



Score-Level Fusion of Face and Palm Vein Biometrics Using Logistic Regression and Support Vector Machines

Sheetal¹, Narender Kumar²

¹Research Scholar, NIILM University, Kaithal, Haryana, India.

²Professor, NIILM University, Kaithal, Haryana, India.

To Cite this Article: Sheetal¹, Narender Kumar², "Score-Level Fusion of Face and Palm Vein Biometrics Using Logistic Regression and Support Vector Machines", *Indian Journal of Computer Science and Technology*, Volume 05, Issue 01 (January-April 2026), PP: 221-224.



Copyright: ©2026 This is an open access journal, and articles are distributed under the terms of the [Creative Commons Attribution License](#); Which Permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract: Multimodal biometric systems have emerged as a robust solution to overcome the limitations of unimodal approaches. This study presents a score-level fusion framework combining **face and palm vein biometrics** using Logistic Regression (LR) and Support Vector Machine (SVM) classifiers. The system employs Z-score normalization to standardize matcher outputs before fusion. Performance is evaluated using Equal Error Rate (EER) and Receiver Operating Characteristic (ROC) curves across five-fold cross-validation. Experimental results demonstrate that LR-based fusion achieves a lower mean EER (0.2116 ± 0.0229) compared to SVM-based fusion (0.2290 ± 0.0269). ROC analysis further confirms the superior performance and stability of LR across different operating points. The findings highlight the effectiveness of multimodal fusion and the suitability of linear probabilistic models for score-level integration.

Key Words: Multimodal Biometrics, Face Recognition, Palm Vein Recognition, Biometric Fusion, Score-Level Fusion, Logistic Regression, Support Vector Machines.

I. INTRODUCTION

Biometric authentication systems have become an integral component of modern security infrastructures, enabling reliable identity verification in applications such as mobile devices, banking systems, surveillance, and border control. These systems rely on physiological or behavioral characteristics, including face, fingerprint, iris, and vascular patterns, to distinguish individuals (Jain et al., 2005). Among these, face recognition is widely adopted due to its non-intrusive nature and ease of acquisition. However, its performance is often affected by variations in illumination, pose, facial expressions, and occlusions.

In contrast, palm vein recognition has emerged as a highly secure biometric modality. It utilizes near-infrared imaging to capture subcutaneous vascular patterns, which are unique to each individual and difficult to forge (Wang & Leedham, 2006). Since vein patterns are internal to the human body, they provide an additional layer of security compared to external traits. Nevertheless, palm vein systems may face challenges related to sensor dependency and acquisition conditions.

To overcome the limitations of unimodal systems, multimodal biometric systems have been proposed, which integrate multiple biometric traits to improve accuracy, robustness, and resistance to spoofing attacks (Ross et al., 2006). By combining complementary modalities, multimodal systems reduce the likelihood of erroneous decisions caused by noisy or missing data. In particular, the combination of face and palm vein biometrics is highly promising, as it integrates a convenient external modality with a secure internal modality, thereby achieving a balance between usability and security.

Fusion in multimodal biometrics can be performed at various levels, including sensor level, feature level, score level, and decision level (Kittler et al., 1998). Among these, score-level fusion is widely preferred due to its simplicity, flexibility, and ability to effectively combine information from heterogeneous sources. However, the effectiveness of score-level fusion depends heavily on the choice of normalization and fusion techniques.

Machine learning-based approaches, such as Logistic Regression (LR) and Support Vector Machines (SVM), have been extensively used for score fusion. Logistic Regression provides a probabilistic framework that models the relationship between input scores and class labels, making it suitable for threshold-based decision systems (Bishop, 2006). On the other hand, SVM constructs optimal decision boundaries and is known for its strong generalization capability, particularly in high-dimensional spaces (Cortes & Vapnik, 1995).

Despite the widespread use of these techniques, there remains a need to systematically evaluate their effectiveness in the context of multimodal fusion of face and palm vein biometrics, particularly under standardized normalization schemes such as Z-score normalization. Furthermore, understanding the behavior of these classifiers in terms of Equal Error Rate (EER) and Receiver Operating Characteristic (ROC) performance is essential for designing reliable biometric systems.

In this paper, we propose a score-level fusion framework that integrates face and palm vein modalities using Logistic Regression and Support Vector Machines. The contributions of this work are threefold:

(i) Development of a multimodal biometric system combining face and palm vein traits,

- (ii) comparative evaluation of LR and SVM for score-level fusion under Z-score normalization, and
- (iii) comprehensive performance analysis using EER and ROC curves across five-fold cross-validation.

The experimental results demonstrate that Logistic Regression consistently outperforms SVM in terms of accuracy and stability, indicating that the fused score space exhibits near-linear separability.

II. RELATED WORK

Multimodal biometric fusion has been extensively studied as a means to improve system performance. Jain and Ross (2004) demonstrated that combining multiple biometric modalities significantly enhances recognition accuracy. Score-level fusion, in particular, provides a good balance between performance and implementation complexity (Kittler et al., 1998).

Logistic Regression has been widely used in fusion tasks due to its probabilistic interpretation and simplicity (Bishop, 2006). On the other hand, Support Vector Machines are known for their strong classification capabilities, especially in high-dimensional and nonlinear spaces (Cortes & Vapnik, 1995).

Palm vein recognition has gained attention due to its high security and uniqueness. Techniques for vein pattern extraction and matching have been explored in several studies (Miura et al., 2004). Combining palm vein with face biometrics has been shown to improve robustness and reduce spoofing risks (Kumar & Zhang, 2006).

III. METHODOLOGY

3.1 System Overview

The proposed system integrates face and palm vein modalities at the score level. Independent matchers generate similarity scores, which are then normalized and fused using machine learning classifiers.

3.2 Feature Extraction and Matching

- **Face Modality:** Features are extracted using standard face recognition techniques.
- **Palm Vein Modality:** Vein patterns are extracted using image processing techniques and matched to produce similarity scores.

3.3 Score Normalization

Z-score normalization is applied to ensure comparability between modalities:

$$Z = \frac{x - \mu}{\sigma}$$

Where x is the raw score, μ is the mean, and σ is the standard deviation.

3.4 Fusion Techniques

- **Logistic Regression (LR-Optimal (Z)):** Combines normalized scores using a linear probabilistic model.
- **Support Vector Machine (SVM-Optimal (Z)):** Uses a decision boundary to separate genuine and impostor classes.

3.5 Evaluation Protocol

The system is evaluated using 5-fold cross-validation. Performance metrics include:

- Equal Error Rate (EER)
- Receiver Operating Characteristic (ROC)

IV. DATASET

The proposed system is evaluated using publicly available biometric datasets.

- Face dataset
 - Celebrities in Frontal-Profile in the Wild
- Palm vein dataset
 - The experiments are conducted using the VERA Palm Vein dataset, which consists of near-infrared images of palm vein patterns collected from multiple subjects under controlled conditions. The dataset provides sufficient variability for evaluating biometric recognition systems and is widely used in palm vein research.

V. RESULTS AND ANALYSIS

Fusion EER Summary

Method	Mean EER	Std Dev	Folds
LR-Optimal(Z)	0.2116	0.0229	5
SVM-Optimal(Z)	0.2290	0.0269	5

The performance of the proposed score-level fusion methods was evaluated using Equal Error Rate (EER) across five-fold cross-validation. The comparative results are summarized in Table no.1.

The Logistic Regression-based fusion (LR-Optimal (Z)) achieved a mean EER of 0.2116 with a standard deviation of 0.0229, indicating strong discriminative capability and consistent performance across all folds. In contrast, the Support Vector Machine-based fusion (SVM-Optimal (Z)) resulted in a higher mean EER of 0.2290 and a standard deviation of 0.0269.

The lower mean EER of LR suggests that it provides better separation between genuine and impostor classes compared to SVM. Furthermore, the smaller standard deviation indicates that LR exhibits greater stability and less variation across different

folds, making it more reliable for practical deployment.

On the other hand, the relatively higher EER and variability observed in SVM indicate that its performance is less consistent, possibly due to sensitivity to parameter settings and limited effectiveness in low-dimensional score fusion scenarios.

Overall, these results demonstrate that Logistic Regression is more effective than SVM for score-level fusion of face and palm vein biometrics, particularly under Z-score normalization. The findings also suggest that the fused score space is likely linearly separable, favouring simpler probabilistic models over more complex classifiers.

ROC Curve Analysis:

The ROC curves illustrate the trade-off between False Acceptance Rate (FAR) and True Acceptance Rate (TAR).

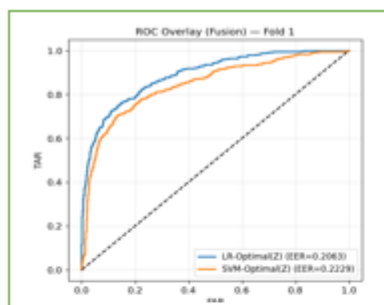


Figure 1: ROC Curve for Fold 1

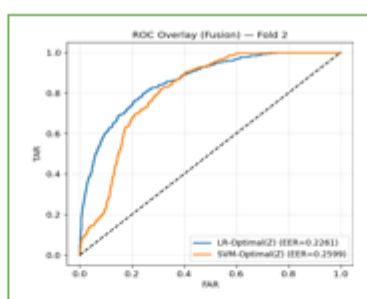


Figure 2: ROC Curve for Fold 2

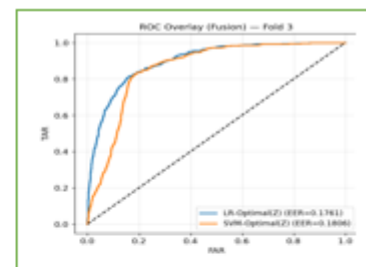


Figure 3: ROC Curve for Fold 3

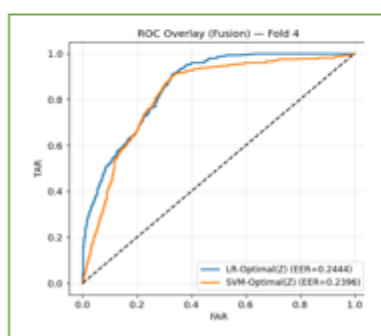


Figure 4: ROC Curve for Fold 4

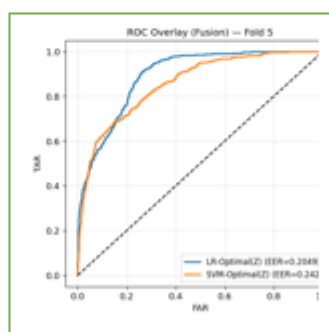


Figure 5: ROC Curve for Fold 5

The ROC curves illustrate the comparative performance of the two fusion methods in terms of True Acceptance Rate (TAR) versus False Acceptance Rate (FAR). It can be observed that the Logistic Regression-based fusion (LR-Optimal (Z)) consistently outperforms the SVM-based fusion (SVM-Optimal (Z)) across most operating regions. The LR curve lies above the SVM curve for a wide range of FAR values, indicating a higher TAR at equivalent false acceptance levels.

At lower FAR regions, both methods show similar behavior; however, as FAR increases, LR demonstrates a more rapid improvement in TAR, approaching near-perfect classification earlier than SVM. The reported Equal Error Rates (EER) further support this observation, with LR achieving a lower EER (0.2049) compared to SVM (0.2422) for this fold.

Additionally, both models significantly outperform the random classifier baseline, represented by the diagonal dashed line. The smoother and more dominant ROC curve of LR suggests better score calibration and stronger discriminative capability in the fused feature space. Overall, the ROC analysis confirms that Logistic Regression provides superior performance and more reliable decision boundaries than SVM for score-level fusion of face and palm vein biometrics.

VI. DISCUSSION

The superior performance of Logistic Regression suggests that the fused score space derived from face and palm vein modalities is approximately linearly separable. This is expected because both modalities independently provide strong discriminative information, and their combination enhances class separability.

SVM, while powerful, may not perform optimally in this context due to:

- Sensitivity to hyper parameter selection
- Limited advantage in low-dimensional score spaces
- Potential over fitting with nonlinear kernels

Additionally, the probabilistic output of LR provides better calibration for threshold-based metrics such as EER, resulting in improved ROC characteristics. The multimodal fusion of face and palm vein also enhances system security by combining an external biometric (face) with an internal biometric (vein), making spoofing significantly more difficult.

VII. CONCLUSION

This study presented a multimodal biometric system that combines face and palm vein modalities using score-level fusion. Experimental results demonstrate that:

- Logistic Regression achieves superior performance compared to SVM
- Fusion significantly improves verification accuracy
- ROC analysis confirms consistent performance across folds

Future work may explore deep learning-based fusion techniques and adaptive weighting strategies to further enhance performance.

References

1. Anil K. Jain and Arun Ross, "Multibiometric systems," *Communications of the ACM*, vol. 47, no. 1, pp. 34–40, 2004.
2. Arun Ross, Karthik Nandakumar, and Anil K. Jain, *Handbook of Multibiometrics*. Springer, 2006.
3. Josef Kittler, Mohamed Hatef, Robert P. W. Duin, and Jiri Matas, "On combining classifiers," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 3, pp. 226–239, 1998.
4. Christopher M. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2006.
5. Corinna Cortes and Vladimir Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.
6. Karthik Nandakumar, Yi Chen, Sanjiv Dass, and Anil K. Jain, "Likelihood ratio-based biometric score fusion," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 2, pp. 342–347, 2008.
7. Ludmila I. Kuncheva, *Combining Pattern Classifiers: Methods and Algorithms*. Wiley, 2014.
8. L. Wang and G. Leedham, "A thermal hand vein pattern verification system," *Pattern Recognition Letters*, vol. 27, no. 5, pp. 498–505, 2006.
9. Naoto Miura, Akio Nagasaka, and Takafumi Miyatake, "Feature extraction of finger-vein patterns based on repeated line tracking," *Machine Vision and Applications*, vol. 15, no. 4, pp. 194–203, 2004.
10. Ajay Kumar and David Zhang, "Personal recognition using hand shape and texture," *IEEE Transactions on Image Processing*, vol. 15, no. 8, pp. 2454–2461, 2006.
11. Tom Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006.
12. Anil K. Jain, Arun Ross, and Sharath Pankanti, "An introduction to biometric recognition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, no. 1, pp. 4–20, 2005.
13. "Celebrities in Frontal-Profile in the Wild" Kaggle, 2020. [Online]. Available: <https://www.kaggle.com/datasets/chinafax/cfpw-dataset>
14. Pedro Tome and Sébastien Marcel, "On the Vulnerability of Palm Vein Recognition to Spoofing Attacks", IAPR International Conference on Biometrics (ICB), 2015.10.1109/ICB.2015.7139056 <http://publications.idiap.ch/index.php/publications/show/3096>