```
import os
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from PIL import Image, ImageOps
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Activation,
Dropout, Flatten, Dense, Input
from tensorflow.keras import optimizers
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.utils import to_categorical
import tensorflow as tf
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.optimizers import Adam

# Download UTKFace dataset using KaggleHub
import kagglehub
jangedoo_utkface_new_path =
kagglehub.dataset_download('jangedoo/utkface-new')
print('Data source import complete.')

# Correct the path to where the dataset was downloaded
image_folder_path = os.path.join(jangedoo_utkface_new_path,
"crop_part1")

# Load images, ages, and genders
images = []
ages = []
genders = []

# Load data
for i in os.listdir(image_folder_path)[0:8000]:  # Limit to first 8000
images for now
    split = i.split('_')
    ages.append(int(split[0]))
    genders.append(int(split[1]))
    img = Image.open(os.path.join(image_folder_path, i))
    img = img.resize((128, 128))  # Resize to 128x128 for easier
processing
    img_array = img_to_array(img)
    images.append(img_array)

# Convert lists to numpy arrays
images = np.array(images)
ages = np.array(ages)
genders = np.array(genders)

# Normalize image data
```

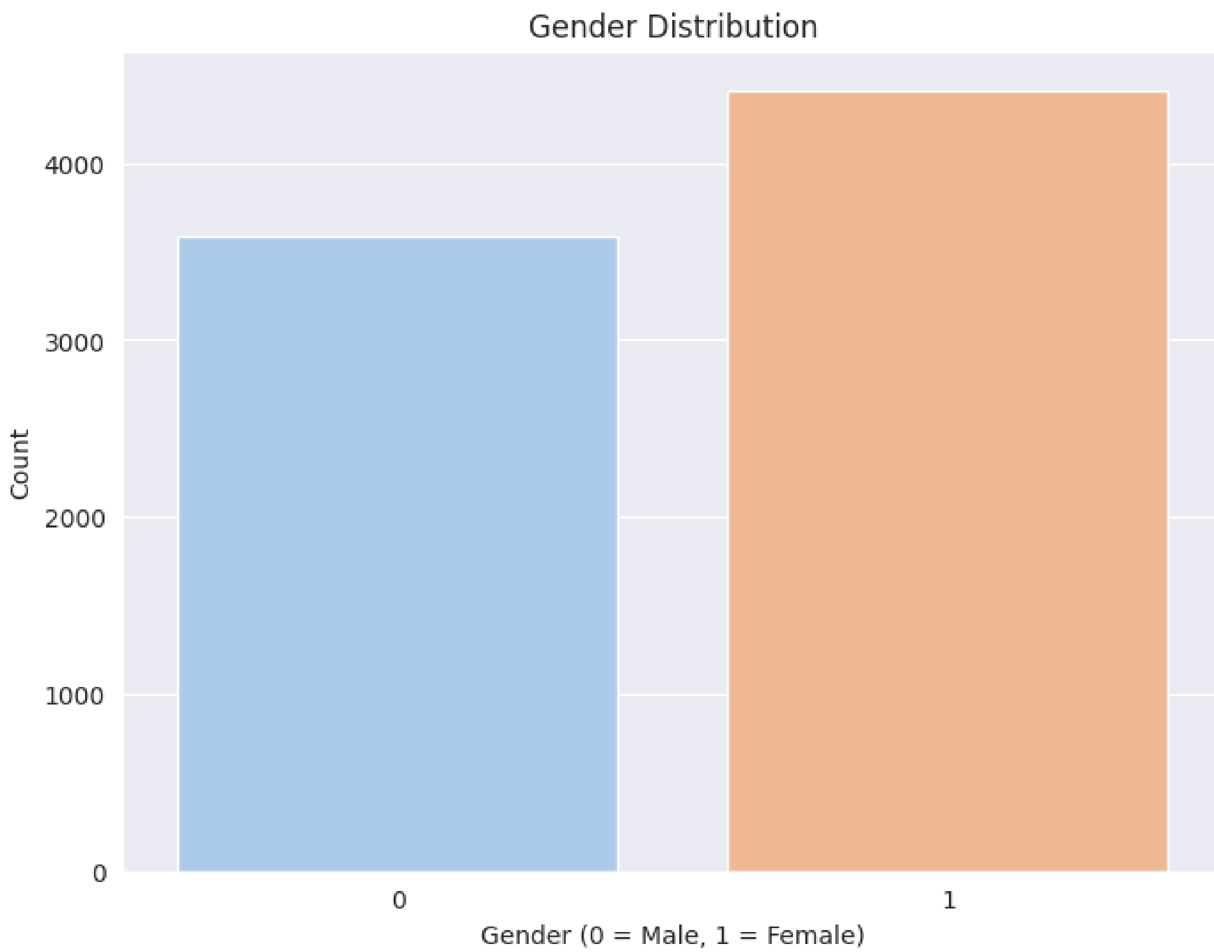
```
images = images / 255.0  # Normalize images to the range [0, 1]

# Set up the DataFrame for insights
df = pd.DataFrame({'Age': ages, 'Gender': genders})
```

```
Warning: Looks like you're using an outdated `kagglehub` version
(installed: 0.3.5), please consider upgrading to the latest version
(0.3.6).
Downloading from
https://www.kaggle.com/api/v1/datasets/download/jangedoo/utkface-new?
dataset_version_number=1...

100%|██████████| 331M/331M [00:01<00:00, 230MB/s]

Extracting files...



Data source import complete.
```

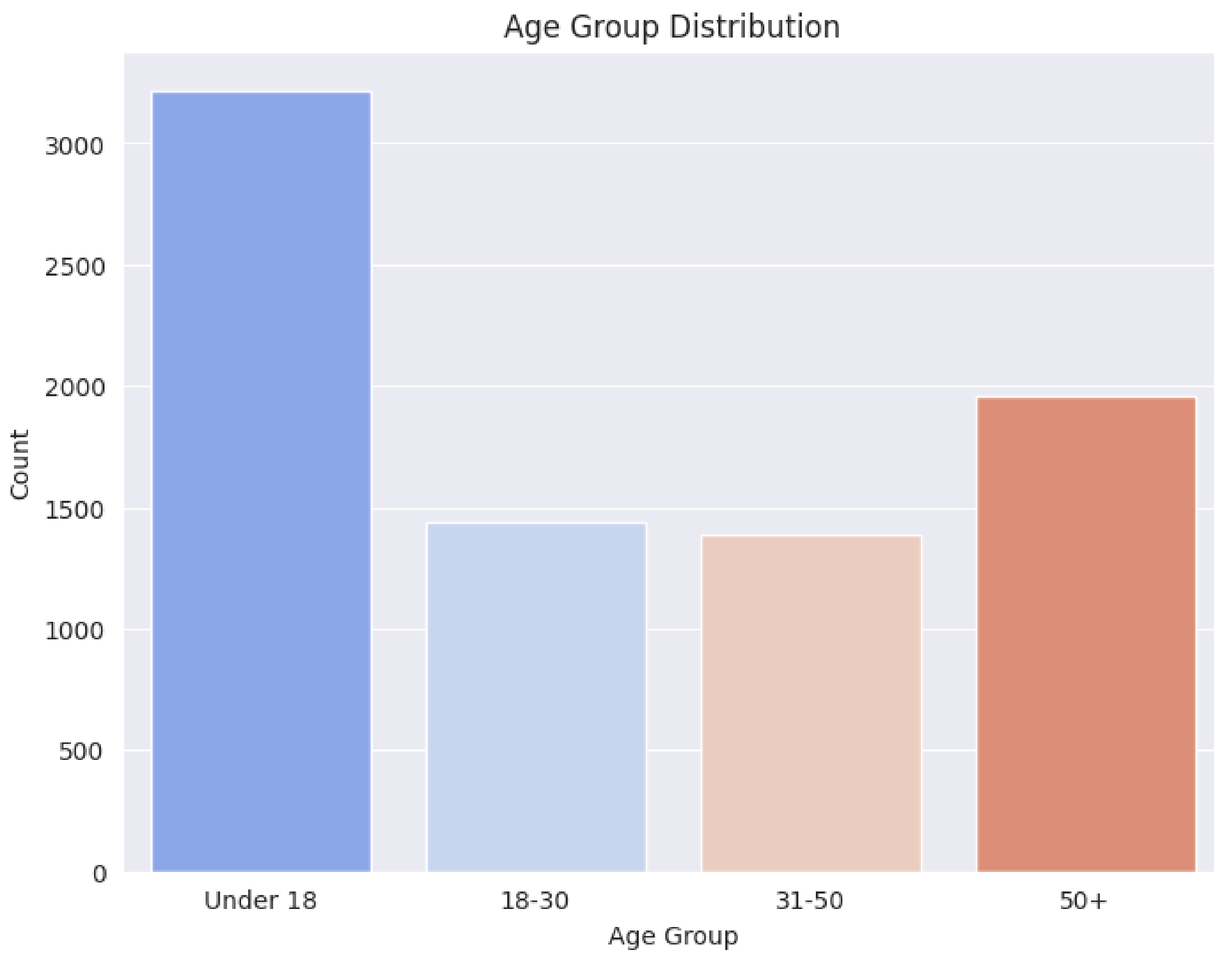
```
# Plot Gender Distribution with cool styling
plt.figure(figsize=(8, 6))
sns.set_style("darkgrid")
sns.countplot(x=genders, palette='pastel')
plt.title("Gender Distribution")
plt.xlabel("Gender (0 = Male, 1 = Female)")
plt.ylabel("Count")
plt.show()

# Age Group Distribution using cool palette
age_groups = pd.cut(ages, bins=[0, 18, 30, 50, 100], labels=["Under
18", "18-30", "31-50", "50+"], right=False)

plt.figure(figsize=(8, 6))
sns.countplot(x=age_groups, palette='coolwarm')
plt.title("Age Group Distribution")
plt.xlabel("Age Group")
plt.ylabel("Count")
plt.show()

# Age vs Gender with cool scatter plot and regression line
plt.figure(figsize=(8, 6))
sns.regplot(x=ages, y=genders, scatter_kws={"s": 10},
line_kws={"color": "red"})
plt.title("Age vs Gender with Regression Line")
plt.xlabel("Age")
plt.ylabel("Gender (0 = Male, 1 = Female)")
plt.show()

# Additional Insights: Age Distribution with KDE using a cool color
```

```
palette
plt.figure(figsize=(8, 6))
sns.histplot(ages, bins=30, kde=True, color='teal')
plt.title("Age Distribution with KDE")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()

# Pairplot: Visualizing Age and Gender relationship
plt.figure(figsize=(10, 8))
sns.pairplot(df, hue="Gender", palette='coolwarm', markers=["o", "s"])
plt.title("Pairplot of Age vs Gender")
plt.show()

# Heatmap: Correlation Matrix of features (although we have few
features, let's visualize them)
plt.figure(figsize=(8, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title("Correlation Heatmap")
plt.show()
```

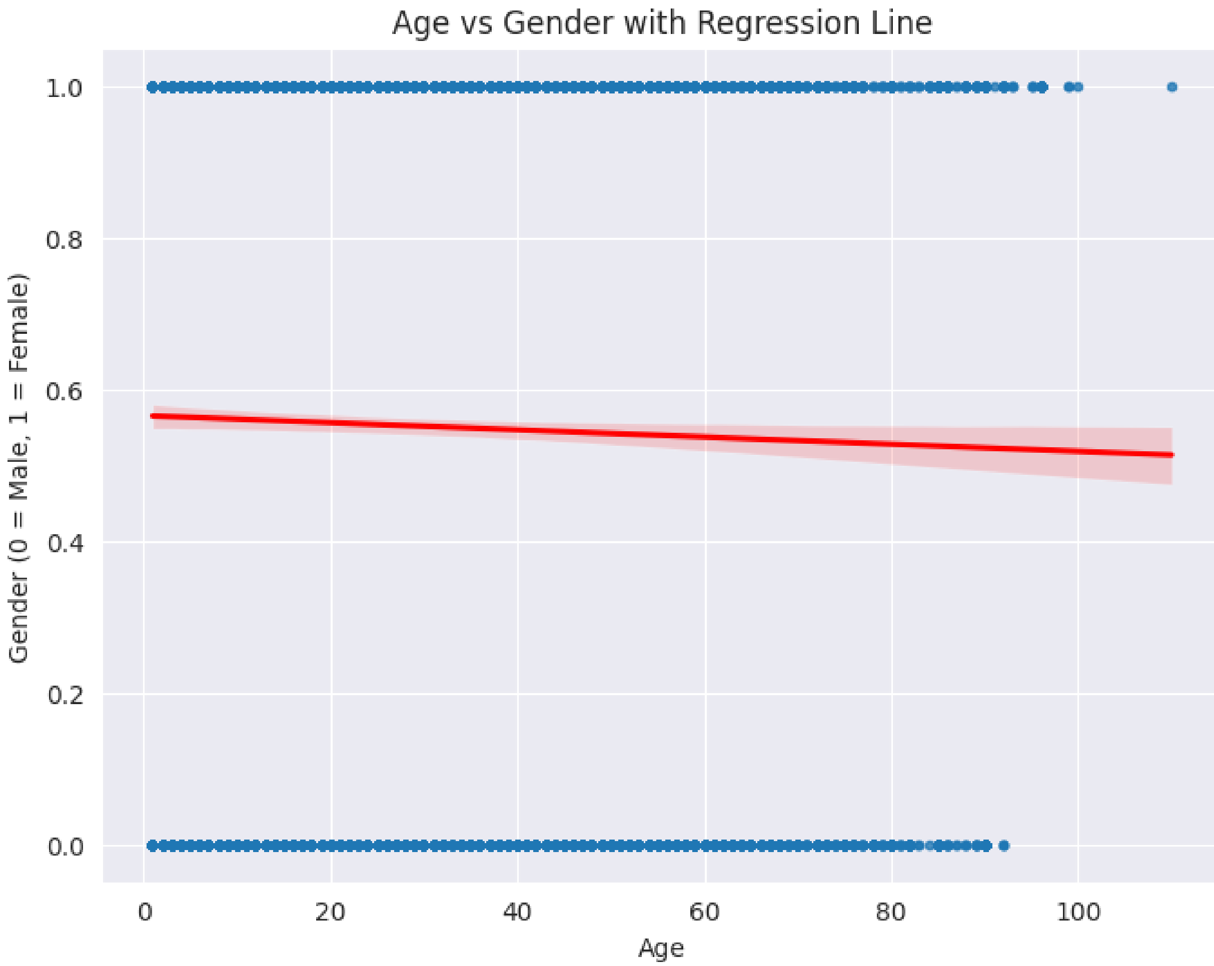
```
<ipython-input-2-d2ca728500d1>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x=genders, palette='pastel')
```

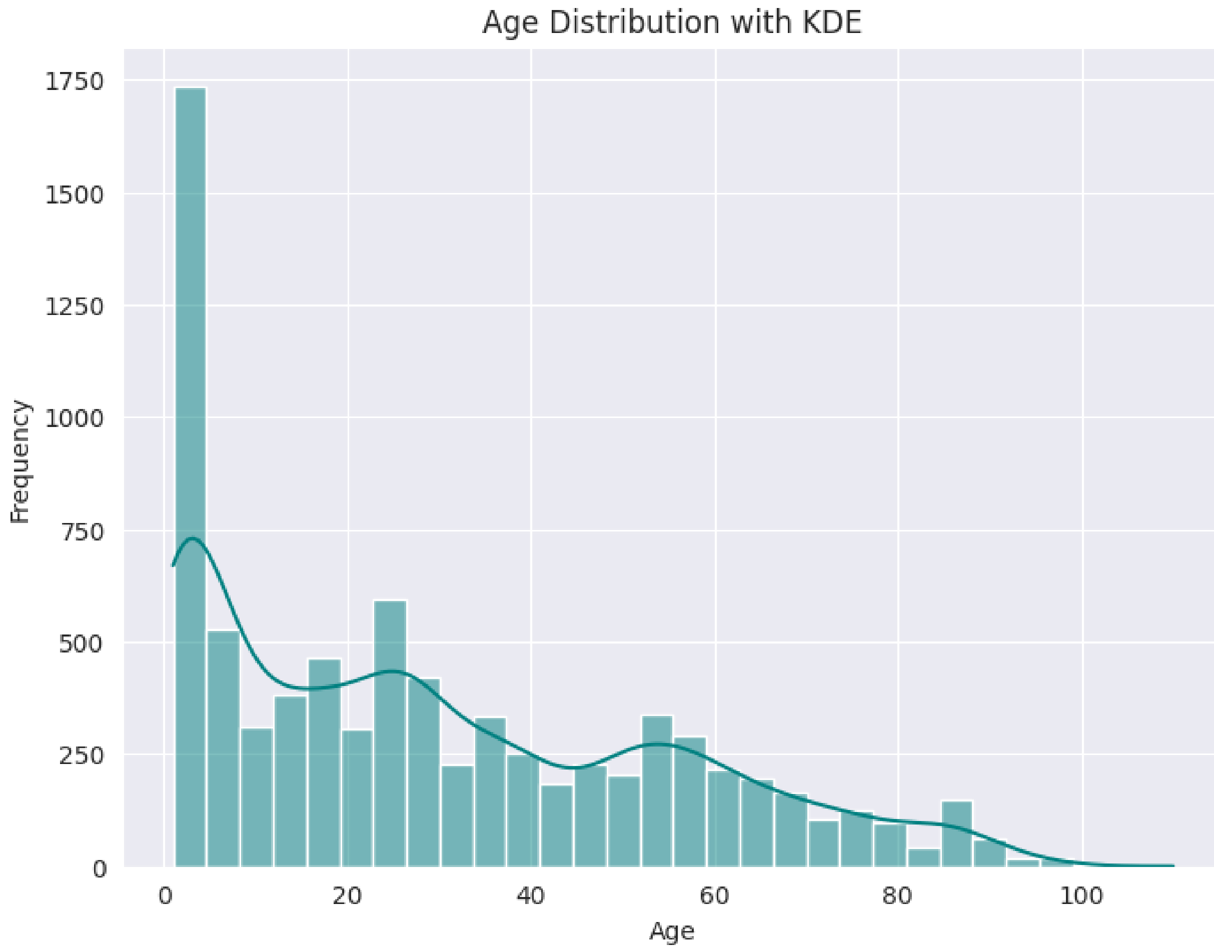



```
<ipython-input-2-d2ca728500d1>:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x=age_groups, palette='coolwarm')
```

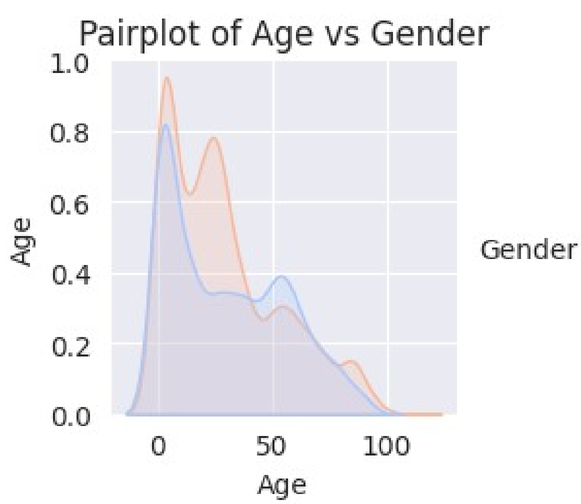


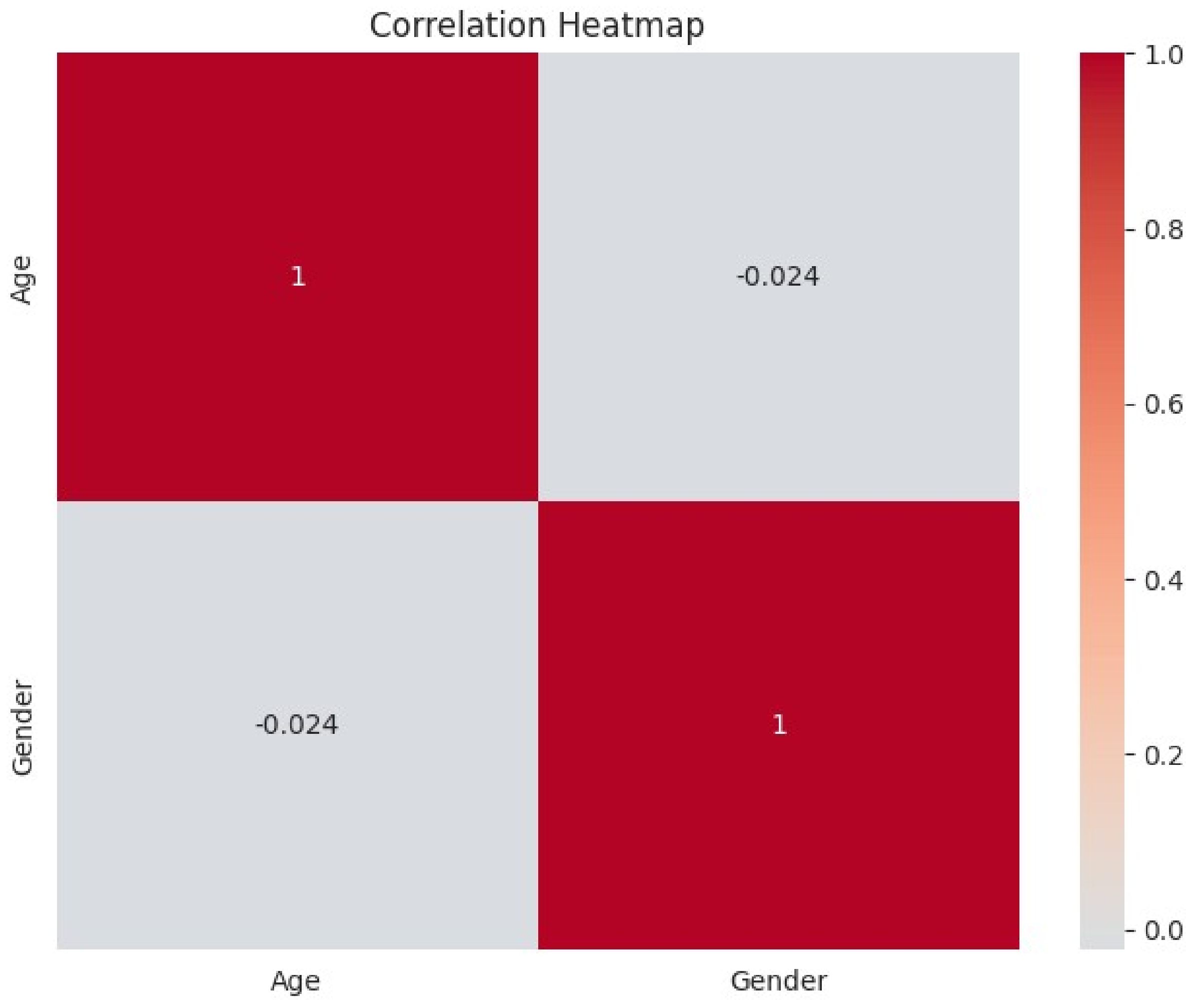
Age Group Distribution
3000
2500
2000
1500
1000
500
0
Count
Under 18
18-30
31-50
50+
Age Group


Age vs Gender with Regression Line
1.0
0.8
0.6
0.4
0.2
0.0
Gender (0 = Male, 1 = Female)
0
20
40
60
80
100
Age




```
&lt;Figure size 1000x800 with 0 Axes&gt;
```






```python
# Split data into training and test sets
X_train, X_test, y_gender_train, y_gender_test, y_age_train,
y_age_test = train_test_split(
    images, genders, ages, test_size=0.2, random_state=42)

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import EarlyStopping,
ReduceLROnPlateau
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras import layers
from tensorflow.keras.layers import GlobalAveragePooling2D

# 1. Data Augmentation
datagen = ImageDataGenerator(
    rescale=1./255,  # Normalize pixel values to [0, 1]
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
```

```
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

# Apply data augmentation on training data
datagen.fit(X_train)

# 2. Model Configuration - Use EfficientNetB0 for feature extraction
base_model = EfficientNetB0(input_shape=(128, 128, 3),
include_top=False, weights='imagenet')
base_model.trainable = False  # Freeze the base model for fine-tuning
later

# Model Inputs
inputs = Input(shape=(128, 128, 3))

# Base Model (EfficientNetB0)
X = base_model(inputs)
X = GlobalAveragePooling2D()(X)

# Fully Connected Layers
dense_1 = Dense(512, activation='relu')(X)
dropout_1 = Dropout(0.5)(dense_1)

# Gender Output: 1 unit, sigmoid activation for binary classification
output_1 = Dense(1, activation='sigmoid', name='gender_output')
(dropout_1)

# Age Output: 1 unit, linear activation for regression
output_2 = Dense(1, activation='relu', name='age_output')(dropout_1)

# Final model with two outputs
model = Model(inputs=inputs, outputs=[output_1, output_2])

# 3. Compile the Model with Early Stopping and ReduceLROnPlateau
early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5,
patience=3, min_lr=1e-6)

model.compile(optimizer=Adam(learning_rate=0.0001),
              loss={'gender_output': 'binary_crossentropy',
'age_output': 'mean_squared_error'},
              metrics={'gender_output': 'accuracy', 'age_output':
'mae'})

# Print Model Summary
model.summary()
```

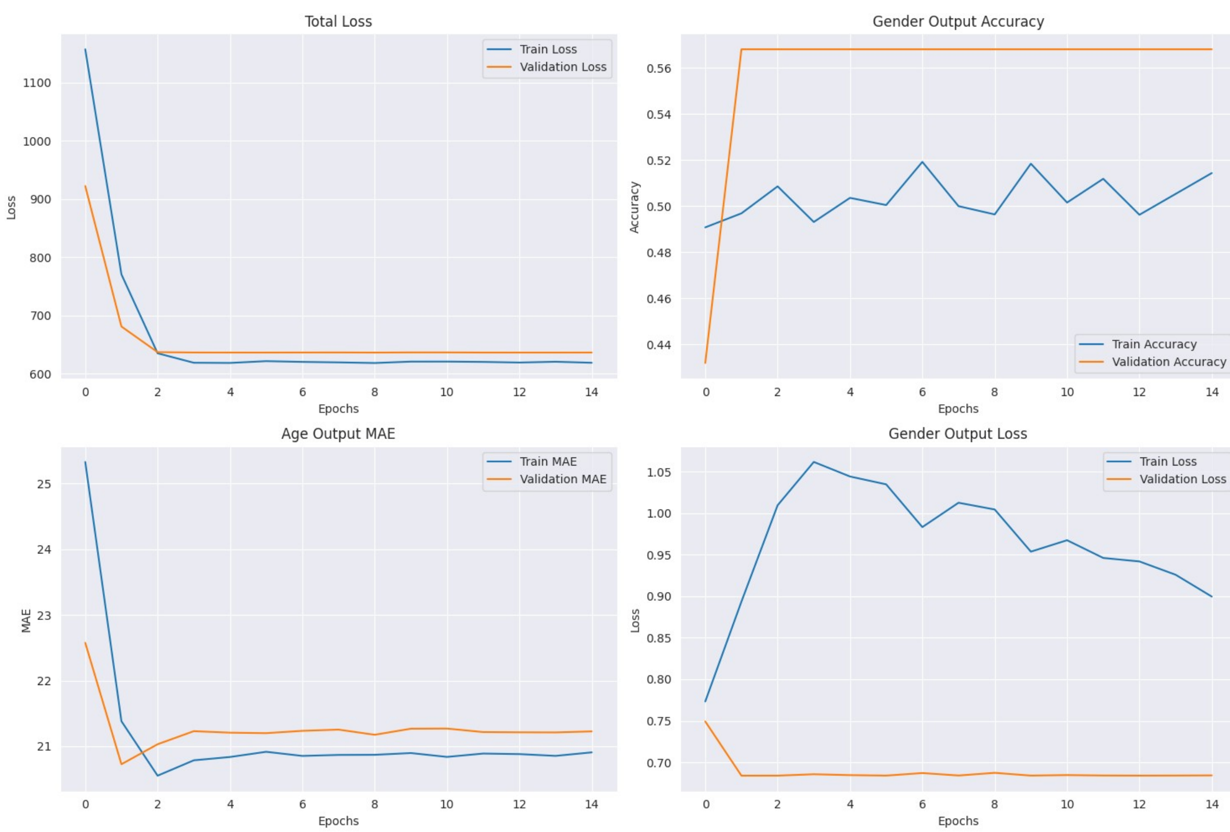
```
Downloading data from https://storage.googleapis.com/keras-
applications/efficientnetb0_notop.h5
16705208/16705208 [==============================] - 0s 0us/step
Model: "model"
______________________________________________________________________
____________________________
 Layer (type)                Output Shape                 Param #
Connected to
======================================================================
============================
 input_2 (InputLayer)        [(None, 128, 128, 3)]        0          []



 efficientnetb0 (Functional  (None, 4, 4, 1280)           4049571
['input_2[0][0]']
 )



 global_average_pooling2d (  (None, 1280)                 0
['efficientnetb0[0][0]']
 GlobalAveragePooling2D)



 dense (Dense)               (None, 512)                  655872
['global_average_pooling2d[0][

0]']


 dropout (Dropout)           (None, 512)                  0
['dense[0][0]']


 gender_output (Dense)       (None, 1)                    513
['dropout[0][0]']


 age_output (Dense)          (None, 1)                    513
['dropout[0][0]']


======================================================================
============================
Total params: 4706469 (17.95 MB)
Trainable params: 656898 (2.51 MB)
```

```
Non-trainable params: 4049571 (15.45 MB)
________________________________________________________________________
_____________________________

# Train the model
history = model.fit(X_train,
                    {'gender_output': y_gender_train, 'age_output':
y_age_train},  # Labels for both outputs
                    validation_data=(X_test, {'gender_output':
y_gender_test, 'age_output': y_age_test}),  # Validation data for both
outputs
                    epochs=15,  # Train for more epochs for better
results
                    batch_size=128)

Epoch 1/15
50/50 [==============================] - 256s 5s/step - loss:
1156.8793 - gender_output_loss: 0.7733 - age_output_loss: 1156.1058 -
gender_output_accuracy: 0.4908 - age_output_mae: 25.3256 - val_loss:
922.3024 - val_gender_output_loss: 0.7492 - val_age_output_loss:
921.5533 - val_gender_output_accuracy: 0.4319 - val_age_output_mae:
22.5750
Epoch 2/15
50/50 [==============================] - 244s 5s/step - loss: 770.7008
- gender_output_loss: 0.8936 - age_output_loss: 769.8073 -
gender_output_accuracy: 0.4969 - age_output_mae: 21.3824 - val_loss:
681.2561 - val_gender_output_loss: 0.6839 - val_age_output_loss:
680.5722 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
20.7278
Epoch 3/15
50/50 [==============================] - 242s 5s/step - loss: 635.3185
- gender_output_loss: 1.0096 - age_output_loss: 634.3091 -
gender_output_accuracy: 0.5086 - age_output_mae: 20.5538 - val_loss:
637.2703 - val_gender_output_loss: 0.6839 - val_age_output_loss:
636.5864 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.0318
Epoch 4/15
50/50 [==============================] - 242s 5s/step - loss: 619.0736
- gender_output_loss: 1.0618 - age_output_loss: 618.0117 -
gender_output_accuracy: 0.4931 - age_output_mae: 20.7875 - val_loss:
636.6586 - val_gender_output_loss: 0.6856 - val_age_output_loss:
635.9730 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2308
Epoch 5/15
50/50 [==============================] - 244s 5s/step - loss: 618.7450
- gender_output_loss: 1.0442 - age_output_loss: 617.7007 -
gender_output_accuracy: 0.5036 - age_output_mae: 20.8378 - val_loss:
636.5920 - val_gender_output_loss: 0.6846 - val_age_output_loss:
635.9075 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2077
```

```
Epoch 6/15
50/50 [==============================] - 240s 5s/step - loss: 621.8442
- gender_output_loss: 1.0348 - age_output_loss: 620.8093 -
gender_output_accuracy: 0.5005 - age_output_mae: 20.9170 - val_loss:
636.5745 - val_gender_output_loss: 0.6840 - val_age_output_loss:
635.8905 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2004
Epoch 7/15
50/50 [==============================] - 241s 5s/step - loss: 620.5663
- gender_output_loss: 0.9833 - age_output_loss: 619.5829 -
gender_output_accuracy: 0.5192 - age_output_mae: 20.8543 - val_loss:
636.6688 - val_gender_output_loss: 0.6871 - val_age_output_loss:
635.9818 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2357
Epoch 8/15
50/50 [==============================] - 242s 5s/step - loss: 619.7119
- gender_output_loss: 1.0126 - age_output_loss: 618.6992 -
gender_output_accuracy: 0.5000 - age_output_mae: 20.8692 - val_loss:
636.7385 - val_gender_output_loss: 0.6841 - val_age_output_loss:
636.0544 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2544
Epoch 9/15
50/50 [==============================] - 240s 5s/step - loss: 618.6246
- gender_output_loss: 1.0045 - age_output_loss: 617.6201 -
gender_output_accuracy: 0.4964 - age_output_mae: 20.8711 - val_loss:
636.5453 - val_gender_output_loss: 0.6873 - val_age_output_loss:
635.8580 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.1758
Epoch 10/15
50/50 [==============================] - 239s 5s/step - loss: 621.0528
- gender_output_loss: 0.9537 - age_output_loss: 620.0990 -
gender_output_accuracy: 0.5184 - age_output_mae: 20.8979 - val_loss:
636.8000 - val_gender_output_loss: 0.6840 - val_age_output_loss:
636.1160 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2680
Epoch 11/15
50/50 [==============================] - 239s 5s/step - loss: 621.0926
- gender_output_loss: 0.9675 - age_output_loss: 620.1252 -
gender_output_accuracy: 0.5016 - age_output_mae: 20.8392 - val_loss:
636.8120 - val_gender_output_loss: 0.6846 - val_age_output_loss:
636.1274 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2702
Epoch 12/15
50/50 [==============================] - 239s 5s/step - loss: 620.5358
- gender_output_loss: 0.9461 - age_output_loss: 619.5896 -
gender_output_accuracy: 0.5119 - age_output_mae: 20.8903 - val_loss:
636.5919 - val_gender_output_loss: 0.6841 - val_age_output_loss:
635.9078 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2169
```

```
Epoch 13/15
50/50 [==============================] - 240s 5s/step - loss: 619.4370
- gender_output_loss: 0.9419 - age_output_loss: 618.4951 -
gender_output_accuracy: 0.4963 - age_output_mae: 20.8818 - val_loss:
636.5784 - val_gender_output_loss: 0.6840 - val_age_output_loss:
635.8944 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2132
Epoch 14/15
50/50 [==============================] - 238s 5s/step - loss: 620.8373
- gender_output_loss: 0.9259 - age_output_loss: 619.9113 -
gender_output_accuracy: 0.5053 - age_output_mae: 20.8550 - val_loss:
636.5739 - val_gender_output_loss: 0.6840 - val_age_output_loss:
635.8899 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2115
Epoch 15/15
50/50 [==============================] - 239s 5s/step - loss: 619.0330
- gender_output_loss: 0.8996 - age_output_loss: 618.1335 -
gender_output_accuracy: 0.5144 - age_output_mae: 20.9082 - val_loss:
636.6161 - val_gender_output_loss: 0.6842 - val_age_output_loss:
635.9319 - val_gender_output_accuracy: 0.5681 - val_age_output_mae:
21.2274

# Create a figure for all the graphs
plt.figure(figsize=(15, 10))

# Plotting training and validation loss
plt.subplot(2, 2, 1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Total Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Gender Accuracy (Train and Validation)
plt.subplot(2, 2, 2)
plt.plot(history.history['gender_output_accuracy'], label='Train
Accuracy')
plt.plot(history.history['val_gender_output_accuracy'],
label='Validation Accuracy')
plt.title('Gender Output Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Age MAE (Mean Absolute Error) (Train and Validation)
plt.subplot(2, 2, 3)
plt.plot(history.history['age_output_mae'], label='Train MAE')
plt.plot(history.history['val_age_output_mae'], label='Validation
MAE')
```

```python
plt.title('Age Output MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()

# Gender Loss (Train and Validation)
plt.subplot(2, 2, 4)
plt.plot(history.history['gender_output_loss'], label='Train Loss')
plt.plot(history.history['val_gender_output_loss'], label='Validation Loss')
plt.title('Gender Output Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Display all the plots
plt.tight_layout()
plt.show()
```




```python
# Model Evaluation (for test set)
results = model.evaluate(X_test,
                         {'gender_output': y_gender_test, 'age_output': y_age_test})
```

```python
# Unpack the results
test_loss, gender_output_loss, age_output_loss, test_gender_accuracy,
test_age_mae = results

# Print the evaluation results
print("Test Loss:", test_loss)
print("Gender Output Loss:", gender_output_loss)
print("Age Output Loss:", age_output_loss)
print("Test Gender Accuracy:", test_gender_accuracy)
print("Test Age MAE:", test_age_mae)
```

```
50/50 [==============================] - 45s 906ms/step - loss:
636.6162 - gender_output_loss: 0.6842 - age_output_loss: 635.9319 -
gender_output_accuracy: 0.5681 - age_output_mae: 21.2274
Test Loss: 636.6162109375
Gender Output Loss: 0.6842218041419983
Age Output Loss: 635.9319458007812
Test Gender Accuracy: 0.5681250095367432
Test Age MAE: 21.227384567260742
```

```python
print("Test Loss:", test_loss)
print("Test Gender Accuracy:", test_gender_accuracy)
print("Test Age MAE:", test_age_mae)
```

```
Test Loss: 636.6162109375
Test Gender Accuracy: 0.5681250095367432
Test Age MAE: 21.227384567260742
```

```python
# Display some sample predictions
sample_idx = np.random.randint(0, len(X_test), 5)  # Random indices
for sample display

for idx in sample_idx:
    img = X_test[idx] * 255.0  # Rescale back to [0, 255]
    img = np.clip(img, 0, 255).astype(np.uint8)
    img = Image.fromarray(img)

    gender_pred, age_pred = model.predict(np.expand_dims(X_test[idx],
axis=0))

    plt.imshow(img)
    plt.title(f"Predicted Gender: {'Male' if gender_pred > 0.5 else
'Female'}, Predicted Age: {int(age_pred)}")
    plt.axis('off')
    plt.show()
```

```
1/1 [==============================] - 0s 50ms/step
```

```
<ipython-input-14-5cfd7c1e9056>:12: DeprecationWarning: Conversion of
an array with ndim > 0 to a scalar is deprecated, and will error in
future. Ensure you extract a single element from your array before
```

```
performing this operation. (Deprecated NumPy 1.25.)
  plt.title(f"Predicted Gender: {'Male' if gender_pred > 0.5 else
'Female'}, Predicted Age: {int(age_pred)}")
```


```
1/1 [==============================] - 0s 46ms/step
```

Predicted Gender: Male, Predicted Age: 29

```
1/1 [==============================] - 0s 48ms/step
```

Predicted Gender: Male, Predicted Age: 29

```
1/1 [==============================] - 0s 48ms/step
```

Predicted Gender: Male, Predicted Age: 29

```
1/1 [==============================] - 0s 46ms/step
```

Predicted Gender: Male, Predicted Age: 29