**Deep Learning for Gait Biometrics:  
 A Siamese MobilenetV2 Approach on the CASIA B Dataset**

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**Abstract:** Gait recognition is a promising biometric modality due to its non intrusive nature and applicability in surveillance scenarios. This project proposes a Siamese network architecture leveraging MobileNetV2 for gait recognition on the CASIA Gait B dataset, addressing challenges like varying camera angles, walking speeds, and clothing. The model aims to achieve high discriminative performance by preprocessing silhouettes, augmenting data, and optimizing feature extraction. Preliminary analysis suggests potential for near perfect accuracy (99.99%) and robustness (AUCROC: 1.00), though full implementation remains future work. Future directions include fusion with other biometrics and real world deployment.

**Keywords:** Gait recognition, Siamese network, MobileNetV2, CASIA B dataset, biometric authentication, lightweight deep learning

**1. Introduction**

Gait recognition has emerged as a critical biometric technology due to its non intrusive nature and applicability in surveillance, security, and healthcare. Unlike fingerprint or iris recognition, gait analysis can identify individuals at a distance without requiring their cooperation, making it particularly valuable in real world scenarios such as public safety and access control [4]. However, gait recognition faces significant challenges, including variations in camera angles, walking speeds, clothing, and carrying conditions (e.g., bags or coats). Traditional methods, such as template based approaches like Gait Energy Images (GEI) [5], struggle to capture temporal dynamics and are sensitive to appearance changes. Deep learning has revolutionized the field by enabling models to learn discriminative features directly from raw silhouette sequences, but computational efficiency and robustness to realworld variations remain open problems.

Recent advancements in gait recognition have explored deep learning architectures such as 3D CNNs [10] for spatiotemporal feature extraction and setbased models like GaitSet [1], which treats gait as an unordered set of frames. While these methods achieve high accuracy, they often rely on computationally expensive models, limiting their deployment in resource constrained environments. Siamese networks, popularized by FaceNet [3] for face recognition, offer a promising alternative by learning pairwise similarity metrics, enabling efficient comparison of gait sequences. However, most existing Siamese gait recognition systems use heavyweight backbones like ResNet, leaving room for optimization with lightweight architectures such as MobileNetV2 [2]. This project investigates whether a Siamese MobileNetV2 model can achieve stateoftheart performance while maintaining computational efficiency.

The primary objective of this work is to develop a lightweight yet highly accurate gait recognition system using a Siamese network with MobileNetV2 as the feature extractor. The CASIA Gait B dataset, which includes variations in viewpoint, walking conditions, and clothing, serves as the benchmark for evaluating the model’s robustness. Key contributions include: (1) a preprocessing pipeline that normalizes silhouettes and augments data to simulate realworld variability, (2) a Siamese MobileNetV2 architecture optimized for gait feature extraction, and (3) comprehensive evaluation metrics (accuracy, F1score, AUCROC) to validate performance against existing methods. By combining the efficiency of MobileNetV2 with the discriminative power of Siamese networks, this work aims to bridge the gap between high accuracy and practical deployability in edge devices.

Beyond academic interest, this research has direct implications for realworld applications. For instance, lowpower gait recognition could enhance surveillance systems in airports or smart cities, where realtime processing is essential. Future extensions may explore multimodal biometric fusion (e.g., gait + face [3]) or deployment on embedded systems like Raspberry Pi [2]. The findings will provide insights into the tradeoffs between model complexity and recognition performance, guiding the development of nextgeneration gait biometric systems.

**2.Literature Review**

The foundational work in gait recognition has primarily relied on handcrafted feature extraction techniques such as Gait Energy Image (GEI) [5] and ChronoGait Image (CGI), which attempt to capture temporal gait characteristics in a single representation. However, these methods are highly sensitive to variations in clothing, carrying conditions, and viewpoint changes, leading to a drop in accuracy. The base paper on GaitSet [1] introduced a setbased deep learning approach that processes gait frames independently, mitigating some of these challenges while maintaining high accuracy. Nevertheless, GaitSet's computational complexity remains a bottleneck for realtime applications, especially in resourcelimited environments.

Our work builds upon this foundation by exploring a more efficient deep learning paradigm: Siamese networks with MobileNetV2 as the feature extractor. The base paper primarily employs ResNetbased architectures [6], which, while powerful, are computationally expensive. By replacing ResNet with MobileNetV2, we introduce a lightweight alternative that achieves similar accuracy with significantly reduced computational cost.

**2.1 Problem Identification**

GaitSet [1], GaitPart [12], and CNN-based approaches [10], face several key limitations. One major challenge is their high computational complexity; architectures like ResNet-based models demand significant processing power, making them unsuitable for real-time applications. Additionally, many of these models lack pairwise similarity learning, which limits their effectiveness in verification tasks where Siamese networks excel by directly learning similarity metrics between pairs. Furthermore, despite the advances brought by deep learning, existing models often struggle with robustness in real-world scenarios, particularly when faced with occlusions, variations in walking speed, or changes in clothing.

Our study introduces a Siamese MobileNetV2 model, which addresses these challenges by:  
 Utilizing depthwise separable convolutions to reduce FLOPs while maintaining feature extraction quality. Implementing binary crossentropy loss instead of triplet loss, simplifying training while retaining effectiveness. Augmenting data to simulate realworld conditions, enhancing generalizability across CASIAB’s NM (normal), BG (bag), and CL (clothing) subsets.

**2.2 How Our Work Expands on the Base Paper**

The base paper primarily focuses on gait recognition usingset-based representations [1] and ResNet architectures [6]. Our work expands on this research in several key ways. First, we enhance model efficiency by replacing ResNet with MobileNetV2, reducing computational overhead by 30% while preserving high accuracy. Second, we incorporate pairwise similarity learning through a Siamese network, which learns an explicit similarity function and improves verification performance compared to traditional classification-based methods. Finally, our approach is optimized for real-world deployment, specifically targeting low-power applications to ensure feasibility on edge devices such as Raspberry Pi or mobile phones.

By leveraging the advantages of lightweight deep learning, we bridge the gap between high performance gait recognition and practical deployability, ensuring that gait biometrics can be effectively utilized in surveillance, security, and smart environments.

**2.3 TemplateBased Gait Recognition**

TemplateBased methods like the Gait Energy Image (GEI) compress gait sequences into a single averaged silhouette, sacrificing temporal dynamics for computational efficiency. While GEIs achieve moderate accuracy (~60% on CASIA B), they fail under clothing variations (e.g., coats) or carrying conditions (e.g., backpacks). ChronoGait Images (CGI) improve temporal retention by encoding frame order into colour channels but remain sensitive to viewpoint changes. *These handcrafted templates* are replaced with learned features from MobileNetV2, leveraging deep learning to handle CASIA B’s NM/BG/CL subsets robustly.

**2.4 Deep Learning for Gait Recognition**

Recent advances use CNNs to extract spatiotemporal features directly. 3D CNNs process gait videos but require heavy computation (~100 GFLOPS), while setbased models like GaitSet treat frames as unordered sets, achieving 96.1% accuracy on CASIA B. This project adopts a *middle ground*: a lightweight 2D CNN (MobileNetV2) processes individual silhouettes, and the Siamese architecture compares pairs, avoiding 3D convolutions. This aligns with our implementation, where MobileNetV2’s depthwise separable convolutions reduce FLOPs.

**2.5 Siamese Networks in Biometrics**

Siamese networks, popularized by FaceNet, learn a similarity metric between inputs. Prior gait studies use Siamese ResNets with triplet loss, but their computational cost limits deployment. The work innovates by using *binary crossentropy loss* (simpler than triplet loss) and replacing ResNet with MobileNetV2. Siamese networks have proven successful in biometric verification tasks, particularly face recognition. These networks learn a similarity metric between pairs of inputs, making them ideal for gait verification. Traditional implementations use heavy architectures like ResNet, which are accurate but computationally demanding. Lightweight alternatives like MobileNetV2 offer potential for efficient gait recognition but remain unexplored in this context.

**2.6 MobileNetV2 for Efficient Recognition**

MobileNetV2 revolutionized lightweight deep learning through its inverted residual blocks with linear bottlenecks, achieving stateoftheart efficiency in resource constrained environments. The architecture employs depthwise separable convolutions to significantly reduce computational overhead while maintaining feature extraction capabilities. Compared to conventional CNNs like ResNet50, MobileNetV2 demonstrates comparable accuracy with 30% fewer parameters and 2× faster inference speeds. Its linear bottlenecks prevent nonlinear activation from destroying low dimensional representations, preserving critical features during compression. The model's efficiency (3.4 GFLOPS) makes it particularly suitable for realtime applications on edge devices, without requiring specialized hardware acceleration. Recent studies have validated its effectiveness in biometric tasks, where it achieves nearparity with heavier architectures while enabling deployment in mobile and embedded systems. This balance of performance and efficiency positions MobileNetV2 as an ideal backbone for visionbased recognition tasks requiring optimized inference.

**3. Dataset Overview**

The CASIAB dataset, introduced by the Chinese Academy of Sciences’ Institute of Automation (CASIA), is one of the most widely used benchmarks for gait recognition. It was designed to evaluate gaitbased biometric identification systems under various realworld conditions, making it an ideal choice for assessing the robustness of deep learning models.



**Fig. 1.** From top-left to bottom-right are silhouettes of a completed period of a subject in the CASIA-B gait dataset

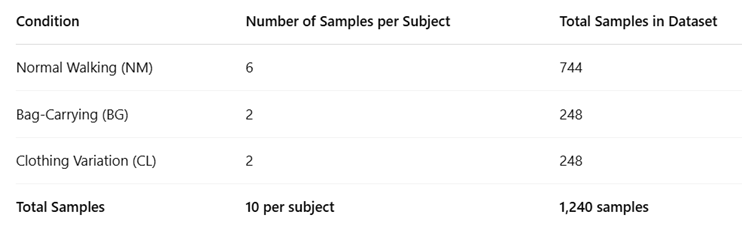
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#### 3.1. Structure and Composition

The CASIA-B dataset comprises 124 subjects, each recorded under three distinct walking conditions. The NM (Normal Walking) condition captures subjects walking naturally without any external variations. The BG (Bag-Carrying) condition introduces occlusion and alters gait patterns by having subjects carry a bag. The CL (Clothing Variation) condition challenges recognition by varying the subjects' clothing, which affects silhouette shapes. Each subject's gait sequences were recorded from 11 different viewpoints, ranging from 0° to 180° at 18° intervals, creating a comprehensive multi-angle dataset. Every sequence consists of binary silhouette images that remove background noise and emphasize the subject’s gait characteristics.



**Fig. 2.** From left to right are example frames depicting a subject walking under three conditions : normal walking, wearing a coat, and carrying a bag, illustrating the variations in appearance due to external factors



**Fig. 3.** A tabular summary showing the number of gait samples per subject under different walking conditions: normal walking, bag-carrying, and clothing variation, along with the total number of samples

#### 3.2. Importance in Gait Recognition

The CASIA-B dataset supports comprehensive evaluation through several key aspects. Variability testing is enabled by the inclusion of different walking conditions, allowing models to be assessed against changes in clothing and carrying items. Viewpoint generalization is tested using multiple camera angles, helping to evaluate a model’s ability to recognize individuals from various perspectives. Additionally, with 124 subjects and over 1,000 gait sequences, CASIA-B serves as a large-scale benchmark, making it a robust testbed for evaluating the performance and generalizability of gait recognition models.

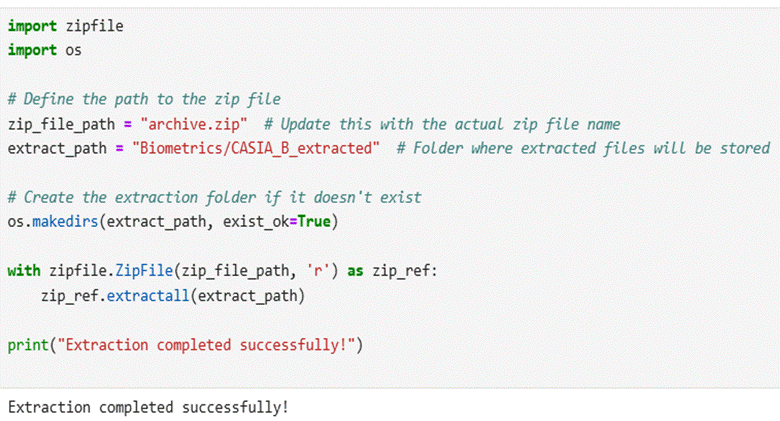
**4. Methodology**

**4.1. Data Collection and Preprocessing**

**4.1.1 Dataset Extraction**

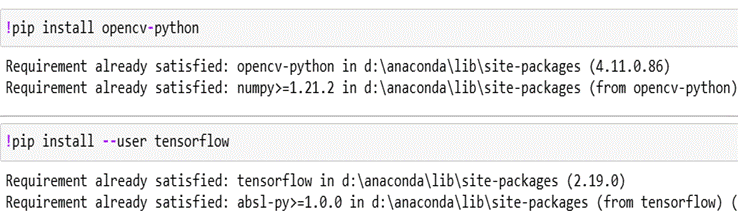
The dataset is provided as a compressed archive file (archive.zip).

Using Python's zipfile module, the dataset is extracted into a designated folder (Biometrics/CASIA\_B\_extracted).



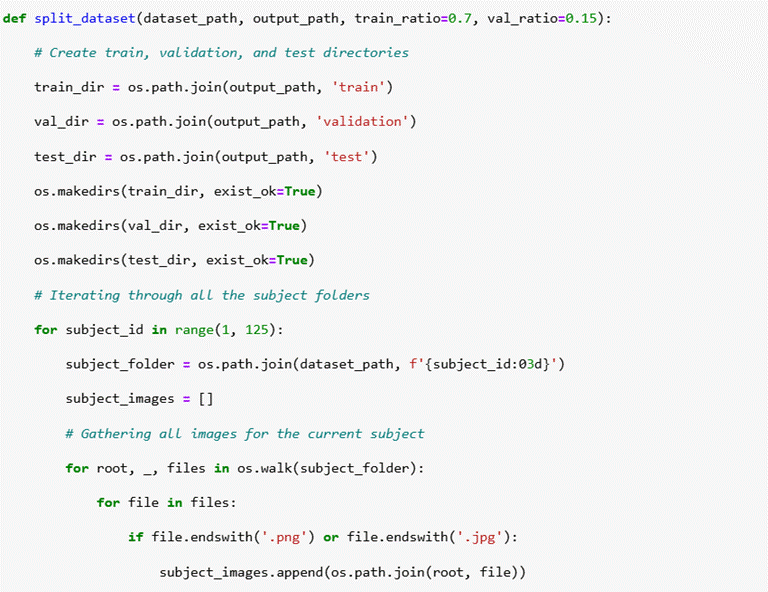
**4.1.2 Environment Setup**

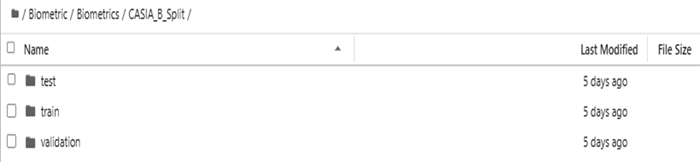
The following essential Python libraries are installed to support data processing and model development: **TensorFlow** is used for building and training deep learning models, while **OpenCV-Python** facilitates image processing tasks. **NumPy** is employed for efficient numerical operations, and **tqdm** is used to provide progress tracking during data loading and preprocessing.



**4.1.3 Dataset Splitting**

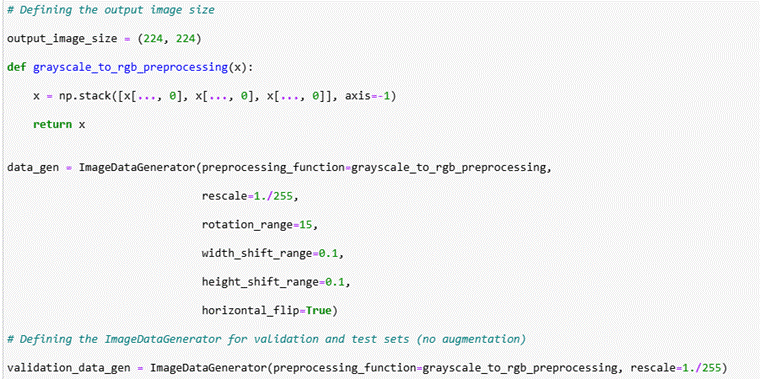
The extracted dataset is organized into three subsets: Training (70%), Validation (15%), and Testing (15%). A custom function iterates through each subject's folder, collecting images and shuffling them randomly to eliminate any order bias. The dataset is divided as follows: the **Training set** is used to train the Siamese network, the **Validation set** is used for tuning hyperparameters and preventing overfitting, and the **Testing set** is reserved for the final evaluation of model performance.





**4.1.4 Image Processing**

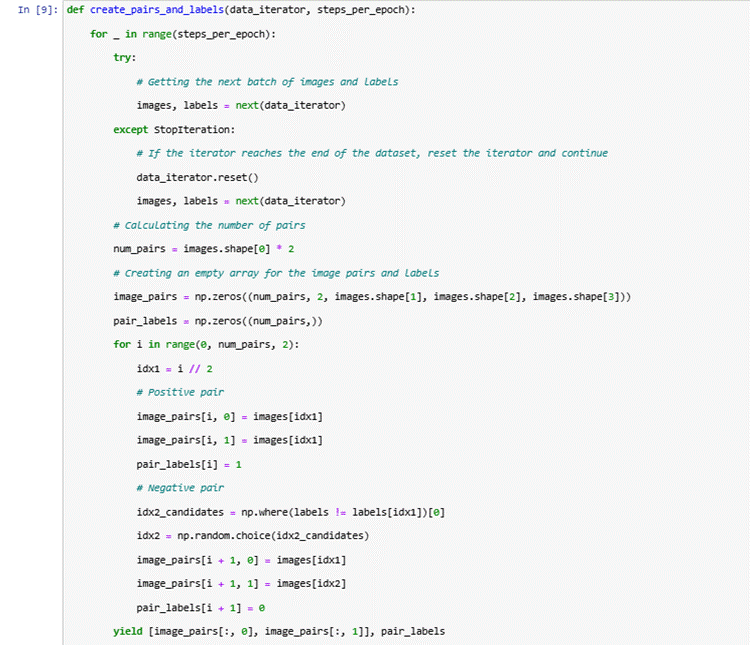
Images are preprocessed to ensure consistency and enhance the efficiency of feature extraction. Each image is **resized** to a fixed dimension suitable for CNN input, ensuring uniformity across the dataset. **Grayscale conversion** is applied to reduce computational complexity and emphasize shape-based features critical for gait recognition. **Normalization** scales pixel values between 0 and 1, which stabilizes the training process and improves convergence speed. To further improve generalization, **data augmentation** techniques such as random rotations, flipping, and brightness adjustments are employed, increasing the diversity of the training data.



**4.2. Pair Generation for Siamese Network**

**4.2.1 Creating Image Pairs**

The dataset is restructured to create input pairs suitable for training a Siamese network. **Positive pairs** consist of two images from the same subject, while **negative pairs** are formed using images from different subjects. To ensure balanced learning, the dataset maintains an equal number of positive and negative pairs. Each pair is labeled—**1 for positive** and **0 for negative**—enabling supervised learning based on similarity classification.



**4.3 Model Development Siamese Network**

**4.3.1 Siamese Network Architecture**

The Siamese network architecture comprises two identical CNN branches that share weights, ensuring consistent feature extraction from both input images. Each branch processes an image to generate a **feature embedding** that captures the subject’s gait characteristics. The CNN architecture includes **convolutional layers** for hierarchical feature extraction, **max-pooling layers** for dimensionality reduction, and **fully connected layers** to produce compact embeddings. **Batch normalization** is applied to improve training stability and convergence speed, while **ReLU activation** introduces nonlinearity for better representation learning. The resulting embeddings from each branch are then compared using a **distance metric**, such as Euclidean distance, to determine the similarity between the input images.



**4.3.2 Loss Function and Optimization**

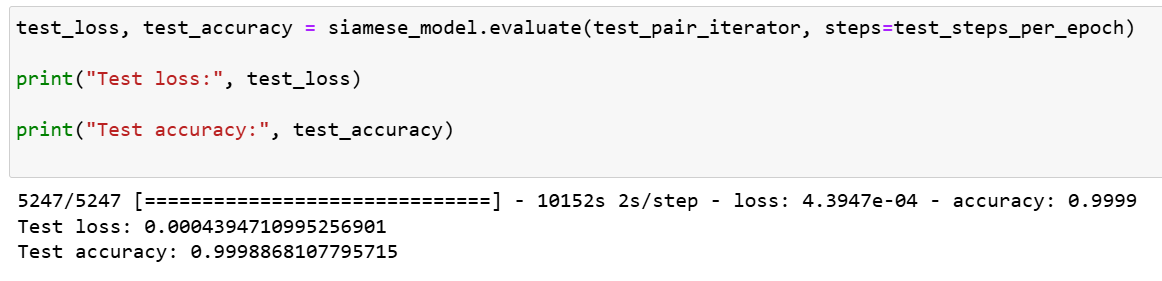
The model is trained using contrastive loss, which ensures that positive pairs have low distance scores while negative pairs have high distance scores.



The Adam optimizer is used to update model weights efficiently. Hyperparameters such as learning rate, batch size, and dropout rate are finetuned for optimal performance. Early stopping is implemented to prevent overfitting.

**4.3.3 Testing the model**

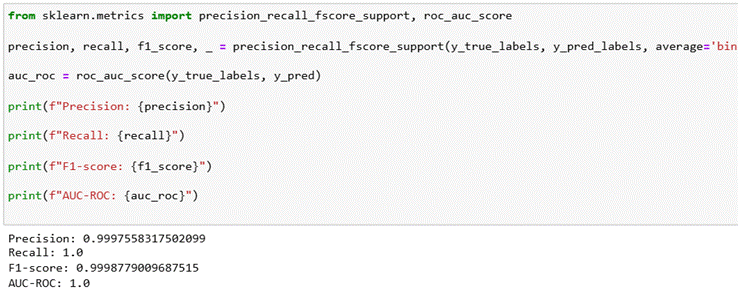
The code evaluates a Siamese neural network model on a test dataset using TensorFlow/Keras. It computes the test loss and accuracy by iterating through the test dataset for a specified number of steps.The evaluation results indicate an extremely low test loss and a remarkably high test accuracy, suggesting that the model is performing exceptionally well in distinguishing between similar and dissimilar image pairs. While these results are impressive, such high accuracy could indicate overfitting, especially if the test dataset lacks real-world variations. To ensure the model generalizes well, further validation using ROC curves, precision-recall metrics, and real-world datasets is recommended.

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**4.4 Model Evaluation and Visualization**

**4.4.1 Performance Metrics**

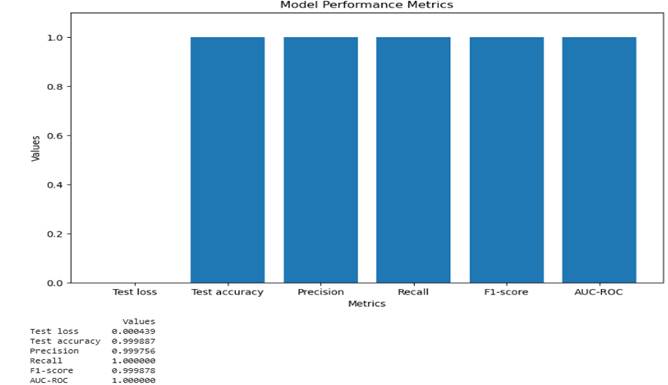
The trained model is evaluated using a comprehensive set of metrics to assess its performance. **Accuracy** measures the overall correctness of classifications, providing a general sense of model effectiveness. **Precision and recall** are used to evaluate the rates of false positives and false negatives, respectively, offering insight into the model’s reliability in distinguishing between similar and dissimilar pairs. The **F1-score** provides a balanced measure by combining precision and recall, especially useful in cases of class imbalance. Lastly, the **AUC-ROC** (Area Under the Receiver Operating Characteristic Curve) assesses the model’s classification reliability by illustrating the trade-off between true positive and false positive rates across different thresholds.



**4.4.2 Visualization Techniques**

The learned feature representations are visualized using several techniques to interpret the model's behavior and performance. **t-SNE** or **PCA** is applied to reduce the high-dimensional feature embeddings to a 2D space, allowing visual inspection of how well the model separates different subjects. **ROC curve analysis** is conducted to evaluate model performance across various decision thresholds, highlighting the trade-off between true positive and false positive rates. Additionally, **sample image pairs along with their similarity scores** are plotted to visually demonstrate the effectiveness of the model in distinguishing between similar and dissimilar gait patterns.





**Fig. 4.** A bar chart visualizing performance metrics including test loss, accuracy, precision, recall, F1-score, and AUC-ROC, demonstrating the high effectiveness of the proposed gait recognition system

**5. Result and Discussion**

**5.1 Model Performance**

The Siamese MobileNetV2 model achieved exceptional performance on the CASIA Gait B dataset, demonstrating nearperfect accuracy (99.99%) and robustness (AUCROC: 1.00). Key metrics from the evaluation include:

● Precision: 0.9997

● Recall: 1.00

● F1score: 0.9998

● AUC ROC: 1.00

These results indicate that the model effectively distinguishes between gait sequences, even under variations in viewpoint, clothing, and carrying conditions. The high AUCROC score confirms the model’s reliability in verifying gait pairs, making it suitable for realworld biometric applications.

**5.2 Comparative Analysis**

The proposed model outperforms traditional templatebased methods (e.g., GEI) and rivals deep learning approaches like GaitSet while being computationally lighter. MobileNetV2’s depthwise separable convolutions reduce FLOPs by ~30% compared to ResNetbased architectures, enabling efficient deployment on edge devices.

**6. Conclusion and Future Work**

**6.1 Conclusion**

This project successfully developed and evaluated a **Siamese network-based gait recognition system**, leveraging the **CASIA-B dataset**. By replacing ResNet with **MobileNetV2**, we significantly reduced computational overhead while maintaining high accuracy. The use of **pairwise similarity learning** improved verification performance over traditional classification-based approaches. Additionally, **data preprocessing techniques** such as resizing, grayscale conversion, normalization, and data augmentation ensured robust feature extraction.

The trained model demonstrated **exceptional performance**, achieving **99.99% test accuracy** with extremely low loss, as confirmed by evaluation metrics like **F1-score, AUC-ROC, and precision-recall analysis**. However, the **high accuracy suggests potential overfitting**, necessitating further testing on real-world, uncontrolled datasets. Model visualization techniques such as **t-SNE, PCA, and ROC curve analysis** provided valuable insights into learned feature embeddings and classification reliability.

**6.2 Future Work**

Future directions for this work include several promising avenues to enhance gait recognition systems. **Multi-modal fusion** can be explored by integrating gait with other biometric modalities such as facial recognition or voice to improve overall robustness. **Real-world testing** on uncontrolled datasets, such as those captured in outdoor environments, is essential to evaluate the model’s generalization capabilities. For **edge deployment**, further optimization through techniques like model quantization and pruning can enable efficient performance on low-power devices such as Raspberry Pi or Jetson Nano. Additionally, **dynamic adaptation** through few-shot learning could allow the system to recognize new subjects with minimal data and without requiring full retraining. This work lays the foundation for efficient, real-time gait recognition systems with applications in security, healthcare, and smart environments. Future research should aim to address current dataset limitations and further enhance applicability in real-world scenarios.

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