

# Skin Lesion Classification Using Deep Learning

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An Application of CNN for Multi-class  
Skin Disease Prediction

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# About Skin Lesions



- What is a Skin Lesion ?

A skin lesion is any abnormal change or growth on the skin, such as moles, sores, or discolorations.

Lesions are categorized into benign (non-cancerous) or malignant (cancerous) types.

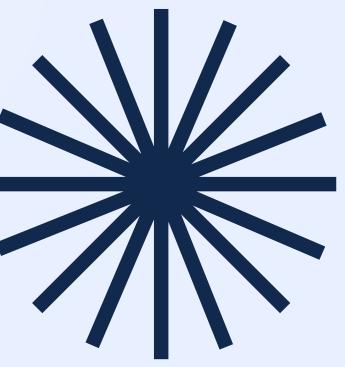
- Causes of Skin Lesions:

-UV Radiation: Sun or tanning bed exposure damages skin cells, increasing cancer risk.

-Genetics: Family history raises the risk of skin lesions, especially cancer.

-Inflammation/Infections: Conditions like acne or eczema cause lesions through ongoing irritation.

# Project Overview



- The Problem:

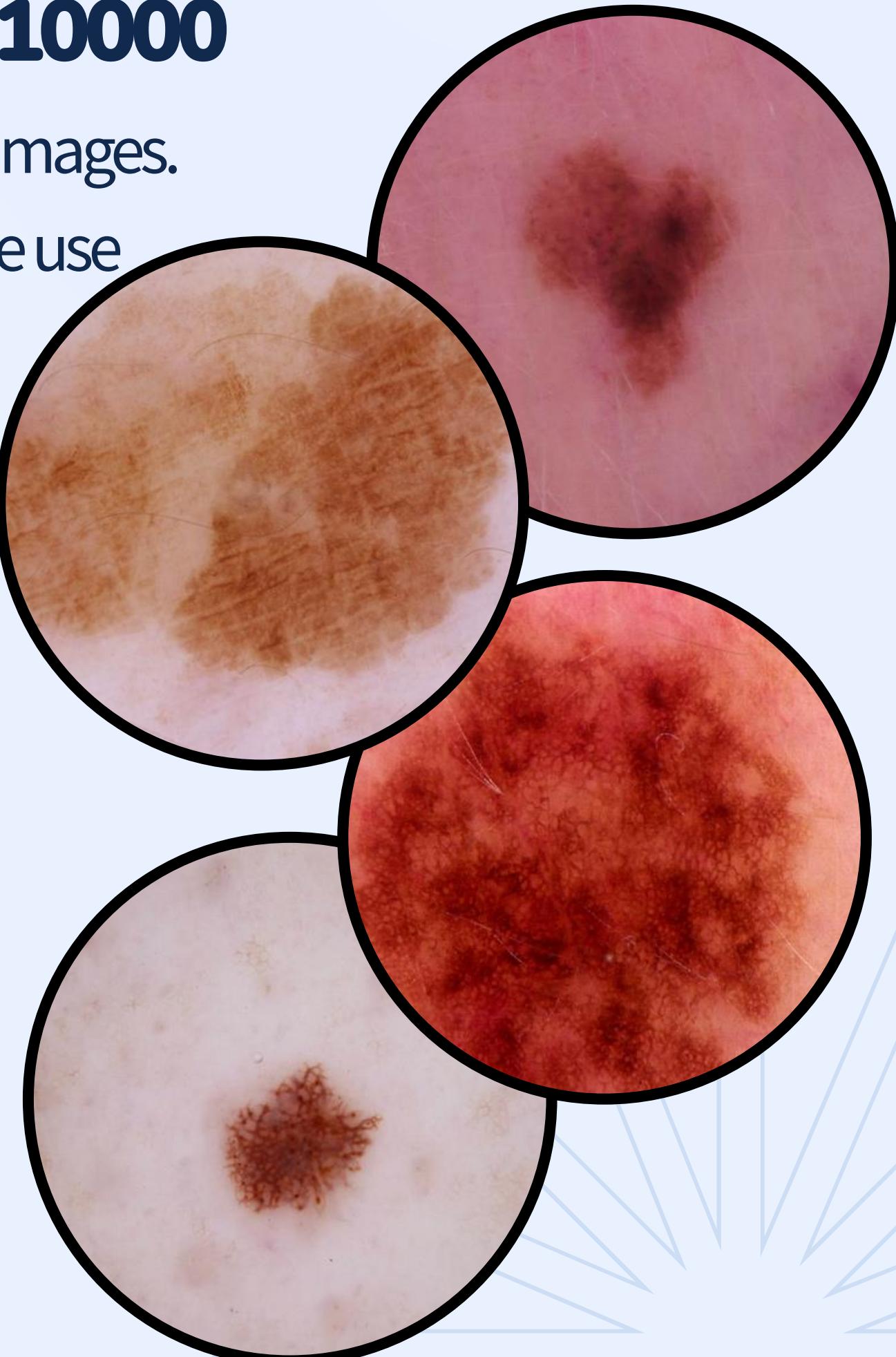
Accurately diagnosing skin cancer is challenging due to the need to distinguish between various types of lesions. Misdiagnosis can lead to treatment delays and negatively impact patient outcomes.

- Why We Choose This Project:

We chose this project to assist doctors in quickly and accurately diagnosing skin lesions.

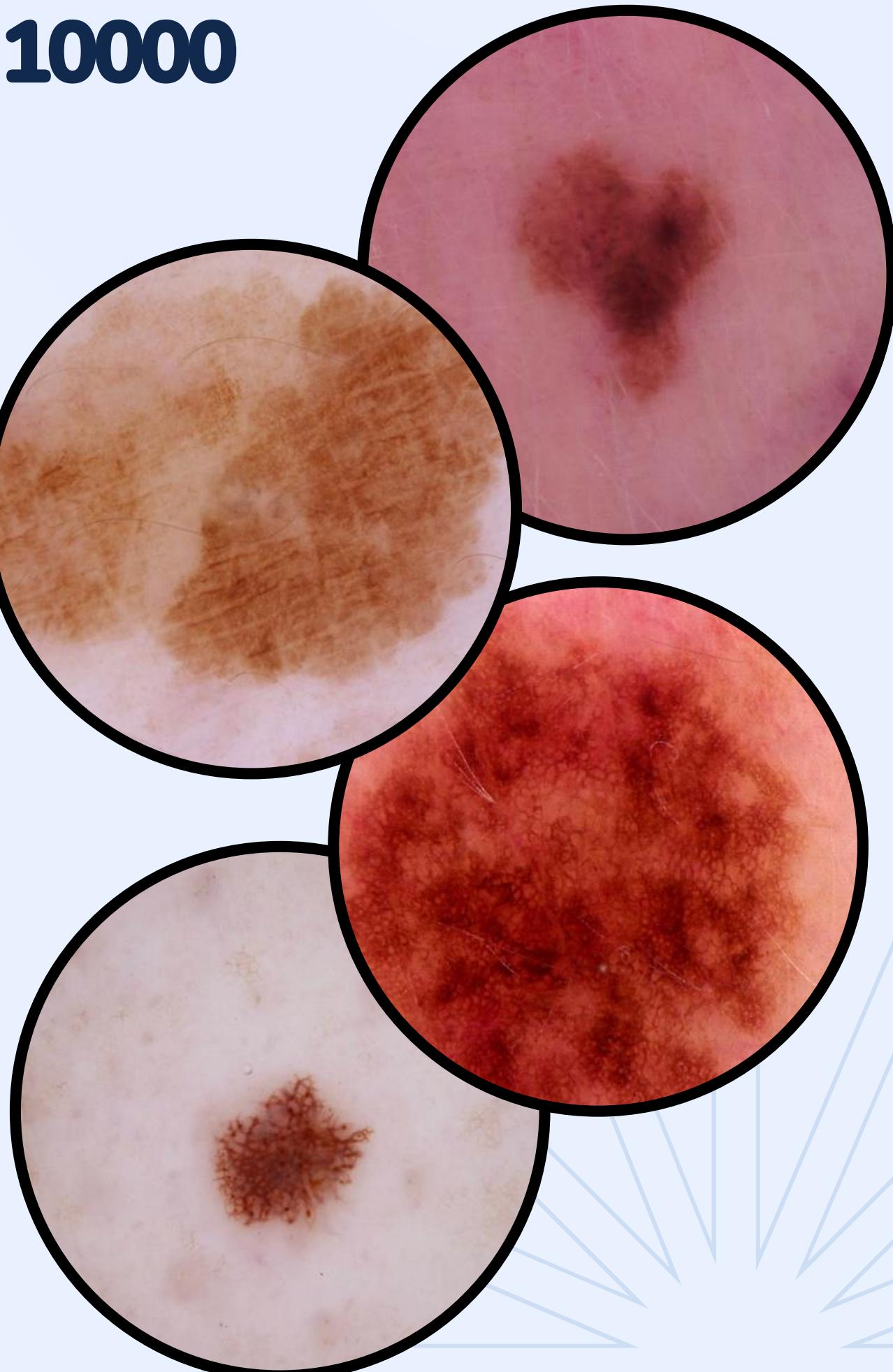
# Dataset Overview: Skin Cancer MNIST: HAM10000

- HAM10000: Human Against Machine with 10,000 Dermatoscopic Images.
- The dataset consists of images and associated with csv text file . We use these modalities together in a multi-class classification model .
- The dataset contains the following columns:
  - `lesion_id`: A unique identifier for each lesion.
  - `image_id`: The corresponding ID for each image in the dataset.
  - `dx`: The diagnosis label for the lesion (e.g., bkl, nv, mel, etc.).
  - `dx_type`: The method used to confirm the diagnosis (e.g., histopathology, follow-up).
  - `age`: The age of the patient.
  - `sex`: The gender of the patient (male or female).
  - `localization`: The anatomical location of the lesion on the body (e.g., scalp, back, etc.).



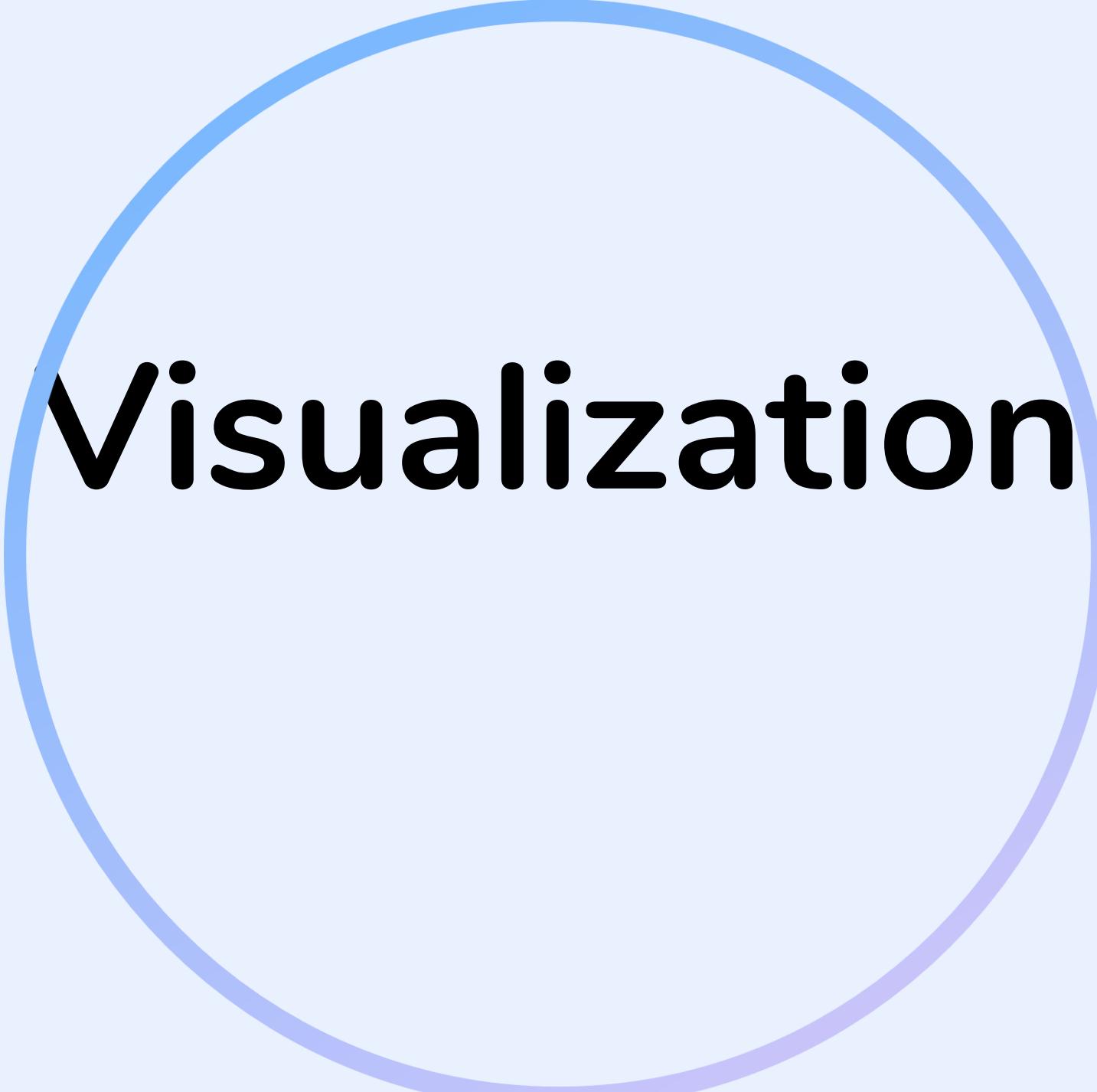
# Dataset Overview: Skin Cancer MNIST: HAM10000

- The dataset contains labeled skin lesion images for 7 different classes:
  - bkl (Benign Keratosis-like lesions)
  - nv (Melanocytic Nevi)
  - df (Dermatofibroma)
  - mel (Melanoma)
  - vasc (Vascular Lesions)
  - bcc (Basal Cell Carcinoma)
  - akiec (Actinic Keratoses and Intraepithelial Carcinoma)

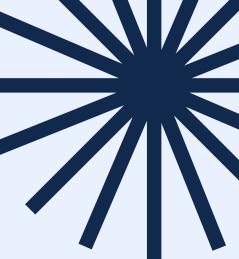


# Essential Phases of the Workflow

- Visualization
- PreProcessing
- Model Architecture
- Evaluation



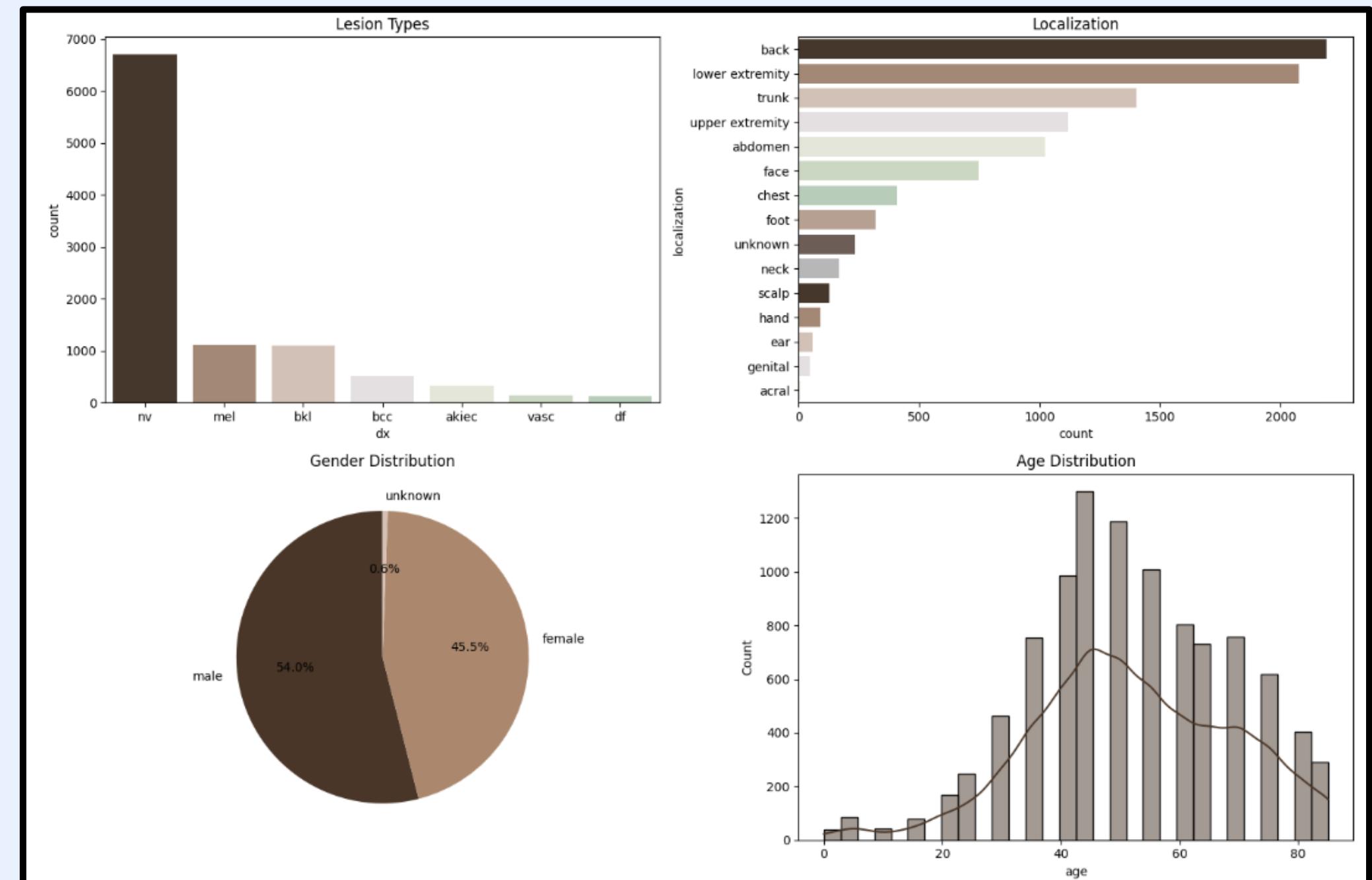
**Visualization**

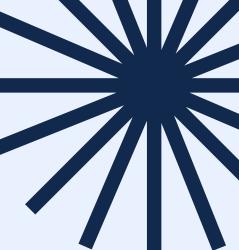


# visualization of data

At first ,We visualized relationships representing the distribution of various dataset features, such as :

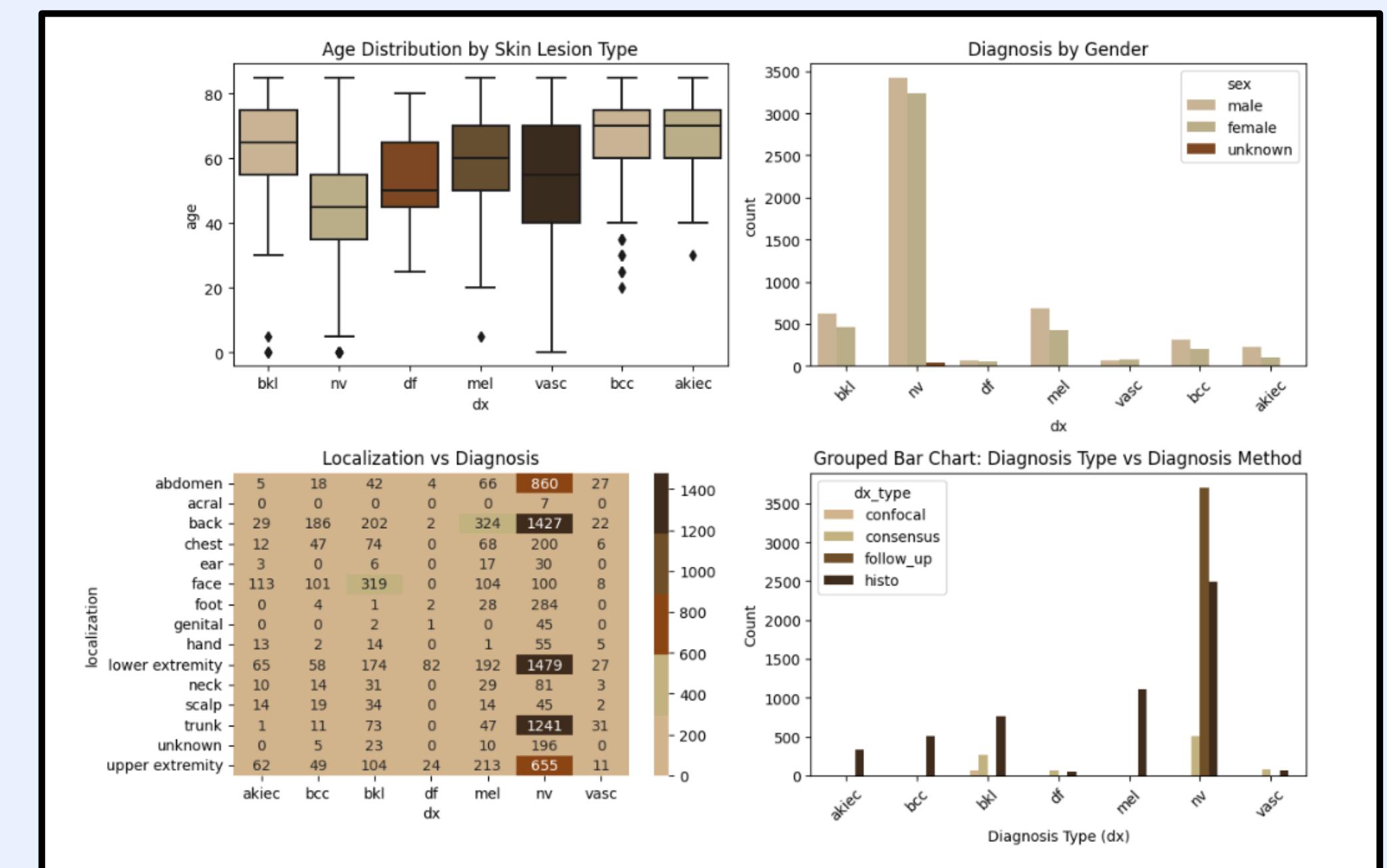
- lesion types count using bar chart.
- lesion locations count using horizontal bar chart .
- gender count using pie chart.
- age distribution using histogram and density curve.





Next, we explored relationships between various features to uncover patterns, such as:

- how age varies across lesion types using poxplot
- gender distribution for each diagnosis using countplot
- lesion localization trends using heatmap.
- the diagnostic methods used for each lesion type using grouped barchart.



# After visualization for image and text data

we know that

- Data is imbalanced
- Find null value
- Find unnecessary column
- Find categorical columns

these all will solved in preprocessing  
stage





**Preprocessing**

**P**Preprocess on images data

**P**Preprocess on text data

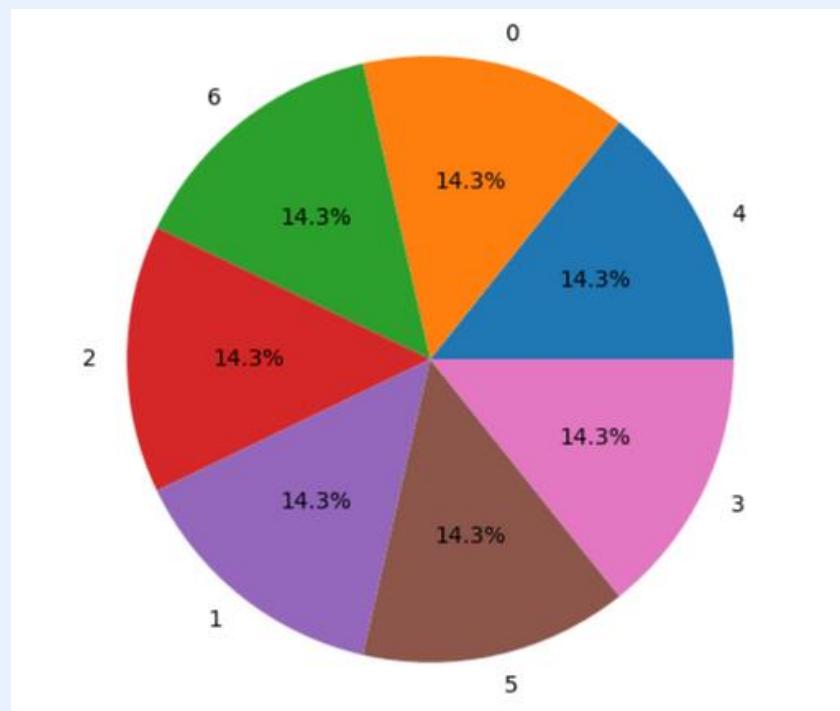
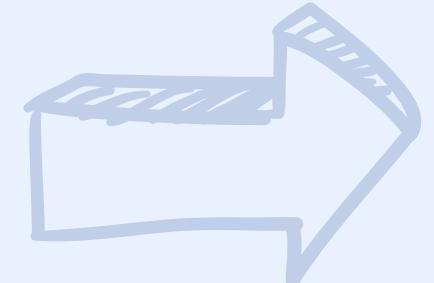
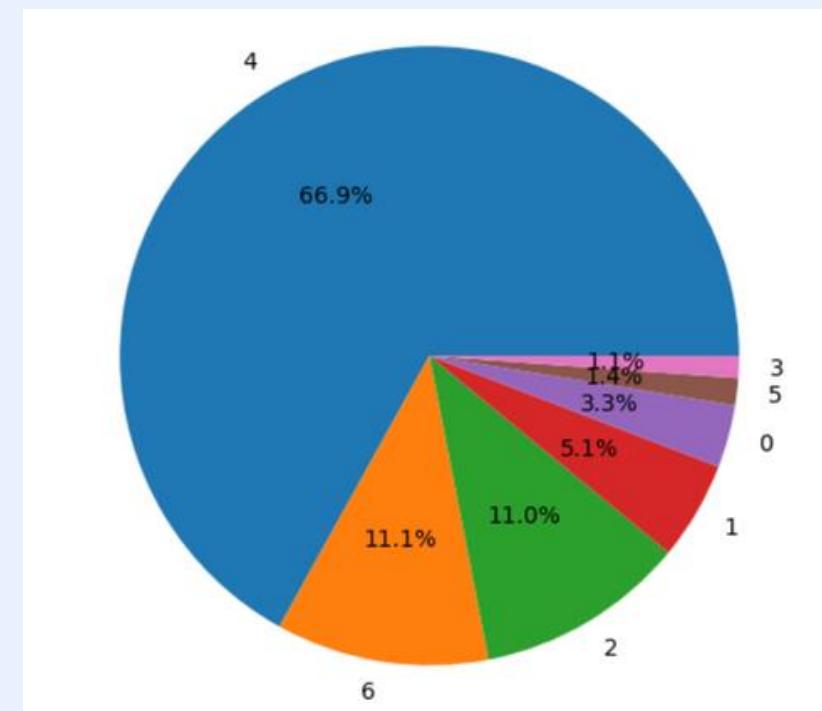
# Preprocessing on images:

## Normalization

scaling data to a specific range  $[0, 1]$ , to improve model performance by ensuring consistent feature magnitudes.

## Augmentation

to solve Imbalanced image data problem



# Preprocessing on Table

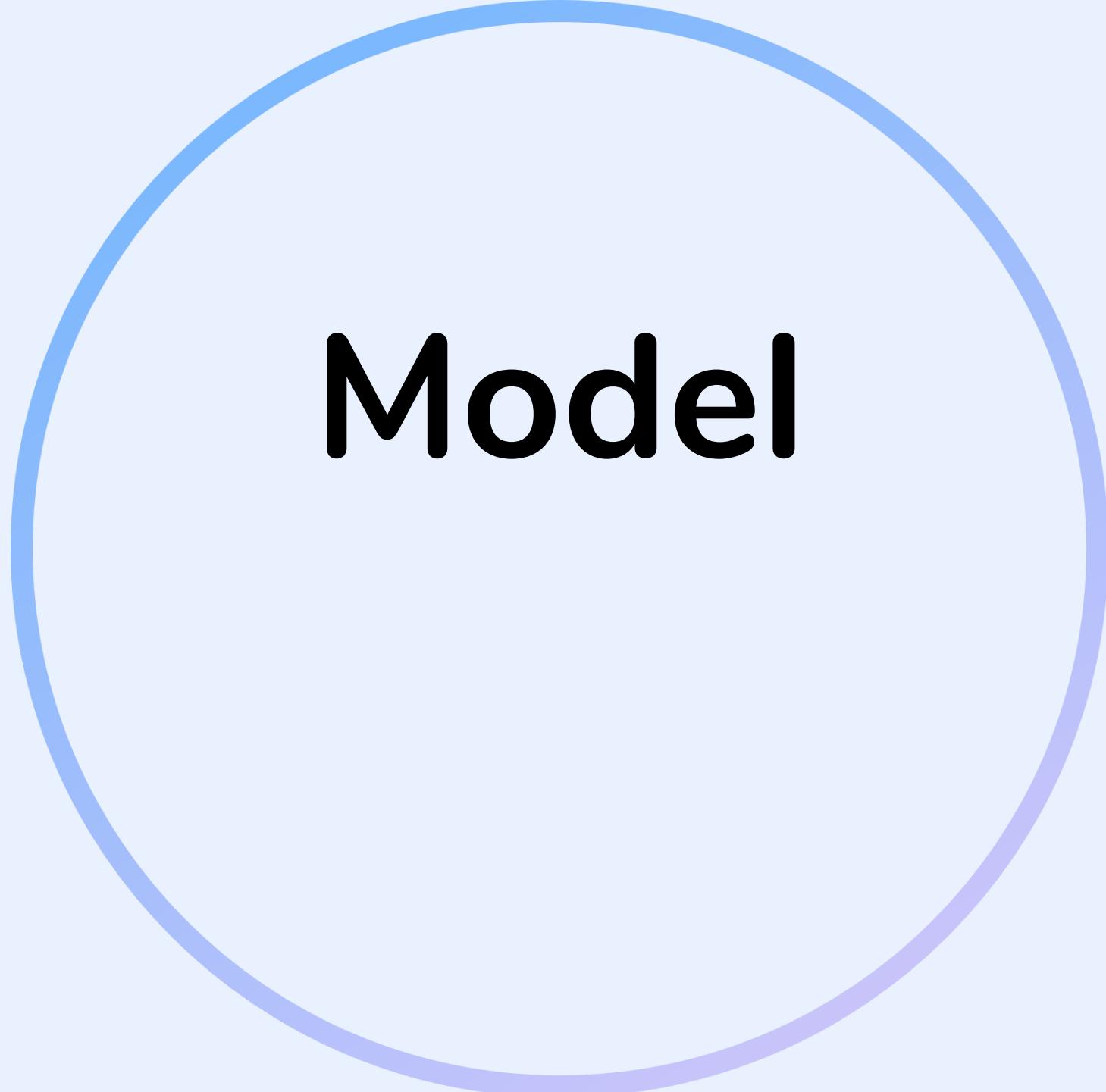
Drop Unnecessary Columns

Handle category columns

Handle Imbalance

Handle Missing value

scale



**Model**

# Model Architecture

- Model on images:

A Convolutional Neural Network (CNN) is used to classify skin lesions into 7 categories. The model includes:

- Input Shape: (28, 28, 3).
- Convolutional Blocks: Three blocks with increasing filters (32, 64), ReLU activation, MaxPooling, and Dropout for regularization.
- Fully Connected Layers: Two dense layers (64, 128 units) and ReLU activation.

- Model on Table:

- input shape: (4,).
- Fully connected layer (16) with ReLU activation.



# Model Architecture

- Combine two models:
  - Combine two models and enter them to another fully connected layers.
  - 5 Fully connected layers (128, 64, 32, 16, 7) with ReLU and SoftMax activation for classification output.
- Model training:
  - Loss Function: Sparse Categorical Crossentropy.
  - Optimizer: Adam
  - Callbacks: EarlyStopping, ModelCheckpoint, and ReduceLROnPlateau for efficient training.

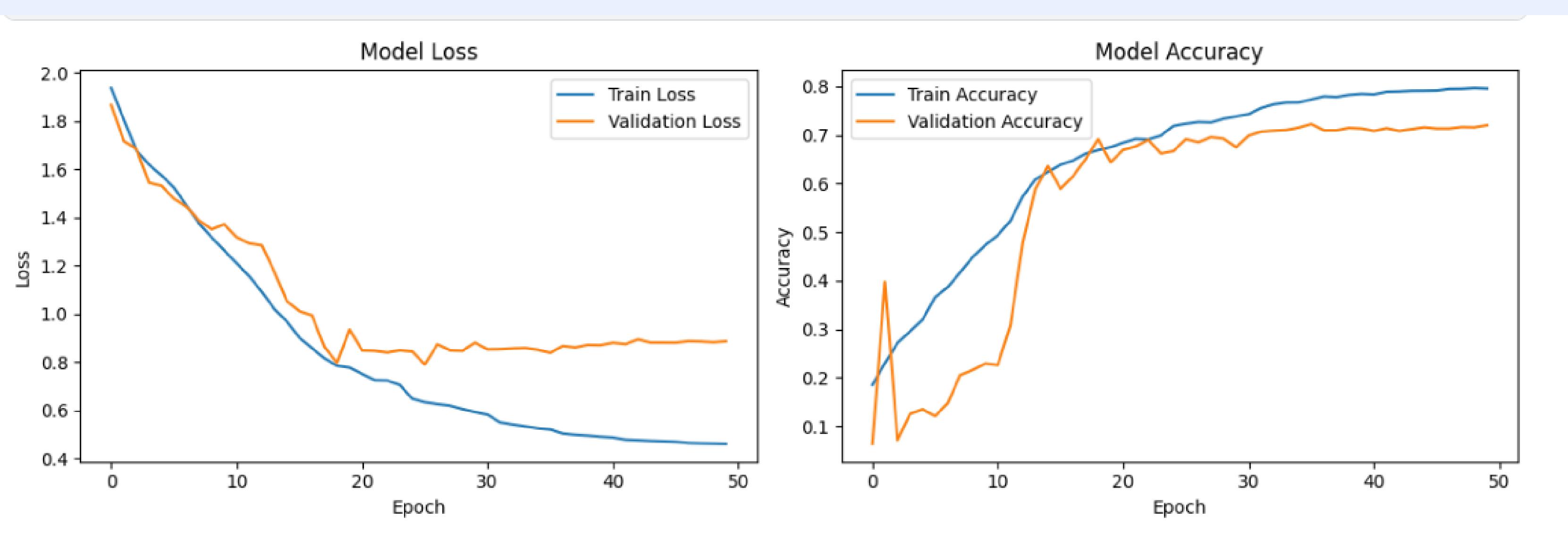




**Evaluation**

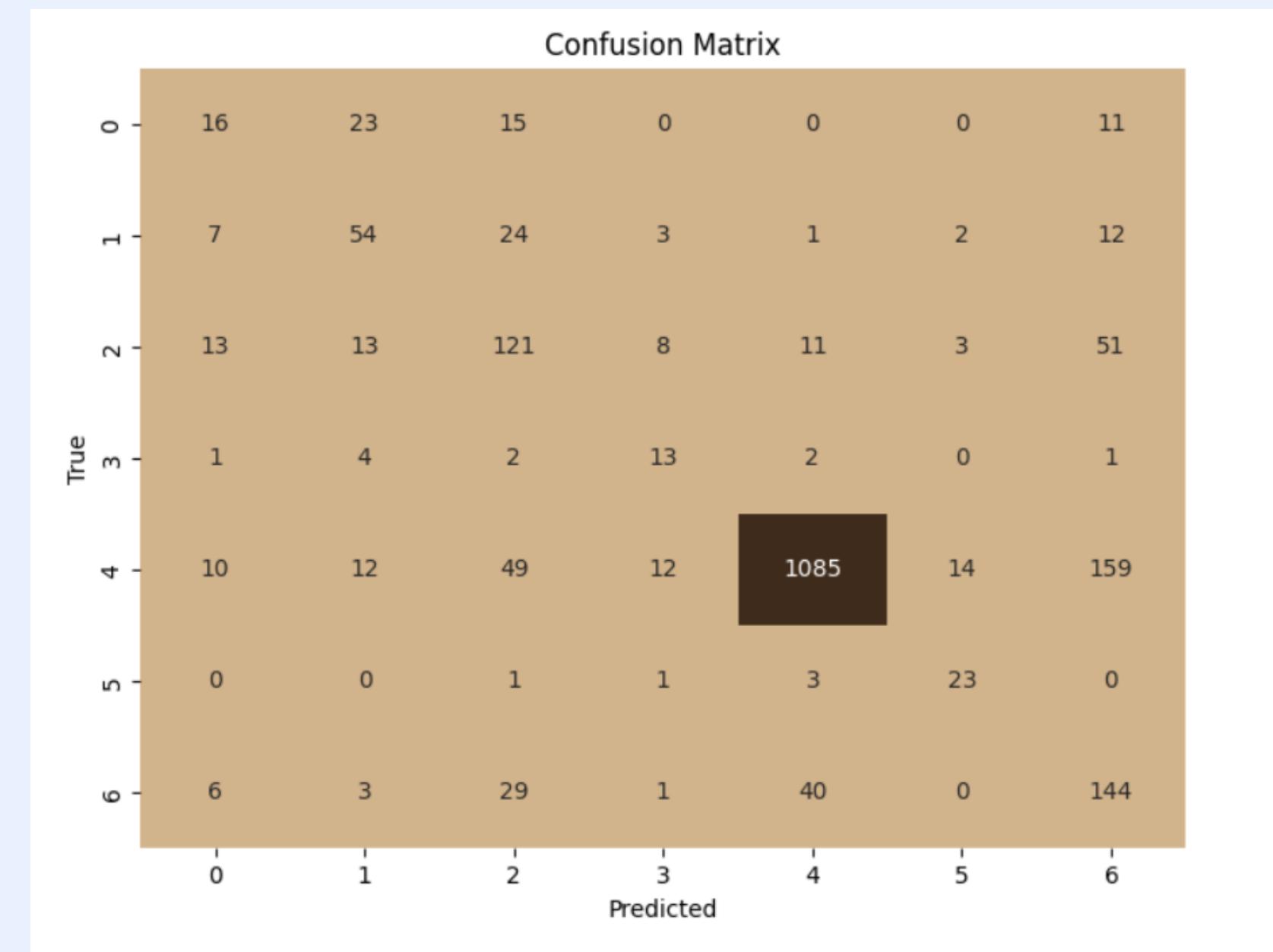
# Model Performance Analysis

- Both Training Accuracy and Validation Accuracy improve over time, demonstrating that the model captures meaningful features from the data.
- Validation Accuracy stabilizes at a satisfactory level, showing the model's ability to generalize well to unseen data.

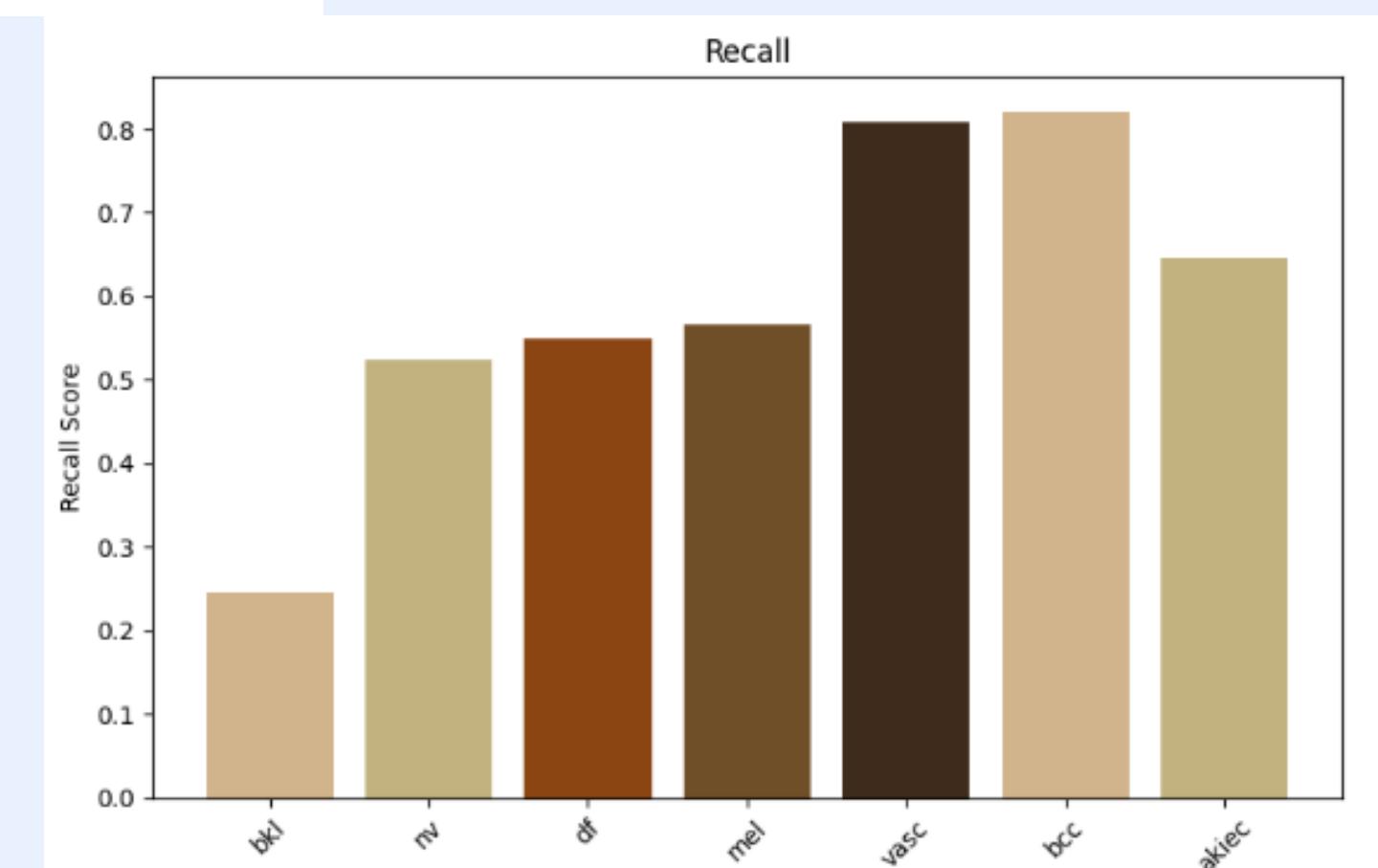
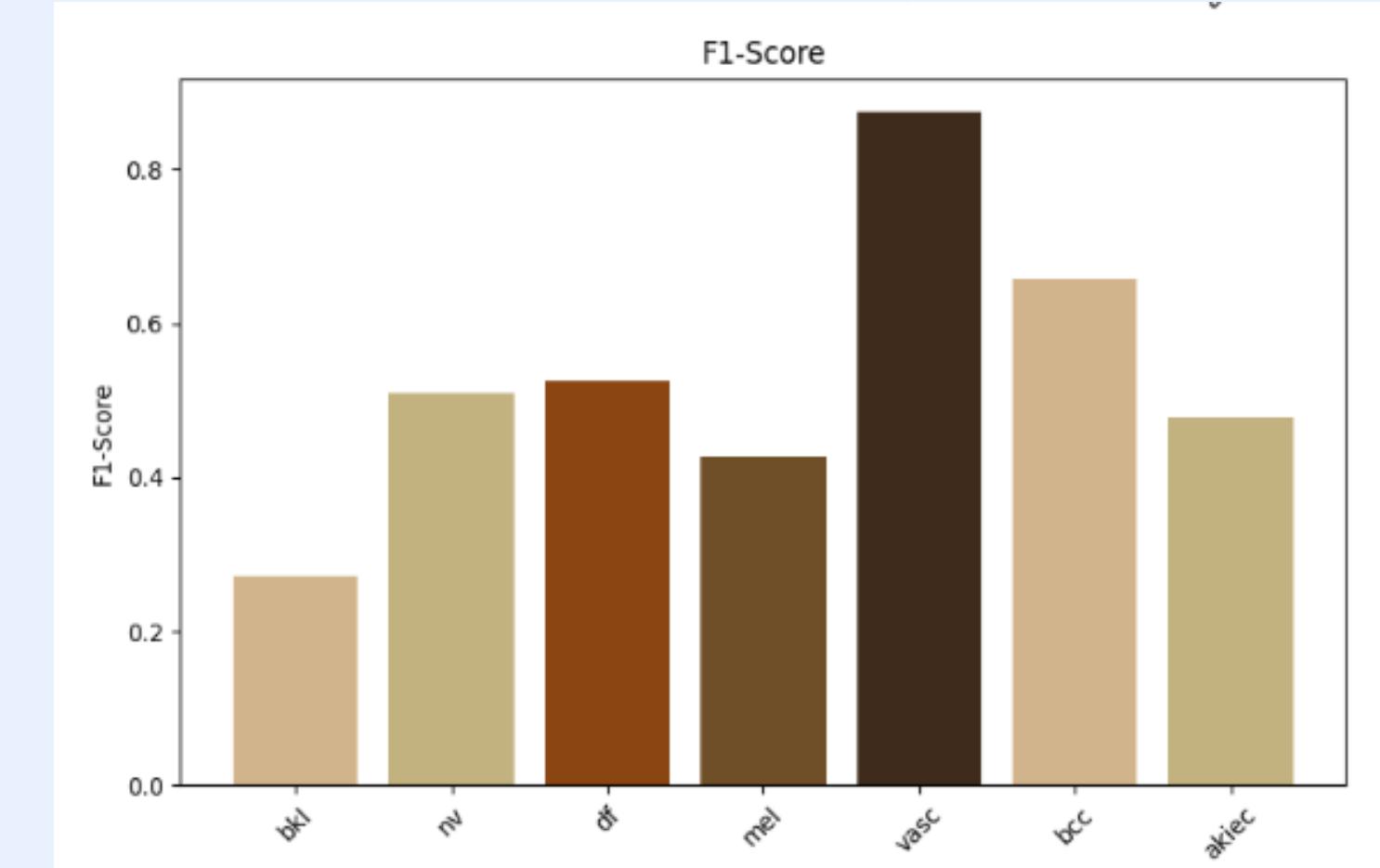
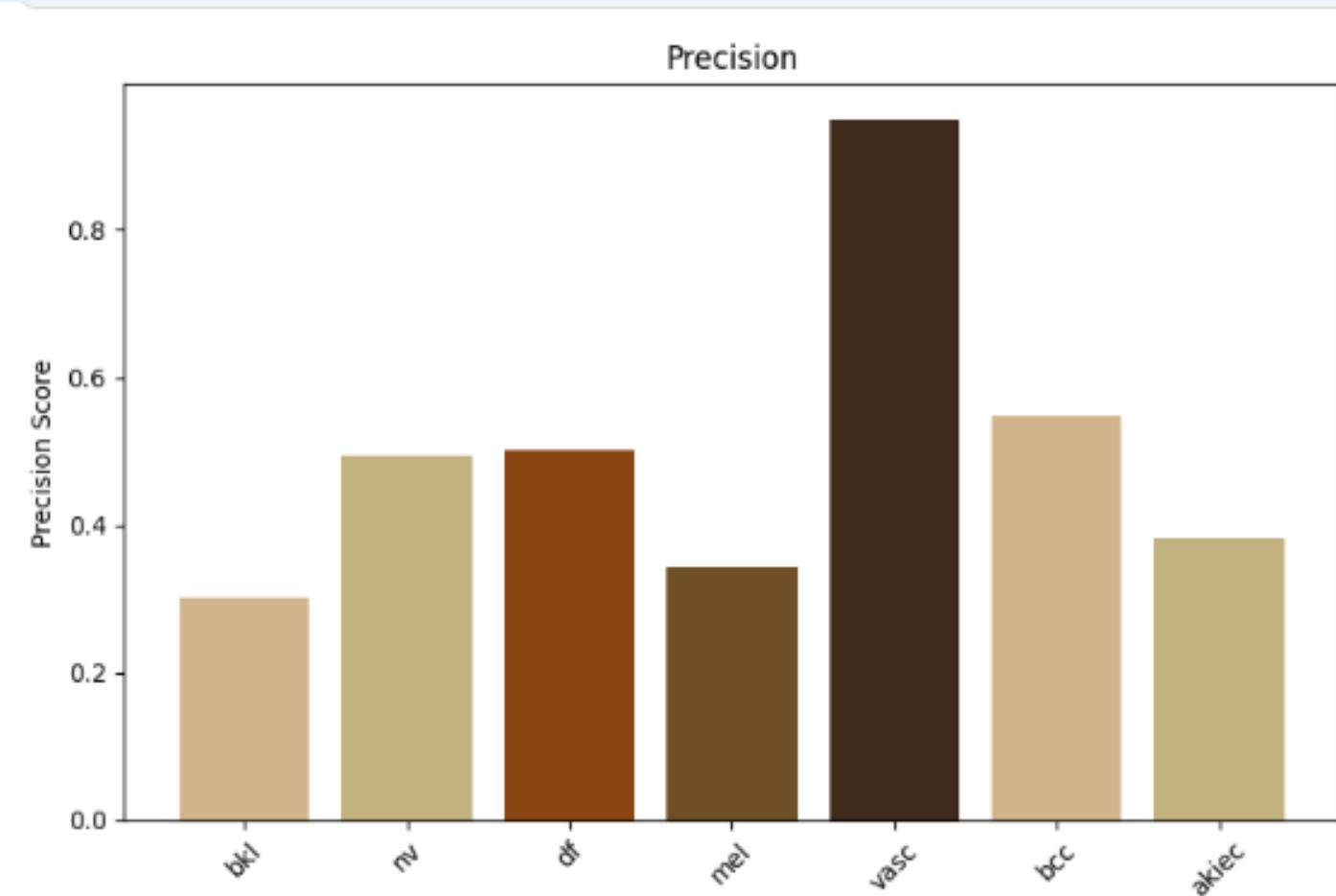


# Model Performance Analysis : Confusion Matrix

- The diagonal values in the confusion matrix represent the number of correct predictions for each class.
- A large proportion of predictions fall along the diagonal, showing that the model performs well in classifying most categories correctly.



# Model Performance Analysis : another metrics



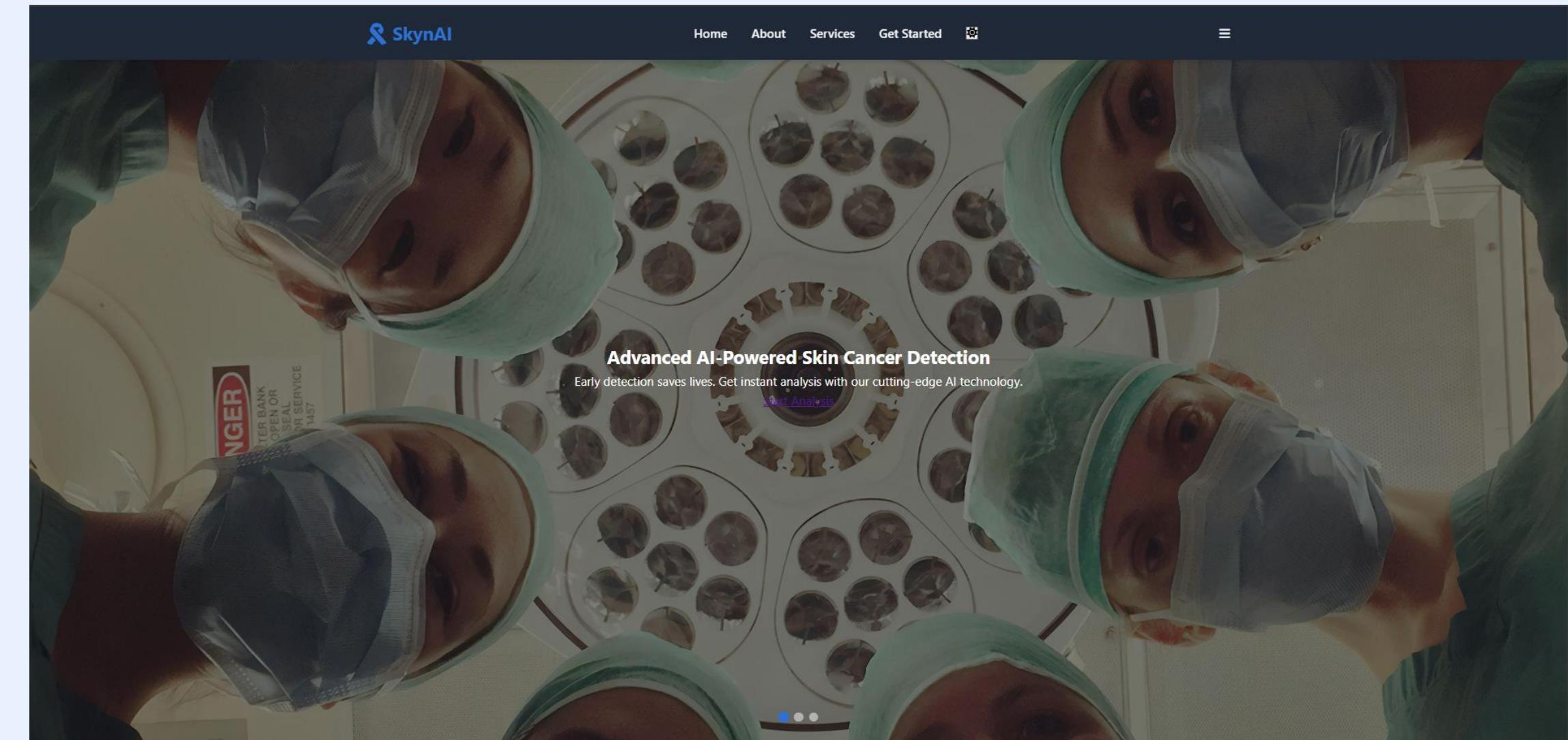
# Deployment



# SkynAI is a web application that helps detect potential skin cancer through image analysis

## Project Structure

```
skynai/
|
├── app.py          # Main Flask application
├── static/
│   ├── js/
│   │   ├── prediction.js # Handle predictions
│   │   └── theme.js      # Dark/light theme toggle
│   └── styles/        #css files
└── templates/
    ├── index.html    # Landing page
    └── predict.html   # Prediction interface
└── model.h5         # Trained ML model
```



# “Enter your information ,upload your skin image and get the diagonal.”

The diagram illustrates the workflow of the SkynAI skin analysis tool:

- Step 1:** The user enters their **Age**, **Sex**, and **Lesion Location**, then **Uploads a skin image** via a drag & drop or click interface.
- Step 2:** A large right-pointing arrow indicates the transition to the next step.
- Step 3:** The user has uploaded a skin image (labeled **ISIC\_0029308.jpg**) and is ready to **Analyze Image**.
- Step 4:** A large left-pointing arrow indicates the transition to the results.
- Step 5:** The **Analysis Results** modal window is displayed, providing a detailed report. Key findings include:
  - Diagnosis:** Benign Keratosis-like Lesions
  - Risk:** Low Risk
  - Age:** 50 | **Sex:** male | **Location:** trunk
  - Detailed Analysis:** Common, harmless skin growths appearing as small, dark or light brown patches or bumps. Includes solar lentigines, seborrheic keratoses, and lichen-planus like keratoses.
  - Possible Treatments:**
    - Electrodesiccation and curettage
    - Cryosurgery
    - Topical 5-Fluorouracil
    - Laser resurfacing
    - Dermabrasion
    - Observation (if asymptomatic)
  - Recommendations:**
    - Consult with a healthcare professional for proper diagnosis
    - Regular skin examinations are recommended
    - Document any changes in skin lesions

A note at the bottom of the modal states: "This analysis is for informational purposes only. Please consult a healthcare professional for proper diagnosis."



# Running



Go to the Repo via this link: [https://github.com/SalmaElgezawy/Skin\\_Cancer\\_classification](https://github.com/SalmaElgezawy/Skin_Cancer_classification)

## 01. Download ZIP

- From the Code button: press **Download ZIP**.
- Unzip the file.
- run the **requirement.txt** to ensure the required libraries is installed.
- Run the code



## 02. Using Git

- git clone  
[https://github.com/SalmaElgezawy/Skin\\_Cancer\\_classification.git](https://github.com/SalmaElgezawy/Skin_Cancer_classification.git)
- cd repository directory
- pip install -r requirements.txt python main.py
- Run the code
- Run the Falsk app with python app.py





**THANK YOU**