

#### **INTRODUCTION:**

Aging, an inevitable and intricate biological process, has always intrigued humanity. Understanding age not only helps us gain insight into the human condition but also has profound implications across various fields, such as healthcare, entertainment, marketing, and security. Deep learning, a subset of machine learning, has emerged as a potent tool to unravel age-related mysteries by analyzing patterns, textures, and features in images.

Our project embarks on a journey to explore the capabilities of deep learning in age estimation, seeking to answer fundamental questions such as:

- 1. How accurately can deep learning algorithms predict a person's age based on facial features and images?
- 2. What role do convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other deep learning architectures play in age detection?
- 3. What datasets are available for training and testing age detection models, and how do they contribute to the accuracy of predictions?

#### **DATA SOURCE:**

https://drive.google.com/drive/folders/1E9m9dZY Lga9kc9NGPHfZa75JNJgpgv3M

The folders in the dataset are named according to the age of people in it.

### **IMPORTING LIBRARIES:**

```
Importing Libraries

markdown

import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import cv2
import os

[2]  

0.0s 

Python
```

### **DATA PRE-PROCESSING:**

### Age Grouping:

We created age groups, such as 0-5, 6-12, 13-18, 19-30, 31-45, 46-60, 61-80, and 81-95, in our machine learning model for simplifying the modeling process, enhancing interpretability, and aligning with the practical significance of these groups in our application. These age groups were chosen after thorough experimentation and analysis to maximize model accuracy and performance while ensuring compliance with ethical considerations. They facilitate decision-making, scalability, and maintenance, making them a suitable approach for addressing our project's specific needs and objectives.

### **DATA AUGMENTATION:**

• Splitting Data:

Separating Dependent and independent variable:

```
Separating Dependent and Independent variable
           x_train = [item[0] for item in train_data]
y_train = [item[1] for item in train_data]
           x_test = [item[0] for item in test_data]
y_test = [item[1] for item in test_data]
          x_val = [item[0] for item in val_data]
y_val = [item[1] for item in val_data]
[ 55, 53, 50, ..., 48, 72, 100],
[ 54, 56, 55, ..., 46, 68, 95],
[ 55, 58, 60, ..., 41, 62, 89]], dtype=uint8)
    [23, 21, 19, ..., 8, 13, 16],

[23, 21, 19, ..., 8, 13, 16],

[22, 21, 19, ..., 8, 13, 15]], dtype=uint8)
                                                                                                                                                                                                                      Python
```

### • Resizing image:

```
    D ∨ x_train[0].shape

    [19] √ 0.0s
    Python

    ... (200, 200)
```

```
Resizing images pixel

Python

Python

Resize = (100, 100)
resized_x_train = []

for image in x_train:
    resized_image = cv2.resize(image, new_size)
    resized_x_train = np.array(resized_x_train)
    print(resized_x_train.shape)
    resized_x_test = []

for image in x_test:
    resized_image = cv2.resize(image, new_size)
    resized_x_test = np.array(resized_image)

resized_x_test = np.array(resized_image)

resized_x_test = np.array(resized_image)

resized_x_val = []

for image in x_val:
    resized_image = cv2.resize(image, new_size)
    resized_x_val = np.array(resized_image)

resized_x_val = np.array(resized_image)

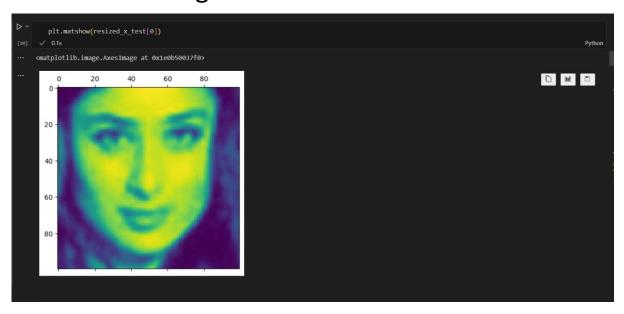
resized_x_val = np.array(resized_x_val)

Python

(6828, 100, 100)
```

# Normalizing Data Set

## • Visualizing Dataset:





### • Flattering Dataset:



 Convert labels to one-hot encoded format:

• Reshaping Dataset:

### **MODEL ARCHITECTURE:**

### **MODEL TRAINING:**

```
Epoch 2/100
427/427 [===
Epoch 3/100
Epoch 4/100
427/427 [===
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
427/427 [===
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
427/427 [===
Epoch 17/100
Epoch 18/100
```

## **LOSS AND ACCURACY CURVE:**

```
Plotting Loss and Accuracy curves

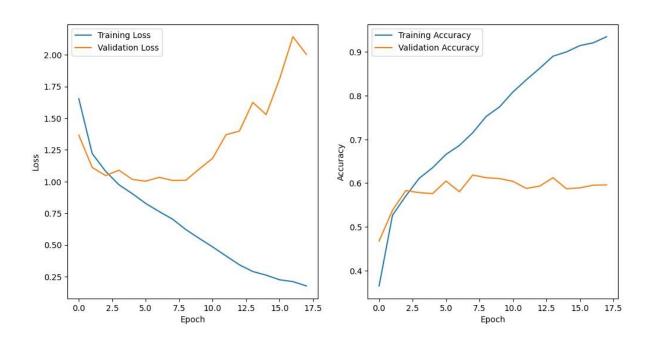
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_acc = history.history['accuracy']
val_acc = history.history['accuracy']

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(train_loss, label='Training Loss')
plt.ylabel('loss, label='Validation Loss')
plt.ylabel('loss')
plt.ylabel('loss')
plt.legend()

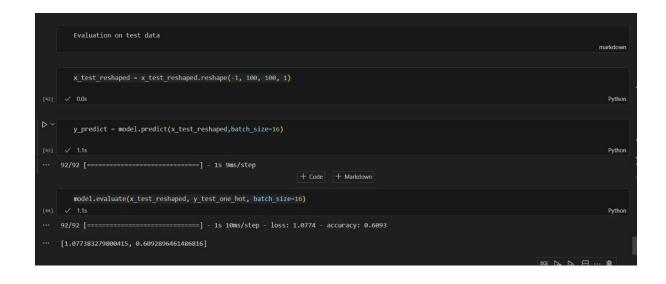
plt.subplot(1, 2, 2)
plt.plot(train_acc, label='Training Accuracy')
plt.ylabel('Accuracy')
plt.ylabel('Accuracy')
plt.ylabel('Accuracy')
plt.legend()

plt.show()

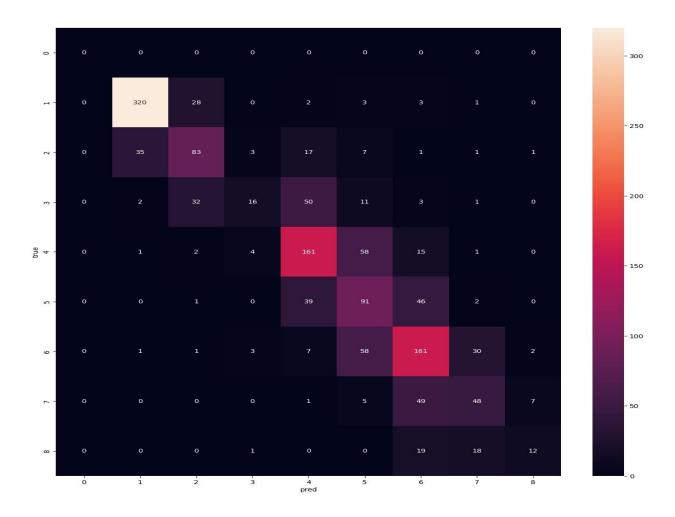
Python
```



## **EVALUATION:**



## **CONFUSION MATRIX:**



# **SAVING THE MODEL:**

```
Saving the model

def predict_with_model(model, input_data):
    return model(input_data)

# save the model
model.save("saved_model")

import tensorflow as tf
loaded_model = tf.keras.models.load_model("saved_model")

Python

Python
```

## **Real Time Testing**

```
Real life Testing

| image = cv2.imread(fing_name, jpg')|
| img_gray = cv2.cvtColor(image, cv2.ColOR_BCR2GRAY)|
| resized_image = cv2.resize(img_gray, (100,100))|
| image_np = np.array(resized_image)|
| resized_image = np.reshape(image_np, (-1, 100, 100, 1))|
| img_normalized = resized_image/ 255.0
| prediction=loaded_model_predict(img_normalized)|
| max_position = np.argmax(prediction)|
| print("VOUR_AGE_IS: ")
| if(max_position==1):
| print("0-5")
| clif(max_position==2):
| print("0-5")
| clif(max_position==3):
| print("1-3-1")
| clif(max_position==3):
| print("1-3-1")
| clif(max_position==6):
| print("1-3-1")
| clif(max_position==6):
| print("1-3-5")
| clif(max_position==6):
| print("3-6")
| elif(max_position==6):
| print("3-6")
| elif(max_position==6):
| print("5-8")
| clif(max_position==6):
| print("5-8")
| clif(max_position==6):
| print("5-8")
```