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Biometric Recognition System Based on Feature Fusion: Face and Palm Print

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Abstract **- This study introduces an advanced biometric recognition system that seamlessly integrates facial and palm print modalities, showcasing outstanding performance across diverse datasets. The facial recognition dataset exhibits remarkable training, validation, and test accuracies at 98.98%, 98.99%, and 99%, respectively. Precision, recall, and F1-score metrics consistently reach 99%, underlining the system's robust and reliable performance in facial identification. Similarly, the palm print dataset demonstrates impressive results, with training, validation, and test accuracies at 98.90%, 99%, and 99%, respectively. Precision, recall, and F1-scores maintain a high level of 99%, emphasizing the system's effectiveness in palm print recognition. The combined "Face and Palm" dataset further highlights the system's exceptional capabilities, achieving perfect scores of 100% in training, validation, and test accuracies, as well as precision, recall, and F1-score. This underscores the system's versatility and proficiency in simultaneously recognizing facial and palm features. The innovative fusion of facial and palm print modalities in this biometric recognition system yields impressive and consistent results across multiple datasets. The system's high accuracy and precision, coupled with its adaptability to various scenarios, position it as a valuable advancement in biometric technology.**

Keywords: Biometric Fusion; Deep Learning; Convolutional Neural Networks; Recognition System; Multi-Modal Biometric System.

I. INTRODUCTION

In today's increasingly digital and interconnected world, the need for secure and efficient methods of identifying individuals is paramount. Human biometric identification stands at the forefront of these efforts, offering a cutting-edge approach to authentication and recognition [1]. Unlike traditional methods such as passwords or PINs, which can be forgotten, lost, or compromised, biometrics leverages unique physical or behavioral characteristics inherent to each person. These traits serve as distinctive markers, enabling the reliable recognition of individuals with a high degree of accuracy [2].

The fundamental premise of human biometric identification is rooted in the fact that no two individuals share identical biometric attributes [3]. Whether it's the patterns of one's fingerprint, the distinct features of their face, the intricate details of their iris, the sound of their voice, or even the rhythm of their typing, each biometric trait is exclusive to an individual. As such, biometric identification provides a robust and reliable means of confirming one's identity, mitigating the vulnerabilities associated with traditional authentication methods [4].

This innovative technology has found widespread application across various domains, from enhancing security measures in government agencies, financial institutions, and airports to simplifying user access to personal devices, buildings, and online accounts [5]. Furthermore, biometric identification has the potential to streamline and enhance user experiences by reducing the friction associated with remembering passwords or carrying physical identification documents [6].

However, the deployment of biometric identification also raises important considerations related to privacy, data security, and ethical implications. Balancing the advantages of biometrics with the need to protect individuals' sensitive information remains a critical challenge for researchers, policymakers, and organizations worldwide [7].

Multibiometric recognition systems are designed to operate in various integration scenarios, each catering to distinct requirements and challenges. These scenarios are depicted in Figure (1) and encompass a range of approaches for combining multiple biometric traits effectively [8].

The first scenario is the "Multi-Sensor" approach, where different sensors capture the same biometric information or body parts. These sensor-level fusion techniques merge the data from diverse sensors, enhancing the system's overall accuracy [9].

In the "Multi-Modal" scenario, various sensors capture different biometric modalities or body parts from the same individual. For instance, this could involve the simultaneous use of retinal and facial recognition, necessitating multiple sensors. Although powerful, this approach may incur higher

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costs due to the need for multiple sensors to capture various biometric traits [10].

The "Multi-Sample" approach involves collecting multiple samples of the same biometric during both the enrollment and recognition phases. For example, a system might capture multiple facial images of the same person. This approach aids in refining recognition accuracy [10].

Figure 1: Types of Multibiometric Recognition [7]

In the "Multi-Algorithmic" scenario, the same sensor is employed, but the data it captures is processed using multiple algorithms for feature extraction and matching. This diversification of algorithms enhances the robustness and reliability of the system [31].

Lastly, the "Multi-Instance" approach leverages the same sensor to capture multiple instances of the same biometric trait or body part. This could involve capturing facial images with different poses or variations. By accommodating various instances, this approach further bolsters the system's adaptability and recognition performance [32].

Multibiometric fusion, as illustrated by these integration scenarios, plays a pivotal role in enhancing the accuracy, reliability, and security of biometric recognition systems. By intelligently combining information from diverse sources, these systems strive to provide a comprehensive and robust means of identifying individuals.

In this research paper, CNN technology will be employed within deep learning techniques with three axes: the first is facial recognition, the second is the palm print, and the third is biometric authentication through them together.

II. RELATED WORKS

Table (1) presents a concise overview of ten distinct research studies focusing on multi-modal biometric recognition systems. Multi-modal biometrics involves the integration of multiple biometric traits, such as face, fingerprint, iris, voice, palm print, and signature, to enhance identification and authentication processes. Each study addresses specific problem statements, sets objectives, employs algorithms, and reports results, accuracy rates, along with highlighting the strengths and weaknesses of their proposed approaches.

Table 1: Related works review

Cite	Problem Statement	Objectives	Algorithm	Results	Accuracy	Strength Points
[11]	Multi-modal biometric identification using face, finger vein, and iris biometrics	To improve biometric identification using multiple features	CNN-based models with VGG-16, Adam optimization, and softmax classifier	100% accuracy with feature-level fusion, 99.39% with score-level fusion	High accuracy, robustness	Limited dataset evaluation
[12]	Using palm print and fingerprint data for multi-modal biometrics	To create a secure, unique identification system using palm and fingerprint data	DNN-based identification	97% accuracy	High accuracy, rich data sources	Limited to two biometrics
[13]	Multi-modal biometric recognition with palm prints, hand veins, and fingerprints	To achieve recognition using multiple biometrics	Feature extraction, fuzzy vault	98.5% accuracy	Improved recognition	Limited discussion on noise handling
[14]	Multi-modal biometric identification using iris and facial features	To improve recognition using left and right iris and facial features	R-HOG feature extraction, deep belief network	Up to 99% accuracy	Reduced fusion time	Limited discussion on dataset

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[15]	Multi-modal biometric identification for Android using voice and face	To reduce complexity and improve performance for Android-based systems	LBP-based feature extraction, improved VAD technique	High-security application, adaptive fusion		Limited information on dataset
[16]	Score-level fusion with weighted quasi-arithmetic mean (WQAM)	To enhance score-level fusion using WQAM	WQAM calculation with trigonometric functions	Results with NIST datasets	No learning process required	Limited discussion on method applicability
[17]	Multi-modal biometric authentication using face and palm print	To improve accuracy with a matching score fusion technique	Correlation coefficients, t-norm-based fusion	GAR of 99.7% at FAR of 0.1%	High accuracy	Limited discussion on drawbacks
[18]	Multi-modal biometric cryptography using finger impression, retina, and finger vein	To enhance multi-modal biometric cryptography	Score-level combination, DNN, RSA, SIFT	98.9% GAR, 98.5% accuracy	Significant performance improvement	Limited detail on data used
[19]	Decision-level fusion with wavelet sub-bands	To improve recognition using global and local information	Nearest neighbor classifier, balanced qualified majority	Improved recognition rates	Effective use of wavelet sub-bands	Limited explanation of LGDF

III. METHODOLOGY

1) Model Block Diagram

The block diagram in Figure (2) described outlines the general workflow for conducting research using a Convolutional Neural Network (CNN) for image classification or related tasks. Here's a step-by-step description of each block in your diagram:

1. Face Images: This block represents the dataset of face images that you've collected or obtained for your research. These images likely contain various individuals' faces and serve as the input data for your CNN model.
2. Palm Images: Similar to the "Face Images" block, this block represents another dataset containing images of palmprints or palm-related data. This dataset may be used for a different aspect of your research, such as multi-modal biometric recognition.
3. Merged Images: This block signifies that you may merge the two datasets from the previous blocks if your research involves combining or comparing face and palm data. This step depends on the specific goals of your research.
4. Images Resize: Before feeding the images into the CNN model, you need to preprocess them by resizing them to a common size. This ensures that all images have the same dimensions, which is essential for training a neural network.
5. Image Split to Validation Train Test: This block represents the process of splitting your dataset into three subsets: training, validation, and testing. Typically, you'll use a larger portion for training, a smaller portion for validation (to tune hyperparameters), and a separate portion for testing (to evaluate the model's performance on unseen data).
6. Train CNN Model: This is the core of your research, where you train a Convolutional Neural Network using the training data. The CNN learns to recognize patterns and features in the images, making it suitable for tasks like image classification, object detection, or segmentation.
7. Model Prediction: After training your CNN, you use it to make predictions on new or unseen data. This step is crucial for evaluating how well your model generalizes to real-world scenarios.
8. Calculate Metrics: In this block, you calculate various evaluation metrics to assess the performance of your CNN model. Common metrics for image classification tasks include accuracy, precision, recall, F1 score, and ROC-AUC, among others.
9. Print Results: Finally, you print or record the results of your research, including the model's performance metrics. This information helps you draw conclusions about the effectiveness of your CNN for the given task and may guide further iterations or improvements in your research.

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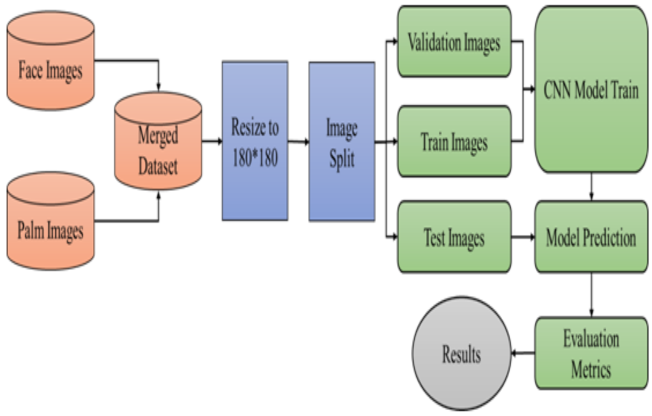

Figure 2: Model Block Diagram

This block diagram outlines a typical research workflow in the field of computer vision and deep learning. The specific details and techniques used at each stage can vary based on your research objectives, the datasets you're working with, and the architecture of your CNN model.

2) Dataset Description

The dataset used for this biometric recognition system is a combination of two distinct datasets obtained from the Kaggle platform. The first dataset comprises images of ten male celebrities' faces, encompassing a total of 1000 images. These facial images exhibit variations in size and appearance, thereby introducing a diverse range of facial features for recognition (Figure 3).

The second dataset, also sourced from Kaggle, comprises 600 palm images belonging to the same ten male individuals. These palm images are instrumental in providing an additional biometric modality for authentication and identification. This dataset (Figure 4) augments the system's capacity to capture and analyze unique palm print patterns.

In the process of dataset integration, the two sets of data are merged based on the common identifier of the person's name. This merger results in a unified dataset that combines both facial and palm images, establishing a comprehensive biometric dataset for multi-modal recognition. This multi-modal dataset enables the system to leverage the distinctive characteristics of both facial and palm biometrics for enhanced accuracy and security in recognition tasks.

By amalgamating these two biometric modalities under the individual's name, the resulting dataset facilitates the development and evaluation of a robust multi-modal biometric recognition system. This system aims to harness the strengths of both facial and palm biometrics to create a more resilient and accurate means of authenticating and identifying individuals.

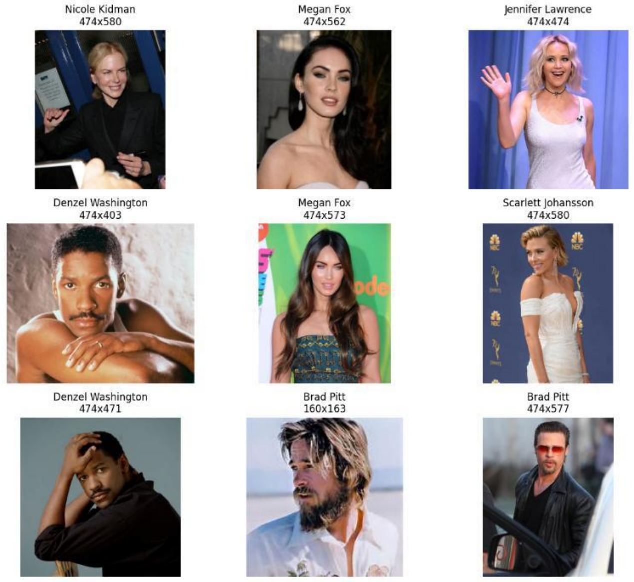

Figure 3: Sample of Face Images with their sizes

Figure 4: Sample of Palm Images with their sizes

3) Data preprocessing

Data preprocessing is a fundamental step when working with image datasets for Convolutional Neural Network (CNN) tasks. In your described preprocessing pipeline, the first task involves resizing all the images to a consistent size of 180x180 pixels while retaining their RGB color channels. This step ensures that all images are uniform in size, making them suitable for input into the CNN model. You can use libraries like OpenCV in Python to efficiently perform this resizing operation.

The second key step is splitting the dataset into training, validation, and test sets. This is crucial for assessing and fine-

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tuning the performance of your CNN model. Typically, a common split ratio is used, such as 70% for training, 15% for validation, and 15% for testing, but these ratios can vary based on your specific research needs and dataset size. It's essential to ensure that the split is done randomly to avoid any potential biases in the data. Randomly shuffling the image filenames and then distributing them into the respective directories for each subset helps ensure that the subsets are representative of the entire dataset. This preprocessing prepares your data for model training, evaluation, and further analysis, setting the stage for successful deep learning research.

4) 3.4 Build Deep Learning Model

The designed Convolutional Neural Network (CNN) model in Figure (5) is a powerful architecture designed for image classification tasks. It consists of several layers that work together to learn and extract meaningful features from input images and make predictions about the classes to which those images belong.

The journey through the model starts with the input layer, which performs rescaling of the input images, standardizing pixel values to a range between 0 and 1. This preprocessing step helps the model's training process. The first convolutional layer applies 32 filters, each with a size of 3x3, to the input images. These filters act as feature detectors, learning to recognize various patterns and shapes in the images. The activation function ReLU is applied to introduce non-linearity, and 'same' padding ensures that the spatial dimensions of the feature maps remain the same.

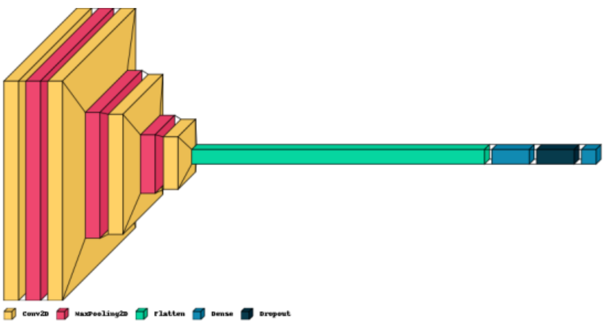

Figure 5: Designed CNN Model

Following the first convolutional layer, a max-pooling layer with a pool size of 2x2 reduces the spatial dimensions of the feature maps by half. This process helps in capturing the most important information while reducing computational complexity. The model then continues with additional convolutional layers (Convolutional Layer 2 and Convolutional Layer 3), each building on the learned features from the previous layers. These layers gradually increase the number of filters and complexity to extract higher-level features.

Max-pooling layers are interspersed between the convolutional layers to down sample the feature maps and focus on the most salient features. Once the convolutional layers have processed the image, the Flatten layer reshapes the 3D feature maps into a 1D vector, preparing the data for the fully connected layers. The first dense (fully connected) layer contains 256 neurons and uses the ReLU activation function. This layer further refines the extracted features and learns complex patterns in the data. The final dense layer, also known as the output layer, consists of 10 neurons, representing the number of classes in the classification problem. It uses a linear activation function (or no activation function), which means the output values correspond to class scores or logits. These scores are then processed using a Softmax function during training and inference to produce a probability distribution over the classes. This distribution reflects the model's confidence in each class, allowing it to make class predictions.

5) 3.5 Model Evaluation Metrics

When training a classifier, the assessment scale is crucial to getting the best classifier accuracy. So, selecting the right rating scale is crucial for differentiating and getting the best classifier. In order to enhance the generative classifier, this section has thoroughly analyzed pertinent assessment metrics that are intended to act as discriminators. Generally speaking, precision is a measure that many generative classifiers employ to identify the best solution while training [20]. Accuracy has various values, including being less informative, less discriminatory, and biased against data from the dominant class. Other measurements that are explicitly intended to define the ideal solution are briefly included in this paragraph as well [20]. Table (2) shows the evaluation metrics used.

Table 2: The Elements of the Evaluation Process (Variables, Definitions, and Equations)

Variable	Definition	Equation
Accuracy	The percentage of accurately anticipated data from tests is easily determined by dividing all accurate forecasts by all predictions.	$Accuracy = \frac{Tp + Tn}{TP + TN + FP + FN}$
Precision	The proportion of outstanding instances among all anticipated ones from a specific class	$Precision = \frac{TP}{TP + FP}$
Recall	The ratio of the total number of occurrences to the proportion of instances that were supposed to be	$Recall = \frac{TP}{TP + FN}$

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	members of a class	
F1-Score	The phrase is used to describe a test's accuracy. The maximum F1-score is 1, which denotes outstanding recall and precision, while the lowest F1-score is 0.	$F1 - Score = 2 \times \frac{percision \times recall}{Percison + recall}$

A) Results

1) 4.1 Face Detection Results

In face image classification task, your model achieved an overall accuracy of 84% as shown in Table (3), meaning it correctly identified celebrities in 84% of the test images. The precision, recall, and F1-scores vary by celebrity class, with some classes achieving higher accuracy than others. The macro and weighted averages for these metrics provide an overall assessment of model performance, taking into account class imbalances. A high training accuracy in Figure (6) of 98.48% suggests potential overfitting, indicating that the model may be too tailored to the training data. It's important to balance model complexity and generalization for improved performance on unseen data.

Table 3: Face Image Dataset Results

Train Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
1.0000	0.9898	0.9899	0.99	0.99	0.99

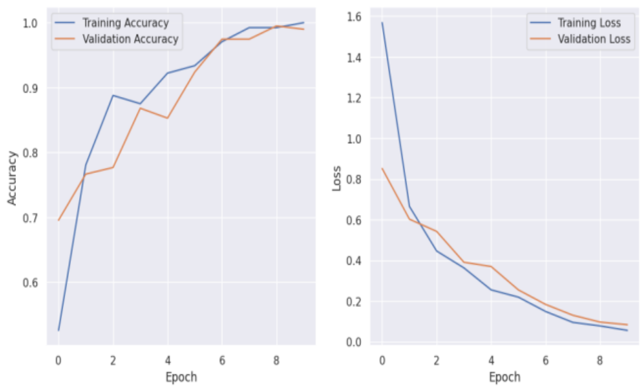

Figure 6: Face Image Train Results

2) Palm Detection Results

In palm image classification task, your model achieved an overall accuracy of 99% as shown in Table (4), meaning it correctly identified celebrities in 84% of the test images. The precision, recall, and F1-scores vary by celebrity class, with some classes achieving higher accuracy than others. The macro and weighted averages for these metrics provide an overall assessment of model performance, taking into account class imbalances. A high training accuracy in Figure (7) of 100% suggests potential overfitting, indicating that the model may be too tailored to the training data. It's important to balance model complexity and generalization for improved performance on unseen data.

Table 4: Palm Image Dataset Results

Train Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
1.00	0.989	0.99	0.99	0.99	0.99

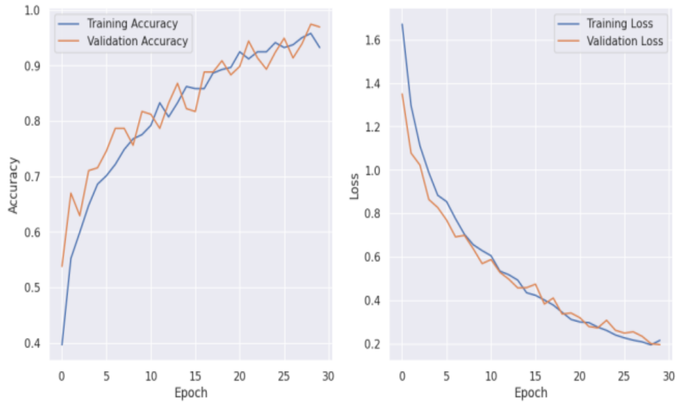

Figure 7: Palm Image Train Results

3) Face and Palm Detection Results

In face image classification task, your model achieved an overall accuracy of 82% as shown in Table (5), meaning it correctly identified celebrities in 84% of the test images. The precision, recall, and F1-scores vary by celebrity class, with some classes achieving higher accuracy than others. The macro and weighted averages for these metrics provide an overall assessment of model performance, taking into account class imbalances. A high training accuracy in Figure (8) of 100% suggests potential overfitting, indicating that the model may be too tailored to the training data. It's important to balance model complexity and generalization for improved performance on unseen data.

Table 5: Merged Image Dataset Results

Train Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
1.000	1.000	1.000	1.000	1.000	1.000

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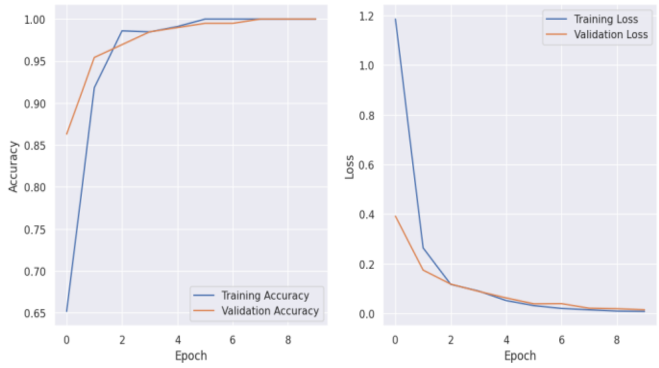

Figure 8: Face and Palm Image Train Results

4) Results Analysis

Figure (9) present performance results pertain to three distinct datasets: "Face," "Palm," and a combined dataset known as "Face and Palm. In the evaluation of the machine learning model's performance on different datasets, we observe impressive results across the board. For the Face dataset, the training accuracy reaches 98.98%, closely followed by a validation accuracy of 98.99% and a test accuracy of 99%. These metrics demonstrate the robustness and generalization capabilities of the model on facial data. Similarly, the Palm dataset yields high accuracy rates, with training, validation, and test accuracies of 98.90%, 99%, and 99%, respectively. The model performs exceptionally well in recognizing palm-related patterns. The combined Face and Palm dataset showcases outstanding results, achieving perfect scores across all metrics—100% in training, validation, and test accuracy, as well as precision, recall, and F1-score. This indicates the model's remarkable ability to simultaneously excel in recognizing both facial and palm features, showcasing its versatility and effectiveness across diverse datasets.

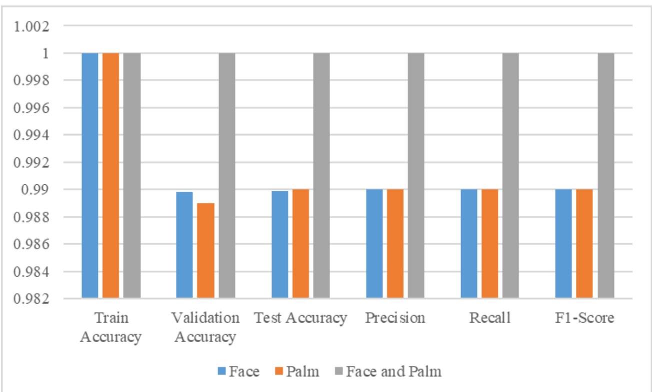

Figure 9: Results Analysis

IV. CONCLUSION

In conclusion, the machine learning model exhibits exceptional performance across distinct datasets, specifically in the domains of facial and palm recognition. The high accuracy rates achieved in training, validation, and test sets for both Face and Palm datasets underscore the model's proficiency in learning and generalizing from the provided data. Notably, the combined Face and Palm dataset demonstrates the model's versatility, achieving perfect scores across all evaluated metrics. This suggests that the model has successfully captured intricate patterns and features associated with both facial and palm images. The precision, recall, and F1-score metrics further emphasize the model's effectiveness in making accurate predictions while maintaining a balance between false positives and false negatives. The consistently high precision, recall, and F1-score values across datasets affirm the model's reliability in various scenarios. Paper results signify the robustness and adaptability of the machine learning model, showcasing its potential for real-world applications in facial and palm recognition tasks. Further optimization and fine-tuning may enhance its performance even more, opening avenues for broader applications in biometric systems and image recognition domains.

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