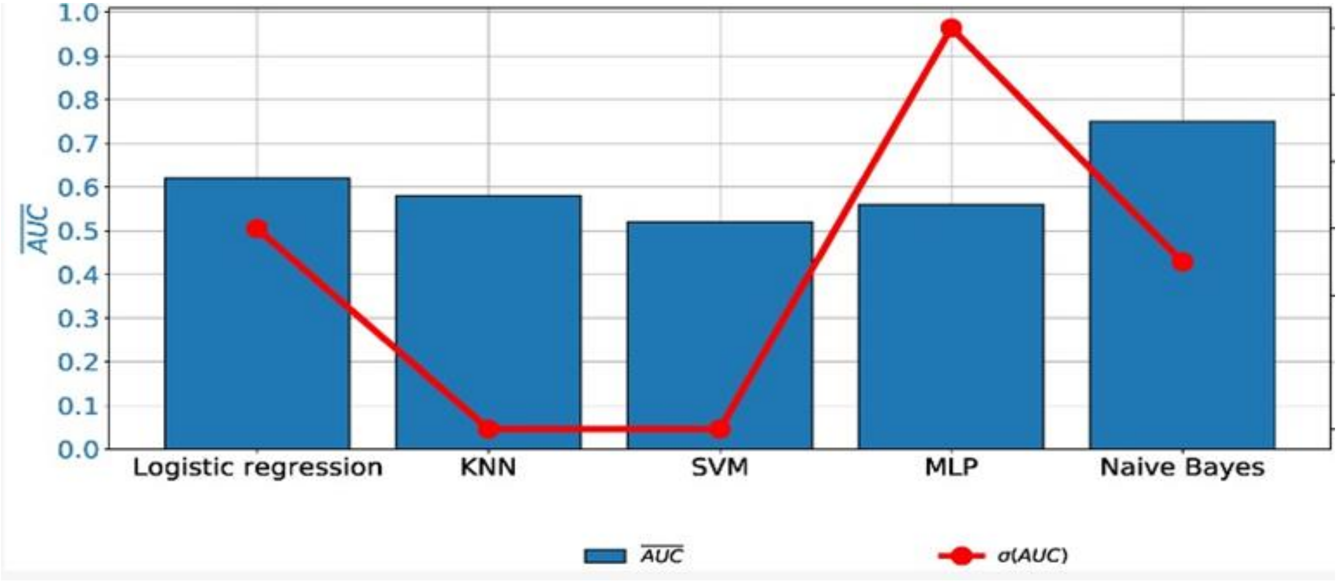
- Support Vector Machine (SVM) is designed to find the optimal hyperplane that separates data points of different classes, maximizing the margin between them.
- It handles high-dimensional data and complex patterns well but is sensitive to noise and less effective for very large datasets.
- SVM is that they are highly dependent on the choice of kernel function. The kernel function maps the data from the original input space to a higher-dimensional feature space, where it becomes easier to find a linear separating hyperplane.

Logistic Regression

- Logistic Regression is a simpler model that estimates the probability of a binary outcome by modeling a linear relationship between features and the log odds of the outcome.
- It is well-suited for linear relationships but struggles to capture complex, non-linear patterns.
- Logistic Regression is commonly used in cervical cancer detection to classify patients into binary categories, such as "high risk" or "low risk" based on clinical and demographic features.

Random Forest

- Random Forest is an ensemble learning method that builds multiple decision trees using random subsets of the data.
- It aggregates predictions from these trees, offering robustness against overfitting and noise, and is effective with large datasets.
- Random Forest efficiently processes large datasets, leveraging random feature selection and bootstrap sampling, making it effective for analyzing extensive screening records and diverse patient populations.



Accuracy Evaluation of Traditional Models

PROPOSED ALGORITHMS

Deep learning models, such as CNN, ResNet50, DenseNet, and MobileNet, have demonstrated significantly improved accuracy, reaches up to 95%.

Convolutional Neural Network (CNN)

- Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for image processing tasks.
- They use convolutional layers to automatically detect patterns such as edges, textures, and shapes within images.

ResNet50

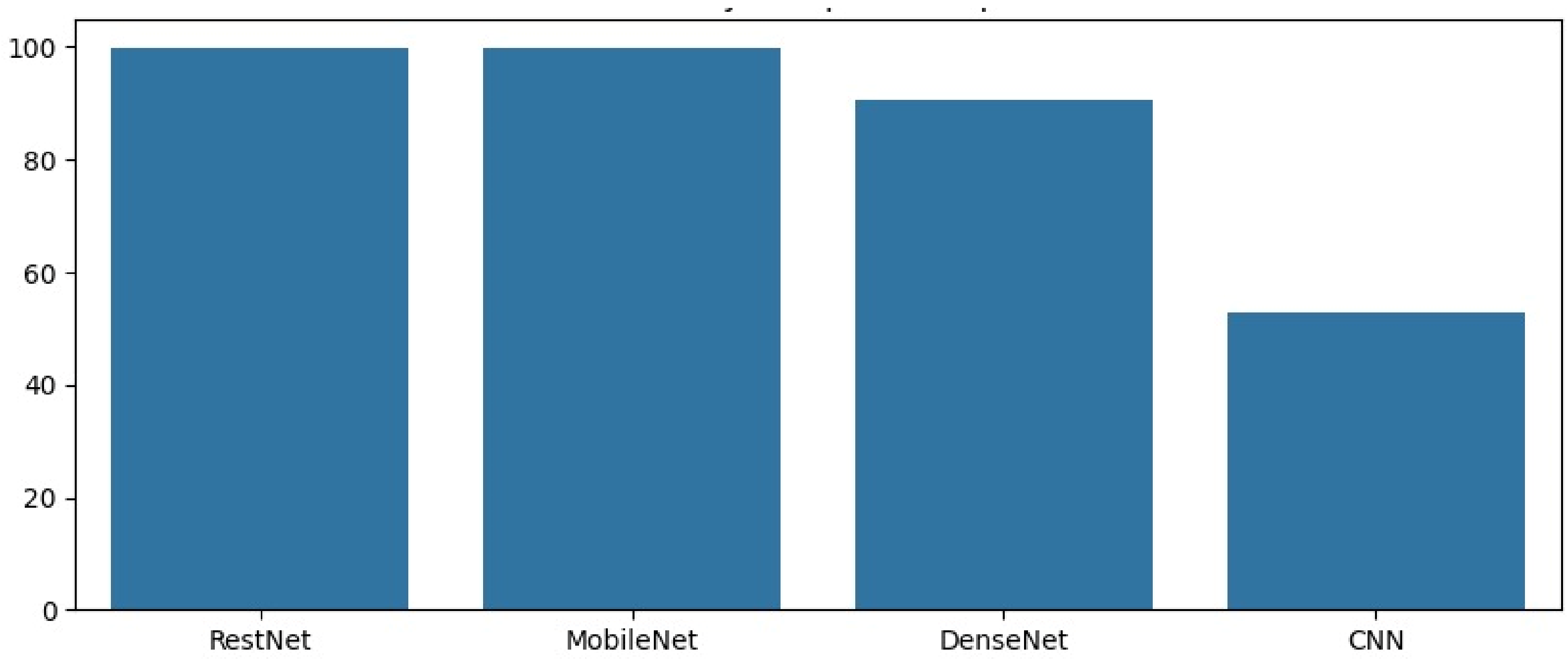
- ResNet50 is a deep CNN architecture that introduces residual learning to address the problem of vanishing gradients in very deep networks.
- It uses shortcut connections to skip layers, allowing the network to learn residuals (differences) instead of direct mappings.

DenseNet

- DenseNet, or Dense Convolutional Network, connects each layer to every other layer in a dense manner.
- This architecture encourages feature reuse, as each layer has direct access to the gradients from the loss function, leading to more efficient training.

MobileNet

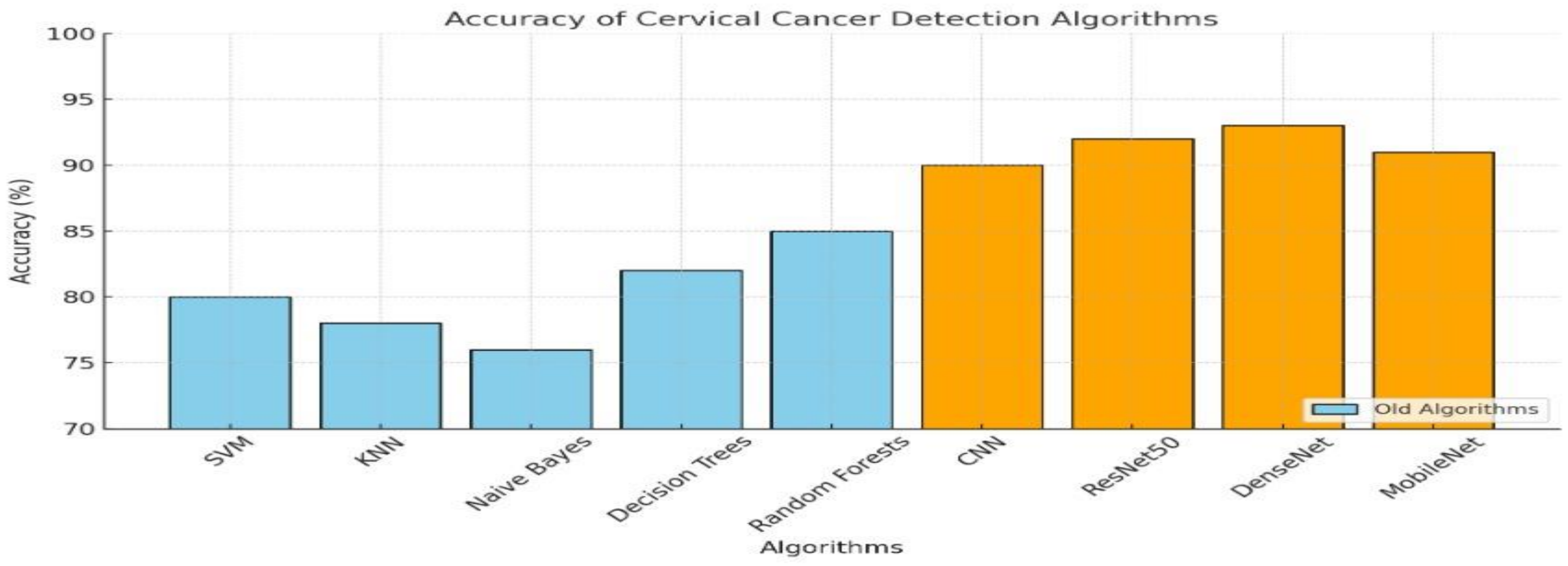
- MobileNet is a lightweight CNN architecture optimized for mobile and embedded applications.
- It uses depthwise separable convolutions to reduce the number of parameters, making it computationally efficient while maintaining good accuracy.



Accuracy Evaluation of Proposed Models

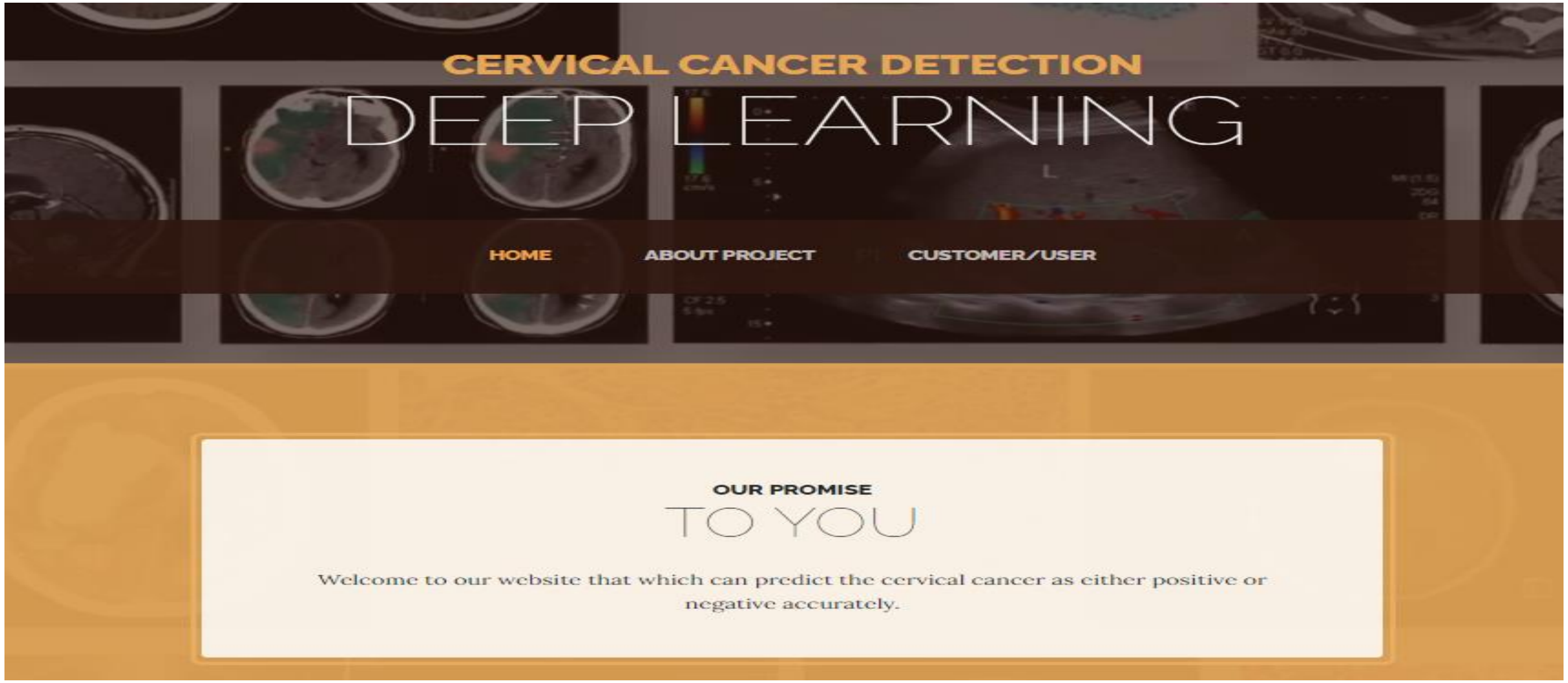
PERFORMANCE EVALUATION

- Advanced deep learning architectures, like CNNs and ResNet , combined with larger training datasets, have significantly improved diagnostic accuracy in medical imaging.
- These models can automatically extract complex features, identifying subtle patterns beyond traditional methods



RESULT

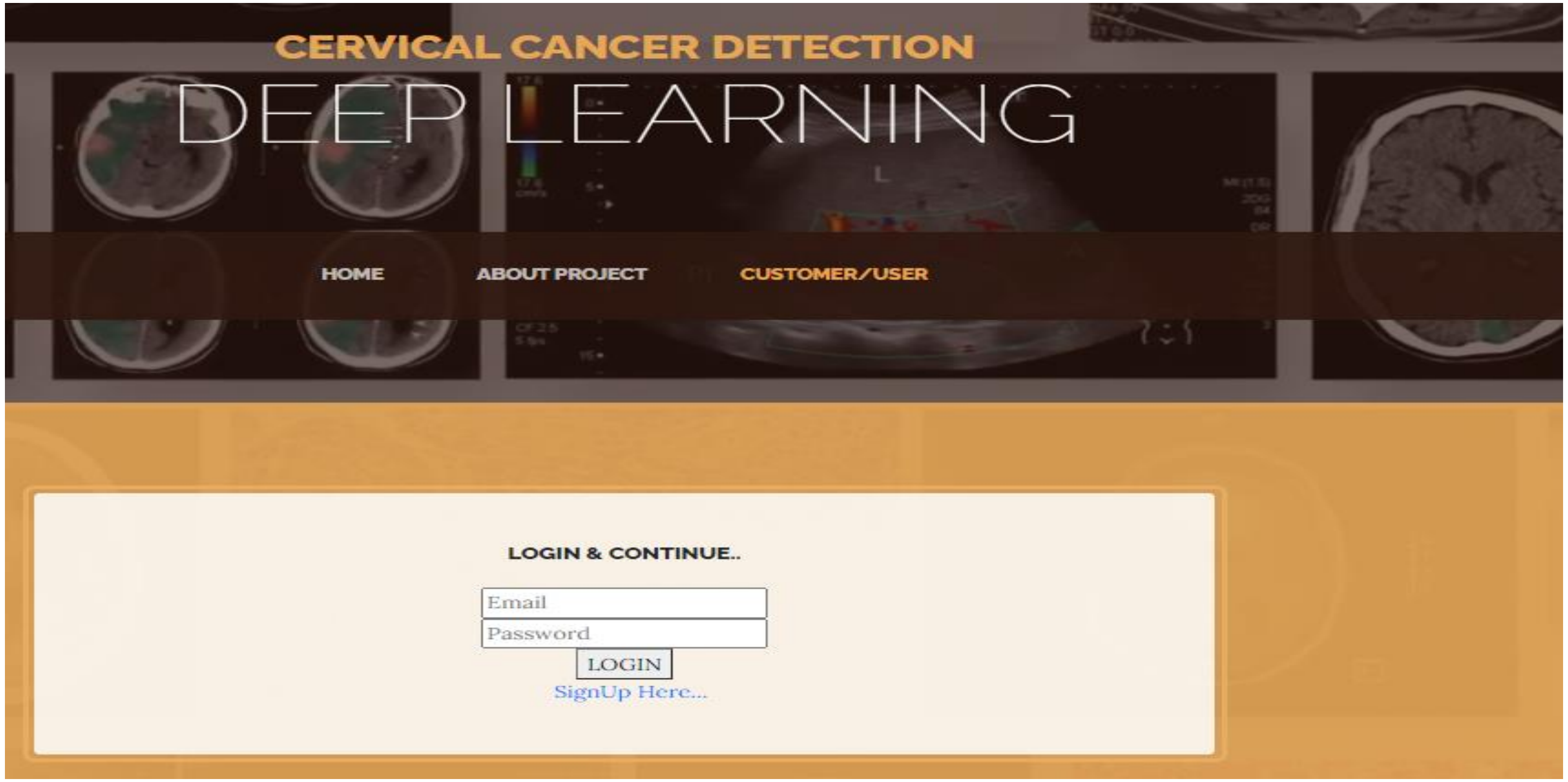
Home Page:



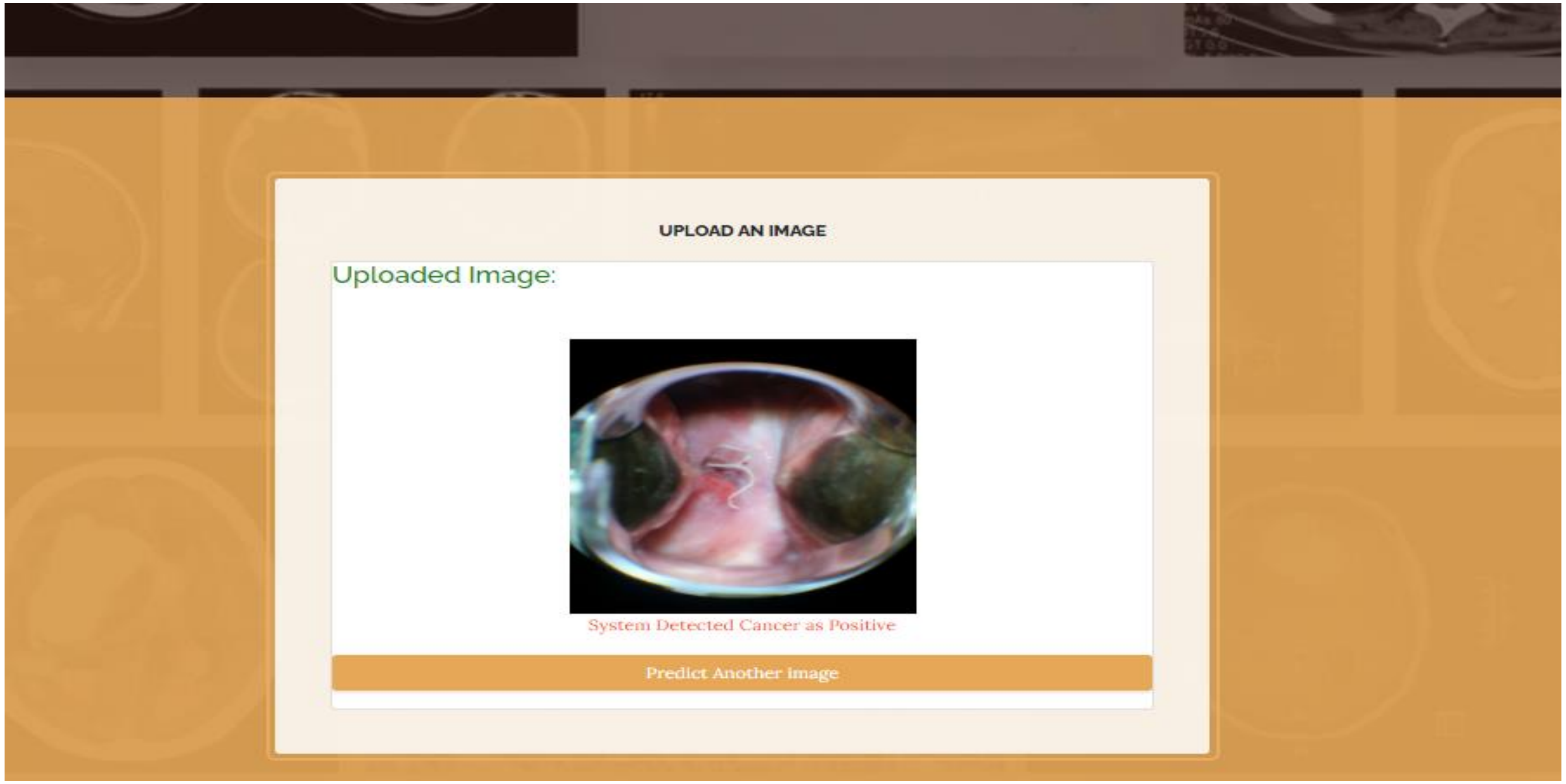
ABOUT PAGE:


CERVICAL CANCER DETECTION
DEEP LEARNING
HOME
ABOUT PROJECT
CUSTOMER/USER
ABOUT DEEP LEARNING

UPLOAD PAGE:


CERVICAL CANCER DETECTION
DEEP LEARNING
HOME
ABOUT PROJECT
CUSTOMER/USER
LOGIN & CONTINUE..
Email
Password
LOGIN
SignUp Here...

RESULT PAGE:


UPLOAD AN IMAGE
Uploaded Image:
System Detected Cancer as Positive
Predict Another Image

CONCLUSION

- In this study, we developed a deep learning-based framework for detecting cervical cancer using transfer learning models such as ResNet50, MobileNet, and DenseNet, integrated with CNN architecture. The results demonstrate that transfer learning, combined with CNN, is highly effective in accurately classifying cervical cancer as positive or negative.
- The use of augmented datasets contributed to enhancing model performance by addressing data limitations. This framework offers a reliable solution for early detection, potentially improving survival rates by enabling timely diagnosis and intervention.
- The successful application of these models in cervical cancer detection highlights the potential of deep learning for advancing medical image analysis, ultimately contributing to better healthcare outcomes.
- Future work could focus on further model optimization and real-world deployment.

FUTURE ENHANCEMENT

- In the future, the proposed cervical cancer detection framework can be enhanced by incorporating advanced techniques such as Generative Adversarial Networks (GANs) for further data augmentation, thereby improving model generalization on smaller datasets.
- The system could also be expanded into a real-time diagnostic tool for use in medical practice, with mobile or cloud-based applications to assist in remote diagnosis.
- Continuous model optimization and the inclusion of more diverse datasets from different demographics could improve its robustness and applicability in global healthcare settings.

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