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PalmSecure - Revolutionizing Transport with Biometric Precision

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PalmSecure - Revolutionizing Transport with Biometric Precision

***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, operational efficiency, and seamless integration with existing infrastructure while paving the way for scalable, cross-industry applications.

***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).**

I. Introduction

The transport industry is an essential backbone of modern society, facilitating the movement of millions 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 due to their sensitivity to environmental factors, 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 nature that ensures hygienic operation, resilience to environmental variations, and high resistance to forgery. These characteristics make it an ideal candidate for enhancing security in the transport sector.

Recent advancements in deep learning, particularly the Comprehensive Competition Network (CCNet), have revolutionized palmprint recognition by introducing mechanisms to extract multi-order texture and spatial features. CCNet enhances recognition accuracy by combining channel and spatial information, offering a robust and scalable solution for biometric identification. These advancements align well with the dynamic and high-security requirements of the transport industry.

This project, titled "PalmSecure," aims to develop a cutting-edge palmprint recognition system tailored to the transport sector. By integrating the CCNet framework into a mobile application, the project seeks to offer a user-friendly, efficient, and scalable identity verification solution. The proposed system is designed to overcome the limitations of traditional biometric methods, addressing challenges related to hygiene, environmental sensitivity, and accuracy. Furthermore, the system has the potential for broader applications in industries such as banking, healthcare, and law enforcement, setting a new standard for security and efficiency.

Through systematic development, rigorous testing, and evaluation, this project aspires to deliver a transformative solution that enhances transport security and operational integrity while safeguarding passenger safety. The following sections will provide a comprehensive overview of the background, problem statement, and methodologies adopted to achieve these objectives.

II. Related Work

Biometric identification has become a cornerstone of modern security systems, offering robust mechanisms for personal identification and verification. Palmprint recognition, a subset of biometric technologies, has gained significant attention due to its hygienic, contactless nature and the richness of unique biometric features, such as ridges and minutiae. This section reviews prior advancements in palmprint recognition, focusing on traditional and modern techniques, the Comprehensive Competition Network (CCNet), and its applicability in various domains, with a particular emphasis on its relevance to our proposed project, *PalmSecure*.

A. Traditional Palmprint Recognition Methods

Initial efforts in palmprint recognition primarily relied on traditional methods, which included feature extraction techniques based on Gabor filters, wavelets, and statistical models. Zhang et al. proposed PalmCode, which used Gabor filters to extract texture features along predefined orientations, achieving moderate success in controlled environments [1]. However, these methods exhibited limitations in robustness, particularly in contactless and dynamic environments such as transportation systems. Sensitivity to lighting conditions, rotation, and image noise restricted their applicability in real-world scenarios [2].

Coding-based techniques like the Binary Orientation Co-occurrence Vector (BOCV) introduced binary coding schemes to improve feature representation and matching speed [4]. While these methods were computationally efficient, they often fell short in handling diverse imaging conditions, such as those prevalent in outdoor environments.

B. Deep Learning in Palmprint Recognition

The advent of deep learning has revolutionized the field of biometrics, enabling the extraction of robust and discriminative features from complex data. Neural networks, particularly Convolutional Neural Networks (CNNs), have been widely adopted for palmprint recognition. PalmNet, for example, combined Gabor filters and Principal Component Analysis (PCA) within a CNN architecture to achieve high accuracy in touchless palmprint recognition [4]. Despite its success, PalmNet's reliance on pre-trained filters and a static network structure posed challenges for adaptability to varying datasets and operational scenarios.
Competitive-based methods also evolved with deep learning. CompNet introduced learnable Gabor kernels, enabling the network to adaptively extract competitive features [3]. However, CompNet's focus on channel-based competition neglected the spatial relationships and higher-order texture information critical for capturing palmprint intricacies in high-traffic, noisy environments like transportation hubs.

C. Comprehensive Competition Network (CCNet)

CCNet emerged as a pivotal advancement in palmprint recognition by reformulating the traditional competition mechanism to incorporate both spatial and channel competition alongside multi-order texture features [1]. Unlike previous approaches that relied heavily on hand-crafted features or limited dimensional analysis, CCNet integrates spatial, channel, and order dimensions to extract comprehensive and robust features. This integration enhances the network's ability to distinguish between subtle texture variations, making it ideal for dynamic and high-security applications.
Extensive evaluations of CCNet on public datasets such as PolyU, IIT Delhi, and CASIA have demonstrated its superiority over traditional and CNN-based methods. CCNet achieved state-of-the-art results, including near-perfect accuracy and robustness against noise, environmental variations, and image distortions [2]. These attributes make CCNet a promising framework for real-world applications.

D. Application in Transportation Security

The transportation industry demands solutions that ensure passenger safety, operational integrity, and seamless user experience. Existing biometric systems, such as fingerprint and facial recognition, face significant challenges in these environments due to hygiene concerns, environmental sensitivity, and limited robustness. Our proposed project, *PalmSecure*, leverages CCNet to address these gaps.
PalmSecure aims to develop a mobile application for real-time palmprint verification tailored to the dynamic requirements of the transport sector. By utilizing CCNet, the system extracts multi-order texture features while maintaining efficiency and scalability. The non-contact nature of palmprint recognition enhances hygiene and usability in high-traffic environments, particularly critical during public health crises. Additionally, the robustness of CCNet ensures reliable operation under diverse lighting and weather conditions, addressing the shortcomings of traditional biometric systems.

E. Beyond Transportation: Future Applications

While the focus of this project is the transportation sector, the potential of CCNet-enabled palmprint recognition extends to other domains. Applications in banking, healthcare, and law enforcement demonstrate the versatility and scalability of the proposed system. For instance, CCNet's robust feature extraction and recognition capabilities can enhance secure access control in sensitive environments and support forensic investigations [1], [3].

F. Challenges and Research Directions

Despite its advantages, CCNet is not without challenges. The reliance on large training datasets and the computational complexity of multi-order feature extraction necessitate efficient optimization techniques. Additionally, cross-domain generalization, such as transitioning from transport applications to healthcare or law enforcement, requires further investigation to ensure adaptability without compromising accuracy. Future research should explore lightweight versions of CCNet for resource-constrained environments and investigate domain adaptation techniques to broaden its applicability [1].
In conclusion, the advancements in palmprint recognition, particularly through CCNet, offer transformative opportunities for biometric identification in the transport sector. By addressing the limitations of traditional systems and leveraging the strengths of deep learning, our proposed system sets a new standard for security, hygiene, and efficiency.

III. Methodology

This section outlines the methodology used to design and implement the Comprehensive Competition Network (CCNet) model for palmprint recognition. It includes details about the network architecture, datasets used, data preprocessing techniques, and model training process.

A. Comprehensive Competition Network (CCNet) Architecture

The Comprehensive Competition Network (CCNet) is designed to enhance palmprint recognition by integrating spatial, channel, and multi-order competition mechanisms. The architecture comprises the following components:

- **Learnable Gabor Filters:** The model employs learnable Gabor filters in its texture extraction layers, enabling automatic adaptation to varying input features.
- **Spatial Competition Module:** Extracts spatial competition features by analyzing the relationships between different regions of the palmprint image.
- **Channel Competition Module:** Extracts channel-based competitive features, determining the dominant texture responses along specific feature channels.
- **Multi-Order Competition Module:** Captures multi-scale and higher-order texture features to improve the robustness and discrimination of the recognition process.
- **Comprehensive Competition Mechanism:** Integrates spatial, channel, and multi-order competition mechanisms into a unified feature extraction framework.

The network's architecture ensures efficient feature extraction and improved recognition accuracy by leveraging the complementary nature of these components.

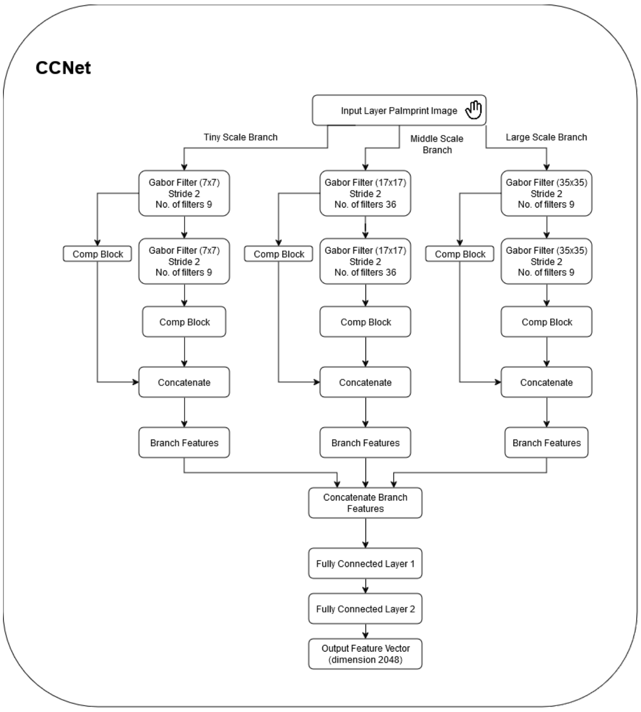

Fig. 1. Comprehensive Competition Network (CCNet) Architecture

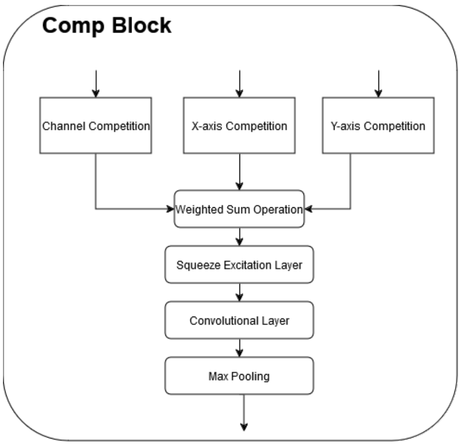

Fig. 2. Comprehensive Competition Network (CCNet) Architecture

B. Datasets

The model was trained and evaluated on the following datasets:

- **Tongji Contactless Palmprint Dataset:** This dataset contains 12,000 images captured from 300 individuals, with each individual contributing images of both palms. The dataset is characterized by its contactless nature, making it suitable for hygienic applications in public environments.
- **CASIA Palmprint Image Database:** The CASIA-Palmprint dataset consists of 5,502 gray-scale images captured from 312 individuals, with each subject contributing palmprint images from both left and right palms. Images are 8-bit JPEG files stored in the format `XXXX_XXXX_(m/f)_(l/r)_XX.jpg`, where:
  – `XXXX`: Unique identifier of individuals, ranging from 0000 to 0312.
  – `(m/f)`: Gender, with `m` for male and `f` for female.
  – `(l/r)`: Palm type, with `l` for left palm and `r` for right palm.
  – `XX`: Image index for the same type of palm, mostly ranging from 1 to 15.
- **COEP Palmprint Dataset:** The COEP (College of Engineering Pune) Palmprint Images Dataset is a well-structured dataset developed by the College of Engineering, Pune, to support research in palmprint recognition systems. It consists of 1,344 palmprint images collected from 168 individuals, with each participant contributing 8 images. This dataset plays a critical role in evaluating the performance and effectiveness of palmprint recognition algorithms under controlled conditions.
  The images include variations in hand orientation and positioning, introducing realistic challenges for palmprint recognition systems. Furthermore, the high resolution of the images enables the extraction of detailed features, which enhances the accuracy of recognition algorithms.
- **Locally Collected Dataset:** The dataset was created using contributions from 30 users, who submitted their data through a Google Form. Each user provided:
  – **Personal Information:** Name and Email (to differentiate users).
  – **Image Submissions:** Two images of each palm taken from variable distances.
  – **Key Characteristics of the Dataset:**
    ∗ **Data Collection:** Users independently captured images using their personal mobile phones, leading to variability in image quality, resolution, and environmental conditions.
    ∗ **Diversity:** The dataset includes images from a range of devices, lighting conditions, and user expertise levels, enhancing its real-world applicability.
    ∗ **Challenges:** The non-uniformity in image quality posed challenges for the model, but its performance underscores its robustness and generalization capabilities.

C. Data Preprocessing

Data preprocessing is a crucial step to enhance the quality of the training data and ensure consistency across different datasets. The following preprocessing steps were applied:

- **Image Resizing:** All images were resized to a uniform size of 224×224 pixels to maintain consistency in the input dimensions for the CCNet model.
- **Normalization:** Pixel intensity values were normalized to the range [0, 1] to standardize the data and improve model convergence.
- **Data Augmentation:** Techniques such as rotation, scaling, flipping, and illumination adjustments were

applied to increase the diversity of the training dataset and prevent overfitting.
- **Noise Reduction:** Median filtering was used to remove noise and enhance the visibility of palmprint features.

D. Model Training

The CCNet model was trained using the following datasets: Tongji, COEP and CASIA datasets. The training process involved the following steps:

- **Optimization Algorithm:** The Adam optimizer was used with an initial learning rate of 0.0005. The learning rate was decayed by a factor of 0.1 after every 10 epochs.
- **Loss Function:** A hybrid loss function combining cross-entropy loss and contrastive loss was used to optimize the network for accurate feature discrimination.
- **Batch Size:** A batch size of 256 was employed to balance computational efficiency and model convergence.
- **Validation Split:** 20% of the training data was used for validation to monitor model performance and prevent overfitting.
- **Training Environment:** The model was implemented using the PyTorch framework and trained on an NVIDIA RTX 3090 GPU.

E. Evaluation Metrics

The performance of the CCNet model was assessed using a comprehensive set of evaluation metrics, including **Equal Error Rate (EER)**, **False Acceptance Rate (FAR)**, **False Rejection Rate (FRR)**, and **Accuracy**. These metrics provide detailed insights into the model's robustness, generalization capability, and overall effectiveness in palmprint recognition.

1) Key Metrics and Their Relevance

1) **Equal Error Rate (EER):**
   - **Definition:** EER is the point where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR). It is a single value that reflects the balance between the two error rates.
   - **Relevance:** In biometric systems like palmprint recognition, EER is considered the most reliable metric because it directly measures the trade-off between security (low FAR) and usability (low FRR). A lower EER indicates better system performance, as it signifies fewer errors in both acceptance and rejection scenarios.
2) **False Acceptance Rate (FAR):**
   - **Definition:** FAR represents the percentage of instances where an unauthorized user is incorrectly accepted by the system.
   - **Relevance:** A low FAR is crucial in ensuring the security of the system, as it reduces the likelihood of unauthorized access.
3) **False Rejection Rate (FRR):**
   - **Definition:** FRR is the percentage of instances where a legitimate user is incorrectly rejected by the system.
   - **Relevance:** A low FRR is essential for user convenience, as it minimizes the chances of a genuine user being denied access.
4) **Accuracy:**
   - **Definition:** Accuracy is the ratio of correctly classified samples (both positive and negative) to the total number of samples.
   - **Relevance:** While accuracy is a widely used metric, it is less preferred in palmprint recognition due to its inability to account for the imbalance between FAR and FRR. In biometric systems, achieving high accuracy does not necessarily mean that the system is balanced or secure, as it may obscure the trade-offs between FAR and FRR.

2) Importance of EER over Accuracy

Although accuracy is easy to interpret, it fails to capture the nuanced trade-off between FAR and FRR, which is critical for evaluating biometric systems. EER, on the other hand, provides a balanced measure of the system's performance by directly addressing this trade-off. As such, EER is the preferred metric for assessing the reliability and effectiveness of palmprint recognition systems, especially in real-world applications where both security and usability are paramount.

IV. Findings and Discussion

This section outlines the findings from the training, cross-validation, and evaluation of the Comprehensive Competition Network (CCNet) model. The experimental settings and datasets used are detailed, followed by an analysis of the results, metrics, and challenges encountered during the process.

A. Experimental Settings and Datasets

The CCNet model was evaluated using two datasets: the Tongji Contactless Palmprint Dataset and the CASIA Palmprint Image Database. The experimental settings and details of the datasets are as follows:

1) Experimental Settings

- **Training Epochs:** 200.
- **Optimizer:** Adam with a learning rate of 0.0005, decayed by a factor of 0.1 every 10 epochs.
- **Loss Function:** A hybrid loss combining cross-entropy loss and contrastive loss for optimal feature discrimination.
- **Batch Size:** 256.
- **Training Environment:** NVIDIA RTX 3090 GPU with the PyTorch framework.

2) Datasets

- **Tongji Contactless Palmprint Dataset:** Contains 12,000 images captured from 300 individuals. Each individual contributed palm images from both hands, collected under a contactless setup to ensure hygiene.
- **CASIA Palmprint Image Dataset:** Consists of 5,502 grayscale images from 312 subjects. Images are annotated for gender (male or female), hand (left or right), and image index (1 to 15). The dataset provides diverse intra-class variations and is suitable for evaluating generalization.

- **COEP Palmprint Image Dataset:** Contains 1,344 high-resolution images (1600×1200 pixels) from 168 individuals, with each individual contributing 8 images. Captured using a digital camera in controlled conditions, the dataset includes variations in hand orientation and position, making it ideal for evaluating palmprint recognition algorithms in a controlled yet realistic setting.
- **Locally Collected Dataset:** Comprises 240 palm images from 30 users. Each user provided two images of the left palm (taken at 1 meter and 3 meters from the camera) and two of the right palm, using personal mobile phones. The dataset exhibits variability in image quality, resolution, and environmental conditions, reflecting real-world diversity.

B. Results

1) Tongji Dataset

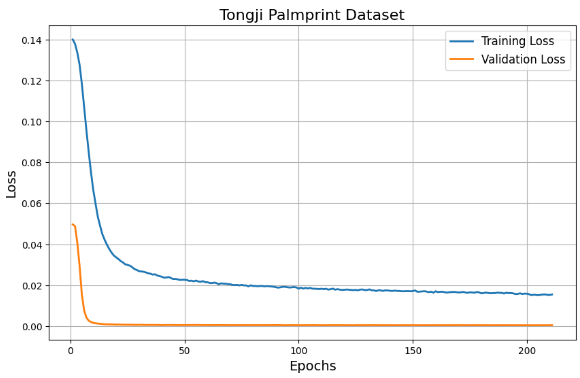

Fig. 3. Tongji Dataset: Loss

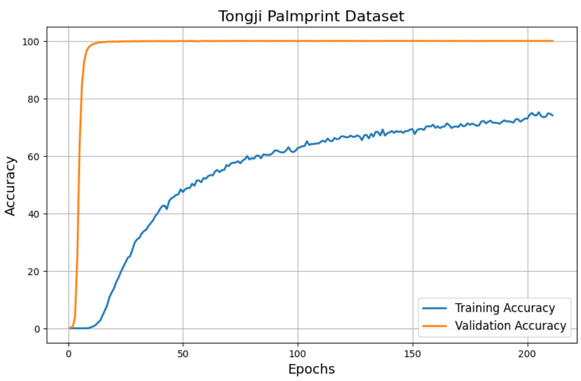

Fig. 4. Tongji Dataset: Model Accuracy

- **Training Loss and Validation Loss:**
  - Training loss: 0.0154
  - Validation loss: 0.0004
- **Matching Score Distribution:**
  - Inner-class scores: [min, max] = [0.0000, 0.5313], mean $\pm$ std = 0.2543 $\pm$ 0.0716.
  - Outer-class scores: [min, max] = [0.3048, 0.6474], mean $\pm$ std = 0.4971 $\pm$ 0.0298.
- **Equal Error Rate (EER):** The model achieved an EER of 0.4%.
- **Accuracy:** The model achieved a testing accuracy of 94%.

a) Comparative Analysis of Results: Our implementation achieved a low Equal Error Rate (EER) of 0.4% on the Tongji dataset, closely matching the state-of-the-art performance of CCM[1]. Upon closer examination, we observed that both our implementation and CCM demonstrated excellent separation in inner-class and outer-class score distributions, indicating effective feature learning and matching[1]. This suggests that both methods are highly accurate in distinguishing between genuine and impostor pairs.

2) CASIA Dataset

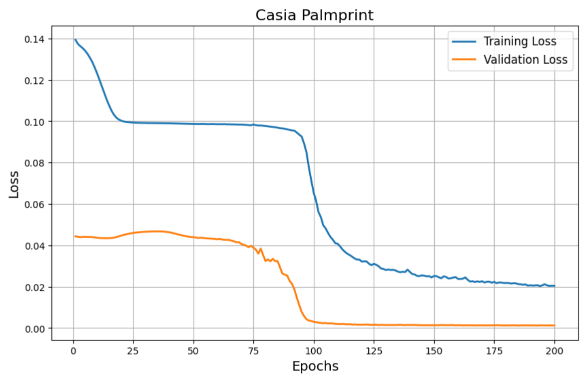

Fig. 5. CASIA Dataset: Loss

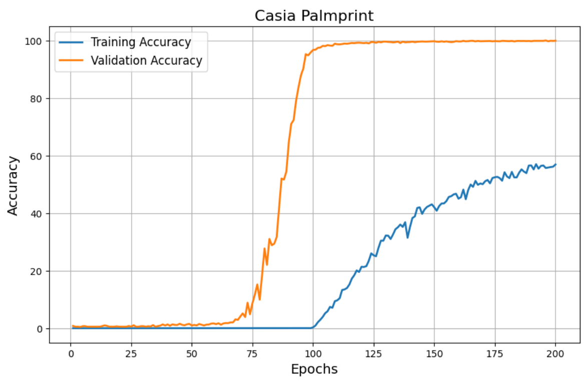

Fig. 6. CASIA Dataset: Model Accuracy

- **Training Loss and Validation Loss:**
  - Training loss: 0.0204.
  - Validation loss: 0.0013.
- **Matching Score Distribution:**
  - Inner-class scores: [min, max] = [0.0000, 0.5916], mean ± std = 0.3859 ± 0.0913.
  - Outer-class scores: [min, max] = [0.2146, 0.6788], mean ± std = 0.4931 ± 0.0402.
- **Equal Error Rate (EER):** The model achieved an EER of 20%.
- **Accuracy:** The model achieved a testing accuracy of 84%.

3) COEP Palmprint Dataset

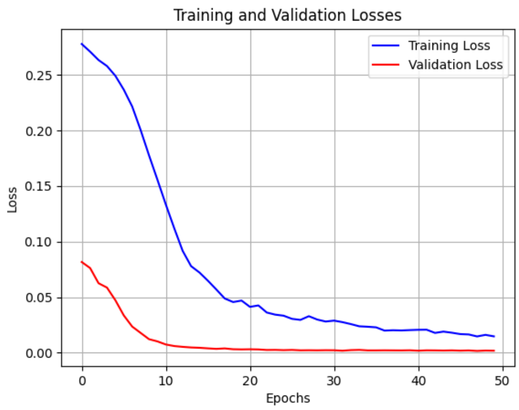

Fig. 7. COEP Dataset: Loss

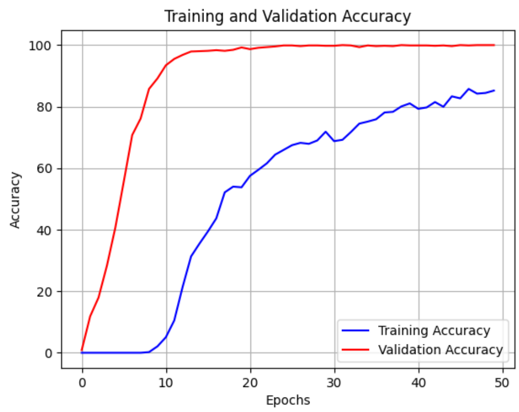

Fig. 8. COEP Dataset: Model Accuracy

- **Training Loss and Validation Loss:**
  - Training loss: 0.0147
  - Validation loss: 0.0017
- **Matching Score Distribution:**
  - Inner-class scores: [min, max] = [0.0000, 0.4931], mean ± std = 0.1861 ± 0.1258.
  - Outer class scores: [min, max] = [0.2616, 0.6346], mean ± std = 0.4858 ± 0.0453.
- **Equal Error Rate (EER):** The model achieved an EER of approximately 5.77%.
- **Accuracy:** The model achieved a testing accuracy of 96%.

C. Discussion

The findings reveal significant insights into the performance of the CCNet model on the Tongji, COEP and CASIA datasets. The following metrics and observations were considered:

1) Metrics Used

- **Equal Error Rate (EER):** Indicates the point where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR). A lower EER signifies better discrimination between genuine and impostor matches.
- **Matching Score Distribution:** Examines the separation between inner-class and outer-class scores. Well-separated distributions improve recognition reliability.
- **Training and Validation Loss:** Monitors model convergence and overfitting tendencies.
- **FAR-FRR Curves:** Visualize the trade-offs between false positives and false negatives at varying thresholds.

2) Analysis of Results

a) Performance on Tongji Dataset:

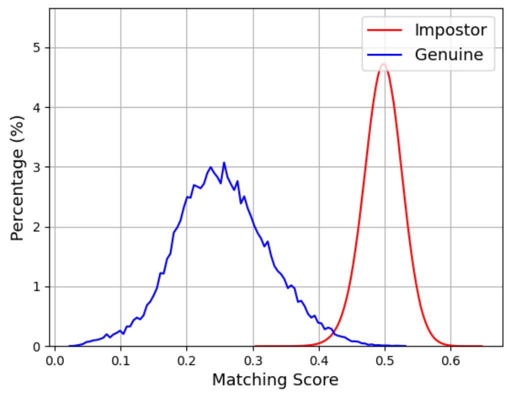

Fig. 9. Tongji Dataset: Genuine-Imposter Matching Score Distribution

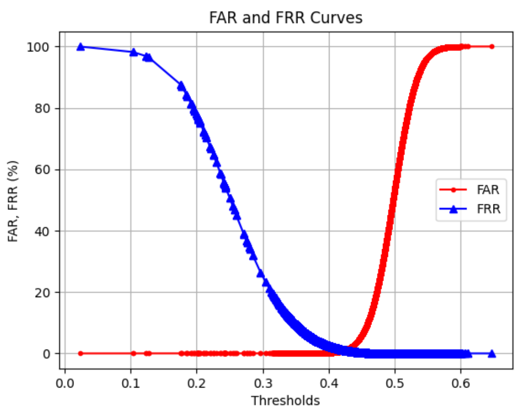

Fig. 10. Tongji Dataset: FAR-FRR curves

The CCNet model demonstrated robust performance with a low EER of 0.4%. The inner-class and outer-class scores were well-separated, reflected by the low overlap in the score distributions. This highlights the effectiveness of CCNet's feature extraction mechanisms, particularly in a contactless setup. However, the training accuracy of 74.78% suggests scope for improvement, possibly through increasing the training time.

b) Performance on CASIA Dataset:

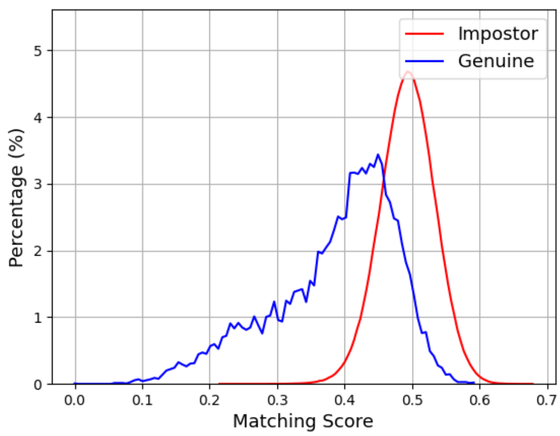

Fig. 11. CASIA Dataset: Genuine-Imposter Matching Score Distribution

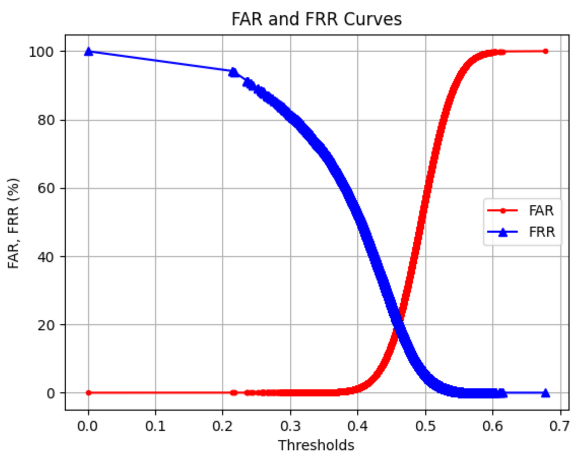

Fig. 12. CASIA Dataset: FAR-FRR curves

The higher EER of 20% on the CASIA dataset indicates challenges in generalization, attributed to greater intra-class variability and noise. While the inner-class and outer-class scores were distinguishable, the overlap in distributions suggests potential improvements through dataset-specific tuning of the CCNet architecture.

c) Performance on COEP Dataset:

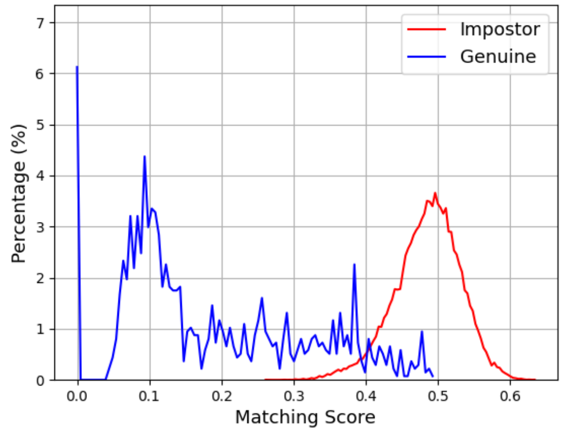

Fig. 13. COEP Dataset: Genuine-Imposter Matching Score Distribution

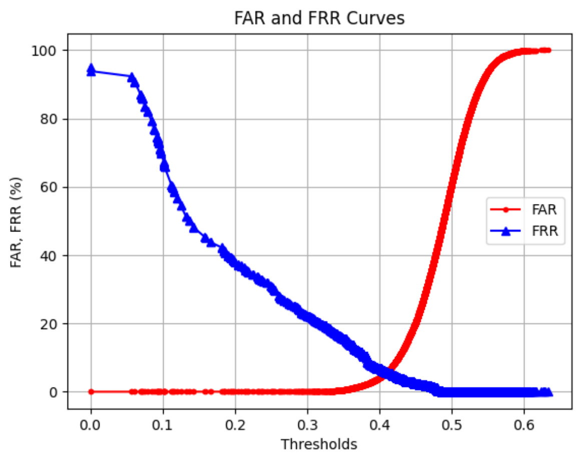

Fig. 14. COEP Dataset: FAR-FRR curves

The CCNet model exhibited strong performance on the COEP Palmprint dataset, achieving a low Equal Error Rate (EER) of approximately 5.77%. The inner-class and outer-class scores demonstrated good separation, as indicated by the minimal overlap in their distributions. This underscores the model's ability to effectively extract discriminative features in a contactless palmprint recognition setup. The final training accuracy of 85.76% and validation accuracy reaching 100.0% reflect the model's high reliability.

d) Challenges:

- **High Training Time:** Training CCNet on high-resolution palmprint images required significant computational resources and time.
- **Dataset Preparation:** Collecting and preprocessing diverse datasets posed challenges, particularly in ensuring consistent quality and sufficient variation.
- **Hyperparameter Optimization:** Achieving the right balance of hyperparameters, including learning rate and loss function weights, required extensive experimentation.

D. Testing on the Local Dataset

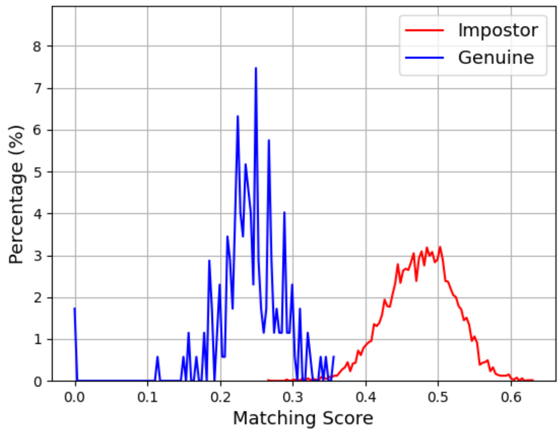

Fig. 15. Locally Collected Dataset: Genuine-Imposter Matching Score Distribution

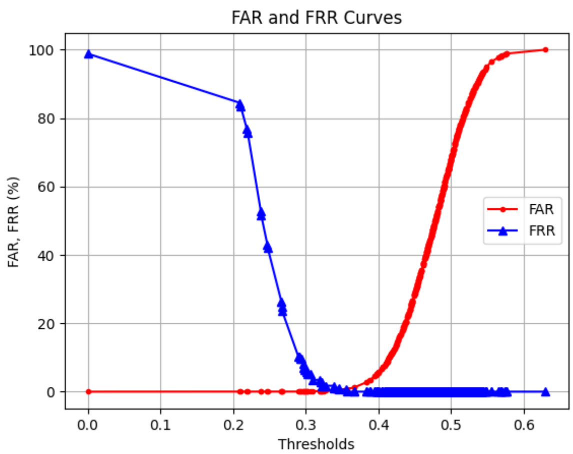

Fig. 16. Locally Collected Dataset: FAR-FRR curves

The model has been evaluated on a locally collected dataset, with promising results demonstrating its robustness and applicability in real-world scenarios. The testing accuracy achieved was an impressive **99%**, with the **Equal Error Rate (EER)** as low as **0.1%**, indicating high reliability and precision.
These results underscore the CCNet model's potential for practical deployment. Despite variations in image quality due to differences in user-collected data, the model's performance remains consistent and robust. This highlights its adaptability to diverse conditions and its potential applicability in scenarios involving non-standardized inputs.

E. Summary Of Results

The results obtained underscore both the strengths and potential areas for improvement in the CCNet model. The evaluation on the COEP Palmprint dataset demonstrates the model's robust performance, achieving a low Equal Error Rate (EER) of approximately 5.77%. The clear separation between inner-class and outer-class scores, as evidenced by the minimal overlap in their distributions, highlights the effectiveness of CCNet's feature extraction mechanisms in a contactless palmprint recognition setup. The high validation accuracy of 100.0% further reinforces the model's ability to generalize well on this dataset. However, the training accuracy of 85.76% points to a possible scope for refinement, potentially through increased training iterations.
Notably, the evaluation on the locally collected dataset provides valuable insights into the CCNet model's adaptability to real-world conditions. The model demonstrated impressive performance, effectively handling variations in input quality and environmental factors often encountered in non-standardized, user-collected datasets. This success suggests that CCNet can be reliably deployed in practical scenarios, where such challenges are prevalent.
Despite these promising results, the disparity in performance across different datasets suggests a need for further enhancements. In addition, additional evaluations on larger and more varied datasets would be instrumental in validating its generalization capabilities and ensuring its readiness for large-scale deployment in real-world applications.

V. Conclusion

This project explored the implementation and evaluation of the Comprehensive Competition Network (CCNet) for palmprint recognition, targeting the security needs of the transport industry. By leveraging advanced feature extraction techniques and datasets like Tongji, CASIA, COEP, and a locally collected dataset, the project demonstrated the potential of CCNet to address the challenges of traditional biometric systems. The findings highlight both the strengths and limitations of the proposed approach, paving the way for future improvements and applications.

A. Key Findings

- **Effectiveness of CCNet:** The CCNet model demonstrated exceptional performance on the Tongji dataset, achieving a low Equal Error Rate (EER) of 0.4% and well-separated matching score distributions. These results validate the model's ability to extract highly discriminative features for accurate palmprint recognition in contactless environments, reinforcing its reliability in controlled settings.
- **Challenges on CASIA Dataset:** The CASIA dataset posed significant challenges, with the model achieving a higher EER of 20%. This was attributed to the dataset's variability in image quality, lighting conditions, and intra-class differences. These results highlight the need for further optimization of preprocessing techniques, data augmentation strategies, and hyperparameter tuning to enhance the model's robustness on diverse datasets.
- **Performance on COEP Palmprint Dataset:** The CCNet model exhibited robust performance on the COEP Palmprint dataset, achieving an Equal Error Rate (EER) of 5.77% with a clear separation between inner-class and outer-class scores. The validation accuracy reached 100%, demonstrating the model's abil-

ity to generalize effectively on this dataset. Furthermore, the matching score distribution showed that the inner-class scores ranged from 0.0000 to 0.4931, with a mean $\pm$ standard deviation of 0.1861 $\pm$ 0.1258, while the outer-class scores ranged from 0.2616 to 0.6346, with a mean $\pm$ standard deviation of 0.4858 $\pm$ 0.0453, reflecting the model's ability to extract features with strong discriminative power in contactless scenarios.

- **Performance on Local Dataset:** Testing on the locally collected dataset yielded outstanding results, demonstrating the model's adaptability to real-world scenarios. The local dataset, contributed by 30 users through a Google Form, introduced variability in image quality, environmental conditions, and device types. Despite these challenges, the model achieved:
  - **Accuracy:** 99% on the local dataset, showcasing its ability to perform reliably with non-standardized and user-collected data.
  - **Equal Error Rate (EER):** As low as 0.1%, indicating minimal false positives and false negatives.

  These results highlight the model's robustness and adaptability, making it a promising candidate for deployment in real-world applications.
- **Scalability for Mobile Applications:** The findings from the local dataset also underscore the feasibility of integrating CCNet into a mobile application for real-time palmprint verification. This approach offers a non-contact, hygienic, and efficient solution for various sectors, including transportation, where user authentication needs to be rapid, accurate, and secure. The model's ability to handle data from diverse devices and settings adds to its scalability for large-scale adoption.

B. Goals for FYP 2

The second phase of this project will focus on expanding and refining the current implementation to achieve the following goals:

- **Completion of Local Dataset Testing:**
  - Finalize the collection and preprocessing of the local dataset.
  - Conduct extensive evaluations to assess the model's performance under real-world conditions, including variations in lighting, hand positioning, and environmental factors.
  - Identify key areas for improvement based on testing outcomes.
- **Performance Enhancement Techniques:**
  - Implement advanced preprocessing techniques such as adaptive normalization, noise reduction, and data augmentation tailored to the local dataset.
  - Optimize hyperparameters, including learning rate, loss function weights, and batch size, to improve accuracy and reduce error rates.
- **Development of Mobile Application:**
  - Design and develop a mobile application named *PalmSecure*, integrating the CCNet model for real-time palmprint recognition.
  - Ensure the application is user-friendly, secure, and efficient, capable of handling real-time data capture, preprocessing, and verification.
  - Incorporate features secure data handling, and seamless integration with transport infrastructure.

C. Closing Remarks

The initial phase of this project established a strong foundation for leveraging CCNet in palmprint recognition, demonstrating its potential to revolutionize biometric security in the transport industry. While challenges remain, particularly with dataset variability and real-world testing, the insights gained provide a clear direction for the second phase of development. By addressing these challenges and expanding the system's capabilities, this project aims to deliver a robust, scalable, and impactful solution that sets a new standard in biometric security.

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APPENDICES

Software Requirements Specification (SRS)

The Software Requirements Specification (SRS) for PalmSecure outlines the system's functional and non-functional requirements. It aims to implement a palmprint recognition system using CCNet, ensuring security, scalability, and real-time performance. The SRS also defines the project's scope and stakeholders.

Software Design Specification (SDS)

The Software Design Specification provides a detailed overview of the system's technical architecture and design. It adopts a modular design approach, prioritizing scalability, maintainability, and security. The system architecture includes CCNet for palmprint verification, a mobile app for user interaction, and backend services for data processing and storage.

Note

Both the SRS and SDS documents are available online and have been submitted as part of the project deliverables. They provide in-depth details for stakeholders seeking a thorough understanding of the system's requirements and design strategies.