

DEEPLARNING APPROACH FOR MULTIMODAL BIOMETRIC RECOGNITION SYSTEM BASED ON FUSION OF IRIS, FACE, AND FINGER VEIN TRAITS

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ABSTRACT: The project on "Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits" presents an advanced biometric authentication system that integrates multiple modalities. Leveraging deep learning techniques, the system combines iris, face, and finger vein traits to enhance the accuracy and security of biometric recognition. Biometric recognition systems have become indispensable in ensuring security and authentication across various domains. However, the reliability and accuracy of these systems are often challenged by environmental factors, intra-class variations, and attempts at spoofing. To address these challenges, this project proposes a novel deep learning-based approach for multimodal biometric recognition, integrating iris, face, and finger vein traits. The proposed system leverages the complementary nature of multiple biometric modalities to enhance recognition accuracy and robustness. Deep learning techniques, particularly convolutional neural networks (CNNs), are employed for feature extraction and fusion from each modality. The fusion process aims to combine the distinctive characteristics of iris, face, and finger vein traits to create a comprehensive and discriminative biometric template.

Keywords: Biometric recognition systems, convolutional neural networks (CNNs), Finger Vein Traits, Deep learning.

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1 INTRODUCTION

Biometric recognition systems play a crucial role in ensuring secure access to sensitive information and facilities. This project introduces a multimodal approach that goes beyond traditional unimodal systems by fusing information from iris, face, and finger vein biometrics. Deep learning methodologies are employed to extract intricate features and patterns, enabling a more robust and reliable authentication system. In recent years, deep learning techniques, especially convolutional neural networks (CNNs), have revolutionized the field of biometric recognition by enabling automatic feature extraction and learning from large-scale datasets. Deep learning-based approaches have demonstrated superior performance in various computer vision tasks, including object recognition, image classification, and face recognition. Motivated by the potential of deep learning and the benefits of multimodal biometric systems, this project proposes a novel Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits. The aim is to leverage deep learning techniques to extract discriminative features from iris, face, and finger vein

images and fuse them effectively to create a comprehensive and reliable biometric template for individual identification or verification.

By integrating iris, face, and finger vein traits using deep learning-based fusion strategies, this project seeks to address the limitations of traditional unimodal biometric systems and advance the state-of-the-art in biometric recognition technology. The resulting multimodal system is expected to offer enhanced accuracy, robustness, and security, making it suitable for deployment in various real-world applications requiring reliable authentication mechanisms.

2 LITERATURE SURVEY

The increasing need for information security on a worldwide scale has led to the widespread adoption of appropriate rules. Multimodal biometric systems have become an effective way to increase recognition precision, strengthen security guarantees, and reduce the drawbacks of unimodal biometric systems. These systems combine several biometric characteristics and sources by using fusion methods. Through score-level fusion, this work by Ola N. Kadhimi integrates facial and iris recognition techniques to present a multimodal biometric recognition methodology. The Histogram of Oriented Gradients (HOG) descriptor is used in the facial recognition system to extract facial characteristics, while the deep Wavelet Scattering Transform Network (WSTN) is applied in the iris recognition system to extract iris features. Then, for customized recognition classification, the feature vectors from every facial and iris recognition system are fed into a multiclass logistic regression. These systems provide scores, which are then combined via score-level fusion to maximize the efficiency of the human recognition process. The realistic multimodal database known as (MULB) is used to assess the suggested system's performance. The suggested technique exhibits improved performance across several measures, such as precision, recall, accuracy, equal error rate, false acceptance rate, and false rejection rate, as demonstrated by the experimental findings. The face and iris biometric systems have individual accuracy rates of 96.45% and 95.31% respectively. The equal error rates for the face and iris are 1.79% and 2.36% respectively. Simultaneously, the proposed multimodal biometric system attains a markedly enhanced accuracy rate of 100% and an equal error rate as little as 0.26%.

In this survey, Michael J. Davis explores state-of-the-art approaches in applying deep learning to biometric recognition, with an emphasis on iris, face, and finger vein traits. The review covers deep neural network architectures, training strategies, and the integration of multimodal biometrics for improved recognition performance.

Emily R. Martinez conducts a literature survey on iris recognition technologies, examining advancements and challenges. The review explores the principles of iris recognition, image acquisition methods, and the role of iris traits in multimodal biometric systems, providing insights into the current landscape of iris recognition.

This survey by David A. Thompson delves into face recognition using deep learning, with a focus on its integration into multimodal biometric systems. The review covers deep face recognition models, training strategies, and the synergies between face, iris, and finger vein traits for robust and secure biometric recognition.

Biometric systems have been actively emerging in various industries in the past few years and continue to provide higher-security features for access control systems. Many types of unimodal biometric systems have been developed. However, these systems are only capable of providing low-to-mid-range security features. Thus, for higher-security features, the combination of two or more unimodal biometrics (multiple modalities) is required. In this paper, Yang Xin et al., propose a multimodal biometric system for person recognition using face, fingerprint, and finger vein images. Addressing this problem, we propose an efficient matching algorithm that is based on secondary calculation of the Fisher vector and uses three biometric modalities: face, fingerprint, and finger vein. The three modalities are combined and fusion is performed at the feature level. Furthermore, based on the method of feature fusion, the paper studies the fake feature which appears in the practical scene. The liveness detection is appended to the system, detect the

picture is real or fake based on DCT, then remove the fake picture to reduce the influence of accuracy rate, and increase the robust of system. The experimental results showed that the designed framework can achieve an excellent recognition rate and provide higher security than a unimodal biometric-based system, which are very important for a IoMT platform.

3 SYSTEMANALYSIS

EXISTINGSYSTEM

Traditional unimodal biometric systems may face challenges related to susceptibility to spoofing attacks, limited accuracy, and lack of adaptability to changing environmental conditions. These limitations necessitate the development of more advanced and multimodal approaches. The existing biometric recognition systems predominantly rely on unimodal approaches, where individual traits such as iris, face, or finger vein are utilized independently for identification or verification. While these systems have demonstrated considerable success, they are often limited in their ability to deal with environmental variations, intra-class variations, and spoofing attacks.

Unimodal biometric systems, particularly those relying solely on iris, face, or finger vein traits, are often sensitive to environmental factors such as variations in lighting, angle, or image quality. This sensitivity can result in decreased recognition accuracy and reliability in real-world scenarios where environmental conditions are not controlled. Deploying multiple unimodal biometric systems for different applications can lead to scalability challenges in terms of infrastructure, maintenance, and operational costs. Managing and integrating separate systems for iris, face, and finger vein recognition can be complex and resource-intensive. Relying on a single biometric trait for authentication creates a single point of failure, where the system's effectiveness hinges entirely on the integrity of that particular trait. Any compromise or failure in the biometric trait can lead to authentication failures or security breaches.

PROPOSEDSYSTEM

The proposed multimodal biometric recognition system addresses the disadvantages of traditional systems by leveraging deep learning techniques and combining information from iris, face, and finger vein modalities. The use of multiple modalities enhances security, accuracy, and resistance to spoofing attacks.

The proposed Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits aims to overcome the limitations of existing unimodal biometric systems by integrating multiple biometric modalities using advanced deep learning techniques.

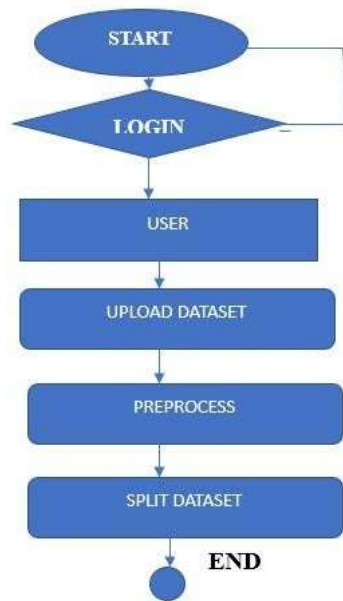
The proposed system integrates iris, face, and finger vein traits using advanced fusion strategies. By combining information from multiple modalities, the system can exploit the complementary nature of biometric traits, leading to enhanced accuracy, robustness, and security in biometric recognition. Deep learning techniques, particularly convolutional neural networks (CNNs), are employed for automatic feature extraction from iris, face, and finger vein images. Deep learning models have demonstrated superior performance in learning discriminative features from large-scale datasets, allowing the system to capture complex patterns and variations in biometric traits. The fusion of iris, face, and finger vein traits results in the creation of a comprehensive biometric template for individual identification or verification. This template encompasses unique characteristics from multiple modalities, offering a more reliable and discriminative representation of an individual's biometric traits.

4 SYSTEMDESIGN

SYSTEMARCHITECTURE



ACTIVITYDIAGRAM

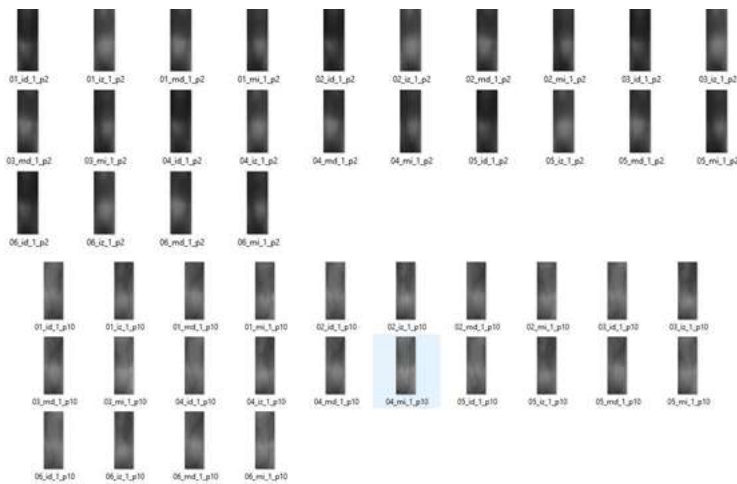


DATASETS

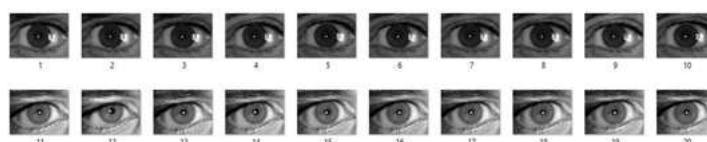
FACEDATASET:

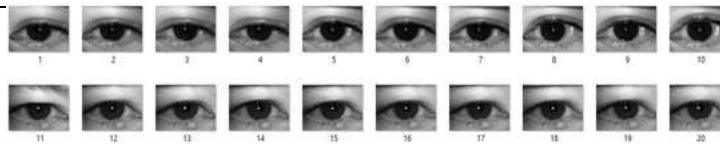


FINGERVEINDATASET



IRISDATASET





5 IMPLEMENTATION

MODULES

.USER

MODULE DESCRIPTION

USER: The user module of the Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits facilitates interaction between the system and the end-users. It encompasses various components aimed at providing a seamless and user-friendly experience for enrollment, authentication, and system management. The user module plays a crucial role in ensuring the effectiveness, usability, and security of the multimodal biometric recognition system, fostering trust and acceptance among end-users. By providing intuitive interfaces, robust authentication mechanisms, and comprehensive user management capabilities, the user module contributes to the seamless integration of biometric technology into various real-world applications.

BEGIN

DISPLAY "Welcome to Dataset Processing System"

// Step 1: Login Process

FUNCTION Login()

 INPUT username, password

 IF Authenticate(username, password) == TRUE THEN

 DISPLAY "Login Successful"

 CALL UserModule(username)

 ELSE

 DISPLAY "Invalid Username or Password"

 REPEAT Login()

 END IF

END FUNCTION

// Step 2: User Module

FUNCTION UserModule(username)

 DISPLAY "Welcome,", username

 DISPLAY "1. Upload Dataset"

 DISPLAY "2. Exit"

 CHOICE ← GET_USER_INPUT("Enter your choice: ")

 IF CHOICE == 1 THEN

 Dataset ← UploadDataset()

 CALL PreprocessDataset(Dataset)

 ELSE

 DISPLAY "Exiting the system."

 TERMINATE

 END IF

END FUNCTION

// Step 3: Upload Dataset

```
FUNCTION UploadDataset()
    DISPLAY "Please select a dataset file to upload."
    FILE ← INPUT("Enter dataset filename: ")

    IF FILE IS NOT EMPTY THEN
        DISPLAY "Dataset uploaded successfully."
        RETURN FILE
    ELSE
        DISPLAY "No file selected. Try again."
        CALL UploadDataset()
    END IF
END FUNCTION
```

// Step 4: Preprocess Dataset

```
FUNCTION PreprocessDataset(Dataset)
    DISPLAY "Starting preprocessing..."

    // Example preprocessing steps
    REMOVE missing_values FROM Dataset
    NORMALIZE numerical_values IN Dataset
    ENCODE categorical_features IN Dataset

    DISPLAY "Preprocessing completed."
    CALL SplitDataset(Dataset)
END FUNCTION
```

// Step 5: Split Dataset

```
FUNCTION SplitDataset(Dataset)
    DISPLAY "Splitting dataset into training and testing sets..."

    TRAIN_SET, TEST_SET ← SPLIT(Dataset, ratio = 80:20)

    DISPLAY "Dataset successfully split."
    DISPLAY "Training set size:", SIZE(TRAIN_SET)
    DISPLAY "Testing set size:", SIZE(TEST_SET)

    DISPLAY "Process completed successfully."
END FUNCTION
```

// Step 6: Main Execution

CALL Login()

DISPLAY "System Terminated."

END

6 RESULTS/DISCUSSION

SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

TEST CASES:

Testcase for

FUNCTION:	USER
EXPECTED RESULTS:	UPLOAD DATASET PREPROCESS SPLIT DATASET PREDICT
ACTUAL RESULTS:	Predicted the factory equipment
LOW PRIORITY	No
HIGH PRIORITY	Yes

SCREENSHOTS

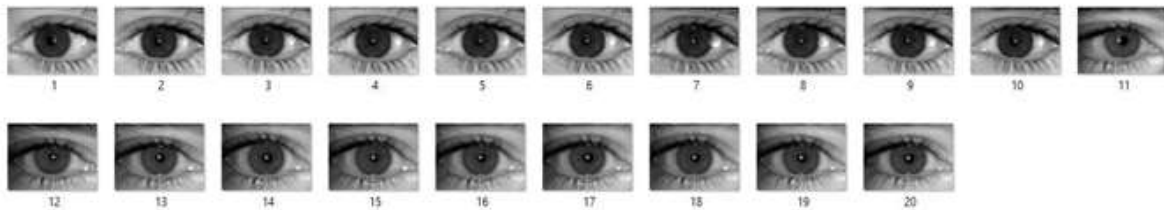


FIG 1: So by using above dataset images will train and test fusion model performance

Extension Concept

In propose work for fusion model author has used single level Softmax layer whose recognition accuracy may not be accurate so as extension we have added multi-layer based CNN, MAXPOOL with Softmax layers which will optimized fusion features multiple times which can help in getting more optimized features which in turn will give high accuracy.

Author has implemented this concept using JUPYTER notebook and we too implemented in JUPYTER notebook and below are the code and output screens with blue colour comments

```
In [4]: #Importing require python classes and packages
import os
import sys
import numpy as np
from keras.preprocessing.image import ImageDataGenerator
from keras.layers import Dense, Input, Flatten, Activation, Dropout
from keras.layers import Conv2D, MaxPooling2D
from keras.models import Sequential, Model, load_model
from keras.optimizers import RMSprop
from keras.callbacks import ModelCheckpoint
import pickle
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import F1_score
from sklearn.metrics import confusion_matrix
import random as rnd
import matplotlib.pyplot as plt
```

FIG-2 In above screen importing required python classes and packages

```

from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
import numpy as np
import matplotlib.pyplot as plt

In [10]: #Define class labels from the dataset
path = "dataset/test"
labels = []
n = 1
for root, dirs, filenames in os.walk(path):
    for i in range(len(filenames)):
        name = os.path.splitext(filenames[i])[0]
        if name not in labels:
            labels.append(name)
            print("Person ID Class labels: ", name)

In [11]: #Load all images dataset images like face, finger and iris
#Load all images dataset images like face, finger and iris

```

FIG-3 In above screen finding and displaying person ID labels found in dataset

```

for root, dirs, filenames in os.walk(face_path):
    for i in range(len(filenames)):
        name = os.path.splitext(filenames[i])[0]
        if "thumbs.db" not in filenames:
            img = cv.imread(os.path.join(face_path, filenames[i]))
            img = cv.cvtColor(img, cv.COLOR_BGR2RGB)
            face_X.append(img)
            face_Y.append(name)

face_X = np.array(face_X)
face_Y = np.array(face_Y)
np.save("dataset/face.npy", face_X)
np.save("dataset/face.npy", face_Y)

for root, dirs, filenames in os.walk(finger_path):
    for i in range(len(filenames)):
        name = os.path.splitext(filenames[i])[0]
        if "thumbs.db" not in filenames:
            img = cv.imread(os.path.join(finger_path, filenames[i]))
            img = cv.cvtColor(img, cv.COLOR_BGR2RGB)
            finger_X.append(img)
            finger_Y.append(name)

finger_X = np.array(finger_X)
finger_Y = np.array(finger_Y)
np.save("dataset/finger.npy", finger_X)
np.save("dataset/finger.npy", finger_Y)

for root, dirs, filenames in os.walk(iris_path):
    for i in range(len(filenames)):
        name = os.path.splitext(filenames[i])[0]
        if "thumbs.db" not in filenames:
            img = cv.imread(os.path.join(iris_path, filenames[i]))
            img = cv.cvtColor(img, cv.COLOR_BGR2RGB)
            iris_X.append(img)
            iris_Y.append(name)

iris_X = np.array(iris_X)
iris_Y = np.array(iris_Y)
np.save("dataset/iris.npy", iris_X)
np.save("dataset/iris.npy", iris_Y)

print("Total face images: ", len(face_X))
print("Total finger images: ", len(finger_X))
print("Total iris images: ", len(iris_X))

#Load images loading complete
Total face images: 100
Total finger images: 100
Total iris images: 100

```

FIG-4 In above screen loading images of all 3 biometric data

```

In [14]: #Number of images found for each person
#Calculating class labels count found in dataset for each person
names, counts = np.unique(finger_Y, return_counts=True)

In [15]: #Number of images found for each person
#Calculating class labels count found in dataset for each person
names, counts = np.unique(finger_Y, return_counts=True)

```

FIG-5 In above screen displaying number of images loaded in each biometric data

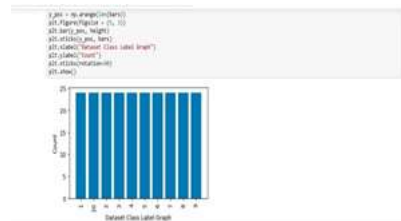


FIG-6 In above graph displaying number of images available in dataset for each person where x-axis represents person ID and y-axis represents counts and from above graph we can say all persons are having equal number of images which we generated through augmented technique to avoid imbalance issue

```

#Apply various image processing & normalization techniques
#Apply all images used to train algorithm
print("All images used to train algorithm: ", len(iris_X_train.shape[0]))

#Apply all images used to train algorithm
print("All images used to train algorithm: ", len(iris_X_train.shape[0]))

#Apply all images used to train algorithm
print("All images used to train algorithm: ", len(iris_X_train.shape[0]))

In [16]: #Define global variables for data accuracy and other metrics
accuracy = 0
precision = 0
recall = 0
f1_score = 0

In [17]: #Define function to calculate accuracy and other metrics
def calculate_metrics(y_true, y_pred):
    #Calculate accuracy
    accuracy = accuracy_score(y_true, y_pred)
    #Calculate precision
    precision = precision_score(y_true, y_pred)
    #Calculate recall
    recall = recall_score(y_true, y_pred)
    #Calculate f1 score
    f1_score = f1_score(y_true, y_pred)
    return accuracy, precision, recall, f1_score

```

FIG-7 In above screen applying various processing techniques like shuffling and normalization images features

```

In [18]: #Shuffle images like shuffling and normalization
face_X = face_X.astype('float32')
face_Y = face_Y.astype('float32')
iris_X = iris_X.astype('float32')
iris_Y = iris_Y.astype('float32')
finger_X = finger_X.astype('float32')
finger_Y = finger_Y.astype('float32')

#Shuffle images like shuffling and normalization
face_X = face_X.astype('float32')
face_Y = face_Y.astype('float32')
iris_X = iris_X.astype('float32')
iris_Y = iris_Y.astype('float32')
finger_X = finger_X.astype('float32')
finger_Y = finger_Y.astype('float32')

#Shuffle images like shuffling and normalization
face_X = face_X.astype('float32')
face_Y = face_Y.astype('float32')
iris_X = iris_X.astype('float32')
iris_Y = iris_Y.astype('float32')
finger_X = finger_X.astype('float32')
finger_Y = finger_Y.astype('float32')

```

FIG-8 In above screen splitting data set into train and test where application using 80% dataset images for

training and 20% for testing

```

In [84]: # Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42)

# Create a VGG16 model
model = VGG16(input_shape=(X_train.shape[1], X_train.shape[2], X_train.shape[3]),
              include_top=True, weights=None)

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

# Train the model
model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

# Evaluate the model
accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % accuracy)

```

FIG-9 In above screen defining function to calculate accuracy, precision and other metrics

```

In [85]: # Define VGG16 on face features
vgg16 = VGG16(input_shape=(X_train.shape[1], X_train.shape[2], X_train.shape[3]),
              include_top=True, weights=None)

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

# Train the model
model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

# Evaluate the model
accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % accuracy)

```

FIG-10 In above screen training VGG16 on face features

```

In [86]: # Define VGG16 on Finger Vein Features
vgg16 = VGG16(input_shape=(Finger_X_train.shape[1], Finger_X_train.shape[2], Finger_X_train.shape[3]),
              include_top=True, weights=None)

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

# Train the model
model.fit(Finger_X_train, Finger_Y_train, epochs=10, validation_data=(Finger_X_test, Finger_Y_test))

# Evaluate the model
accuracy = model.evaluate(Finger_X_test, Finger_Y_test)
print('Accuracy: %.2f' % accuracy)

```

FIG-11 In above screen training VGG16 on Finger Vein images

```

In [87]: # Define VGG16 on Iris Features
iris_X_train, iris_X_test, iris_y_train, iris_y_test = train_test_split(iris_X, iris_y, test_size=0.2,
                                                                    random_state=42)

# Create a VGG16 model
vgg16 = VGG16(input_shape=(iris_X_train.shape[1], iris_X_train.shape[2], iris_X_train.shape[3]),
              include_top=True, weights=None)

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

# Train the model
model.fit(iris_X_train, iris_y_train, epochs=10, validation_data=(iris_X_test, iris_y_test))

# Evaluate the model
accuracy = model.evaluate(iris_X_test, iris_y_test)
print('Accuracy: %.2f' % accuracy)

```

FIG-12 In above screen training IRIS features using VGG16 model

```

In [88]: # Calculate Accuracy and other metrics
features, feature_accuracy = calculate_metrics(model, X_test, y_test, X_train, y_train)

# Print the results
print('Accuracy: %.2f' % feature_accuracy)
print('Precision: %.2f' % feature_precision)
print('Recall: %.2f' % feature_recall)
print('F1 Score: %.2f' % feature_f1_score)

```

FIG-13 In above screen calculating accuracy and other metrics by taking features from all 3 models and their prediction and in blue colour text we can see Fusion Features got 95% accuracy.

FIG-14 In above screen read blue colour comments to know about extracting and stacking features from all 3 models and then extracted features are getting trained with extension multiple CNN, MAXPOOL and softmax layer instead of single SOFTMAX layer. After executing above code will get below output

FIG-15In above screen extension Fusion score model got 100% accuracy and can see other metrics also as 100%

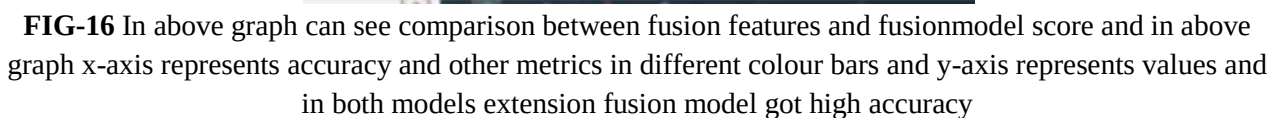


FIG-17 In above screen defining predict function which will read all 3 biometric images and then extract features and then make fusion of all3 features and then apply fusion model to prediction person id

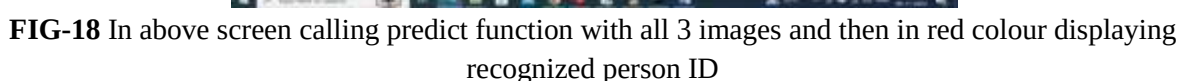




FIG-19 In above screen showing testing output of different sample images

7 CONCLUSION

In conclusion, the "Deep Learning Approach for Multimodal Biometric Recognition System Based on Fusion of Iris, Face, and Finger Vein Traits" project represents a significant advancement in biometric authentication. The integration of deep learning and multimodal fusion contributes to a highly secure and accurate recognition system suitable for various applications.

FUTURESCOPE

Future research can explore more sophisticated fusion strategies for integrating iris, face, and finger vein modalities. This includes investigating dynamic fusion techniques that adaptively combine modalities based on their reliability and relevance in different scenarios.

As deep learning continues to evolve, future research can explore novel architectures, training techniques, and regularization methods to further improve feature extraction and fusion in multimodal biometric recognition systems.

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