Internship Project Report

DermalScan: AI Facial Skin Aging Detection App

Submitted By:

Kamsali Niharika

Under guidance of Mentor **Mr. Praveen**

Infosys Springboard Virtual Internship

Problem Statement

Develop an AI-powered facial skin–aging detection system using EfficientNetB0 that classifies aging indicators such as **wrinkles, dark spots, puffy eyes, and clear skin** from uploaded images.
The pipeline includes:

- Face detection via Haar Cascades
- Preprocessing & augmentation
- Deep learning classification
- Web-based visualization with bounding boxes
- Prediction export and logging

Objectives

- Build a deep learning classifier using **EfficientNetB0** with at least **90% accuracy**.
- Detect aging regions and output **percentage-based predictions**.
- Create a **Streamlit UI** for real-time inference (≤5 seconds).
- Prepare dataset → preprocess → augment → train → evaluate → deploy.

Milestone 1: Dataset Preparation & Preprocessing

Module 1: Dataset Setup and Image Labeling

The dataset was manually curated and organized into four classes:

- **puffy_eyes**
- **wrinkles**
- **dark_spots**
- **clear_skin**

Each image was placed into the corresponding folder and renamed in a structured format (e.g., puffy_eyes_1.jpg, wrinkles_42.jpg) using an automated Python renaming script.

1. Image Counting per Class

Sample Code:

```
for cls in CLASSES:
    folder = DATA_DIR / cls
    count = len(list(folder.glob("*.*")))
    print(cls, ":", count)
```

Purpose: ensure that the dataset is correctly loaded and classes are balanced.

2. Class Distribution Visualization

Sample Code:

```
sns.barplot(x=df_counts.index, y=df_counts['count'])
plt.title("Number of Images per Class")
plt.xlabel("Class")
plt.ylabel("Image Count")
plt.show()
```

Output:

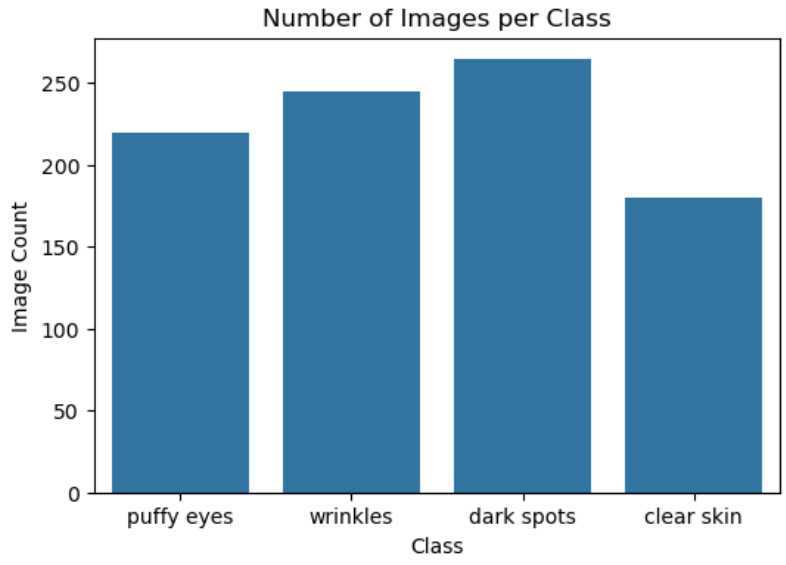


Fig – 1

3. Sample Image Visualization

Sample Code:

show_samples("clear skin", n=6)

Output:

This helped confirm:

- Images were placed in correct categories

4. Image Dimension Analysis

Sample Code:

sns.histplot(df_sizes["width"], kde=True, label="Width")

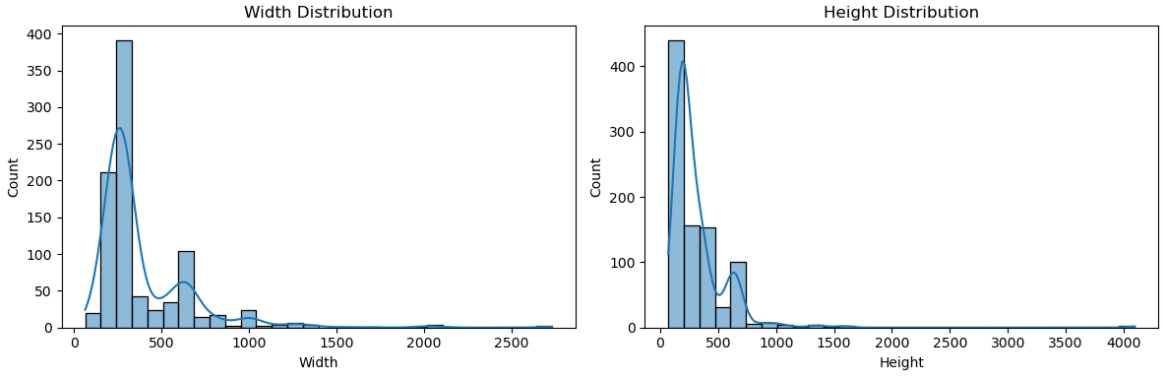
sns.histplot(df_sizes["height"], kde=True, label="Height")

plt.legend()

plt.title("Image Width & Height Distribution")

plt.show()

Output:



Ensured consistency in image shapes before resizing.

5. Brightness Distribution per Class

A KDE plot was generated to analyze lighting differences between classes:

Code:

sns.kdeplot(data=df_bright, x="brightness", hue="class", fill=True)

Output:

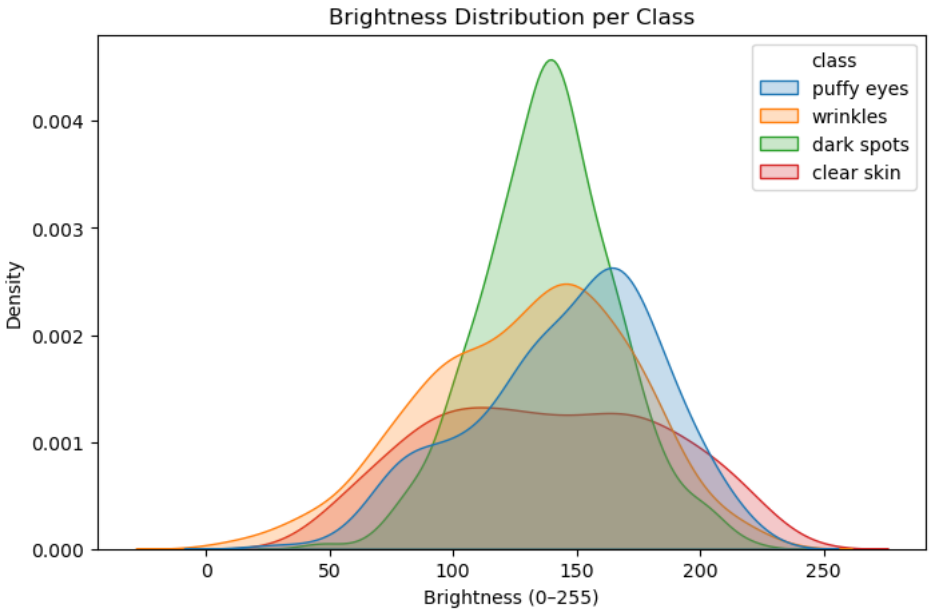


Fig – 4

Module 2: Image Preprocessing and Augmentation

Images were resized, normalized, augmented, and label – encoded as required by EfficientNetB0.

1. Resizing & Normalizing (224×224):

Sample Code:

img = Image.open(img_path).convert("RGB")

img = img.resize((224, 224))

img = np.array(img) / 255.0

Output:

X shape: (908, 224, 224, 3)

y shape: (908, 4)

2. One-Hot Encoding of Labels

Sample Code:

```
y_encoded = tf.keras.utils.to_categorical(labels, num_classes=4)
```

3. Data Augmentation

Sample Code:

```
datagen = ImageDataGenerator(
    rotation_range=15,
    zoom_range=0.1,
    horizontal_flip=True
)
aug_iter = datagen.flow(sample_img, batch_size=1)
plt.imshow(next(aug_iter)[0])
```

Output:

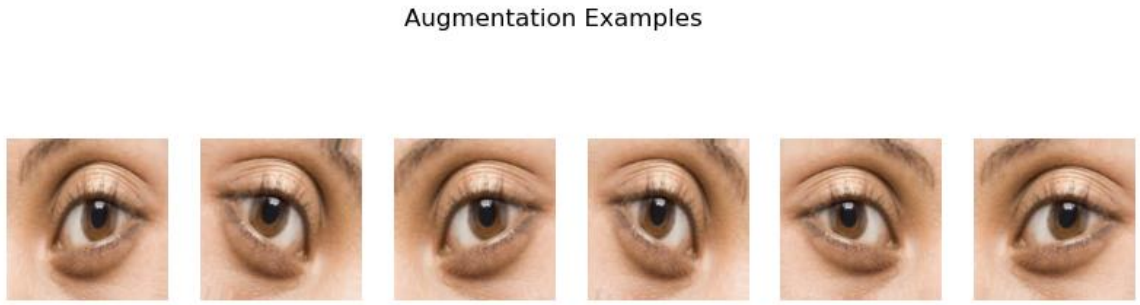


Fig – 5 (Rotation, Zoom, Flip)

6. Augmentation Quality Visualization

Sample Code:

```
plt.figure(figsize=(8,4))

sns.histplot(X.ravel(), bins=50, color="blue", label="Original", stat="density")


aug_batch = datagen.flow(X, y, batch_size=100)

augmented_sample, _ = next(aug_batch)


sns.histplot(augmented_sample.ravel(), bins=50, color="red", label="Augmented",
stat="density")


plt.legend()

plt.title("Pixel Intensity Distribution Before vs After Augmentation")

plt.show()
```

Output:

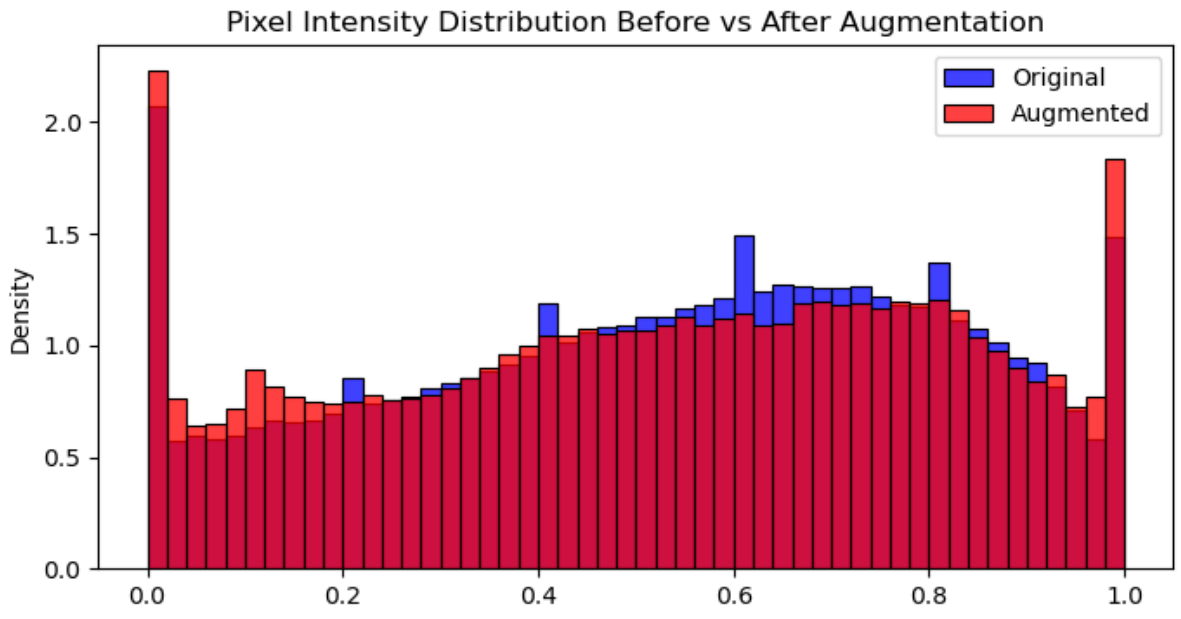


Fig – 6

After preprocessing and augmentation, the final dataset was split into training, validation, and testing subsets using the stratified train-test split method to maintain class balance.
An 80/10/10 ratio was used, which is widely accepted for deep learning tasks.
All six final arrays (X_train, y_train, X_val, y_val, X_test, y_test) were saved for efficient loading during model training.