

# ENHANCING DERMATOLOGY DIAGNOSIS THROUGH AN AI-DRIVEN WEB-BASED ONLINE RECOGNITION SYSTEM

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## ABSTRACT

The title of this project is "Enhancing Dermatology Diagnosis Through an AI-driven Web-based Online Recognition System," it focuses on utilizing artificial intelligence to assist in diagnosing skin diseases. Skin conditions are prevalent and challenging to diagnose accurately without specialized expertise, often leading to delays or misdiagnoses due to limited access to dermatological care. To address this issue, the project proposes an AI-driven web-based system named "CutiScan," which utilizes a machine learning model to classify images of skin diseases. This system aims to provide preliminary diagnostic assistance, helping users identify potential skin conditions and seek timely medical advice.

The development strategy involved several stages, starting with data acquisition by combining resources from "DermNet" and "Skin-Disease-Classification" dataset downloaded from Kaggle, supplemented with additional classes and data augmentation to expand the dataset. Three models (InceptionV3, ResNet50, and VGG16) were trained, with InceptionV3 selected based on its superior performances. This model was integrated into the backend of a web application, and a database was constructed to store disease information. A user-friendly web

interface was developed to facilitate interaction with the system, initially hosted using Ngrok to generate temporary links for testing and feedback. In the future, the web hosting has the potential to be migrated to a permanent server with a dedicated domain name for “CutiScan”.

The final result is a functional AI-driven web application capable of classifying skin disease images, providing users with preliminary diagnostic information. This system has the potential to improve access to dermatological care by offering an accessible tool for early diagnosis and guidance on seeking professional medical evaluation.

Keywords: AI, InceptionV3, Skin Disease, Classification

## IDENTITY

In recent years, the field of dermatology has faced numerous challenges, there is a need of innovative solutions to address the growing need for accurate diagnosis and treatment recommendations. The shortage of dermatologists, the raising prevalence of skin diseases, the cost and unconvince of in-person appointments as well as the advancing in AI (Artificial Intelligence) technologies are main points that led to the identification of this problem.

Skin diseases have seen a significant increase in prevalence, and affect almost 900 million people in the world at any time (World Health Organization: WHO, 2018). This surge in skin conditions, combined with a shortage of dermatologists in many regions, highlights the pressing need for innovative and accessible diagnostic solutions.

The key problem addressed by this project is the shortage of professional dermatologists, coupled with the rising prevalence and awareness of skin diseases, and the inconvenience caused by off-line diagnosis. Traditional in-person dermatology consultations are often costly and inconvenient, creating a need for accessible, user-friendly self-diagnosis tools. This project proposes the development of an AI-driven web-based system with visual diagnostic capabilities to bridge this gap, offering a convenient online platform for users to diagnose skin conditions from the comfort of their homes.

The primary objectives of this project are to develop an AI-driven dermatology diagnosis system, improve accessibility to dermatological care, offer reliable treatment recommendations, and optimize AI models for enhanced accuracy. The system employs advanced AI techniques, including convolutional neural networks, to analyze user-uploaded images and provide accurate diagnoses and treatment suggestions.

## STUDY METHODOLOGY

The methodology used in the development of this project is the AI Development Life Cycle, which focuses on using data to make decisions and continuously improving AI models throughout the project lifecycle. This methodology was chosen because it allows for adaptability as the project progresses, making it a great fit for creating an accurate and user-friendly diagnostic system in the ever-evolving field of AI. By employing this methodology, a high-quality final product can be achieved.

### Phase of analysis

In the analysis phase, the focus was on identifying and defining the key system requirements to align with the project's objectives. This involved gathering both functional and non-functional requirements from stakeholders to ensure the system's effectiveness and usability. The functional requirements centered around enabling users to upload images, processing these images to identify skin diseases, and displaying results along with relevant treatment information. Non-functional requirements addressed aspects such as usability, compatibility and performance, ensuring the system is user-friendly, secure, and efficient.

A thorough literature review of 10 relevant research papers was conducted to understand current trends and challenges in dermatology diagnostics using AI. This review revealed that CNN models, including InceptionV3, VGG, and ResNet, are among the most effective for skin disease classification. However, common limitations in past studies included inadequate datasets and high computational complexity. Based on these findings, the decision was made

to utilize the InceptionV3 model for its superior performance while also comparing it with VGG16 and ResNet50 to ensure robust and accurate diagnostic capabilities.

## Design phase

The design phase focuses on determining the architecture of the system, which includes the development of databases, architectural designs, algorithms, and interfaces. The architectural design outlines the structure of the system, detailing how components interact and function together to achieve the project goals.

In this project, the database design includes a table that stores information about various skin diseases for result display purposes. This design ensures that users receive detailed information about the diagnosed condition.

The chosen architectural design is the Client-Server architecture (Lile, 1993). In this approach, the system is divided into two main components: the client, which is the user interface accessible through a web browser, and the server, which processes user requests, performs the skin disease classification using the InceptionV3 model, and retrieves relevant information from the database.

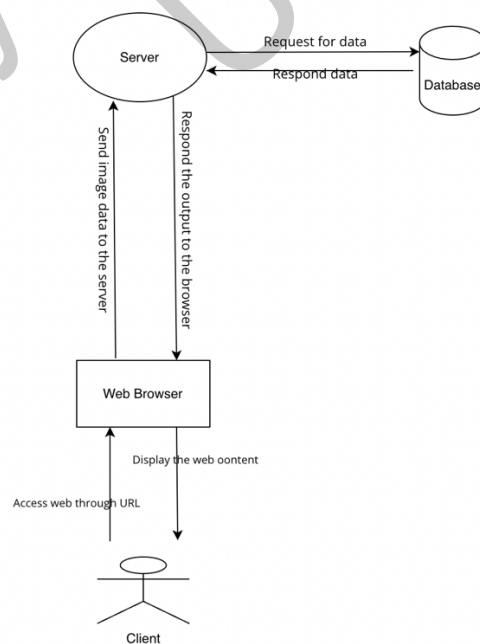


Figure 1 Client-Server Architecture

The InceptionV3 model (Szegedy et al., 2015) plays a crucial role in providing system functions for the skin recognition solution. The process begins by checking for an input image. If an image is provided, it undergoes preprocessing where the raw pixel values are resized to 299x299 pixels and normalized. This standardized input is then processed by initial convolutional layers that extract low-level features such as edges and textures.

InceptionV3 is built using a series of Inception modules, each designed to capture multi-scale features by performing convolutions with multiple filter sizes in parallel. These modules can be categorized into three types: Inception Module A, B, and C, as depicted in the provided graph. Each module type performs convolutions with varying kernel sizes and concatenates the outputs, allowing the network to capture a variety of features at different scales.

The architecture includes grid size reduction layers to downsample the feature maps, reducing computational complexity and increasing the receptive field. Additionally, an auxiliary classifier is used during training to help with gradient propagation and to improve the convergence of the model.

The provided graph illustrates the architecture of InceptionV3, highlighting the arrangement of Inception Modules A, B, and C, along with grid size reduction stages and the auxiliary classifier:

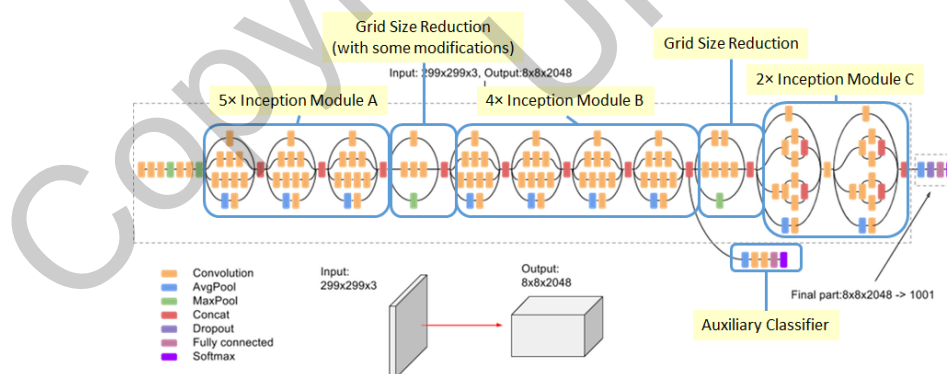


Figure 2 InceptionV3 Architecture

The algorithm design involves the use of the InceptionV3 model for image processing and disease identification.

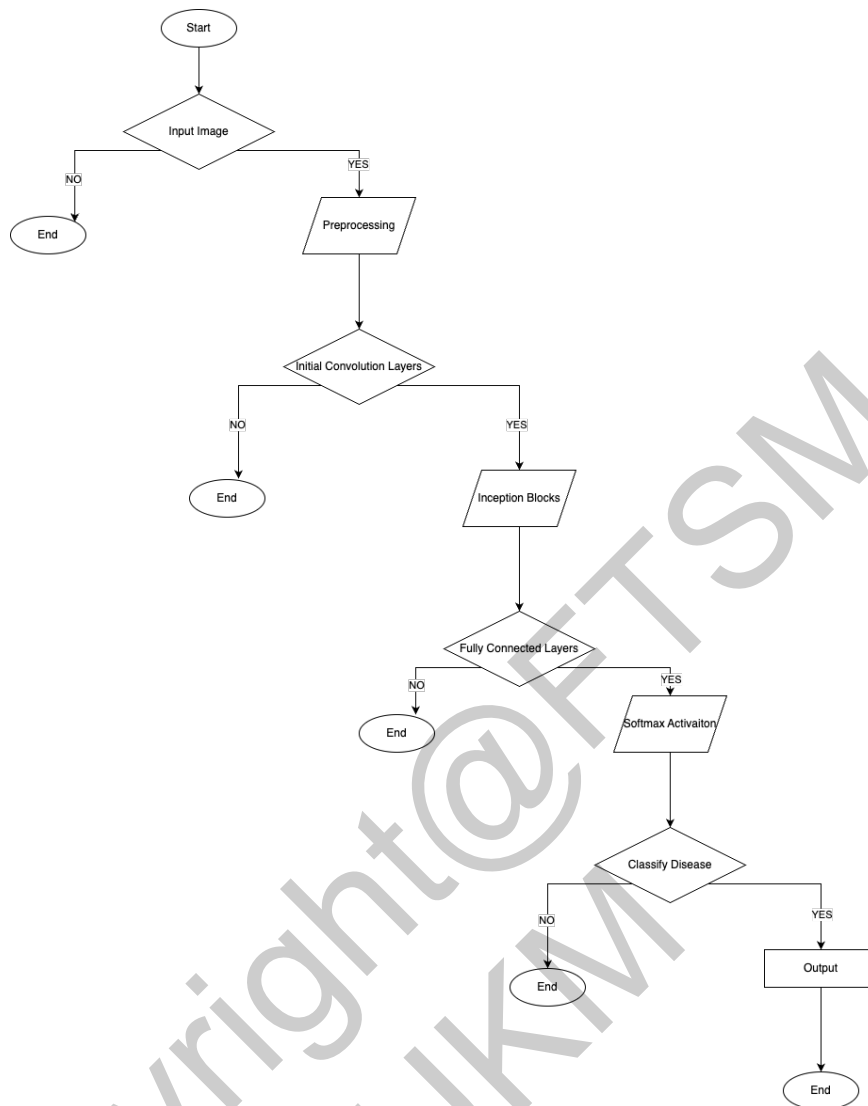


Figure 3 Decision Tree of InceptionV3 model

At the beginning, it checks if there is an input image. If there is, it undergoes preprocessing, where the raw pixel values get resized and normalized. Following this, the algorithm heads into the initial convolution layers, which are responsible for essential image processing. The decision tree then guides the flow, navigating through repeated inception blocks, each employing multiple parallel convolutional pathways.

Once the features are extracted, the algorithm faces a decision: whether to proceed to fully connected layers. If yes, the Softmax activation step takes over, converting the final layer's output into probability scores. Another decision determines whether to classify the skin disease, if the decision is yes, the system proceeds to the final classification. This flow ensures that the algorithm processes input images, extracts relevant features, and makes informed

decisions about the recognized skin diseases.

The interface design aims to provide a user-friendly experience, ensuring that users can easily navigate through the image uploading and diagnosis process. Clear instructions and intuitive design elements are incorporated to guide users, making the system accessible even to those with basic computer skills. The focus on usability, privacy, and security in the design phase ensures that the system meets the needs of its users while protecting their data and providing timely and accurate diagnoses.

### **Implementation phase**

The implementation phase of "CutiScan" encompasses data acquisition, model development, deployment, database construction, web development, and hosting. Data acquisition involved combining images from the "DermNet (Kaggle, 2020)" and "Skin-Disease-Classification (Kaggle, 2023)" datasets downloaded from Kaggle to create a new dataset for this system. While "DermNet" provided a large volume of images, its data quality was inconsistent and most of the classes do not fall into the inclusion of this project since they are related to skin cancer and tumors. The other dataset, though smaller, contained classes pertinent to the system. The final dataset was created by retaining 8 classes from "Skin-Disease-Classification", adding 4 additional classes from "DermNet", and using data augmentation techniques to ensure each class from all 12 classes has approximately 1,000 images. This dataset was split into 80% for training and 20% for testing since such a splitting is the most common and effective practice in machine learning to ensure robust model evaluation and validation (Géron, n.d.).

For model development, the InceptionV3 architecture was utilized with pre-trained weights from ImageNet. Custom layers were added, including a dropout layer to mitigate overfitting. The model was compiled with the Adam optimizer and categorical cross-entropy loss. Early stopping was employed to prevent overfitting and to restore the best weights based on validation loss. The model was trained using a batch size of 68 and an image size of 299x299 pixels.

In the deployment phase, the trained model was integrated into a Flask-based web application.

Flask was used to handle image uploads, preprocessing, and classification. Routes were set up to manage user interactions and display results. The "CutiScan" database was created using phpMyAdmin, including a table for storing disease names, descriptions, and treatments. The web application's frontend was developed using HTML, CSS, and JavaScript, featuring pages for introducing the system, uploading images, and displaying results. Finally, the application was hosted locally using Ngrok, which provided a public URL by creating a secure tunnel to the local server.

### **Testing phase**

The testing phase is integral to the "CutiScan" project's methodology, ensuring that the system meets both functional and non-functional requirements. Testing is conducted at three levels: component, integration, and system. At the component level, individual parts of the system are tested to confirm they work correctly in isolation. Integration testing ensures that these components interact seamlessly, while system testing evaluates the overall performance and reliability to ensure user requirements are met.

Functional testing includes verifying features like image upload, cropping, and result display. System testing simulates real-world usage scenarios, and model validation assesses the performance of the trained models using metrics such as precision, recall, and accuracy. Non-functional testing covers performance, compatibility, and usability aspects. Performance testing ensures the system's responsiveness under various conditions, compatibility testing confirms its operation across different devices and browsers, and usability testing evaluates the user interface and overall user experience.

Exit criteria for the testing phase include executing and passing at least 90% of planned test cases, covering all requirements, and receiving positive user feedback without critical issues. Model testing compares InceptionV3, ResNet50, and VGG16, with InceptionV3 showing the best performance in terms of accuracy and other metrics. Web functions and compatibility are tested for correct image handling and consistent performance across platforms. User feedback and performance testing further validate the system's reliability and user satisfaction, demonstrating that "CutiScan" meets the predefined benchmarks for response time and stability.



## RESULTS AND DISCUSSION

The training phase involved three models: InceptionV3, ResNet50, and VGG16, all using the same parameters and dataset. InceptionV3 achieved the best performance, training over 15 epochs. By the final epoch, the model reached a training accuracy of 0.9340 and a validation accuracy of 0.9232, indicating an ideal training outcome. The evaluation on a separate test set yielded an accuracy of 0.9127, precision of 0.9168, recall of 0.9127, and an F1-score of 0.9121. These metrics underscore the robustness of InceptionV3, which outperformed ResNet50 and VGG16, whose performance metrics were significantly lower.

```

... Epoch 1/15
103/103 ----- 638s 6s/step - accuracy: 0.3977 - loss: 1.8889 - val_accuracy: 0.7974 - val_loss: 0.8159
Epoch 2/15
103/103 ----- 632s 6s/step - accuracy: 0.7590 - loss: 0.8258 - val_accuracy: 0.8301 - val_loss: 0.5599
Epoch 3/15
103/103 ----- 643s 6s/step - accuracy: 0.8247 - loss: 0.5975 - val_accuracy: 0.8627 - val_loss: 0.4728
Epoch 4/15
103/103 ----- 648s 6s/step - accuracy: 0.8525 - loss: 0.4937 - val_accuracy: 0.8775 - val_loss: 0.4100
Epoch 5/15
103/103 ----- 644s 6s/step - accuracy: 0.8647 - loss: 0.4277 - val_accuracy: 0.9003 - val_loss: 0.3777
Epoch 6/15
103/103 ----- 640s 6s/step - accuracy: 0.8834 - loss: 0.3872 - val_accuracy: 0.9020 - val_loss: 0.3399
Epoch 7/15
103/103 ----- 640s 6s/step - accuracy: 0.8882 - loss: 0.3684 - val_accuracy: 0.9020 - val_loss: 0.3182
Epoch 8/15
103/103 ----- 642s 6s/step - accuracy: 0.9019 - loss: 0.3162 - val_accuracy: 0.8889 - val_loss: 0.3131
Epoch 9/15
103/103 ----- 642s 6s/step - accuracy: 0.9126 - loss: 0.2912 - val_accuracy: 0.8938 - val_loss: 0.2968
Epoch 10/15
103/103 ----- 642s 6s/step - accuracy: 0.9109 - loss: 0.2815 - val_accuracy: 0.9232 - val_loss: 0.2700
Epoch 11/15
103/103 ----- 639s 6s/step - accuracy: 0.9120 - loss: 0.2591 - val_accuracy: 0.9101 - val_loss: 0.2790
Epoch 12/15
103/103 ----- 639s 6s/step - accuracy: 0.9286 - loss: 0.2364 - val_accuracy: 0.9003 - val_loss: 0.2773
Epoch 13/15
...
Epoch 14/15
103/103 ----- 641s 6s/step - accuracy: 0.9315 - loss: 0.2230 - val_accuracy: 0.9167 - val_loss: 0.2361
Epoch 15/15
103/103 ----- 631s 6s/step - accuracy: 0.9340 - loss: 0.2087 - val_accuracy: 0.9232 - val_loss: 0.2325

```

Figure 4 InceptionV3 Model Training on New Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
InceptionV3	91%	92%	91%	91%
ResNet50	61%	66%	61%	60%
VGG16	72%	74%	72%	71%

Table 1 Model Comparison

The web application, "CutiScan," features several key pages designed to enhance user experience and provide accurate dermatological diagnoses. The index page serves as the landing page, offering a welcoming and branded interface. It includes a hover effect on the "Cutiscan" text, changing it to "AI SKIN DISEASE RECOGNITION," and a skincare-related background image with a semi-transparent overlay to maintain readability. The page also has a call-to-action button directing users to the upload page.

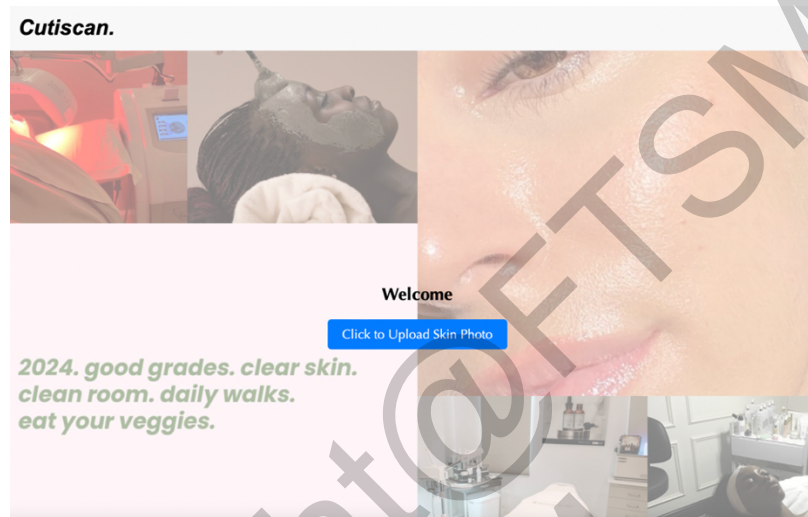


Figure 5 Index Page

The upload page supports both direct image uploading and a crop-first option, catering to users with large or messy background images. This functionality ensures flexibility and ease of use for users preparing their images for classification.

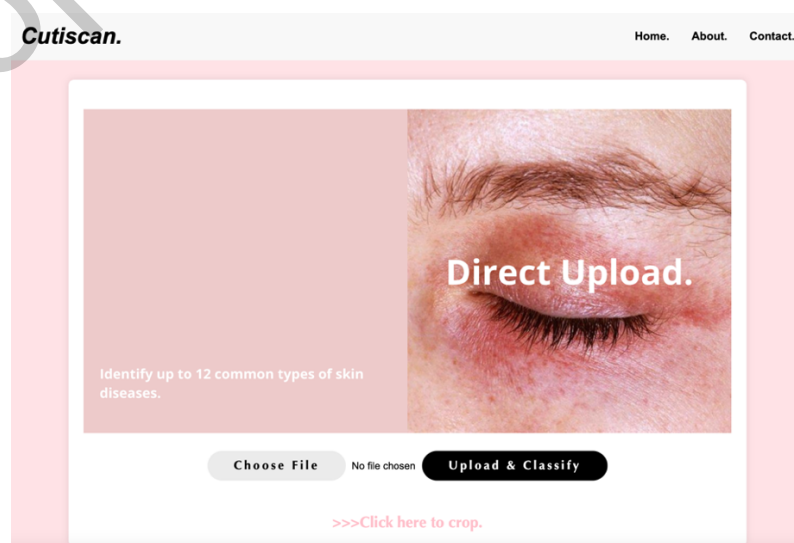


Figure 6 Upload Page (Direct Uploading Option)

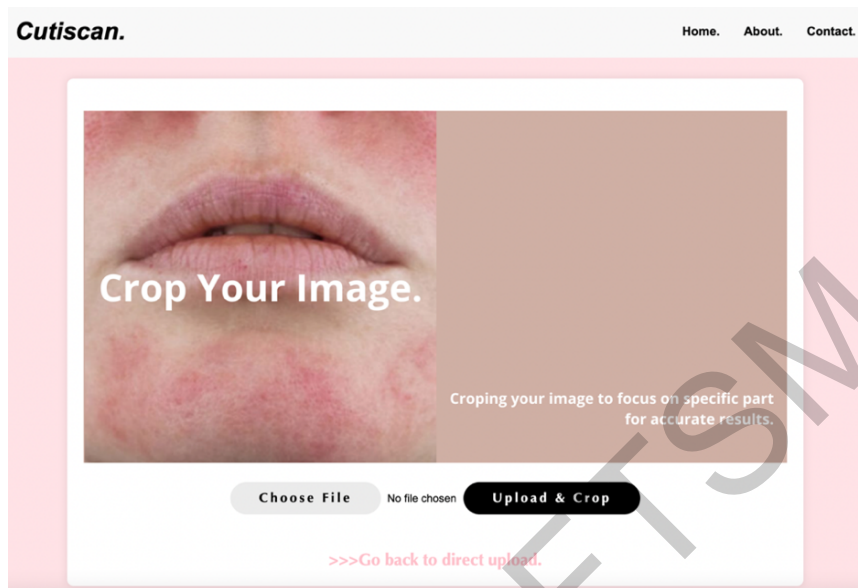


Figure 7 Upload Page (Cropping Option)

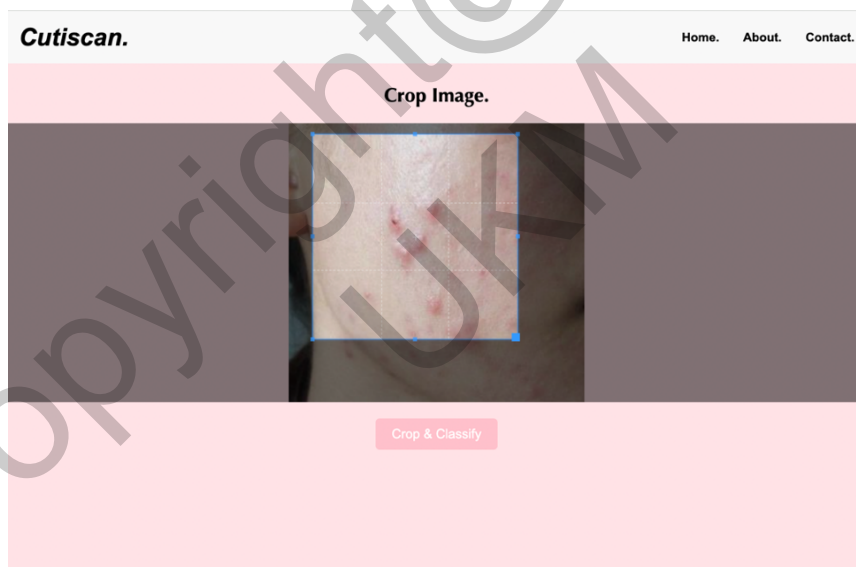


Figure 8 Crop Image Page

The result page displays the classification results. Once an image is uploaded, it is processed by the trained AI model, which predicts the most likely skin disease and its confidence score. The application then queries the database to retrieve detailed information about the disease, including its name, overview, and possible treatments. This information is rendered on the result page, and users can follow a link to an information page for more details.

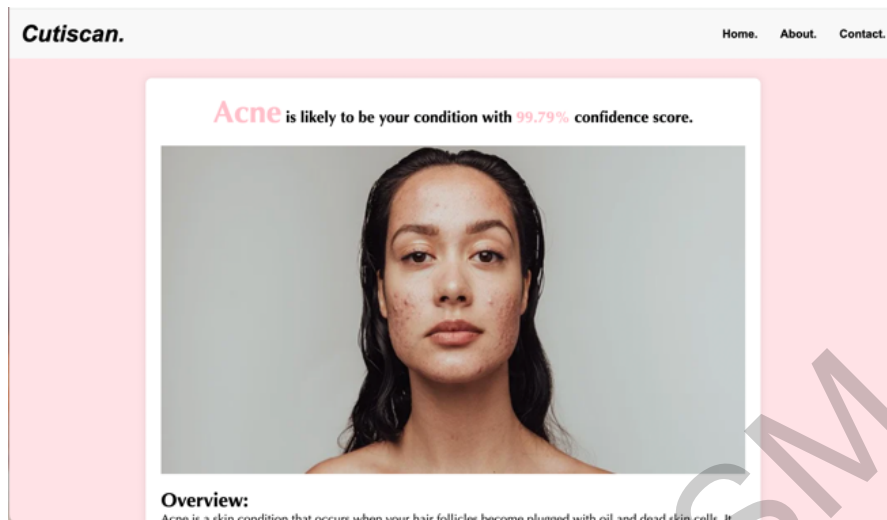


Figure 9 First Half of Result Page

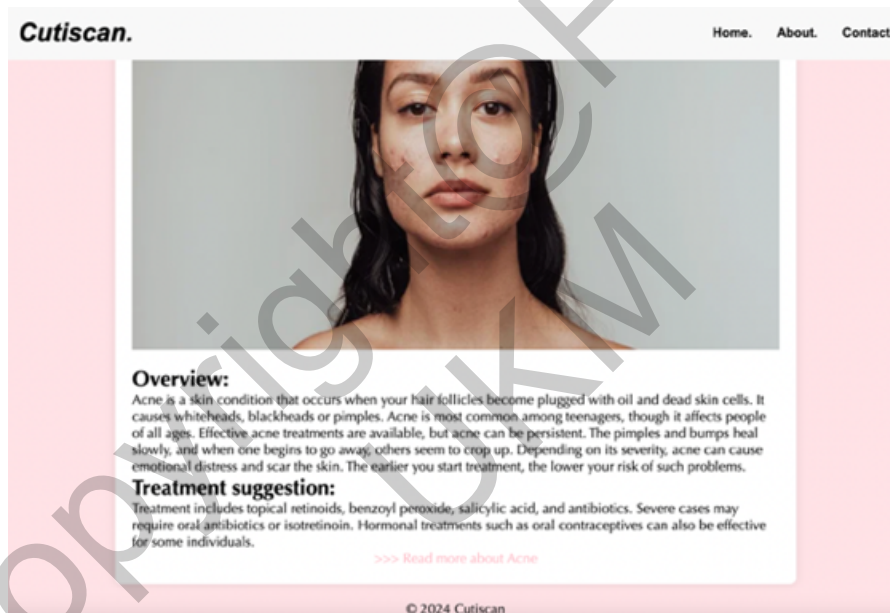


Figure 10 Second Half of Result Page

The information page offers comprehensive details about each of the 12 skin diseases included in the "CutiScan" system. This includes rarity and prevalence, symptoms, and prevention/treatment options, providing users with valuable information.

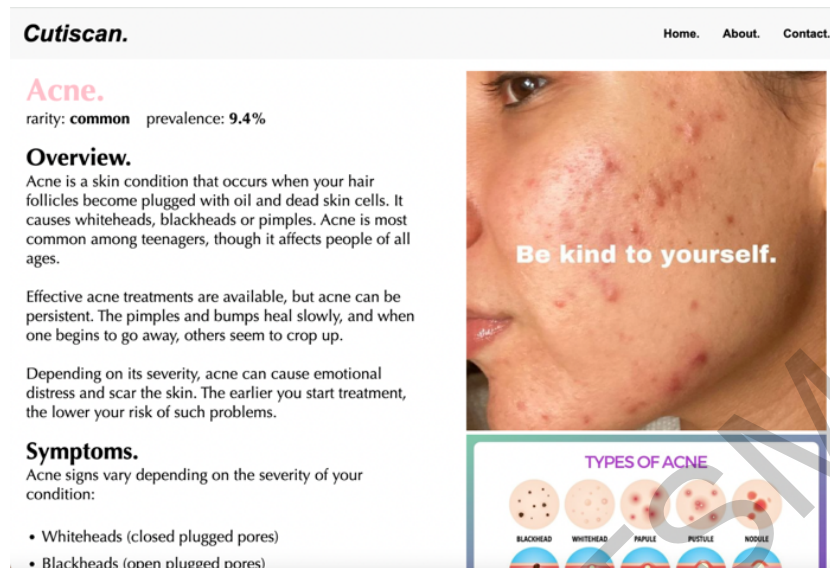


Figure 11 Information Page

Web hosting was facilitated using Ngrok, which enabled the system to be accessible online. Ngrok creates a secure tunnel to localhost, allowing the locally hosted web application to be accessed via a public URL. This method provided a straightforward and efficient solution for temporary hosting and real-time testing. The public URL generated by Ngrok is temporary, ensuring that the system is available for testing and user feedback without requiring immediate permanent hosting solutions such as purchasing a domain name. Users were able to access the application from various devices and browsers, ensuring broad compatibility and gathering valuable user feedback. This approach also allowed for easy iteration and immediate testing of updates, enhancing the development process and ensuring the application met user expectations in real-world scenarios.

```

ngrok
Policy Management Examples http://ngrok.com/apigwexamples (Ctrl+C to quit)

Session Status      online
Account             sandracee04@gmail.com (Plan: Free)
Update              update available (version 3.10.1, Ctrl-U to update)
Version             3.10.0
Region              Asia Pacific (ap)
Latency             15ms
Web Interface        http://127.0.0.1:4040
Forwarding           https://5ae0-2001-f40-935-d7b-17f-4c82-49ef-e3cd.ngrok-free.app -> http://localhost:5001

Connections
  ttl   opn   rt1   rt5   p50   p98
   8    0    0.06  0.02  0.02  1.46

HTTP Requests
-----
GET /upload          200 OK
GET /upload          200 OK
GET /static/bkg.jpg  200 OK
GET /                200 OK
POST /classify       200 OK

```

Figure 12 Public URL Generated by Ngrok

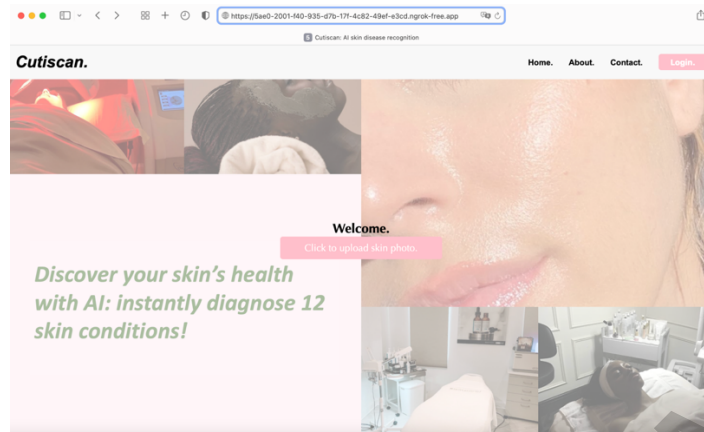


Figure 13 Accessing “Cutiscan” Through Generated Link

## Usability Testing

Usability testing is a process that involves evaluating the system's usability by gathering feedback from user representatives and stakeholders. The purpose of usability testing is to assess the user experience, collect quantitative data, and evaluate overall user satisfaction with the system.

For "CutiScan," usability testing was conducted to identify usability issues and areas for improvement. The testing involved distributing Google Forms surveys to collect structured feedback and conducting offline meetings and focus groups with a sample of users to gather qualitative insights and direct feedback.

### Steps Taken:

1. Distributed Google Forms surveys to users to collect structured feedback on their experience with "CutiScan."
2. Conducted offline meetings and focus groups with a sample of users to gather qualitative insights and direct feedback.

Table 1 below summarizes the demographics of the testers, providing insights into their age, gender, occupation, platform used, and their satisfaction level.

Table 2 Demographics of Testers

User	Age	Sex	Occupation	Platform	Satisfaction
1	22	Female	Student	Online	High
2	21	Male	Student	Online	High
3	23	Female	Student	Online	Moderate
4	22	Female	Student	Online	High
5	23	Male	Student	Offline	Low
6	24	Female	Student	Online	High
7	24	Female	Student	Online	Moderate
8	24	Male	Student	Offline	High
9	26	Male	Student	Online	High
10	27	Male	Student	Offline	High
11	19	Female	Student	Offline	Moderate
12	20	Male	Student	Online	High
13	22	Female	Student	Online	Moderate
14	23	Female	Student	Online	High
15	49	Female	Dermatologist	Online	High
16	38	Male	Security Guard	Offline	High
17	51	Female	Housewife	Online	High
18	12	Female	Student	Offline	Moderate
19	66	Female	Retired	Offline	High
20	45	Male	Security Guard	Online	High
21	23	Male	Student	Offline	Moderate
22	45	Female	Security Guard	Online	High
23	67	Male	Retired	Online	High
24	55	Male	Dermatologist	Online	High
25	14	Male	Student	Online	Low
26	12	Male	Student	Online	High
27	37	Male	Waiter	Online	High
28	36	Male	Waiter	Online	High
29	32	Female	Chef	Online	High
30	21	Male	Student	Online	High

The user testing demographic table consists of 30 participants, including a diverse range of ages, occupations, and satisfaction levels. The majority of participants are students, with ages predominantly between 12 and 27, but also includes professionals such as dermatologists, security guards, housewives, chef, and retirees, extending up to the age of 67. The gender distribution is relatively balanced, with a slight female majority. Most users accessed the platform online, while a smaller segment used offline methods. Satisfaction levels vary, with a notable majority reporting high satisfaction, although there are instances of moderate and low satisfaction, particularly among students.

Table 3 User Feedback Analysis

Satisfaction Level	Number of Users	Percentage
High	22	73.33%
Moderate	6	20.00%
Low	2	6.67%

Based on the respondents' answers and the analysis made, it can be concluded that the usability of "CutiScan" is on a positive scale. The majority of users reported high satisfaction with the system, indicating that the application effectively meets user needs and expectations. The feedback gathered during usability testing has provided valuable insights into areas for further improvement, ensuring that "CutiScan" continues to evolve and enhance the user experience.

### Compatibility Testing

"CutiScan" functioned correctly across all tested browsers and devices, displaying consistent performance and user interface, thus ensuring accessibility and usability for a broad user base.

Table 4 Environment Compatibility Testing

Platform	Browser	Device	Result
Windows	Google Chrome	Desktop	PASS
Windows	Firefox	Desktop	PASS
MacOS	Google Chrome	Desktop	PASS



MacOS	Safari	Desktop	PASS
MacOS	Baidu	Desktop	PASS
Android	Google Chrome	Mobile Phone	PASS
Android	Baidu	Mobile Phone	PASS
IOS	Google Chrome	iPhone	PASS
IOS	Safari	iPhone	PASS
IOS	Safari	iPad	PASS

Only JPEG, JPG, and PNG formats are accepted and processed by the system. Unsupported formats such as GIF, MP4, and PDF are not accepted, ensuring the system handles only appropriate image data.

Table 5 Image Format Compatibility Testing

Image Format	Result	Notes
JPEG	PASS	Image uploaded and processed correctly
JPG	PASS	Image uploaded and processed correctly
PNG	PASS	Image uploaded and processed correctly
GIF	FAIL	Unsupported file format
MP4	FAIL	Unsupported file format
PDF	FAIL	Unsupported file format

### Proposed Improvements

After conducting a thorough study, in order to enhance “CutiScan”, the AI-driven dermatology diagnosis system, several key improvements are proposed.

Expanding the dataset to include a wider range of skin conditions will increase the system's comprehensiveness and diagnostic accuracy. Providing users with detailed instructions on capturing high-quality images, along with real-time feedback on image quality, will further enhance user engagement and outcomes.

Additionally, integrating the system with teledermatology services would allow users to consult with professional dermatologists for more complex cases, effectively blending AI capabilities with human expertise. Developing a mobile application would improve accessibility, enabling users to perform self-diagnoses directly from their smartphones.

Lastly, transitioning from Ngrok to a dedicated hosting solution with a permanent domain name for “Cutiscan” will provide users with a consistent and professional web address. These improvements will significantly enhance the overall user experience and credibility of the platform, paving the way for future advancements in dermatological care.

## CONCLUSION

The development of the “CutiScan” system marks a significant step towards making dermatological care more accessible and efficient. While the system has demonstrated its potential in accurately diagnosing common skin conditions, ongoing improvements and expansions are essential for maintaining its relevance and effectiveness. The integration of AI in healthcare, as exemplified by this project, holds great promise for addressing the challenges posed by the shortage of dermatologists and the rising prevalence of skin diseases. Continued research and development in this field will be crucial for realizing the full potential of AI-driven diagnostic tools in improving patient care.

### System Strength

#### 1. Accuracy and Reliability:

The AI model, InceptionV3, was selected based on its superior performance in terms of accuracy, precision, recall, and F1 score compared to other models like ResNet50 and VGG16. This ensures reliable diagnostic results for users.

## 2. User-Friendly Interface:

The web-based platform features an intuitive and easy-to-navigate interface, making it accessible to users with basic computer skills. This is crucial for ensuring widespread adoption and usability.

## 3. Cost-Efficiency:

By providing a convenient self-diagnosis tool, the system helps reduce the need for in-person dermatologist visits for non-severe conditions, saving time and money for users.

## System Weaknesses

### 1. Limited Scope of Diagnosable Conditions:

The system currently covers a finite number of common skin diseases, which may limit its comprehensiveness. Rare conditions are not included due to the lack of extensive training data.

### 2. Dependence on Image Quality:

The accuracy of the diagnosis heavily relies on the quality of the uploaded images. Poor image quality can lead to misdiagnosis, which highlights the need for users to upload clear and well-lit images.

### 3. Need for Continuous Improvement:

AI models require continuous training and updating to maintain their accuracy and adapt to new data. This necessitates ongoing efforts in data collection and model refinement.

## APPRECIATION

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I would like to thank all third-year undergraduate students of FTSM for their help, friendship, and creating a pleasant studying environment throughout my years in UKM.

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