In [135…

```
#importing necessary packages
import pandas as pd
import numpy as np
import tensorflow as tf
import glob
import os
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn import metrics
from sklearn.metrics import confusion_matrix
```

In [136…

```
# reading the csv file
data = pd.read_csv("train.csv")
```

In [137…

```
data.head()
```

Out[137…

	ID	Class
0	377.jpg	MIDDLE
1	17814.jpg	YOUNG
2	21283.jpg	MIDDLE
3	16496.jpg	YOUNG
4	4487.jpg	MIDDLE

In [138…

```
data['Class'].value_counts()
```

Out[138…

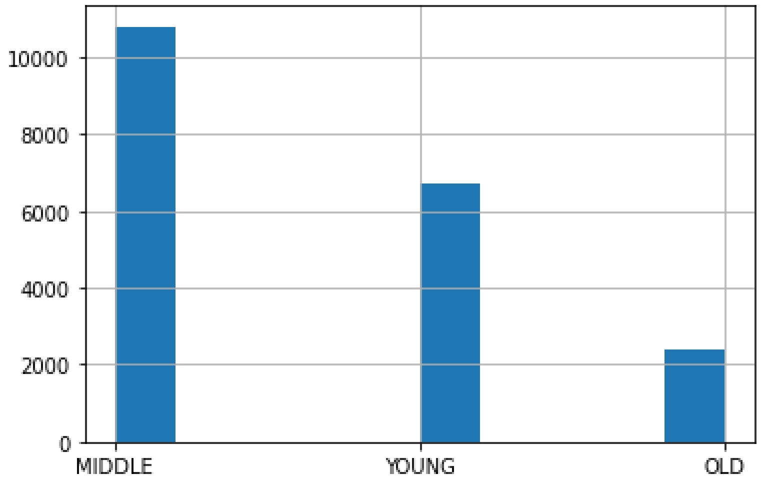
```
MIDDLE    10804
YOUNG      6706
OLD        2396
Name: Class, dtype: int64
```

In [139…

```
data['Class'].hist()
```

Out[139…

```
<AxesSubplot:>
```



In [140…

```
#classfication problem so encoding class into 0,1,2
# young=0,middle=1,old=2
data['Class'].replace(['YOUNG','MIDDLE','OLD'],[0,1,2],inplace=True)
```

In [141…

```
data['Class'].value_counts()
```

Out[141…

```
1    10804
0     6706
2     2396
Name: Class, dtype: int64
```

In [142…

```
#used in a image purpose for resizing
def readImage(path,ch = 3, resize=(150,150)):
    img = tf.io.read_file(path)
    img = tf.image.decode_jpeg(img, channels=ch)
    img = tf.image.convert_image_dtype(img, dtype=tf.float32)
    img = tf.image.resize(img, resize)
    return img
```

In [143…

```
# function to load the data that includes images and respective labels
def load_data(image_path, label):
    img = readImage(image_path, 3, (150,150))
    return (img, label)
```

In [144…

```
# built the list of image paths and list of respective responses of the images
PATH = "Train"
image_paths = []
for path in os.listdir(PATH):
    image_paths.append(PATH+"/"+path)
print(len(image_paths))

label_list = []

for i in image_paths:
    _,tail = os.path.split(i)
    label = data.loc[data['ID'] == tail]['Class'].values[0]
    label_list.append(label)
print(len(label_list))
```

```
19906
19906
```

In [145…

```
# split the dataset into train and test dataset
train_size = int(0.9*(len(image_paths)))
print(f"The training dataset size is {train_size}")
test_size = int(0.1*(len(image_paths)))
print(f"The testing dataset size is {test_size}")
#slicing dataset
train_set = tf.data.Dataset.from_tensor_slices((image_paths[:train_size], label_list[:train_size]))
test_set = tf.data.Dataset.from_tensor_slices((image_paths[test_size:], label_list[test_size:]))
```

```
The training dataset size is 17915
The testing dataset size is 1990
```

In [146…

```
#autotuning train dataset
train_set = (train_set
    .map(load_data, num_parallel_calls=tf.data.AUTOTUNE)
    .batch(64)
    .prefetch(tf.data.AUTOTUNE)
)
```

In [147…

```
#autotuining test dataset
test_set = (test_set
    .map(load_data, num_parallel_calls=tf.data.AUTOTUNE)
    .batch(64)
    .prefetch(tf.data.AUTOTUNE)
)
```

In [148…

```
# building cnn layers
cnn_model = models.Sequential([
    layers.Conv2D(filters=30, kernel_size=(3, 3), activation='relu', input_shape=(150, 150, 3), padding = 'same'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding = 'same'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dense(3, activation='softmax')
])
```

In [149…

```
# view the summary of the cnn model
cnn_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_7 (Conv2D)            (None, 150, 150, 30)      840
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 75, 75, 30)        0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 75, 75, 64)        17344
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 37, 37, 64)        0
_________________________________________________________________
flatten_3 (Flatten)          (None, 87616)             0
_________________________________________________________________
dense_6 (Dense)              (None, 64)                5607488
_________________________________________________________________
dense_7 (Dense)              (None, 3)                 195
=================================================================
Total params: 5,625,867
```

```
Trainable params: 5,625,867
Non-trainable params: 0
_________________________________________________________________
```

In [174…

```
# compile the model
cnn_model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

In [175…

```
# fit the model
cnn_model.fit(train_set, epochs=20, validation_data=test_set)
#as we didn't performed data augmentation so we used 20 epochs
```

```
Epoch 1/20
280/280 [==============================] - 26s 90ms/step - loss: 0.0966 - accuracy: 0.9661 - val_loss: 0.3528 - val_accuracy: 0.90
71
Epoch 2/20
280/280 [==============================] - 26s 92ms/step - loss: 0.0791 - accuracy: 0.9717 - val_loss: 0.4092 - val_accuracy: 0.90
28
Epoch 3/20
280/280 [==============================] - 24s 87ms/step - loss: 0.0762 - accuracy: 0.9733 - val_loss: 0.4560 - val_accuracy: 0.89
69
Epoch 4/20
280/280 [==============================] - 24s 86ms/step - loss: 0.0774 - accuracy: 0.9718 - val_loss: 0.3995 - val_accuracy: 0.91
09
Epoch 5/20
280/280 [==============================] - 25s 89ms/step - loss: 0.0684 - accuracy: 0.9763 - val_loss: 0.4812 - val_accuracy: 0.89
65
Epoch 6/20
280/280 [==============================] - 27s 95ms/step - loss: 0.0604 - accuracy: 0.9794 - val_loss: 0.4071 - val_accuracy: 0.91
99
Epoch 7/20
280/280 [==============================] - 24s 84ms/step - loss: 0.0592 - accuracy: 0.9793 - val_loss: 0.4302 - val_accuracy: 0.91
66
Epoch 8/20
280/280 [==============================] - 24s 86ms/step - loss: 0.0700 - accuracy: 0.9760 - val_loss: 0.4150 - val_accuracy: 0.92
10
Epoch 9/20
280/280 [==============================] - 26s 92ms/step - loss: 0.0519 - accuracy: 0.9821 - val_loss: 0.4497 - val_accuracy: 0.91
62
Epoch 10/20
280/280 [==============================] - 25s 90ms/step - loss: 0.0494 - accuracy: 0.9829 - val_loss: 0.4352 - val_accuracy: 0.92
```

```
27
Epoch 11/20
280/280 [==============================] - 24s 87ms/step - loss: 0.0452 - accuracy: 0.9850 - val_loss: 0.4649 - val_accuracy: 0.92
42
Epoch 12/20
280/280 [==============================] - 24s 87ms/step - loss: 0.0480 - accuracy: 0.9835 - val_loss: 0.4510 - val_accuracy: 0.92
47
Epoch 13/20
280/280 [==============================] - 23s 83ms/step - loss: 0.0498 - accuracy: 0.9826 - val_loss: 0.3829 - val_accuracy: 0.93
74
Epoch 14/20
280/280 [==============================] - 23s 82ms/step - loss: 0.0421 - accuracy: 0.9855 - val_loss: 0.4396 - val_accuracy: 0.92
94
Epoch 15/20
280/280 [==============================] - 24s 85ms/step - loss: 0.0424 - accuracy: 0.9855 - val_loss: 0.4028 - val_accuracy: 0.93
55
Epoch 16/20
280/280 [==============================] - 23s 83ms/step - loss: 0.0352 - accuracy: 0.9893 - val_loss: 0.3847 - val_accuracy: 0.94
51
Epoch 17/20
280/280 [==============================] - 23s 83ms/step - loss: 0.0379 - accuracy: 0.9879 - val_loss: 0.3967 - val_accuracy: 0.94
14
Epoch 18/20
280/280 [==============================] - 24s 86ms/step - loss: 0.0356 - accuracy: 0.9878 - val_loss: 0.4196 - val_accuracy: 0.93
93
Epoch 19/20
280/280 [==============================] - 26s 92ms/step - loss: 0.0235 - accuracy: 0.9912 - val_loss: 0.3919 - val_accuracy: 0.95
24
Epoch 20/20
280/280 [==============================] - 25s 89ms/step - loss: 0.0332 - accuracy: 0.9878 - val_loss: 0.4078 - val_accuracy: 0.94
93
```

Out[175…

```
<keras.callbacks.History at 0x7c037c0a03d0>
```

In [176…

```python
#evaluating training set
cnn_model.evaluate(train_set)
```

```
280/280 [==============================] - 13s 47ms/step - loss: 0.0603 - accuracy: 0.9813
```

Out[176…

```
[0.0603117011487484, 0.9813005924224854]
```

In [177…

```python
# test accuracy
cnn_model.evaluate(test_set)
```

Out[177…

```
280/280 [==============================] - 12s 44ms/step - loss: 0.4078 - accuracy: 0.9493
[0.40782010555267334, 0.9492632150650024]
```

In [178…

```
#test set predictions
test_pred = cnn_model.predict(test_set)
test_pred
```

Out[178…

```
array([[1.00e+00, 2.00e-16, 6.65e-26],
       [1.00e+00, 4.52e-04, 6.27e-07],
       [4.98e-09, 1.00e+00, 2.04e-10],
       ...,
       [6.09e-01, 3.91e-01, 8.88e-15],
       [9.83e-01, 1.75e-02, 2.70e-16],
       [1.95e-04, 9.84e-01, 1.57e-02]], dtype=float32)
```

In [179…

```
y_labels = [np.argmax(item) for item in test_pred] #extract the predicted label for each
print("Test Predictions response sample:",y_labels[:10])

test_response = response_list[test_size:]
print("Test True response sample:", test_response[:10])

#checking for first 10 samples
```

```
Test Predictions response sample: [0, 0, 1, 1, 1, 1, 0, 1, 0, 1]
Test True response sample: [0, 0, 1, 1, 1, 1, 0, 1, 0, 1]
```

In [181…

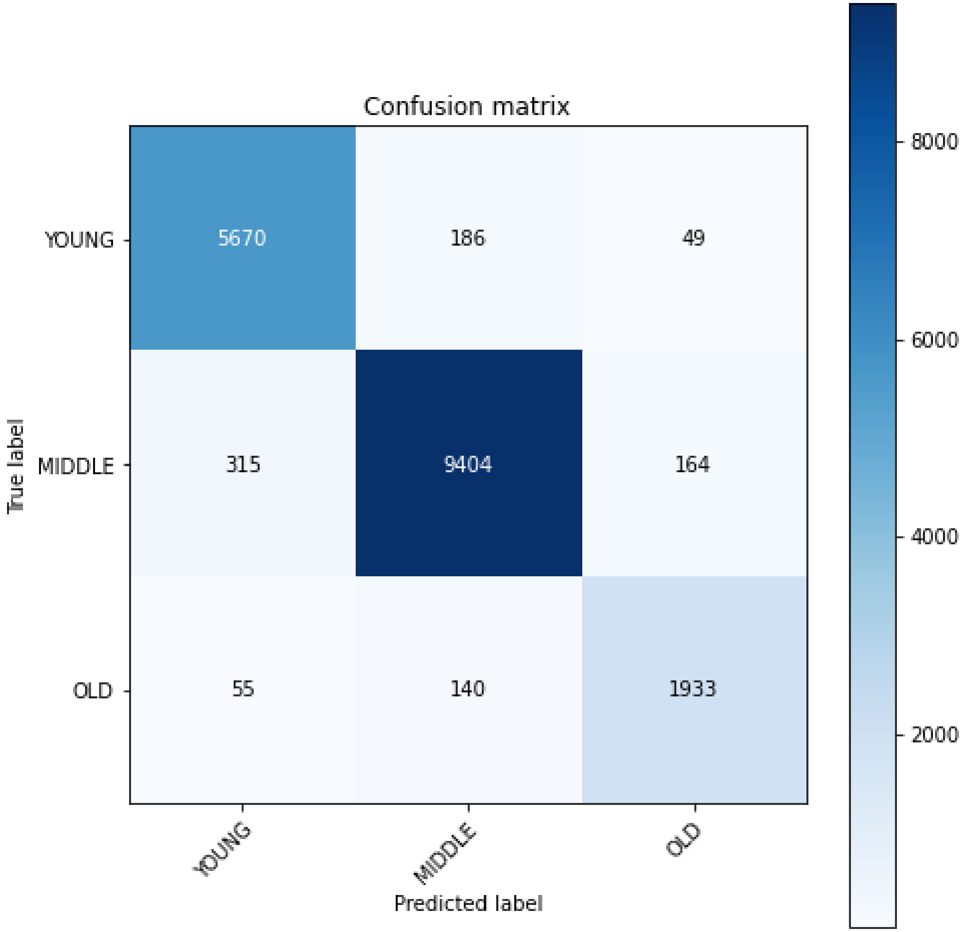
```
# funtion to plot confusion matrix to check the accuracy of each class value
def plot_confusion_matrix(y_true, y_pred, classes,
                          title=None,
                          cmap=plt.cm.Blues):

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    fig, ax = plt.subplots(figsize=(7,7))
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # show all ticks
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")
    # Loop over data dimensions and create text annotations.
    fmt = 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax


np.set_printoptions(precision=2)
# plotting confusion matrix
plot_confusion_matrix(y_labels, test_response, classes=class_names,
                      title='Confusion matrix')
```

```
Out[181…  <AxesSubplot:title={'center':'Confusion matrix'}, xlabel='Predicted label', ylabel='True label'>
```



In [182…

```
# accuracy of our model
print("Accuracy of CNN Model is:   %0.3f percentage" % (metrics.accuracy_score(test_response, y_labels)*100))
```

```
Accuracy of CNN Model is:   94.926 percentage
```

In [183…

```
#Finding the values from our new test dataset

# built the list of image paths and list of respective responses of the images
PATH = "Test"
image_paths_1 = []
for path in os.listdir(PATH):
    image_paths_1.append(PATH+"/"+path)
print(len(image_paths_1))
```

```
10
```

In [184…

```
import cv2
#preprocessing for our new dataset
def preprocess_image(image_paths_1):
    image = cv2.imread(image_paths_1)
    image = cv2.resize(image, (150,150))
    return image
```

In [ ]:

```
res=[]
file=[]
for image_path in image_paths_1:
    image = preprocess_image(image_path)
    image = np.expand_dims(image, axis=0)
    # Get the predictions
    predictions = cnn_model.predict(image)
    y_labels_1 = [np.argmax(item) for item in predictions]
    label_mapping = {0: 'YOUNG', 1: 'MIDDLE', 2: 'OLD'}
    y_labels_1 = [label_mapping[label] for label in y_labels_1]
    file.append(os.path.basename(image_path))
    res.append(''.join(y_labels_1))
```

In [190…

```
#creating dataframe
results_df = pd.DataFrame({"Image": file, "Class": res})
```

In [191…

```
#final result
results_df
```

Out[191…

	Image	Class
0	26526.jpg	MIDDLE
1	26528.jpg	MIDDLE
2	26527.jpg	MIDDLE
3	26524.jpg	YOUNG

	Image	Class
4	26523.jpg	MIDDLE
5	26505.jpg	MIDDLE
6	26521.jpg	MIDDLE
7	26492.jpg	MIDDLE
8	26530.jpg	MIDDLE
9	26483.jpg	YOUNG