A User-friendly Platform for Skin Disease Identification and Self-evaluation with Deep Learning

UNDER THE GUIDENCE OF

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Introduction

- Skin covers the entire body and plays a crucial role in protecting against infection.
- Automated computer applications for skin disease identification are essential.
- Installation of such applications in medical facilities like rural health clinics is necessary.
- Remote areas often lack access to skin specialists, making automated diagnosis crucial.
- These applications aid in early detection and timely treatment of skin conditions.
- Improved access to skin disease classification enhances healthcare outcomes in underserved regions.

Abstract

- This project uses advanced deep learning technology called convolutional neural networks (CNNs) to identify skin diseases.
- This method is non-invasive and affordable, enabling early diagnosis and treatment.
- Tests show the model works well, making it a valuable tool in dermatology.
- We've also created a user-friendly website where people can upload images for diagnosis, access prevention tips, and get detailed reports.
- This approach improves dermatological care, leading to better patient outcomes and advancing precision medicine.

Existing System

- Diagnosing skin diseases relies heavily on visual examination by dermatologists, but this method is time-consuming, subjective, and prone to errors.
- Accessibility to dermatologists is limited, leading to delays in diagnosis and treatment. Misdiagnosis or delayed diagnosis can have serious consequences.
- The existing system lacks scalability and efficiency, particularly in high-demand areas.

Proposed System

- A deep learning-based system for skin disease identification provides quick and accurate diagnoses, ensuring timely treatment.
- It minimizes human error and misdiagnosis through computing algorithms. Enhancing healthcare accessibility, it bridges gaps in specialist availability, especially in remote areas.
- Utilizing annotated datasets, it learns patterns to improve identification across various conditions.
- Healthcare professionals can upload images via a user-friendly interface, receiving real-time predictions and detailed condition information.

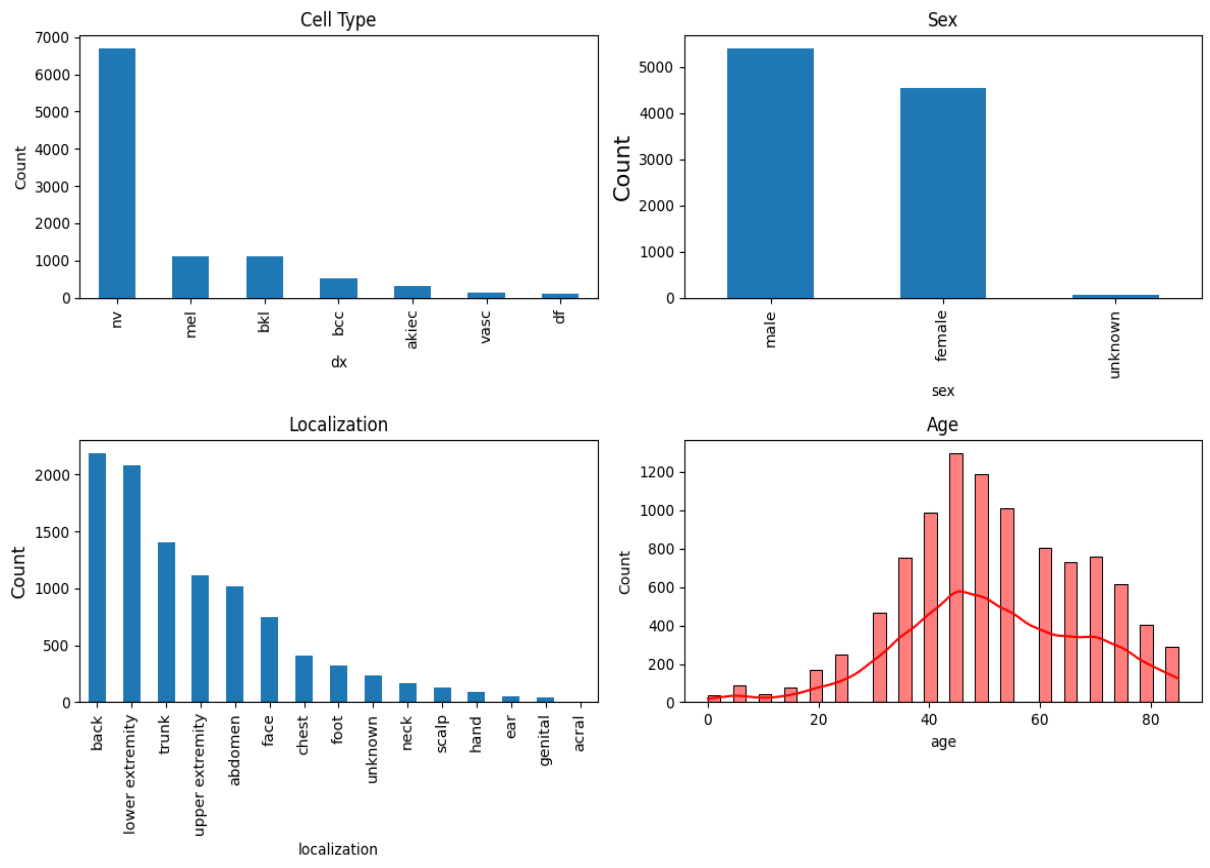
Dataset Overview

- This the HAM10000 (”Human Against Machine with 10000 training images”) dataset.
- It consists of 10015 dermatoscopic images which are released as a training set for academic deep learning purposes and are publicly available through the ISIC archive.
- It has 7 different classes of skin cancer which are listed below:

1. Melanocytic nevi
2. Melanoma
3. Benign keratosis-like lesions
4. Basal cell carcinoma
5. Actinic keratoses
6. Vascular lesions
7. Dermatofibroma

A	B	C	D	E	F	G
lesion_id	image_id	dx	dx_type	age	sex	localization
HAM_0000118	ISIC_0027419	bkl	histo	80	male	scalp
HAM_0000118	ISIC_0025030	bkl	histo	80	male	scalp
HAM_0002730	ISIC_0026769	bkl	histo	80	male	scalp
HAM_0002730	ISIC_0025661	bkl	histo	80	male	scalp
HAM_0001466	ISIC_0031633	bkl	histo	75	male	ear
HAM_0001466	ISIC_0027850	bkl	histo	75	male	ear
HAM_0002761	ISIC_0029176	bkl	histo	60	male	face

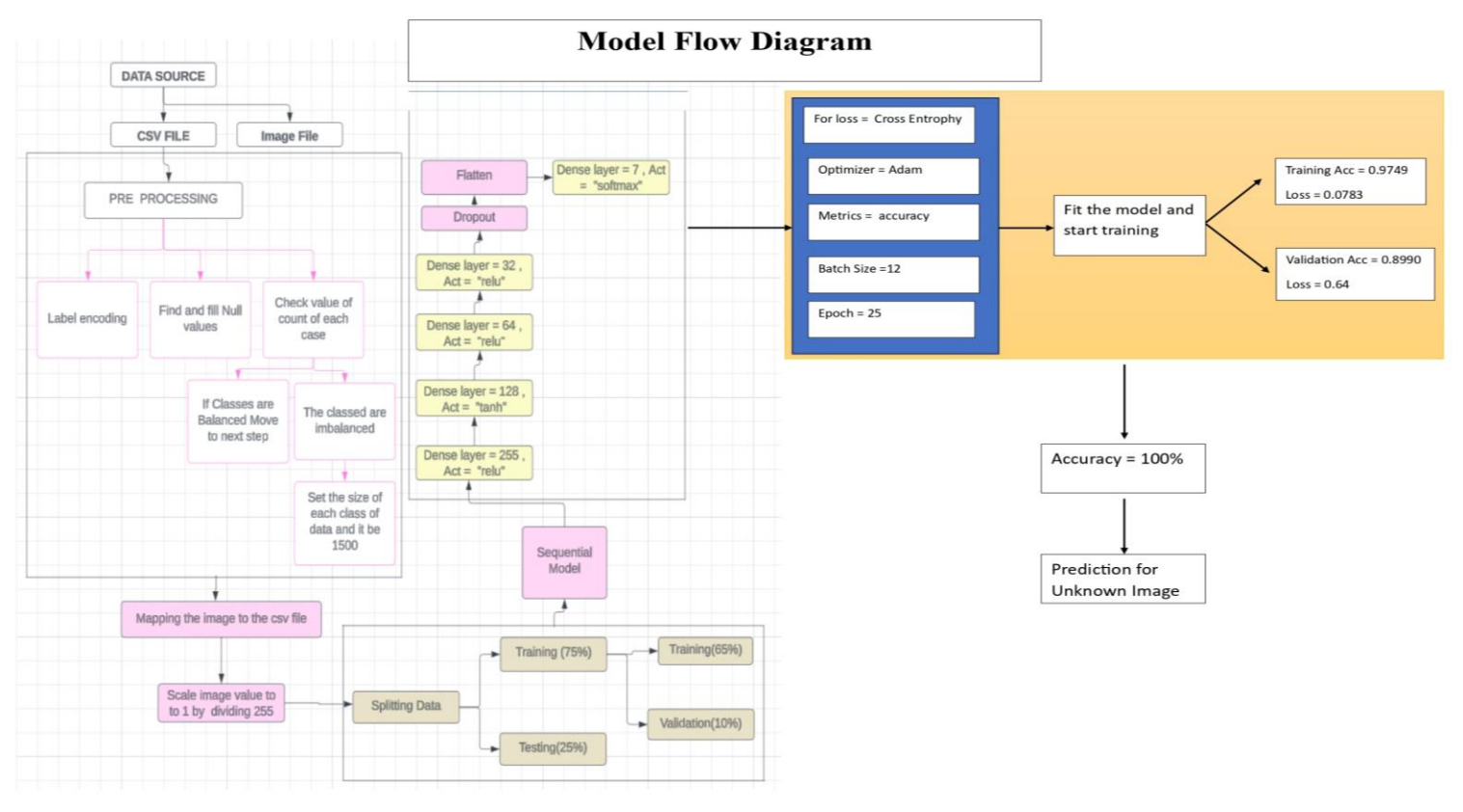
Observation



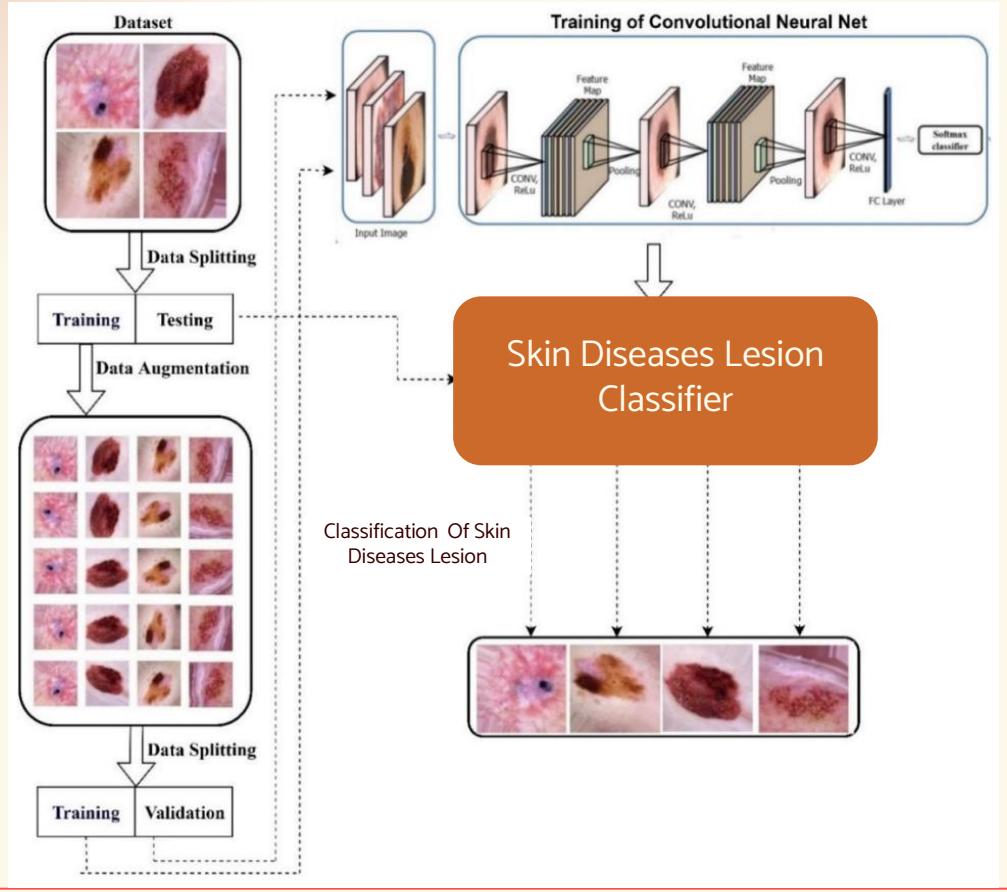
Observation

- The main thing to keep in mind is the unbalance between the different classes of skin lesion. Approximately **67% of** data accounts for **Melanocytic Nevi samples.**
- The **least** represented classes are **Dermatofibroma lesions and Vascular skin lesions**, with only 115 and 142 samples, respectively.
- The samples are mostly Male participants, approximately 55%, **not a significant difference between Genders.**
- It seems back , lower extremity, trunk and upper extremity are **heavily compromised regions** of skin diseases.
- It seems that there are **larger instances** of patients having age from 30 to 60.
- The samples are **predominantly from patients** within **40 - 55 years old**.
- The number of samples rises sharply **after 25 years old**, doubling the samples for **30 years old** and almost doubling again for **35 years old**.

Flow Diagram

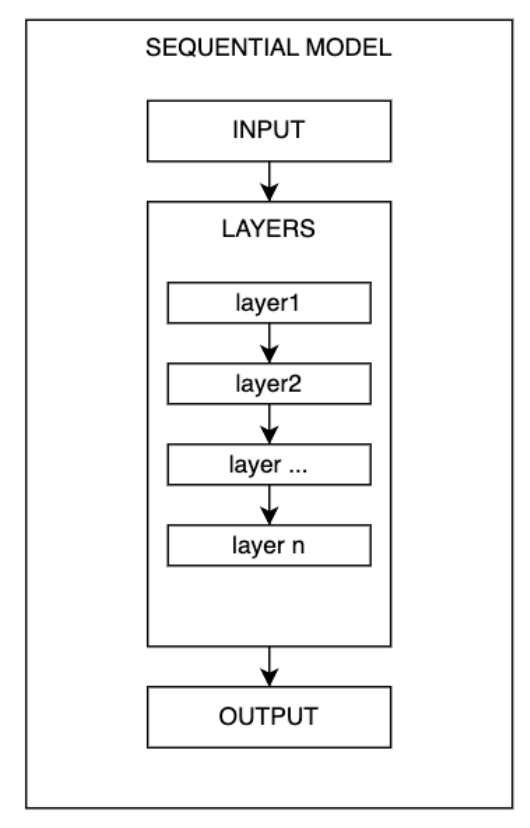


Flow Diagram



Sequential Model

- In deep learning, a sequential model refers to a type of neural network architecture where layers are arranged sequentially, one after the other.
- Each layer in the model receives input from the previous layer and passes its output to the next layer.
- This sequential arrangement allows for the creation of a linear stack of layers, making it one of the simplest and most used architectures in deep learning.
- In a sequential model, each layer typically performs a specific transformation on the input data, such as convolutions, pooling, or dense (fully connected) layers, among others.
- The final layer of the model usually produces the desired output.



Model Summary

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 32, 32, 256)       1024

 dense_1 (Dense)             (None, 32, 32, 128)       32896

 dense_2 (Dense)             (None, 32, 32, 64)        8256

 dense_3 (Dense)             (None, 32, 32, 32)        2080

 dropout (Dropout)           (None, 32, 32, 32)        0

 flatten (Flatten)           (None, 32768)             0

 dense_4 (Dense)             (None, 7)                 229383

=================================================================
Total params: 273639 (1.04 MB)
Trainable params: 273639 (1.04 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

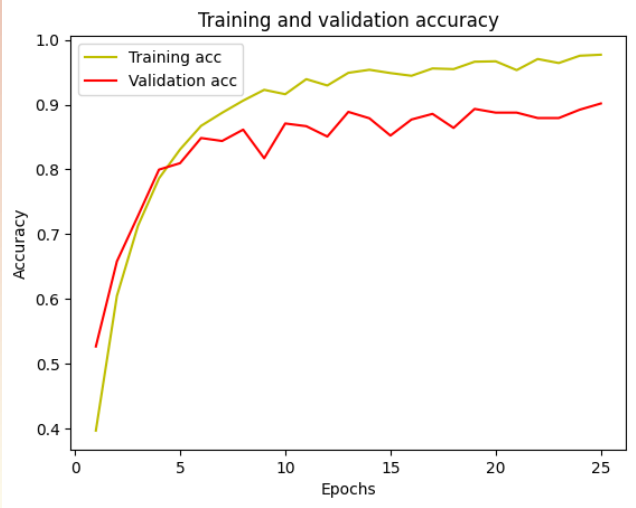
- Number of Classes is **7.**
- Model Used Sequential Model.
  - Layer 1 = **Dense** with **“Relu”** Activation Function.
  - Layer 2 = **Dense** with **“Tanh”** Activation Function.
  - Layer 3 = **Dense** with **“Relu”** Activation Function.
  - Layer 4 = **Dense** with **“Relu”** Activation Function.
  - Layer 5 = **Dropout**
  - Layer 6 = **Flatten**.
  - Layer 7 = **Dense** with **“Softmax”** Activation Function.

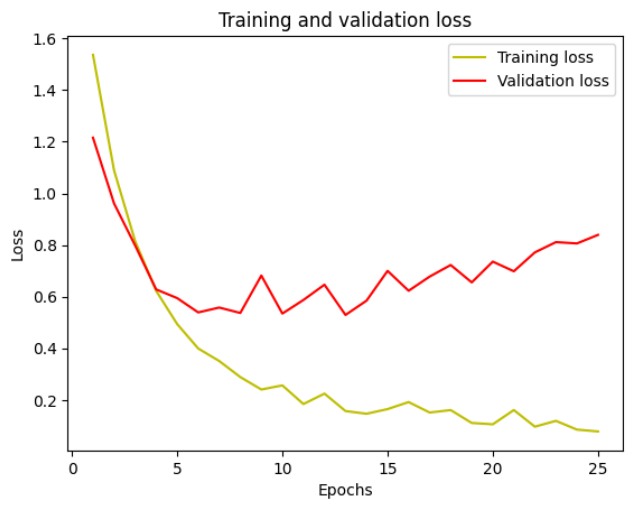
Model Implementation

- Training Size : **70%**
- Validation Size : **20%**
- Testing Size : **10%**
- Loss : **Categorical Crossentropy**
- Optimizer: **Adam**
- Metrics: **Accuracy**
- Batch Size: **12**
- Epoch: **25**

```
657/657 - 36s - loss: 1.5083 - acc: 0.4086 - val_loss: 1.2138 - val_acc: 0.5512 - 36s/epoch - 55ms/step
Epoch 2/25
657/657 - 28s - loss: 1.0692 - acc: 0.6089 - val_loss: 0.9936 - val_acc: 0.6297 - 28s/epoch - 43ms/step
Epoch 3/25
657/657 - 27s - loss: 0.8166 - acc: 0.7081 - val_loss: 0.8363 - val_acc: 0.6930 - 27s/epoch - 42ms/step
Epoch 4/25
657/657 - 28s - loss: 0.6959 - acc: 0.7597 - val_loss: 0.8212 - val_acc: 0.7352 - 28s/epoch - 42ms/step
Epoch 5/25
657/657 - 28s - loss: 0.5336 - acc: 0.8179 - val_loss: 0.6375 - val_acc: 0.7989 - 28s/epoch - 43ms/step
Epoch 6/25
657/657 - 27s - loss: 0.4819 - acc: 0.8354 - val_loss: 0.6868 - val_acc: 0.8107 - 27s/epoch - 42ms/step
Epoch 7/25
657/657 - 28s - loss: 0.4158 - acc: 0.8590 - val_loss: 1.1415 - val_acc: 0.7124 - 28s/epoch - 42ms/step
Epoch 8/25
657/657 - 27s - loss: 0.3754 - acc: 0.8742 - val_loss: 0.6128 - val_acc: 0.8248 - 27s/epoch - 41ms/step
Epoch 9/25
657/657 - 28s - loss: 0.2853 - acc: 0.9051 - val_loss: 0.5710 - val_acc: 0.8564 - 28s/epoch - 43ms/step
Epoch 10/25
657/657 - 27s - loss: 0.2957 - acc: 0.9002 - val_loss: 0.6985 - val_acc: 0.8080 - 27s/epoch - 42ms/step
Epoch 11/25
...
Epoch 24/25
657/657 - 25s - loss: 0.0783 - acc: 0.9745 - val_loss: 0.8178 - val_acc: 0.8811 - 25s/epoch - 38ms/step
Epoch 25/25
657/657 - 25s - loss: 0.0852 - acc: 0.9740 - val_loss: 0.7389 - val_acc: 0.8975 - 25s/epoch - 38ms/step
```

Performance Metrics & Result





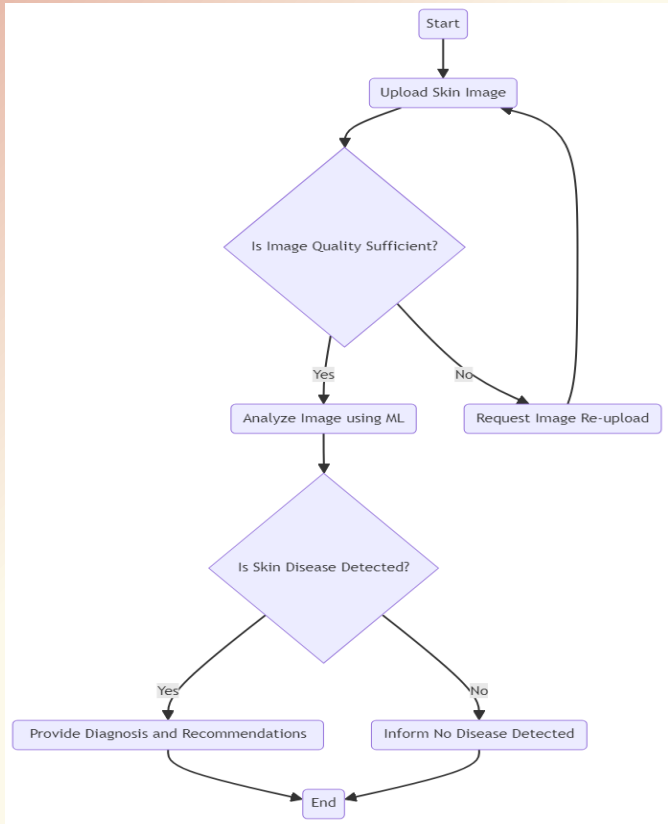
Training Accuracy : **97%**

Validation Accuracy : **90%**

Training Loss : **0.0783**

Validation Loss : **0.8393**

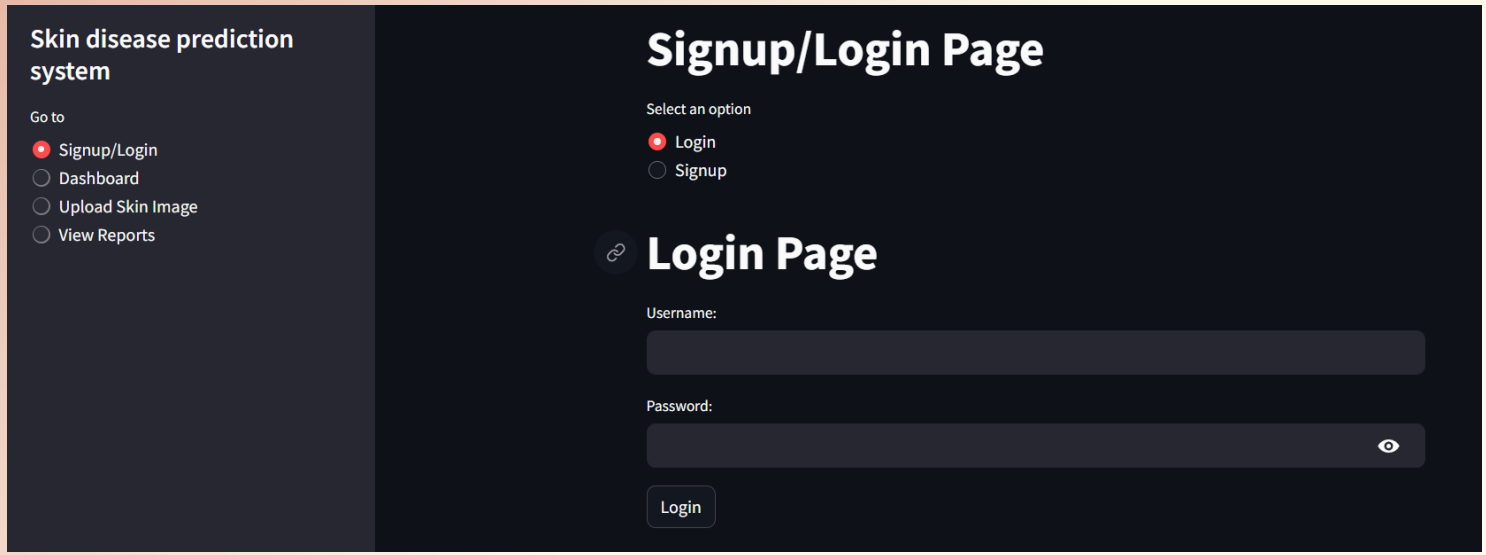
User Friendly Interface



The process starts with uploading an image of the skin.

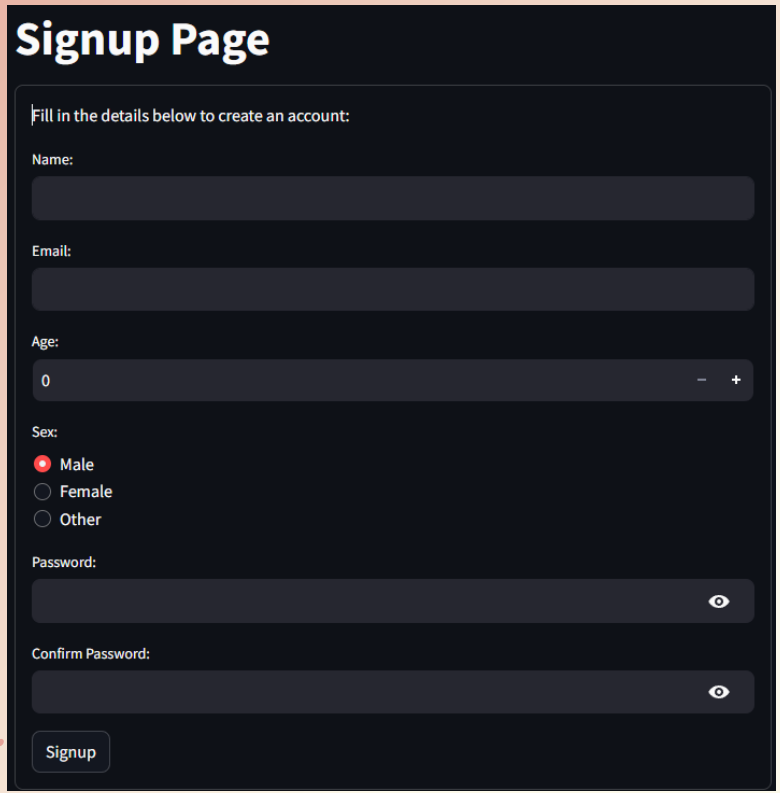
- The system then assesses whether the image quality is sufficient for analysis.
- If the image quality is sufficient, a deep learning model analyzes the image to detect the presence of a skin disease.
- If a skin disease is identified, the system provides diagnoses and recommendations.
- On the other hand, if the image quality is insufficient or no skin disease is detected, the system informs the user accordingly.

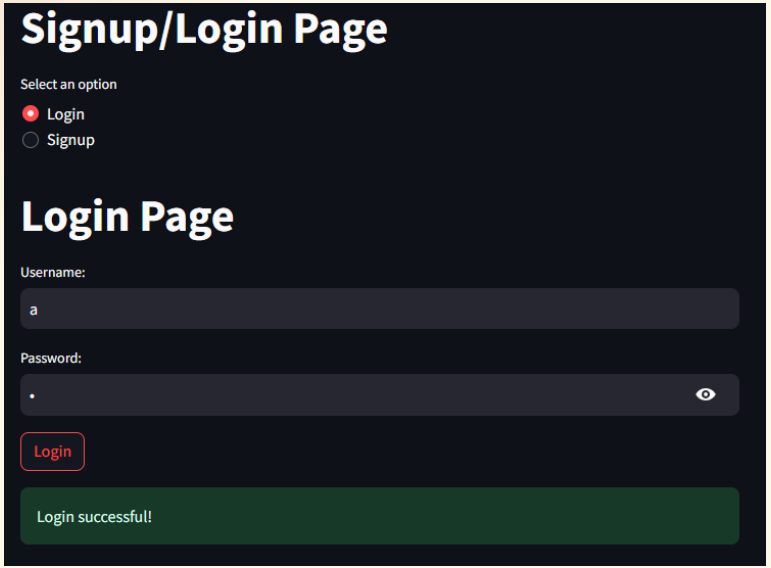
Screenshot Of Host Website



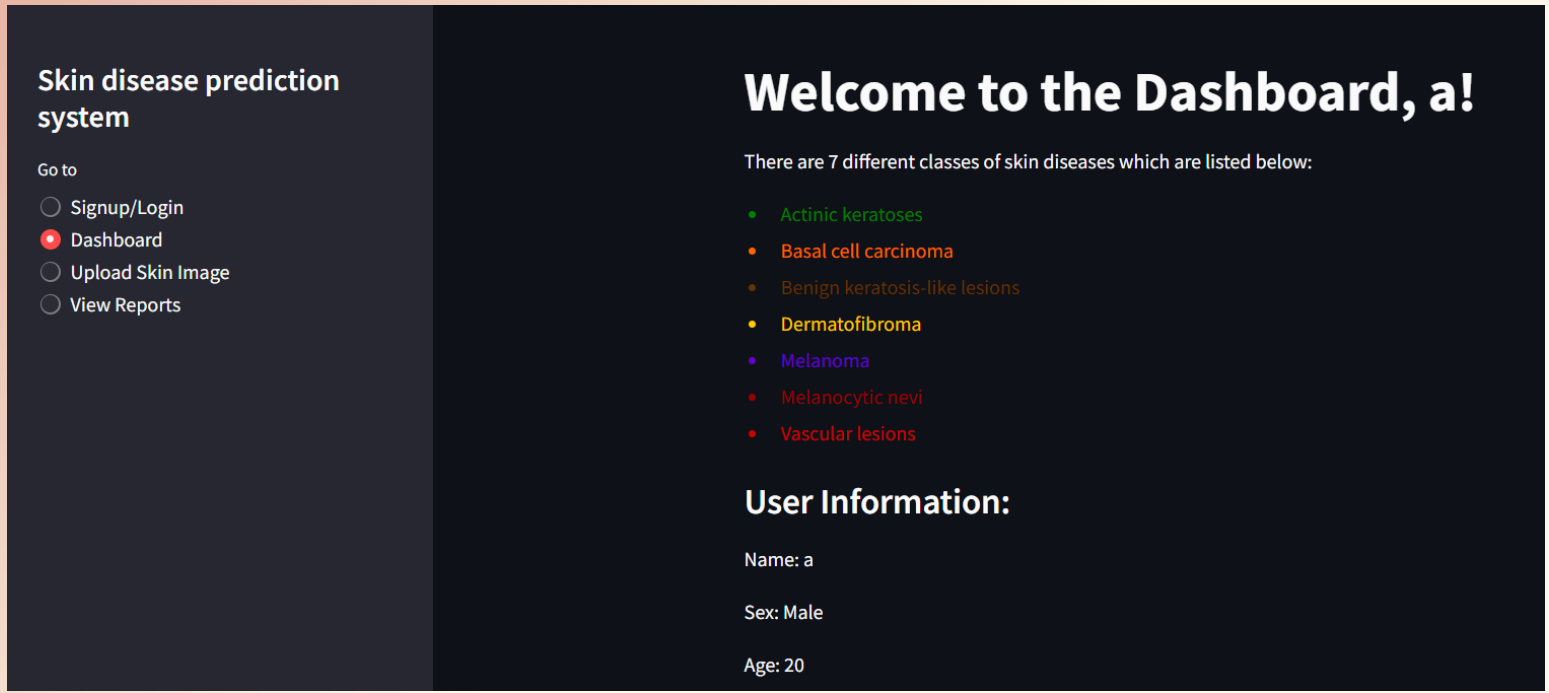
Webpage for skin disease identification

Signup & Login to the site

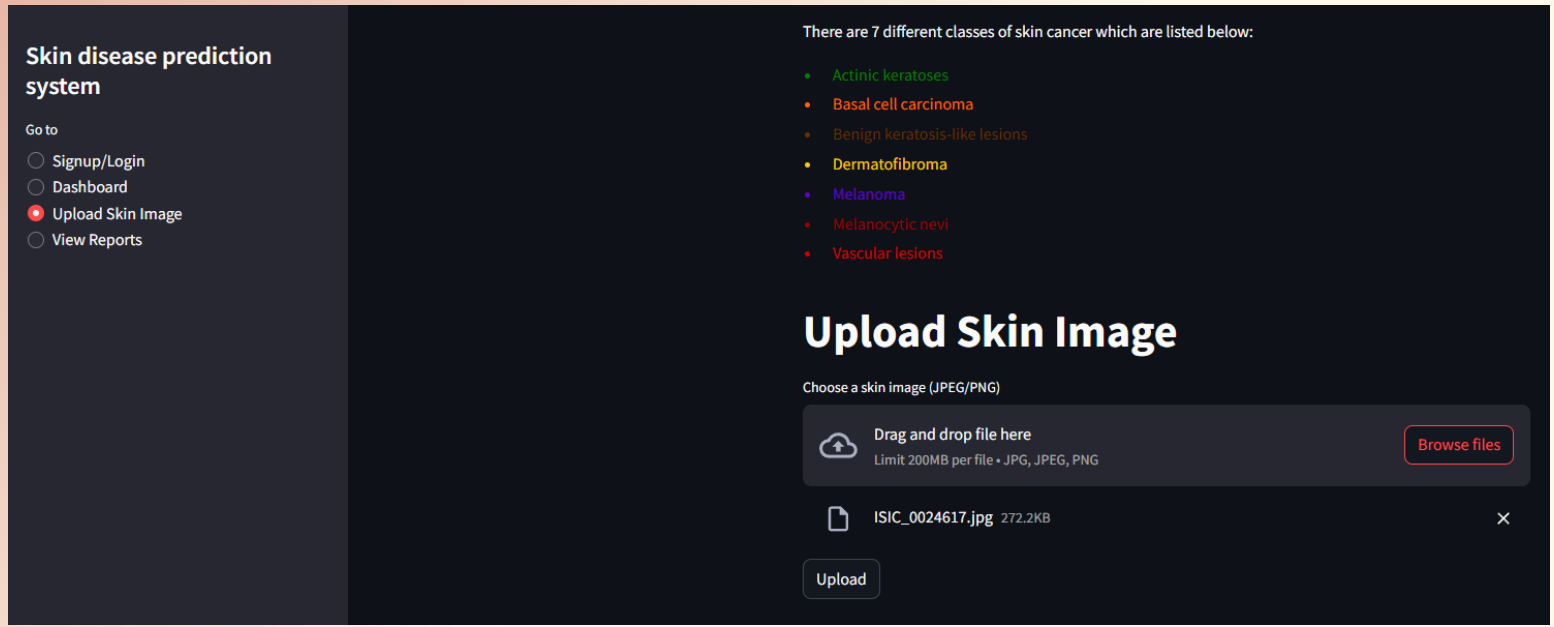




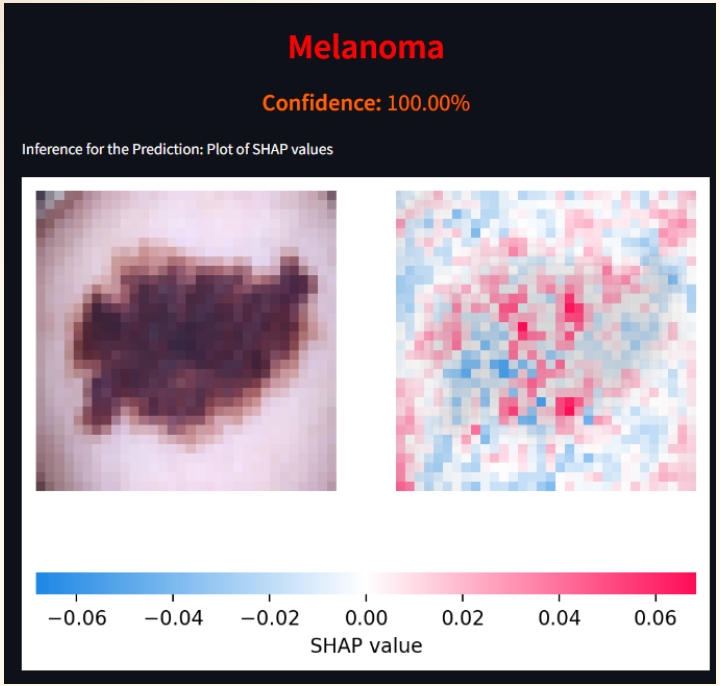
Dashboard to the User



To Upload the Image



After Upload the Image



Report of the Patient

Conclusion

Result :

- Deep learning techniques demonstrated high accuracy in identifying skin diseases using image datasets, indicating potential for automated diagnosis.
- The research underscores deep learning's capacity to enhance early detection and classification of skin conditions, potentially reducing diagnostic errors and improving patient outcomes, thus revolutionizing dermatology.

Conclusion:

- The use of deep learning in skin disease identification shows significant promise in improving diagnosis accuracy and efficiency, By leveraging algorithms, healthcare professionals can analyze large datasets of skin images to identify patterns and classify different skin diseases with high accuracy.
- This technology can assist in early detection, leading to timely intervention and improved patient outcomes. However, further research is needed to refine these algorithms and ensure their effectiveness in real-world settings.

Future Scope

- Integration with telemedicine platforms and mobile applications can make skin disease diagnosis more accessible and convenient for patients.
- Collaboration with dermatologists and healthcare providers can ensure the development of reliable and efficient diagnostic tools for early detection and treatment of skin diseases.

References

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THANK YOU