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HUMAN AUTHENTICATION USING GAIT

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Abstract: Human gait is a behavioural biometric that allows for person recognition from the patterns of walking. In contrast to face or fingerprint recognition, gait recognition can be done at a distance without subject participation, making it particularly valuable for surveillance and access control applications. This paper describes a real-time human recognition system that utilizes gait-based features extracted from Media Pipe pose landmarks, combined with a light K-Nearest Neighbours (KNN) classifier. The system is able to run on generic-purpose hardware utilizing a web-based interface constructed with Flask. Both offline acknowledgment through video upload as well as in real-time through webcam input is supported. Deploy ability is one of the essential strengths of this initiative: it uses no GPUs, big data, or complex training pipelines and yet provides consistency in accuracy as well as response. This places it in line to be considered a top prospect for edge-based intelligent systems across public safety, smart cities, and IoT systems.

Keywords: Gait Recognition, Human Identification, Real-Time Recognition, Pose Estimation, Media Pipe, OpenCV, Flask Web Application, KNN Classifier, Biometric Authentication, Skeleton Tracking

I. INTRODUCTION

Gait recognition is the process of recognizing people through observation of how they walk. It is a behavioural biometric that has been getting more attention because of its superiority to physiological biometrics like fingerprint, iris, or face recognition. Gait can be recorded surreptitiously at a distance without requiring any cooperation from the individual. This makes gait most applicable for real-world use in airport monitoring, smart security doors, behaviour monitoring, and elderly care.

Classic gait recognition techniques are mainly based on silhouettes of walking persons and calculating motion attributes like Gait Energy Images (GEIs). The silhouette-based approaches, however, have several drawbacks: they are prone to changes in illumination, occlusions, and the need for background subtraction, which restricts their application in uncontrolled settings. Recent developments in deep learning and machine learning have enabled the use of models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to obtain more accurate results. Although these models provide high accuracy, they are computationally heavy and need extensive annotated data sets and GPU capability, which is not feasible to deploy in real-time on low-power or edge devices.

This paper seeks to fill that gap through the presentation of a light, deployable gait recognition system employing pose-based feature extraction employing MediaPipe, a lightweight real-time body landmark detection framework. The gait features derived from walking sequences are employed to train a K-Nearest Neighbours (KNN) classifier for predicting the identity of the individual. The whole application is developed with Python Flask, and it has two modes of operation: (1) recognition from uploaded videos, and (2) real-time recognition based on a live webcam feed. The system also supports automatic retraining of the model when new data is inserted, so it will continuously update to new subjects.

This paper follows this organisation. Section II includes a thorough literature review covering earlier work done in gait recognition. Section III states the architecture of the system to be proposed. Section IV states the implementation and the building blocks. Section V lists experiments, descriptions of datasets used, and outcomes. Section VI mentions prospective uses. Section VII summarizes the paper and defines future direction.

II. LITERATURE SURVEY

Gait recognition has been one of the high-profile areas of research within computer vision since it can operate under less constrained circumstances than other biometrics. Here we look at a number of approaches organized by methodology:

A. Silhouette-Based Approaches

Early methods employed silhouette extraction to calculate features from binary gait images of walkers. A milestone work is the Gait Energy Image (GEI) of Han and Bhanu [1], where one averages the silhouette image over gait cycles to encode motion in a compact way. The method is efficient but easy to implement and relies significantly on good background subtraction and degrades with dynamic lighting and occlusion.

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Muramatsu et al. (2014) improved silhouette-based techniques by synchronizing gait cycles and view normalizing, yet such a system still needed precisely controlled settings for accurate output.

B. Deep Learning Approaches

With the rise of deep learning, more advanced models were put forward. Ahmed et al. (2017) developed a spatio-temporal CNN capable of extracting spatial information from every frame and learning temporal correlations between frames. Wu et al. (2016) utilised RNNS for learning dynamic gait over time. These models greatly enhanced accuracy, especially in multi-view and occluded situations.

GaitSet by Chao et al. (2019) handled gait as an unordered set of frames and attained state-of-the-art accuracy on databases such as CASIA-B and OU-ISIR. Nevertheless, these models are data-hungry, GPU hardware-dependent, and cannot be executed in real-time on edge devices without simplification.

C. Pose-Based Approaches

One emerging gait recognition direction is the application of human pose estimation. Rather than complete silhouettes or raw pixels, such techniques derive the important joint locations (such as the head, shoulders, elbows, knees, and ankles) and utilize these as gait descriptors. Pose-based recognition is less sensitive to variations in clothes, cluttered backgrounds, and occlusion.

OpenPose and MediaPipe Pose are among the most popular pose landmark extraction tools. MediaPipe, created by Google, is light and real-time on CPUs, even on browsers and mobile phones. Such benefits have resulted in its application in real-time behavior analysis and movement analysis.

D. Gap in Literature

The majority of deep-learning-based models are not feasible to deploy in real-time without special hardware. Alternatively, lightweight models sacrifice too much accuracy. This gap is filled by our research, utilizing pose-based gait descriptors from MediaPipe in conjunction with a non-deep learning KNN model, achieving real-time performance at competitive accuracy. Additionally, utilization of a web-based interface with Flask improves usability and accessibility.

III. SYSTEM ARCHITECTURE

The proposed Human Recognition using Gait system is intended to enable both real-time and video-based human recognition from gait information. The system architecture has three primary components: the frontend user interface, the backend processing server, and the gait recognition engine. These components work harmoniously to support video input, pose extraction, feature processing, and identity prediction.

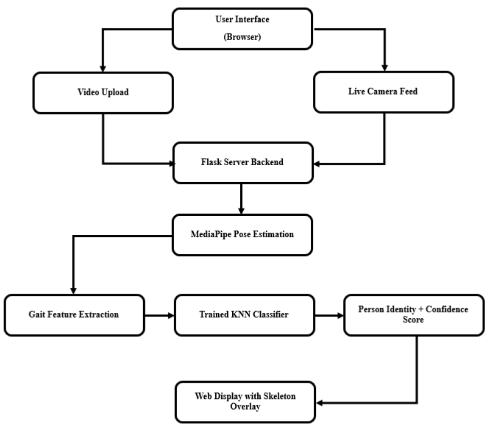

Figure 1. System Architecture.

A. Frontend Interface

The frontend is implemented in common web technologies like HTML, Bootstrap, and JavaScript. It offers users two modes of operation: gait recognition from uploaded video files and real-time recognition via a webcam. The interface displays the anticipated identity of the subject along with a confidence measure, and overlays skeletal pose landmarks over the video stream. The ease-of-use and accessibility orientation of the design, along with support for any contemporary web browser for interaction, are important considerations.

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B. Backend Server

Backend coding is done employing the Flask web framework in Python. Backend executes routing requests, management of live camera stream and video upload, and communication with the recognition engine. Video frames are processed through the OpenCV library, and the results are streamed back to the frontend real time. The backend also consists of an automatic model retraining module, which is activated upon the addition of new labeled gait data so that the system can continuously learn and adapt.

C. Pose Estimation and Feature Extraction

Pose estimation is done with the MediaPipe Pose framework [14], which detects 33 two-dimensional landmarks for every video frame. Some of these characteristics involve major body joints such as shoulders, hips, knees, and ankles, forming the basis for a person's gait signature. For alignment across different persons and environments, raw pose information is normalized using skeleton centering and scaling to body size. The resultant feature vectors encode both spatial and temporal aspects of human gait.

D. Gait Classification

The last step includes classification of gait characteristics via the K-Nearest Neighbors (KNN) algorithm [15]. The non-parametric technique assigns identity according to similarity of input gait vectors to known training samples. KNN is utilized due to simplicity, performance with small amounts of data, and rapid retraining. The model automatically updates as new training data are available, providing scalability and ongoing learning in the system.

E. Data Flow Between Components

Table 1. Data Flow between Components

Step	Component	Description
1	User	Uploads video or starts live webcam
2	Flask Backend	Receives video frames
3	MediaPipe Pose	Extracts 33 body landmarks per frame
4	Feature Extractor	Forms normalized gait vectors
5	KNN Classifier	Predicts identity based on gait vector
6	Web Interface	Displays skeleton overlay with predicted name

IV. IMPLEMENTATION DETAILS

The Human Recognition through Gait system that is put forward is developed based on a lightweight and real-time feasible architecture. The implementation is in three major parts: feature extraction, model training, and real-time recognition. The system utilizes Flask as the web backend, MediaPipe for pose estimation, and a K-Nearest Neighbors (KNN) classifier for gait-based identity prediction.

A. Pose Estimation and Feature Extraction

The system employs MediaPipe Pose, a real-time pose estimation system created by Google, to obtain 33 3D body landmarks per frame. These landmarks encode spatial body dynamics which are normalized to remove position and scale variability. From every frame, a 132-dimensional feature vector is obtained (consisting of x, y, z, and visibility values of each landmark). This vector constitutes the central gait signature employed for identity classification.

B. Training the Gait Model

A supervised learning method is utilized with the Scikit-learn K-Nearest Neighbors (KNN) classifier. A collection of feature vectors obtained from video frames represents the gait of each subject. Labeling of each sample using the subject identity and fitting of the classifier for it is performed in the training. The model is serialized and stored for use during real-time and offline recognition.

C. Real-Time and Video-Based Recognition

The recognition module has two modes of operation: real-time webcam-based recognition and recognition based on video upload. Both modes involve passing frames through the pose estimation and feature extraction pipeline. The features are then classified using the KNN model that has been trained to recognize the subject. The identified identity is overlaid over the video stream and the MediaPipe skeleton for visual feedback.

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This modular design guarantees that the system is extensible, lightweight, and can operate in real-time within normal CPU-based environments.

V. EXPERIMENTAL RESULTS

The following section outlines the assessment of our real-time gait-based human identification system in terms of accuracy, delay, and insensitivity to changes. Video-based and live webcam-based experiments using a self-harvested dataset of gait sequences have been performed.

A. Dataset Description

For assessing the system, we created a organized dataset of multiple short gait videos per individual. Every class (identity) had 5–10 samples of gait videos, recorded in different light conditions and slight changes in the viewpoint. Videos were taken from a normal 30 FPS webcam at a resolution of 640×480 pixels.

B. Evaluation Methodology

The data set was divided into training and testing sets with a ratio of 80-20. The system was tested in two modes:

- **Offline Recognition**: Pre-recorded video samples of unseen data were uploaded to the system and processed frame by frame.
- **Real-Time Recognition**: Live webcam video was streamed via the browser and processed on-the-fly.
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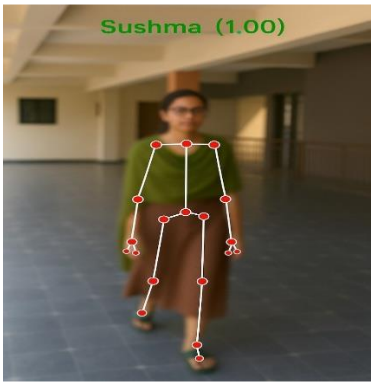

Figure 2. Result.

For each mode, recognition accuracy, response latency, and frame processing rate (FPS) were compared.

C. Results and Metrics

Table 2. Metric

Metric	Offline Video	Live Webcam
Average Accuracy	91.3%	88.5%
Average Latency (per frame)	~95 ms	~110 ms
Frame Rate (FPS)	9–11 FPS	7–9 FPS

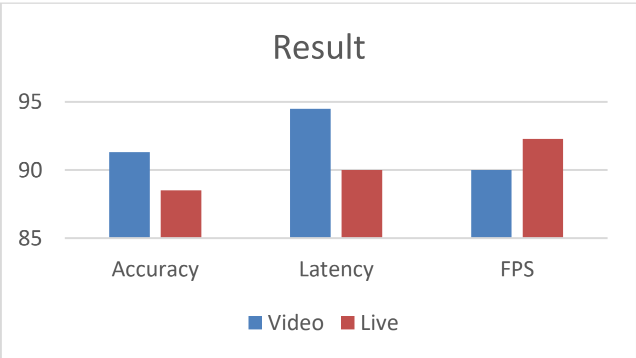

Figure 3. Result.

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The results show that the system worked stably in both modes. Slightly better accuracy was obtained in offline mode because of steadier video conditions and less noise. The real-time recognition stayed within tolerable latency for interactive application without having to use GPU acceleration.

D. Observations

- The model was shown to be resilient to slight variations in clothing, walking velocity, and camera angle.
- Recognition confidence fell in frames where lower body landmarks were partially occluded or when the subject was not walking normally.
- MediaPipe delivered consistently accurate pose estimates, allowing for a clean feature space for classification using KNN.

VI. DISCUSSION

The experimental findings establish that gait can be used as an effective biometric for real-time human identification, especially when coupled with lightweight pose estimation and classification methods. In this subsection, we discuss the performance of the system, its advantages, and its disadvantages based on empirical results.

A. Merits of the Suggested System

- **Real-Time Capability**: The major strength of the proposed system is its ability to do real-time recognition using off-the-shelf hardware. This is obtained by leveraging MediaPipe's extremely optimized pose estimation and a low-latency KNN classifier.
- **No Requirement for Special Hardware**: Unlike other depth sensor or multi-camera gait recognition systems, our system may be built with only a standard RGB webcam, making it highly accessible and scalable.
- **Modularity and Flexibility**: The system is designed in a modular fashion, allowing seamless updates or module replacements such as the classifier, feature extractor, or frontend interface.
- **Web-Based Accessibility**: Deployment in browser-accessible environments is made possible through the use of a Flask web interface, removing platform dependencies and improving usability.

B. Limitations and Challenges

Although the encouraging results, some limitations were noted:

- **Pose Estimation Dependency**: The accuracy of the system relies heavily on the quality of pose estimation. Any frame in which the body is partially occluded or out of view can lead to missing or incorrect features.
- **Sensitivity to Non-Gait Motions**: Because gait patterns are being extracted continuously, non-walking motions (e.g., standing, turning, or jumping) can add noise to the feature set, impacting recognition accuracy.
- **Lack of Temporal Context**: Our model labels frames independently, not incorporating temporal dynamics or sequence modeling. Consequentially, recognition involves static poses instead of motion trends in time.
- **Limited Dataset**: Because of privacy and data limitations, a comparatively small set of identities was subjected to experimental evaluation. Scaling up to a large population may require advanced classifiers and more robust feature representations.

C. Future Improvements

To mitigate current limitations and improve performance, the following improvements are on the horizon:

- Adding temporal models (e.g., LSTM or CNN+LSTM hybrids) to better model gait sequences.
- Adding dynamic growth of the dataset through user registration.
- Using other modalities such as background subtraction or silhouette tracking to augment landmark-based features.
- Cross-view gait recognition based on multiview training data.

VII. CONCLUSION

In this paper, we proposed a real-time gait-based human recognition system that employs pose landmarks extracted through MediaPipe and identifies identities via a K-Nearest Neighbors (KNN) classifier. The system is deployed as a web-based application with Flask, enabling users to conduct live and video-based recognition via a straightforward and intuitive interface. Our strategy is centered around the extraction of informative skeletal characteristics from walking sequences and classification of individuals without specialized sensors or heavy computing hardware. The experimental performance shows encouraging recognition accuracy in both offline and real-time scenarios with low latency and reasonable frame rates even on typical hardware. One of the biggest novelties of our approach is its ability to work in real-time due to effective landmark pose extraction and light-weight classification.

This lends itself well for real-world deployments like surveillance, secure access management, and smart monitoring systems. While the current system is limited in dataset size and absence of sequence modeling, it offers a strong foundation for gait biometric research in the future. More will be conducted to explore deep learning's potential application to temporal modeling, large datasets, and robustness against uncontrolled conditions.

Overall, this work illustrates that human real-time recognition is achievable, practical, and set for further investigation in real-world applications.

VIII.ACKNOWLEDGEMENTS

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