Customer Age Estimation

Project description

A retail supermarket is implementing a computer vision system to process customer photos. Capturing images at the checkout area will help determine the age of customers in order to:

- Analyze purchases and recommend products that may be of interest to that age group;
- Control cashier compliance when selling alcohol.

Task: Build a model that estimates a person's approximate age from a photo.

Data: A dataset of customer photos with age labels

Exploratory Data Analysis

In [1]:

```
import pandas as pd
import numpy as np

from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
```

Data loading

In [2]:

```
labels=pd.read_csv('')
labels.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7591 entries, 0 to 7590
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   file_name  7591 non-null   object
 1   real_age   7591 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 118.7+ KB
```

In [3]:
```python
datagen = ImageDataGenerator()
```

In [4]:
```python
# Extracting data from the folder
datagen_flow = datagen.flow_from_directory(
    # Folder where the dataset is stored
    '',
    # Target image size
    target_size=(150, 150),
    # Batch size
    batch_size=16,
    # Label format
    class_mode='sparse',
    # Random seed
    seed=12345)
```

```
Found 7591 images belonging to 1 classes.
```

In [5]:
```python
print(datagen_flow.class_indices)
```

```
{'final_files': 0}
```

Sample Size

- The dataset includes 7,591 images.
- Images are represented as 4D tensors (475 batches), where each batch contains 16 images of size 150x150 with 3 color channels.

In [6]:
```python
# 4D tensor containing 16 images of size 150x150 with three color channels
features, target = next(datagen_flow)
print(features.shape)
```

```
(16, 150, 150, 3)
```

In [7]:
```python
len(datagen_flow)
```

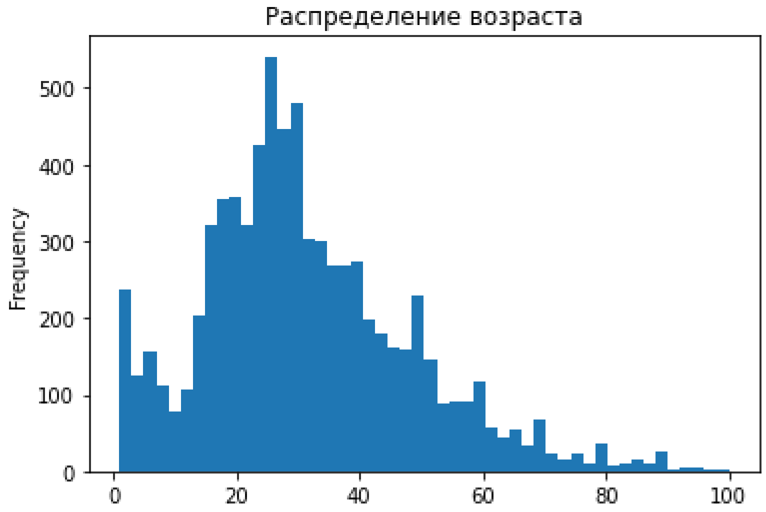
Out[7]:
```
475
```

Age Distribution Chart

Age distribution: Statistical analysis shows that a quarter of people are under 20 years old, half under 29, and 75% under 41. The average age in the dataset is 31 years. The histogram of age distribution reveals two main groups: children and adults.

In [8]:

```
plot1=labels['real_age'].plot(kind='hist', bins=50, title='Распределение возраста')
```



Dataset Structure: 10–15 Photos

In [9]:

```
import os, random
from matplotlib.image import imread
```

In [10]:

```
random_images = random.sample(
    os.listdir(''),
    k=15
)

print('random_images', random_images)
print()
# Get all image file paths
image_files = [
    os.path.join('', f)
    for f in random_images
]
```

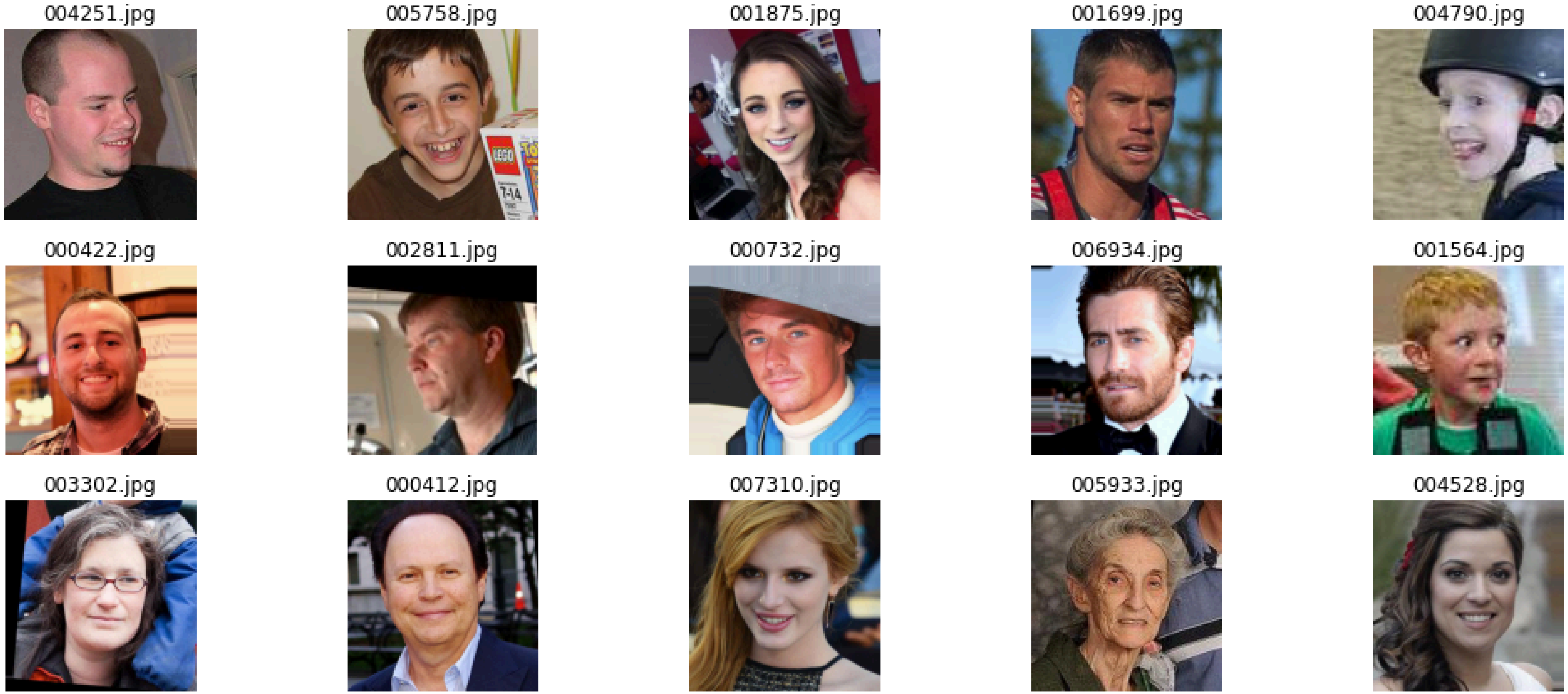
```python
print('image_files', image_files)
print()
# Create a grid for displaying images
fig, axes = plt.subplots(3, 5, figsize=(15, 6))

# Display each image in the grid
for ax, img_path in zip(axes.flatten(), image_files):
    img = imread(img_path)
    ax.imshow(img)
    ax.axis('off')  # Hide axes
    ax.set_title(os.path.basename(img_path))  # Show image filename (optional)

plt.tight_layout()
plt.show()
```

```
random_images ['004251.jpg', '005758.jpg', '001875.jpg', '001699.jpg', '004790.jpg', '000422.jpg', '002811.jpg', '000732.jpg', '006
934.jpg', '001564.jpg', '003302.jpg', '000412.jpg', '007310.jpg', '005933.jpg', '004528.jpg']

image_files ['/datasets/faces/final_files/004251.jpg', '/datasets/faces/final_files/005758.jpg', '/datasets/faces/final_files/00187
5.jpg', '/datasets/faces/final_files/001699.jpg', '/datasets/faces/final_files/004790.jpg', '/datasets/faces/final_files/000422.jp
g', '/datasets/faces/final_files/002811.jpg', '/datasets/faces/final_files/000732.jpg', '/datasets/faces/final_files/006934.jpg',
'/datasets/faces/final_files/001564.jpg', '/datasets/faces/final_files/003302.jpg', '/datasets/faces/final_files/000412.jpg', '/dat
asets/faces/final_files/007310.jpg', '/datasets/faces/final_files/005933.jpg', '/datasets/faces/final_files/004528.jpg']
```



Conclusions:

The analysis shows that there are no predefined classes, so this is a regression task rather than classification (with a single output neuron returning a prediction and the loss functions MAE and MSE). The ReLU activation function is suitable for age prediction, since it leaves positive values unchanged and maps negative values to zero (there is no negative age). The dataset is relatively small — 7,591 color images. Various augmentations can be applied. The age distribution follows a log-normal curve shifted to the left (towards younger customers). Consequently, the proportion of younger people in predictions may be higher.

It is also important to note the characteristics of the dataset images. There are both color and black-and-white photos. Images vary in zoom: some show only faces, others the entire body, and some include several people without clearly visible faces. Certain images are rotated or shifted. Image quality also varies, with some containing artifacts. These factors complicate the model's task, but are not critical.

Model Training

The notebook contains the model training code and its output results. (The code in this section was run on a separate GPU environment, which is why it is presented as text rather than as an executable code cell.)

```
import os

import numpy as np
import pandas as pd
from tensorflow.keras.applications.resnet import ResNet50
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.layers import (
    BatchNormalization,
    Conv2D,
    Dense,
    Dropout,
    Flatten,
    GlobalAveragePooling2D,
    GlobalMaxPooling2D,
    MaxPooling2D,
)
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.regularizers import l2


def load_train(path):
    datagen = ImageDataGenerator(validation_split=0.25, rescale=1.0 / 255,
                                 rotation_range=90,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode="nearest",
                                )
    labels=pd.read_csv(os.path.join(path, ''))

    train_datagen_flow = datagen.flow_from_dataframe(
        # Folder where the dataset is stored,
```

```python
        dataframe=labels,
        x_col="file_name",
        y_col="real_age",
        directory=os.path.join(path, ''),
        # Target image size
        target_size=(150, 150),
        # Batch size
        batch_size=16 ,
        classes=None,
        # Label format
        class_mode="raw",
        # Indicate that this is the training data loader
        subset="training",
        # Random seed
        seed=12345,
    )
    return train_datagen_flow

def load_test(path):
    datagen = ImageDataGenerator(validation_split=0.25, rescale=1.0 / 255)
    labels=pd.read_csv(os.path.join(path, ''))

    val_datagen_flow = datagen.flow_from_dataframe(
        # Folder where the dataset is stored,
        dataframe=labels,
        x_col="file_name",
        y_col="real_age",
        directory=os.path.join(path, ''),
        # Target image size
        target_size=(150, 150),
        # Batch size
        batch_size=16 ,
        classes=None,
        # Label format
        class_mode="raw",
        subset="validation",
        seed=12345,
    )
```

```
    return val_datagen_flow

def create_model(input_shape):
    optimizer = Adam(learning_rate=0.00001)
    path = ''

    # ResNet50 backbone without the top layers
    backbone = ResNet50(input_shape=(150, 150, 3),
                        weights=path if os.path.exists(path) else 'imagenet',
                        include_top=False)
    # Building the model
    model = Sequential()
    model.add(backbone)
    model.add(GlobalAveragePooling2D())
    model.add(BatchNormalization())
    model.add(Dropout(0.4))

    # Fully connected network
    model.add(Dense(256, activation="relu", kernel_regularizer="l2"))
    model.add(Dropout(0.5))  # Additional regularization
    model.add(Dense(128, activation="relu", kernel_regularizer="l2"))
    model.add(Dropout(0.5))

    # Output layer
    model.add(Dense(1, activation='linear'))  # Age prediction, regression task

    model.compile(optimizer=optimizer,
                   loss='mean_squared_error',
                  metrics=['mae'])
    return model



def train_model(
    model,
    train_data,
    test_data,
    batch_size=None,
    epochs=25,
```

```
    steps_per_epoch=None,
    validation_steps=None,
):

    model.fit(
        train_data,
        validation_data=test_data,
        batch_size=batch_size,
        epochs=epochs,
        steps_per_epoch=steps_per_epoch,
        validation_steps=validation_steps,
        verbose=2,
    )
    return model


if __name__ == "__main__":
    labels = pd.read_csv(r"")

    path = r""
    train_datagen_flow = load_train(path)

    val_datagen_flow = load_test(path)

    input_shape = (150, 150, 3)
    model = create_model(input_shape)
    train_model(
        model,
        train_datagen_flow,
        val_datagen_flow,
    )
```
`

< copied output result here >

Found 5694 validated image filenames. Found 1897 validated image filenames.

Train for 356 steps, validate for 119 steps Epoch 1/25

356/356 - 106s - loss: 1084.1613 - mae: 28.0798 - val_loss: 919.7560 - val_mae: 25.4265 Epoch 2/25 356/356 - 76s - loss: 889.9902 - mae: 24.8488 - val_loss: 699.2781 - val_mae: 21.5819 Epoch 3/25 356/356 - 72s - loss: 615.6782 - mae: 20.0682 - val_loss: 231.1202 - val_mae: 11.6488 Epoch 4/25 356/356 - 72s - loss: 349.3874 - mae: 14.5632 - val_loss: 152.4129 - val_mae: 9.5609 Epoch 5/25 356/356 - 73s - loss: 259.6312 - mae: 12.3126 - val_loss: 158.5465 - val_mae: 9.5088 Epoch 6/25 356/356 - 73s - loss: 238.7720 - mae: 11.8095 - val_loss: 139.1908 - val_mae: 8.8386 Epoch 7/25 356/356 - 73s - loss: 227.3345 - mae: 11.5364 - val_loss: 129.0461 - val_mae: 8.4613 Epoch 8/25 356/356 - 76s - loss: 213.9164 - mae: 11.0792 - val_loss: 111.3144 - val_mae: 7.9295 Epoch 9/25 356/356 - 77s - loss: 209.1289 - mae: 10.9979 - val_loss: 132.9900 - val_mae: 8.6558 Epoch 10/25 356/356 - 79s - loss: 202.8597 - mae: 10.8698 - val_loss: 110.8691 - val_mae: 7.8322 Epoch 11/25 356/356 - 78s - loss: 197.8652 - mae: 10.6388 - val_loss: 111.6436 - val_mae: 7.8367 Epoch 12/25 356/356 - 79s - loss: 186.8420 - mae: 10.4367 - val_loss: 108.7572 - val_mae: 7.7028 Epoch 13/25 356/356 - 78s - loss: 180.2066 - mae: 10.1265 - val_loss: 119.3273 - val_mae: 7.9509 Epoch 14/25 356/356 - 72s - loss: 180.8386 - mae: 10.1878 - val_loss: 109.3808 - val_mae: 7.6495 Epoch 15/25 356/356 - 72s - loss: 176.4480 - mae: 9.9921 - val_loss: 111.5077 - val_mae: 7.6617 Epoch 16/25 356/356 - 73s - loss: 166.2928 - mae: 9.6828 - val_loss: 115.1434 - val_mae: 7.8189 Epoch 17/25 356/356 - 72s - loss: 165.1584 - mae: 9.7879 - val_loss: 113.5917 - val_mae: 7.7544 Epoch 18/25 356/356 - 79s - loss: 166.9420 - mae: 9.6697 - val_loss: 108.9907 - val_mae: 7.6847 Epoch 19/25 356/356 - 77s - loss: 163.4138 - mae: 9.6433 - val_loss: 113.9345 - val_mae: 7.7520 Epoch 20/25 356/356 - 78s - loss: 155.4891 - mae: 9.4050 - val_loss: 107.9959 - val_mae: 7.5331 Epoch 21/25 356/356 - 79s - loss: 162.1810 - mae: 9.5786 - val_loss: 106.5743 - val_mae: 7.4651 Epoch 22/25 356/356 - 72s - loss: 153.7422 - mae: 9.3440 - val_loss: 110.4260 - val_mae: 7.6465 Epoch 23/25 356/356 - 76s - loss: 146.6287 - mae: 9.1726 - val_loss: 103.6560 - val_mae: 7.4158 Epoch 24/25 356/356 - 77s - loss: 147.2016 - mae: 9.1717 - val_loss: 106.1355 - val_mae: 7.5407 Epoch 25/25 356/356 - 78s - loss: 150.0113 - mae: 9.1739 - val_loss: 109.0483 - val_mae: 7.6381

Trained Model Analysis

The project consists of two main parts:

- The first part contains the results of the exploratory data analysis.
- The second part includes the model training code and its output results.

  The data were loaded, and the initial dataset consisted of 7,591 images of people of different ages (both color and black-and-white). Each image had a corresponding real age label. Images were loaded using ImageDataGenerator(), which processed them in batches of 16 with a size of 150x150. Based on the analysis, there were no predefined classes, so the task was treated as regression.

  A histogram of the age distribution showed: a quarter of the people were under 20, half were under 29, and 75% were under 41. The average age was 31. The histogram revealed two distinct groups: children and adults. The age distribution followed a log-normal pattern, shifted toward younger ages. Consequently, the share of younger people in the predictions was expected to be higher.

- The task was regression, with a single output neuron returning the prediction,
- The task was regression, with a single output neuron returning the prediction,
- Metric: mae,
- Activation functions: relu (suitable for age prediction because it does not alter positive values and maps negative values to zero — negative age does not exist) and linear in the output layer,
- Data augmentation applied: rotations, shifts, zooms, flips, stretching, and the "nearest" strategy for filling newly generated pixels,
- To achieve the required MAE threshold (<8), a pre-trained ResNet50 model was used (include_top=False, backbone.trainable = False). Additional layers included: GlobalAveragePooling2D(), two fully connected layers with 256 and 128 neurons, and a final fully connected layer with one output neuron and linear activation,
- By the 10th epoch, the MAE metric on the validation data dropped to 7.8322 and did not rise above 8 afterward, which met the project’s requirements.

In [ ]: