

**GAIT RECOGNITION AS A BIOMETRIC SIGNAL, INVESTIGATING
SKELETAL TRAJECTORY EXTRACTION AND CLASSIFICATION
APPROACHES**

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**A RESEARCH REPORT SUBMITTED TO THE DIRECTORATE OF GRADUATE
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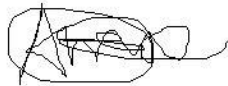
DECLARATION

I, AKOL JOSEPH, hereby declare that this research report is my original work, except where appropriate acknowledgments have been provided. I further declare that this work has not been submitted to any other university or institution of higher learning for any academic award.

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SUPERVISORS' APPROVAL

This research report titled “*Gait recognition as a biometric signal, investigating skeletal trajectory extraction and classification approaches*” is submitted for examination with the approval of the following academic supervisor(s);

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DEDICATION

I dedicate this research first and foremost to my Lord and Savior, Jesus Christ, whose guidance and grace have sustained me through every season of this journey.

To my parents, Mrs. Amongin Lucy and Mr. Opio Basil, I extend my deepest gratitude for their unwavering support, encouragement, and belief in my potential.

I also dedicate this work to my loving wife, Immaculate Atyang, and my siblings, whose patience and understanding carried me through the demanding phases of this study. Their sacrifices and steadfast presence provided the strength I needed to persevere.

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ABBREVIATIONS

2D	Two-Dimensional
3D	Three-Dimensional
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
GNN	Graph Neural Network
SVM	Support Vector Machine
HMM	Hidden Markov Model
GEI	Gait Energy Image
RNN	Recurrent Neural Network
FPR	False Positive Rate
ROC-AUC	Receiver Operating Characteristic - Area Under Curve
JSON	JavaScript Object Notation
WE	White European
BE	Black European
AR	Arab
AS	Asian
AF	African
fps	Frames per Second
CVPR	Conference on Computer Vision and Pattern Recognition
ICPR	International Conference on Pattern Recognition
ICCV	International Conference on Computer Vision
IEEE	Institute of Electrical and Electronics Engineers
SC	Soft Computing (Springer Journal)
PR	Pattern Recognition (Journal)
GAN	Generative Adversarial Network
PyTorch	Python Torch (Deep Learning Framework)
Kinect	Microsoft's motion-sensing input device
ICPC	International Conference on Pattern Classification
OULP	Osaka University Large Population (Gait Dataset)
CASIA-B	Chinese Academy of Sciences Institute of Automation Gait Database B
GAID	Gait from Audio, Image and Depth (TUM Dataset)
MP	MediaPipe
BGR	Blue-Green-Red (color channel order used in OpenCV)
RGB	Red-Green-Blue (standard color model)
cv2	OpenCV (Computer Vision library in Python)
np	NumPy (Python library abbreviation)
CNN-LSTM	Hybrid of Convolutional Neural Network and Long Short-Term Memory
GEV	Gait Energy Volume
EER	Equal Error Rate
GPU	Graphics Processing Unit
U-Net	A convolutional network architecture for image segmentation

ABSTRACT

Gait recognition, a non-intrusive biometric method effective at a distance, serves as a practical alternative to traditional identification techniques like fingerprints or facial recognition, particularly in forensic and surveillance contexts. This study aims to design and compare 2D and 3D models for gait recognition with the general objective of analyzing their comparative performance. Specific objectives include: (1) identifying a robust gait dataset recorded across various environmental conditions and camera angles, (2) extracting 2D and 3D skeletal keypoints using OpenPose and MediaPipe, respectively, (3) developing and evaluating the accuracy of 2D and 3D gait recognition models, and (4) analyzing their performance under varying environmental conditions. The research addresses the effectiveness of dataset utilization, comparative model accuracy, and key performance influencers. Results show the 2D model excels in occlusion handling, achieving a 0% false positive rate (FPR) for unknown instances, while the 3D model better generalizes to unseen sequences at higher thresholds, with a 74.55% FPR. However, the 2D model struggles with single-frame performance (80% FPR), and the 3D model exhibits significant bias and poor occlusion handling (100% FPR). Recommendations include enhancing dataset diversity, incorporating temporal features via LSTM layers, and improving 3D keypoint robustness through occlusion augmentation. This study provides a replicable framework, offering insights into model trade-offs and advancing gait recognition for resource constrained environments, forensic applications, and academic research.

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