Peer Evaluation System UI/UX

We worked on the signature recognition model and developed a system to detect whether a signature is real or forged.

The code for the model and the output screenshots are attached below: -

- **Python code: -**
    1. **For signature verification -**

```
import os
import cv2
import numpy as np
from google.colab import drive
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam
from keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

drive.mount('/content/drive')


# Define image dimensions
IMG_WIDTH = 128
IMG_HEIGHT = 64

# Load images from the dataset directory
def load_images(folder):
    images = []
    labels = []

    # Iterate over files in the dataset folder
    for filename in os.listdir(folder):
        img_path = os.path.join(folder, filename)
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
```

```
        img = cv2.resize(img, (IMG_WIDTH, IMG_HEIGHT))
        img = img / 255.0  # Normalize pixel values to [0,1]
        images.append(img)

        # Determine label based on filename
        if 'original' in filename:
            labels.append(0)  # Label for original signatures
        elif 'forgeries' in filename:
            labels.append(1)  # Label for forged signatures

    return np.array(images), np.array(labels)

# Load dataset
dataset_folder = '/content/drive/MyDrive/Sign_Data/Train'
X, y = load_images(dataset_folder)
X = X.reshape(-1, IMG_WIDTH, IMG_HEIGHT, 1)  # Reshape for CNN input


# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Data augmentation
datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

# CNN model
model = Sequential()

# Convolutional layer 1
model.add(Conv2D(32, (3, 3), input_shape=(IMG_WIDTH, IMG_HEIGHT, 1),
activation='relu'))
model.add(BatchNormalization())
```

```
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 2
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 3
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Flatten layer
model.add(Flatten())

# Dense layer
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))

# Output layer
model.add(Dense(1, activation='sigmoid'))

# Compile model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

# Define early stopping callback
early_stopping = EarlyStopping(
    monitor='val_loss',  # Can also use 'val_accuracy'
    patience=5,  # Number of epochs with no improvement after which training
will be stopped
    restore_best_weights=True  # Restore model weights from the epoch with the
best value of the monitored quantity
)

# Fit the model
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_test, y_test),
    epochs=30,
```

```
    callbacks=[early_stopping]
)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Accuracy: {accuracy * 100:.2f}%')

# Save the model
model.save('/content/drive/MyDrive/Sign_Data/signature_recognition_model.h5')

# Load dataset for testing
test_folder = '/content/drive/MyDrive/Sign_Data/Test'
X_test, y_test = load_images(test_folder)
X_test = X_test.reshape(-1, IMG_WIDTH, IMG_HEIGHT, 1)  # Reshape for
CNN input

# Load the trained model
model = load_model('signature_recognition_model.h5')

# Make predictions
y_pred = (model.predict(X_test) > 0.5).astype("int32")

# Evaluate the model
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy: {accuracy * 100:.2f}%')

# Print classification report
print("Classification Report:")
print(classification_report(y_test, y_pred, target_names=['Original', 'Forged']))

# Compute and plot confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Original',
'Forged'], yticklabels=['Original', 'Forged'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
```

```
plt.title('Confusion Matrix')
plt.show()


# Define image dimensions
IMG_WIDTH = 128
IMG_HEIGHT = 64


# Preprocess a single image
def preprocess_image(image_path):
    img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)  # Load image in grayscale
    img = cv2.resize(img, (IMG_WIDTH, IMG_HEIGHT))  # Resize image to match training input size
    img = img / 255.0  # Normalize pixel values to [0,1]
    img = img.reshape(1, IMG_WIDTH, IMG_HEIGHT, 1)  # Reshape to add batch dimension and channels for CNN input
    return img

# Load the trained model
model = load_model('signature_recognition_model.h5')

# Path to the image you want to test
image_path = '/content/drive/MyDrive/Sign_Data/Test/forgeries_34_24.png'  # Replace with the path to your single image

# Preprocess the image
image = preprocess_image(image_path)

# Make prediction
prediction = model.predict(image)

# Determine class based on prediction
if prediction > 0.5:
    print("The signature is forged.")
else:
    print("The signature is original.")
```

2. **For signature mapping -**

```
import os
import cv2
import numpy as np
from google.colab import drive
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Dropout, BatchNormalization
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam
from keras.callbacks import EarlyStopping
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

drive.mount('/content/drive')

# Define image dimensions
IMG_WIDTH = 256
IMG_HEIGHT = 256

# Load images from the dataset directory
def load_images(folder):
    images = []
    labels = []
    person_labels = {}

    # Iterate over files in the dataset folder
    for filename in os.listdir(folder):
        if 'original' in filename:  # Only process original signatures
            img_path = os.path.join(folder, filename)
            img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img, (IMG_WIDTH, IMG_HEIGHT))
            img = img / 255.0  # Normalize pixel values to [0,1]
            images.append(img)

            # Extract person number from filename
```

```
            person_id = filename.split('_')[1]  # Assuming the filename is
original_Per_imgno

            # Assign a unique label to each person
            if person_id not in person_labels:
                person_labels[person_id] = len(person_labels)

            labels.append(person_labels[person_id])

    return np.array(images), np.array(labels)


# Load dataset
dataset_folder = '/content/drive/MyDrive/Sign_Data/Real'  # Update with your
dataset folder
X, y = load_images(dataset_folder)

# Reshape images for CNN input
X = X.reshape(-1, IMG_WIDTH, IMG_HEIGHT, 1)

# Encode labels (e.g., Person_1, Person_2 to numerical labels)
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# One-hot encode the labels
y_onehot = to_categorical(y_encoded)

# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y_onehot, test_size=0.2,
random_state=42)

# Data augmentation
datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
```

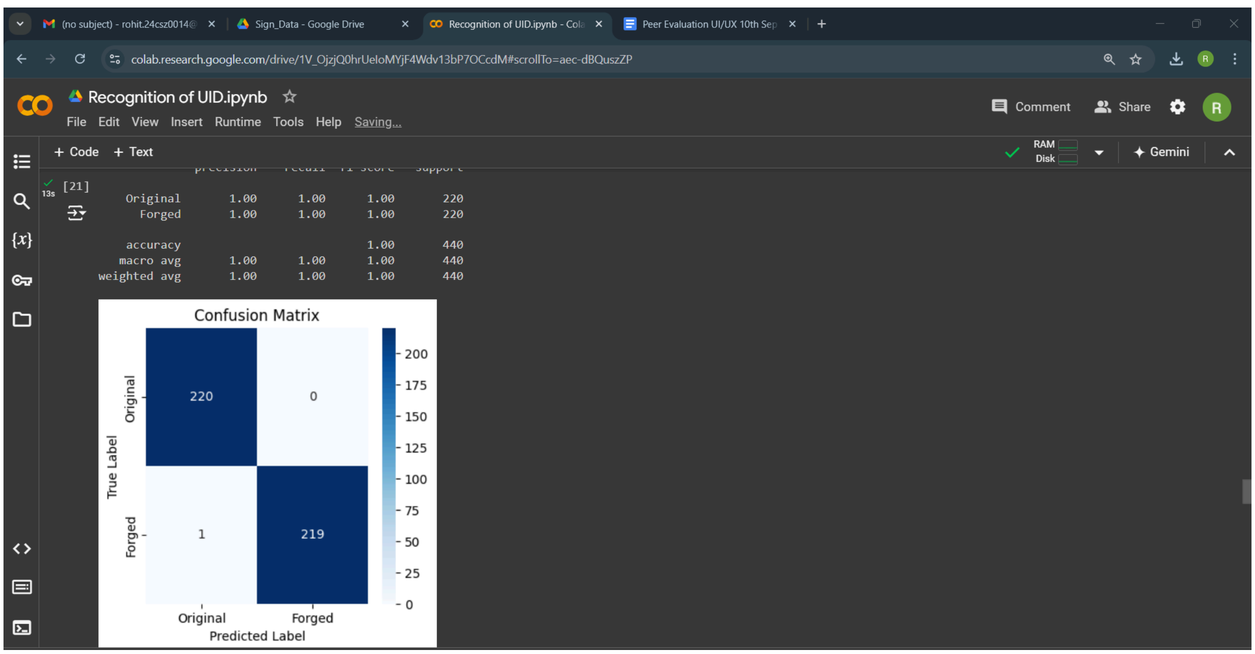
```
)

# CNN model
model = Sequential()

# Convolutional layer 1
model.add(Conv2D(64, (3, 3), input_shape=(IMG_WIDTH, IMG_HEIGHT, 1),
activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 2
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 3
model.add(Conv2D(256, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Convolutional layer 4 (new layer for additional complexity)
model.add(Conv2D(512, (3, 3), activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))

# Flatten layer
model.add(Flatten())

# Dense layer
model.add(Dense(512, activation='relu'))  # Increased number of units for better
learning capacity
model.add(Dropout(0.5))  # Increased dropout to reduce overfitting

num_classes = len(np.unique(y_encoded))  # Number of unique persons in your
dataset
# Output layer (softmax for multi-class classification)
model.add(Dense(num_classes, activation='softmax'))

# Compile model
```

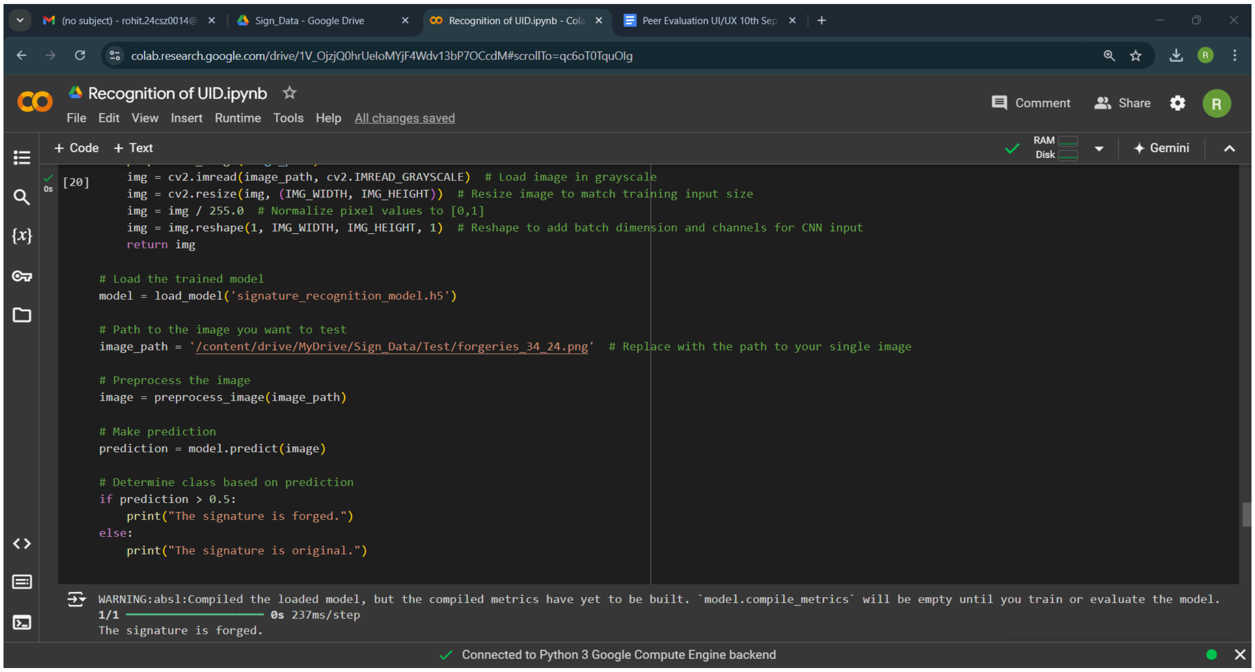
```
model.compile(optimizer=Adam(learning_rate=0.0001),
loss='categorical_crossentropy', metrics=['accuracy'])

# Define early stopping callback
early_stopping = EarlyStopping(
    monitor='val_accuracy',
    patience=15,  # Increased patience to allow the model more time to improve
    restore_best_weights=True
)

# Fit the model
history = model.fit(
    datagen.flow(X_train, y_train, batch_size=32),
    validation_data=(X_test, y_test),
    epochs=200,
    callbacks=[early_stopping]
)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Accuracy: {accuracy * 100:.2f}%')

# Save the model
model.save('/content/drive/MyDrive/Sign_Data/signature_recognition_person_mo
del.h5')

# Ensure that the y_test and y_pred are one-hot encoded or properly encoded
before applying argmax
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true_classes = np.argmax(y_test, axis=1)

# If label_encoder is not used, we'll define the class names based on unique labels
in the dataset
class_names = [f'Person_{i}' for i in range(1, num_classes + 1)]  # Assuming
`num_classes` gives the number of persons

# Print classification report
print(classification_report(y_true_classes, y_pred_classes,
target_names=class_names))
```

```
# Confusion Matrix
cm = confusion_matrix(y_true_classes, y_pred_classes)

# Plot Confusion Matrix
plt.figure(figsize=(15, 15))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names,
yticklabels=class_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()

# Function to load and preprocess a single image
def preprocess_image(img_path):
    img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
    img = cv2.resize(img, (IMG_WIDTH, IMG_HEIGHT))  # Resize to match the
input dimensions
    img = img / 255.0  # Normalize pixel values to [0,1]
    img = img.reshape(1, IMG_WIDTH, IMG_HEIGHT, 1)  # Reshape to match
model input shape
    return img

# Path to the image you want to predict
image_path = '/content/drive/MyDrive/Sign_Data/Real/original_18_16.png'  #
Provide the path to your image

# Preprocess the image
single_image = preprocess_image(image_path)

# Predict the class
prediction = model.predict(single_image)

# Get the predicted class index
predicted_class_index = np.argmax(prediction)

# Assuming your class names are formatted as Person_1, Person_2, ...,
Person_num_classes
class_names = [f'Person_{i}' for i in range(1, num_classes + 1)]

# Get the predicted class name
```

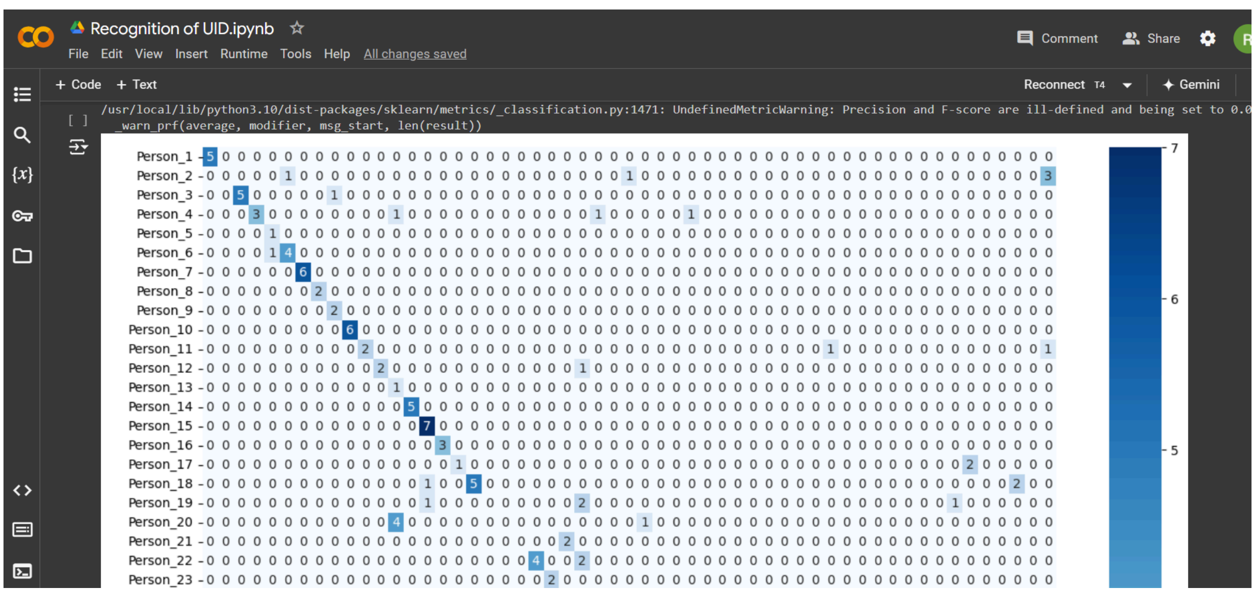
```
predicted_class_name = class_names[predicted_class_index]

# Output the predicted class
print(f'Predicted class: {predicted_class_name}')

# Optionally, display the image and the prediction
plt.imshow(cv2.imread(image_path, cv2.IMREAD_GRAYSCALE), cmap='gray')
plt.title(f'Predicted: {predicted_class_name}')
plt.axis('off')
plt.show()
```

- **The screenshots of the output: -**





(no subject) - rohit.24csz0014@
Sign_Data - Google Drive
Recognition of UID.ipynb - Cola
Peer Evaluation UI/UX 10th Sep
colab.research.google.com/drive/1V_OjzjQ0hrUeloMYjF4Wdv13bP7OCcdM#scrollTo=qc6oT0TquOlg
Recognition of UID.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment Share
+ Code + Text
RAM Disk
Gemini
[20]
img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE) # Load image in grayscale
img = cv2.resize(img, (IMG_WIDTH, IMG_HEIGHT)) # Resize image to match training input size
img = img / 255.0 # Normalize pixel values to [0,1]
img = img.reshape(1, IMG_WIDTH, IMG_HEIGHT, 1) # Reshape to add batch dimension and channels for CNN input
return img
# Load the trained model
model = load_model('signature_recognition_model.h5')
# Path to the image you want to test
image_path = '/content/drive/MyDrive/Sign_Data/Test/forgeries_34_24.png' # Replace with the path to your single image
# Preprocess the image
image = preprocess_image(image_path)
# Make prediction
prediction = model.predict(image)
# Determine class based on prediction
if prediction > 0.5:
print("The signature is forged.")
else:
print("The signature is original.")
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
1/1 0s 237ms/step
The signature is forged.
Connected to Python 3 Google Compute Engine backend



Recognition of UID.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Comment Share
+ Code + Text
Reconnect T4
Gemini
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1471: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0
_warn_prf(average, modifier, msg_start, len(result))
Person_1
Person_2
Person_3
Person_4
Person_5
Person_6
Person_7
Person_8
Person_9
Person_10
Person_11
Person_12
Person_13
Person_14
Person_15
Person_16
Person_17
Person_18
Person_19
Person_20
Person_21
Person_22
Person_23
7
6
5


+ Code + Text
Reconnect T4
Gemini
plt.axis('off')
plt.show()
1/1 0s 196ms/step
Predicted class: Person_50
Predicted: Person_50
import os
import cv2
import numpy as np
from google.colab import drive
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.preprocessing.image import ImageDataGenerator