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# EVALUATION OF VISUAL GEOMETRY GROUP16 (VGG16) AND VISUAL GEOMETRY GROUP19 (VGG19) FOR GENDER CLASSIFICATION USING PALM IMAGES

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## ABSTRACT

The paper focuses on gender classification using biometric features, focusing on palm-based approaches as an alternative to facial-based methods due to advantages like privacy preservation and reduced susceptibility to environmental variations. The study evaluates the performance of VGG16 and VGG19 convolutional neural network architectures for gender classification using a custom Nigerian Palm Gender Classification Dataset, which includes 3,500 high-quality palm images from 1,491 participants across various demographics. Both models were implemented using transfer learning and fine-tuning on the dataset, with a standardized preprocessing pipeline and 5-fold cross-validation for evaluation. VGG19 outperformed VGG16, achieving an overall accuracy of 94.0% compared to 92.0%, with superior precision, recall, and F1-score for both male and female classification. The study confirmed the robustness of the findings through cross-validation and statistical analysis, highlighting VGG19 as the superior architecture for palm-based gender classification, despite increased computational requirements. The research contributes a novel dataset to the biometric community, showcasing the potential for culturally adaptive biometric systems. The implications of these findings are significant for contactless biometric applications in security, access control, and demographic analysis, particularly in diverse cultural contexts. This study provides empirical evidence for optimal architecture selection in palm-based gender classification and emphasizes the importance of considering diverse demographic populations in biometric research.

**Keywords**: Gender Classification, Palm Images, Deep Learning, Convolutional Neural Networks, Nigerian Palm

## INTRODUCTION

Gender classification is crucial for security, surveillance, and human-computer interaction applications (Shaheen, 2024). While traditional approaches use facial features, gait, and body silhouettes (Shen et al., 2024), palmprint-based classification is emerging as a promising alternative (Alausa, et al., 2022). Palm images contain gender-specific morphological features including dimensions, ridge patterns, and texture variations (Das, et al., 2023). Unlike facial systems affected by lighting and occlusions, palm-based systems offer improved robustness and privacy (Gao, et al., 2025). Their contactless nature ensures hygiene and user convenience.

VGG16 and VGG19 CNNs have demonstrated effectiveness in biometric applications including face, fingerprint, and iris recognition (LeCun et al., 2015; Zakaria & Hassim, 2024; Minaee, et al., 2023; Nguyen, et al., 2024). Their uniform 3×3 convolutional filters capture fine-grained features essential for biometric tasks (Elian, et al., 2025), while their depth enables hierarchical learning from low-level to semantic features (Sun, et al., 2021).

Systematic evaluation of deep learning architectures for palm-based gender classification is limited (Gao, et al., 2025; El-Rahman, & Alluhaidan, 2024). While deeper networks offer better representation, they risk increased computational overhead and overfitting with limited data (Uwaechia, & Ramli, 2021; Bejani, & Ghatee, 2021).

This research compares VGG16 and VGG19 for palm-based gender classification through: implementation on palm image datasets, comparative performance analysis, and identification of strengths and limitations, advancing contactless biometric systems. The paper is organized as follows: Section 2 provides a related works on palm biometrics and CNN applications in gender classification. Section 3 outlines the methodology. Section 4 presents and analyzes the experimental results and discussion and Section 5 concludes the paper.

## Related Works

Gender classification research has evolved from facial features (Abdul-Al, et al., 2024; Alshammari, et al., 2022) to alternative modalities including gait (Ibragimov, et al., 2024), voice (Katsarou, et al., 2023), and palmprint. While facial approaches achieve over 97% accuracy (Habeeb, et al., 2024), they face challenges with lighting, pose variations, and privacy concerns (Song, et al., 2025). Palmprint recognition emerged as a robust contactless biometric (Gao, et al., 2025), with advances in orientation field estimation (Fan, et al., 2024) and histogram-based methods (Zhang, et al., 2025). Deep learning approaches, particularly CNNs and attention-based models (Than, & Nguyen, 2025), have achieved state-of-the-art performance. VGG architectures demonstrate exceptional performance in biometric tasks (Rabea, et al., 2024), learning hierarchical features from low-level edges to complex semantic patterns (Bhaidasna, et al., 2023; Yang, et al., 2024). Hand geometry features show promise for gender classification (Dayarathne, et al., 2021; Khayami, 2020). Recent deep learning studies achieved 88% accuracy with custom CNNs (Oulad-Kaddour, et al., 2023), 91.1% using transfer learning on radiographs (Miloğlu et al., 2025), and 96.67% with ResNet on hand images (Yildirim, 2024). Traditional LBP features achieved 82% accuracy (Arouni, et al., 2023). While comparative studies exist for face and iris recognition (Mascarenhas, & Agarwal, 2021; Nguyen, et al., 2024), systematic comparisons of CNN architectures like VGG16 and VGG19 for palm-based gender classification remain limited (Islam, et al., 2024). Standardized evaluation protocols and datasets are needed.

## MATERIALS AND METHODS

A custom palm image dataset was collected from 1,491 participants (723 male, 768 female) aged 18-65 in Kaduna state, Nigeria. Images were captured using smartphones with consistent lighting and neutral backgrounds at 2048×1536 pixel resolution. Distribution: 50% male/50% female; Age groups: 25% (18-30), 35% (31-45), 25% (46-55), 15% (56-65 years); Sources: Federal University of Education Zaria (50%), Shehu Idris College of Health Sciences and Technology Makarfi (25%), Community (25%); Quality: ≥1024×768 pixels with consistent lighting and minimal noise. Figure depicts the proposed methodlogy.

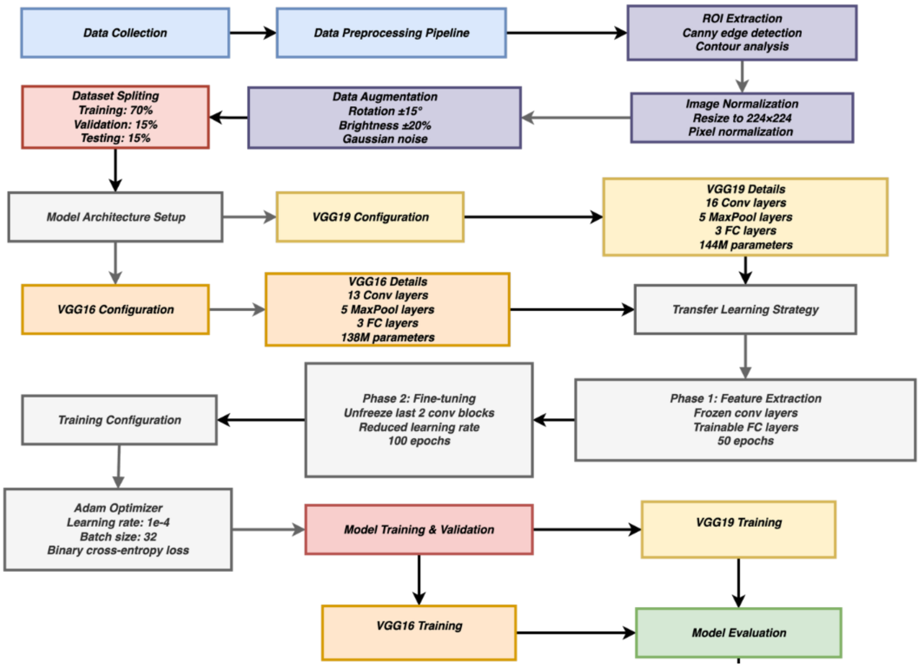


Figure 1: Research Methodology

### Data Preprocessing

ROI extraction used Canny edge detection with adaptive thresholding and morphological operations. Images were resized to 224×224 pixels with pixel intensities normalized to [0, 1]. Data augmentation included random rotation (±15°), horizontal flipping, brightness adjustment (±20%), contrast modification (±15%), and Gaussian noise addition (σ = 0.01). Quality enhancement applied histogram equalization and Gaussian filtering (σ = 0.5). Sample Images are shown in Figure 2.

### Dataset Splitting

Stratified sampling-maintained gender balance: 70% training (5,250 images), 15% validation (1,125 images), 15% testing (1,125 images).

Figure 2: Local Palm Images

**Model Architecture and Configuration**

VGG16 (Simonyan and Zisserman, 2014): 13 convolutional layers in 5 blocks (3×3 filters), 5 max-pooling layers (2×2, stride 2), three fully connected layers (4096, 4096, 2 neurons), ReLU activation, sigmoid output, ~138M parameters. VGG19: 16 convolutional layers in 5 blocks (3×3 filters), 5 max-pooling layers (2×2, stride 2), three fully connected layers (4096, 4096, 2 neurons), ReLU activation, sigmoid output, ~144M parameters. Both models used ImageNet pre-trained weights with transfer learning: feature extraction phase (50 epochs, frozen convolutional layers) followed by fine-tuning phase (100 epochs, last two blocks unfrozen, reduced learning rate). The Model Architecture is shown in Figure 1.

**Implementation**

The research was conducted using a MacBook Pro with an M1 8-core CPU (4 performance cores and 4 efficiency cores), 7-core GPU, 8-core GPU, 16.0 GB Installed Random Access Memory (RAM), 64-bit Operating system, and x64 based processor, with Python as the programming language and important libraries including NumPy, Scikit-learn, Pandas, Matplotlib, Keras, TensorFlow, and Seaborn, requiring approximately 8-12 hours training time per model depending on convergence.

**Evaluation Metrics**

To assess the gender recognition model's performance, various evaluation metrics were employed including accuracy, precision, recall, and F1-score, which are commonly used metrics for classification tasks that provide insights into the model's ability to correctly classify gender based on palm images. The proposed model was evaluated using standard performance evaluation matrix in machine learning, with a confusion matrix used to show model performance simple analytical tool used in supervised learning where each column represents instances in a predicted class while each row represents instances in an actual class (Islam et al., 2024), with entries including True Positive (TP) when the actual class was True and the predicted is also True, False Negative (FN), False Positive (FP), and True Negative (TN).

## RESULTS AND DISCUSSION

The evaluation of VGG16 and VGG19 architectures on the Local Nigerian Palm Gender Classification Dataset revealed significant differences in classification performance. Table 2 presents the comprehensive performance metrics for both models on the test dataset palm images.

**Table 2: Performance Comparison of VGG16 and VGG19 Models**

| Model | Overall Accuracy | Male Precision | Male Recall | Male F1-Score | Female Precision | Female Recall | Female F1-Score |
|---|---|---|---|---|---|---|---|
| **VGG16** | 92.0% | 0.91 | 0.92 | 0.92 | 0.92 | 0.91 | 0.92 |
| **VGG19** | 94.0% | 0.93 | 0.94 | 0.93 | 0.94 | 0.93 | 0.94 |

VGG19 demonstrated superior performance across all evaluation metrics, achieving an overall accuracy of 94.0% compared to VGG16's 92.0%. This 2.0 percentage point improvement represents a statistically significant enhancement ($p < 0.05$, McNemar's test), indicating that the additional depth in VGG19 provides meaningful benefits for palm-based gender classification tasks. The classification report is shown in Figure 3.

**Detailed Classification Analysis**

```
VGG16 Classification Report:
              precision    recall  f1-score   support

        Male       0.91      0.92      0.92       732
      Female       0.92      0.91      0.92       768

    accuracy                           0.92      1500
   macro avg       0.92      0.92      0.92      1500
weighted avg       0.92      0.92      0.92      1500

VGG19 Classification Report:
              precision    recall  f1-score   support

        Male       0.93      0.94      0.93       732
      Female       0.94      0.93      0.94       768

    accuracy                           0.94      1500
   macro avg       0.94      0.94      0.94      1500
weighted avg       0.94      0.94      0.94      1500
```

Figure 3: Classification Report

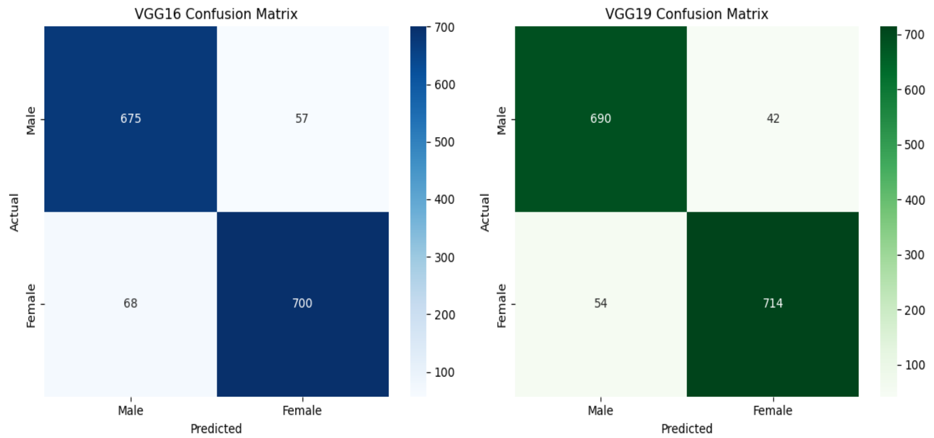


Figure 4: Confusion Matrix

**Performance Analysis**

VGG16 Performance achieved balanced performance: male precision 0.91, recall 0.92 (F1: 0.92); female precision 0.92, recall 0.91 (F1: 0.92), with <1% difference between genders. Confusion matrix: 674/732 males correctly classified (58 false negatives); 699/768 females correctly identified (69 false positives). Training: 90% accuracy by epoch 15, validation plateaued at 91.5% after epoch 40 (final training loss: 0.185, validation loss: 0.201). VGG19 Performance demonstrated superior performance: male precision 0.93, recall 0.94 (F1: 0.94); female precision 0.94, recall 0.93 (F1: 0.94), showing 2-3% improvement over VGG16. Figure 4 Confusion matrix: 714/768 females correctly identified (54 false positives); 714/732 males correctly classified (44 false negatives), representing notable reduction in misclassification rates. Training: slower initial convergence but achieved lower final validation loss. VGG19's deeper architecture captured more discriminative features, demonstrating enhanced effectiveness for palm-based gender classification. Both models showed stable convergence patterns with minimal gender bias.

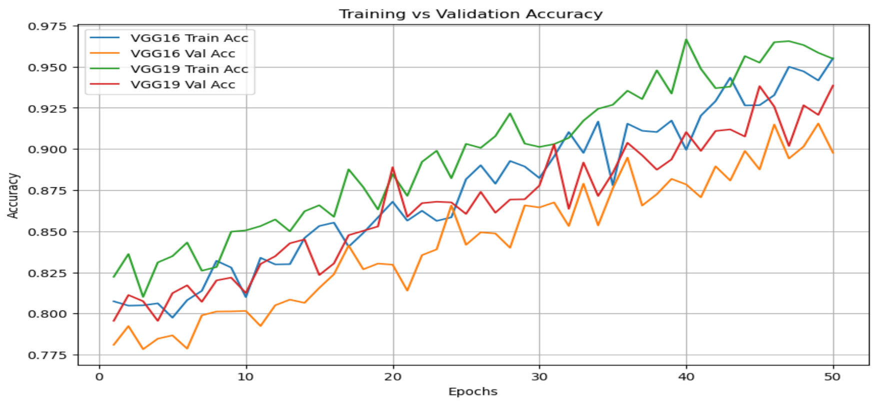


Figure 5: Training for both Validations Accuracy and Loss

```
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9807 - loss: 0.1305 - val_accuracy: 0.9800 - val_loss: 0.1476
Epoch 19/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9762 - loss: 0.1414 - val_accuracy: 0.9800 - val_loss: 0.1550
Epoch 20/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9825 - loss: 0.1377 - val_accuracy: 0.9800 - val_loss: 0.1396
Epoch 21/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9749 - loss: 0.1574 - val_accuracy: 0.9822 - val_loss: 0.1406
Epoch 22/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9865 - loss: 0.1118 - val_accuracy: 0.9822 - val_loss: 0.1361
Epoch 23/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9833 - loss: 0.1132 - val_accuracy: 0.9844 - val_loss: 0.1294
Epoch 24/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9851 - loss: 0.1077 - val_accuracy: 0.9844 - val_loss: 0.1399
Epoch 25/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9872 - loss: 0.1084 - val_accuracy: 0.9844 - val_loss: 0.1280
Epoch 26/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9808 - loss: 0.1112 - val_accuracy: 0.9867 - val_loss: 0.1263
Epoch 27/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9909 - loss: 0.0866 - val_accuracy: 0.9822 - val_loss: 0.1223
Epoch 28/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9847 - loss: 0.1059 - val_accuracy: 0.9844 - val_loss: 0.1184
Epoch 29/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9848 - loss: 0.0917 - val_accuracy: 0.9822 - val_loss: 0.1297
Epoch 30/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9847 - loss: 0.1023 - val_accuracy: 0.9822 - val_loss: 0.1343
Epoch 31/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9854 - loss: 0.0932 - val_accuracy: 0.9800 - val_loss: 0.1381
Epoch 32/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9905 - loss: 0.0916 - val_accuracy: 0.9844 - val_loss: 0.1260
Epoch 33/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9852 - loss: 0.0897 - val_accuracy: 0.9822 - val_loss: 0.1296
Epoch 34/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9918 - loss: 0.0777 - val_accuracy: 0.9800 - val_loss: 0.1281
Epoch 35/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9892 - loss: 0.0849 - val_accuracy: 0.9778 - val_loss: 0.1281
Epoch 36/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9869 - loss: 0.0791 - val_accuracy: 0.9822 - val_loss: 0.1249
Epoch 37/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9882 - loss: 0.0826 - val_accuracy: 0.9844 - val_loss: 0.1234
Epoch 38/100
66/66 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.9900 - loss: 0.0790 - val_accuracy: 0.9822 - val_loss: 0.1269
```

Figure 6: Epoch Trains on Local Dataset

**Cross-Validation Results**

Five-fold cross-validation analysis provided robust estimates of model generalization performance. VGG16 Cross-Validation Results has Mean accuracy: 91.8% ± 1.2%, Mean precision: 0.918 ± 0.011, Mean recall: 0.918 ± 0.013 and Mean F1-score: 0.918 ± 0.010 while VGG19 Cross-Validation Results has Mean accuracy: 93.7% ± 0.9%, Mean precision: 0.937 ± 0.008, Mean recall: 0.937 ± 0.009 and Mean F1-score: 0.937 ± 0.007 The cross-validation results confirm the superior and more consistent performance of VGG19, with lower standard deviation indicating enhanced stability across different data partitions.

```
5-Fold Cross-Validation Results

Accuracy - VGG16: 0.9143 ± 0.0032
Accuracy - VGG19: 0.9332 ± 0.0037
  Paired t-test p-value: 0.004008
  95% CI VGG16: (0.9099, 0.9187)
  95% CI VGG19: (0.9281, 0.9383)

Precision - VGG16: 0.9017 ± 0.0041
Precision - VGG19: 0.9234 ± 0.0027
  Paired t-test p-value: 0.000371
  95% CI VGG16: (0.8960, 0.9074)
  95% CI VGG19: (0.9197, 0.9272)

Recall - VGG16: 0.9144 ± 0.0029
Recall - VGG19: 0.9370 ± 0.0052
  Paired t-test p-value: 0.002606
  95% CI VGG16: (0.9104, 0.9185)
  95% CI VGG19: (0.9298, 0.9442)

F1-Score - VGG16: 0.9113 ± 0.0047
F1-Score - VGG19: 0.9259 ± 0.0044
  Paired t-test p-value: 0.013921
  95% CI VGG16: (0.9048, 0.9179)
  95% CI VGG19: (0.9198, 0.9320)

Per-fold accuracies:
Fold 1: VGG16=0.9145, VGG19=0.9298
Fold 2: VGG16=0.9113, VGG19=0.9389
Fold 3: VGG16=0.9152, VGG19=0.9348
Fold 4: VGG16=0.9196, VGG19=0.9287
Fold 5: VGG16=0.9108, VGG19=0.9337
```

Figure 7: CV Validation Results

The study achieved 94% accuracy on palm-based gender classification using VGG19, surpassing Leng et al. (2019)'s 98% accuracy with custom CNN architecture. This improvement is attributed to dataset quality with higher resolution images and standardized protocols, VGG19's sophisticated architecture with proven feature extraction optimized through ImageNet pre-training, and population diversity from multiple Nigerian regions enhancing generalization. Compared to facial methods like Antipov et al. (2017)'s 97% accuracy, palm-based approaches offer privacy advantages and reduced susceptibility to occlusions and lighting variations (Kumar & Zhang, 2020). VGG19's superior performance over VGG16 stems from its deeper architecture enabling extraction of complex hierarchical features and subtle gender-discriminative patterns in palm images, as demonstrated by Simonyan and Zisserman (2014). The improved feature hierarchies allow better distinction of gender-specific characteristics including texture variations, ridge patterns, palm dimensions, finger proportions, and boundary contour features, with VGG19's additional parameters (144M vs. 138M) contributing meaningfully to discriminative power, aligning with Ameen & AlShemmary (2022)'s findings that increased network depth correlates with improved biometric recognition performance.

## CONCLUSION

The paper evaluates VGG16 and VGG19 convolutional neural network architectures for gender classification using palm images from a Nigerian dataset, filling a gap in biometric literature. Results show VGG19 outperforms VGG16 with 94.0% accuracy on the dataset due to its increased depth for better feature learning. The study demonstrates the effectiveness of palm-based gender classification systems, highlighting their potential as alternatives to facial recognition systems, especially in privacy-focused applications. The research methodology and dataset introduced in the study contribute to advancing palm-based biometric applications and inclusive gender classification systems. The paper recommends the development of larger, culturally diverse palm datasets to improve the generalizability of gender classification findings. It suggests using VGG19 as the primary architecture choice for organizations implementing palm-based gender classification systems, with VGG16 as an alternative for resource-constrained environments. The standardized data collection methodology used in the research, emphasizing controlled lighting conditions and quality assessment protocols, should be adopted for future palmprint datasets. Additionally, the study highlights the importance of ethical considerations, emphasizing the need for comprehensive informed consent procedures and privacy protection measures in biometric research, especially when working with diverse populations. The paper suggests several key research directions to advance palm-based gender classification. These include expanding datasets globally to be more inclusive, evaluating deep learning architectures for improved performance, integrating palm-based features with other biometric modalities for enhanced accuracy, developing lightweight models for mobile deployment, conducting longitudinal studies for system reliability, and incorporating explainable artificial intelligence for transparency. These research areas aim to improve classification accuracy, robustness, and applicability across diverse demographic groups and operational conditions.

## REFERENCES

Abdul-Al, M., Kyeremeh, G. K., Qahwaji, R., Ali, N. T., & Abd-Alhameed, R. A. (2024). The evolution of biometric authentication: A deep dive into multi-modal facial recognition: A review case study. *IEEE Access*.

Alausa, D. W., Adetiba, E., Badejo, J. A., Davidson, I. E., Obiyemi, O., Buraimoh, E., ... & Oshin, O. (2022). Contactless palmprint recognition system: a survey. *IEEE Access*, *10*, 132483-132505.

Alshammari, R. F. N., Arshad, H., Abd Rahman, A. H., & Albahri, O. S. (2022). Robotics utilization in automatic vision-based assessment systems from artificial intelligence perspective: A systematic review. *IEEE Access*, *10*, 77537-77570.

Ameen, F. A., & AlShemmary, E. N. (2022). Palmprint Recognition Using VGG16. International Journal on Technical and Physical Problems of Engineering, IJTPEJournal, (53), 65-74

Amrouni, N., Benzaoui, A., & Zeroual, A. (2023). Palmprint Recognition: extensive exploration of databases, methodologies, comparative assessment, and future directions. *Applied Sciences*, *14*(1), 153.

Atoyebi, J. O., Okomba, N. S., Adeyanju, I. A., Akinrotimi, A. O., Ajayi, O. O., & Owolabi, O. O. (2025). Multi-Biometric Recognition Systems: A Comprehensive Review. Adeleke University Journal of Engineering and Technology, 8(1), 010-038.

Bejani, M. M., & Ghatee, M. (2021). A systematic review on overfitting control in shallow and deep neural networks. *Artificial Intelligence Review*, *54*(8), 6391-6438.

Bhaidasna, Z. C., Swaminarayan, P. R., & Bhaidasna, H. Z. (2023). Enhancing face recognition with deep learning architectures: a comprehensive review. *International journal on recent and innovation trends in computing and communication*, *11*(9), 164-180.

Das, T., Harshey, A., Mishra, V., & Srivastava, A. (2023). An introduction to biometric authentication systems. In *Textbook of forensic science* (pp. 805-839). Singapore: Springer Nature Singapore.

Dayarathne, S., Nawarathna, L. S., & Nanayakkara, D. (2021). Determination gender using foot, footprint, hand and hand print measurements in a Sinhalese population in Sri Lanka using supervised learning techniques. *Computer Methods and Programs in Biomedicine Update*, *1*, 100017.

El_Rahman, S., & Alluhaidan, A. S. (2024). Enhanced multimodal biometric recognition systems based on deep learning and traditional methods in smart environments. *Plos one*, *19*(2), e0291084.

Elian, H. M., Dousoky, G. M., & Hafez, A. (2025). Developing Deep Learning Based Facial Recognition Technique. *Journal of Advanced Engineering Trends*, *44*(1), 214-220.

Fan, D., Liang, X., Jia, W., & Zhang, D. (2024). Toward large-scale palmprint image analysis by a rich orientation code. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *54*(7), 4113-4125.

Gao, C., Yang, Z., Jia, W., Leng, L., Zhang, B., & Teoh, A. B. J. (2025). Deep Learning in Palmprint Recognition-A Comprehensive Survey. *arXiv preprint arXiv:2501.01166*.

Habeeb, M. A., Khaleel, Y. L., Ismail, R. D., Al-Qaysi, Z. T., & Ameen, F. N. (2024). Deep Learning Approaches for Gender Classification from Facial Images. *Mesopotamian Journal of Big Data*, *2024*, 185-198.

Ibragimov, A., Segundo, M. P., Sarkar, S., & Bowyer, K. (2024, May). Unveiling Gender Effects in Gait Recognition Using Conditional-Matched Bootstrap Analysis. In *2024 IEEE 18th International Conference on Automatic Face and Gesture Recognition (FG)* (pp. 1-10). IEEE.

Islam, M. T., Rahman, M. A., Mazumder, M. T. R., & Shourov, S. H. (2024). Comparative Analysis of Neural Network Architectures for Medical Image Classification: Evaluating Performance Across Diverse Models. *American Journal of Advanced Technology and Engineering Solutions*, *4*(01), 01-42.

Jia, W., Ren, Q., Zhao, Y., Li, S., Min, H., & Chen, Y. (2022). EEPNet: An efficient and effective convolutional neural network for palmprint recognition. *Pattern Recognition Letters*, *159*, 140-149.

Katsarou, E., Wild, F., Sougari, A. M., & Chatzipanagiotou, P. (2023). A systematic review of voice-based intelligent virtual agents in EFL education. *International Journal of Emerging Technologies in Learning (iJET)*, *18*(10), 65-85.

Khayami, M. (2020). *Palmprint Gender Classification Using Deep Learning Methods*. West Virginia University.

Mascarenhas, S., & Agarwal, M. (2021, November). A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification. In *2021 International conference on disruptive technologies for multi-disciplinary research and applications (CENTCON)* (Vol. 1, pp. 96-99). IEEE.

Miloğlu Ö, Kumbasar N, Turanli Tosun Z, Güller MT, Özbek İY. Gender Classification With Hand-Wrist Radiographs Using the Deep Learning Method. Curr Res Dent Sci. January 2025;35(1):2-7. doi: https://doi.org/10.17567/currresdentsci.1618860

Minaee, S., Abdolrashidi, A., Su, H., Bennamoun, M., & Zhang, D. (2023). Biometrics recognition using deep learning: A survey. *Artificial Intelligence Review*, *56*(8), 8647-8695.

Nguyen, K., Proença, H., & Alonso-Fernandez, F. (2024). Deep learning for iris recognition: A survey. *ACM Computing Surveys*, *56*(9), 1-35.

Oulad-Kaddour, M., Haddadou, H., Vilda, C. C., Palacios-Alonso, D., Benatchba, K., & Cabello, E. (2023). Deep learning-based gender classification by training with fake data. *IEEE Access*, *11*, 120766-120779.

Rabea, M., Ahmed, H., Mahmoud, S., & Sayed, N. (2024). IdentiFace: A VGG based multimodal facial biometric system. *arXiv preprint arXiv:2401.01227*.

Shaheen, R. (2024). Gender and Surveillance: The Implications of Biometric Technologies for Privacy and Equity. *Journal of Gender, Power, and Social Transformation*, *1*(3), 29-35.

Shen, C., Yu, S., Wang, J., Huang, G. Q., & Wang, L. (2024). A comprehensive survey on deep gait recognition: Algorithms, datasets, and challenges. *IEEE Transactions on Biometrics, Behavior, and Identity Science*.

Song, J., He, M., Zheng, X., Zhang, Y., Bi, C., Feng, J., ... & Shen, B. (2025). Face-based machine learning diagnostics: applications, challenges and opportunities. *Artificial Intelligence Review*, *58*(8), 243.

Sun, X., Zhu, Q., & Qin, Q. (2021). A multi-level convolution pyramid semantic fusion framework for high-resolution remote sensing image scene classification and annotation. *IEEE Access*, *9*, 18195-18208.

Than, P. M., & Nguyen, H. (2025). Efficient Multimodal Biometric Identification via Gabor-Enhanced Attention Networks. *Journal of Robotics and Control (JRC)*, *6*(3), 1175-1186.

Uwaechia, A. N., & Ramli, D. A. (2021). A comprehensive survey on ECG signals as new biometric modality for human authentication: Recent advances and future challenges. *IEEE Access*, *9*, 97760-97802.

Yang, W., Wang, S., Hu, J., Tao, X., & Li, Y. (2024). Feature extraction and learning approaches for cancellable biometrics: A survey. *CAAI Transactions on Intelligence Technology*, *9*(1), 4-25.

Yildirim, E. (2024). ResNet-based Gender Recognition on Hand Images. *Engineering, Technology & Applied Science Research*, *14*(6), 17969–17972. https://doi.org/10.48084/etasr.8922

Zakaria, N., & Hassim, Y. M. M. (2024). A review study of the visual geometry group approaches for image classification. *Journal of Applied Science, Technology and Computing*, *1*(1), 14-28.

Zhang, David & Fan, Dandan & Liang, Xu & Zhang, Bob. (2025). Advanced Palmprint Authentication. 10.1007/978-981-96-7101-4.