

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, __, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session

/kaggle/input/imagesaegpred/rajni.jpg
/kaggle/input/age-gender-and-ethnicity-face-data-csv/age_gender.csv
```

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▼ Importing relevent libraries

```
from google.colab import drive
drive.mount('/content/gdrive')

Mounted at /content/gdrive

!ls

data gdrive sample_data

import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow.keras.layers as L
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import plotly.express as px
from sklearn.model_selection import train_test_split
```

▼ Loading Dataset

```
data = pd.read_csv('gdrive/MyDrive/age_gender.csv')

## Converting pixels into numpy array
data['pixels']=data['pixels'].apply(lambda x:  np.array(x.split(), dtype="float32"))

data.head()
```

	age	ethnicity	gender	img_name	pixels
0	1	2	0	20161219203650636.jpg.chip.jpg	[129.0, 128.0, 128.0, 126.0, 127.0, 130.0, 133...
1	1	2	0	20161219222752047.jpg.chip.jpg	[164.0, 74.0, 111.0, 168.0, 169.0, 171.0, 175....
2	1	2	0	20161219222832191.jpg.chip.jpg	[67.0, 70.0, 71.0, 70.0, 69.0, 67.0, 70.0, 79...
3	1	2	0	20161220144911423.jpg.chip.jpg	[193.0, 197.0, 198.0, 200.0, 199.0, 200.0, 202...
4	1	2	0	20161220144914327.jpg.chip.jpg	[202.0, 205.0, 209.0, 210.0, 209.0, 209.0, 210...

```
print('Total rows: {}'.format(len(data)))
print('Total columns: {}'.format(len(data.columns)))

Total rows: 23705
Total columns: 5
```

▼ Distributions

```
## normalizing pixels data
data['pixels'] = data['pixels'].apply(lambda x: x/255)

## calculating distributions
age_dist = data['age'].value_counts()
ethnicity_dist = data['ethnicity'].value_counts().rename(index={0:'White',1:'Black',2:'Asian', 3:'Indian', 4:'Others'})
gender_dist = data['gender'].value_counts().rename(index={0:'Male',1:'Female'})

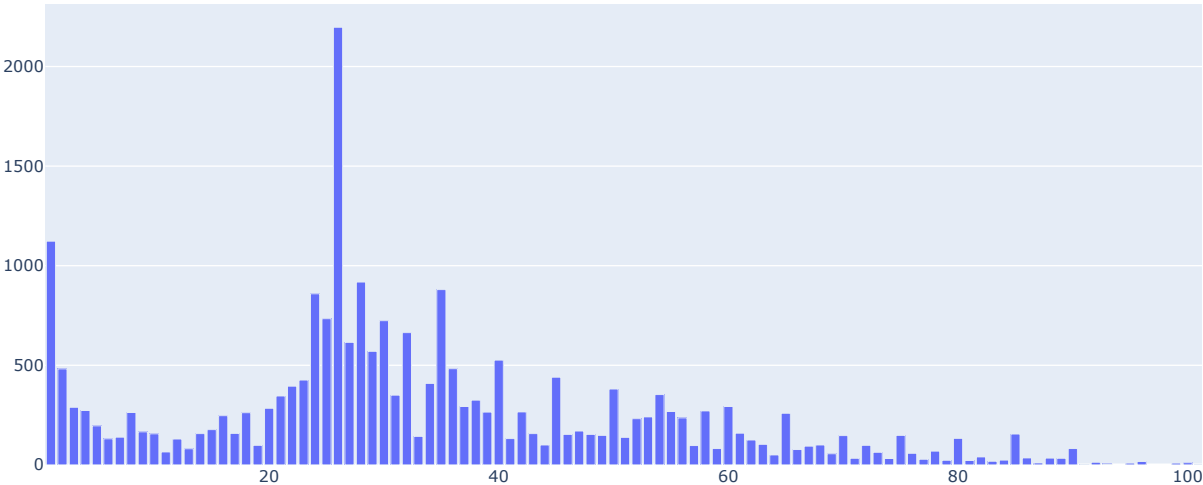
def ditribution_plot(x,y,name):
    fig = go.Figure([
        go.Bar(x=x, y=y)
    ])

    fig.update_layout(title_text=name)
    fig.show()
```

▼ Age Distribbtion

```
ditribution_plot(x=age_dist.index, y=age_dist.values, name='Age Distribution')
```

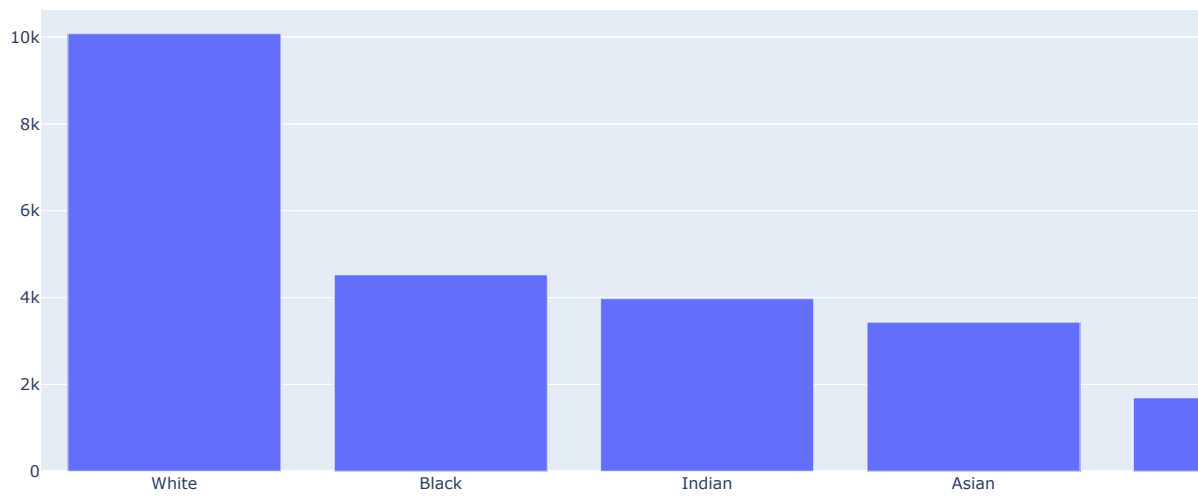
Age Distribution



▼ Ethnicity Distribution

```
distribution_plot(x=ethnicity_dist.index, y=ethnicity_dist.values, name='Ethnicity Distribution')
```

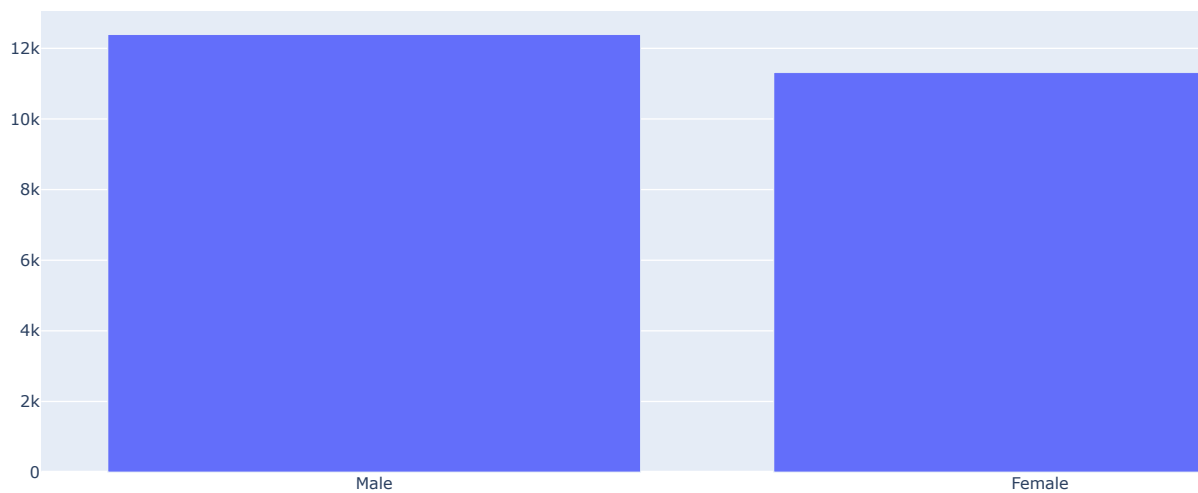
Ethnicity Distribution



▼ Gender Distribution

```
distribution_plot(x=gender_dist.index, y=gender_dist.values, name='Gender Distribution')
```

Gender Distribution

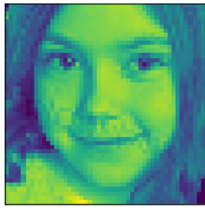


```
X = np.array(data['pixels'].tolist())
#converting pixels from 1D to 3D
X = X.reshape(X.shape[0],48,48,1)
```

▼ Sample Images

```
plt.figure(figsize=(16,16))
for i in range(1200,1220):
    plt.subplot(5,5,(i%25)+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
```

```
plt.imshow(data['pixels'].iloc[i].reshape(48,48))
plt.xlabel(
    "Age:"+str(data['age'].iloc[i])+
    " Ethnicity:"+str(data['ethnicity'].iloc[i])+
    " Gender:"+ str(data['gender'].iloc[i])
)
plt.show()
```



Age:10 Ethnicity:0 Gender:1



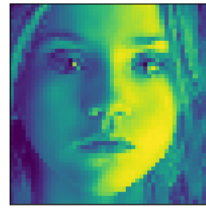
Age:10 Ethnicity:1 Gender:1



Age:10 Ethnicity:0 Gender:1



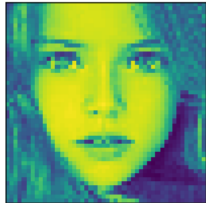
Age:10 Ethnicity:0 Gender:1



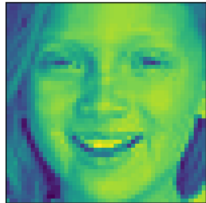
Age:10 Ethnicity:0 Gender:1



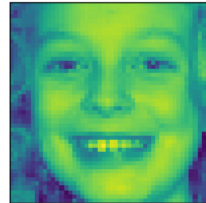
Age:10 Ethnicity:0 Gender:1



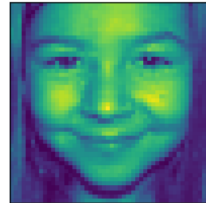
Age:10 Ethnicity:0 Gender:1



Age:10 Ethnicity:0 Gender:1



Age:10 Ethnicity:0 Gender:1



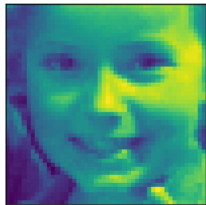
Age:10 Ethnicity:0 Gender:1



Age:10 Ethnicity:0 Gender:1



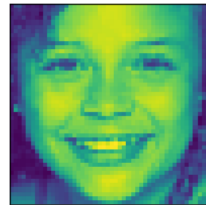
Age:10 Ethnicity:0 Gender:1



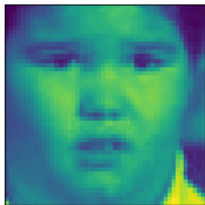
Age:10 Ethnicity:0 Gender:1



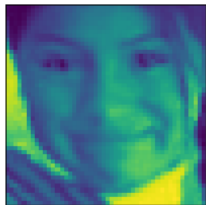
Age:10 Ethnicity:1 Gender:1



Age:10 Ethnicity:1 Gender:1



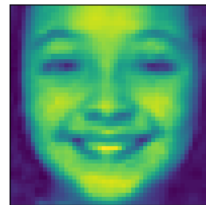
Age:10 Ethnicity:4 Gender:1



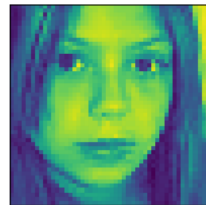
Age:10 Ethnicity:4 Gender:1



Age:10 Ethnicity:4 Gender:1



Age:10 Ethnicity:4 Gender:1



Age:10 Ethnicity:4 Gender:1

▼ CNN Model for Gender Prediction

▼ Split data into train/test

```
y = data['gender']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.22, random_state=37
)
```

▼ Build and train model

```
model1 = tf.keras.Sequential([
    L.InputLayer(input_shape=(48,48,1)),
    L.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    L.BatchNormalization(),
    L.MaxPooling2D((2, 2)),
    L.Conv2D(64, (3, 3), activation='relu'),
    L.MaxPooling2D((2, 2)),
    L.Flatten(),
    L.Dense(64, activation='relu'),
    L.Dropout(rate=0.5),
    L.Dense(1, activation='sigmoid')
])

model1.compile(optimizer='sgd',
               loss=tf.keras.losses.BinaryCrossentropy(),
               metrics=['accuracy'])
```

```
## Stop training when validation loss reach 0.2700
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if(logs.get('val_loss')<0.2700):
            print("\nReached 0.2700 val_loss so cancelling training!")
            self.model.stop_training = True

callback = myCallback()

model1.summary()

Model: "sequential"
_____
Layer (type)                Output Shape                Param #
=====
conv2d (Conv2D)              (None, 46, 46, 32)         320
batch_normalization (Batch Normalization) (None, 46, 46, 32)         128
max_pooling2d (MaxPooling2D) (None, 23, 23, 32)         0
conv2d_1 (Conv2D)            (None, 21, 21, 64)         18496
max_pooling2d_1 (MaxPooling2D) (None, 10, 10, 64)         0
flatten (Flatten)            (None, 6400)               0
dense (Dense)                (None, 64)                 409664
dropout (Dropout)            (None, 64)                 0
dense_1 (Dense)              (None, 1)                 65
=====
Total params: 428,673
Trainable params: 428,609
Non-trainable params: 64
_____

history_age = model1.fit(
    X_train, y_train, epochs=20, validation_split=0.1, batch_size=64, callbacks=[callback]
)

Epoch 1/20
260/260 [=====] - 60s 228ms/step - loss: 0.5354 - accuracy: 0.7295 - val_loss: 0.6088 - val_accuracy: 0.77
Epoch 2/20
260/260 [=====] - 58s 224ms/step - loss: 0.4041 - accuracy: 0.8180 - val_loss: 0.4371 - val_accuracy: 0.80
Epoch 3/20
260/260 [=====] - 61s 236ms/step - loss: 0.3588 - accuracy: 0.8401 - val_loss: 0.3377 - val_accuracy: 0.85
Epoch 4/20
260/260 [=====] - 56s 216ms/step - loss: 0.3321 - accuracy: 0.8517 - val_loss: 0.3212 - val_accuracy: 0.86
Epoch 5/20
260/260 [=====] - 62s 238ms/step - loss: 0.3164 - accuracy: 0.8631 - val_loss: 0.3112 - val_accuracy: 0.86
Epoch 6/20
260/260 [=====] - 56s 215ms/step - loss: 0.3037 - accuracy: 0.8686 - val_loss: 0.3093 - val_accuracy: 0.86
Epoch 7/20
260/260 [=====] - 56s 217ms/step - loss: 0.2978 - accuracy: 0.8697 - val_loss: 0.3006 - val_accuracy: 0.86
Epoch 8/20
260/260 [=====] - 58s 223ms/step - loss: 0.2795 - accuracy: 0.8804 - val_loss: 0.3080 - val_accuracy: 0.85
Epoch 9/20
260/260 [=====] - 56s 216ms/step - loss: 0.2748 - accuracy: 0.8803 - val_loss: 0.2857 - val_accuracy: 0.87
Epoch 10/20
260/260 [=====] - 56s 216ms/step - loss: 0.2655 - accuracy: 0.8840 - val_loss: 0.2806 - val_accuracy: 0.87
Epoch 11/20
260/260 [=====] - 58s 225ms/step - loss: 0.2582 - accuracy: 0.8904 - val_loss: 0.2772 - val_accuracy: 0.87
Epoch 12/20
260/260 [=====] - 56s 216ms/step - loss: 0.2546 - accuracy: 0.8904 - val_loss: 0.2931 - val_accuracy: 0.86
Epoch 13/20
260/260 [=====] - 57s 218ms/step - loss: 0.2486 - accuracy: 0.8963 - val_loss: 0.3243 - val_accuracy: 0.86
Epoch 14/20
260/260 [=====] - 58s 224ms/step - loss: 0.2392 - accuracy: 0.9004 - val_loss: 0.2772 - val_accuracy: 0.88
Epoch 15/20
260/260 [=====] - ETA: 0s - loss: 0.2322 - accuracy: 0.9004
Reached 0.2700 val_loss so cancelling training!
260/260 [=====] - 59s 228ms/step - loss: 0.2322 - accuracy: 0.9004 - val_loss: 0.2661 - val_accuracy: 0.89
```

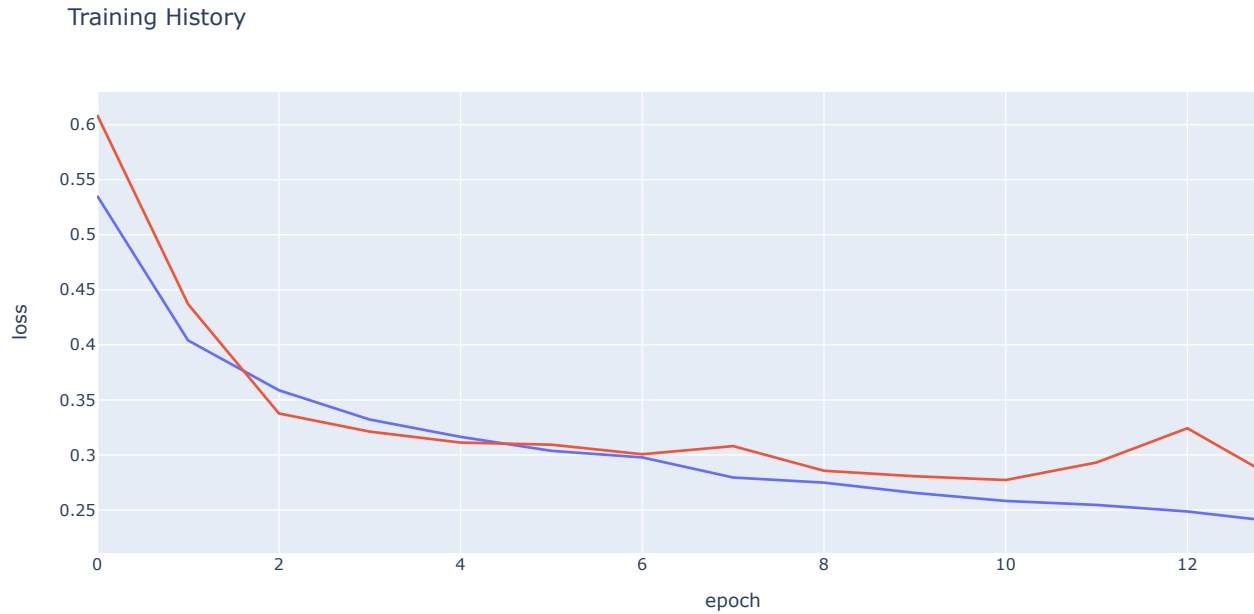
▼ Evaluate training history

```
fig = px.line(
    history_age.history, y=['loss', 'val_loss'],
```

```

labels={'index': 'epoch', 'value': 'loss'},
title='Training History')
fig.show()

```



```

loss1, acc1 = model1.evaluate(X_test,y_test,verbose=0)
print('Test loss: {}'.format(loss1))
print('Test Accuracy: {}'.format(acc1))

```

```

Test loss: 0.2589429020881653
Test Accuracy: 0.8863113522529602

```

▼ RNN Model for Gender Prediction

▼ Split data into training and testing

```

y = data['gender']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.22, random_state=37
)

```

▼ Build and train model

```

from keras.layers import Dropout
from keras.layers import Dense, Embedding, LSTM, Bidirectional

vocabulary_size = 48
embedding_dim = 12
model_2 = tf.keras.Sequential([
    L.InputLayer(input_shape=(48,48,1)),
    L.Flatten(),
    L.Embedding(vocabulary_size, embedding_dim, input_shape=(48,48)),
    L.Bidirectional(LSTM(12)),
    L.Dropout(rate=0.5),
    L.Dense(24, activation='sigmoid'),
    L.Dense(1,activation='sigmoid')
])
model_2.compile(optimizer='sgd',
                loss=tf.keras.losses.BinaryCrossentropy(),
                metrics=['accuracy'])

## Stop training when validation loss reach 0.2700
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if(logs.get('val_loss')<0.2700):
            print("\nReached 0.2700 val_loss so cancelling training!")

```

```

self.model.stop_training = True
callback = myCallback()
model_2.summary()

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 2304)	0
embedding (Embedding)	(None, 2304, 12)	576
bidirectional (Bidirectional)	(None, 24)	2400
dropout_1 (Dropout)	(None, 24)	0
dense_2 (Dense)	(None, 24)	600
dense_3 (Dense)	(None, 1)	25

```

Total params: 3,601
Trainable params: 3,601
Non-trainable params: 0

```

```

history_age2 = model_2.fit(
    X_train, y_train, epochs=5, validation_split=0.1, batch_size=64, callbacks=[callback]
)

```

```

Epoch 1/5
260/260 [=====] - 389s 1s/step - loss: 0.7031 - accuracy: 0.5008 - val_loss: 0.6918 - val_accuracy: 0.5268
Epoch 2/5
260/260 [=====] - 384s 1s/step - loss: 0.6922 - accuracy: 0.5241 - val_loss: 0.6918 - val_accuracy: 0.5268
Epoch 3/5
260/260 [=====] - 376s 1s/step - loss: 0.6922 - accuracy: 0.5241 - val_loss: 0.6919 - val_accuracy: 0.5268
Epoch 4/5
260/260 [=====] - 379s 1s/step - loss: 0.6922 - accuracy: 0.5241 - val_loss: 0.6917 - val_accuracy: 0.5268
Epoch 5/5
260/260 [=====] - 376s 1s/step - loss: 0.6922 - accuracy: 0.5241 - val_loss: 0.6917 - val_accuracy: 0.5268

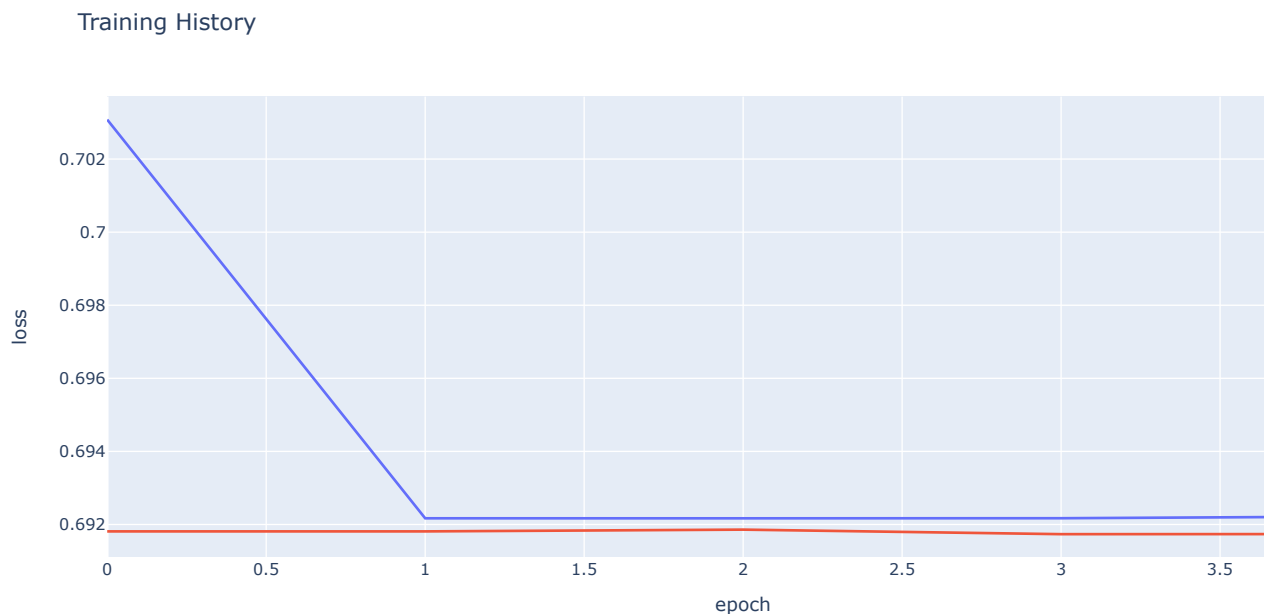
```

▼ Evaluating training history

```

fig = px.line(
    history_age2.history, y=['loss', 'val_loss'],
    labels={'index': 'epoch', 'value': 'loss'},
    title='Training History')
fig.show()

```



```
loss2, acc2 = model_2.evaluate(X_test,y_test,verbose=0)
print('Test loss: {}'.format(loss2))
print('Test Accuracy: {}'.format(acc2))
```

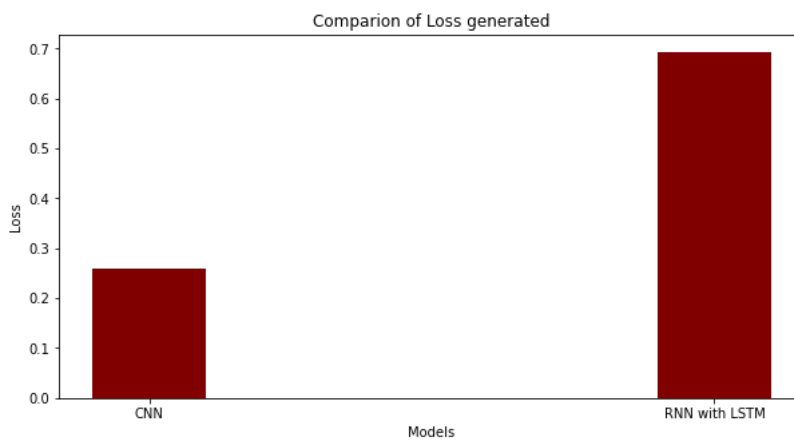
```
Test loss: 0.6929293870925903
Test Accuracy: 0.5168711543083191
```

▼ Comparison of the two models

▼ Loss Comparison

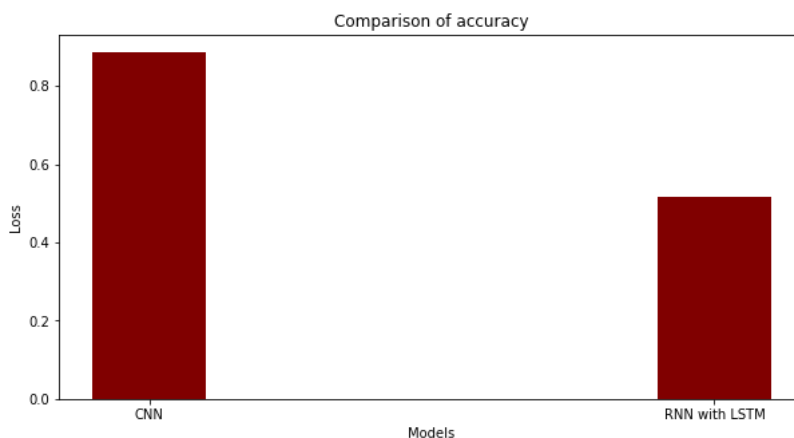
```
loss = [loss1, loss2]
models = ['CNN', 'RNN with LSTM']
fig = plt.figure(figsize = (10, 5))
plt.bar(models, loss, color = 'maroon',
        width = 0.2)

plt.xlabel("Models")
plt.ylabel("Loss")
plt.title("Comparion of Loss generated")
plt.show()
```



▼ Accuracy comparison

```
accuracy = [acc1, acc2]
models = ["CNN", "RNN with LSTM"]
fig = plt.figure(figsize = (10, 5))
plt.bar(models, accuracy, color = 'maroon',
        width = 0.2)
plt.xlabel("Models")
plt.ylabel("Loss")
plt.title("Comparison of accuracy")
plt.show()
```



Models for Age prediction

▼ CNN Model for Age prediction

▼ Split data into train/test

```
y = data['age']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.22, random_state=37
)
```

▼ Build and train model

```
model3 = tf.keras.Sequential([
    L.InputLayer(input_shape=(48,48,1)),
    L.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    L.BatchNormalization(),
    L.MaxPooling2D((2, 2)),
    L.Conv2D(64, (3, 3), activation='relu'),
    L.MaxPooling2D((2, 2)),
    L.Conv2D(128, (3, 3), activation='relu'),
    L.MaxPooling2D((2, 2)),
    L.Flatten(),
    L.Dense(64, activation='relu'),
    L.Dropout(rate=0.5),
    L.Dense(1, activation='relu')
])

sgd = tf.keras.optimizers.SGD(momentum=0.9)

model3.compile(optimizer='adam',
               loss='mean_squared_error',
               metrics=['mae'])
```

```
## Stop training when validation loss reach 110
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if(logs.get('val_loss')<110):
            print("\nReached 110 val_loss so cancelling training!")
            self.model.stop_training = True
```

```
callback = myCallback()
```

```
model3.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
=====		
conv2d_2 (Conv2D)	(None, 46, 46, 32)	320
batch_normalization_1 (Batch Normalization)	(None, 46, 46, 32)	128
max_pooling2d_2 (MaxPooling2D)	(None, 23, 23, 32)	0
conv2d_3 (Conv2D)	(None, 21, 21, 64)	18496
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_2 (Flatten)	(None, 2048)	0
dense_4 (Dense)	(None, 64)	131136
dropout_2 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 1)	65
=====		
Total params: 224,001		

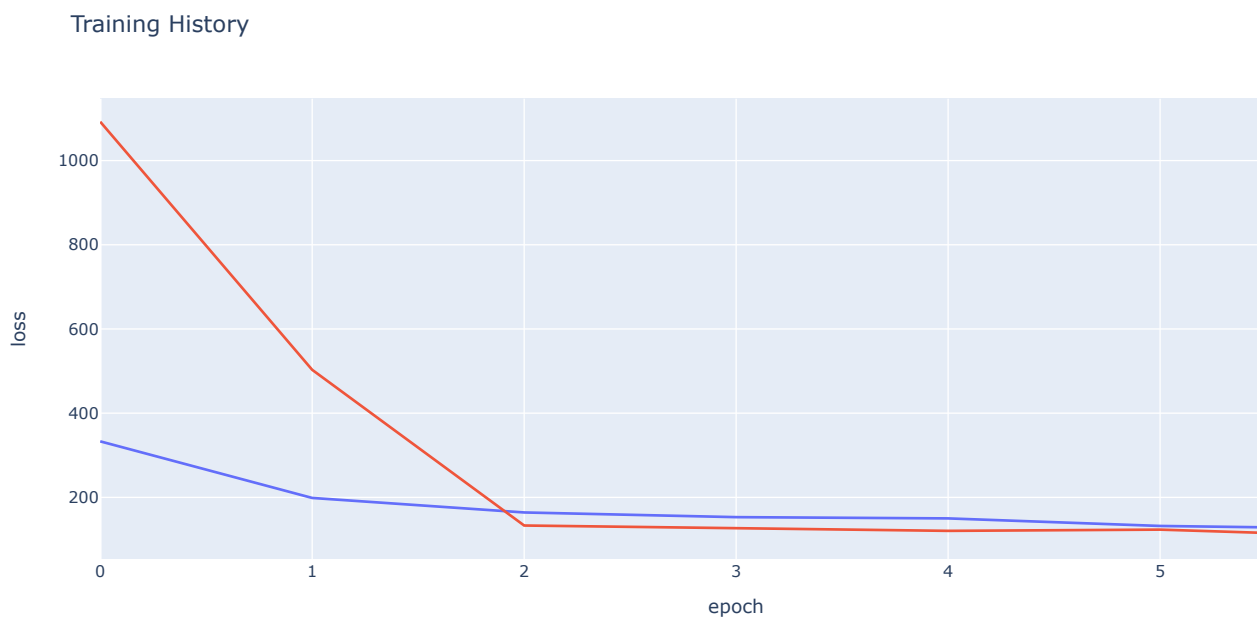
Trainable params: 223,937
Non-trainable params: 64

```
history3 = model3.fit(
    X_train, y_train, epochs=20, validation_split=0.1, batch_size=64, callbacks=[callback]
)

Epoch 1/20
260/260 [=====] - 69s 263ms/step - loss: 333.0560 - mae: 13.9185 - val_loss: 1092.3511 - val_mae: 27.1980
Epoch 2/20
260/260 [=====] - 66s 255ms/step - loss: 198.6328 - mae: 10.6444 - val_loss: 502.9794 - val_mae: 17.1490
Epoch 3/20
260/260 [=====] - 67s 256ms/step - loss: 164.1415 - mae: 9.6218 - val_loss: 133.1310 - val_mae: 8.5623
Epoch 4/20
260/260 [=====] - 68s 263ms/step - loss: 153.0076 - mae: 9.2144 - val_loss: 127.7266 - val_mae: 8.1612
Epoch 5/20
260/260 [=====] - 67s 256ms/step - loss: 150.0498 - mae: 9.1009 - val_loss: 120.4612 - val_mae: 8.0542
Epoch 6/20
260/260 [=====] - 68s 262ms/step - loss: 132.0890 - mae: 8.5055 - val_loss: 123.3694 - val_mae: 8.5678
Epoch 7/20
260/260 [=====] - ETA: 0s - loss: 125.5112 - mae: 8.2767
Reached 110 val_loss so cancelling training!
260/260 [=====] - 66s 256ms/step - loss: 125.5112 - mae: 8.2767 - val_loss: 107.6022 - val_mae: 7.7532
```

▼ Evaluate training history

```
fig = px.line(
    history3.history, y=['loss', 'val_loss'],
    labels={'index': 'epoch', 'value': 'loss'},
    title='Training History')
fig.show()
```



```
mse1, mae1 = model3.evaluate(X_test,y_test,verbose=0)
rmse1 = np.sqrt(mse1)
print('Test Mean squared error: {}'.format(mse1))
print('Test Mean absolute error: {}'.format(mae1))
print('Test Root mean squared error: {}'.format(rmse1))
```

Test Mean squared error: 101.03685760498047
Test Mean absolute error: 7.5271782875061035
Test Root mean squared error: 10.051709188241594

▼ RNN model for Age Prediction

```
y = data['age']
```

```
X_train, X_test, y_train, y_test = train_test_split(
```

```
X, y, test_size=0.22, random_state=37
)
```

▼ Build and train model

```
vocabulary_size = 48
embedding_dim = 12
model4 = tf.keras.Sequential([
    L.InputLayer(input_shape=(48,48,1)),
    L.Flatten(),
    L.Embedding(vocabulary_size, embedding_dim, input_shape=(48,48)),
    L.GRU(12),
    L.Dense(64, activation='relu',input_shape=(48, 48)),
    L.Dropout(0.2),
    L.Dense(5, activation='relu')
])

model4.compile(optimizer='adam',
               loss='mean_squared_error',
               metrics=['mae'])
```

```
## Stop training when validation loss reach 110
class myCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs={}):
        if(logs.get('val_loss')<110):
            print("\nReached 110 val_loss so cancelling training!")
            self.model.stop_training = True
```

```
callback = myCallback()
model4.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
flatten_3 (Flatten)	(None, 2304)	0
embedding_1 (Embedding)	(None, 2304, 12)	576
gru (GRU)	(None, 12)	936
dense_6 (Dense)	(None, 64)	832
dropout_3 (Dropout)	(None, 64)	0
dense_7 (Dense)	(None, 5)	325
=====		
Total params: 2,669		
Trainable params: 2,669		
Non-trainable params: 0		

```
history_4 = model4.fit(
    X_train, y_train, epochs=5, validation_split=0.1, batch_size=64, callbacks=[callback]
)
```

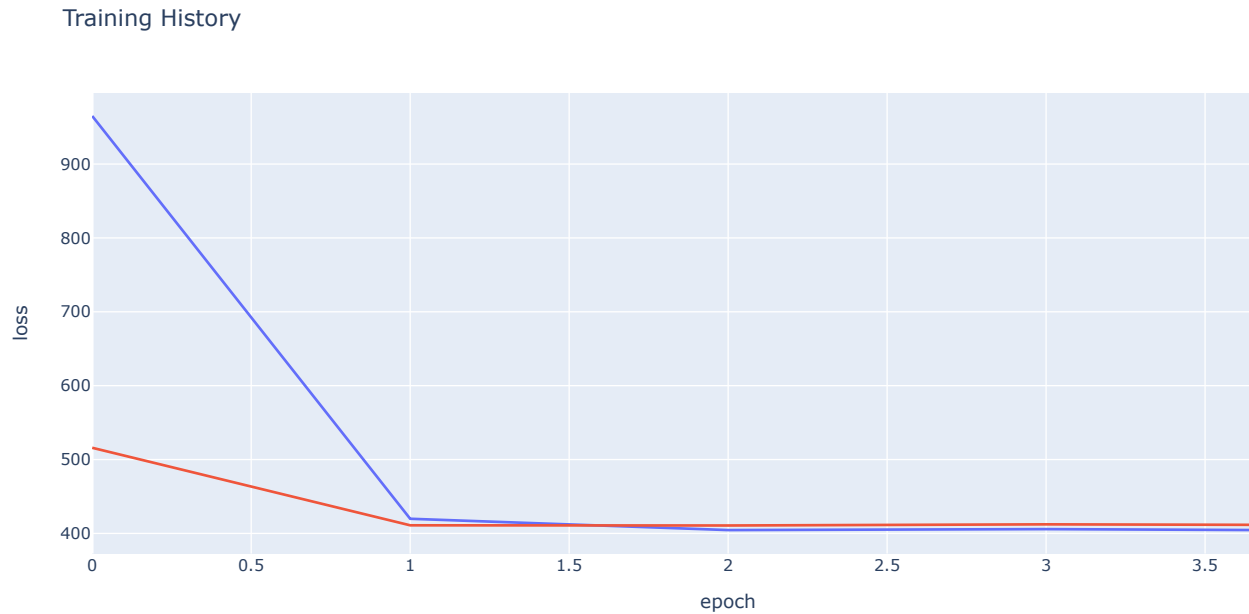
```
Epoch 1/5
260/260 [=====] - 241s 919ms/step - loss: 965.0621 - mae: 24.6728 - val_loss: 515.9121 - val_mae: 17.3673
Epoch 2/5
260/260 [=====] - 232s 894ms/step - loss: 419.8175 - mae: 15.7619 - val_loss: 410.9612 - val_mae: 15.4428
Epoch 3/5
260/260 [=====] - 237s 911ms/step - loss: 404.5070 - mae: 15.4871 - val_loss: 410.7066 - val_mae: 15.4577
Epoch 4/5
260/260 [=====] - 235s 903ms/step - loss: 405.8113 - mae: 15.5045 - val_loss: 412.2664 - val_mae: 15.3703
Epoch 5/5
260/260 [=====] - 236s 907ms/step - loss: 403.8784 - mae: 15.4823 - val_loss: 411.2592 - val_mae: 15.4092
```

```
mse2, mae2 = model4.evaluate(X_test,y_test,verbose=0)
rmse2 = np.sqrt(mse2)
print('Test Mean squared error: {}'.format(mse2))
print('Test Mean absolute error: {}'.format(mae2))
print('Test Root mean squared error: {}'.format(rmse2))

Test Mean squared error: 397.44775390625
Test Mean absolute error: 15.199275970458984
Test Root mean squared error: 19.936091741017094
```

```
fig = px.line(
    history_4.history, y=['loss', 'val_loss'],
    labels={'index': 'epoch', 'value': 'loss'},
```

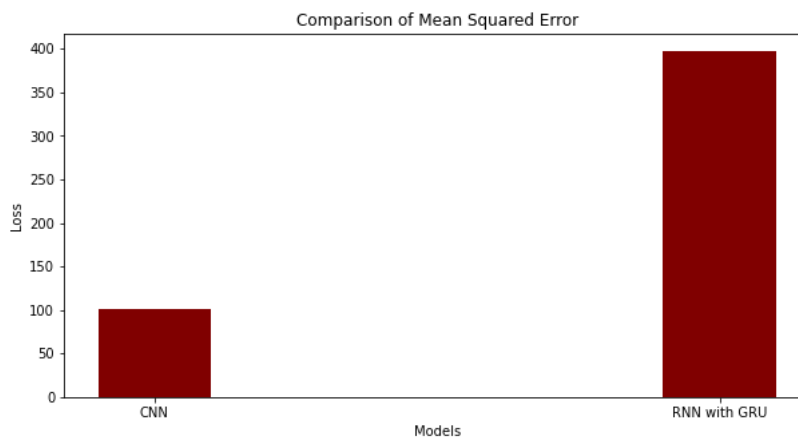
```
title='Training History')
fig.show()
```



▼ Comparison for CNN and RNN models for Age Prediction

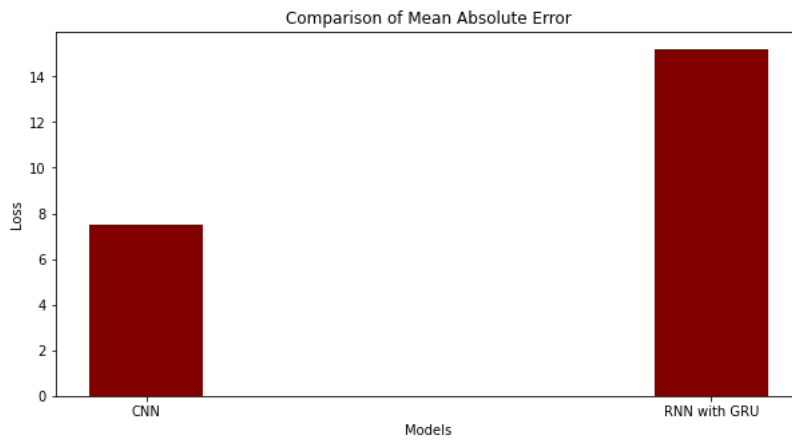
▼ Mean Squared error

```
mse = [mse1, mse2]
models = ["CNN", "RNN with GRU"]
fig = plt.figure(figsize = (10, 5))
plt.bar(models, mse, color = 'maroon',
        width = 0.2)
plt.xlabel("Models")
plt.ylabel("Loss")
plt.title("Comparison of Mean Squared Error")
plt.show()
```



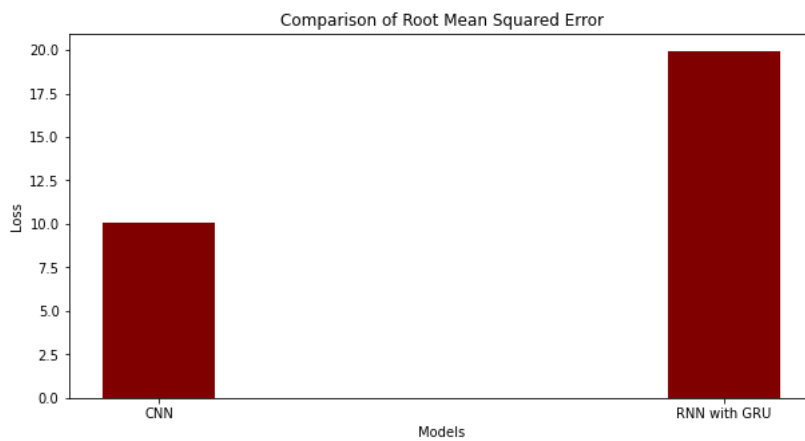
▼ Mean absolute error

```
mae = [mae1, mae2]
models = ["CNN", "RNN with GRU"]
fig = plt.figure(figsize = (10, 5))
plt.bar(models, mae, color = 'maroon',
        width = 0.2)
plt.xlabel("Models")
plt.ylabel("Loss")
plt.title("Comparison of Mean Absolute Error")
plt.show()
```



▼ Root Mean Squared error

```
rmse = [rmse1, rmse2]
models = ["CNN", "RNN with GRU"]
fig = plt.figure(figsize = (10, 5))
plt.bar(models, rmse, color = 'maroon',
        width = 0.2)
plt.xlabel("Models")
plt.ylabel("Loss")
plt.title("Comparison of Root Mean Squared Error")
plt.show()
```



Double-click (or enter) to edit

✓ 0s completed at 4:03 PM

