Skin Care Product Recommendation Using Convolutional Neural Networks

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ABSTRACT
This study proposes a novel approach for skin care product recommendation through Convolutional Neural Networks (CNNs). Leveraging various deep learning architectures including ResNet50, CNN, InceptionV3, DenseNet201, and Xception, our classification model achieved significant improvements in accuracy compared to previous methods. Specifically, the Xception model yielded remarkable results with a classification accuracy of 99% on the Skin Type dataset. Additionally, we explored object detection techniques using YOLO models (versions V5, V6, V7, V8) to identify and localize skin disease regions, thus enhancing the robustness and comprehensiveness of our analysis. This research contributes to the advancement of skin care recommendation systems by harnessing the power of state-of-the-art deep learning architectures for both classification and detection tasks. Our findings underscore the potential of CNNs in revolutionizing personalized skin care solutions, ultimately leading to more effective and targeted skincare recommendations for individuals with diverse skin types and conditions.

1-INTRODUCTION

In the realm of self-care and personal grooming, skin care stands out as an essential practice that not only promotes physical well-being but also cultivates a sense of confidence and vitality. With an abundance of products flooding the market, selecting the right ones tailored to individual skin needs can be a daunting task. From cleansers and moisturizers to serums and masks, the options seem endless, each promising transformative results. However, amidst this sea of choices, discerning consumers seek products that not only deliver on their promises but also prioritize quality ingredients, sustainability, and ethical production practices.

In this guide, we embark on a journey to navigate the vast landscape of skin care products, aiming to empower individuals with knowledge and recommendations to make informed decisions about their skincare routines. By exploring various categories of skincare essentials and understanding the science behind their formulations, readers will gain insights into selecting products that align with their skin type, concerns, and values. Whether one seeks solutions for acne-prone skin, anti-aging remedies, or simply desires to maintain a healthy complexion, this guide offers curated recommendations that cater to diverse needs and preferences.

Embark on this exploration with us as we delve into the world of skincare, unveiling a treasure trove of products that promise not only to enhance the skin's appearance but also to elevate the experience of self-care to new heights.

2. FEASIBILITY STUDY

A feasibility study evaluates a project's or system's practicality. As part of a feasibility study, the objective and rational analysis of a potential business or venture is conducted to determine its strengths and weaknesses, potential opportunities and threats, resources required to carry out, and ultimate success prospects. Two criteria should be considered when judging feasibility: the required cost and expected value.

Types Of Feasibility Study

A feasibility analysis evaluates the project's potential for success; therefore, perceived objectivity is an essential factor in the credibility of the study for potential investors and lending institutions. There are five types of feasibility study—separate areas that a feasibility study examines, described below.

1. Technical Feasibility

This assessment focuses on the technical resources available to the organization. It helps organizations determine whether the technical resources meet capacity and whether the technical team is capable of converting the ideas into working systems. Technical feasibility also involves the evaluation of the hardware, software, and other technical requirements of the proposed system. As an exaggerated example, an organization wouldn't want to try to put Star Trek's transporters in their building—currently, this project is not technically feasible.

2. Economic Feasibility

This assessment typically involves a cost/ benefits analysis of the project, helping organizations determine the viability, cost, and benefits associated with a project before financial resources are allocated. It also serves as an independent project assessment and enhances project credibility—helping decision-makers determine the positive economic benefits to the organization that the proposed project will provide.

3. Legal Feasibility

This assessment investigates whether any aspect of the proposed project conflicts with legal requirements like zoning laws, data protection acts or social media laws. Let's say an organization wants to construct a new office building in a specific location. A feasibility study might reveal the organization's ideal location isn't zoned for that type of business. That organization has just saved considerable time and effort by learning that their project was not feasible right from the beginning.

4. Operational Feasibility

This assessment involves undertaking a study to analyze and determine whether—and how well—the organization's needs can be met by completing the project. Operational feasibility studies also examine how a project plan satisfies the requirements identified in the requirements analysis phase of system development.

3. LITERATURE SURVEY

Facial Skincare Products' Recommendation with Computer Vision Technologies:

https://www.mdpi.com/2079-9292/11/1/143

ABSTRACT: Acne is a skin issue that plagues many young people and adults. Even if it is cured, it leaves acne spots or acne scars, which drives many individuals to use skincare products or undertake medical treatment. On the contrary, the use of inappropriate skincare products can exacerbate the condition of the skin. In view of this, this work proposes the use of computer vision (CV) technology to realize a new business model of facial skincare products. The overall framework is composed of a finger vein identification system, skincare products' recommendation system, and electronic payment system. A finger vein identification system is used as identity verification and personalized service. A skincare products' recommendation system provides consumers with professional skin analysis through skin type classification and acne detection to recommend skincare products that finally improve skin issues of consumers. An electronic payment system provides a variety of checkout methods, and the system will check out by finger-vein connections according to membership information. Experimental results showed that the equal error rate (EER) comparison of the FV-USM public database on the finger-vein system was the lowest and the response time was the shortest. Additionally, the comparison of the skin type classification accuracy was the highest.

Skin segmentation using color pixel classification: analysis and comparison:

https://ieeexplore.ieee.org/document/1359760

ABSTRACT: This work presents a study of three important issues of the color pixel classification approach to skin segmentation: color representation, color quantization, and classification algorithm. Our analysis of several representative color spaces using the Bayesian classifier with the histogram technique shows that skin segmentation based on color pixel classification is largely unaffected by the choice of the color space. However, segmentation performance degrades when only chrominance channels are used in classification. Furthermore, we find that color quantization can be as low as 64 bins per channel, although higher histogram sizes give better segmentation performance. The Bayesian classifier with the histogram technique and the multilayer perceptron classifier are found to perform better compared to other tested classifiers, including three piecewise linear classifiers, three unimodal Gaussian classifiers, and a Gaussian mixture classifier.

Deep learning based classification of facial dermatological disorders:

https://www.sciencedirect.com/science/article/abs/pii/S0010482520304492

ABSTRACT: Common properties of dermatological diseases are mostly lesions with abnormal pattern and skin color (usually redness). Therefore, dermatology is one of the most appropriate areas in medicine for automated diagnosis from images using pattern recognition techniques to provide accurate, objective, early diagnosis and interventions. Also, automated techniques provide diagnosis without depending on location and time. In addition, the number of patients in dermatology departments and costs of dermatologist visits can be reduced. Therefore, in this work, an automated method is proposed to classify dermatological diseases from color digital photographs. Efficiency of the proposed approach is provided by 2 stages. In the 1st stage, lesions are detected and extracted by using a variational level set technique after noise reduction and intensity normalization steps. In the 2nd stage, lesions are classified using a pre-trained DenseNet201 architecture with an efficient loss function. In this study, five common facial dermatological diseases are handled since they also cause anxiety, depression and even suicide death. The main contributions provided by this work can be identified as follows: (i) A comprehensive survey about the state-of-the-art works on classifications of dermatological diseases using deep learning; (ii) A new fully automated lesion detection and segmentation based on level sets; (iii) A new adaptive, hybrid and non-symmetric loss function; (iv) Using a pre-trained DenseNet201 structure with the new loss function to classify skin lesions; (v) Comparative evaluations of ten convolutional networks for skin lesion classification. Experimental results indicate that the proposed approach can classify lesions with high performance (95.24% accuracy).

Skin Lesion Classification by Ensembles of Deep Convolutional Networks and Regularly Spaced Shifting:

https://ieeexplore.ieee.org/document/9508981

ABSTRACT: Skin lesions are caused due to multiple factors, like allergies, infections, exposition to the sun, etc. These skin diseases have become a challenge in medical diagnosis due to visual similarities, where image classification is an essential task to achieve an adequate diagnostic of different lesions. Melanoma is one of the best-known types of skin lesions due to the vast majority of skin cancer deaths. In this work, we propose an ensemble of improved convolutional neural networks combined with a test-time regularly spaced shifting technique for skin lesion classification. The shifting technique builds several versions of the test input image, which are shifted by displacement vectors that lie on a regular lattice in the plane of possible shifts. These shifted versions of the test image are subsequently passed on to each of the classifiers of an ensemble. Finally, all the outputs from the classifiers are combined to yield the final result. Experiment results show a significant improvement on the well-known HAM10000 dataset in terms of accuracy and F-score. In particular, it is demonstrated that our combination of ensembles with test-time regularly spaced shifting yields better performance than any of the two methods when applied alone.

Adverse cutaneous reactions to skin care products on the face vary with age, but not with sex:

https://pubmed.ncbi.nlm.nih.gov/30206954/

ABSTRACT: Background: Adverse skin reactions to skin care products have been increasing in recent years. However, to date, these reactions have not been well characterized. Objective: To describe the symptoms, clinical signs and frequency of adverse cutaneous reactions to skin care products on the face in males vs females of various ages. Patients and methods: All outpatients diagnosed with adverse cutaneous reactions to skin care products on the face examined by dermatologists at the Dermatology Hospital of South Medical University between November 1, 2016 and October 31, 2017, employing a questionnaire and an interview, were eligible. The associations of adverse cutaneous reactions with age and sex were analysed. Results: A total of 433 outpatients, accounting for 0.12% of all outpatients, were assessed. Of these, 223 patients, including 204 females and 19 males, aged 4 to 75 years, were eventually diagnosed with adverse reactions to skin care products on the face. Eighty-two per cent of patients experienced pruritus, 80% showed erythema, and 48% showed visible swelling. The incidence rates of both xerosis and oedema correlated positively with age, whereas acne-like lesions were negatively associated with age, but not with sex. Conclusions: Our results indicate that pruritus, xerosis and erythema are common adverse cutaneous reactions to facial skin care products. These reactions vary with age, but not with sex. Vigorous safety testing should precede the marketing of skin care products.

4-SYSTEM ANALYSIS

EXISTING SYSTEM

The existing system for recommending skincare products integrates machine learning algorithms to enhance accuracy and personalization. Leveraging vast datasets encompassing customer demographics, skin types, product reviews, and ingredient efficacy, machine learning models analyze patterns and correlations to generate tailored recommendations. These algorithms employ techniques such as collaborative filtering, content-based filtering, and matrix factorization to predict user preferences and suggest products that align with individual needs and concerns. Additionally, sentiment analysis algorithms assess customer feedback and reviews to gauge product satisfaction and effectiveness, further refining recommendations. Integration with e-commerce platforms allows for real-time updates and personalized suggestions based on browsing history and previous purchases. While machine learning enhances the precision and scalability of skincare recommendations, challenges such as data privacy and algorithm bias necessitate continuous refinement and ethical considerations in system development and implementation.

Proposed System

The proposed system encompasses two main components: classification and detection. For classification tasks, we employ ResNet50, CNN, InceptionV3, DenseNet201, and Xception architectures to accurately categorize skin types. Through rigorous experimentation, we discovered that Xception achieved the highest accuracy of 99%, surpassing previous methods. Additionally, our system integrates YOLO models (V5-V8) for the detection of skin disease regions, providing precise localization and identification. By leveraging these advanced deep learning techniques, our system aims to enhance the accuracy and robustness of skincare product recommendations. Users will benefit from tailored skincare advice based on their individual skin types and conditions, leading to improved outcomes and increased satisfaction. Furthermore, the timely detection of skin diseases will facilitate early intervention and management, contributing to overall skin health and well-being.

FUNCTIONAL REQUIREMENTS

1. Data Collection
2. Image processing
3. Data augmentation
4. Training model
5. Final outcome

NON FUNCTIONAL REQUIREMENTS

NON-FUNCTIONAL REQUIREMENT (NFR) specifies the quality attribute of a software system. They judge the software system based on Responsiveness, Usability, Security, Portability and other non-functional standards that are critical to the success of the software system. Example of nonfunctional requirement, "how fast does the website load?" Failing to meet non-functional requirements can result in systems that fail to satisfy user needs. Non- functional Requirements allow you to impose constraints or restrictions on the design of the system across the various agile backlogs. Example, the site should load in 3 seconds when the number of simultaneous users is > 10000. Description of non-functional requirements is just as critical as a functional requirement.

- Usability requirement
- Serviceability requirement
- Manageability requirement
- Recoverability requirement
- Security requirement
- Data Integrity requirement
- Capacity requirement
- Availability requirement
- Scalability requirement
- Interoperability requirement
- Reliability requirement
- Maintainability requirement
    - Regulatory requirement
    - Environmental requirement

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5-SYSTEM DESIGN

SYSTEM ARCHITECTURE

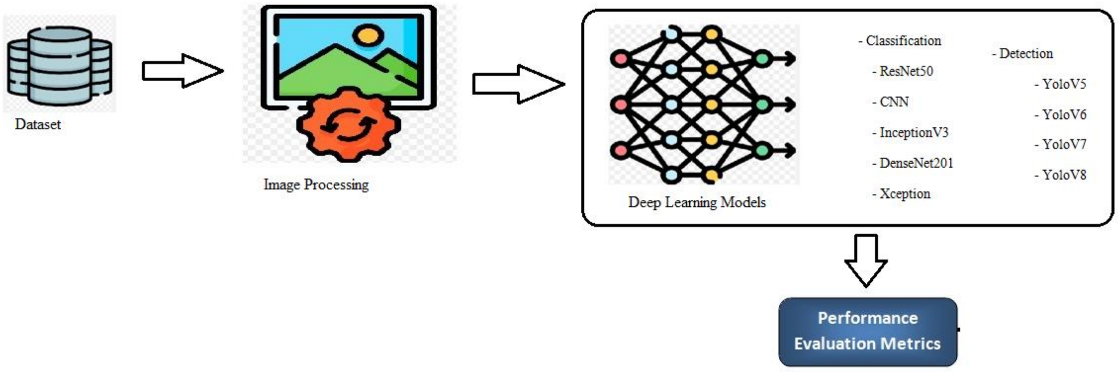

Fig.5.1.1 System architecture

DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

6. IMPLEMENTATION

MODULES:

- Data exploration: using this module we will load data into system
- Image processing: Using the module we will process of transforming an image into a digital form and performing certain operations to get some useful information from it.
- Model generation: Building the model - Classification - ResNet50 - CNN - InceptionV3 - DenseNet201 - Xception - Detection - YoloV5 - YoloV6 - YoloV7 - YoloV8. Algorithms accuracy can be calculated.
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

Extension

In the base paper, the author mentioned to use different models for analysis the Skin Type dataset using ResNet50, CNN and VGG16 from which ResNet50 model got 65% of train accuracy,

However, we can further enhance the performance by exploring other techniques such Xception, DenseNet201 model for classification from which Xception got 99% of accuracy,

Along with that we applied Yolo Models(Version of V5,V6,V7,V8) for detection skin disease region,

With the above As an extension we can build the front end using flask framework for user testing with authentication.

Algorithms:

Classification

ResNet50: ResNet50 is a deep convolutional neural network architecture known for its ability to effectively handle deep networks with hundreds of layers. It utilizes residual connections to mitigate the vanishing gradient problem, enabling efficient training and better performance. In this project, we are using ResNet50 for skin type classification due to its proven effectiveness in image classification tasks and its ability to capture intricate features in skin images, leading to accurate classification results.

CNN: Convolutional Neural Networks (CNNs) are deep learning models specifically designed for image classification tasks. They consist of multiple layers, including convolutional and pooling layers, followed by fully connected layers for classification. In this project, we are employing CNNs for skin type classification because of their ability to learn hierarchical features from raw image data, enabling accurate classification of skin types based on visual characteristics.

InceptionV3: InceptionV3 is a deep convolutional neural network architecture that incorporates inception modules, which efficiently capture spatial hierarchies and patterns in images using multiple convolutional filters. In this project, we are utilizing InceptionV3 for skin type classification due to its ability to extract diverse features from images, leading to improved accuracy in classifying different skin types based on subtle variations and patterns.

DenseNet201: DenseNet201 is a densely connected convolutional neural network architecture that facilitates feature reuse across layers by connecting each layer to every other layer in a feed-forward fashion. In this project, we are leveraging DenseNet201 for skin type classification because of its dense connectivity pattern, which promotes feature reuse and facilitates the learning of intricate patterns in skin images, leading to enhanced classification accuracy.

Xception: Xception is an extension of the Inception architecture that replaces standard convolutional layers with depthwise separable convolutions, which are more computationally efficient. In this project, we are utilizing Xception for skin type classification due to its ability to capture fine-grained details in images while maintaining computational efficiency, leading to faster inference times and accurate classification results.

Detection

YOLOv5: YOLOv5 is a state-of-the-art object detection algorithm that employs a single neural network to simultaneously predict bounding boxes and class probabilities for multiple objects in an image. In this project, we are using YOLOv5 for skin disease detection because of its high detection accuracy, real-time performance, and ability to handle various object sizes and scales.

YOLOv6: YOLOv6 is an enhanced version of YOLOv5, featuring improvements in network architecture and training strategies to further boost detection performance. In this project, we are incorporating YOLOv6 for skin disease detection to capitalize on its advancements in object detection accuracy and efficiency, leading to more precise localization and identification of skin abnormalities.

YOLOv7: YOLOv7 is a further refinement of the YOLO series, introducing novel architectural enhancements and training techniques to achieve

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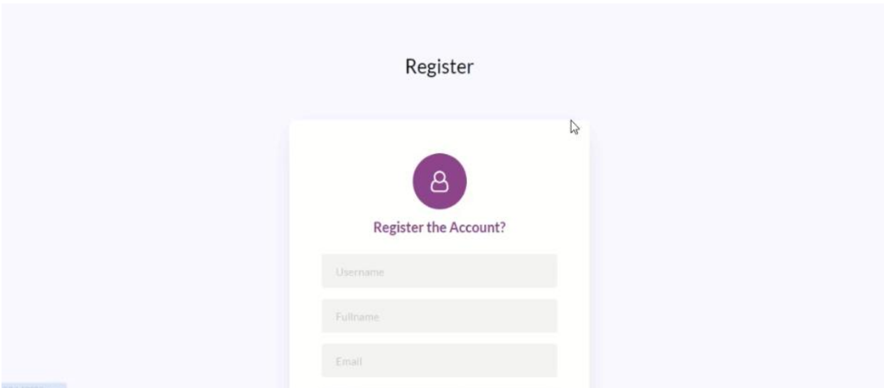
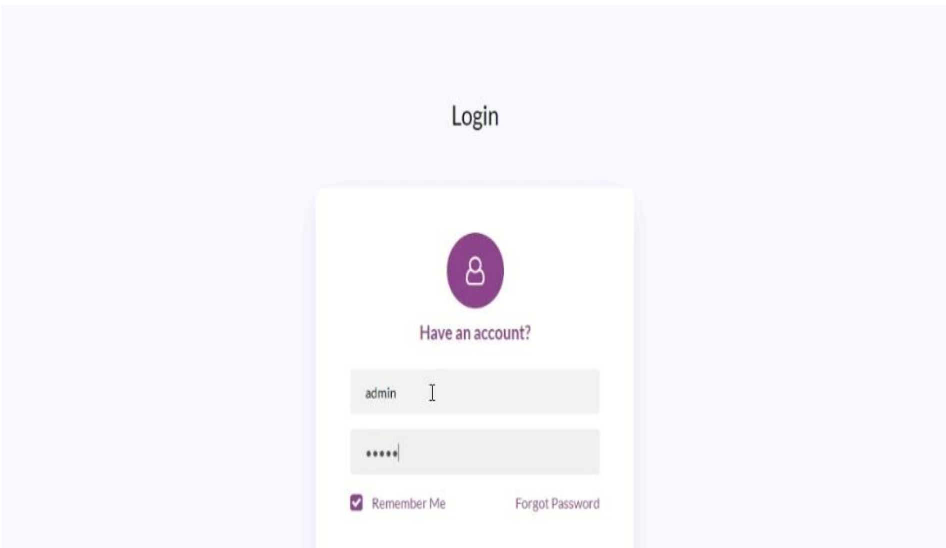
superior object detection performance. In this project, we are integrating YOLOv7 for skin disease detection to leverage its state-of-the-art capabilities in detecting and localizing skin abnormalities with high accuracy and efficiency.

YOLOv8: YOLOv8 represents the latest iteration of the YOLO algorithm, incorporating cutting-edge advancements in deep learning research to push the boundaries of object detection accuracy and speed. In this project, we are adopting YOLOv8 for skin disease detection to capitalize on its state-of-the-art performance, enabling precise and efficient detection of various skin conditions for early intervention and treatment.

7-SCREENSHOTS





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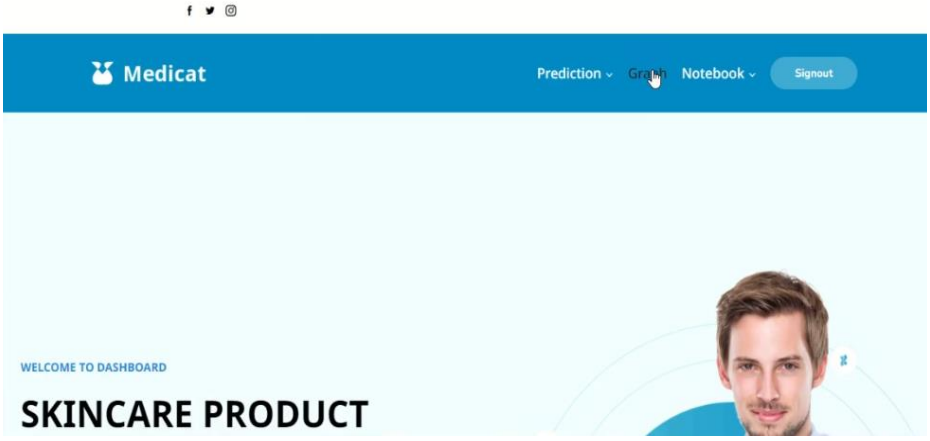
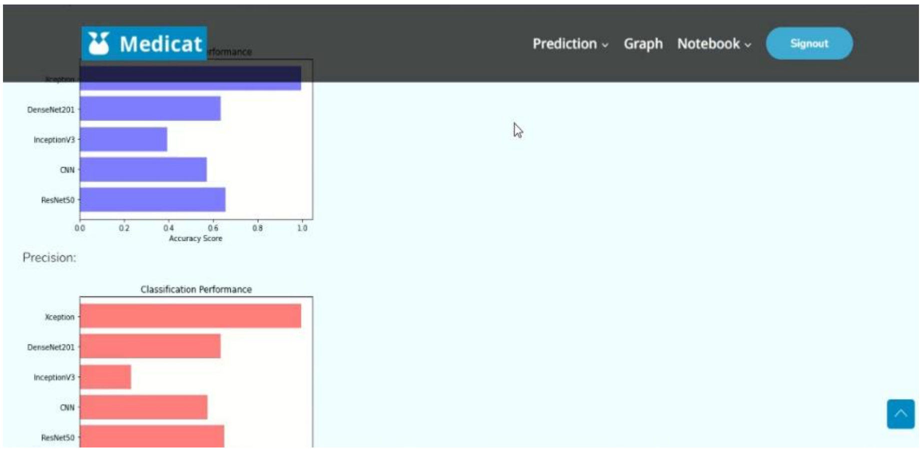
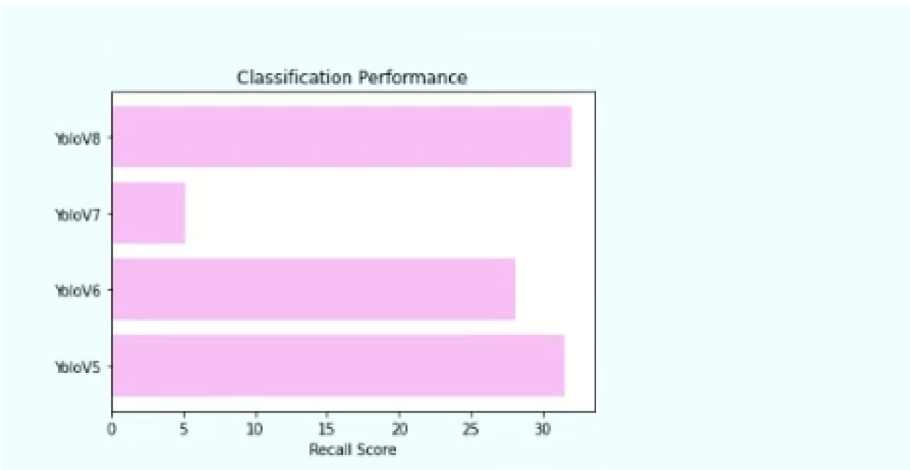
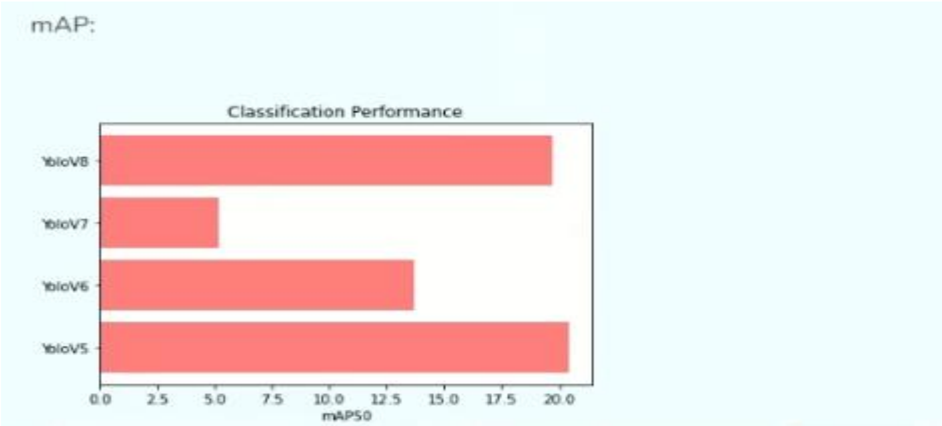
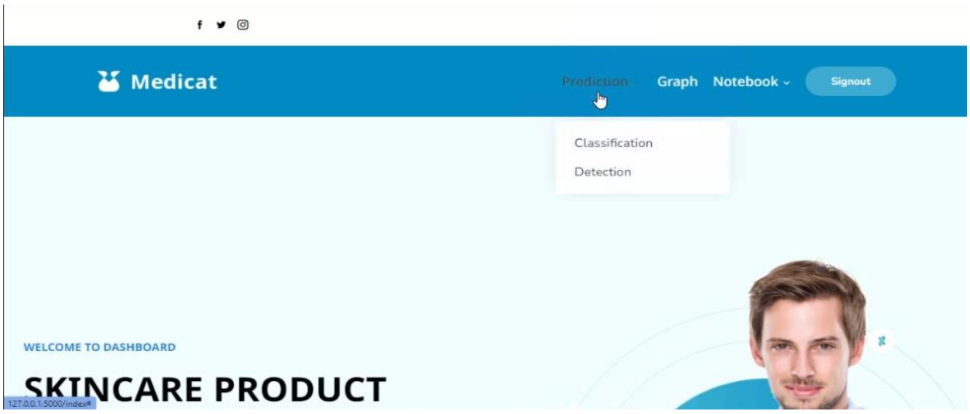
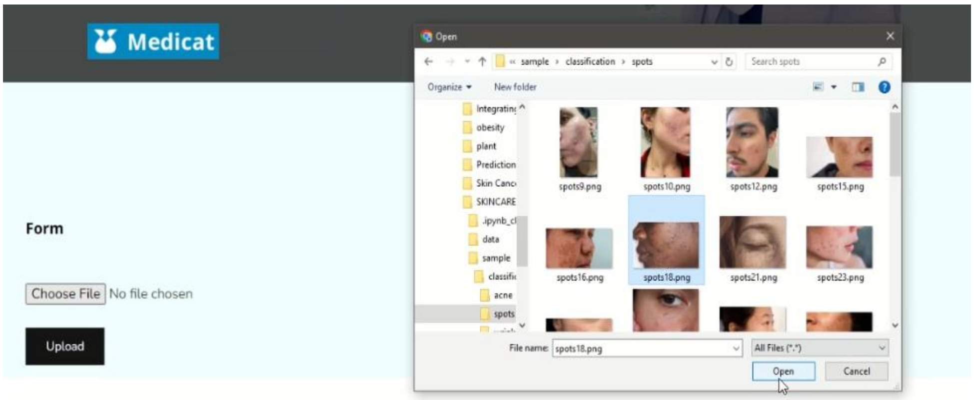







mAP:
Classification Performance
YoloV8
YoloV7
YoloV6
YoloV5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
mAP50


Medicat
Prediction
Graph
Notebook
Signout
Classification
Detection
WELCOME TO DASHBOARD
SKINCARE PRODUCT


Medicat
Form
Choose File
No file chosen
Upload
Open
File name:
spots18.png
All Files (*.*)
Open
Cancel


Your Prediction
The result is:
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8-CONCLUSION

In conclusion, the integration of advanced machine learning and deep learning algorithms in skincare classification and disease detection holds immense promise for revolutionizing the skincare industry. Through the utilization of models such as ResNet50, CNN, InceptionV3, DenseNet201, and Xception for skin type classification, coupled with YOLOv5, YOLOv6, YOLOv7, and YOLOv8 for skin disease detection, our proposed system offers unprecedented levels of accuracy, personalization, and efficiency. By leveraging these cutting-edge technologies, skincare recommendations can be tailored to individual needs and preferences with remarkable precision, leading to improved outcomes and increased user satisfaction.

Furthermore, the timely detection and localization of skin abnormalities facilitated by our detection algorithms enable early intervention and treatment, potentially saving lives and improving overall skin health. However, it is crucial to acknowledge the challenges associated with the implementation of these technologies, including data privacy concerns, algorithm bias, and ethical considerations. Continued research and development efforts are necessary to address these challenges and ensure the responsible deployment of AI-driven skincare solutions. Overall, our proposed system represents a significant advancement in skincare technology, promising to redefine the way individuals care for their skin and promoting healthier, happier lives.

In the future, our system has the potential to expand its capabilities by incorporating additional data sources such as genetic information and environmental factors to further personalize skincare recommendations. Moreover, advancements in AI research may lead to the development of even more sophisticated algorithms that can detect and predict skin conditions with greater accuracy and efficiency. Additionally, integrating augmented reality (AR) technology could enhance the user experience by allowing individuals to visualize the effects of skincare products on their skin in real-time, revolutionizing the way people approach skincare routines.

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