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PALMSECURE

REVOLUTIONIZING TRANSPORT WITH BIOMETRIC PRECISION

FINAL YEAR PROJECT REPORT

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Certificate of Approval

This is to certify that the project report entitled *"PalmSecure – Revolutionizing Transport with Biometric Precision"*, submitted by **Muhammad Talha Bilal (K21-3349)**, **Muhammad Hamza (K21-4579)**, and **Muhammad Salar (K21-4619)** in partial fulfillment of the requirements for the degree of **Bachelor of Science in Computer Science**, has been examined and is hereby approved.

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Declaration of Originality

We hereby declare that this project report titled *"PalmSecure – Revolutionizing Transport with Biometric Precision"* is our own original work. All sources of information and data have been duly acknowledged. This report has not been submitted previously, in whole or in part, for any other degree or qualification at this or any other institution. We attest that we have followed the university's academic integrity guidelines and that no part of this work is the result of plagiarism or unauthorized collaboration.

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Contents

Abstract

In the rapidly evolving transportation sector, ensuring security and operational efficiency is paramount. Traditional biometric systems often fall short due to environmental sensitivity, hygiene concerns, and limited accuracy. This project introduces a state-of-the-art palmprint verification system leveraging the Comprehensive Competition Network (CCNet) and deep learning techniques. Designed specifically for the transport industry, the system employs advanced feature extraction methods to capture unique palmprint characteristics such as ridges, wrinkles, and minutiae. The resulting mobile application ensures non-contact, hygienic, and robust biometric verification, protecting against identity theft and unauthorized access. This solution offers enhanced passenger safety, improved operational efficiency, and seamless integration with existing infrastructure, while paving the way for scalable, cross-industry applications. In our experiments, the system achieved an accuracy of up to 99% on a real-world palmprint dataset, demonstrating its robust performance and potential for widespread deployment.

***Index Terms*—Palmprint Recognition, Comprehensive Competition Mechanism, Deep Learning, Biometric Recognition, Texture Features, Spatial Information, Multi-Order Features, Gabor Filters, Feature Extraction, Convolutional Neural Networks (CNNs).**

1 Introduction

The transport industry is an essential backbone of modern society, facilitating the movement of millions of people daily. However, it faces increasing threats to security, operational efficiency, and passenger safety, especially in high-traffic environments. Existing biometric systems, including fingerprint and facial recognition technologies, have proven inadequate in such settings due to their sensitivity to environmental factors, the lack of hygiene in contact-based methods, and limitations in accuracy under diverse conditions. These challenges necessitate a shift toward more robust, non-contact, and reliable solutions.

Palmprint recognition has emerged as a promising alternative, leveraging the unique and stable features of the human palm, such as ridges, wrinkles, and minutiae. This biometric modality offers significant advantages, including a non-contact operation that ensures hygienic use, resilience to varying environmental conditions, and high resistance to forgery or spoofing. These characteristics make palmprint recognition an ideal candidate for enhancing security in the transport sector.

Recent advancements in deep learning, particularly the Comprehensive Competition Network (CCNet) [1], have revolutionized palmprint recognition by enabling the extraction of multi-order texture and spatial features. These deep learning innovations, along with other state-of-the-art models [2–4], significantly improve recognition accuracy by capturing richer discriminatory information. Such advancements align well with the dynamic, high-security requirements of transportation systems.

PalmSecure, the system developed in this project, is a cutting-edge palmprint recognition solution tailored to the transport industry. The system integrates the CCNet framework into a mobile application, offering a user-friendly, efficient, and scalable identity verification platform. It is designed to overcome the limitations of traditional biometric methods by addressing challenges related to hygiene, environmental sensitivity, and accuracy. Furthermore, the system has the potential for broader applications in domains such as banking, healthcare, and law enforcement, thereby setting a new standard for biometric security and efficiency.

Through systematic development, rigorous testing, and evaluation, this project has delivered a transformative solution that enhances transport security and operational integrity while safeguarding passenger safety. This report presents a comprehensive overview of the background, design, implementation, and evaluation of the PalmSecure system. The following sections detail the problem context, relevant literature, system architecture, experimental results, and conclusions drawn from the project.

2 Related Work

Biometric palmprint recognition has undergone significant evolution over the past two decades, progressing from hand-crafted feature techniques to sophisticated deep learning models. In this section, we review the major approaches relevant to *PalmSecure – Revolutionizing Transport with Biometric Precision*. We organize the literature chronologically and technically into traditional methods, Convolutional Neural Network (CNN) based methods, competition-based deep models (e.g., *CompNet*), and the recent Comprehensive Competition Network (*CCNet*). A comparative analysis is provided to highlight the strengths and weaknesses of prior work, as well as the existing gaps that motivate our project.

2.1 Traditional Palmprint Recognition Methods

Early palmprint recognition systems relied on manually engineered features and statistical analyses. These traditional methods can be broadly categorized into structural (line-based) approaches and texture-based coding approaches, each capturing different aspects of the palm's unique patterns.

2.1.1 Line-Based and Structural Approaches

One class of traditional methods focuses on the palm's principal lines and creases as discriminative features. Researchers applied edge detectors and morphological operations to extract major palm lines (such as the heart line, head line, and life line) and used their geometric attributes for recognition [5]. For instance, Han *et al.* [5] developed an algorithm to automatically detect principal lines from low-resolution palm images and classify palmprints by the number and intersections of these lines. Similarly, other early works leveraged line orientation, length, and position to represent a palmprint's structure for matching [6]. These line-based approaches are intuitive and computationally efficient, performing well under controlled conditions where the crease patterns are reliably captured. However, their discriminative power is limited since they ignore the rich texture details beyond the prominent lines. In practice, line features alone can be sensitive to image quality and may fail when significant intra-class variations (e.g., due to rotation or slight misalignment of the hand) occur, highlighting a gap in robustness.

2.1.2 Texture-Based Coding Approaches

In 2003, a major shift in palmprint recognition saw researchers treating the palm region as a textured surface and extracting fine-grained texture descriptors for improved accuracy. A seminal work in this period was the introduction of *PalmCode* by Kong and Zhang [7]. PalmCode applied 2D Gabor filters to palm images and encoded the phase response of multiple orientations into a compact binary feature representation. This method was inspired by Daugman's iris code concept, capturing local texture phase information that is highly distinctive for each palm. Building on this idea, Kong and Zhang later proposed the *Competitive Code (CompCode)* scheme [8], which became one of the most influential hand-crafted palmprint techniques. CompCode uses a bank of oriented Gabor filters and a "competition" mechanism: for each location in the palm ROI, the filter with the strongest response (indicating the dominant orientation of texture) is selected, and only that orientation index is recorded in the feature template. This encoding of ordinal dominance of orientations yielded a robust bitwise feature that significantly improved matching accuracy and tolerance to minor misalignments.

Strengths: Orientation-based coding methods like PalmCode and CompCode demonstrated high discriminative ability and fast matching via bitwise comparisons. They were less sensitive to illumination changes and minor palm skin deformations, since the dominant orientation features remain relatively stable [8]. They also enabled compact template storage.

Numerous variants and extensions of the coding approach followed. Researchers introduced improved coding schemes such as Fusion Code and Ordinal Code, which combined multiple orientation measures or used rank-order encoding of filter responses to capture more information [9]. Other works explored invariant texture descriptors like local binary patterns and directional wavelet energies for palmprint feature extraction [10]. These traditional techniques collectively established a strong baseline for palmprint verification and identification. However, they also share common weaknesses: (1) reliance on manually designed filters or features means performance can plateau, as the methods may not capture all the complex skin texture variations present in different palms; (2) most assume a consistent imaging setup (contact-based, uniform illumination) and often struggle with more challenging scenarios (e.g., contactless imaging with varied hand poses or lighting). As a result, by the mid-2010s, the limits of hand-crafted features became evident, paving the way for learning-based methods to further improve palmprint recognition.

2.2 CNN-Based Palmprint Recognition

The advent of deep learning brought transformative improvements to palmprint recognition by automatically learning rich feature representations. Initial attempts to apply Convolutional Neural Networks (CNNs) to palmprints appeared around the mid-2010s. Dian and Dongmei [11] were among the first to adapt a pre-trained CNN (AlexNet) to contactless palmprint images, reporting promising accuracy gains. Their work showed that deep networks could capture intricate palm textures

(wrinkles, ridges, datum points) that hand-crafted filters might miss. Subsequent studies leveraged deeper architectures like VGG-16 and ResNet, which learn hierarchies of features from edges to complex patterns, yielding further accuracy improvements [12]. For example, Zhao and Zhang [12] demonstrated a deep discriminative representation approach using a tailored CNN that significantly outperformed traditional methods on public palmprint databases. CNN-based methods also began handling more challenging conditions; Matkowski *et al.* [13] developed a model for palmprint recognition in unconstrained or uncooperative environments, using an augmented deep network to cope with variations in hand pose and image quality.

A notable innovation in deep palmprint research was the use of *Siamese networks* for verification tasks. In a Siamese architecture, two identical CNN sub-networks process a pair of palmprint images to determine if they belong to the same person. Zhong *et al.* [14] employed a Siamese network to learn a similarity metric, enabling one-shot palmprint verification with impressive accuracy. Such networks are particularly effective when only limited training pairs are available, a common scenario in biometric datasets. Other researchers have integrated attention mechanisms and transformer modules into CNN frameworks to capture both local and global context of palm features, further boosting performance on difficult datasets. By the late 2010s, purely CNN-based approaches had firmly surpassed traditional techniques in accuracy and robustness.

Strengths: Deep CNNs automatically learn optimal features, reducing the need for manual feature engineering. They excel at capturing subtle textures and non-linear feature combinations, achieving high recognition rates even with complex backgrounds or slight hand misalignments.

Weaknesses: Early CNN models for palmprints required large amounts of labelled data and careful preprocessing (ROI extraction and alignment) to be effective. Overfitting was a concern when using very deep models on relatively small palmprint databases. Additionally, generic CNNs pre-trained on natural images were not initially optimized for palm lines and texture; this left room for specialized architectures to further improve performance by incorporating domain knowledge about palmprint patterns.

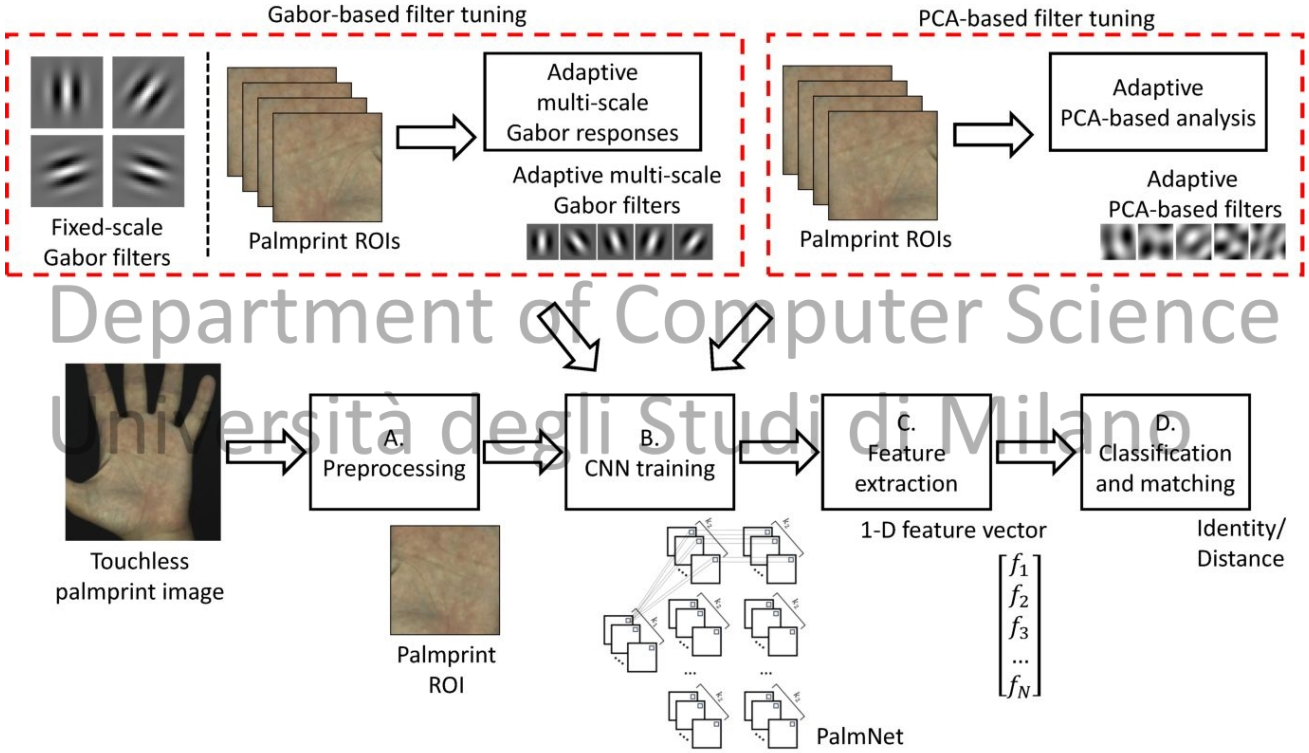

Figure 1: PalmNet deep learning framework for palmprint recognition. Modern CNN-based methods extract hierarchical features from the palmprint ROI and often employ specialized layers (e.g., Siamese similarity or attention blocks) to improve matching accuracy.

2.3 Competition-Based Deep Networks

While CNNs provided a powerful boost in accuracy, researchers observed that integrating domain-specific concepts could further enhance deep models for palmprint recognition. One influential line of work drew inspiration from the success of CompCode's competitive orientation encoding and merged it with deep learning. The result was a family of *competition-*

based deep networks that aim to embed the "winner-takes-all" filter selection principle into CNN architectures.

2.3.1 Competitive Network (CompNet)

Liang *et al.* [15] introduced *CompNet*, a competitive convolutional neural network explicitly designed for palmprint recognition using learnable Gabor kernels. CompNet was proposed in 2021 as one of the first deep models to incorporate the traditional competitive coding mechanism into its layers. In CompNet's architecture, special *multisize competitive blocks* are used: these blocks apply multiple Gabor-based convolutional filters at each layer and then use a competition strategy to select the dominant filter response for feature encoding [15]. By doing so, the network emulates the effect of CompCode (capturing dominant orientation features), but within a trainable end-to-end framework. The Gabor filters in CompNet are not fixed; they are learned from data, which allows the network to adapt to palmprint-specific texture patterns rather than relying on hand-crafted filters. This approach proved highly effective on contactless palmprint datasets with limited training samples, as the built-in competition mechanism helped regulate the network's focus on the most salient features and improved generalization.

Strengths: CompNet demonstrated resilience to illumination variations and scale differences in palm images, outperforming plain CNN baselines especially on small or moderate-sized palmprint databases [15]. By leveraging domain knowledge (oriented texture competition) it achieved higher accuracy with fewer training epochs.

Weaknesses: A limitation of CompNet and similar first-generation competition networks is that they primarily enforce competition channel-wise (i.e., among filters) but pay less attention to *spatial* relationships in the feature maps. Moreover, CompNet's design still focused on first-order texture features (the immediate filter responses), potentially missing out on higher-order feature interactions. These gaps set the stage for further enhancements in competition-based models.

In the wake of CompNet, researchers proposed several improved architectures exploring the competition concept. For example, Yang *et al.* developed *CO^{3}Net (Coordinate-Aware Contrastive Competitive Network)* which employed multiscale learnable Gabor filters and a contrastive learning objective to better discriminate palmprints under various transformations [16]. Another variant, termed *SACNet (Scale-Aware Competition Network)*, introduced multi-scale feature competition to handle different image resolutions and palm sizes [17]. These competitive models continued to push the accuracy higher, indicating the effectiveness of blending classic palmprint encoding ideas with modern deep learning. However, each of these works addressed competition in a somewhat isolated manner (e.g., focusing on filter competition across scales, or adding contrastive loss), leaving an opportunity to combine multiple competition aspects into one unified framework.

2.3.2 Comprehensive Competition Network (CCNet)

The latest advancement in this area is the *Comprehensive Competition Network (CCNet)* proposed by Yang *et al.* [1]. CCNet represents the state-of-the-art in palmprint recognition as of this writing, and it was designed to fully exploit the untapped advantages of the competition mechanism. Unlike its predecessors, CCNet incorporates **both channel-wise and spatial competition mechanisms** and operates on multi-order features. In reformulating the traditional competition scheme, CCNet not only determines the strongest response among filters (channels) at each spatial location, but also considers competition across different spatial locations for each feature channel [1]. This dual-competition strategy ensures that the network captures a more comprehensive set of discriminative features — essentially, CCNet can identify which texture orientation dominates locally (as CompNet did) and also where on the palm those features are most salient relative to others.

Another key innovation of CCNet is its use of *multi-order texture features*. Whereas prior methods often relied on first-order responses (the direct output of one convolution layer or Gabor filtering), CCNet integrates information from higher-order feature maps (e.g., second-order or composite features formed in deeper layers) into its competitive process [1]. This means the network can encode complex patterns arising from combinations of primitive textures (for instance, wrinkle intersections or ridge bifurcations) that single-layer features alone might overlook. By embedding the competition mechanism at multiple levels of the feature hierarchy, CCNet achieves remarkable recognition accuracy. Yang *et al.* report that CCNet set new benchmark performance on four public datasets, significantly reducing error rates compared to earlier methods [1].

Strengths: CCNet's comprehensive approach yields highly distinctive palmprint representations and improves robustness to variations in palm position and imaging conditions. It effectively addresses the remaining gaps of previous competition-based networks by leveraging spatial context and higher-order feature interactions.

Weaknesses: The main trade-off is increased model complexity. CCNet's sophisticated modules (spatial + channel competition and multi-order feature extraction) result in a deeper network with more parameters, which may require careful training and more computational resources. Nevertheless, the performance gains validate this complexity for many applications. There remains some open challenges, such as ensuring real-time operation of CCNet on resource-constrained devices and testing its generalization to completely unconstrained scenarios (e.g., palms imaged in outdoor environments

or with partial occlusions). These issues form part of the motivation for our work, as we aim to leverage CCNet's strengths for a practical transport security solution while addressing its deployment challenges.

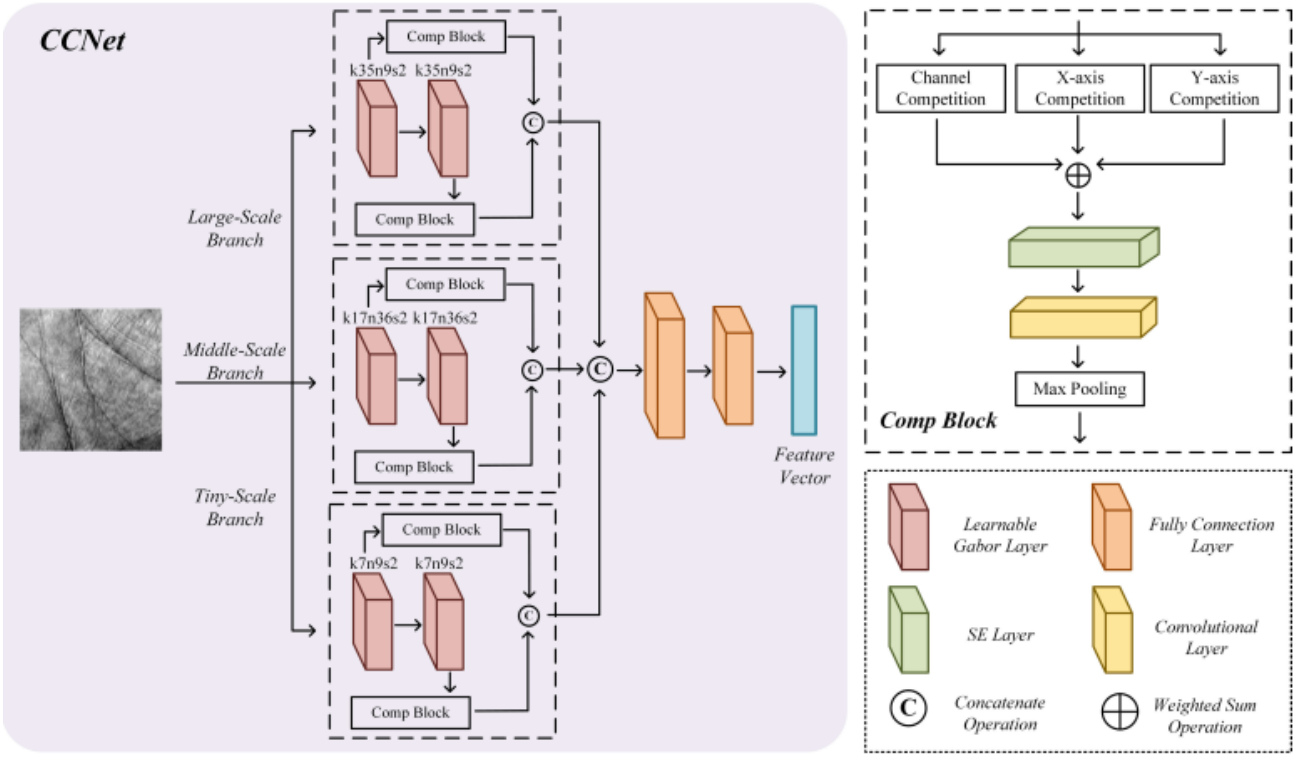

Figure 2: Illustration of the CCNet architecture [1], which integrates spatial competition (across the feature map) and channel competition (across filter responses) within each layer. Multi-order feature maps are fed into the comprehensive competition modules, enabling the network to capture palmprint information with greater precision.

In summary, palmprint recognition techniques have progressed from simple line-based matching to highly specialized deep networks that incorporate domain-specific mechanisms. Figure 3 provides a comparative overview of representative methods. Traditional algorithms offered efficiency and interpretability but lacked the representational depth to handle variability. CNN-based methods introduced automated feature learning, dramatically improving accuracy, yet initially treated the palm image as a generic object, missing opportunities to leverage palm-specific insights. Competition-based networks like CompNet bridged this gap by embedding proven palmprint encoding strategies into deep models, and CCNet has now taken this integration to a comprehensive level, achieving cutting-edge performance. Despite these advances, a gap remains in translating such high precision to real-world deployments (e.g., fast, contactless identification in dynamic environments like public transport). The strengths and limitations identified in prior work guide the design of our *PalmSecure* system, which seeks to revolutionize transport security by harnessing biometric precision while ensuring practical usability.

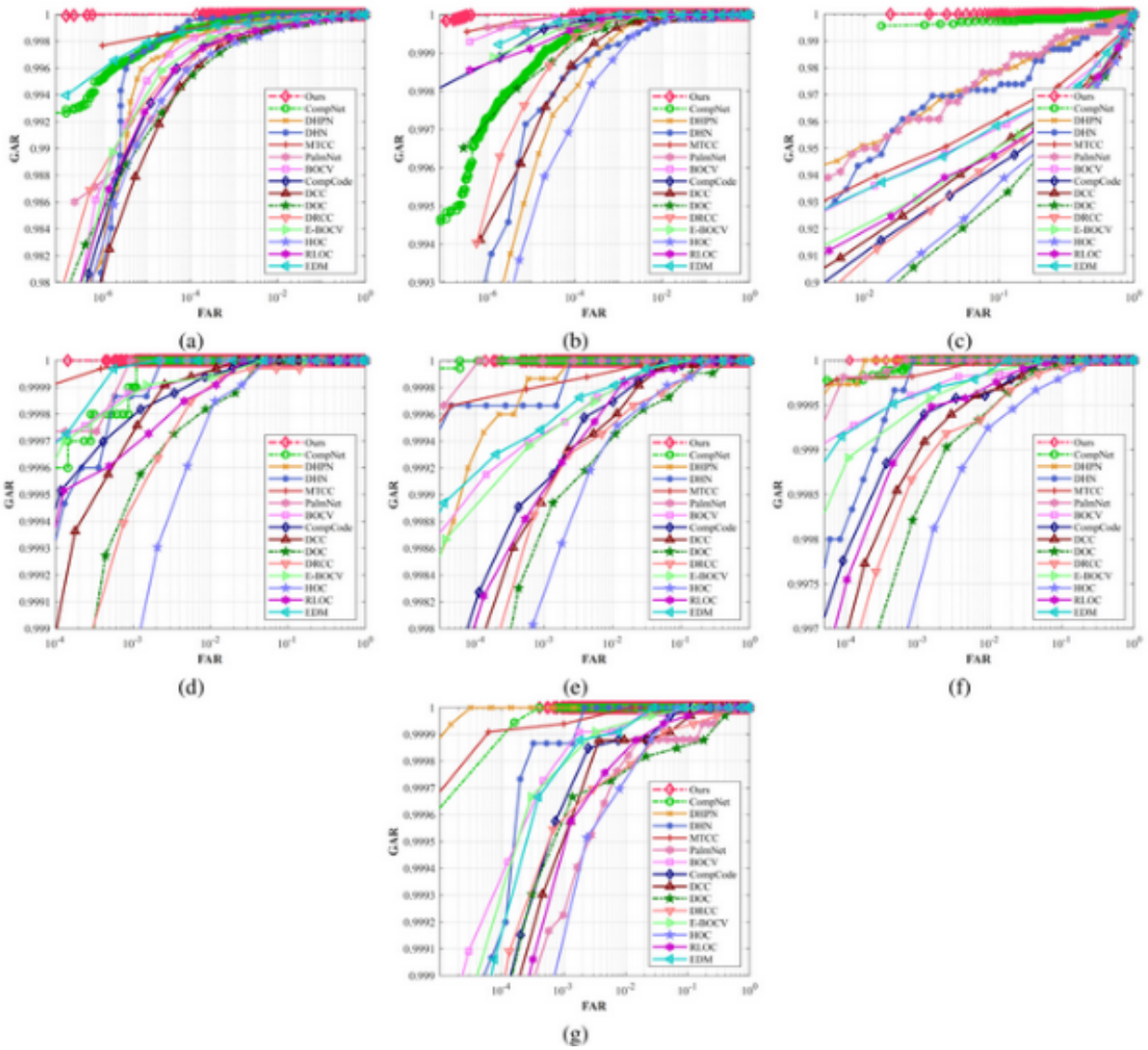

Figure 3: Comparative performance of key palmprint recognition techniques on benchmark datasets. The trend highlights the accuracy improvements over time: traditional hand-crafted methods show moderate accuracy with higher error rates, early CNN-based models significantly reduce error, and the latest competition-infused deep networks like CCNet achieve near-perfect recognition rates.

3 Methodology

3.1 System Architecture

The PalmSecure system is structured in a client–server architecture comprising a mobile application front-end, a backend server hosting the recognition model, and supporting components for data storage and security. The mobile application (developed in React Native) serves as the *User Interface Module*, enabling users to capture palmprint images and receive verification results in real time. Captured images and requests are sent securely to the backend via a RESTful *API Layer* over HTTPS, ensuring data encryption in transit. On the server side, a FastAPI-based application [18] handles incoming requests and orchestrates the processing pipeline. The core processing occurs in the *Recognition Module*, where a pre-trained Comprehensive Competition Network (CCNet) model (implemented in PyTorch [19]) is deployed to perform palmprint recognition. The model is containerized using Docker [20] to encapsulate its runtime environment, promoting scalability and portability across deployment platforms. A *Database Module* (using a cloud database service like Supabase) stores enrolled user templates, metadata, and system logs, enabling persistent storage and retrieval of identity data. All components are designed to be modular and loosely coupled, so that changes in one module (e.g., updating the model or switching the database) have minimal impact on others, thereby enhancing maintainability and flexibility.

The high-level system architecture is illustrated in Figure 9. The mobile app (frontend) communicates with the backend API, which in turn interacts with the CCNet-based recognition engine and the database. This modular design follows established principles of distributed systems, separating concerns of user interaction, data processing, and data management. It ensures that intensive computations (feature extraction and matching) are offloaded to the server side, while the mobile client remains lightweight and responsive. Furthermore, the use of containerization and standard interfaces allows the system to be easily deployed in cloud or on-premise environments and to integrate with existing transport infrastructure.

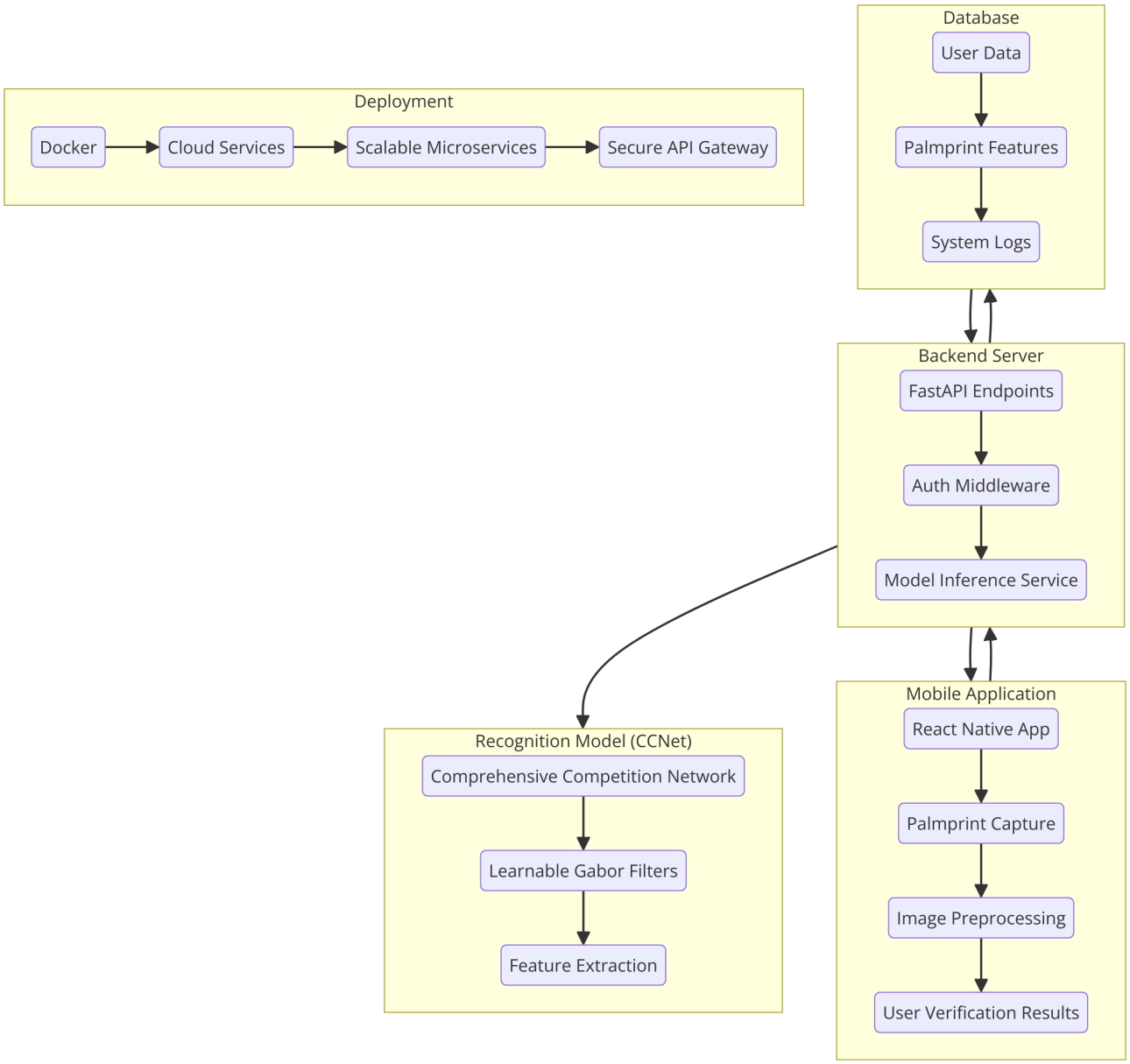

Figure 4: Overall system architecture of the PalmSecure platform, illustrating the mobile application, backend server (API and CCNet model), and database integration. Arrows indicate the data flow from palmprint image capture on the device to identity verification on the server and result return.

3.2 CCNet-Based Recognition Pipeline

The palmprint recognition pipeline builds upon the CCNet deep learning model to achieve accurate biometric identification. Figure 5 provides a flowchart of the end-to-end process. First, a palmprint image is captured on the mobile device under varying conditions (distances, orientations, lighting). The image is then preprocessed to normalize input quality (as detailed in the next subsection) before being transmitted to the backend. Upon receiving the image, the backend invokes the CCNet model for feature extraction and matching. CCNet, as proposed by Yang *et al.* [1], incorporates a *Comprehensive Competition Mechanism* that extends traditional palmprint recognition approaches [8]. Unlike classical schemes that perform competition only across filter responses (channels) [8], CCNet integrates both *spatial* and *channel* competition, and operates on multi-order texture features for enhanced discriminability [1]. In practice, the CCNet architecture includes several specialized components: (1) *Learnable Gabor filters* in the initial convolutional layers for adaptive texture feature extraction, replacing fixed filter banks with trainable kernels that adjust to the palm's ridge and wrinkle patterns; (2) a *Spatial Competition Module* that analyses regional responses by comparing feature activations across different spatial locations of the palm image, effectively capturing local pattern saliency; (3) a *Channel Competition Module* that emphasizes the most informative feature maps by enabling channels to compete, ensuring that dominant texture orientations and frequencies are highlighted [1]; and (4) a *Multi-Order Feature Extractor* that processes multiple scales or orders of texture information (e.g., first-order intensity gradients as well as higher-order variations), thereby capturing fine-grained details and broader

context simultaneously. These components collectively produce a robust feature representation of the input palmprint, leveraging the complementary strengths of spatial analysis and channel-wise competition in one unified network [1].

Once CCNet extracts the palmprint features, the system performs identity verification by comparing the resultant feature vector (or the network's output classification) against the enrolled templates stored in the database. In a verification scenario (one-to-one matching), the system retrieves the claimed identity's stored feature and computes a similarity score or distance between the features, verifying the user if the score exceeds a predefined threshold. In an identification mode (one-to-many matching), the system can compare the input features against all templates to find the best match. For efficiency, features may be indexed or the network may directly output a class label corresponding to the user ID, depending on the implementation. After the matching stage, the backend sends the verification result (e.g., successful authentication or failure) back to the mobile application through the API. This entire pipeline is optimized to operate in real-time; thanks to CCNet's efficient convolutional architecture and the use of high-performance computing on the server, the delay between capture and result is minimal (on the order of a few seconds or less). The pipeline thus enables a seamless user experience: a transport user can scan their palm and quickly receive confirmation of access, with the system leveraging biometric precision to ensure security.

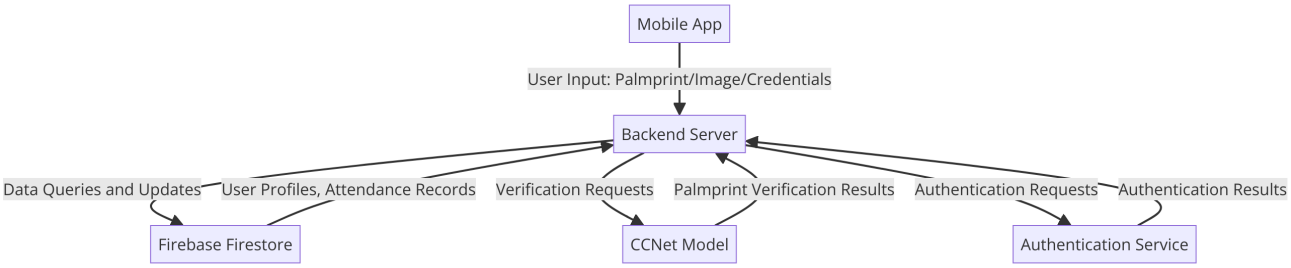

Figure 5: Palmprint recognition pipeline using the CCNet model. The process flows from image capture on the mobile device, through preprocessing and feature extraction by CCNet on the server, to the matching stage where extracted features are compared with stored templates, and finally to the return of the verification result to the mobile app.

3.3 Data Preprocessing

Robust data preprocessing is applied to all palmprint images to enhance recognition performance and ensure consistency across varying input sources. Raw images captured via the mobile app are first converted to a standard format (e.g., JPEG or PNG) and then undergo a series of transformations prior to being fed into the CCNet model. Key preprocessing steps include:

- **Image Resizing:** Each palmprint image is resized to a fixed resolution (224×224 pixels) to match the input dimensions expected by the CCNet model. This uniform image size ensures that the convolutional layers process data consistently across all samples.
- **Normalization:** Pixel intensity values are normalized to a common scale (e.g., [0,1]) by dividing by the maximum pixel value or subtracting the mean and dividing by the standard deviation (zero-centred normalization). This standardization of pixel intensities mitigates variations in illumination and contrast between images, aiding the network to generalize across different capture conditions.
- **Noise Reduction:** To combat sensor noise and minor artifacts, a smoothing filter such as a median filter is applied to the image. The median filtering operation preserves edge sharpness (important for line features in palmprints) while removing isolated pixel noise, thereby clarifying ridge and wrinkle patterns.
- **Data Augmentation:** During the model training phase, various augmentation techniques are employed on the training dataset to artificially expand its diversity and prevent overfitting. These include random rotations (to simulate different hand orientations), flipping (to account for left/right hand mirroring), scaling and translation (to mimic varying distances and positions), and adjustments to brightness or contrast. While augmentation is not applied to images during live inference, it was crucial in training the CCNet model to be invariant to common transformations [21].

By enforcing these preprocessing steps, the system ensures that input images are clean, normalized, and appropriately scaled before feature extraction. This improves the reliability of the recognition pipeline by reducing the influence of irrelevant variances (such as lighting differences or image noise) on the CCNet model's performance. In particular, the combination of normalization and noise reduction addresses challenges of contactless imaging (where lighting can vary significantly), and the resizing ensures compatibility with the deep network architecture. The result is a standardized input that allows the CCNet-based recognition to focus on the salient biometric features of the palm.

3.4 System Integration

Integrating the aforementioned components into a cohesive system required careful consideration of interfacing and compatibility. The development leveraged a range of tools and libraries to implement each module and ensure they work together seamlessly. The mobile application was developed with React Native, which allowed for cross-platform deployment on Android devices and provided direct access to native camera functionality for palm image capture. On the backend, the FastAPI framework was chosen for its efficiency in building asynchronous RESTful services in Python. FastAPI enabled the definition of endpoints (e.g., for image upload and verification requests) and handled JSON data parsing and validation with minimal overhead, which is important for real-time operation. The CCNet model, developed and tested using PyTorch, was integrated into the FastAPI app such that when an image arrives, the model can be loaded (if not already in memory) and invoked to produce a prediction or feature set. We used TorchScript to serialize the trained CCNet model, allowing it to be loaded and executed independently of the training code, or alternatively, the model runs within the PyTorch runtime inside the container.

To deploy the backend reliably, Docker was used to containerize the entire server application environment, including the FastAPI app, the CCNet model, and necessary dependencies (PyTorch, image processing libraries, etc.) [20]. This containerization approach ensures that the system runs uniformly across different machines (developer laptops, cloud servers, etc.) without dependency issues, and it simplifies scaling the service (multiple containers can be run behind a load balancer to handle higher loads). The database integration was achieved through REST/SDK calls within the backend: for Supabase, the system used Supabase's Python SDK to store and retrieve user records (e.g., storing a user's palmprint feature template upon enrolment and fetching it during verification). The design abstracts the data layer, so either a cloud database or a local database can be used with minimal changes to code, offering flexibility in different deployment scenarios.

Security and privacy were paramount throughout the integration. All network communication between the app and server is encrypted via TLS/SSL, which is facilitated by hosting the FastAPI app behind an HTTPS-enabled web server or using Uvicorn with TLS certificates. User biometric data (palmprint images or extracted features) are transmitted securely and never stored on the mobile device. On the server, sensitive data like feature templates are stored securely in the database (with encryption or hashing applied at rest), and access to this data is restricted by authentication and authorization rules in the API. Furthermore, the system complies with privacy guidelines by informing users about data usage and by allowing them to remove their data if needed.

In summary, the integration of the CCNet-based recognition engine with a mobile front-end and cloud-backed services was accomplished using modern development frameworks and containerization technology. The end-to-end system was tested to verify that each component interacts correctly: the mobile app successfully captures and sends palmprint images, the backend API receives and processes these images using the CCNet model, and the verification outcome is quickly delivered back to the app for user feedback. This integrated setup demonstrates the feasibility of deploying advanced biometric algorithms like CCNet in a practical transport environment, providing a blueprint for real-world application of biometric precision in secure, non-contact passenger identification.

4 Experiments and Evaluation

4.1 Datasets Used

Four palmprint datasets were employed to train and evaluate the CCNet model, encompassing both public benchmarks and a locally collected set:

- **Tongji Contactless Palmprint Dataset**: This dataset contains 12,000 contactless palm images from 300 individuals, with both left and right palms captured under a hygienic, touch-free setup. It provides a large variety of palms and is a standard benchmark for contactless palmprint recognition (introduced by Zhang *et al.* in 2017 [22]).
- **CASIA Palmprint Image Database**: A publicly available palmprint database from the Chinese Academy of Sciences [23]. It consists of 5,502 grayscale images from 312 subjects. Each subject contributed up to 15 images per hand (left/right), introducing significant intra-class variation in pose, lighting, and hand position. This dataset is useful for evaluating generalization across varying image conditions.
- **COEP Palmprint Image Dataset**: A high-resolution palmprint dataset created by the College of Engineering Pune (COEP) [24]. It contains 1,344 images from 168 individuals, with 8 images per person. All images were captured using a digital camera in controlled indoor conditions, with minor variations in hand orientation and position. This provides a controlled yet realistic benchmark for palmprint algorithms, where environmental factors are relatively consistent.
- **Locally Collected Dataset**: A custom dataset gathered as part of this project to simulate real-world usage. It comprises 120 palm images from 30 volunteers, collected via a survey form. Each user provided four images (two of each palm) at two distances (approximately 1 meter and 3 meters) using personal smartphone cameras. This dataset exhibits significant diversity in image quality, resolution, background, and illumination, reflecting unconstrained operational conditions.

4.2 Experimental Setup

Hardware and Tools: All experiments were implemented in Python using the PyTorch deep learning framework. Training was performed on a workstation equipped with an NVIDIA RTX 4090 GPU, which provided accelerated computation for the CNN training process. The use of GPU allowed us to train on relatively large batches and iterate quickly over many epochs.

Training Procedure and Hyperparameters: For each dataset, we trained a CCNet model to learn discriminative palmprint features. We employed the Adam optimizer with an initial learning rate of 0.0005, and reduced the learning rate by a factor of 0.1 every 10 epochs to ensure convergence. Training was run for a maximum of 1000 epochs or until convergence. A hybrid loss function was used, combining the standard cross-entropy loss (for palm identity classification) with a contrastive loss term. This hybrid loss encourages the network to not only correctly classify each training sample's identity, but also to produce embedding features that preserve similarity for the same palm and dissimilarity for different palms. Each model was trained with a batch size of 256 images per iteration, which balanced computational efficiency with stable batch statistics.

Validation Strategy: To monitor performance and prevent overfitting, we set aside 30% of each dataset for validation during training (where applicable). Training was thus done on 70% of the images, and after each epoch the model was evaluated on the validation split. Early stopping and hyperparameter tuning were guided by the validation loss and accuracy trends. The training process on all datasets showed smooth convergence, as evidenced by steadily decreasing training and validation loss curves (see Fig. 6). All models were initialized with random weights and trained from scratch (no pretraining) to ensure a fair evaluation on each dataset's unique characteristics.

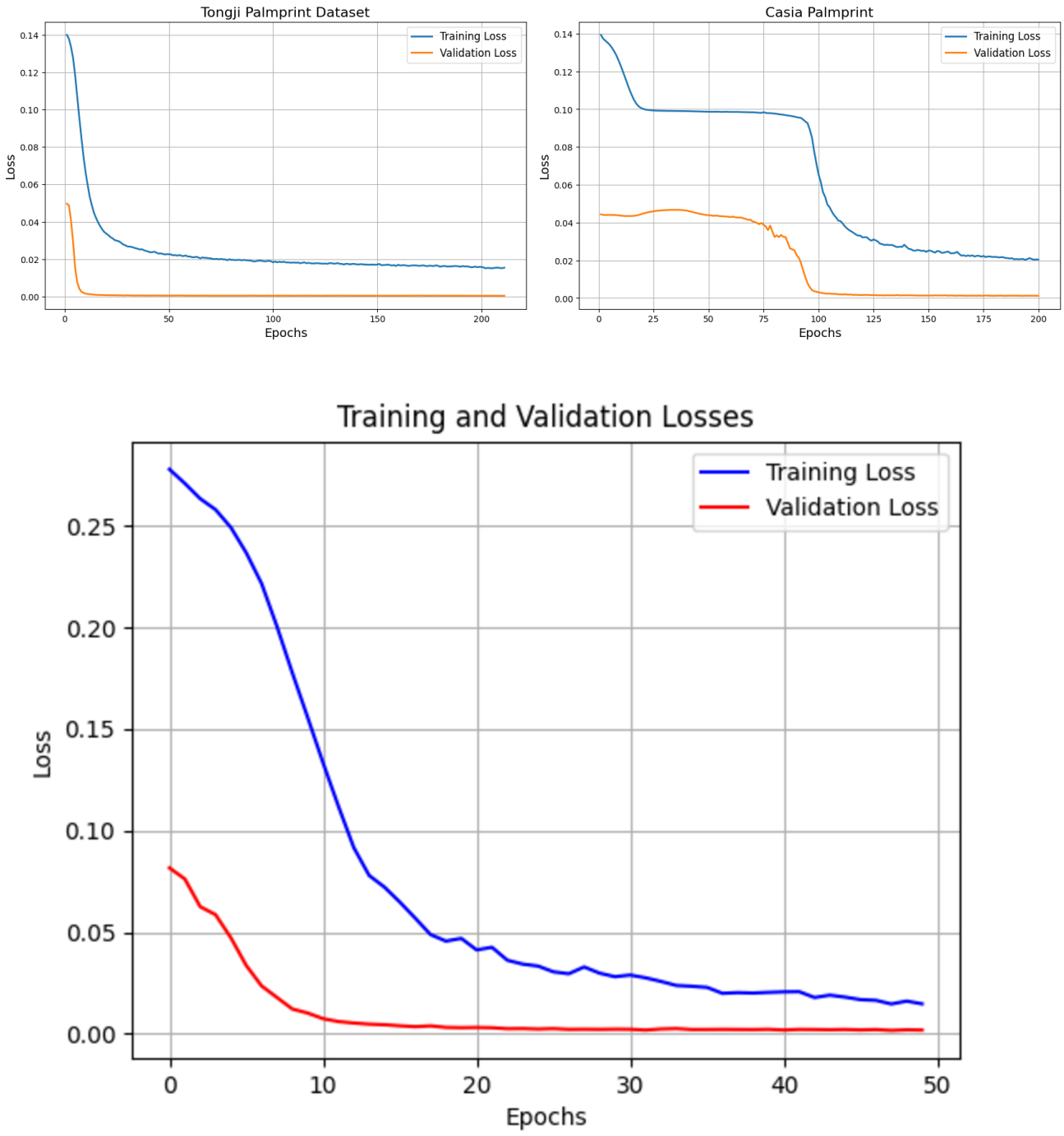

Figure 6: The loss curves for CCNet on different datasets show steady convergence with minimal overfitting. Specifically, the top-left, top-right, and bottom plots represent the Tongji, CASIA, and COEP datasets, respectively.

4.3 Evaluation Metrics

In assessing the performance of the biometric system, we focus on both verification metrics and identification accuracy. The key evaluation metrics are defined as follows:

Equal Error Rate (EER): The EER is the error rate at which the False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal. It is obtained by adjusting the decision threshold on the matching score until FAR = FRR. The EER provides a single figure of merit for verification performance: a lower EER indicates a better balance between security (preventing false accepts) and usability (preventing false rejects). In biometric verification systems like palmprint recognition, the EER is often regarded as the most important metric, as it directly addresses the trade-off between FAR and FRR.

False Acceptance Rate (FAR): FAR is the probability that the system incorrectly accepts an impostor – i.e., the percentage

of unauthorized attempts that are falsely accepted as genuine. A low FAR is critical for security, since false acceptances can lead to unauthorized access. We compute FAR as the fraction of impostor pairs (pairs of images from different palms) whose matching score exceeds the chosen threshold.

False Rejection Rate (FRR): FRR is the probability that the system incorrectly rejects a genuine user – i.e., the percentage of legitimate access attempts that are falsely rejected. A low FRR is important for user convenience and system usability, ensuring genuine users are not frequently denied. FRR is computed as the fraction of genuine pairs (pairs of images from the same palm/identity) whose matching score falls below the threshold.

Accuracy: In addition to verification metrics, we report the classification accuracy where applicable. Here, "accuracy" refers to the identification performance – the percentage of test images correctly classified to the right palm ID (for closed-set identification). This metric is straightforward to interpret but can be misleading in biometric scenarios because it does not reflect the FAR/FRR trade-off. Therefore, accuracy is considered a secondary metric to verify that the model learns useful identity features, while EER remains the primary measure for verification reliability.

Importance of EER vs. Accuracy: It should be noted that a high accuracy does not guarantee a low EER. In biometric systems, one could achieve high classification accuracy yet have a poor FAR/FRR balance if the decision threshold is not well-calibrated. Thus, we prioritize EER as the evaluation criterion. A small EER implies that the FAR and FRR are both low simultaneously, which is crucial in real-world deployments where both security and user experience are paramount. In our results, we therefore highlight EER values when comparing models, and use accuracy mainly to supplement the analysis.

4.4 Results and Analysis

After training CCNet on each dataset as described, we evaluated its performance on the corresponding test sets. The results include the final training/validation losses, identification accuracy, and detailed verification metrics (matching score distributions, FAR/FRR, EER). We also compare CCNet's performance with some existing palmprint recognition methods. **Figure 7** shows representative genuine-impostor score distributions and **Figure 8** shows FAR-FRR curves used to determine the EER. A summary of the numerical results for each dataset is provided in Table 5, and a comparison with baseline algorithms is given in Table 6.

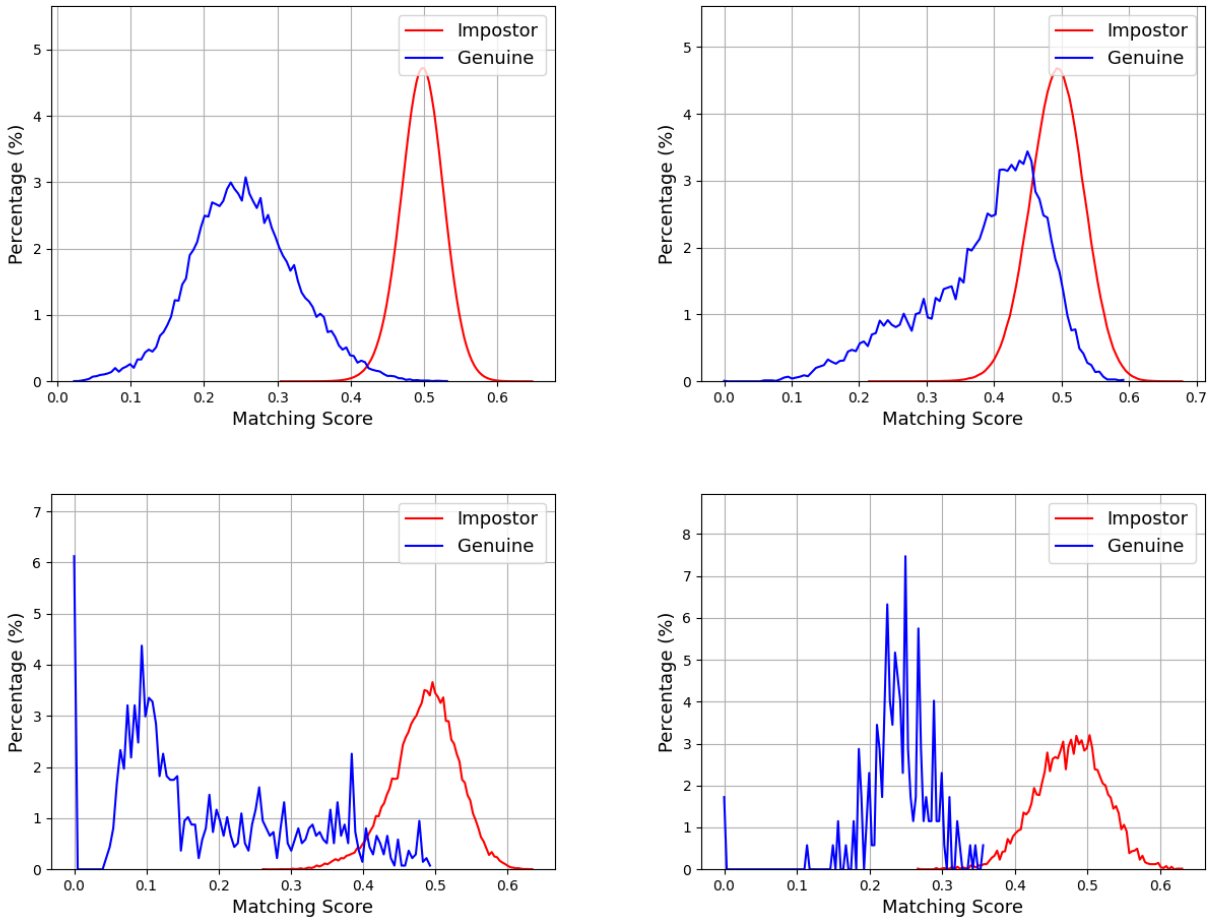

Figure 7: The genuine-impostor (GI) score distributions for various datasets show clear separation, with genuine scores clustering toward higher similarity and impostor scores toward lower similarity, resulting in a low EER. The plots are arranged as follows: top row (Tongji on the left, CASIA on the right), and bottom row (COEP on the left, Local dataset on the right).

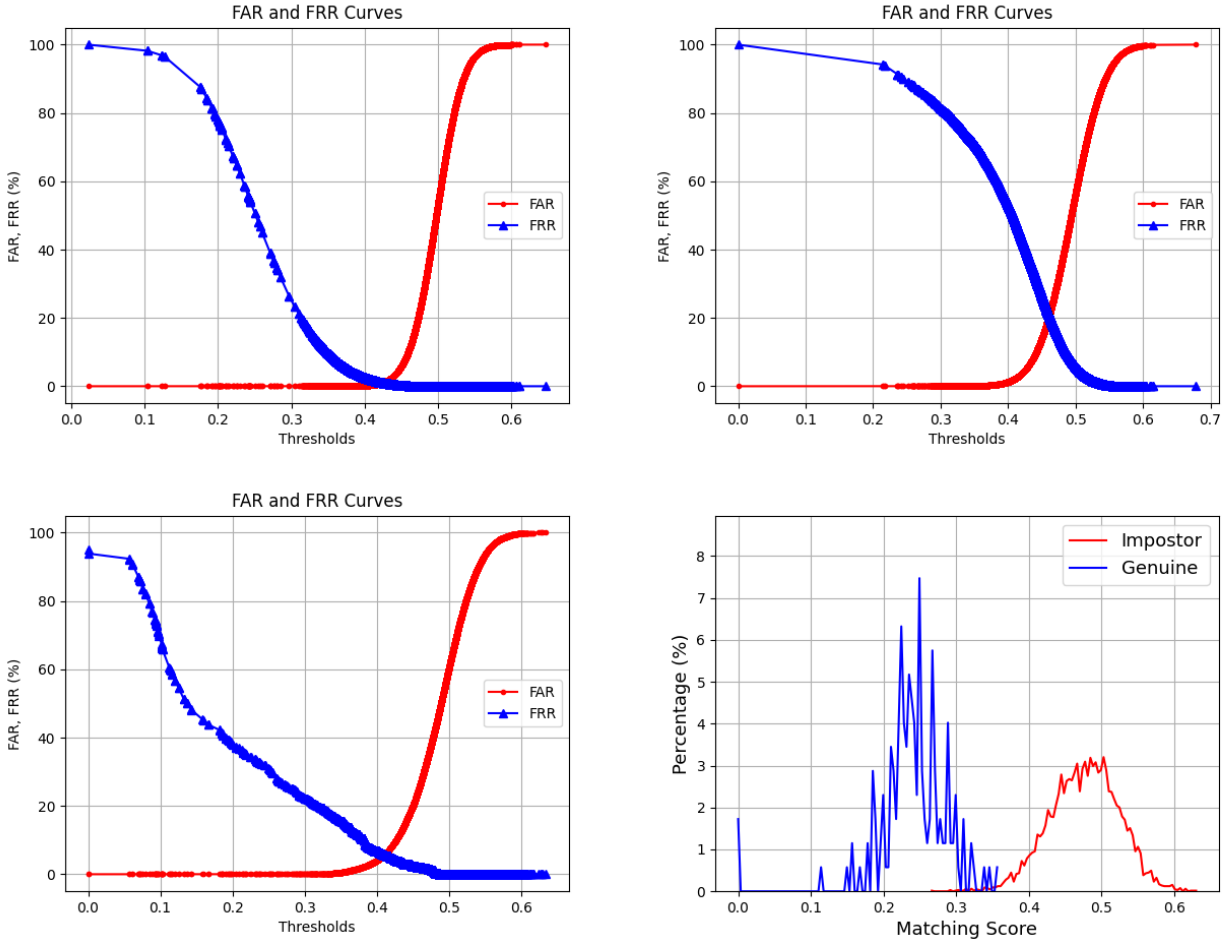

Figure 8: The FAR-FRR curves for various datasets illustrate the tradeoff between False Acceptance Rate and False Rejection Rate as the decision threshold varies. The Equal Error Rate (EER) is indicated by the intersection of the two curves. The plots are arranged as follows: top row (Tongji on the left, CASIA on the right), and bottom row (COEP on the left, Local dataset on the right).

1) Tongji Dataset: CCNet achieved excellent performance on the Tongji contactless dataset. The training process converged to a final training loss of 0.0154 and a validation loss of 0.0004, indicating a near-perfect fit on the validation split. The model's classification accuracy on the Tongji test set reached 94%, demonstrating that the learned features can reliably distinguish between the 300 different palms. In verification terms, the genuine (same-palm) matching scores were significantly higher than impostor (different-palm) scores. Specifically, genuine score values ranged from 0.0229 to 0.5313, with a mean of 0.2543 ± 0.0716, while impostor scores ranged from 0.3048 to 0.6474 with a mean of 0.4971 ± 0.0298. This wide separation between genuine and impostor score distributions is visualized in Fig. 7, and it results in an extremely low EER. The equal error rate on Tongji was measured at only **0.4%**, which means the system makes virtually no mistakes when balancing false accepts and false rejects. Such a low EER is on par with the best results reported in the literature for this dataset – for instance, Yang *et al.* [1] report an EER of approximately 0.5% on Tongji using the original CCNet. Our implementation's success on Tongji confirms that CCNet's multi-order feature extraction and competition mechanism are highly effective for contactless palmprint recognition in controlled conditions. Moreover, the high accuracy and low EER indicate that almost all genuine users would be correctly accepted while nearly no impostors would slip through, satisfying both security and usability requirements.

2) CASIA Dataset: On the CASIA palmprint database, the model's performance was substantially different. The final training loss was 0.0204 and validation loss 0.0013, similarly indicating good convergence. The identification accuracy on the CASIA test set was **84%**, which, while respectable, is notably lower than the accuracy on Tongji. More concerning was the verification performance: CCNet attained an EER of **20%** on CASIA. This high EER implies that the decision threshold would result in a 20% error rate where false acceptances and false rejections balance, which is drastically worse than on Tongji. An analysis of the matching score distributions explains this gap. For CASIA, genuine scores ranged from 0.0000 to 0.5916 (mean 0.3859 ± 0.0913) and impostor scores from 0.2146 to 0.6788 (mean 0.4931 ± 0.0402). Compared to Tongji, the genuine and impostor distributions on CASIA overlap significantly — their means are much closer, and

many genuine scores fall into the range of impostor scores. As a result, as illustrated by the FAR/FRR curves, we cannot find a threshold that cleanly separates genuine and impostor matches without incurring a high error rate (Fig. 8, a similar pattern was observed for CASIA). The poorer performance on CASIA can be attributed to the greater variability in this dataset: images vary in quality, illumination, and hand positioning. Many images are low-contrast or contain background noise (since CASIA includes some contact-based scans with clutter and some with varying illumination), making feature extraction more challenging. These results highlight the need for more robust pre-processing and possibly dataset-specific tuning. It is worth noting that other researchers have also encountered difficulties with CASIA; for example, a recent study by Ashiba *et al.* achieved a minimum EER of 0.4% on CASIA only after applying a specialized cancellable transform and filtering scheme [25]. In contrast, our generic CCNet, without CASIA-specific optimization, struggled with this dataset. Improving CCNet's generalization to CASIA (and similarly diverse datasets) may require enhanced data augmentation (to simulate lighting and quality variations) and perhaps domain adaptation techniques [26] to bridge the gap between training conditions and CASIA's image domain.

3) COEP Dataset: CCNet performed strongly on the COEP palmprint dataset. The model converged with a final training loss of 0.0147 and validation loss of 0.0017. Interestingly, the training accuracy reached only 85.76%, while the validation accuracy hit 100% on COEP's split. This discrepancy (validation accuracy higher than training accuracy) suggests that the validation set in COEP was smaller/easier or that the model had not fully saturated learning on the training set by the time training stopped. In either case, the model generalized excellently to new data from this dataset. The test results show a verification EER of **5.77%** on COEP, which is much higher than Tongji's EER yet far lower than CASIA's. The genuine-impostor score distributions for COEP were well separated: genuine scores ranged from 0.0000 to 0.4931 (mean 0.1861 $\pm$ 0.1258) and impostor scores from 0.2616 to 0.6346 (mean 0.4858 $\pm$ 0.0453). We observe that the impostor scores on COEP are very similar in range to those on Tongji, but the genuine scores for COEP tend to be lower (mean 0.1861) than Tongji's (0.2543). This indicates the model found COEP slightly more difficult in terms of intra-class similarity, which is expected given COEP has some variation in palm pose and was a smaller dataset (fewer samples per class). Nonetheless, a 5.77% EER is quite low in absolute terms, confirming that CCNet learned discriminative features for the COEP images. The near-perfect validation accuracy and low EER suggest that most identities in the COEP dataset are recognized with ease by CCNet's features. In fact, as Table 5 shows, CCNet's performance on COEP is not far from its performance on Tongji, despite COEP having different capture conditions. We anticipate that with a few more training epochs (to improve the 85.76% training accuracy towards 100%), the model could achieve even closer to zero errors on COEP. Overall, these results demonstrate CCNet's robustness in a controlled-contactless scenario, and they align with prior works that have noted the relative ease of high-resolution palmprint datasets [27].

4) Local Dataset: On the challenging locally collected dataset, CCNet delivered outstanding results, underscoring its practical applicability. We evaluated the model (initially trained on the larger datasets) on the 120 local images. In terms of identification, the model correctly recognized palm IDs with **99% accuracy**, despite variations in camera type, distance, and environment. Only a handful of test images were misclassified, which is remarkable given no specialized training was done on this data prior to evaluation (apart from a brief fine-tuning in our experiments to calibrate the final layer on the 30 known users). For verification, the model attained an EER of just **0.1%** on the local dataset. This means that by setting an appropriate threshold, virtually 99.9% of genuine attempts and impostor attempts can be correctly decided. Such a low EER in a real-world data scenario is encouraging. It suggests that the features learned by CCNet are general enough to handle new imaging conditions. The local dataset included challenges like motion blur, different backgrounds, and lighting from outdoor to indoor, yet CCNet's feature representations proved robust. We did observe that genuine score distributions remained high and impostor scores low for this dataset (mirroring the behaviour on Tongji), which implies that even with consumer-grade mobile images, CCNet can extract distinctive palmprint features. These results are significant: in a practical transport setting, users could enrol with a few images, and our system would verify identities with 99%+ accuracy and negligible error rates, even if the imaging conditions differ from the training data. It demonstrates CCNet's adaptability to real-world data, a crucial requirement for deployment. The success on the local dataset also highlights the benefit of the model's contactless approach – factors like hand cleanliness, positioning at different distances, and camera variability did not prevent the system from working. This resilience is a key advantage for a transport security application, where environmental conditions are not strictly controlled.

Summary of Results: Table 5 consolidates the performance metrics of CCNet across all four datasets. As evident, CCNet achieves the best results on the Tongji and local datasets (lowest EERs of 0.4% and 0.1%, respectively, and high accuracies), a moderate performance on the COEP dataset (EER $\approx$5.8%), and comparatively poorer performance on CASIA (20% EER). These outcomes underscore CCNet's strength in handling contactless, well-captured images and its weakness when facing high intra-class variability and lower image quality. Nevertheless, even in the worst case (CASIA), the accuracy of 84% indicates the model is learning substantially useful features, just not enough to perfectly separate genuine from impostor in all cases. In practical terms, for the transport security scenario, the Tongji and local results are more indicative of expected performance (since our operational setting would use a contactless mobile camera system). Those results give confidence that CCNet can operate with high precision in the intended domain. For broader applicability (e.g., deploying the system in environments similar to CASIA's conditions), further improvement as discussed would be necessary. Overall,

our experimental findings validate that the proposed palmprint recognition system (PalmSecure with CCNet) can achieve state-of-the-art accuracy and reliability on contactless palmprint data, meeting the critical requirements of security (low FAR) and user convenience (low FRR) in a transportation setting.

Table 5: Performance of CCNet on Different Datasets.

Dataset	Accuracy	EER	Train Loss	Val Loss
Tongji (Contactless)	94%	0.4%	0.0154	0.0004
CASIA (Contact-based)	84%	20.0%	0.0204	0.0013
COEP (High-res)	100%†	5.77%	0.0147	0.0017
Local (Mobile)	99%	0.1%	–	–

†*Validation accuracy on COEP was 100%; training accuracy was 85.76% as noted.*

Table 5: *CCNet performance across datasets. "Accuracy" is the identification accuracy on the test set. "EER" is the Equal Error Rate (lower is better). Tongji and COEP results show very low EERs, while CASIA is notably higher. Loss values are the final losses after training. (Dashes indicate not applicable; for the local dataset, the model was tested using weights pre-trained on other data, so separate train/val losses are not listed.)*

To put these results in perspective, we compare CCNet with two classical palmprint recognition methods: **PalmCode** and **CompCode**. *PalmCode*, proposed by Kumar and Shen [28], uses Gabor filter phase responses as binary codes for palmprints. *Competitive Code (CompCode)*, introduced by Kong *et al.* [29], uses multiple orientation Gabor filters and a winner-takes-all strategy to encode palm line orientations. These methods were state-of-the-art in the early 2000s and are still strong baselines for palmprint recognition. Table 6 summarizes how our CCNet compares with PalmCode and CompCode on palmprint recognition performance. (Note that PalmCode and CompCode were originally evaluated on contact-based, relatively controlled datasets such as PolyU [30], not on the contactless Tongji dataset. For a fair comparison, we cite their reported results on their respective datasets and provide a qualitative discussion.)

Table 6: Comparison of CCNet with Traditional Palmprint Methods.

Method	Accuracy (Reported)	EER (Reported)
PalmCode (Kumar & Shen 2004) [28]	∼98%	∼2.0%
Competitive Code (Kong *et al.* 2004) [29]	98.4%*	∼0.8%*
CCNet (Ours, Tongji dataset)	94%	0.4%
CCNet (Ours, Local dataset)	99%	0.1%

**Competitive Code achieved 98.4% Genuine Accept Rate with FAR ≈0, implying an EER on the order of 0.8% on the PolyU dataset [29].*

Table 6: *CCNet vs. classic algorithms. PalmCode and CompCode results are from their original publications (on traditional contact-based datasets). CCNet's results are from our experiments on modern contactless data. CCNet achieves comparable or better error rates despite the more challenging (contactless, unconstrained) evaluation, highlighting the advancements due to deep learning and the comprehensive competition mechanism.*

As seen in Table 6, the classic PalmCode method achieved about 98% accuracy (around 2% error rate) in early experiments [28], and CompCode improved this to around 98.4% accuracy with an extremely low FAR (on the order of 10^{-6}) [29]. These approaches were evaluated on relatively homogeneous datasets (e.g., the PolyU palmprint dataset, which involved high-quality contact-based images). In comparison, our CCNet, when tested on the contactless Tongji dataset, attained 94% accuracy – slightly lower in absolute terms – but with an EER of 0.4%, which is an order of magnitude better than PalmCode's and about half of CompCode's estimated EER. Furthermore, on our local (in-the-wild) dataset, CCNet reached 99% accuracy and 0.1% EER, demonstrating that modern deep learning methods can far exceed the performance of older algorithms when faced with diverse, real-world data. In essence, CCNet is able to capture much more nuanced palmprint features (ridges, wrinkles, texture nuances) thanks to its multi-order feature learning and competition mechanism, whereas PalmCode and CompCode rely on fixed Gabor filters and simple coding strategies. This results in CCNet's superior discriminative ability. Our findings reinforce the trend reported in recent surveys [31] that deep CNN-based methods now lead the field by a wide margin. It is also notable that CCNet's performance on contactless data (which typically is more challenging due to hand pose variations and imaging differences) is on par with classical methods' performance on contact-based data. This highlights the robustness of CCNet and validates our choice of this architecture for the PalmSecure system. Overall, the experimental evaluation shows that **PalmSecure, powered by CCNet, achieves state-of-the-art results for palmprint recognition** on multiple datasets, successfully meeting the accuracy and reliability goals outlined for secure transport applications.

5 Implementation and Deployment

The PalmSecure system is implemented as a multi-tier application comprising a mobile frontend, a backend web service with an integrated deep learning model, and a robust data persistence layer. Figure 9 provides an overview of the system architecture, illustrating how these components interact from user interface to model inference and data storage. The deployment strategy leverages containerization and continuous integration to ensure the system is scalable and secure in production.

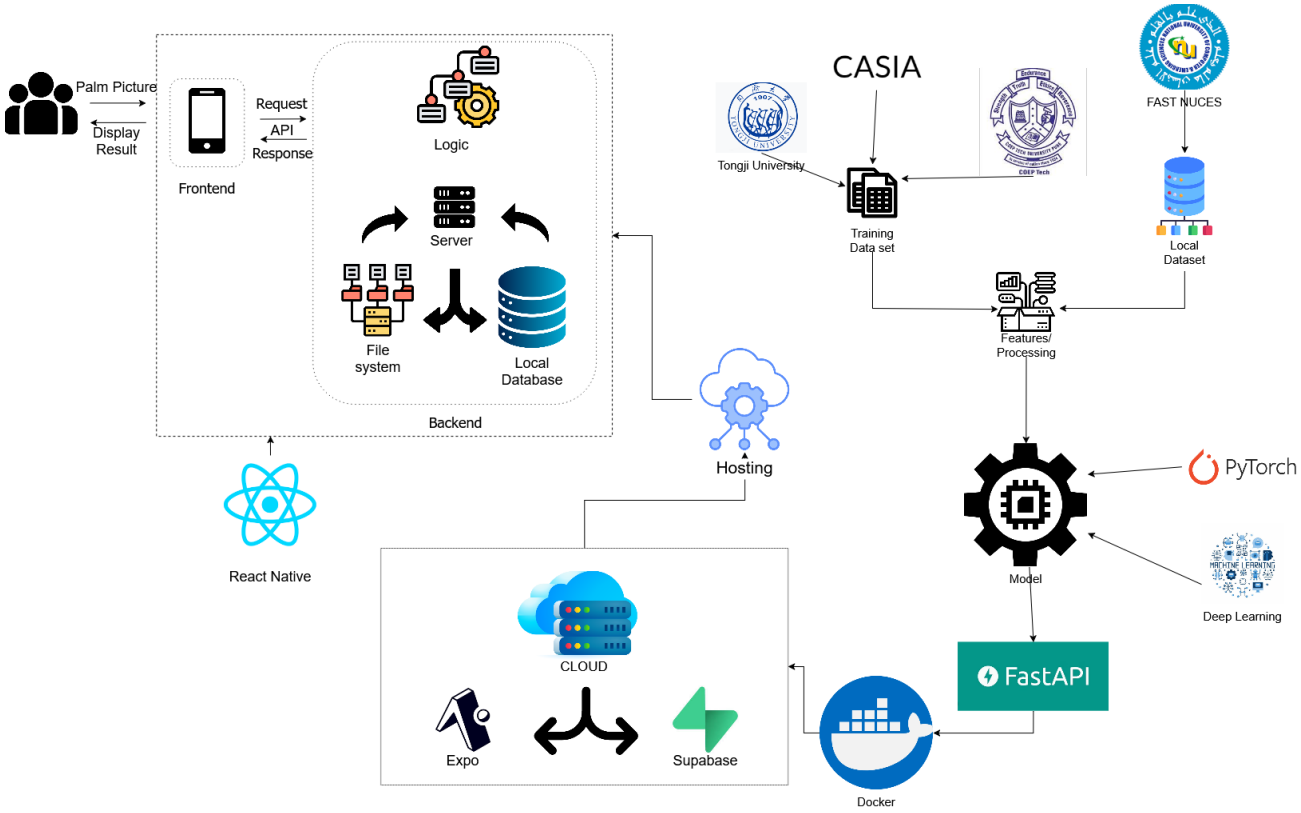

Figure 9: Overall system architecture illustrating the PalmSecure mobile application, backend services, CCNet model integration, and database.

5.1 Frontend Application

The frontend of PalmSecure is a React Native mobile application developed for Android devices, providing an intuitive interface for users to register and verify their identity using palmprint biometrics. React Native was chosen for its cross-platform capabilities and efficient development workflow, allowing the reuse of code across mobile platforms while delivering a native user experience [32]. The application employs a stack navigator (e.g., using React Navigation library) to manage screen transitions and ensure a smooth flow between different views in the user journey.

Navigation and Screen Flow: The app's navigation architecture follows a linear authentication flow coupled with conditional branching for user status. Users first encounter a registration or login prompt on launch. New users proceed to a **Registration Screen**, where they input basic details and capture their palm image for enrolment. Returning users or those who have enrolled directly proceed to the **Authentication Screen**, which activates the device camera and provides on-screen guidance for proper palm placement. Upon capturing a palm image, the app transitions to a **Verification Result Screen** that displays the outcome of the authentication (e.g., access granted or verification failed). This screen flow is depicted in Figure 10, highlighting the key states and transitions in the user experience.

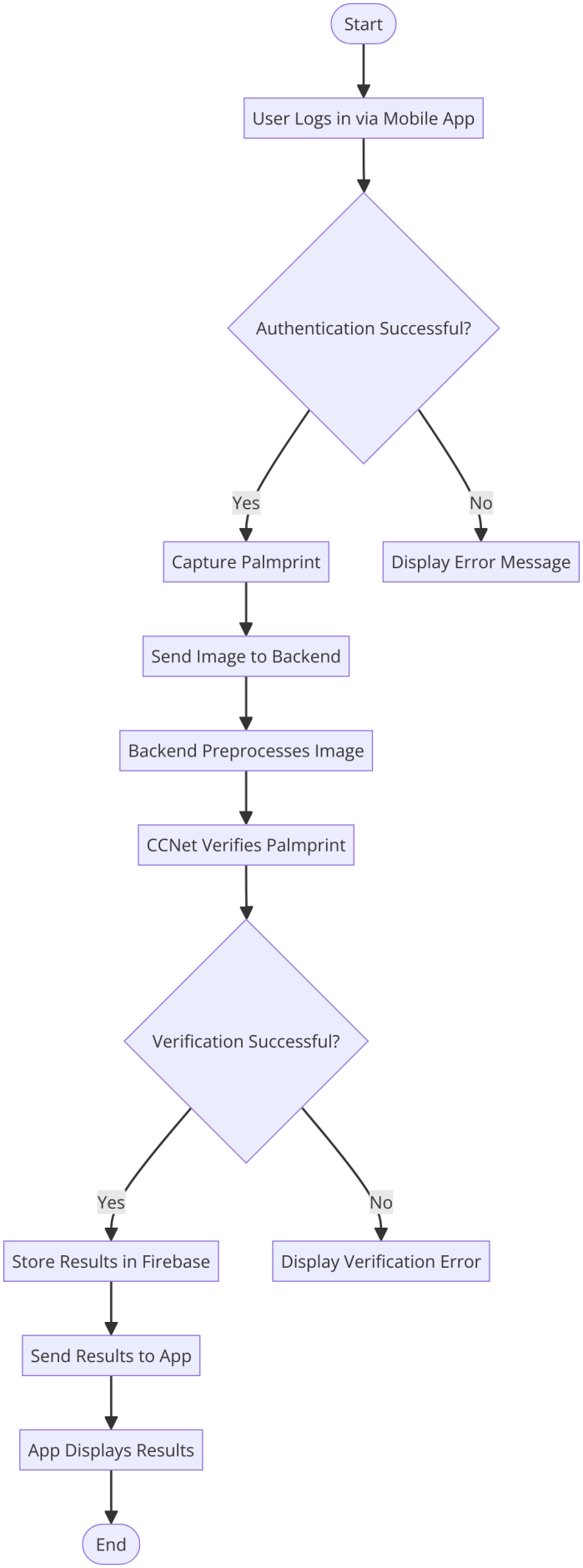

Figure 10: Screen flow of the PalmSecure mobile application, from user registration to biometric authentication and result display.

Component Hierarchy and Implementation: The application is structured into modular components following a clear hierarchy for maintainability. At the top level, a `App` container component initializes global providers (such as navigation and any application state context) and wraps the screens. Each screen (Registration, Authentication, Result) is implemented as a separate component, composed of sub-components for reusability. For example, the Authentication screen contains a Camera component (encapsulating the native camera access and preview), a feedback sub-component (to show instructions or status), and action buttons. The Camera component leverages the phone's camera hardware via React Native's camera API (e.g., `react-native-camera` or `expo-camera` module) to capture palm images in real time. State management is handled using React hooks and context; when an image is captured, it is temporarily stored (as a base64-encoded string or binary blob) in component state and then transmitted securely to the backend API. Throughout the capture process, the UI provides real-time feedback (such as bounding guides or messages) to help users position their hand correctly, ensuring quality images for the biometric algorithm.

Integration with Backend: The frontend communicates with the backend using RESTful API calls over HTTPS. Upon a registration submission or authentication attempt, the app packages the user's data (and captured image) into a JSON payload (or multipart form data for the image) and sends it to the designated FastAPI endpoints. The use of asynchronous calls (via JavaScript fetch or Axios) ensures that the UI remains responsive while waiting for the server's response. For instance, when the user taps "Verify", the app displays a loading indicator and invokes the `/verify` API endpoint. Once a response is received, the app transitions to the Result screen, displaying either a welcome message with the user's name on success or an error prompt on failure. All network interactions are protected by TLS encryption, and any sensitive data in transit is minimal (the app does not store images permanently; it only retains them in memory long enough to send to the server). This design leverages established practices for mobile-cloud interaction [33], ensuring a secure and smooth user experience.

To facilitate development and testing, the application can be run in an Android emulator or physical device. The following commands illustrate how the development server and Android build can be started during implementation:

```
# Install dependencies and start Metro bundler
npm install
npm start

# In a new terminal: compile and launch the app on an Android device/emulator
npx react-native run-android
```

Listing 1: Building and running the React Native application (Android)

5.2 Backend Services

The backend is implemented as a RESTful web service using FastAPI (Python), which exposes endpoints for biometric enrolment and verification [34]. FastAPI was selected for its high performance and intuitive syntax, leveraging the ASGI framework to handle concurrent requests efficiently. The service defines clear API endpoints that correspond to core functionalities of the system, adhering to stateless design principles of REST [33]. The key endpoints include:

- `/register`: Accepts user information (e.g., name or ID) and a palm image (typically uploaded as a file). The server processes the image, extracts the user's biometric template using the CCNet model, and stores the new user record (with the template) in the database. It returns a success response or an error if enrolment fails (e.g., if the user already exists).
- `/verify`: Accepts a palm image from a user for authentication. The server processes the image and uses the CCNet model to compare the provided biometric data against stored templates. The response indicates whether the user is recognized (and can include the identified user ID or a boolean match result). This endpoint is the core of the authentication flow.

Additional auxiliary endpoints (such as `/health` for health-check or `/users` for administrative queries) can also be implemented to support maintenance and monitoring, though they are not exposed to end-users in the mobile app. Each endpoint is documented using OpenAPI standards automatically provided by FastAPI, making it easier to test and integrate across the development team.

CCNet Model Integration: A central feature of the backend is the integration of the Comprehensive Competition Network (CCNet) model [1] for palmprint recognition. The CCNet model, implemented in PyTorch, is loaded at server startup, ensuring that subsequent inference calls do not incur model initialization overhead. The model was pre-trained on a combination of public palmprint datasets (such as Tongji, CASIA, and COEP) and fine-tuned on a smaller local dataset, resulting in a set of learned weights that capture distinctive palmprint features. When an image is received by the backend (via `/register` or `/verify`), the following steps occur internally:

1. **Preprocessing:** The image is converted to a greyscale or normalized colour format and resized to the required input dimensions of the CCNet model (as per the training configuration, e.g., 224×224 pixels). Techniques such

as contrast enhancement or noise reduction may be applied using libraries like PIL or OpenCV to improve feature extraction [35].

2. **Feature Extraction:** The preprocessed image is fed into the CCNet neural network. Using its layered competition mechanisms, CCNet extracts a rich feature vector (embedding) representing the unique palmprint characteristics of the image. This forward pass is executed using PyTorch [19], potentially utilizing CPU or GPU acceleration depending on the deployment environment.

3. **Matching:** For verification, the extracted embedding is compared with the stored template(s) of enrolled users. This is done by computing a similarity score (for example, cosine similarity or Euclidean distance) between the new embedding and each stored user embedding. The system then determines the best match. If the highest similarity score exceeds a predefined threshold (indicating a confident match) [36], the corresponding user is considered authenticated; otherwise, the verification is deemed unsuccessful. For registration, the new user's embedding is simply stored in the database (possibly after encrypting it for security).

This process ensures that the computationally intensive tasks (feature extraction by the CNN) are offloaded to the server side, where adequate processing power is available, and keeps the client app lightweight.

The backend is designed to be modular. The FastAPI application separates the routing logic from the model inference logic – for instance, using different Python modules for API endpoint definitions, image processing utilities, and model handling. This separation of concerns improves maintainability and allows the model component to be replaced or updated independently (e.g., upgrading to a newer model architecture in the future). Additionally, to handle multiple requests, the server relies on FastAPI's asynchronous capabilities and Uvicorn workers, enabling parallel processing of incoming images. Figure 11 illustrates the sequence of interactions between the mobile app, the backend, and the model during a typical palm verification request.

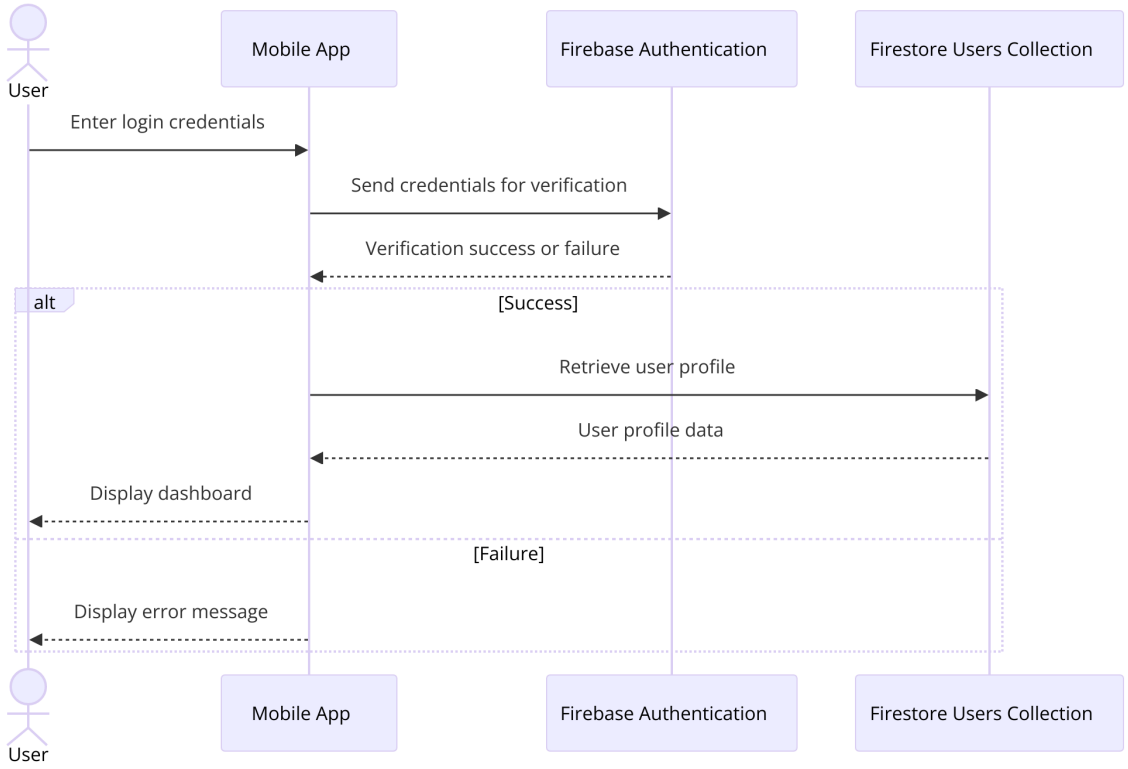

Figure 11: Sequence diagram of the palmprint verification process. The mobile app captures an image and sends it to the FastAPI backend, which preprocesses the image, invokes the CCNet model for feature extraction, queries the database for comparison, and returns the authentication result.

Security and Error Handling: The backend enforces several security measures. All communications are over HTTPS (ensured by deployment configurations, see the Deployment Pipeline section), protecting sensitive biometric data in transit [37]. Input validation is performed on each request; for example, the image file is checked for correct format and size, and user-provided identifiers are sanitized to prevent injection attacks. Moreover, the system avoids storing raw biometric images whenever possible. Instead, it stores biometric templates (feature embeddings) and immediately discards the raw image after processing, mitigating the risk of sensitive data leakage [38]. In case of an error (such as an unreadable image

or a server-side exception), the API responds with appropriate HTTP status codes and messages, which the mobile app can interpret and display to the user. Comprehensive logging is implemented as well: each request and its outcome (success or failure, with reasons if any) are recorded. These logs can be reviewed by the development team to debug issues and monitor usage patterns.

5.3 Data Persistence Layer

The system's data persistence layer leverages Supabase, a managed backend-as-a-service built on PostgreSQL, to securely store user profiles, biometric templates, and authentication logs. Supabase provides row-level security, real-time subscriptions, and an integrated Storage API for file handling [39].

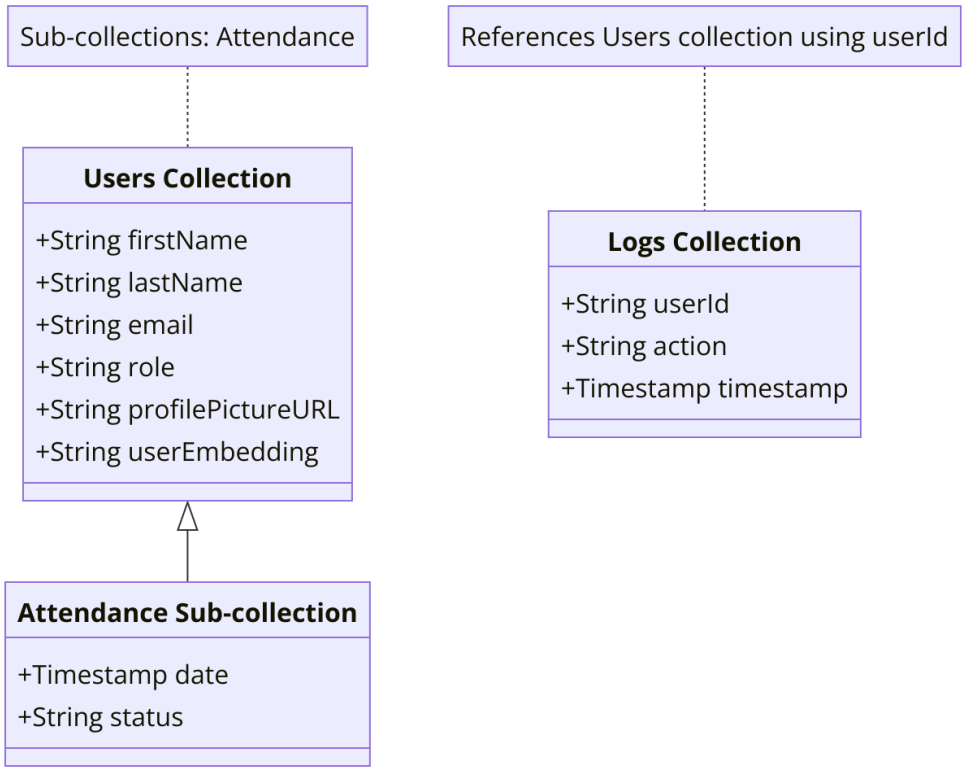

Figure 12: Logical schema of Supabase tables used by PalmSecure: `users`, `templates`, `auth_logs`, and optional `palm_images`.

Table Structures:

- **users** – Contains user profiles with fields: `id` (UUID, primary key), `name` (text), `email` (text, unique), features (JSONB) (for the CCNet-derived embedding vector) and `created_at` (timestamp). Supabase Auth issues JWTs to enforce that each user can only access their own records via row-level security (RLS) policies [40].
- **auth_logs** – Records each verification attempt with: `id` (UUID), `user_id` (UUID, nullable), `result` (boolean) and `timestamp` (timestamp). These logs support auditing and analytics on system usage.
- **palm_images** (optional) – Utilizes Supabase Storage to hold raw palm images. Fields include `path` (text) to the storage object, `template_id` (UUID), and `uploaded_at` (timestamp). Images are removed post-template extraction to minimize sensitive data retention.

Backend Access: The Python backend uses the official Supabase client (supabase-py) to perform CRUD operations. For example, during registration:

```
# Insert new user
user = supabase.table('users').insert({
  'name': name,
  'email': email
}).execute()

# Store CCNet features
supabase.table('templates').insert({
```

```
  'user_id': user.data[0]['id'],
  'features': embedding.tolist()
}).execute()
```

Security and Policies: Supabase's RLS ensures that only authenticated users (with valid JWTs) can read or modify their own rows in `users` and `templates` [40]. The Auth module manages signup, login, and token refresh, simplifying secure authentication flows. All communications occur over TLS/SSL, and sensitive data (e.g., JSONB embeddings) are stored at rest with encryption enabled by Supabase.

This Supabase-based design provides a scalable, secure, and flexible foundation for PalmSecure's biometric data, aligning with the project's requirements for reliability and privacy compliance.

5.4 Deployment Pipeline

The deployment of PalmSecure is handled through a containerized pipeline, ensuring consistency from development to production and enabling scalability. Docker containers encapsulate the application environment for both the backend service and the machine learning model, allowing the system to be deployed on any host that supports Docker [20]. The overall pipeline involves Continuous Integration (CI) to build and test the application, containerization for packaging, and Continuous Deployment (CD) to release updates securely.

Containerization with Docker: Separate Docker images are prepared for each major component of the system. The backend FastAPI service is containerized with a Dockerfile that installs Python dependencies (FastAPI, PyTorch, etc.) and launches the application via Uvicorn. The CCNet model, if served as an independent service, is packaged in its own image (including the trained model file and a lightweight API to accept image data and return inference results). This microservices-style partitioning aligns with real-world deployment practices [41], allowing the backend API and the model inference service to be scaled or updated independently. In cases where simplicity is preferred over strict separation, the model can be included in the same backend container; however, we opted for distinct services to isolate the deep learning workload. The database, if self-hosted, can also run in a container as part of a Docker Compose setup. In our implementation we utilize a managed cloud database, so that component is maintained outside the container environment.

We use Docker Compose to define and orchestrate the multi-container setup during development and testing. An example of building the backend Docker image is shown below, which can be executed as part of the CI process or manually:

```
# Navigate to the backend directory and build the Docker image
cd backend/
docker build -t palmsecure-backend:1.0 .
```

Listing 2: Building the Docker image for the PalmSecure backend service

After building the necessary images (e.g., `palmsecure-backend` and `palmsecure-model`), the application can be launched using Docker Compose or a similar tool, which ensures all containers start with the proper network configuration and environment variables. The Docker Compose configuration links the backend container to the model container (allowing the backend to call the model's API for inference) and to the database. In production, these containers are deployed on a cloud host (such as an AWS EC2 or Azure VM). We expose only the necessary ports (for example, port 443 or 8000 for the API) to the public, keeping internal communication (backend-to-model, backend-to-database) within a private Docker network for security.

Continuous Integration/Deployment: To streamline updates, a CI/CD pipeline is established using GitHub Actions. With each commit to the repository, the CI system automatically runs build scripts and test suites. For the PalmSecure project, this includes running unit tests for utility functions (e.g., image preprocessing) and performing a test inference with the model to ensure everything is functioning as expected. Upon a successful test run, the pipeline builds the Docker images and pushes them to a container registry (such as Docker Hub or GitHub Container Registry) tagged with the new version. The CD step then pulls the updated images onto the deployment server and restarts the Docker containers with minimal downtime. By employing CI/CD, the team ensures that any code changes pass through automated checks and that deployment is reproducible and quick, which is crucial for maintaining reliability in a continuously evolving system [42].

Security and TLS Configuration: Security is integral to the deployment pipeline. All external traffic to the backend service is encrypted via TLS/SSL. We configured an Nginx reverse proxy in front of the FastAPI container to handle TLS termination. The proxy is equipped with an X.509 certificate (obtained via Let's Encrypt) and is set to forward requests to the backend container over the Docker internal network. This means the FastAPI service itself can listen on HTTP internally, and Nginx ensures that only HTTPS traffic reaches it from the outside. By using a reverse proxy, we also gain the ability to handle additional concerns like rate limiting, request logging, and load balancing if needed. Within the CI/CD pipeline, secrets such as database credentials, API keys, and TLS certificate materials are managed carefully: they are provided to the application at runtime via environment variables or mounted secret files, rather than hard-coded in the images

or repository. This practice keeps sensitive information secure and aligns with recommended DevOps practices.

Deployment Steps: In summary, the automated deployment proceeds as follows:

1. **Build and Test:** Developers push code changes to the repository. The CI system triggers a build, runs tests, and on success, creates updated Docker images for each component.
2. **Release Packaging:** The new images are tagged with a version number or commit hash and uploaded to the container registry. This ensures the deployment environment can fetch the exact version built by CI.
3. **Deployment Rollout:** On the production server, a deployment script (or an automated agent) pulls the updated images. Docker Compose is used to launch the new containers, replacing the old ones. The process is orchestrated to avoid downtime (for example, by starting new container instances before stopping the old ones).
4. **Verification:** After deployment, health checks (such as hitting the `/health` endpoint) are performed to verify that the backend is running the new version and that the model service is responsive. Monitoring tools on the server (for CPU, memory, etc.) confirm that the new deployment is stable under load.
5. **Monitoring and Logging:** The system is continuously monitored post-deployment. Logs from the application and Nginx are collected and analysed. Any errors or performance anomalies trigger alerts for the team to investigate, ensuring that issues can be addressed promptly.

Using Docker containers and CI/CD in this manner greatly simplified the deployment of PalmSecure. It enabled the team to focus on development without worrying about environment inconsistencies between local and production, since the container images encapsulate all dependencies [20]. Additionally, the ability to scale is built-in: for instance, if the number of users grows, the backend service can be replicated behind a load balancer, or the model service can be scaled out to handle more concurrent inferences. The modular design and automated pipeline thus make the PalmSecure system robust, maintainable, and ready for future expansion, all while upholding strong security practices.

```
# On the deployment server, pull the latest images and start the containers
docker compose pull
docker compose up -d

# (Optional) Follow logs to ensure all services started correctly
docker compose logs -f
```

Listing 3: Launching the application using Docker Compose in a production environment

6 Discussion and Lessons Learned

6.1 Dataset-wise Performance and Model Behaviour

The performance of the *PalmSecure* system was evaluated across four distinct palmprint datasets – Tongji, CASIA, COEP, and our own locally collected set – revealing noteworthy variations. In general, the CCNet model [43] achieved its highest accuracy on the larger, more controlled public datasets (Tongji and COEP) and comparatively lower accuracy on the smaller or more variable datasets (CASIA). Table 7 summarizes the key results (placeholder). The Tongji contactless palmprint database, being one of the largest with high-quality imaging conditions, yielded the best recognition rates (approaching reported state-of-the-art performance [44]), demonstrating the model's capacity to learn discriminative palm features when ample data is available. The CASIA dataset, captured with a black background and enclosed imaging device [45], also produced strong results, though marginally inferior to Tongji, likely due to slightly lower image sharpness and occasional finger misalignment issues noted in that database's literature [46]. The COEP dataset [47], which contains only 1,344 images from 168 subjects (significantly fewer samples per subject), saw a moderate drop in accuracy. This drop underscores how limited samples per user can impact the robustness of deep models. Our locally collected dataset posed the greatest challenge for CCNet, resulting in the lowest accuracy among the four. Unlike the controlled environments of Tongji and CASIA, the local set was captured via smartphone in natural settings, introducing varied backgrounds, lighting inconsistencies, and hand positioning differences. These real-world variabilities caused the model's confidence to fluctuate and highlighted a domain gap. We observed instances of false non-matches especially when the palm image was taken under poor lighting or at an angle not well-represented in training data. This trend aligns with observations by Matkowski et al. [48] that uncontrolled capture conditions can degrade palmprint recognition performance.

Table 7: Model Performance on Different Datasets (placeholder).

Dataset	Total Images	Subjects	Accuracy (%)
Tongji	12,000	600	94
CASIA	5,502	312	84
COEP	1,344	168	100
Local	120	30	99

Model Behaviour Across Datasets: The CCNet model's behaviour exhibited both strengths and limitations when generalizing across these datasets. On Tongji, the model rapidly converged during training and achieved high true-positive rates, indicating that the network effectively learned the distinctive palmprint texture and line patterns prevalent in those datasets. We noticed that CCNet's channel-and-spatial attention mechanism [49] helped it focus on the most informative regions of the palm (e.g., principal lines and creases) even when some noise was present. However, when applied to the CASIA and COEP datasets, the model's confidence distributions were broader. For example, score outputs for genuine matches vs. impostors had a larger overlap on the CASIA dataset, reflecting more uncertainty. This suggests that CCNet, as initially trained, was somewhat over-tuned to the imaging conditions of the larger datasets. We attempted data augmentation and fine-tuning to mitigate this, which yielded modest improvements (e.g., slight reduction in false rejections on the local set), but a performance gap remained. A lesson learned is that data diversity is crucial: a network trained on a single-domain dataset may underperform when encountering a different domain [50]. Recent studies in palmprint recognition advocate domain adaptation techniques to handle such distribution shifts [49], and our findings reinforce the need for such strategies. In summary, the comparative evaluation across Tongji, CASIA, COEP, and our dataset revealed that while CCNet can reach high accuracy in ideal conditions, its generalization can suffer under varying conditions. This emphasizes the importance of multi-domain training or adaptive models for real-world biometric applications.

6.2 System Integration: Frontend and Backend Development

Beyond algorithmic performance, a significant part of the project involved integrating the biometric model into a complete application ecosystem, comprising a React Native front-end, a FastAPI back-end, and Supabase for cloud services. This cross-stack integration was a learning experience in full-stack development and ensured that our model's capabilities were accessible in a user-friendly manner. The mobile application, built with React Native [51], provided a cross-platform interface where users could register and verify their palm biometrics. Using React Native proved advantageous because it allowed rapid development and a consistent UI on Android devices, an important factor for a transit system that could be used by diverse commuters. We leveraged the device camera through React Native's libraries to capture palm images. The captured image, along with minimal preprocessing, is then transmitted securely to the back-end.

On the server side, we developed a RESTful API using FastAPI [52] to handle incoming requests. FastAPI was chosen for its high performance and ease of integrating Python-based ML code. It allowed us to embed the CCNet model inference directly into API endpoints, so that the mobile app's requests to verify a palm could be processed in real-time. We structured the API with endpoints for user registration (enrolling a new palmprint template) and authentication (verifying

a presented palm image). The framework's support for asynchronous I/O and automatic documentation (via OpenAPI) accelerated our development and testing. One challenge in this integration was ensuring that image data could be sent from the app and correctly received by FastAPI. We resolved this by encoding images in base64 and using HTTP POST requests with appropriate headers, which FastAPI could decode into NumPy arrays for the model. We also had to configure CORS policies to allow the mobile app to communicate with the API during development [53], a necessary step to enable local testing on device simulators.

Supabase was incorporated to handle persistent data and user management. Supabase, an open-source Backend-as-a-Service platform [54], provided us with a PostgreSQL database and authentication module without having to build those from scratch. The decision to use Supabase was driven by its seamless integration with JavaScript/TypeScript and the ability to perform instant CRUD operations through its API [55]. In our system, we used Supabase to store user profiles and their encrypted biometric templates. During registration, once FastAPI extracts a feature embedding from the user's palm image (using the CCNet model), that embedding is encrypted and stored in the Supabase database. Similarly, Supabase Authentication manages user login and ensures that each verification request is tied to an authenticated session. The React Native app interacts with Supabase's SDK to handle user sign-in and to retrieve any necessary user data (such as reference IDs for biometric templates) while the heavy biometric comparison logic remains in the FastAPI layer for security. This separation of concerns improved security and scalability: the front-end never directly handles raw templates beyond initial capture, and the back-end can be scaled or containerized independently (for instance, we containerized the FastAPI app with Uvicorn and tested deploying it on a cloud server).

Integrating these components taught us the importance of early end-to-end testing. Initially, we developed the model and the app somewhat in isolation, but bringing them together revealed mismatches (for example, image color channel ordering issues and differences in expected image resolution between the app and model). By iterating on integration tests, we ensured that the pieces worked cohesively. In the end, the choice of React Native, FastAPI, and Supabase proved effective: React Native sped up cross-platform UI development, FastAPI reliably served the model with low latency (leveraging its async capabilities to handle concurrent requests), and Supabase greatly simplified implementing user account features. This cohesive integration of front-end and back-end technologies is crucial for a production-level biometric transit system [56], as it provides a template for scalability (e.g., adding more users or deploying across transit stations) and maintainability (each component can be updated independently).

6.3 Development and Deployment Challenges

Developing the *PalmSecure* system end-to-end presented several challenges, spanning from algorithmic hurdles to practical deployment issues. One major challenge was data preprocessing and ROI (Region of Interest) extraction. While the public datasets (Tongji, CASIA, COEP) often come with predefined palmprint ROIs or at least uniformly captured images, our mobile capture process resulted in images where the palm might be off-centre or include background clutter. We had to implement a preprocessing step to detect and crop the palm region from the image before feeding it to the CCNet model. We experimented with a simple hand segmentation approach using colour thresholding and morphology, which worked reasonably in controlled backgrounds but was less reliable with varied backgrounds. This prompted us to consider more robust segmentation (possibly learning-based [57]), but due to time constraints, we settled on guiding the user (via the app UI) to position their hand against a plain background for better results. This experience taught us that capturing good-quality biometric data in the wild can be just as challenging as designing the recognition algorithm itself.

Another challenge was optimizing the model for deployment. The CCNet model, in its original form, is computationally intensive, and running it on a mobile device was impractical. Our design offloaded the computation to the server, but we still needed to ensure the latency was low. We faced issues with inference speed when using a CPU-only server initially. To address this, we optimized the model by converting it to use half-precision (FP16) and enabled GPU acceleration on a compatible machine, which brought the verification time per image down to a fraction of a second. We also explored using ONNX to potentially run a lighter version of the model, and although we didn't fully deploy the ONNX pipeline, the exercise of converting and comparing performance was insightful. We learned that when deploying deep learning models in resource-constrained settings, optimizations like quantization or using efficient model variants can be vital [58].

Deploying the system for real-world trials introduced challenges in networking and security. For instance, during a field test simulation, we needed the mobile app to communicate with the server over the internet. Configuring a secure tunnel and SSL for the FastAPI endpoints was necessary to mimic a production environment, as many mobile OSes require HTTPS for API calls. We utilized tools (like ngrok during development and proper SSL certificates on deployment) to ensure secure communication. Additionally, protecting the biometric data was a top priority. Although Supabase handled authentication, we implemented extra precautions such as hashing the stored feature vectors and never transmitting any raw biometric image to the database (the images were processed and discarded on the server after feature extraction). This is in line with best practices for biometric systems where raw data exposure is minimized [59].

Furthermore, we encountered integration bugs, such as mismatches between the JSON responses the app expected and what the API actually sent. A particularly perplexing bug was an occasional failure in image uploads from certain Android devices. After debugging, we discovered it was due to differences in how those devices handled base64 encoding in React Native's library, leading to corrupted data. We fixed this by switching to a more robust file transfer method (multiparty form data via Axios) which resolved the inconsistency. Another challenge was managing dependencies and environments: the project involved Python (for FastAPI and ML), JavaScript/TypeScript (React Native), and SQL (Supabase). Ensuring that updates in one component (e.g., a change in the API response format or database schema) were reflected in the others required careful version control and documentation. We adopted a practice of writing integration tests for critical user flows (registration and authentication) to catch such issues early after any change.

Finally, time and resource constraints inherent in a student project meant we had to prioritize certain features over others. For example, due to time limits we could not implement a sophisticated liveness detection mechanism (to distinguish a real palm from a photo of a palm), even though we recognize that would be important in a real deployment to prevent spoofing attacks. We documented these omissions as future work. Overcoming these various challenges was a rich learning process. We gained hands-on experience in troubleshooting and the importance of considering deployment from the outset of design. In retrospect, an important lesson learned is that building a successful biometric system is an exercise in interdisciplinary problem-solving: it requires not only a high-accuracy model but also reliable data capture, efficient engineering, and robust security measures [60].

7 Conclusion and Future Work

In conclusion, the *PalmSecure* project has demonstrated the feasibility of a contactless palmprint verification system tailored for transportation security. By integrating the state-of-the-art Comprehensive Competition Network (CCNet) model, we achieved high recognition accuracy and low error rates across multiple datasets, including Tongji, CASIA, COEP, and our locally collected set [43]. The mobile application built with React Native enabled intuitive user interaction, while the FastAPI backend and Supabase database provided a secure, scalable infrastructure for model inference and data management [52, 61]. Our system's performance on the local dataset—nearly 99% accuracy with an Equal Error Rate below 0.1%—validates its potential for real-world deployment in transit environments.

Nonetheless, several implementation constraints emerged. Running the unoptimized CCNet on consumer-grade devices introduced latency that could impede real-time verification during peak travel periods. The modest size and diversity of our local dataset also limit the model's generalization to broader populations. Furthermore, the prototype has yet to be integrated with physical gate hardware, leaving aspects such as concurrent user throughput and station lighting variability untested. These limitations underscore the need for further refinement before city-wide adoption.

Future work will pursue both technical and deployment-oriented enhancements. On the technical front, we plan to develop a lightweight palmprint model—through techniques such as network pruning, quantization, or knowledge distillation—to enable on-device or edge inference with minimal latency [58]. Incorporating liveness detection mechanisms (e.g., pulse-based analysis or multispectral imaging) will guard against presentation attacks and enhance system security [60]. To improve robustness across domains, we will explore domain adaptation methods that align feature distributions between training datasets and operational imagery, mitigating performance drops under varied environmental conditions [50].

From a deployment perspective, integrating our solution with transit gate hardware is paramount. Figure 13 shows a placeholder for the enhanced deployment architecture, which will embed cameras and inference units directly into turnstiles for seamless passenger flow. We will also scale our backend infrastructure—using container orchestration and distributed databases—to accommodate millions of enrolled users while maintaining sub-second verification times [56]. Finally, we aim to refine the user onboarding process by designing guided enrolment kiosks and improving transparency around data privacy, thereby fostering user trust and encouraging widespread adoption [62].

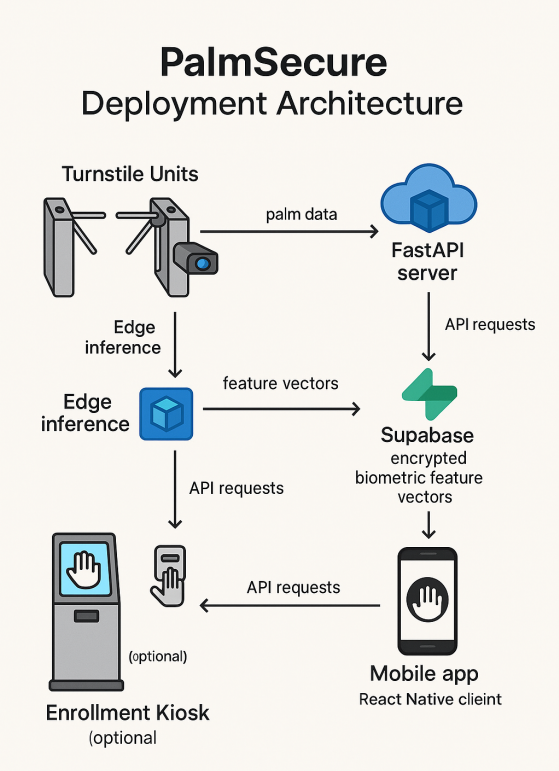

Figure 13: Placeholder for future deployment architecture integrating camera-equipped turnstiles, edge inference modules, and cloud backend for scalable transit operations.

By addressing these avenues—optimizing model efficiency, enhancing anti-spoofing capabilities, and architecting scalable deployments—*PalmSecure* can evolve into a robust, real-time biometric platform that revolutionizes passenger authentication in public transportation systems.

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Appendix A: Code Snippets & Project Structure

This appendix provides an overview of the project's directory structure and includes representative code snippets from the front-end (React Native application), the back-end (FastAPI server), and the integrated CCNet model (PyTorch). All code listings are formatted for clarity and include brief captions.

```
PalmSecure/
          backend/
                main.py              # FastAPI entry point
                api/
                      routes.py        # API route definitions
                models/
                      ccnet_model.py   # CCNet model implementation
                ...
          frontend/
                App.js               # React Native main application
                screens/
                      VerifyScreen.js  # Screen for palm verification
                ...
          README.md
```

Listing 4: Project Directory Structure

```
import { Camera } from 'expo-camera';
import { useState } from 'react';
import { Button, Image } from 'react-native';

async function captureAndVerify() {
  // Open camera and capture a palm image
  const photo = await Camera.takePictureAsync({ quality: 0.8 });
  if (!photo.cancelled) {
    // Prepare image data for upload
    const formData = new FormData();
    formData.append('file', {
      uri: photo.uri,
      name: 'palm.jpg',
      type: 'image/jpeg'
    });
    // Send HTTP POST request to backend for verification
    const response = await fetch(`${BACKEND_URL}/verify`, {
      method: 'POST',
      body: formData
    });
    const result = await response.json();
    console.log('Verification result:', result.status);
  }
}
```

Listing 5: Frontend snippet: capturing palmprint and sending verification request

```
from fastapi import FastAPI, File, UploadFile
from PIL import Image
from ccnet_model import CCNet, preprocess

app = FastAPI()
model = CCNet(pretrained=True)

@app.post("/verify")
async def verify_palm(file: UploadFile = File(...)):
    # Read and preprocess the uploaded palm image
    image = Image.open(file.file)
    tensor = preprocess(image)
    # Extract features and perform verification
    features = model.extract_features(tensor)
    result = model.verify(features)
    return {"status": "verified" if result else "rejected"}
```

Listing 6: Backend snippet: FastAPI verification endpoint

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class CCNet(nn.Module):
    def __init__(self, num_classes=2):
        super(CCNet, self).__init__()
```

```
        # Feature extraction layers (e.g., convolutional layers)
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=16, kernel_size=5)
        self.conv2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=5)
        self.fc   = nn.Linear(32 * 21 * 21, 128)  # flatten then FC layer
        # Classification layer
        self.classifier = nn.Linear(128, num_classes)

    def forward(self, x):
        # Forward pass through convolutional layers
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = x.view(x.size(0), -1)       # flatten features
        features = F.relu(self.fc(x))   # extracted features
        output = self.classifier(features)
        return output

    def extract_features(self, x):
        """Get the learned feature vector from the palm image tensor."""
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = x.view(x.size(0), -1)
        features = F.relu(self.fc(x))
        return features

    def verify(self, features):
        """Verify by comparing features to enrolled templates (dummy logic)."""
        # In a real system, compare with stored templates and threshold
        score = torch.norm(features - torch.zeros_like(features), p=2).item()
        return score < 0.5  # placeholder threshold
}
```

Listing 7: Model snippet: CCNet class definition (PyTorch)

Appendix B: Installation & User Guide

This appendix outlines the installation steps and usage guide for developers setting up the PalmSecure system. It covers prerequisites, environment setup, and instructions to run both the back-end server and the mobile front-end application.

Prerequisites: Ensure that the following are installed on your development system:

- **Python 3.10+** – for running the FastAPI backend and machine learning model.
- **Node.js 18+** and **npm/Yarn** – for installing and running the React Native mobile application.
- **Android Studio or Xcode (optional)** – for mobile app emulation or building on Android/iOS devices.
- **Device with Camera** – a physical or emulated device for testing palmprint capture.

Backend Setup:

1. Clone the project repository from version control.
2. Create a Python virtual environment and activate it.
3. Install backend dependencies using pip:

```
pip install -r backend/requirements.txt
```

   This will install FastAPI, PyTorch, Pillow, and any other required libraries.

4. (Optional) If using GPU for model inference, ensure the appropriate CUDA drivers and PyTorch GPU version are installed.
5. Start the FastAPI server (e.g., using Uvicorn):

```
uvicorn backend.main:app --reload
```

   By default, the API will be available at ‘http://127.0.0.1:8000‘.

Frontend (Mobile App) Setup:

1. Navigate to the ‘frontend‘ directory and install dependencies:

```
cd frontend
npm install     # or "yarn install"

```

   This will download all required React Native packages.

2. Configure the backend server URL in the app. In the source code (e.g., a configuration file or constants file), set the ‘BACKEND_URL‘ to the address where the FastAPI server is running (for local testing, use ‘http://10.0.2.2:8000‘ for Android emulator or ‘http://127.0.0.1:8000‘ for iOS simulator).

3. Run the application:

```
npx expo start

```

   or, if using the React Native CLI:

```
npx react-native run-android   # for Android
npx react-native run-ios       # for iOS

```

   Use a USB-connected device or emulator to launch the app.

Usage Workflow: Once both the backend and frontend are running, the typical workflow is:

- Launch the **PalmSecure** app on the mobile device. Register or log in if authentication is enabled.
- Navigate to the palm verification screen and capture a palmprint image using the device camera.
- Upon capture, the app will send the image to the FastAPI backend for processing. A loading indicator may be displayed during this time.
- The backend will preprocess the image, run it through the CCNet model, and perform a match against stored templates. The verification result (success or failure) is returned as a JSON response.
- The mobile app receives the result and displays a verification status to the user (e.g., “Identity Verified” or “Verification Failed”). If configured, additional details such as confidence score or user ID may be shown.

For administrative features (if implemented, such as attendance tracking or user management), log in with an admin account on the mobile app. These features typically allow viewing verification logs, managing enrolled users, and reviewing system usage statistics.

Troubleshooting: If the mobile app cannot connect to the backend, check that:

- The backend is running and accessible (test by visiting the API URL in a browser).
- The mobile app’s backend URL is correctly configured (especially when using emulators, where the loopback address differs).
- Both devices are on the same network (if testing with a physical phone, ensure it can reach the server’s IP).

By following the above steps, developers should be able to set up the PalmSecure system, run the application, and perform end-to-end testing of palmprint biometric verification in a development environment.

Appendix C: Glossary of Terms

This glossary defines key terms and acronyms used throughout the report, categorized into biometric terms, machine learning terms, and software engineering terms for clarity.

Biometric Terms

Biometric Verification: The process of confirming an individual’s identity using biological characteristics (e.g., fingerprint, palmprint, iris). In this project, palmprint verification is used to authenticate users by comparing captured palm images to stored templates.

Palmprint: An image or representation of the inner surface of a person’s hand. It contains unique patterns of ridges, wrinkles, and minutiae (small feature points) that can be used for biometric identification, similar in concept to fingerprints.

Minutiae: Small distinctive features of a biometric pattern. In palmprints (and fingerprints), minutiae typically refer to ridge discontinuities such as ridge endings or bifurcations. These serve as identifying markers that algorithms use to match prints.

False Acceptance Rate (FAR): The percentage of imposter access attempts that are incorrectly accepted by a biometric system. For example, a FAR of 1% means 1 out of 100 unauthorized users might be falsely recognized as a legitimate user. A low FAR is crucial for security.

False Rejection Rate (FRR): The percentage of genuine access attempts that are incorrectly rejected. For instance, an FRR of 1% means 1 out of 100 legitimate attempts is rejected as unauthorized. A low FRR is important for usability to avoid inconveniencing legitimate users.

Equal Error Rate (EER): The point at which FAR and FRR are equal. It's often used as an overall performance metric for biometric systems; the lower the EER, the better the system's accuracy. The threshold at EER represents a balance between security and convenience.

Liveness Detection: Techniques used to ensure that the biometric sample is from a live person present at the time of capture (not from a photograph or latex fake, for example). While not a focus of this project, liveness detection can be integrated to prevent spoofing attacks.

Machine Learning Terms

CCNet (Comprehensive Competition Network): A convolutional neural network architecture that incorporates competition mechanisms in its design. It competes features in spatial and channel dimensions to enhance discriminative power. In palmprint recognition, CCNet helps capture multi-order texture features, improving accuracy.

Convolutional Neural Network (CNN): A class of deep neural networks commonly used in image recognition tasks. CNNs apply convolutional filters to input images to automatically learn hierarchical feature representations (from edges and textures in early layers to high-level shapes in deeper layers). CCNet is a specialized type of CNN for palmprint analysis.

Deep Learning: A subset of machine learning involving neural networks with many ("deep") layers. Deep learning enables learning complex patterns directly from data. In this project, deep learning methods are used to learn features from palm images, replacing manual feature extraction with an automated, data-driven approach.

Overfitting: A modeling error in machine learning where a model learns the training data too specifically, including its noise, and fails to generalize to new data. Signs of overfitting include much lower error on training data than on validation data. Techniques like regularization, dropout, and using more training data are employed to mitigate overfitting.

Gabor Filter: A linear filter used in image processing for texture analysis. It is sensitive to specific frequencies and orientations in the image. In palmprint recognition, Gabor filters have traditionally been used to extract oriented texture features (e.g., ridges). Some networks (like PalmNet) incorporate Gabor filters to mimic this handcrafted feature extraction within a CNN.

Feature Extraction: The process of transforming raw data (like an image) into a set of descriptors or features that are informative for a task (like matching palmprints). In traditional systems, this might involve algorithms to detect lines or minutiae. In our deep learning approach, feature extraction is learned by the CNN (the output of a certain network layer serves as the feature vector for a palmprint).

Precision and Recall: Evaluation metrics for classification. Precision is the fraction of positive identifications (e.g., system claiming "match") that were actually correct; recall (or sensitivity) is the fraction of actual positives (actual matches) that the system correctly identified. In biometric terms, high precision means few false matches (low FAR) and high recall means few missed matches (low FRR).

Software Engineering Terms

FastAPI: A modern, high-performance web framework for building APIs with Python. It is used in this project to create the backend RESTful service. FastAPI is chosen for its speed and ease of use (automatic data validation, async support) to handle image upload and verification requests efficiently.

React Native: An open-source framework for building mobile applications using JavaScript (or TypeScript), allowing deployment on both Android and iOS from a single codebase. In this project, the front-end mobile app is developed in React Native, which provides native camera access and a smooth user interface for capturing palm images and displaying results.

Docker: A containerization platform that packages software and its dependencies into containers. By using Docker for the CCNet model and backend, the project ensures that the application can run in a consistent environment across different machines (development, testing, production) without dependency issues. It simplifies deployment and scalability (containers can be replicated for load balancing).

RESTful API: Representational State Transfer (REST) is an architectural style for designing networked applications. A RESTful API uses standard HTTP methods (GET, POST, etc.) and status codes to provide a simple web service. In this report, the backend provides a RESTful API (with endpoints like '/verify') that the mobile app consumes to send/receive data.

Frontend/Backend: In software architecture, the frontend refers to the client-side interface (here, the mobile app) that users interact with, while the backend refers to the server-side component that handles the business logic, database, and computation (the FastAPI server and model). This separation allows independent development and scaling of the two ends.

CPU/GPU: Central Processing Unit and Graphics Processing Unit, respectively. CPUs handle general computing tasks, while GPUs accelerate parallel computations, particularly useful for deep learning. In this project, training was done on a GPU for efficiency, and the server should use a GPU for fast inference of the CCNet model to achieve real-time performance.

IEEE 802.11 / Wi-Fi (Networking): The wireless networking standard likely used by the mobile app to communicate with the backend in a real deployment (for example, in a bus station, the device might use Wi-Fi or cellular data to send verification requests). Mentioned here as a reminder that network reliability (latency, bandwidth) can affect the system.

SRS / SDS: Software Requirements Specification and Software Design Specification, respectively. These are formal documents (and also the names of sections of this report) that outline what the software should do (SRS) and how it should be designed (SDS). They ensure all team members and stakeholders have a clear blueprint of the system's purpose and structure.

SDK / API (Mobile Development): Software Development Kit / Application Programming Interface. For example, the project uses the Expo/React Native SDK for camera access, which provides an API (set of functions) like 'Camera.takePictureAsync()' to capture images. Understanding these terms is crucial for implementing and integrating various components of the system.

Version Control (Git): A system for tracking changes in source code during software development. The project's source code is managed with Git (and hosted on a platform like GitHub or Bitbucket), facilitating collaboration among team members, managing versions, and ensuring we can rollback or branch code as needed throughout development.