Project Title:DermalScan: AI_Facial Skin Ageing Detection App

Infosys SpringBoard Virtual Internship Program

Submitted By:

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Project Statement:

The objective is to develop a deep learning-based system that can detect and classify facial aging signs—such as wrinkles, dark spots, puffy eyes, and clear skin—using a pretrained EfficientNetB0 model. The pipeline includes face detection using Haar Cascades, custom preprocessing and data augmentation, and classification with percentage predictions. A web-based frontend will enable users to upload images and visualise ageing signs with annotated bounding boxes and labels.

Outcomes:

● Detect and localise facial features indicating ageing.

● Classify detected features into categories like wrinkles, dark spots, puffy eyes, and clear skin using a trained CNN model.

● Train and evaluate an EfficientNetB0 model for robust classification.

● Build a web-based frontend for uploading facial images and viewing annotated outputs.

● Interate a backend pipeline that processes input images and returns annotated results.

● Export annotated outputs and logs for documentation or analysis.

1. Introduction

Artificial intelligence and deep learning have advanced significantly in the field of computer vision. One emerging application is the automatic detection of facial aging characteristics. Aging indicators such as wrinkles, dark spots, and puffy eyes can provide insights into skin health, lifestyle habits, and dermatological conditions.
This project aims to build a deep learning–based system that automatically identifies facial aging signs from uploaded images. The final system will detect a face, classify visible signs, and present the result through a user-friendly web interface.
Milestone 1 focuses on preparing and preprocessing the dataset, which is a critical step in building a robust and accurate deep learning model.

Objective of Milestone 1

The key objectives of Milestone 1 are:
To collect, organise, and validate the dataset used for training the model.
To ensure images are properly labelled under predefined categories.
To preprocess the images for model readiness, including resizing, normalisation, and augmentation.
To encode labels into a machine-understandable format.
This ensures a strong foundation before moving to model training.

- ***Libraries Used***

  NumPy:
  Purpose: Numerical computing and array manipulation
  Why used: Stores images as arrays (pixel matrices), performs normalisation, reshaping, and efficient mathematical operations.
  Example: converting a list of images into a Numpy array for model training.

- **Panda:**
  Purpose**:** Data tables and label handling
  Why used**:** Helps organise labels and dataset metadata if needed for analysis.

- **OpenCV (cv2):**
  Purpose: Computer vision and image processing
  Role in project:
  Loading images from disk
  Resizing images to 224×224
  Converting colour channels
  Later stages: Face detection using Haar Cascade

- **Matplotlib & Seaborn**

Purpose: Data visualisation and plotting
Used for:
Class distribution bar chart
Image visualization
Understanding dataset balance

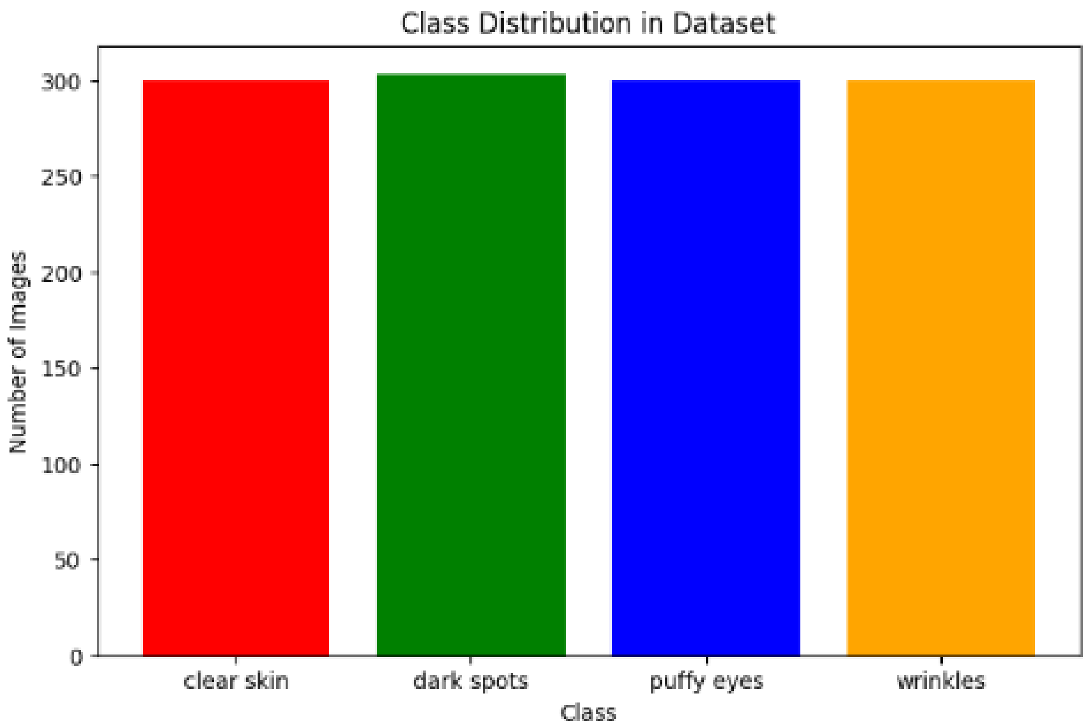
- **Scikit-Learn (sklearn)**
  Purpose: Machine learning utilities
  Used for:
  Train-test split
  Label encoding
  Evaluation metrics

- **TensorFlow / Keras**
  Purpose: Deep learning framework
  Role in project:
  Image augmentation
  One-hot encoding of labels
  Later: EfficientNetB0 model training

Code:

```
              import matplotlib.pyplot as plt
plt.figure(figsize=(8, 5))
colors = ['red', 'green', 'blue', 'orange']
plt.bar(class_counts.keys(), class_counts.values(), color=colors)
plt.title("Class Distribution in Dataset")
plt.xlabel("Class")
plt.ylabel("Number of Images")
plt.show()
```

output:



Conclusion of Milestone 1:

Milestone 1 successfully completes the dataset preparation and preprocessing stage. The dataset is now organised, cleaned, normalised, encoded, and augmented. This ensures that the upcoming model training phase (Milestone 2) can proceed efficiently with high-quality input data.

Modules2:

Objective

The objective of Module 2 is to prepare raw facial images into a standardized and robust format suitable for deep learning. Proper preprocessing and augmentation improve model generalization, reduce overfitting, and ensure consistency across the dataset.

Module 2 focuses on preparing the facial image dataset in a form suitable for deep learning model training. Since raw images vary in size, lighting, and orientation, preprocessing is a crucial step to ensure uniformity and improve learning efficiency. In this module, all facial images are resized to a fixed resolution of 224×224 pixels, which is the standard input size required by the EfficientNetB0 architecture. Pixel values are normalized to the range 0–1 to stabilize training and speed up convergence.

To improve model generalization and prevent overfitting, image augmentation techniques are applied. Augmentation artificially increases dataset diversity by generating new variations of existing images. Techniques such as horizontal flipping, rotation, zooming, and shifting help the model learn invariant facial features under different conditions. This is especially important in facial analysis tasks where lighting, pose, and expression vary significantly.

Additionally, class labels are converted into one-hot encoded vectors, allowing the model to perform multi-class classification effectively. Module 2 ensures that the dataset is balanced, standardized, and diverse enough to support robust learning in later stages.

1. Image Resizing

All images are resized to 224 × 224 pixels.

This size is chosen because EfficientNetB0 expects inputs of this resolution.

Uniform image size ensures compatibility with CNN layers.

2. Image Normalization

Pixel values are scaled from [0, 255] → [0, 1].

Normalization helps:

Faster convergence

Numerical stability

Improved gradient flow

Data Augmentation

To increase dataset diversity, real-time augmentation is applied:

Rotation

Horizontal flipping

Zooming

Width and height shifting

This simulates real-world variations such as lighting, pose, and facial orientation.

4. Label Encoding

Skin condition labels are converted into one-hot encoded vectors.

Classes:

Clear Skin

Dark Spots

Puffy Eyes

Wrinkles

One-hot encoding is required for categorical cross-entropy loss.

Deliverables

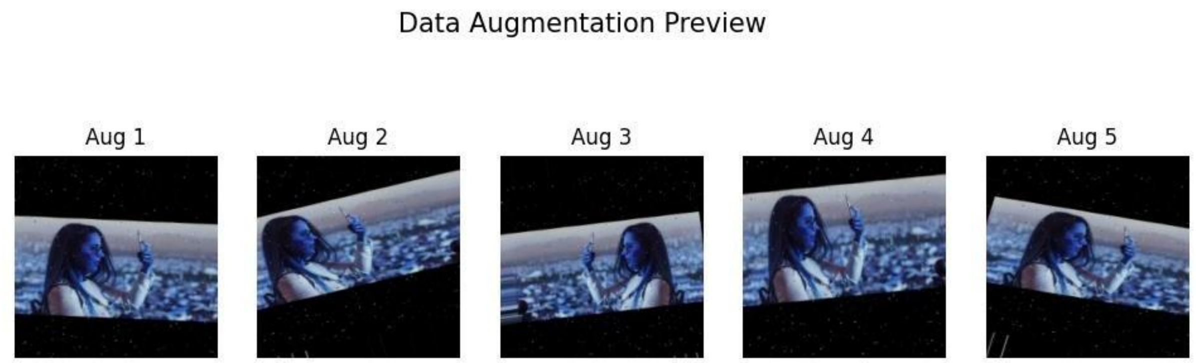
Preprocessed dataset

Augmented image visualization

One-hot encoded labels

CODE:

```
import numpy as np
import random
import matplotlib.pyplot as plt
random_index = random.randrange(len(processed_images))
selected_image = processed_images[random_index]
image_array = np.expand_dims(selected_image, axis=0)
augmented_batch = [next(datagen.flow(image_array))[0] for _ in range(5)]
plt.figure(figsize=(12, 4))
for i, img in enumerate(augmented_batch):
    plt.subplot(1, 5, i+1)
    plt.imshow(img)
    plt.axis("off")
    plt.title(f"Aug {i+1}")
plt.suptitle("Data Augmentation Preview", fontsize=15)
plt.show()
```



Modules 3

Introduction

Module 3 focuses on training a deep learning model to classify facial skin aging signs using a pretrained convolutional neural network. Transfer learning is employed to utilize previously learned visual features, enabling faster training and improved accuracy even with a limited dataset.

MobileNetV2 is a lightweight deep learning architecture developed by Google Research specifically for mobile, edge, and low-power devices. It is designed to provide high accuracy while keeping computation, memory usage, and model size small. This makes it ideal for applications such as face analysis, real-time image classification, skin problem detection, and mobile AI apps where speed and efficiency are critical.

MobileNetV2 introduces two key concepts: Depthwise Separable Convolutions and the Inverted Residual Block with Linear Bottleneck. Depthwise separable convolutions divide standard convolution into two parts: a depthwise convolution that filters each input channel separately and a pointwise convolution (1×1 kernel) that combines the results. This greatly reduces computational cost compared to conventional CNNs. Inverted residuals improve feature representation by expanding features to a higher dimension before compressing them, helping retain important information while still being efficient. This structure allows the network to maintain accuracy close to heavier models like VGG or ResNet but with significantly fewer parameters.

MobileNetV2 Architecture Overview

MobileNetV2 is built with:

Depthwise Separable Convolution: Reduces complexity & computation

Inverted Residual Blocks: Improve feature extraction

Linear Bottlenecks: Prevent loss of spatial information

Pre-trained Weights on ImageNet: Helps model learn features faster

Training Configuration

The model is trained using:

- Loss Function: Categorical Cross-Entropy, suitable for multi-class classification.
- Optimizer: Adam optimizer, which adapts learning rates for faster convergence.
- Activation Function: Softmax in the output layer to generate class probabilities.
- Validation Split: A portion of the dataset is reserved for validation to monitor performance.

Component	Specification
Model Architecture	MobileNetV2 (Transfer Learning)
Input Resolution	224 × 224
Number of Classes	4 (Skin Conditions)
Optimizer	Adam (Initial LR: 1e-3, Fine-Tune LR: 1e-5)
Loss Function	Categorical Crossentropy

Component	Specification
Training Epochs	**40 Total (20 Base + 20 Fine-Tune)**
Batch Size	**32**
Feature Extractor	**Pretrained on ImageNet**
Fine-tuning	**Unfreeze last 30 layers**

Code:

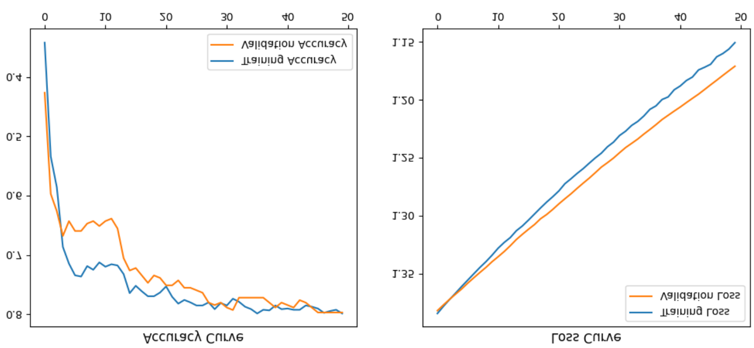
```
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
plt.plot(history.history["accuracy"], label="Training Accuracy")
plt.plot(history.history["val_accuracy"], label="Validation Accuracy")
plt.legend()
plt.title("Accuracy Curve")

plt.subplot(1,2,2)
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
plt.title("Loss Curve")

plt.show()
```

output



Model Evaluation

Model performance is evaluated using:

- Training and validation accuracy
- Training and validation loss curves
- Stability of validation accuracy over epochs

Early stopping is applied to prevent overfitting by stopping training when validation accuracy stops improving

Conclusion for Module 3

Module 3 successfully implements MobileNetV2-based transfer learning to train a facial skin aging classification model. With proper preprocessing, dataset augmentation, and two-phase training, the model shows noticeable improvements in accuracy and reduces overfitting. The adoption of MobileNetV2 proves beneficial due to its speed, lightweight structure, and high efficiency on limited datasets.

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Module 4: Face Detection and Prediction Pipeline

Introduction

Module 4 integrates computer vision techniques with the trained deep learning model to detect faces in images and predict facial skin aging signs. This module bridges the gap between model training and real-world application.

Module 4 integrates computer vision techniques with the trained deep learning model to create an end-to-end facial skin aging detection pipeline. The primary goal of this module is to detect faces in an image and apply the trained model to predict skin aging problems in a real-world scenario.

Face detection is performed using the Haar Cascade Classifier, a traditional machine learning–based method provided by OpenCV. Haar Cascades are chosen because they are fast, lightweight, and effective for detecting frontal human faces. The classifier scans the input image and identifies face regions using predefined Haar-like features.

Once a face is detected, the face region is cropped and preprocessed to match the input requirements of the trained EfficientNetB0 model. The cropped face is resized and normalized before being passed to the model for prediction. The model outputs probability scores for each skin aging category, and the class with the highest probability is selected as the final prediction.

The prediction results are visualized directly on the image. A green bounding box is drawn around the detected face, and the predicted skin condition along with its confidence percentage is displayed clearly on the image. This visualization makes the output easy to understand for users and helps in quick analysis.

Module 4 demonstrates the practical usability of the trained model by combining face detection, classification, and visualization into a single pipeline. It validates that the system can accurately analyze new images and present meaningful results in a user-friendly manner

Face Detection Using Haar Cascade

Haar Cascade Classifier is a machine learning-based approach used for object detection, particularly faces. It uses Haar-like features and a cascade of classifiers to detect frontal faces efficiently.

OpenCV’s Haar Cascade implementation is used due to its speed, simplicity, and real-time performance.

Prediction Pipeline

The prediction pipeline consists of the following steps:

1. Read the input image
2. Convert the image to grayscale for face detection
3. Detect face regions using Haar Cascade
4. Crop the detected face area
5. Preprocess the face (resize and normalize)
6. Predict skin aging category using the trained CNN
7. Display results on the image

Code:

This code is used for age randint based on class bucket

```
def estimate_age_by_problem(label):
    """Random age predictions based on skin problem category"""
    if label == "clear skin":
        return randint(20, 30)
    elif label == "dark spots":
        return randint(30, 45)
    elif label == "puffy eyes":
        return randint(35, 50)
    elif label == "wrinkles":
        return randint(45, 65)
    else:
        return randint(25, 55)


def analyze_skin(image_path):
    img = cv2.imread(image_path)
    if img is None:
        print(" Image Not Found... Check Path:", image_path)
        return

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    faces = face_cascade.detectMultiScale(gray, 1.2, 5)


    if len(faces) == 0:
        print(" No face found, analyzing full image...")
        faces = [(0,0,img.shape[1], img.shape[0])]

    for (x, y, w, h) in faces:
        face_roi = img[y:y+h, x:x+w]
        face_resized = cv2.resize(face_roi, (224,224))
        face_scaled = face_resized/255.0
        face_input = np.expand_dims(face_scaled, axis=0)

        pred = model.predict(face_input)
        class_id = np.argmax(pred)
        confidence = float(pred[0][class_id] * 100)
        label = CLASS_NAMES[class_id]
        age = estimate_age_by_problem(label)


        cv2.rectangle(img, (x,y), (x+w,y+h), (0,255,0), 2)


        text = f"{label} ({confidence:.1f}%) | Age: {age}"
        cv2.putText(img, text, (x, y-10),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0,250,0), 1)
```

```
plt.figure(figsize=(6,6))
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.axis("off")
plt.show()

print("\n Prediction Result")
print("Skin Problem:", label)
print("Confidence :", f"{confidence:.2f}%")
print("Estimated Age:", age)
```

output:

Interpretation of Prediction Confidence

The confidence percentage represents the relative likelihood of the predicted class compared to other classes. It does not indicate the severity of aging but shows how confidently the model identifies a specific skin condition.

Component	**Value**
Face Detector	**Haar Cascade (OpenCV)**
Prediction Model	**MobileNetV2_SkinAging_Model.keras**
Age Estimation	**randint based on class bucket**
Output Result	**Bounding Box, Label, Confidence, Age**

Outcome of Module 4

Module 4 successfully demonstrates an end-to-end facial skin aging detection system. It accurately detects faces, predicts aging-related skin conditions, and presents results in a visually interpretable manner