LITERATURE REVIEW & ELABORATION OF PROBLEM

PALMSECURE - REVOLUTIONIZING TRANSPORT WITH BIOMETRIC PRECISION

VERSION: 00.01

Project Code: F24-10

Internal Supervisor: Dr. Muhammad Atif Tahir

Project Team:

- Muhammad Talha Bilal (K21-3349)
- Muhammad Hamza (K21-4579)
- Muhammad Salar (K21-4619)

Submission Date: December 11, 2024

Foundation of Advancement of Science and Technology
National University of Computer and Emerging Sciences
Department of Computer Science
Karachi, Pakistan

Document History

Version	Name of Person	Date	Description of Change
00.01	Talha, Hamza, Salar	Nov 17, 2024	Added Abstract, Background and Justification, Problem Statement
00.01	Talha, Hamza, Salar	Nov 24, 2024	Added Literature Review
00.01	Talha, Hamza, Salar	Dec 1, 2024	Added Methodology
00.01	Talha, Hamza, Salar	Dec 8, 2024	Results, Conclusion, Expected Outcomes

Distribution List

Name	Role
Dr. Muhammad Atif Tahir	Supervisor
Dr. Ghufran Ahmed	Internal Jury Member
Mr. Fahad Hussain	Internal Jury Member
Mr. Saad Manzoor	FYP Project Coordinator

Document Sign-Off

Version	Sign-off Authority	Project Role	Sign-off Date
00.01	Dr. Muhammad Atif Tahir	Supervisor	December 11, 2024

Contents

1 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.

2 Background and Justification

The transport industry faces increasing threats to security, operational integrity, and passenger safety. Traditional biometric systems, such as fingerprint and facial recognition, have been unable to meet the growing demands for reliable, hygienic, and accurate verification in high-traffic environments.

Palmprint recognition has emerged as a promising alternative, owing to its:

- **Non-contact Nature:** Ensures hygienic and efficient operation.
- **Resistance to Environmental Factors:** Operates effectively under diverse lighting and temperature conditions.
- **Unique and Stable Features:** Offers a robust biometric signature less prone to forgery or duplication.

Biometric identification has become increasingly prevalent in modern society, with applications in electronic payment, entrance control, and forensic identification. Palmprint recognition has emerged as a reliable and efficient solution for person identification due to its rich biometric information and high antispoof capability. This project seeks to integrate these advancements into a scalable solution tailored to the dynamic requirements of the transport industry.

3 Problem Statement

The transport industry faces critical security challenges that threaten passenger safety, operational efficiency, and revenue integrity. Current biometric systems fail to meet industry demands due to:

- **Environmental Sensitivity:** Systems relying on fingerprints and facial recognition fail in poor lighting or extreme weather.
- **Hygiene Concerns:** Contact-based methods heighten disease transmission risks in public environments.
- **Inaccuracy Under Diverse Conditions:** Limited feature extraction reduces the effectiveness of traditional systems.

This project proposes a palmprint recognition system using the CCNet approach to:

- Offer non-contact verification for hygiene safety.
- Achieve superior accuracy through multi-order texture feature analysis.
- Provide an efficient, user-friendly mobile application for the transport sector.

4 Literature Review

Palmprint images can be categorized into touch-based and touchless, with the latter preferred for their hygiene and convenience, especially during the current epidemic situation.
Palmprint recognition has gained significant attention in recent years due to its high accuracy and reliability. Various approaches have been proposed to improve palmprint recognition, including the Comprehensive Competition Mechanism [1], Coordinate Attention (CA) [6], Competitive Neural Network (CNN) [7], CO3Net [2], and 3D Gabor template with block feature refinement [5] and PalmNet [4].
The Comprehensive Competition Network approach [1] proposes a novel framework for palmprint recognition by introducing a comprehensive competition mechanism. This mechanism enables the network to learn robust features by competing with each other. However, this approach relies on a complex network architecture and requires a large amount of training data.
The CA approach [2] introduces a coordinated attention mechanism to selectively focus on informative regions in palmprint images. This approach has shown promising results in palmprint recognition, but its reliance on supervised training and complex network architecture may limit its generalizability.
The CNN approach [3] proposes a competitive neural network for palmprint recognition. This approach enables the network to learn discriminative features by competing with each other. However, this approach requires a large amount of training data and may not generalize well to unseen data.
The CO3Net approach [4] proposes a coordinate-aware contrastive competitive neural network for palmprint recognition. This approach enables the network to learn robust features by leveraging coordinate information and contrastive learning. However, this approach relies on a complex network architecture and requires a large amount of training data.
The 3D Gabor template with block feature refinement approach [5] proposes a novel framework for touchless palmprint recognition. This approach enables the network to learn robust features by leveraging 3D Gabor templates and block feature refinement. However, this approach may not generalize well to unseen data and requires a large amount of training data.
PalmNet [6] proposes a Gabor-PCA convolutional network for touchless palmprint recognition. This approach has shown promising results in palmprint recognition, but its reliance on pre-trained filters and complex network architecture limits its generalizability.

To overcome the limitations of these approaches, our project proposes the implementation of the Comprehensive Competition Network approach [1]. Comprehensive Competition Network has demonstrated superior performance in palmprint recognition by extracting multi-order texture and spatial features. Comprehensive Competition Network addresses the limitations of existing approaches by providing robust feature extraction mechanisms, eliminating the need for class labels or pre-trained filters, improving recognition accuracy and robustness, and reducing computational complexity and memory requirements.

4.1 Palmprint Recognition Techniques

4.1.1 Overview of Approaches

Palmprint recognition methods can be broadly categorized into:

- **Subspace-based Methods:** Reduce dimensionality of palmprint features using techniques like PCA.
- **Statistical Methods:** Use handcrafted statistical measures for feature extraction.
- **Coding-based Methods:** Employ Gabor filters to analyze palmprint textures.
- **Deep Learning Methods:** Utilize neural networks for robust feature learning.

4.1.2 Limitations

Existing approaches often face limitations such as:

- High sensitivity to lighting and imaging conditions.
- Reliance on manually designed filters, which are less adaptable to diverse datasets.
- Limited ability to incorporate spatial competition relationships.

4.2 The Comprehensive Competition Mechanism (CCM)

The CCM leverages multi-order texture analysis and spatial-channel competition to address these limitations. This project builds on CCM's ability to:

- Extract high-order features for enhanced discrimination.
- Combine spatial and channel-based competition mechanisms for improved accuracy.

5 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.

5.1 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.

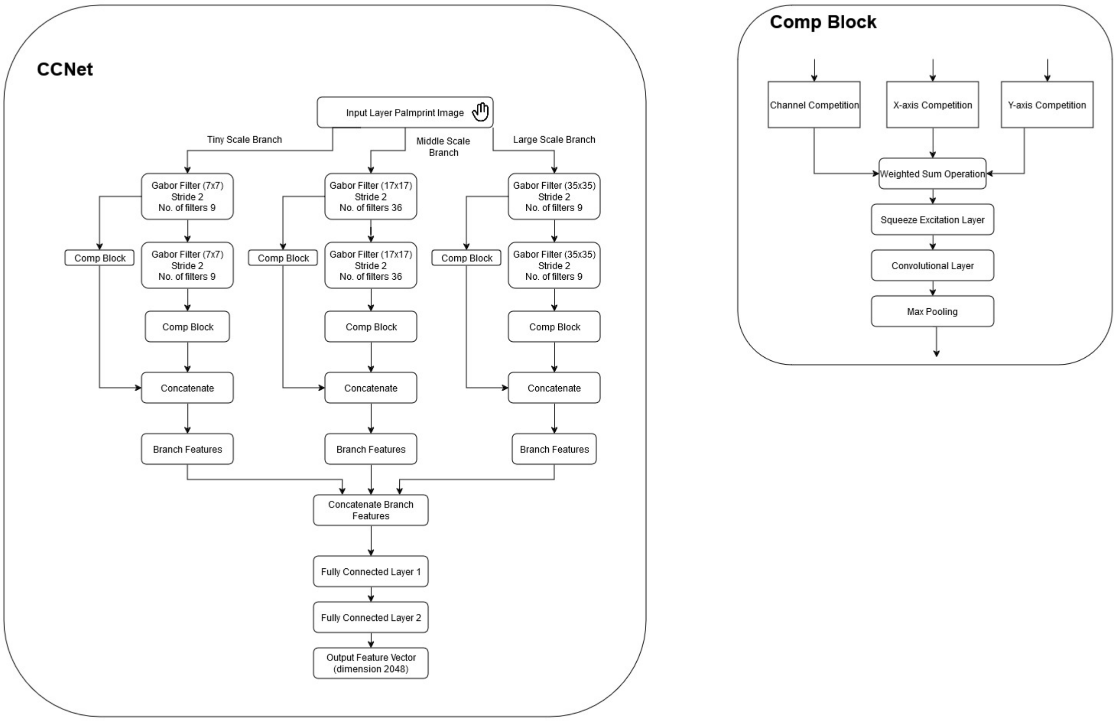

Figure 1: Comprehensive Competition Network (CCNet) Architecture

5.2 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 contributing images of both palms. The dataset is characterized by its contactless nature, making it suitable for hygienic applications in public environments [8].

- **CASIA Palmprint Image Database:** The CASIA-Palmprint dataset consists of 5,502 grayscale images captured from 312 individuals, with each subject contributing palmprint images from both left and right palms[9]. Images are 8-bit JPEG files stored in the format `XXXX_XXXX_(m/f)_(l` 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[10].

5.3 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.

5.4 Model Training

The CCNet model was trained using a combination of the Tongji 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:** 30% 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.

6 Results

6.1 Tongji Dataset

- **Training Loss and Validation Loss:**
  - Training loss: 0.0154
  - Validation loss: 0.0004
- **Matching Score Distribution:**
  - Inner-class scores: [min, max] = [0.0229, 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%.

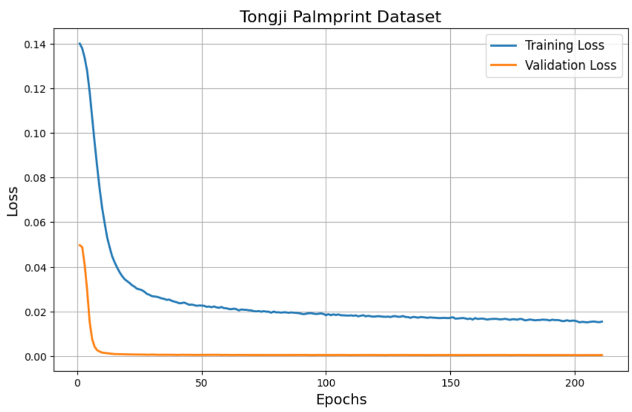

Figure 2: Tongji Dataset: Loss

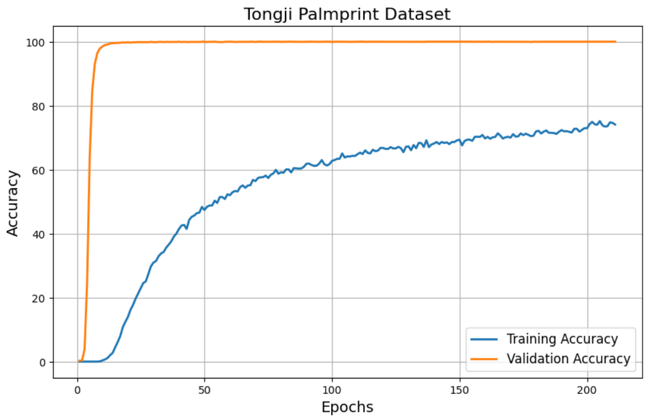

Figure 3: Tongji Dataset: Model Accuracy

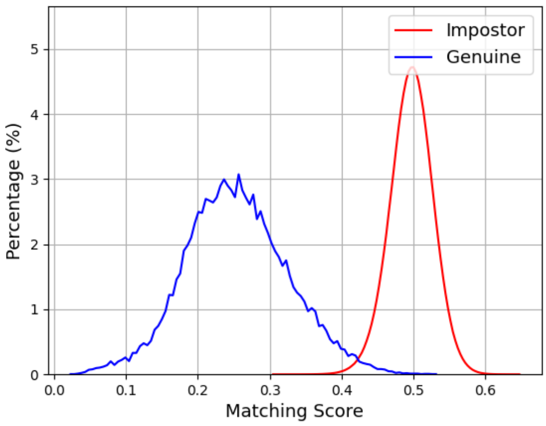

Figure 4: Tongji Dataset: Genuine-Imposter Matching Score Distribution

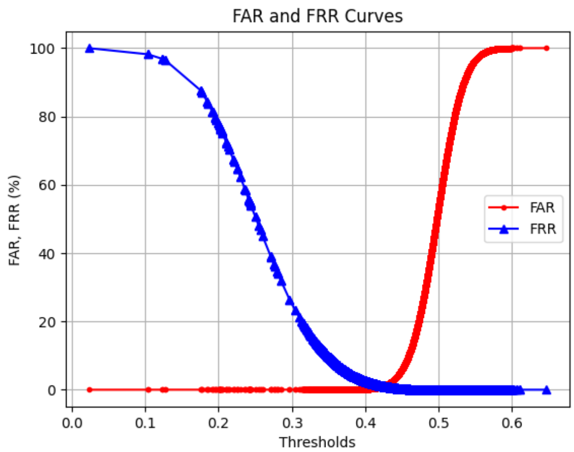

Figure 5: Tongji Dataset: FAR-FRR Curves

6.2 CASIA Dataset

- **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 $\pm$ std = 0.3859 $\pm$ 0.0913.
  - Outer-class scores: [min, max] = [0.2146, 0.6788], mean $\pm$ std = 0.4931 $\pm$ 0.0402.
- **Equal Error Rate (EER):** The model achieved an EER of 20%.

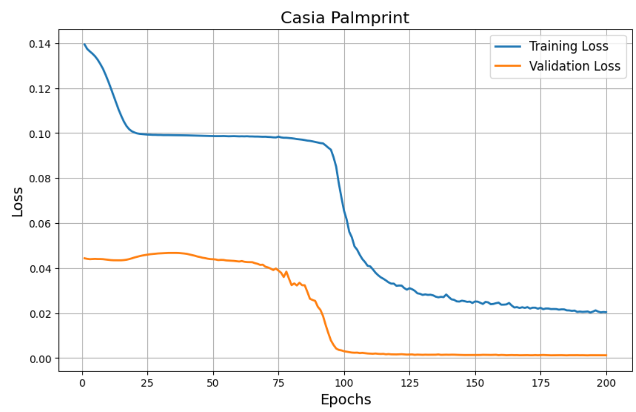

Figure 6: CASIA Dataset: Loss

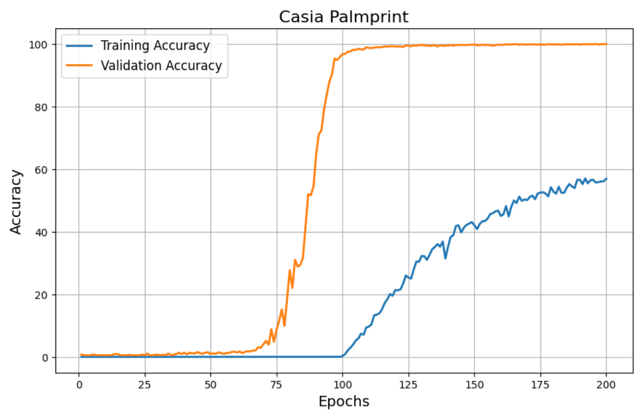

Figure 7: CASIA Dataset: Model Accuracy

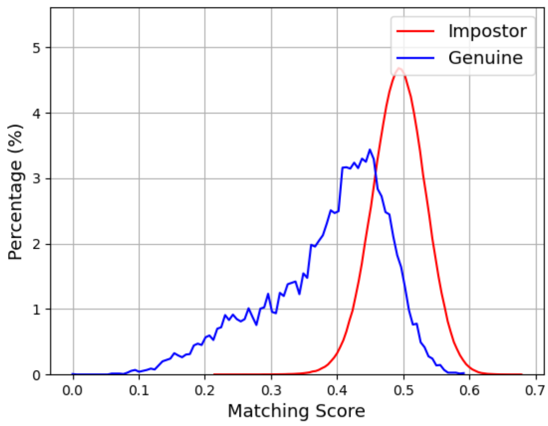

Figure 8: CASIA Dataset: Genuine-Imposter Matching Score Distribution

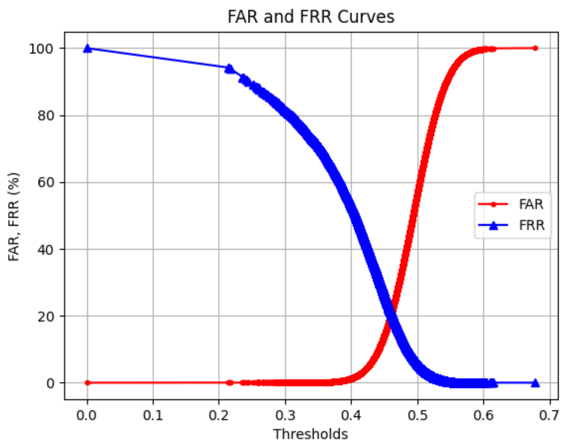

Figure 9: CASIA Dataset: FAR-FRR Curves

6.3 COEP Palmprint Dataset

- **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 $\pm$ std = 0.1861 $\pm$ 0.1258.
  - Outer-class scores: [min, max] = [0.2616, 0.6346], mean $\pm$ std = 0.4858 $\pm$ 0.0453.
- **Equal Error Rate (EER):** The model achieved an EER of 5.77%.

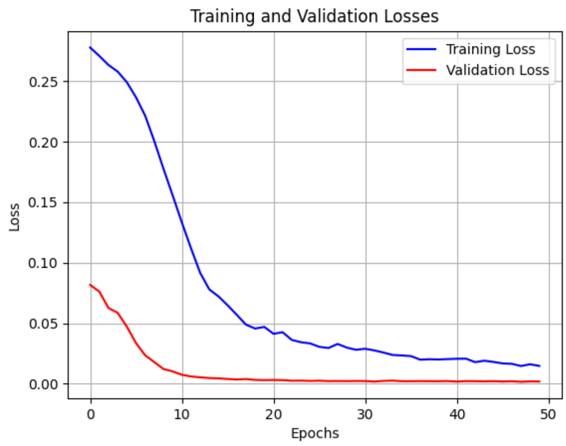

Figure 10: COEP Dataset: Loss

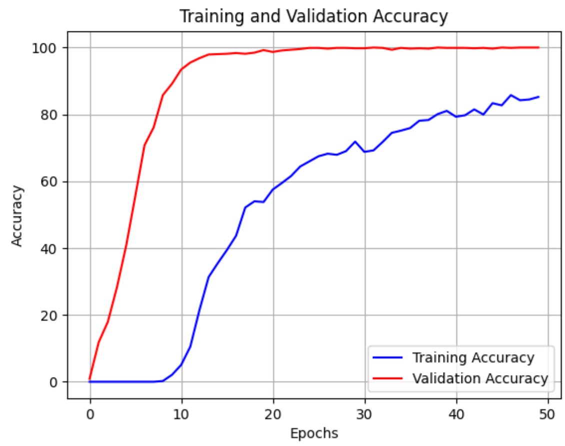

Figure 11: COEP Dataset: Model Accuracy

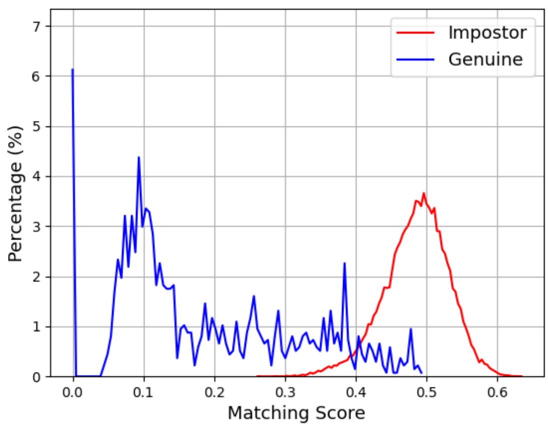

Figure 12: COEP Dataset: Genuine-Imposter Matching Score Distribution

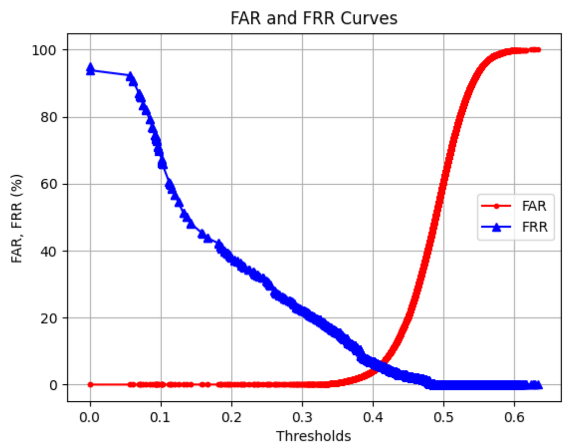

Figure 13: COEP Dataset: FAR-FRR Curves

6.4 Discussion

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

6.4.1 Metrics Used

- **False Acceptance Rate (FAR):** The percentage of impostor attempts that are incorrectly accepted as genuine.
  FAR = (Number of False Acceptances) / (Total Number of Impostor Attempts)

- **False Rejection Rate (FRR):** The percentage of genuine attempts that are incorrectly rejected.
  FRR = (Number of False Rejections) / (Total Number of Genuine Attempts)

- **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.

Both FAR and FRR are crucial metrics in evaluating the performance of a palmprint recognition system. A good palmprint recognition system should aim to minimize both FAR and FRR.

- A low FAR ensures that the system is secure and resistant to impostor attempts.
- A low FRR ensures that the system is user-friendly and minimizes the frustration caused by false rejections.

The Equal Error Rate (EER) is the point at which FAR equals FRR, providing a single metric to evaluate the overall performance of the palmprint recognition system.

6.4.2 Analysis of Results

Performance on Tongji Dataset: The CCNet model exhibited strong performance on the Tongji dataset, achieving a low Equal Error Rate (EER) of 0.4%. The clear separation between inner-class and outer-class scores, as evidenced by minimal overlap in the score distributions, highlights the model's robust feature extraction capabilities in a contactless palmprint recognition setup. However, the model's training accuracy of 74.78% indicates room for improvement, through increased training time.
When compared to the results presented in the Comprehensive Competition Mechanism (CCM)[1], which also evaluated the Tongji dataset, our EER of 0.4% closely aligns with the state-of-the-art performance reported in the CCM study. The CCM approach also demonstrated sub-1% EER on this dataset, leveraging its multi-scale texture branches and learnable Gabor filters to achieve such a low error rate. One notable advantage of the CCM approach is its integration of spatial competition mechanisms, which enhance feature discriminability.

Performance on CASIA Dataset: 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.

Performance on COEP Palmprint Dataset: The CCNet model demonstrated strong performance on the COEP Palmprint dataset, achieving a low EER of 5.77%, reflecting minimal overlap between inner-class and outer-class score distributions. The inner-class scores ranged from 0.0000 to 0.4931 with a mean $\pm$ std of 0.1861 ± 0.1258, while the outer-class scores ranged from 0.2616 to 0.6346 with a mean $\pm$ std of 0.4858 ± 0.0453. The validation accuracy of 100.0% indicates the model's excellent generalization on this dataset.

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.

7 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 and CASIA, 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.

7.1 Key Findings

- **Effectiveness of CCNet:** The CCNet model demonstrated robust 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 architecture's ability to extract discriminative features for reliable palmprint recognition in contactless environments.
- **Challenges on CASIA Dataset:** The CASIA dataset posed challenges with a higher EER of 20%, highlighting the need for further optimization. The variability in image quality and intra-class differences in the dataset necessitate advanced preprocessing and tuning techniques.
- **Performance on COEP Palmprint Dataset:** On the COEP Palmprint dataset, the CCNet model exhibited robust performance, achieving an EER of 5.77% with a clear separation between inner-class and outer-class scores. These results validate the ability of the architecture to extract discriminative features for reliable palmprint recognition in contactless environments.
- **Preliminary Testing on Local Dataset:** Although still in progress, testing on the local dataset aims to evaluate the model's practical utility in real-world scenarios. This will provide additional insights into its robustness and generalizability.
- **Scalability for Mobile Applications:** The findings underscore the feasibility of integrating CCNet into a mobile application for real-time palmprint verification, offering a non-contact, hygienic, and efficient solution for the transport sector.

8 Expected Outcomes

This project is designed to deliver a comprehensive palmprint recognition system leveraging the Comprehensive Competition Network (CCNet). The expected outcomes are divided into two phases: FYP 1, which focuses on model development and initial testing, and FYP 2, which expands on the work to include real-world testing, performance enhancements, and mobile application development.

8.1 Outcomes of FYP 1

The first phase (FYP 1) lays the foundation for the project, focusing on the development, training, and evaluation of the CCNet model. The expected outcomes for FYP 1 include:

- **Model Development:** Successful implementation of the CCNet model for palmprint recognition, designed to integrate spatial, channel, and multi-order competition mechanisms for robust feature extraction.

- **Dataset Integration and Training:**
  - Training the CCNet model on benchmark datasets such as Tongji Contactless Palmprint Dataset, CASIA Palmprint Image Database, COEP Palmprint Dataset and Locally Collected Dataset.
  - Ensuring the model achieves competitive performance metrics such as low Equal Error Rates (EER) and well-separated matching score distributions.
- **Performance Evaluation:**
  - Detailed analysis of model performance using metrics such as accuracy, loss curves, ROC curves, and FAR-FRR curves.
  - Identification of key areas for improvement, including preprocessing techniques, dataset variability, and hyperparameter optimization.
- **Preliminary Local Testing:**
  - Initial testing of the CCNet model on a locally collected dataset to evaluate its generalizability to real-world conditions.
  - Gathering insights into potential challenges in local dataset processing and application-specific performance requirements.

8.2 Outcomes of FYP 2

The second phase (FYP 2) builds upon the outcomes of FYP 1 by refining the model, conducting comprehensive real-world testing, and developing a mobile application for practical deployment. The expected outcomes for FYP 2 include:

- **Completion of Local Dataset Testing:**
  - Final testing of the CCNet model on the local dataset, capturing diverse environmental conditions and operational scenarios.
  - Detailed evaluation of the model's performance on the local dataset, including updates to the preprocessing pipeline and hyperparameters based on testing results.
- **Mobile Application Development:**
  - Development of the *PalmSecure* mobile application, integrating the CCNet model for real-time palmprint recognition.
  - Features to include efficient data capture, secure processing, and a user-friendly interface.
  - Ensuring the application supports multi-language interfaces and secure integration with transport infrastructure.
- **Real-World Validation:**
  - Validation of the mobile application through pilot testing in the transport sector, assessing usability and reliability under real-world conditions.
  - Exploring the potential for cross-industry applications in areas such as banking, healthcare, and access control systems.

8.3 Broader Impact

By the end of the project, the integration of CCNet into a scalable and efficient palmprint recognition system is expected to set a new standard in biometric security. The solution will not only address current challenges in transport systems but also pave the way for broader adoption in other industries requiring robust, hygienic, and non-contact biometric solutions.

References

[1] Z. Yang, H. Huangfu, L. Leng, B. Zhang, A. B. J. Teoh and Y. Zhang, "Comprehensive Competition Mechanism in Palmprint Recognition," in IEEE Transactions on Information Forensics and Security, vol. 18, pp. 5160-5170, 2023, doi: 10.1109/TIFS.2023.3306104.

[2] Z. Yang et al., "CO3Net: Coordinate-Aware Contrastive Competitive Neural Network for Palmprint Recognition," in IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-14, 2023, Art no. 2514114, doi: 10.1109/TIM.2023.3276506.

[3] X. Liang, J. Yang, G. Lu and D. Zhang, "CompNet: Competitive Neural Network for Palmprint Recognition Using Learnable Gabor Kernels," in IEEE Signal Processing Letters, vol. 28, pp. 1739-1743, 2021, doi: 10.1109/LSP.2021.3103475.

[4] A. Genovese, V. Piuri, K. N. Plataniotis and F. Scotti, "PalmNet: Gabor-PCA Convolutional Networks for Touchless Palmprint Recognition," in IEEE Transactions on Information Forensics and Security, vol. 14, no. 12, pp. 3160-3174, Dec. 2019, doi: 10.1109/TIFS.2019.2911165.

[5] Xu Liang, Zhaoqun Li, Dandan Fan, Jinxing Li, Wei Jia, David Zhang, Touchless palmprint recognition based on 3D Gabor template and block feature refinement, in Knowledge-Based Systems, vol. 249, 2022, 108855, ISSN 0950-7051, doi: 10.1016/j.knosys.2022.108855.

[6] A. W.-K. Kong and D. Zhang, “Competitive coding scheme for palm-print verification,” in Proc. 17th Int. Conf. Pattern Recognit., 2004, pp. 520–523.

[7] L. Fei, G. Lu, W. Jia, S. Teng, and D. Zhang, “Feature extraction methods for palmprint recognition: A survey and evaluation,” IEEE Trans. Syst., Man, Cybern., Syst., vol. 49, no. 2, pp. 346–363, Feb. 2019.

[8] "Towards contactless palmprint recognition", Lin Zhang, Lida Li, Anqi Yang, Ying Shen, and Meng Yang, `https://cslinzhang.github.io/ContactlessPalm/`

[9] "BIT", Idealtest.org, 2024, `http://biometrics.idealtest.org`

[10] "COEP Technological University", COEP Technological University, `https://www.coeptech.ac.in/`