IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 11, Issue 3, March 2024

DOI: 10.17148/IARJSET.2024.11348

Skin Disease Detection System Using Convolutional Neural Network

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Abstract: Creating a skin disease detection system using Convolutional Neural Networks (CNNs) involves leveraging deep learning techniques to classify skin conditions from images. CNNs are particularly well-suited for image recognition tasks due to their ability to automatically learn hierarchical features from data. The first step in building such a system would be to gather a dataset of skin disease images, categorized by their respective conditions. This dataset should ideally be diverse, containing images of various skin diseases, with different severities, angles, and lighting conditions to ensure robustness.

Keywords: Convolutional Neural Networks (CNN), Medical image processing, Data augmentation, Machine Learning, Deployment, Training dataset.

I. INTRODUCTION

Skin diseases are among the most prevalent health issues globally, affecting millions of people of all ages and backgrounds. Timely and accurate diagnosis of skin conditions is crucial for effective treatment and management. However, dermatological diagnosis can be challenging, often requiring specialized expertise. In recent years, advancements in artificial intelligence, particularly in deep learning, have shown promising results in automating the diagnosis of various medical conditions, including skin diseases. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image recognition tasks, making them well-suited for dermatological image analysis. CNNs can automatically learn and extract intricate patterns and features from images, enabling accurate classification of skin lesions and diseases. Leveraging CNNs in a skin disease detection system holds the potential to revolutionize dermatological diagnosis by providing rapid and reliable assessments, even in settings where access to dermatologists is limited.

By harnessing the capabilities of CNNs and deep learning, our skin disease detection system aims to offer an efficient and accessible solution for diagnosing a wide range of skin conditions. Through automated analysis and classification of skin lesions, we envision empowering healthcare professionals, improving patient outcomes, and ultimately advancing the field of dermatology.

II. LITERATURE SURVEY

Skin disease recognition and observing is a major challenge looked by the medical industry. Because of expanding contamination and utilization of lousy nourishment, the tally of patients experiencing skin related issues is expanding at a quicker rate. Well-being isn't the main concern, however unfortunate skin hurts our certainty. Customary and appropriate skin checking is a significant advance towards early discovery of any destructive or starting changes in skin that may bring about skin disease. Machine learning methods can add to the improvement of capable frameworks which can order various classes of skin illnesses. To identify skin maladies, first, it is required to separate the skin and non-skin. In this paper, five diverse machine learning algorithms have been chosen and executed on skin infection data set to anticipate the exact class of skin disease. Out of a few machine learning algorithms, we have worked on Random forest, naive bayes, logistic regression, kernel SVM and CNN. A similar examination dependent on confusion matrix parameters and training accuracy has been performed and delineated utilizing graphs. It is discovered that CNN is giving best training precision for the right expectation of skin diseases among all selected. Skin disease recognition and observing is a major challenge looked by the medical industry. Because of expanding contamination and utilization of lousy nourishment, the tally of patients experiencing skin related issues is expanding at a quicker rate. Well-being isn't the main concern, however unfortunate skin hurts our certainty. Customary and appropriate skin checking is a significant advance towards early discovery of any destructive or starting changes in skin that may bring about skin disease. Machine learning methods can add to the improvement of capable frameworks which can order various classes of skin illnesses. To identify skin maladies, first, it is required to separate the skin and non-skin.

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III. METHODOLOGY

DEEP LEARNING: Data Collection And Preprocessing:
Gather a comprehensive dataset of dermatological images containing various skin diseases and conditions. Utilize publicly available datasets like ISIC (International Skin Imaging Collaboration) or HAM10000 (Human Against Machine with 10,000 training images) or collect data from clinical sources. Preprocess the dataset by resizing images to a uniform size, typically square dimensions, normalize pixel values, and apply augmentation techniques such as rotation, flipping, and zooming to increase dataset diversity and prevent overfitting.

2.Model Architecture And Design:
Design a Convolutional Neural Network (CNN) architecture suitable for skin disease classification. Start with a base architecture such as VGG (Visual Geometry Group), ResNet (Residual Network), or Inception, and customize it according to the specific requirements of the task. Experiment with different architectures, varying the number of layers, filter sizes, and activation functions to optimize performance.

3.Data Splitting:
Split the dataset into training, validation, and test sets. Typically, use around 70-80% for training, 10-15% for validation, and the remaining for testing. Ensure that each set contains a balanced representation of different skin conditions.

4.Training Setup:
Set up the training pipeline with appropriate hyperparameters such as learning rate, batch size, and number of epochs. Implement data augmentation techniques during training to increase model robustness and generalization.

5.Model Training:
Train the CNN model on the training dataset using backpropagation and gradient descent-based optimization algorithms such as stochastic gradient descent (SGD), Adam, or RMSprop. Monitor training progress by evaluating performance metrics on the validation set, such as accuracy, precision, recall, and F1-score. Utilize techniques like learning rate scheduling and early stopping to prevent overfitting and improve convergence.

IV. MODELLING AND ANALYSIS

1.Model Training:
Train the CNN model using the training dataset. Utilize techniques such as transfer learning by initializing the model with weights pretrained on large datasets like ImageNet. Fine-tune the model's parameters on the skin disease dataset to adapt it to the specific task.

2.Model Evaluation:
Evaluate the trained model using the validation dataset. Compute performance metrics such as accuracy, precision, recall, and F1-score to assess the model's effectiveness in detecting skin diseases. Visualize the model's predictions and analyze any misclassifications to identify common patterns or challenges.

3.Validation And Deployment:
Validate the final trained model on the test dataset to confirm its generalization performance and readiness for deployment. Deploy the trained model as part of a skin disease detection system, integrating it into a user-friendly interface for healthcare professionals or patients. Ensure compliance with regulatory standards and ethical guidelines, particularly regarding patient privacy, data security, and medical device regulations.

SNAPSHOTS:
As an AI text-based model, I'm unable to provide snapshots directly. However, I can describe the key components and features of a skin disease detection system using CNNs.

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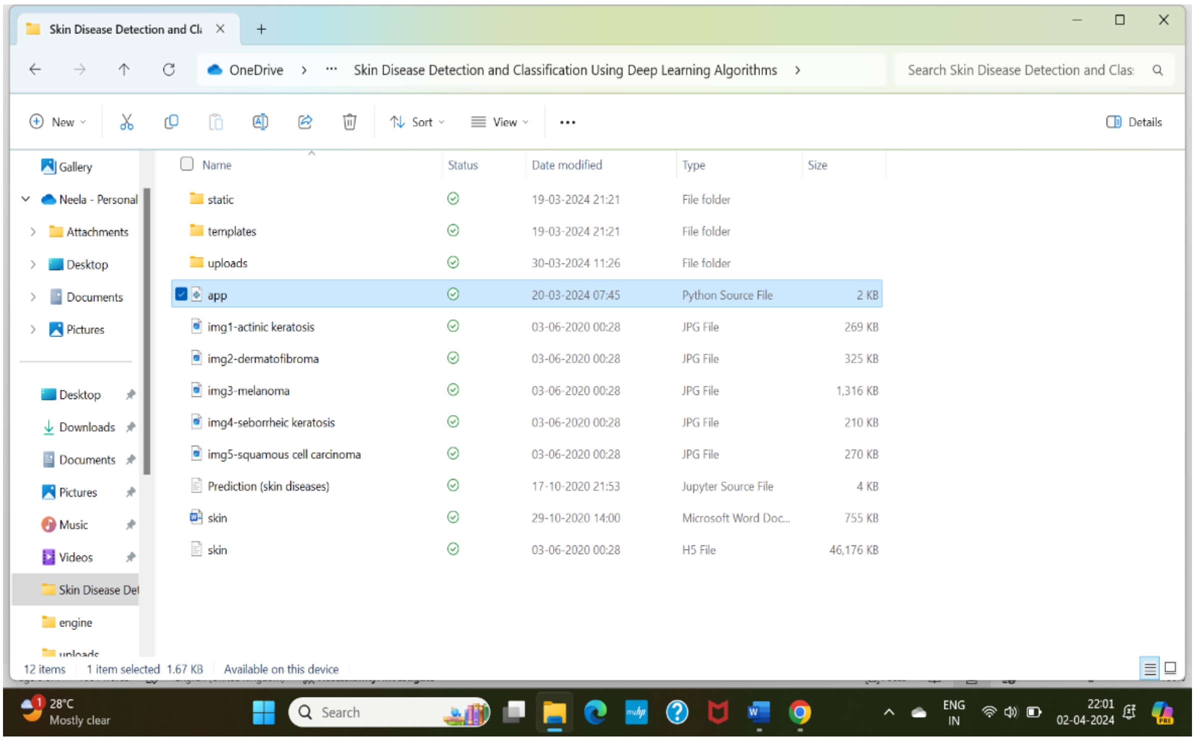
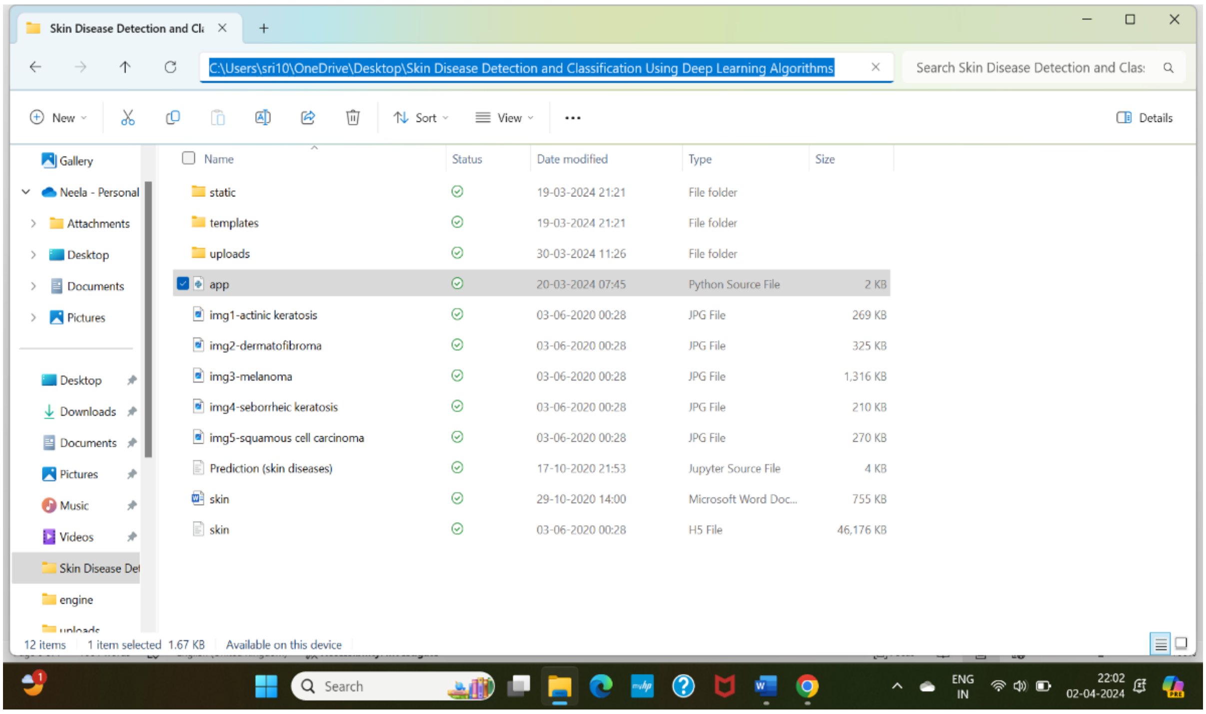
To get output we have to type python app.py in terminal





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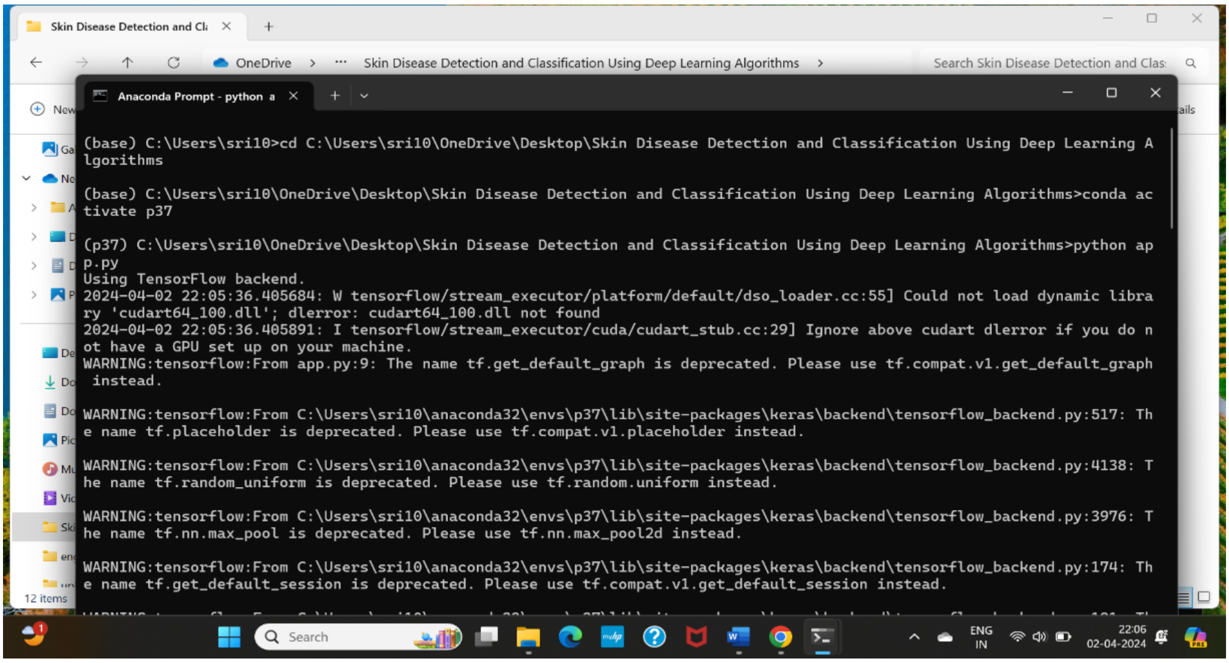

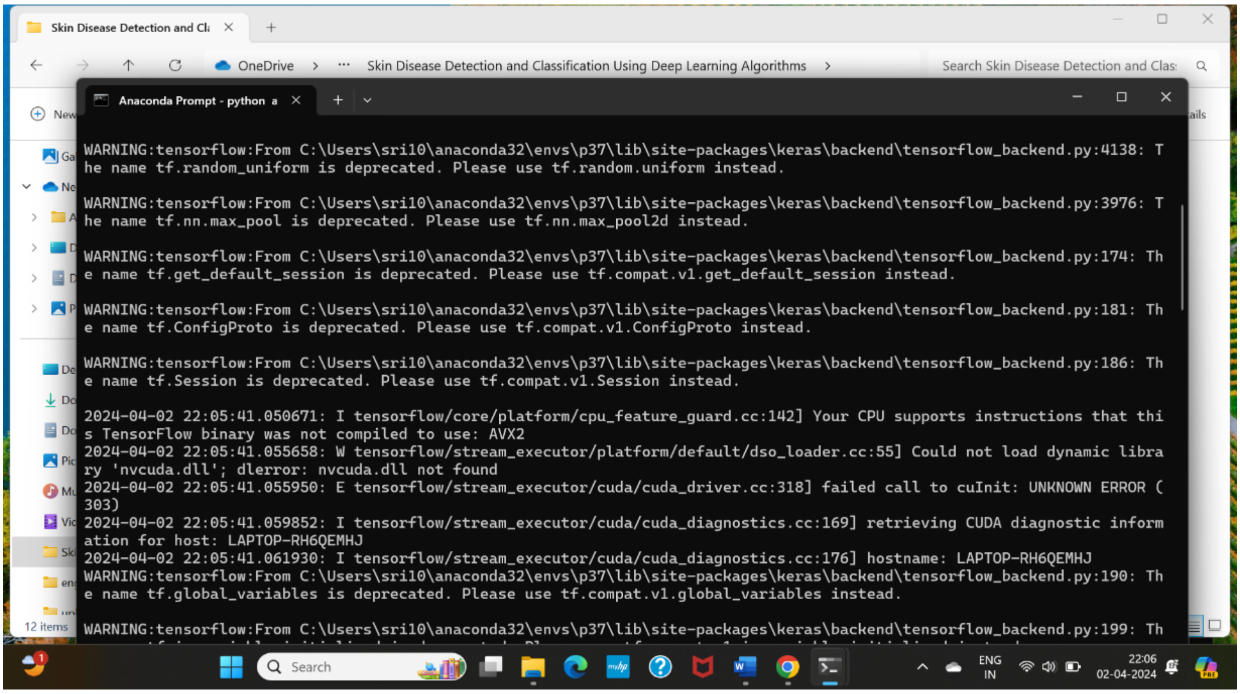

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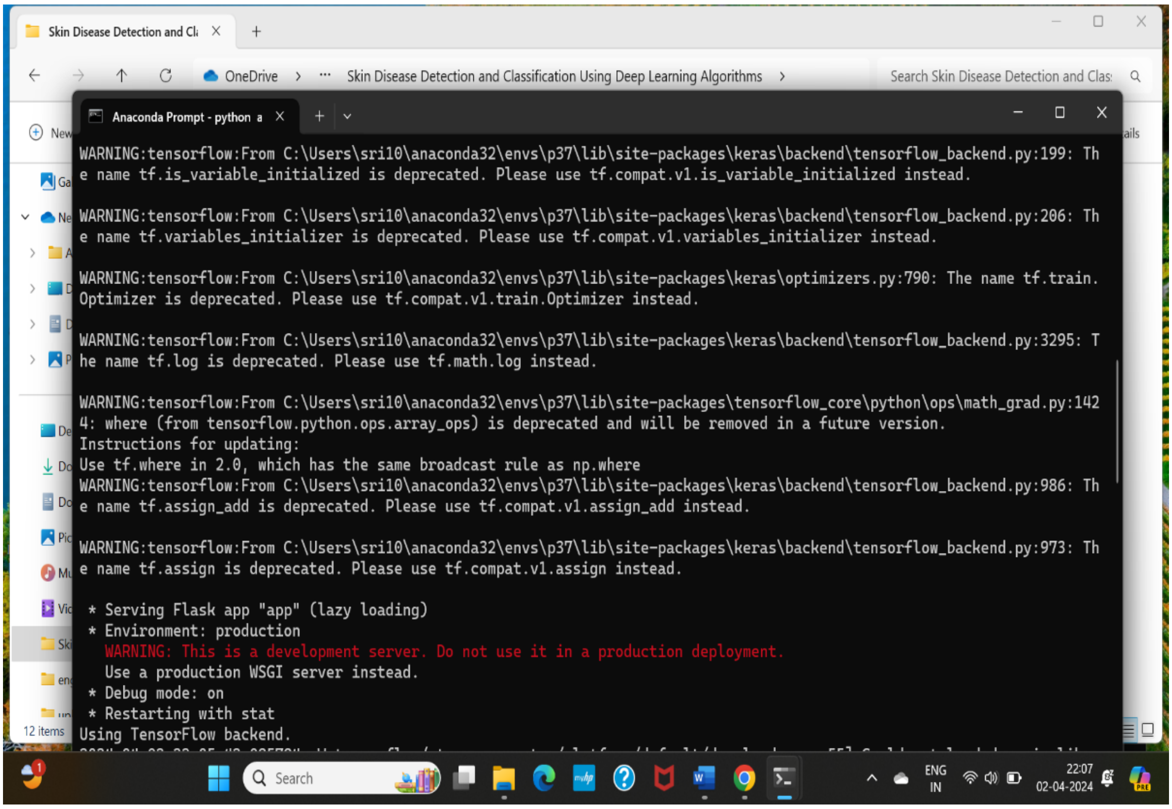

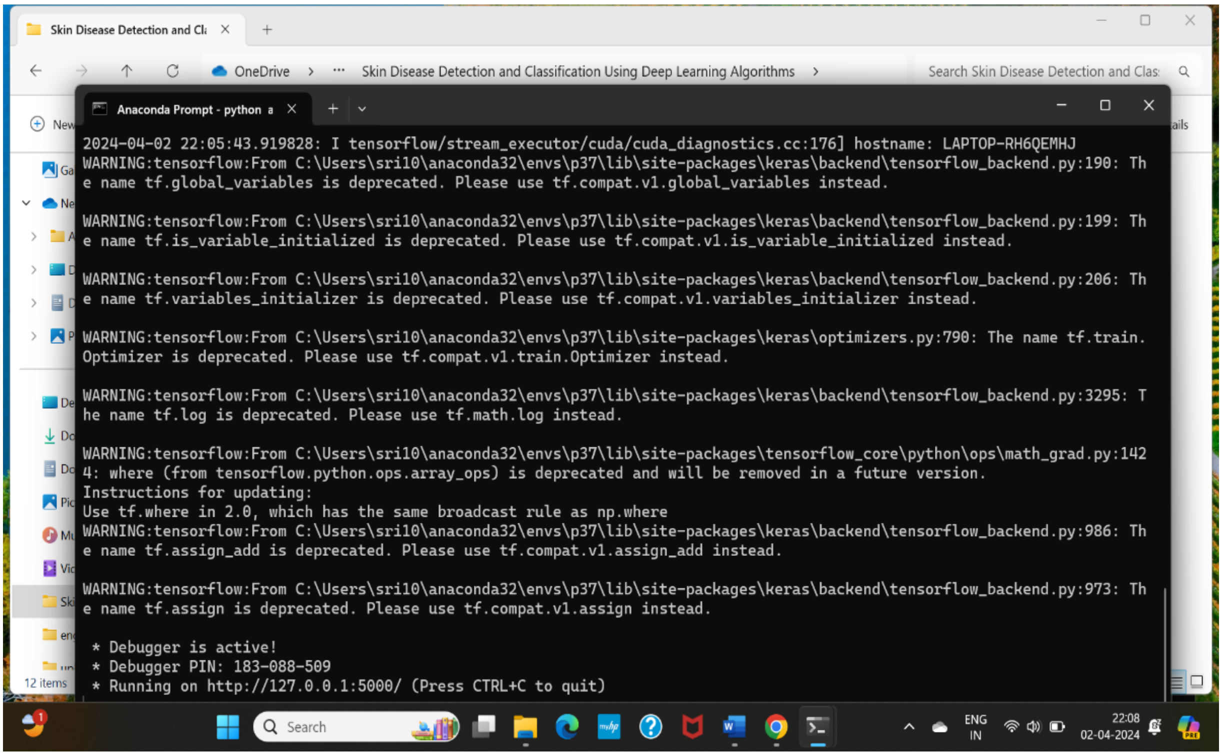

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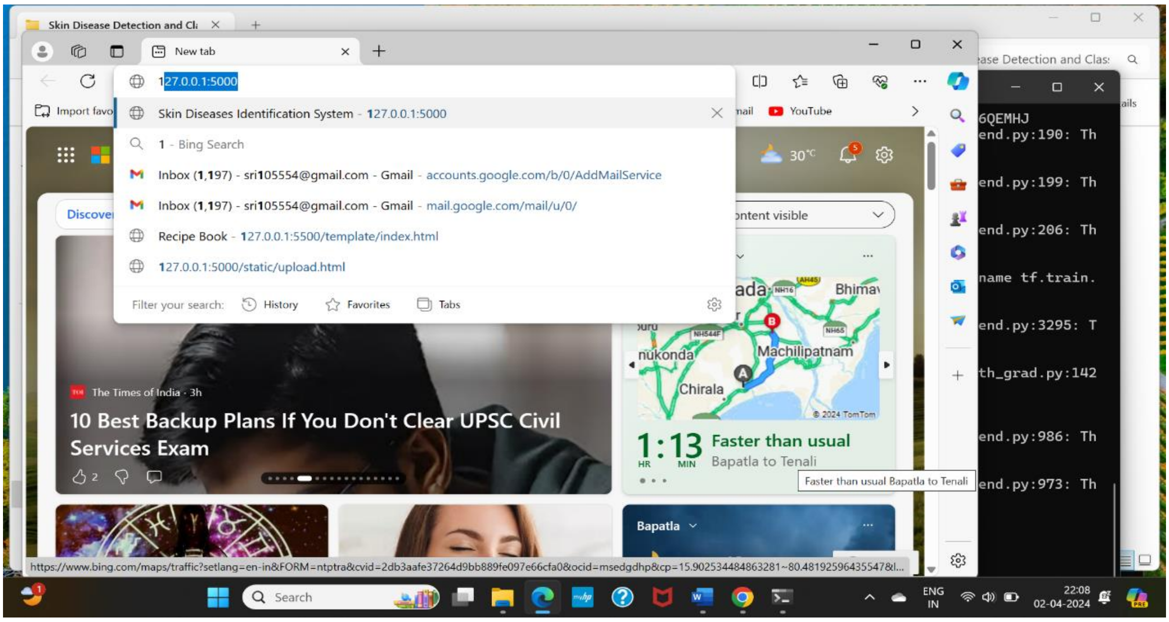

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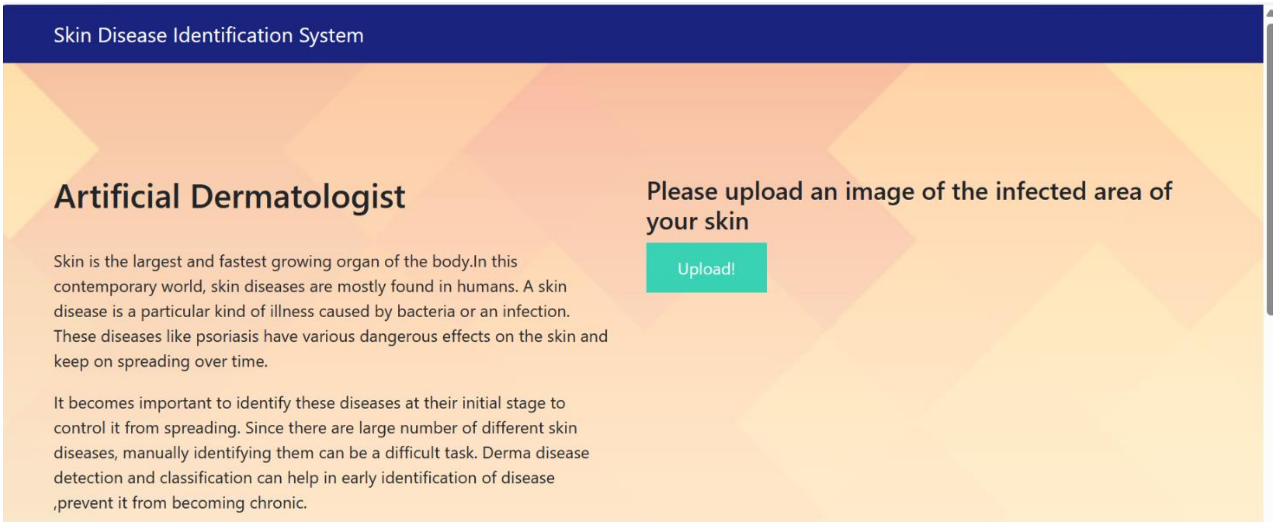

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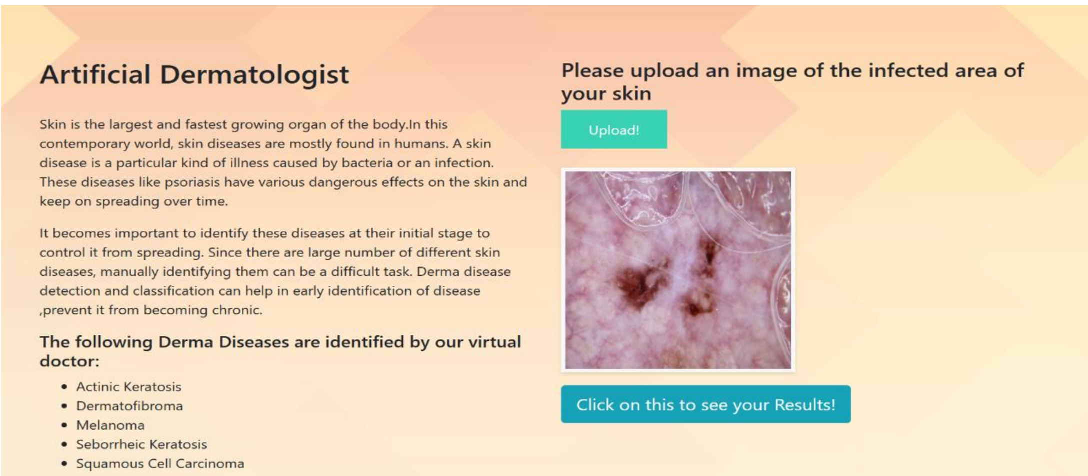

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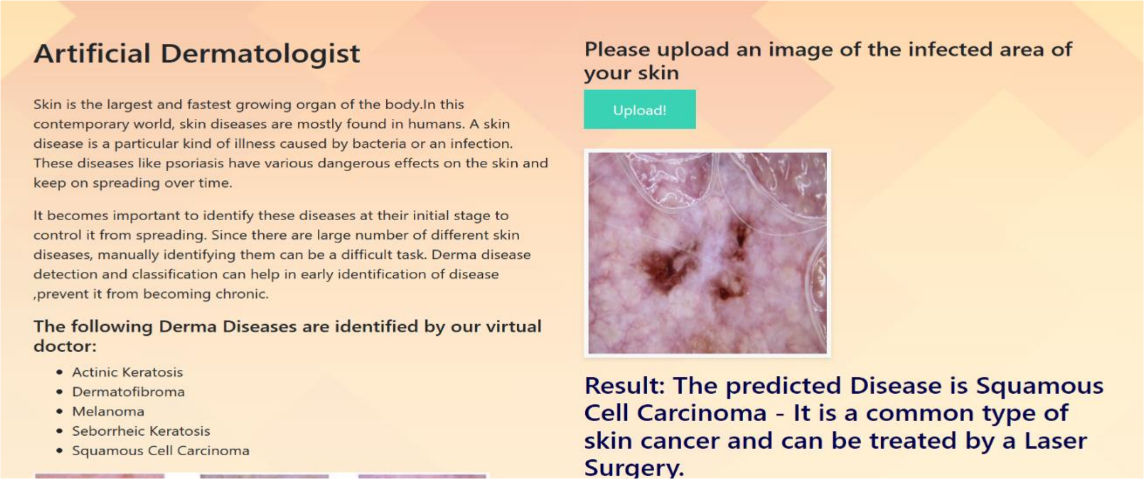
Click on this to see your results



V. CONCLUSION

Furthermore, the interpretability and explainability of CNN models facilitate better understanding of the underlying factors contributing to each diagnosis, enhancing transparency and trust in the diagnostic process. Visualizations such as heatmaps and feature maps enable clinicians to interpret the model's predictions and gain insights into the features driving the classification decisions.

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