DermalScan:AI_Facial Skin Aging Detection App

Infosys SpringBoard Virtual Internship Program

Submitted By,

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Project Statement:

Facial skin aging shows signs like wrinkles, dark spots, and puffiness, which can be hard to identify correctly without a specialist. As AI is becoming more common in healthcare, there is a need for an easy, reliable, and automatic system to detect and classify these aging signs. This project aims to create such a system using deep learning and computer vision.

Expected outcome:

1. **A fully structured facial skin aging dataset** organized into four classes:

- Clear Skin
- Dark Spots
- Puffy Eyes
- Wrinkles

2. **A DataFrame (df)** containing all image filepaths and corresponding labels extracted from folder structure.
3. **Successfully preprocessed images**, resized to 256×256, normalized (0–1 scaling), and stored in an array ready for deep learning models.
4. **Automated data augmentation pipeline** using Keras ImageDataGenerator to improve dataset variability and reduce overfitting.
5. **Label encoding with one-hot vectors**, enabling compatibility with classification models.
6. **Class distribution visualization** for dataset balance analysis and **Augmentation preview visualization** showing how transformations modify sample images.

Tech Stack Used

1. Programming Language

- **Python 3.10.11**

2. Deep Learning Frameworks

- **TensorFlow / Keras**
  - Image loading and augmentation
  - One-hot encoding
  - Data pipeline utilities

3. Image Processing Libraries

- **OpenCV (cv2)**
  - Image reading
  - Resizing
  - Color conversion

- **Pillow (PIL)**
  - Safe image opening
  - Handling corrupted images

5. Visualization Libraries

- **Matplotlib**
  - Augmentation preview
  - Image display

- **Seaborn**
  - Class distribution plots

6. Machine Learning Tools

- **Scikit-Learn**
  - Train/Validation split
  - Data shuffling

7. Development Environment

- **Jupyter Notebook / JupyterLab**

MILESTONE 1: Dataset Preparation and Preprocessing

MODULE 1: Dataset Setup & Image Labeling

Module 1 focuses on preparing the dataset so the model can understand it later. In deep learning, data preparation is one of the most important steps because the model's accuracy completely depends on clean, well-organized data.

1. **Dataset Setup**
   The dataset was structured into four separate class folders — **Wrinkles**, **Dark Spots**, **Puffy Eyes**, and **Clear Skin** — each containing images representing that skin condition.

   Code Snippet

   ```
   base_dir = "data"
   classes = ["Wrinkles", "Dark Spots", "Puffy Eyes", "Clear
   Skin"]
   ```

   Folder structure is like:
   data/
   ├── Wrinkles
   ├── Dark Spots
   ├── Puffy Eyes
   └── Clear Skin

2. **Building a DataFrame of Filepaths & Labels**

   We create a function to walk through each class folder, pick up image paths, and store them with their correct label.

   This helps convert the raw dataset into a *machine-readable table*.

3. **Creating the Final Dataset Table**

   After collecting the image filepaths and class labels from all four folders, we organized this information into a structured pandas DataFrame. This table acts as the central dataset index, where each row represents one image along with its corresponding label. The DataFrame contains two main columns:
   - filepath: the complete directory path to the image file

- label: the class to which the image belongs (Wrinkles, Dark Spots, Puffy Eyes, or Clear Skin)

Code Snippet

```
df = build_df_from_folders(base_dir, classes)

print("Total images:", len(df))
print(df["label"].value_counts())
df.head()
```

Output

label	count
Dark Spots	303
Wrinkles	300
Puffy Eyes	300
Clear Skin	300

4. Class Distribution

The bar chart shows the number of images available for each skin condition category in the dataset. There are four classes:

- Wrinkles
- Dark Spots
- Puffy Eyes
- Clear Skin

Code Snippet

```
plt.figure(figsize=(8,5))

colors = ["blue", "yellow", "green", "purple"]

sns.countplot(data=df, x="label", hue="label", palette=colors,
legend=False)

plt.title("Class Distribution", fontsize=14)

plt.xlabel("Class")

plt.ylabel("Number of Images")

plt.xticks(rotation=20)

plt.tight_layout()

plt.show()
```
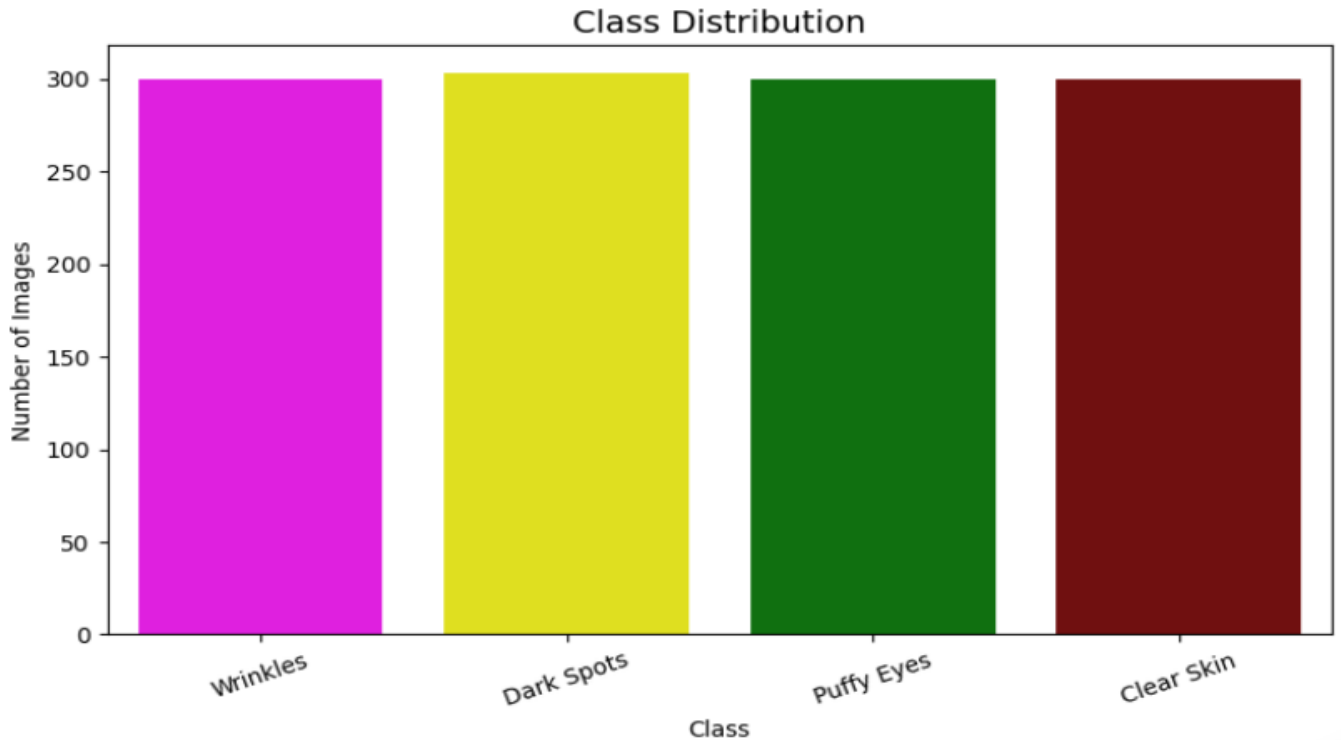
Fig 1. Class Distribution Plot

☐ Observation From Fig. 1

- All classes contain **approximately 300 images** each.
- No class shows significant under-representation or over-representation.
- The distribution is nearly uniform across all four categories.

☐ Importance of Balanced Distribution

- Prevents the model from becoming biased toward a class with more samples.
- Ensures fair learning and equal exposure to all facial aging conditions.
- Reduces the need for additional techniques like oversampling, undersampling, or class weighting.

☐ Impact on Model Training

- Leads to **more stable training performance**.
- Helps improve model **accuracy, generalization, and robustness**.
- Provides a reliable foundation for preprocessing, augmentation, and later model training.

Module 2: Image Preprocessing and Augmentation

In this module, all facial images are resized to a fixed resolution of **224×224 pixels**, normalized to the range **[0, 1]**, and passed through a set of augmentation operations. These augmentations—such as rotation, flipping, shifting, and zooming—help artificially expand the dataset and introduce variability. This makes the model more generalizable and reduces overfitting.

Additionally, class labels are encoded using **one-hot encoding**, which converts categorical labels (Clear Skin, Dark Spots, Puffy Eyes, Wrinkles) into numerical vectors suitable for training a multi-class classification model.

1. Image Loading & Preprocessing

Every image from Module 1 (df) is:

- Loaded with Pillow (PIL)

- Converted to RGB (ensures color consistency)

- Resized to **224 × 224** (IMG_SIZE = 224)

- Normalized to values between **0 → 1**

2. Data Augmentation

We use **ImageDataGenerator** to apply transformations such as:

- Rotation

- Horizontal shift

- Vertical shift

- Zoom

- Horizontal flipping

Code Snippet:

```
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.15,
    horizontal_flip=True,
    fill_mode='nearest')
```

Fig 2. Augmented Image Preview

3. Label Encoding

```
label_map = {
    "Clear Skin": 0,
    "Dark Spots": 1,
    "Puffy Eyes": 2,
    "Wrinkles": 3
}
```

Then labels are converted to **one-hot vectors**, such as:

```
Wrinkles → [0, 0, 0, 1]
```

5. Train–Validation Split

This allows testing the model on unseen data to measure performance.

Code Snippets:

```
X_train, X_val, y_train, y_val = train_test_split(
    images,
    labels_onehot,
    test_size=0.2,
    random_state=42,
    shuffle=True
)
```

Conclusion

Milestone 1 successfully prepares the dataset through structured organization, preprocessing, labeling, and augmentation. This ensures the data is clean, balanced, and sufficiently diverse to support high-performance model training in subsequent modules. Both Module 1 and Module 2 meet the milestone requirements and complete the foundation for the **DermalScan AI Facial Aging Detection System**.

MILESTONE 2: Model Training and Evaluation

Module 3: Model Training

Objective

In this module, a deep learning–based experimental framework was designed to train and evaluate multiple pretrained Convolutional Neural Network (CNN) models for facial skin aging classification. This module aims to identify the best-performing model that provides high validation accuracy.

The **Categorical Cross-Entropy loss** function was used for training all models. The **Adam optimizer** was employed for model training.

To improve training efficiency and prevent overfitting, multiple callbacks were applied during model training:

- **EarlyStopping**
- **ReduceLROnPlateau**
- **ModelCheckpoint**

Callbacks Configuration

```
callbacks = [

    EarlyStopping(

        monitor="val_loss",

        patience=5,

        restore_best_weights=True

    ),

    ReduceLROnPlateau(

        monitor="val_loss",

        factor=0.3,

        patience=3,
```

```
        min_lr=1e-6
    ),
    ModelCheckpoint(
        "best_model.h5",
        monitor="val_accuracy",
        save_best_only=True
    )
]
```

Models Trained and Observations

1. MobileNetV2

MobileNetV2 was trained as a baseline model using transfer learning. The model was trained for a maximum of 50 epochs using the training and validation datasets prepared in Module 2. A moderate learning rate (1×10^{-4}) was used with the Adam optimizer.

To analyze the learning behavior of the MobileNetV2 model, line charts were plotted for training and validation accuracy and loss across all epochs.
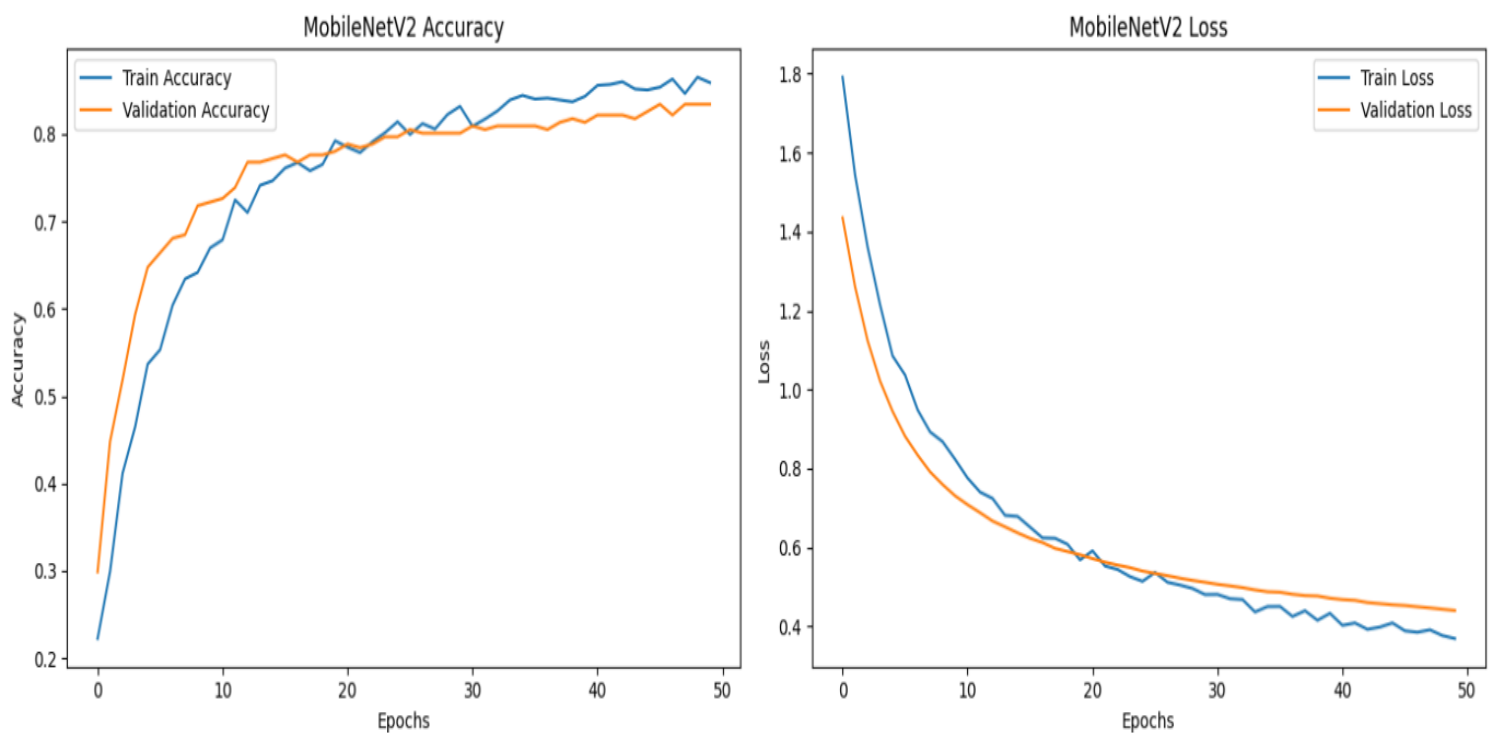

Fig 3. Line Chart of Accuracy and Loss

2. EfficientNetB0

EfficientNetB0 was trained using transfer learning to evaluate its performance on facial skin aging classification. The model was trained using the training and validation datasets prepared in Module 2 with a low learning rate (1e-5) and the Adam optimizer.

To study the learning behavior of the EfficientNetB0 model, line charts were plotted for training and validation accuracy and loss across epochs.
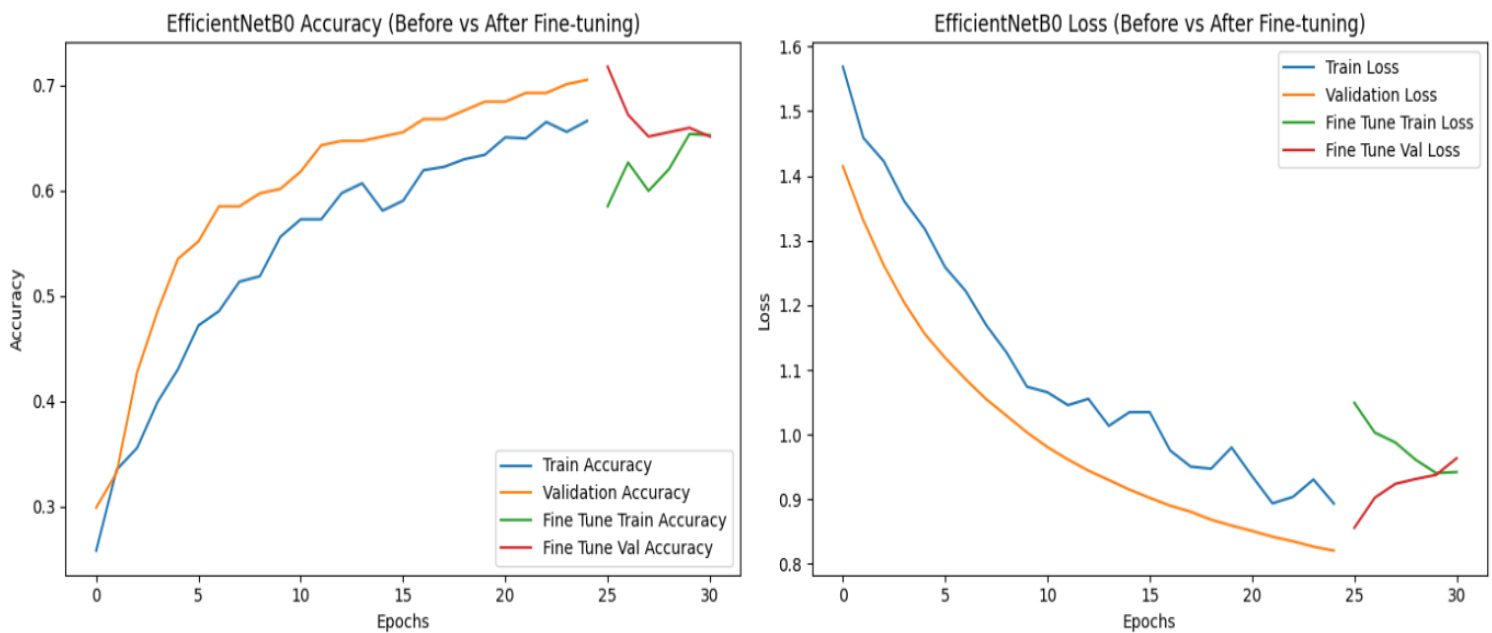

Fig 4. Line Chart of Accuracy and Loss

3. ResNet50

ResNet50 was trained using transfer learning due to its strong feature extraction capability and suitability for complex image classification tasks. The model was trained on the training and validation datasets prepared in Module 2 using the Adam optimizer with a very low learning rate (1e-5)

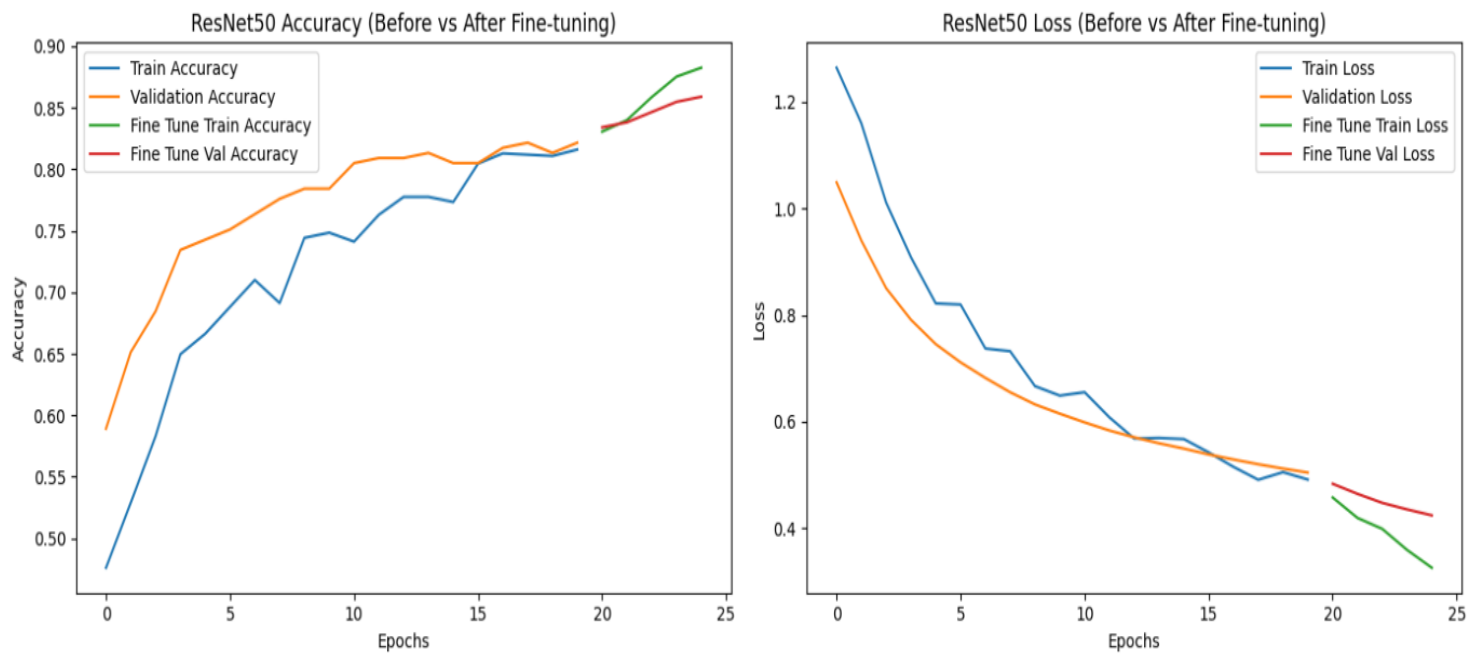Line charts were plotted to visualize training and validation accuracy and loss for the ResNet50 model.

Fig 5. Line Chart of Accuracy and Loss

Model Comparison Table

Model Name	Epochs	Training Accuracy	Validation Accuracy
MobileNetV2	50	86	83
EfficientNetB0	40	65	65
ResNet50	25	88	86

ResNet50 demonstrated the best balance between accuracy and generalization.

Module 4: Face Detection and Prediction Pipeline

Objective
The objective of Module 4 is to perform face detection on input images, extract the detected facial region, and apply the trained deep learning model (ResNet50) to classify facial skin aging signs. The final output displays the predicted class, confidence percentage, and estimated age group using bounding boxes on the image.

Face Detection using Haar Cascade
Haar Cascade is a classical object detection technique provided by OpenCV. It is lightweight, fast, and suitable for real-time applications.

Loading Haar Cascade

```
face_cascade = cv2.CascadeClassifier(
    cv2.data.haarcascades +
"haarcascade_frontalface_default.xml"
)

assert not face_cascade.empty(), "Haar Cascade not
loaded"
```

Class Labels and Age Mapping

The predicted class is selected based on maximum probability. An age group is assigned using rule-based mapping.

```
def estimate_age(predicted_class, confidence):
    age_map = {
        "clear skin": (18, 25),
        "dark spots": (25, 35),
        "puffy eyes": (30, 45),
        "wrinkles": (45, 60)
    }

    low, high = age_map[predicted_class]
    age = int(low + (1 - confidence / 100) * (high -
low))
    return age
```

Visualization of Final Output

The final output image displays a **bounding box** around the face along with **predicted class, confidence percentage, and age group**.

```
label = class_names[class_index]
        confidence = preds[class_index] * 100
        age = estimate_age(label, confidence)

        text = f"{label}: {confidence:.2f}% | Age:
{age}"

        cv2.rectangle(rgb, (x, y), (x+w, y+h), (0,
255, 0), 2)
        cv2.putText(
            rgb, text, (x, y-10),
            cv2.FONT_HERSHEY_SIMPLEX, 0.8,
            (255, 0, 0), 2
```
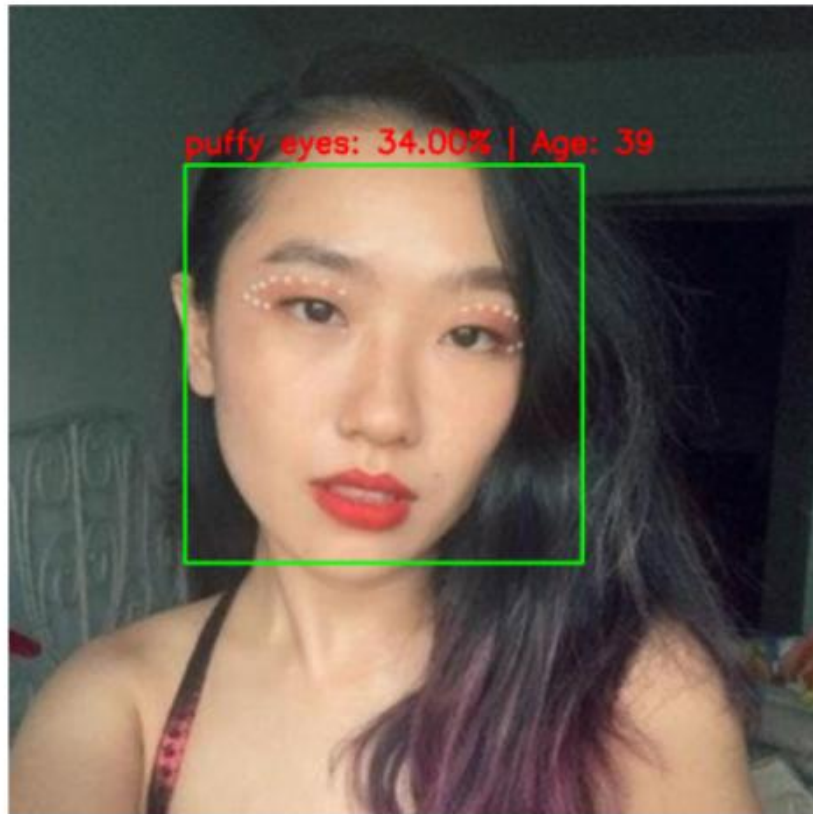
Fig 6. Predicted image

Final Output

A predicted image (annotated image)
Specifically, the function returns:

- Face bounding box
- Predicted skin-aging class
- Confidence percentage
- Estimated age

Conclusion

In this Milestone, pretrained CNN models were evaluated for facial skin aging classification, with ResNet50 achieving the best accuracy and generalization. The selected model was successfully integrated with OpenCV-based face detection to perform end-to-end prediction, displaying skin condition, confidence percentage, and age group through bounding box visualization.