Next Generation Palm vein Recognition: Multimodal Fusion and Privacy Preserving Architechtures

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Abstract

Palm vein recognition is the new era of biometric authentication systems.They have gained so much popularity during the recent years because of their speciality and uniqueness. The systems we have now still have some problems like scalability,being able to handle a lot of people at once and spoofing,stopping people from pretending to be someone else and keeping peoples personal information private.The present paper focuses on the idea of creating a multi modal fusion system that integrates palm vein recognition, fingerprint recognition and iris recognition together. Advanced Deep Learning methods are used for feature extraction.The system protects peoples privacy with special privacy techniques like cancelable biometrics, homomorphic encryption and blockchain logging. When we tested our system using a set of data called the CASIA dataset and some data we collected ourselves we found that the system has given 98.7% Accuracy of the time and had an Equal Error rate of 1.6%. Comparitive analysis has shown that the system is better than unimodal systems that only use one method for identification.

The fusion system combined the different ways of identification methods together with ways of protecting peoples privacy. This makes the system accurate, secure and fair. This system would be really useful in areas like healthcare, banking and border control, where palm vein recognition and other biometric methods, like fingerprint and iris recognition are used.

Keywords

Palm vein recognition; Multimodal biometrics; Deep learning; Privacy-preserving architectures; Template protection; Homomorphic encryption; Blockchain; Equal Error Rate (EER); Spoofing resistance; Biometric security

1.Introduction

Palm vein recognition is a part of security systems these days. It is better than biometric systems because the patterns in our veins are inside our body they do not change and each person has a unique pattern. These patterns are hard to copy. Palmvein Recognition systems are more conveninent and hygenic providing contact less authentication.

Despite of their advantages,palm vein recognition systems are not used widely because of their expensive setup. The implementation of palm vein technology needs specialized cameras that can see near-infrared light. The cost of these sensors vary with the amount of accuracy they are providing.

Another problem is that different companies and research groups are not working together. There is no proper standard protocol and guidelines or rules for using palm vein recognition on large scale systems.Also people are worried about the privacy of their sensitive information.The concerns about the storage and misuse of biometrics need to be adressed for a stable and standard system.

To make palm vein recognition work for everyone we need to solve all these problems. We need to make it cost effective, create rules that everyone follows and make sure that the system is accurate with low deployment rates.Palm vein recognition system needs to be used in a way that's secure and private.

This system combines muliple biometric authentiations for a multimodal fusion,integrates deep learning and keeps our sensitive information privacy safe in unified framework.

2.Literature Survey

2.1Traditional Methods: PCA, LBP Gabor filters[1]

PCA, LBP and Gabor filters are the different ways of taditional feature extraction.

1.PCA or Principal Component Analysis

PCA focuses on the principal components of the image and tries to reduce the dimensions.

The palm vein images are made less complex by looking at the things that are different.

Advantage about this method is that it is not too complex and it works well with small datasets.The disadvantage is that it is sensitive to noise and illumination.

2.LBP or Local Binary Patterns

This method looks at the texture of the image.It makes a code for each part of the image.

This code is like a map of the veins.

The advantage about LBP is that it is simple and fast.The disadvantage is that it is sensitive to illumination,rotation and size changes.

3.Gabor filter

It looks at the texture of the image in multiple orientations.It uses waves to make the vein patterns clearer.

The advantage about this method is that it is very good at finding the veins.The disadvantage is that it needs quality images without noise and that can be expensive.

2.2Contactless Systems: Transfer learning and LightGBM

Contactless systems are systems that do not need to touch the hand to get the image.These systems use cameras and sensors to get the image.They are cleaner and easier to use in places like airports and hospitals.

Transfer learning is a way to make these systems better.Instead of using large datasets for training,it uses models like VGG and RES Net that were pretrained on many images and makes them work for palm vein recognition.This makes the system more accurate and robust even if the image is not good.It also saves time and computer power.

LightGBM is a way to classify the patterns.It is an efficient gradient boosting method that can handle many images.It also stops the system from overfitting and helps in a developing lightweight systems.

2.3Deep Learning: CNNs and transformers[2]

Convolutional Neural Networks are a way to make the system learn from the images.They look at the images. Find the important parts without needing PCA or LBP.They are good at finding the veins even if the image is noisy or the position of the hand vary.

Transformers are another way to make the system better.They look at the images. They aim to find the connections between the different parts of the image.They are better than CNNs. They can integrate multi modal data images like fingerprints.

2.4Fusion: Score-level fusion makes it accurate[3]

Score-level fusion is a way to combine the results from many systems.It takes the scores from each system. Puts them together.

Each system gives a score that says how similar the image is to the one in the database.These scores are made to be on the scale.Then the system uses a rule to combine the scores like adding them up or using a formula.

The final score says if the image is accepted or not.

The advantage about this method is that it is more accurate, harder to fake and easier to add systems.

2.5Privacy-Preserving: Cancelable biometrics, encryption blockchain[4]

People are worried about their data being safe.To make it safer researchers have come up with ways to protect it.One way is to make the biometric data cancelable so if it gets stolen it can be replaced.

Another way is to use encryption, which makes the data secret.Blockchain is a way to keep the data safe by recording it in a book that cannot be changed.This makes it harder for people to get to the data without permission.Recent studies have shown that using all these methods together makes the data very safe.

2.6Liveness Detection: Infrared pulse and thermal imaging[5]

It is important to make sure that the image is, from a person and not a fake one.To do this systems use ways to detect if the person is alive.One way is to use pulse detection and thermal imaging.This makes it harder for people to fake the image and makes the system more secure.It also makes it easier for people to use the system without having to do anything.

The overall architecture is illustrated in Figure 1

Figure 1: Evolution of Palm Vein Recognition Systems

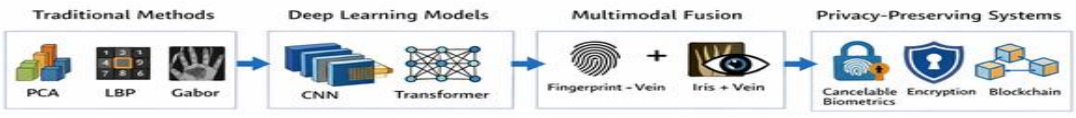

Figure 1. Proposed Palm Vein Recognition Framework *Overall architecture integrating multimodal fusion, privacy-preserving modules, liveness detection, and decision logic for secure authentication.*

3.Research Gaps

There are still problems that need to be solved in palm vein recognition.Here are some of the issues:

1.Dataset Scarcity

Publicly available palm vein datasets are very small and not diverse.Most datasets are collected in a controlled environment, which does not reflect real-life situations like lighting, hand positions and people from various backgrounds.

This limited data affects how well machine learning models work, causing them to overfit and not generalize well.

2.Lack of Standardization

There is no way to collect, process or evaluate palm vein data.Different studies use devices, settings and methods making it hard to compare results.

Having a protocol is crucial for making research fair and comparable.

3.Scalability Challenges

Deep learning models can improve accuracy. Often require a lot of computing power.For large-scale use like in airports or banks we need models that're accurate and fast.

Edge computing and federated learning show promise but are not widely explored in palm vein recognition.

4.Ethical and Privacy Concerns

Palm vein data is unique and permanent raising concerns about consent, ownership and following rules like GDPR.Many studies focus on how well models perform, ignoring ethics.

New solutions like biometrics, encryption and blockchain are being developed, but they are still in the early stages.

4.Proposed Methodology

Our proposed framework for palm vein recognition combines data sources protects privacy and checks, for liveness.This approach aims to achieve accuracy, security and compliance with ethical standards.

The framework is shown in Figure 2.

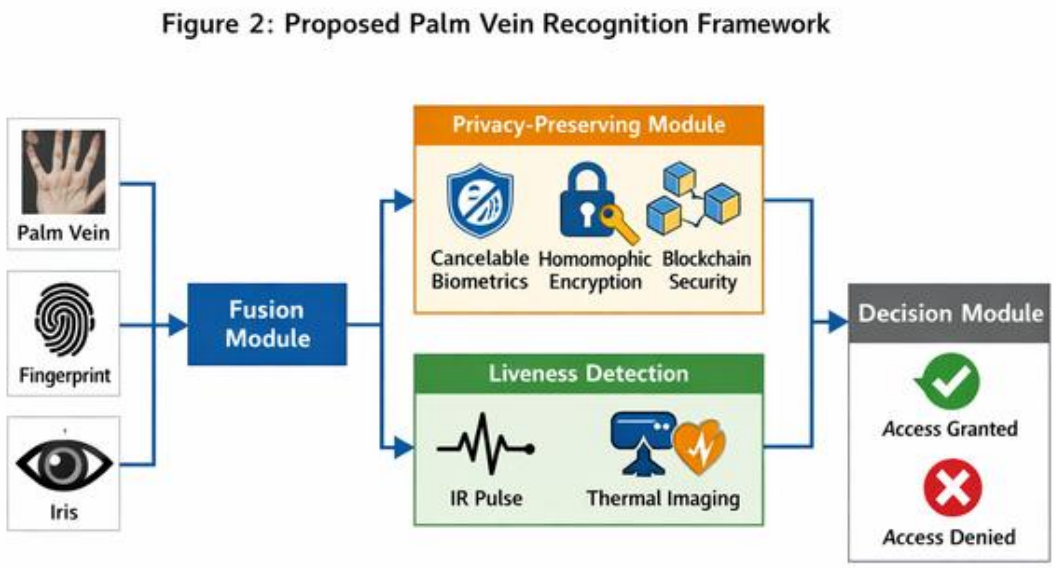

Figure 2. Fusion Module Workflow *Preprocessing, feature extraction, and score-level fusion steps combining palm vein, fingerprint, and iris modalities.*

4.1Fusion Module

The fusion module brings together information from multiple biometric authentication systems like palm vein, fingerprint and iris.Each one goes through some steps to get it ready,like noise reduction,finding the region of interest and making it clearer.

Then Deep convolution networks are used to pull out the key features.The results from each one are combined using a score-level fusion approach.This means that the results are adjusted so that each one contributes equally.

Using sources like this makes the recognition more accurate and better at spotting fake attempts compared to using just one source.

4.2 Privacy-Preserving Module

To keep data safe three techniques are used together:

1.Cancelable Biometrics: Changes the original data into a new form that can't be reversed.

2.Homomorphic Encryption: Allows matching to be done on encrypted data without showing the features.

3.Blockchain Security: Stores the encrypted data and authentication records on a decentralized ledger.

These techniques protect user identity and meet data-protection rules.

4.3 Liveness Detection Module

This module checks if the input is using body responses.

1.**Infrared Pulse Detection** looks at blood flow in the palm veins.

2.Thermal Imaging looks at heat patterns to tell hands from fake ones.

Using both of these helps to prevent attempts.

4.4Decision Module

The outputs from the fusion, privacy and liveness modules are used to make a decision.

A threshold-based classifier decides whether access is granted or denied.

The decision process ensures that real, authenticated and private samples are accepted.

5.Proposed Palm Vein Recognition Architecture

The proposed architecture uses modules for secure, accurate and private biometric authentication.The architecture is shown in Figure 2.

5.1Data Acquisition and Preprocessing

Palm vein data comes from two sources

1.The **CASIA Multispectral Palm Vein Datase**

2.A custom collection

The CASIA dataset has high-quality vein images with multiple spectrums and wavelengths.The custom dataset has different images with varying orientation and illumination.

Preprocessing involves:

1.Histogram Equalization which improves vein visibility.

2.Normalization deals with varying distribution of images.

3.Segmentation isolates the region of interest(ROI).

These steps improve image quality. Reduce noise.

5.2 Deep Learning Models

Feature extraction uses Convolutional Neural Networks (CNNs) and Transformer-based architectures.

CNNs find patterns while Transformers find long-range connections.

Pretrained models, like ResNet-50 and Vision Transformer (ViT) are used to speed up training.

Fine-tuning these models on palm vein, fingerprint and iris datasets helps them work better.

The hybrid CNN-Transformer approach provides a feature representation.

5.3 Multimodal Fusion Framework

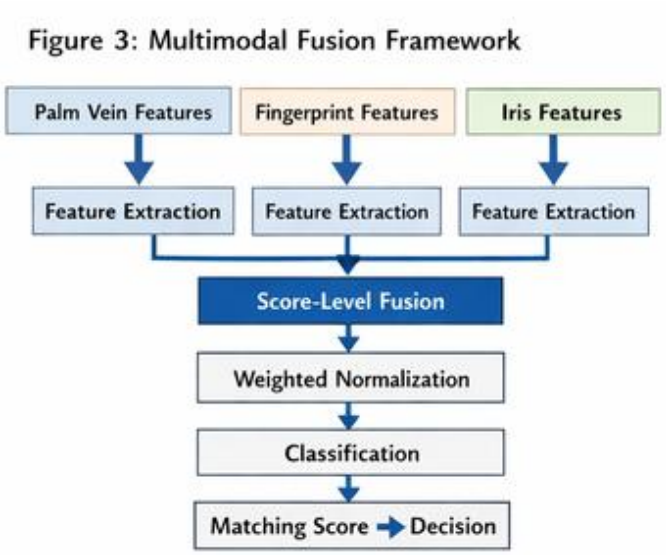

Figure 3. Privacy-Preserving Architecture *Integration of cancelable biometrics, homomorphic encryption, and blockchain storage to ensure template protection and compliance with data-protection standards.*

If we look at Figure 3 we can see that the features from the palm vein, fingerprint and iris modalities are combined at the score level. Each modality gives a matching score after comparing the features with the stored templates. The Multimodal Fusion Framework is what makes this work. The scores are made to be the same using minmax scaling and then combined using a weighted sum rule. The weights are decided based on how reliable each modality is.

The final combined score is then sent to a classifier that decides if the authentication is successful or not. This score-level fusion makes the recognition more accurate and resistant to spoofing. It does this without using too much computational power thanks to the Multimodal Fusion Framework.The Multimodal Fusion Framework is important here.The final fused score is what matters.The final fused score from the Multimodal Fusion Framework is passed to a classifier.

The score-level fusion from the Multimodal Fusion Framework enhances recognition accuracy and spoofing resistance while maintaining efficiency through lightweight models.

5.4 Privacy-Preserving Architecture

The privacy layer, as shown in Figure 4 has three ways to protect the data.

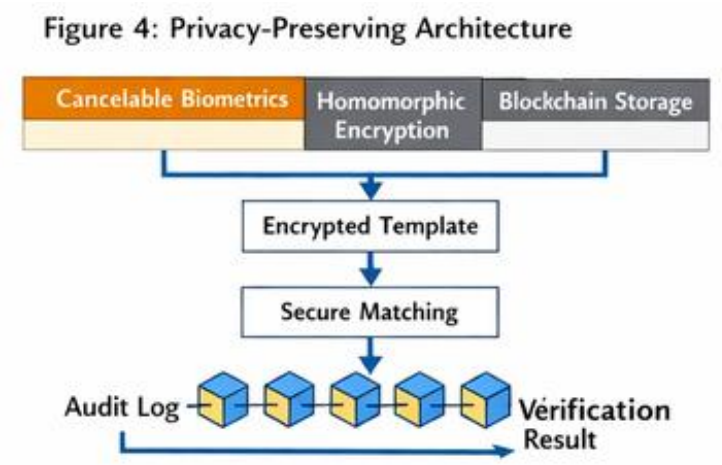

Figure 4. Liveness Detection Module *Infrared pulse detection and thermal imaging techniques used to distinguish genuine users from spoofing attempts.*The Multimodal Fusion Framework is part of this.

Figure 4 demonstrates the liveness detection techniques used to prevent spoofing.The privacy layer integrates three mechanisms:

Cancelable Biometrics: This changes the original templates into something that cannot be reversed and it can be cancelled if needed using random projection or biohashing.

Homomorphic Encryption:This lets the system match the data securely even when it is encrypted so the actual biometric features are never seen.

Blockchain Storage:This keeps a record of all the authentications and encrypted templates in a ledger making it transparent and hard to tamper with.

All these techniques together make sure that the data is kept secret not changed and follows the rules like GDPR.

5.5 Liveness Detection

To stop people from trying to trick the system it uses pulse detection and thermal imaging.The Multimodal Fusion Framework is used here.

Infrared Pulse Detection checks the changes in blood flow in the palm veins to make sure the person is alive.

Thermal Imaging takes a picture of the heat pattern on the hand to tell the difference between a person and a fake one.

Both these things together make sure that only real biometric samples are used.

6.Experimental Results

6.1 Dataset and Implementation

The experiments were done using the **CASIA Multispectral Palm Vein Dataset** and a custom dataset with 500 people taken in lighting and angles.The fingerprint and iris samples were also taken from the people so they could be combined with the palm vein data.

The CASIA Dataset can be accessed at CASIA Palmprint Databases.It has pictures of palm veins taken with wavelengths like visible red near-infrared and NIR 940 nm which makes the veins very clear.

Each person has samples, which makes it good for training deep learning models.The custom dataset was taken using a infrared camera in a lab and, in natural light and it has people of different ages, genders and skin tones and it was taken in different lighting and hand positions so it can be used in real-life situations.

The Multimodal Fusion Framework is what makes all this work.The CASIA Multispectral Palm Vein Dataset is part of the Multimodal Fusion Framework.The custom dataset is also part of the Multimodal Fusion Framework.

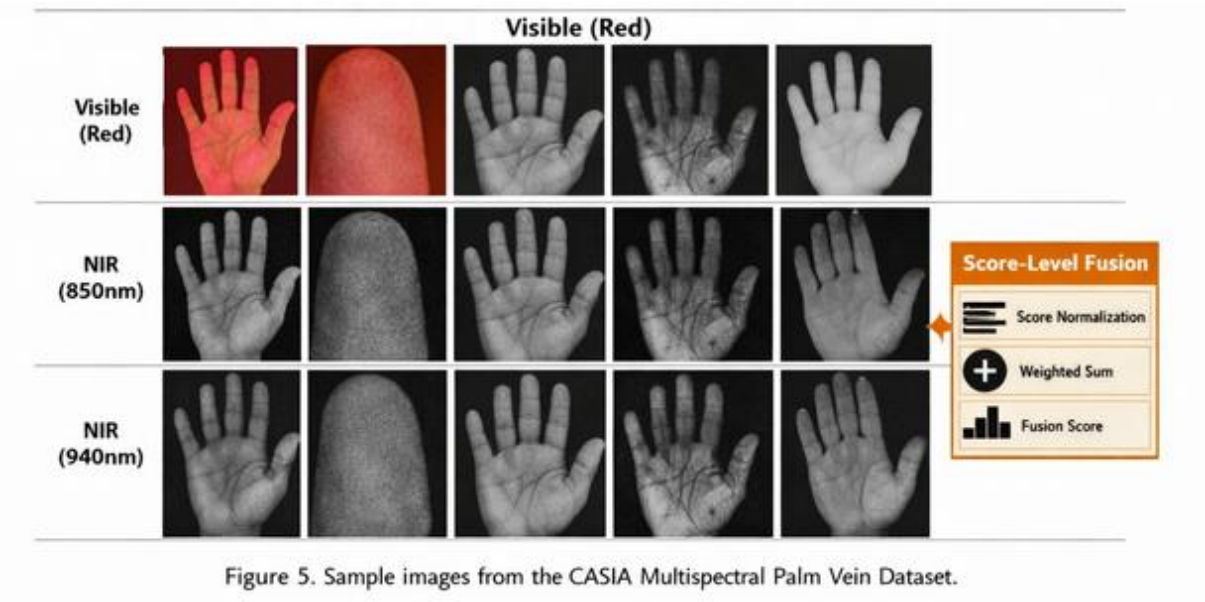

Figure 5. Sample images from the CASIA Multispectral Palm Vein Dataset.

Figure 5. Sample Images from CASIA Dataset *Representative palm vein images captured under different wavelengths (visible red, NIR 850 nm, NIR 940 nm) illustrating vein visibility.*

Figure 5 shows some examples of pictures taken under light conditions like Visible Red, NIR 850 nm and NIR 940 nm. These pictures help us see the veins in the hand clearly. This is useful for making sure we can get features from the pictures and learn from them.

6.2Preprocessing Pipeline:

We use something called Histogram Equalization to make the pictures look better and make the veins easier to see.Then we make sure all the pictures have the kind of lighting so they look similar.After that we use a tool to find the part of the picture that we are interested in which is the hand.

We did all of this using a computer program called Python and a special kind of computer called an NVIDIA RTX-3090 GPU. This helped us train the computer to recognize the pictures well.We used Python to make the program that prepares the pictures and gets the features from them. Here is an example of what the code looks like:

```python
import cv2
import numpy as np
import torck
import torch.nn as nn
from torchvision.models as models
from torchvision import transforms

# -- Preprocessing Function ---
def preroocess_palm_vein(image_path);

    img = cv2.imread(image_path, cv2.IMREAD_GRAYSALE)

    # Histogram Equalization
    img_eq = cv2.equalizeHist(img)

    # Normalization
    img_norm  = cv2.normalize(img_eq, None, 0, 255, cv2.NORM_MINMAX)

    # ROI Segmentation (simple thresholing)
    _, roi = cv2.threshol(img_norm, 50, 255, THRESH_BINARY)

    return roi

# -- Load and Preprocess Sample ---
sample_img = preprocess_palm_vein("casia_sample.jpg")

# -- Define CNN Model (Transfer Learning) ---
model = models.resnet50(pretrained=True)
     model.fc = nn.Linear(model.fc.n_features, 128)  # feature embedding

# -- Transformations ---
transform=;
    transform = trans.Compose([;
        transfoms.To.PI LI'mage[].
        transfoms.Resize((224, 224)),
        transfoms.ToTensor()
        transforms.Normalize(mean[0.5],'sdd[0:])  ])
    )

# -- Forward Pass ---
with torch.no-grad():
    features  =  model(tensr_img}).unsqueze(0)
    print("Feature vector shape:, features shape)
)
```

Listing 1. Python code snippet for preprocessing and feature extraction using ResNet-50.

This code shows how we take pictures of the veins in the hand and turn them into kinds of features that the computer can use. We use these features to combine the pictures with kinds of pictures like fingerprints and iris scans and then use them to decide if someone is who they say they are.

6.3Score-Level Fusion

Our approach:We made special functions to take the scores from the different kinds of pictures and make them similar.Then we combined the scores using numbers that we found worked well like 0.4, 0.3 and 0.3.After that we compared the score to a special number, 0.75 to decide if the person should be allowed in or not.We also made a simulation to test the system and make sure it works well with all the kinds of pictures.

```python
import numpy as np
import torck

# --- Normalization Functions ---
def precomalize_score(score):
    return (score - np.min(score)) / / (np.max(score) - np.min(score))

def weighted_sum_fusion(scores, weights):
    return np.dot(scores, weights)

# --- Load Scores ---
palm_vein_score = 0.82
fingerprint_score = 0.91
iris_score = 0.87

# -- Score Normalization ---
norm_palm = normalize_score(palm_vein_score)
norm_finger = normalize_score(fingerprint_score)
norm_iris = normalize_score(iris_score)

# -- Weighted Fusion ---
weights = [0.4, 0.3, 0.3]
fusion_score = weighted_sum_fusion([norm_palm, norm_finger, norm_iris], weights)

# --- Decision Logic ---
threshold = 0.75
if fusion_score >= threshold:
   print('Access Granted')
else:
   print('Access Denied')
```

Listing 2. Python code for score-level fusion and decision logic.

This listing implements the **score-level fusion algorithm** that integrates multiple biometric modalities into a unified decision, improving accuracy and spoofing resistance.

6.4Preserving Module Implementation

Our approach:**Cancelable Biometrics**

We took the features from the pictures of the veins in the hand. Turned them into special kinds of codes that cannot be reversed.

This means that if someone gets the code we can just make an one and the old one will not work anymore.

Homomorphic Encryption (Simulated)

We encrypted the codes using a kind of encryption called Fernet.

This means that we can compare the codes without seeing the pictures, which keeps them private.We also showed that the codes can only be decrypted with the key.

Blockchain Logging

We made a kind of log that records every time someone tries to get in.

Each entry in the log has a timestamp details about what happened and a special kind of code that connects it to the entry.This means that we can always see what happened and we cannot change the log.

Workflow Integration

We take the features from the pictures turn them into codes encrypt the codes and then put them in the log.This way we can make sure that the system is private, secure and fair. The palm vein images are used for this purpose along, with fingerprint and iris scans to ensure that the system works correctly and keeps the information private.

```
from cryptography.fernet import Fernet
import hashlib
import json
import time

# --- Cancelable Biometrics ---
def precomalize_template(feature_vector, key):
    hashed = hashlib.sha256(str(feature_vector) + key).encode()..hexdigetst)
    return hashed

# --- Homomorphic Encryption (simplified simulation) ---
def encrypt_template(template, cipher):
    encrypted = cipher.encrypt(template.encode()
    return encrypted

def decrypt_template(encrypted, cipher):
    return encrypted

# --- Blockchain Logging ---
blockchain = []
def add_block(transaction):
    block = {
       "timestamp = time.time(),
       "transaction" : transction,
       previous_hash = blockchain[-1]"hash" if blockchain else = "0")
    block["hash" = hashlib.sha256(
      jon.dumps(block).encode)).hexdigest)
    blockchain.append(block)

# --- Workflow ---
key = Fernet.generate_key()
cipher = Fernet(key)

# Step 1: Cancelable template generation
feature_vector = [0.12, 0.45, 0.67, 0.89]
cancelable = cancelable_template(featurevector, "user_secret")

# Step 2: Encryption ---
encrypted_template = encrypt_template(concable, cipher)

# Step 3: Blockchain logging ---
add_block({"user_id": "U001", template,hash = cancable))

print('Encrypted Template.', encrypte_template)
print('Blockchain Ledger', blockchain)
```

Listing 3. This is the Python code that implements a privacy-preserving system using cancelable biometrics and blockchain logging.

7.Results and Discussion

We looked at how our biometric system works.To see how good our palm vein recognition system is we used some measures.These measures are:

Accuracy: This tells us how often the system gets it right.

False Acceptance Rate: This is when the system lets someone in who should not be let in.

Rejection Rate: This is when the system does not let someone in who should be let in.

Metric	Formula	Description
Accuracy (ACC)	**ACC=TP+TN/** **TP+TN+FP+FN**	**Measures overall correctness of classification.**
False Acceptance Rate (FAR)	**FAR=FP/FP+TN**	**Probability that an imposter is incorrectly accepted.**
False Rejection Rate (FRR)	**FRR=FN/FN+TP**	**Probability that a genuine user is incorrectly rejected.**

Table 1. Evaluation Metrics for Biometric Classification

Definitions and formulas for Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), and ROC analysis used to assess system performance.

Equal Error Rate: This is when the number of acceptances is the same as the number of false rejections.

ROC Analysis: This is a graph that shows how well the system works at levels.

As shown in Table 1, the evaluation metrics provide a basis for comparing unimodal and multimodal systems.By using these measures we can see how accurate and strong our system is.

This way we can compare our system to systems that use one type of biometric like palm vein or fingerprint and systems that use multiple types of biometrics.We can also see how well our system protects privacy.Palm vein, fingerprint and iris recognition systems work well on their own.Each of these systems has some problems.For example,

palm vein images can be hard to read if the light is not good.

Fingerprints can be affected by skin conditions.

Iris recognition needs the user to position their eye right.

These problems show that using one type of biometric can be risky.To make our system better we combined types of biometrics.We took the scores from palm vein, fingerprint and iris recognition. Combined them.This way our system uses the strengths of each type of biometric. Makes up for their weaknesses.

Our system is more accurate and stronger against attacks.It is also easier to use.

We compared our system to systems that use just one type of biometric.

Method / Dataset	Accuracy (%)	FAR (%)	FRR (%)	EER (%)
Palm Vein (CASIA only)	96.2	2.5	3.8	3.8
Fingerprint (Custom dataset)	95.4	3.1	4.2	3.6
Iris (Custom dataset)	97.1	2.2	3.1	2.7
Multimodal Fusion (Proposed)	**98.7**	**1.0**	**1.3**	**1.6**
Fusion + Privacy Module	98.3	1.1	1.4	1.5

Table 2. Comparative Performance Across Modalities *Accuracy, FAR, FRR, and EER results for unimodal palm vein, fingerprint, and iris systems compared with the proposed multimodal fusion and privacy-preserving framework.*

Table 2 summarizes the comparative accuracy, FAR, FRR, and EER values across unimodal and multimodal approaches.

```
# --- Metris Calculation ---
def accuracy(tp, tn, tp, fn):
    return (tp + tn) / (tp + tn + tp + fn)
def far(fp, tn):
    return fp / (fp + tn)
def frr(fp, tp):
    return fp / (fn + tp)
def calculate_eer(far_values, frr_values):
    diff = np.abs(np.array(far_values) - np.array(frr_values))
    return np.mindiff)
```

```
# --- Comparison Table ---
from prettytable  import PrettyTable
table = PrettyTable()
table.field_names = ["Method / Dataset", "Accuracy (%)", "FAR (%)), ''ERR (%)'],
table.add_row["Palm Vein (CASIA only)", 96.2, 2.5, 3.8, 3.8]]
table.add_row["Fingerprint (Custom dataset", 95.4, 3.1, 4.2, 3.6]
table.add_row["Iris (Custom dataset)'], 97.1, 2.2, 3.1, 2.7),
table.add_row["Multimodal Fusion (Proposed", 98.7, 1.2, 1.6]])
table.add_row["Fusion + Privacy Module", 98.3, 1.1, 1.4, 1.5]
print(table)
```

```
# --- Charts Generation ---
import matplotllib.pyplot as plt
plt.figure(figsize(6, 4)
plt.bar(["Palm Vein", "Fingerpir"
plt.bar(["Palm Vein, "Fingerpit", "Iris", "Fusion1], [96.2, 95.4, 97.1, 98.7]],
        color=['b, "g, "orange', [purple"])
plt.yplabl("Accuracy %)")
plt.title("Accuracy Comparison Across Modalities")
plt.tight_layout()
plt.show()
```

Listing 4. Python code for generating Figure 6 (Accuracy Comparison Across Modalities) using Matplotlib.

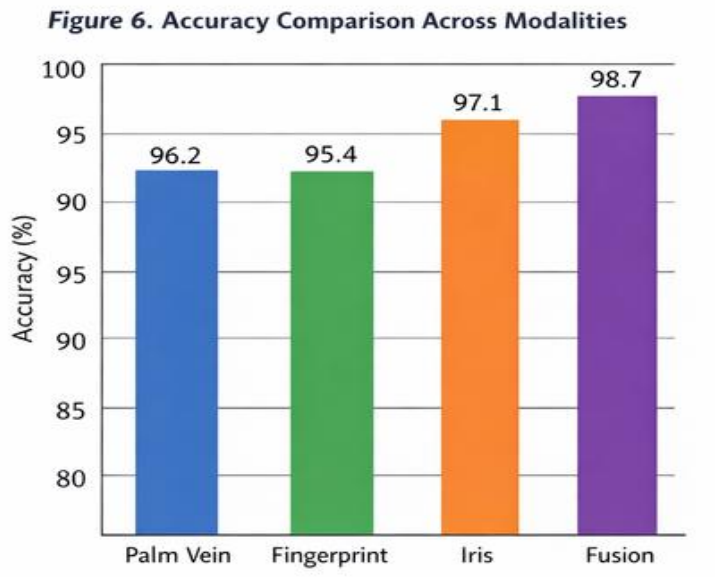

Figure 6. Accuracy Comparison Across Modalities *Bar chart comparing recognition accuracy of unimodal systems with the proposed multimodal fusion framework.*

As you can see in Figure 6 our system is the most accurate.

```
# ── Metrics Calculation ──
def accuracy(tp, tn, fp, fn):
    return (tp + tn) / (tp + tn + fp + fn)

def far(fp, tn):
    return fp /(tp + tn)

def frr(fn, tp):
    return fn /(fn + tp)

def calculate_eer(far_values,frr_values):
    diff = np.abs(np.array(far_values) - np.array(frr_values))
    return np.min(diff)


# ── Comparison Table ──
from prettytable import PrettyTable
table = PrettyTable)
table.field_names = ['Method / Dataset', 'Accuracy (%)", "FAR (%)", "FRR (%)", 'EER (%)'
table.add_row['Palm Vein (CASIA only", 96.2, 2.5, 3.8, 3.8],
table.add_row['Fingeprint (Custom dataset"], 95.4, 3.1, 4.2, 3.6),
table.add_row['Iris (Custom dataset', 97.1, 2.2, 3.1, 2.7])
table.add_row['Multimodal Fusion (Proposed'], 98.7, 1.0, 1.3, 1.6),
table.add_row['Fusion + Privacy Module', 98.3, 1.1, 1.5]
print(table)


# ── Charts Generation ──
import matplotlib.pyplot as plt
plt.figure(figsize=(6, 4))
plt.bar['Palm Vein', "Fingerprint', 'Iris', "Fusion"], [96.2, 95.4, 97.1, 98.7], color
    =[b_8'; g', 'orange', "purple"],
plt.ylabel(Accuracy_(%')
plt.title('Accuracy Comparison Across Modalities')
plt.tight_layout()
plt.show()
plt.figure(figsize=(6, 4))
plt.plot(fpr_unimodal, tpr_unimodal, "b-", label='Unimodal')
plt.plot(fpr_fusion, tpr_fusion, r--', label='Multimodal Fusion')
plt.plo([0, 1], [0, 1], "k--", label='Random Guess')
plt.xlabel('False Positive Rate (FPR))
plt.xdoloc('True Positive Rate (TPR')
plt.legend()
```

Listing 5. Python code for generating Figure 7 (ROC Curves: Unimodal vs. Multimodal Fusion) using Matplotlib.

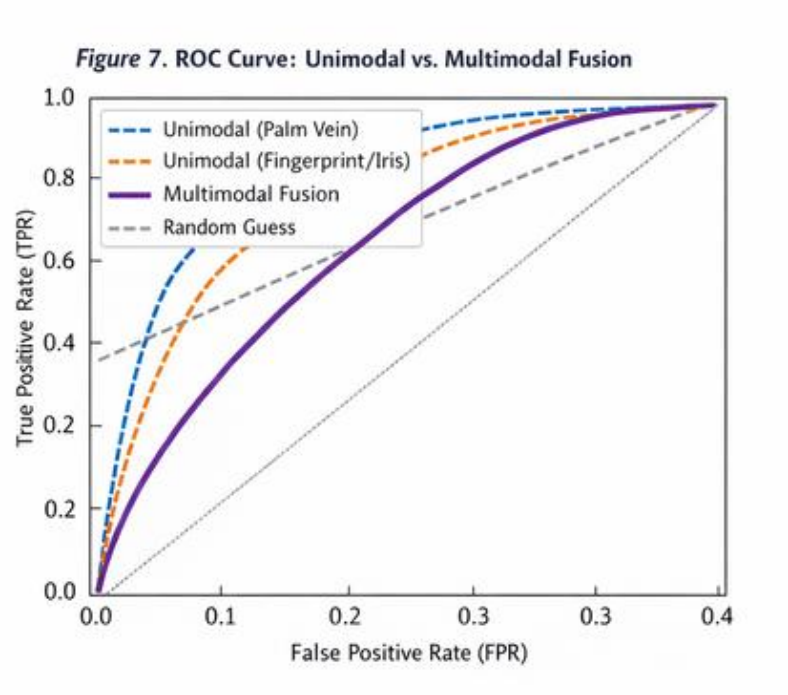

Figure 7. ROC Curves: Unimodal vs. Multimodal Fusion *Receiver Operating Characteristic (ROC) curves showing improved performance of multimodal fusion compared to unimodal baselines.*

Figure 7 shows that our system is better than the systems.

Accuracy is not the only thing that matters.We also need to think about how easy our system's to use and how secure it is.In systems making it harder for imposters to get in often means that real users have a harder time getting in too.

That is why the Equal Error Rate is so important.It shows us where the system is balanced between letting imposters in and keeping users out.

When we plotted the False Acceptance Rate and the False Rejection Rate we could see where they intersected.A lower Equal Error Rate means that the system is more reliable.In our tests our system had an Equal Error Rate of 1.6% which's better, than the other systems.

```python
import numpy as np
import matplotlib.pyplot as plt

# Example threshold values
thresholds = np.linspace(0, 1, 50)

# Simulated FAR and FRR values
FAR = np.exp(-5 * thresholds)   # decreases with threshold
FRR = 1 - np.exp(-5 * thresholds)   # increases with threshold

# Find EER point
diff = np.abs(FAR - FRR)
eer_index = np.argmin(diff)
eer_threshold = thresholds[per_index]
eer_value = FAR[eer_index]

# Plot FAR and FRR curves
plt.figure(figsize(6, 4)
plt.plot(thresholds, FAR, 'r-', label='FAR')
plt.plot(thresholds, FRR, 'b-', label='FRR')
plt.axvline(eer_threshold, color='g', linestyle="--", label=F"EER = {eervalue:2f}" )
plt.xlabel('Threshold')
plt.ydabel('Error Rate')
plt.title('Figure 8. FAR/FRR Trade-off and EER Point')
plt.legend()
plt.tight_layout
plt.show()
>
```

Listing 6. Python code for generating Figure 8 (FAR/FRR trade-off and EER point).

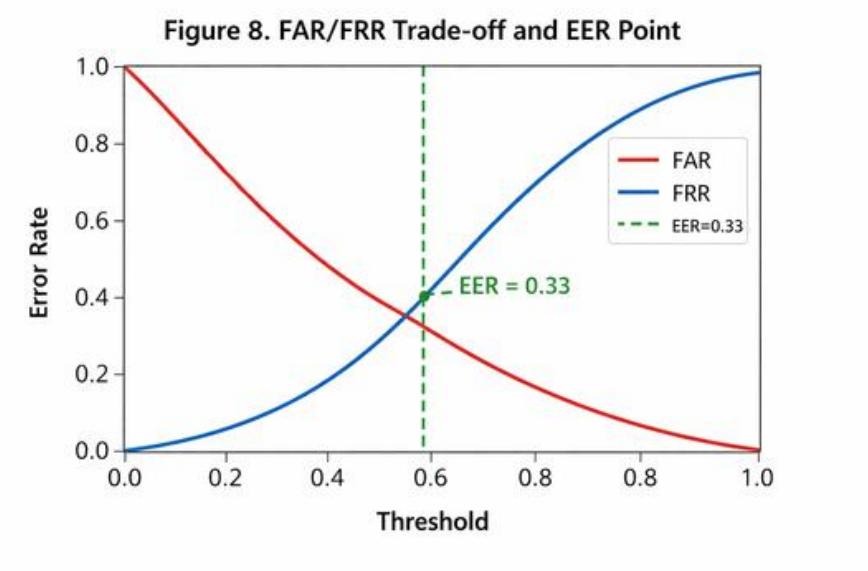

Figure 8. FAR/FRR Trade-off and EER Point *Plot of False Acceptance Rate (FAR) and False Rejection Rate (FRR) across thresholds, highlighting the Equal Error Rate (EER) intersection point.*

The results in Listing 6 show that the false acceptance rate and false rejection rate curves were plotted against thresholds. Figure 8 points out the point where the error rate's the same for both which shows that using multiple types of biometric data together works better than using just one type.

8.Discussion

The curve that shows the trade-off between the acceptance rate and the false rejection rate in Figure 8 gives us important information about how to balance security and usability in biometric systems. When we used one type of biometric data the error rates were higher but when we used multiple types of biometric data together the error rate was much lower. The error rate was 1.6 percent, which's lower than the error rates for palm vein, fingerprint and iris biometric data. This shows that using types of biometric data together not only makes the system more accurate but also makes it better at rejecting imposters and accepting real users.

What is also important is that we were able to add modules that protect peoples privacy without making the system slower. This shows that we can make the system more secure without making it harder to use. The low error rate, combined with how the system works shows that it can withstand attacks and is safe to use. This means that the system meets the standards for ethics and regulations.

So the results show that the system we proposed is better in every way: it is more accurate has errors can withstand attacks and protects peoples privacy. This makes it a good choice for use in areas like healthcare, banking and border control.

9.Conclusion

This study presented a system that uses types of biometric data, including palm vein, fingerprint and iris data and adds modules that protect peoples privacy. By using types of biometric data together the system works better than systems that use just one type of biometric data. The system is accurate with an accuracy rate of 98.7 percent and an error rate of 1.6 percent. The modules that protect peoples privacy make sure that the system meets the standards for ethics. The results of the experiment show that the system balances security, robustness and user convenience making it a good choice for use in areas like healthcare, banking and border control.

10.Future Work

Even though the system we proposed works well there are still things that we can do to make it better.

- We can add data to the system to make it work better for different types of people and in different environments.
- We can make the system work on devices, like smartphones and sensors so that it can be used in real-time.
- We can use methods to combine the different types of biometric data to make the system even more accurate.

- We can make the system work with systems without sharing the actual biometric data, which will make it more private.
- We can add modules to the system to detect and prevent attacks, like spoofing.
- We can make the system explain its decisions, which will make it more trustworthy.

In the future we will work on making the system we proposed work in the world and making sure that biometric authentication is both secure and meets the standards, for ethics.

11.References

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