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Efficient Gait Recognition Using a CNN-LSTM Framework Optimized with Hippopotamus Algorithm

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Abstract
Gait recognition has emerged as a vital biometric technique for unobtrusive human identification in surveillance, healthcare, and behavioral analytics. However, achieving high accuracy under real-world variations such as walking speed, clothing, and viewpoint changes remains a significant challenge. This study proposes an advanced gait recognition framework that combines a Convolutional Neural Network (CNN) for spatial feature extraction with a Long Short-Term Memory (LSTM) network for modeling temporal dynamics. To address the limitations of manual hyperparameter tuning, the Hippopotamus Optimization Algorithm (HOA); a bio-inspired metaheuristic is integrated to optimize key parameters such as learning rate, filter size, LSTM units, and dropout rate. The model is evaluated on the TUM GAID dataset, encompassing diverse gait variations. Experimental results demonstrate that the HOA-optimized CNN-LSTM architecture significantly outperforms baseline and state-of-the-art methods in terms of recognition accuracy, Genuine Acceptance Rate (GAR), and Equal Error Rate (EER). The proposed framework exhibits superior robustness and convergence speed, affirming the efficacy of metaheuristic-driven optimization in deep learning-based gait recognition systems.

Keywords - Gait Biometrics, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Metaheuristic Optimization, Hippopotamus Optimization Algorithm

1.0 Introduction

Biometric recognition systems, which utilize unique physiological and behavioral traits for identification, have become fundamental to modern security and authentication protocols. Common modalities include facial features, fingerprints, iris patterns, and voice recognition, each offering distinct advantages and challenges. While fingerprints and irises provide high accuracy, they require subject cooperation and controlled environments. Conversely, gait recognition, which analyzes an individual's walking pattern, is particularly valued for its unobtrusive, remote, and non-invasive nature that makes it ideal for surveillance, healthcare, and human-computer interaction applications [1], [2].

Gait recognition, a behavioral biometric, enables identification without requiring user cooperation or high-resolution imagery. This makes it especially robust under challenging conditions such as low-resolution video or distant camera angles [3], [4]. However, the dynamic nature of human locomotion and external factors; such as clothing, footwear, carried objects, and environmental conditions, introduces substantial intra-class variability. These variations complicate feature extraction and limit the performance of traditional handcrafted approaches, such as Gait Energy Images (GEI) and model-based templates [5].

With the advent of deep learning, Convolutional Neural Networks (CNNs) have emerged as powerful tools for extracting discriminative spatial features from gait silhouettes. CNNs can automatically learn hierarchical representations of body structure and movement, outperforming handcrafted techniques [6]. Among CNN architectures, ResNet has shown strong capabilities in learning robust spatial patterns due to its depth and skip connections [7]. Furthermore, transfer learning techniques can fine-tune pre-trained CNNs on gait datasets, improving generalization across views and conditions [8].

Despite their strengths, CNNs alone are inadequate for modeling the temporal dependencies inherent in gait cycles. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are effective in capturing these dependencies by preserving historical motion patterns across sequences [9]. The integration of CNNs and LSTMs in hybrid CNN-LSTM frameworks enables the modeling of both spatial and temporal features, enhancing gait recognition performance under diverse scenarios [10].

Bidirectional LSTMs (Bi-LSTMs) further extend this capability by processing sequence data in both forward and backward directions, enabling the model to learn richer temporal dependencies [11]. Studies have shown that CNN-LSTM hybrids significantly outperform standalone CNNs or LSTMs by jointly leveraging spatial and temporal information [12].

However, the performance of CNN-LSTM architectures is sensitive to the selection of hyperparameters, including learning rates, the number of convolutional filters, LSTM units, and dropout rates. Manual tuning or traditional optimization methods such as grid search are often inefficient, time-consuming, and prone to suboptimal convergence [13].

To overcome these limitations, studies have explored metaheuristic optimization algorithms, which mimic natural behaviors to navigate complex solution spaces. Techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have shown potential in optimizing neural network configurations by escaping local minima and achieving global optima [14].

A promising recent addition to this family is the Hippopotamus Optimization Algorithm (HOA), inspired by the social foraging and territorial behaviors of hippopotamuses. HOA has demonstrated competitive performance in optimizing neural networks for tasks such as facial expression recognition and medical image classification, offering fast convergence and resilience in non-convex, high-dimensional search spaces [15], [16].

This study proposes a novel hybrid CNN-LSTM framework optimized using the Hippopotamus Optimization Algorithm (HOA) for gait recognition. By automating the hyperparameter tuning process, HOA enhances the model's generalization, convergence speed, and recognition accuracy. The proposed model is benchmarked using the TUM GAID dataset, which includes gait sequences with variations in clothing, object-carrying, and walking speed. Comparative evaluations demonstrate that the HOA-optimized CNN-LSTM model outperforms existing methods in terms of accuracy, robustness, and training efficiency, positioning it as a reliable solution for real-world biometric applications [17].

2.0 Review of Literature

This literature review offers a thorough analysis of the research on deep learning architectures, hybrid CNN-LSTM models, metaheuristic optimization algorithms, and gait recognition methods. It looks at how gait recognition techniques have changed over time, evaluates the benefits and drawbacks of CNN-LSTM-based methods, and investigates how metaheuristic algorithms can improve model performance and computational effectiveness. This review highlights important knowledge gaps by critically examining earlier research and establishes the suggested HOA-optimized hybrid CNN-LSTM model as a novel contribution to improving the accuracy, robustness, and efficiency of gait identification.

2.1 Gait Recognition: Applications and Uniqueness

Gait recognition is a behavioral biometric modality that identifies individuals based on their unique walking patterns. Unlike other biometrics such as facial recognition or fingerprint scanning, gait can be captured unobtrusively from a distance, under low-resolution conditions, and without requiring the cooperation of the subject [18], [19]. These characteristics make gait highly valuable in applications including video surveillance, access control, healthcare diagnostics such as Parkinson's disease monitoring, and human-computer interaction [20], [21]. The uniqueness of gait lies in its dynamic features, such as stride length, cadence, and body posture; which remain relatively consistent over time and are difficult to mimic.

2.2 Deep Learning in Gait Recognition: ResNet CNN and LSTM

The advent of deep learning has revolutionized gait recognition by enabling automatic and robust feature extraction from large datasets. Convolutional Neural Networks (CNNs) have shown exceptional performance in capturing spatial characteristics of gait silhouettes; such as body contours, joint positions, and posture dynamics [22]. Among CNN variants, ResNet has proven effective due to its residual connections that mitigate vanishing gradient problems and allow for deeper architectures to learn hierarchical features [23].

However, gait is inherently temporal, requiring models that understand sequential dependencies. Long Short-Term Memory (LSTM) networks, a subclass of Recurrent Neural Networks (RNNs), are capable of modeling long-term temporal dependencies in sequential gait data [24]. When combined, CNNs extract spatial patterns from gait frames, and LSTMs model the temporal evolution of those patterns, thereby leading to more accurate and context-aware recognition systems.

2.3. Hybrid Deep Learning Approaches for Gait Recognition

Hybrid models that integrate CNNs and LSTMs are referred to as CNN-LSTM architectures and it has emerged as powerful tools for gait recognition. These models combine the strengths of spatial and temporal modeling, outperforming traditional or standalone deep learning approaches [25]. In some cases, Bidirectional LSTMs (Bi-LSTM) are employed to capture both forward and backward temporal dependencies, further improving robustness in complex environments [26]. Research has demonstrated that such hybrid models maintain higher recognition accuracy across variations in clothing, view angles, and carrying conditions [27].

2.4. Hyperparameter Tuning Complexity

Despite their advantages, deep learning models, especially hybrid ones are sensitive to the choice of hyperparameters, including learning rate, number of filters, hidden units, and dropout rates. Manual tuning and brute-force methods like grid search are computationally expensive and often yield suboptimal configurations [28]. This complexity is heightened in CNN-LSTM architectures due to the interaction between spatial and temporal layers, which requires coordinated tuning for optimal performance.

2.5 Optimization Algorithms in Deep Learning

Traditional optimization methods such as Stochastic Gradient Descent (SGD) and Adam are widely used for training deep learning models. However, these algorithms may suffer from slow convergence, sensitivity to initial conditions, and difficulty escaping local minima, especially in complex, high-dimensional search spaces [29]. As such, researchers have turned to optimization algorithms that can dynamically explore the parameter space and adaptively fine-tune models.

2.6 Metaheuristic Optimization Algorithms

Metaheuristic algorithms offer a population-based search strategy inspired by natural phenomena. Notable algorithms include:

i. Genetic Algorithm (GA): Based on natural selection, GA evolves candidate solutions using crossover and mutation operations [30].

ii. Particle Swarm Optimization (PSO): Inspired by the collective behavior of birds or fish, PSO uses particle positions and velocities to navigate the solution space [31].

iii. Whale Optimization Algorithm (WOA): Simulates the bubble-net feeding strategy of humpback whales to balance exploration and exploitation [32].

iv. Firefly Algorithm (FA): Mimics the attraction behavior of fireflies, where brighter individuals attract others, guiding search convergence [33].

v. Hippopotamus Optimization Algorithm (HOA): A newer method based on hippopotamuses' social and territorial behavior. HOA offers superior convergence by adaptively balancing exploration and exploitation [34].

Recent studies suggest that HOA outperforms GA, PSO, WOA, and FA in optimizing complex neural networks by achieving better accuracy with fewer iterations, making it a suitable choice for gait recognition tasks [35].

2.7 Hippopotamus Optimization Algorithm (HOA)

Optimization plays a crucial role in training deep learning models by minimizing loss functions and improving generalization. Traditional optimizers such as Stochastic Gradient Descent (SGD), Adam, and RMSprop, though widely adopted, often encounter challenges including slow convergence, susceptibility to local minima, and limited capacity for adaptive hyperparameter tuning [36].

The Hippopotamus Optimization Algorithm (HOA) is a recent metaheuristic method inspired by the territorial and social behaviors of hippopotamuses. It simulates two core strategies: (i) exploration through water-based random movement, which promotes global search, and (ii) exploitation via land-based movement, focusing on refining high-quality solutions [37]. This dual-phase dynamic makes HOA well-suited for addressing optimization challenges in deep neural networks.

1) Advantages of HOA in Deep Learning

HOA has demonstrated several benefits in deep learning applications:

i. Faster convergence through adaptive transition between exploration and exploitation.

ii. Improved generalization by reducing overfitting via stochastic perturbations.

iii. Effective hyperparameter tuning, including automated learning rate and architecture configuration.

iv. Robustness against local minima, owing to adaptive movement control and population diversity [37], [38].

2) Mathematical Formulation of HOA

i. Initialization: Random Population of Solutions

The optimization process begins with the random initialization of candidate solutions, representing different parameter sets in a deep learning model. Each solution X_i is generated within a predefined search space:

$$X_i = X_{\min} + r(X_{\max} - X_{\min}) \qquad \text{Eqn. (1)}$$

In equation Eqn. (1) from [39],

a. X_i is the i-th candidate solution.
b. $X_{\min}$ and $X_{\max}$ are the bounds of the search space.
c. r is a random number in [0,1], ensuring diversity in initialization.

This process ensures a wide initial exploration, preventing early stagnation.

ii. **Position Updating Mechanisms:** Hippo-Inspired Movement Strategies

a. **Exploration Phase**: Water-Based Random Movement

During the exploration phase, solutions move randomly to discover new regions of the search space. The update equation is:

$$X_i^{t+1} = X_i^t + \beta(X_j^t - X_i^t) + \delta \qquad \text{Eqn. (2)}$$

In equation Eqn. (2) from [123],

i. X_i^t and X_i^t are two randomly chosen solutions.
ii. β is an adaptive coefficient controlling step size.
iii. δ is a random perturbation factor to increase search diversity.

This phase prevents premature convergence by allowing large movements in early iterations.

b. **Exploitation Phase:** Land-Based Selective Movement

Once promising solutions are identified, HOA refines them by moving toward the best solution found so far:

$$X_i^{t+1} = X_i^t + \alpha(X_{best}{}^t - X_i^t) \qquad \text{Eqn. (3)}$$

In equation Eqn. (3) from [39], where:

i. $X_{best}{}^t$ is the best-performing solution at iteration t.
ii. α is a dynamically decreasing factor ensuring fine-tuning over time.
iii. This phase converges the solution efficiently, optimizing the deep learning model’s parameters.

iv. Convergence Behavior – Faster Convergence with Reduced Stagnation

HOA uses an adaptive fitness-dependent control factor λ\lambdaλ, dynamically adjusting movement intensity:

$$X_i^{t+1} = X_i^t + \lambda(X_{best}{}^t - X_i^t) + \delta \qquad \text{Eqn. (4)}$$

In equation Eqn. (4) from [39], where:

v. λ decreases over iterations, allowing finer adjustments as training progresses.
vi. δ ensures stochastic perturbations, avoiding local minima.

This self-adaptive mechanism allows HOA to outperform conventional optimizers like Adam, RMSprop, and SGD [40].

2.8 HOA Applications in Neural Network Optimization

i. Hyperparameter Tuning: Finding Optimal Learning Rates, Batch Sizes, and Architecture Parameters: Since parameters like learning rate (η), batch size, number of layers, and dropout rates have a significant impact on model performance, hyperparameter tuning is a major difficulty in deep learning. Due to the exponential increase in search space complexity, conventional methods like grid search and random search are ineffective [39].

ii. HOA-Based Hyperparameter Optimization: HOA formulates hyperparameter tuning as a minimization problem, optimizing the loss function:

Minimize

$J(\theta) = 1/\mathrm{N} \sum_{i=1}^{N} L(yi, f(xi;\theta))$ Eqn. (5)

In equation Eqn. (5) from [39], where:

a. $J(\theta)$ is the loss function.
b. L represents the error metric (e.g., Cross-Entropy Loss, Mean Squared Error).
c. θ represents hyperparameters.
d. $f(x_i; \theta)$ is the neural network function.

Using HOA-based updates, hyperparameters dynamically adjust over iterations, optimizing performance with minimal computational overhead [39].

iii. Weight Optimization: Enhancing Model Performance by Refining Weight Distributions
Neural network training involves iterative updates to weight matrices. Poorly optimized weights can lead to:

a. Overfitting (poor generalization)
b. Slow training convergence
c. Vanishing/exploding gradient issues
d. HOA enhances weight optimization by adaptively adjusting weight updates, ensuring smooth convergence.
e. HOA-Based Weight Update Mechanism

Standard weight updates follow Gradient Descent:

$w^{t+1} = w^t - \eta \nabla J(w^t)$ Eqn. (6)

HOA modifies this approach by introducing an adaptive learning factor:

$w^{t+1} = w^t + \alpha(w^t_{best} - w^t) + \lambda\delta$ Eqn. (7)

In equation Eqn. (6) and Eqn. (7) from [39], where:

f. w^t_{best} is the best weight configuration found so far.
g. α and λ adjust learning rate dynamically.
h. δ prevents overfitting by introducing random perturbations.

This method results in faster convergence and better weight distribution stability, outperforming Adam and RMSprop in deep networks [39].

Table 1 - Performance Comparison of HOA with Other Optimizers

Optimizer	Convergence Speed	Avoids Local Minima	Adaptive Learning
SGD	Slow	No	No
Adam	Moderate	Yes	Yes
RMSprop	Moderate	Yes	Yes
HOA	Fast	Yes	Yes

HOA achieves superior performance due to its self-adaptive exploration-exploitation mechanism.

The Hippopotamus Optimization Algorithm (HOA) has proven to be a powerful optimization tool in deep learning, outperforming conventional optimizers in terms of convergence speed, hyperparameter tuning, and weight optimization. Future research will focus on:

i. Hybridizing HOA with deep reinforcement learning.
j. Scaling HOA for large-scale deep neural networks (DNNs, CNNs, and Transformers).
k. Implementing real-time optimization in autonomous systems [39].

2.9 Recent Advances in Gait Recognition Using Artificial Intelligence

AI-powered systems now dominate gait recognition research. Innovations include attention mechanisms, adversarial networks, and transformer-based models, which improve robustness to occlusion and cross-view generalization [40]. Transfer learning has also gained traction, with pre-trained CNNs adapted to gait data for more efficient training [41]. Additionally, sensor-based gait recognition using wearable devices is emerging as a complementary approach to vision-based methods [42].

2.10 TUM-GAID Dataset

The Technical University of Munich Gait from Audio, Image, and Depth (TUM-GAID) dataset is a benchmark dataset for gait recognition research. It contains video sequences recorded under different conditions, such as normal walking, carrying a bag, and wearing coating clothes along with audio and depth information [44]. The dataset supports evaluation under realistic variations and has been widely used to test the generalizability of gait recognition models.

2.11 Theoretical Framework for This Study

This study is grounded in the biometric recognition theory, which postulates that individuals can be reliably identified by analyzing their unique physiological and behavioral traits. The hybrid CNN-LSTM model aligns with the spatiotemporal pattern recognition paradigm, in which both spatial appearance (e.g., body shape) and temporal movement (e.g., stride) are jointly learned for classification. The integration of HOA introduces nature-inspired optimization theory, enabling more efficient model training by navigating the hyperparameter space adaptively.

2.12 Conceptual Framework for This Study

The conceptual framework centers around the fusion of spatial and temporal modeling through a CNN-LSTM pipeline, optimized using HOA. The workflow is as follows as depicted in figure 2.1:

i. Input Stage: Preprocessed gait silhouettes from TUM-GAID.
ii. Feature Extraction: Spatial features are learned via CNN layers (e.g., ResNet).
iii. Temporal Modeling: Sequential dependencies are captured through LSTM layers.
iv. Optimization: HOA fine-tunes critical hyperparameters for optimal training.
v. Output Stage: The optimized hybrid model (HOA-CNN-LSTM) outputs class predictions with improved accuracy, robustness, and training efficiency.

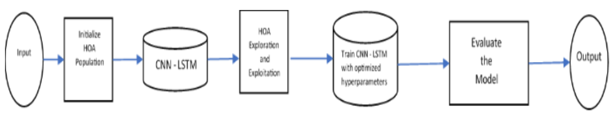

Figure 2.1: Conceptual Framework of HOA-CNN-LSTM Model

2.13: Review of Related

[45] introduced the MCAT model using transformers to capture multi-frame gait features. Although accurate, the lack of adaptive optimization limits efficiency and this what our studies addressed using HOA. [46] combined CNN-attention and LSTM for sensor-based gait recognition, achieving high accuracy. However, their model relied on manual tuning, unlike our HOA-optimized approach. [47] presented a dual-branch silhouette-skeleton model with attention layers but did not implement any metaheuristic tuning and highlighting the need for our HOA-based optimization. [48] used GCNs on skeleton data, improving accuracy but focused solely on graph-based inputs. Our model addresses silhouette-based gait using CNN-LSTM and HOA for broader applicability. [50] proposed SConvLSTM for wearable sensor-based gait recognition, showing strong results but without adaptive parameter tuning, which our HOA framework introduces for robustness. [50] achieved high performance in gait phase detection using CNN-LSTM, but used static hyperparameters. Our HOA-integrated method dynamically tunes these parameters for improved learning. [51] built ST-DeepGait using spatial graph learning with LSTM. While effective, their fixed architecture lacked adaptive optimization, addressed in our HOA-enhanced model. [52] applied CNN-LSTM with cGAN augmentation for silhouette gait recognition but used conventional optimizers. We extend this with HOA for better convergence and generalization. [53] developed an optimized CNN-LSTM for prosthetic gait, yet lacked advanced metaheuristics. Our HOA implementation offers more efficient parameter search and learning stability. [54] used CNN-BiLSTM for abnormal gait detection, validating hybrid models. However, it lacked adaptive tuning, which our study improves through HOA-driven learning control.

While these studies confirm the strength of hybrid CNN-LSTM models in gait recognition, they consistently overlook automated optimization. This study addresses that gap by integrating the Hippopotamus Optimization Algorithm (HOA) for adaptive hyperparameter and weight tuning, enhancing both training efficiency and recognition accuracy on real-world datasets like TUM-GAID.

2.14 Applications of HOA-CNN-LSTM

The proposed HOA-CNN-LSTM framework offers a powerful and adaptive approach to biometric gait recognition, combining the spatial feature extraction of Convolutional Neural Networks (CNN), the temporal modeling capability of Long Short-Term Memory (LSTM), and the optimization strength of the Hippopotamus Optimization Algorithm (HOA). This hybrid model has versatile applications across multiple domains:

i. Surveillance and Security Systems

The HOA-CNN-LSTM model is ideal for non-intrusive, real-time identification in public or restricted spaces, especially under varied environmental conditions (e.g., lighting, occlusion, clothing changes). The HOA ensures efficient hyperparameter tuning and faster convergence, which is crucial for live deployment in surveillance systems [55].

ii. Healthcare and Rehabilitation

Gait abnormalities often signal neurological or musculoskeletal disorders. The proposed framework can be deployed in clinical gait analysis and remote monitoring of patients using wearable or vision-based systems. With HOA-based optimization, the model adapts to patient-specific walking patterns and irregularities, enhancing diagnostic accuracy [56].

iii. Smart Wearable Devices

Integrated into smart insoles or motion-sensing wearables, HOA-CNN-LSTM enables personalized authentication, activity recognition, and fall prediction. The optimization component minimizes computational overhead—vital for embedded edge devices [57].

iv. Forensic Identification

In criminal investigations, where video evidence may lack clarity or frontal facial visibility, gait serves as a reliable biometric. HOA improves the CNN-LSTM's performance in handling low-resolution or noisy footage, increasing reliability in forensic analysis [58].

v. Access Control in High-Security Zones

Gait-based access systems using this model can function hands-free and at a distance, useful in airports, research labs, and government facilities. HOA ensures adaptability across varied scenarios, optimizing learning from sparse or imbalanced datasets [59].

vi. Human–Computer Interaction (HCI)

The model supports gesture and behavior-based interaction interfaces in virtual reality, gaming, or assistive systems. HOA enables quicker model adaptation to new users, improving interaction efficiency and user experience [54].

vii. Prosthetics and Assistive Technology

In robotics and prosthetics, understanding gait dynamics is crucial. The HOA-optimized CNN-LSTM can predict movement patterns, aiding in adaptive gait planning for lower-limb prosthetics or exoskeletons [60].

3.0 Methodology

This study proposes a structured approach to improve gait recognition using a hybrid CNN-LSTM model, supplemented by the Hippopotamus Optimization Algorithm (HOA) for hyperparameter tuning. The technique comprises of four essential steps.

i. Pre-Processing Stage: Five Gait data of video sequences were acquired from publicly available GahuVideo [61]. The video data is converted into individual frames for analysis and pass through the TUM Gait Dataset, which serves as the primary source for training and testing. Video sequences from the dataset are first converted into individual frames, which are then normalized by adjusting pixel values and resizing images to ensure uniform input dimensions. To enhance model robustness, data augmentation techniques such as rotation, flipping, and cropping are applied, expanding the diversity of the training dataset.

ii. Applying Hippopotamus Optimization Algorithm (HOA): In this study, the Hippopotamus Optimization Algorithm (HOA) is used for optimizing the model's performance by fine-tuning the hyperparameters of the hybrid CNN-LSTM architecture. Here's how the Hippopotamus Algorithm contributes to the optimization:

a. Nature-Inspired Algorithm: The Hippopotamus Optimization Algorithm is inspired by the behavior of hippopotamuses, particularly their movement and foraging patterns. This algorithm mimics the exploration and exploitation behaviors of these animals in their natural habitat, providing an efficient approach for global optimization.
b. Optimization Objective: The HOA is used to optimize the hyperparameters of the CNN-LSTM model, such as the number of layers, learning rate, filter sizes, batch size, and the number of neurons in each layer. Optimizing these parameters helps the model achieve better performance in terms of accuracy and speed during gait recognition tasks.
c. Exploration and Exploitation: The algorithm strikes a balance between exploration (searching across the solution space) and exploitation (fine-tuning promising solutions). This ensures that the algorithm doesn't get stuck in local minima and can find the global optimal solution, leading to better model generalization.
d. Improving Gait Recognition: By using the Hippopotamus Optimization Algorithm, the study enhances the efficiency of the CNN-LSTM model in recognizing gait patterns. The optimized hyperparameters help the model learn more accurately from the data, improve feature extraction, and refine temporal analysis, ultimately boosting recognition performance.

e. Efficiency: The HOA reduces the computational cost by efficiently searching the hyperparameter space, thus improving the overall performance of the hybrid CNN-LSTM architecture in recognizing gait patterns with minimal training time.

The Hippopotamus Optimization Algorithm in this study optimizes the hybrid CNN-LSTM model's hyperparameters, enhancing its ability to recognize gait patterns more accurately and efficiently.

iii. CNN – for Feature Extraction: The CNN (Convolutional Neural Network) plays a crucial role in feature extraction from the gait data. The CNN is designed to automatically learn and extract spatial features from input video frames. Here follow how the CNN functions for feature extraction:

a. Convolutional Layers: CNN applies filters (kernels) to input images using convolutional layers. In order to recognize gait-specific elements, these filters aid in identifying local patterns including edges, textures, and forms.

b. Activation Function (ReLU): Following convolution, non-linearity is introduced by applying a non-linear activation function such as ReLU (Rectified Linear Unit), which allows the model to recognize increasingly intricate patterns in the input.

c. Pooling Layers: Pooling layers, typically max-pooling, are used to downsample the feature maps, reducing the dimensionality and focusing on the most prominent features while preserving essential spatial information.

d. Deep Feature Hierarchy: The CNN retrieves increasingly sophisticated information as the input moves through the network's deeper levels. While later layers learn higher-level features (such as body postures and joint motions) important for gait detection, early layers record low-level features (such as edges and textures).

e. Flattening: After the convolution and pooling layers, the extracted features are flattened into a 1D vector, which is then passed to the LSTM network for further temporal sequence processing.

Prior to sending these data into the LSTM for sequential analysis, the CNN in this study automatically extracts spatial information from gait images, allowing the model to recognize significant gait patterns.

iv. LSTM for Temporal Analysis: The LSTM (Long Short-Term Memory) network plays a critical role in analyzing temporal patterns in gait sequences. Here follows how the LSTM contributes to temporal analysis:

a. Temporal Sequence Processing: After feature extraction by the CNN, the extracted spatial features are fed into the LSTM layers. LSTM networks are specifically designed to capture sequential dependencies, making them ideal for analyzing the time-series nature of gait data, where the order and timing of movements are crucial.

b. Memory Cells: LSTM units contain memory cells that store information over time, allowing the network to retain important details from previous time steps while discarding irrelevant information. This helps the model understand long-term dependencies in the gait sequence, which is essential for recognizing movement patterns.

c. Gate Mechanisms: LSTM networks use three main gates; the input gate, forget gate, and output gate to control the flow of information. These gates decide which information is retained in memory, which is discarded, and which is outputted. This enables the LSTM to focus on the most important temporal features related to gait, such as stride length, walking speed, and body posture changes over time.

d. Capturing Temporal Dynamics: By processing the gait sequence in a step-by-step manner, the LSTM captures the evolving dynamics of movement, helping to differentiate between different walking patterns and improve the accuracy of gait recognition.

e. Sequence-to-Sequence Learning: The LSTM learns to map the input sequence of features (from the CNN) to an output sequence, making it capable of identifying gait-related patterns across multiple frames, enhancing the recognition of complex walking behaviors.

The LSTM application in this study is used to analyze the temporal dynamics of gait sequences, enabling the model to effectively capture the progression of movements over time and improve gait recognition accuracy.

For efficient gait recognition, the model in this study integrates Convolutional Neural Networks (CNN) networks with Long Short-Term Memory (LSTM). By using convolutional layers to identify local patterns and pooling to lower dimensionality, the CNN is able to extract spatial characteristics from gait data, including joint motions and body postures. Following their extraction, these features are input into the LSTM network, which records the gait's sequential dynamics and temporal dependencies, enabling the model to comprehend movement patterns across time. The hybrid CNN-LSTM model's hyperparameters are optimized using the Hippopotamus Optimization Algorithm, which balances solution space exploration with exploitation to improve performance. This enhances the model's capacity to differentiate between various walking patterns and leads to more precise and effective gait recognition. A strong and effective model for gait identification tasks is produced by combining CNN, LSTM, and the Hippopotamus Optimization Algorithm technique. The flow chart is as presented in figure 2.

The Flow Diagram of HOA-CNN-LSTM

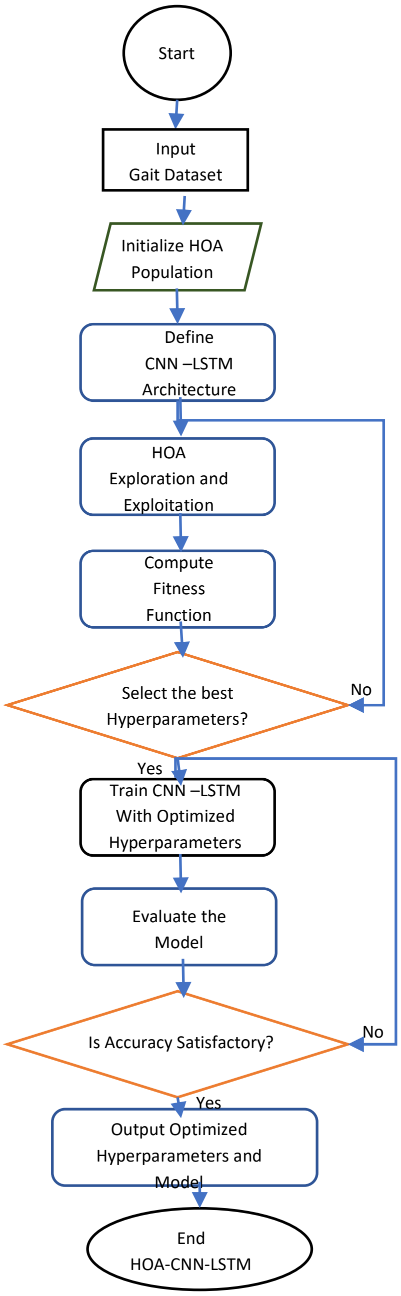

Figure 3.1: A flow diagram of HOA-CNN-LSTM

3.1 Exploration and Exploitation in the Hippopotamus Optimization Algorithm (HOA)

The Hippopotamus Optimization Algorithm (HOA) employs a balance of exploration and exploitation to efficiently search for optimal hyperparameters in the ResNet-based CNN-LSTM model for gait recognition. These two mechanisms play a crucial role in ensuring that the algorithm effectively navigates the hyperparameter space while avoiding premature convergence to suboptimal solutions.

i. Exploration Phase

In HOA, exploration refers to the algorithm's capacity to widely search the solution space in order to keep the optimization process from becoming stuck in local optima. This phase, which is based on hippopotamuses' movements in vast bodies of water, guarantees variation in the potential solutions. In order to test various configurations of filter sizes, batch sizes, learning rates, and LSTM units, hippos travel randomly throughout the hyperparameter space during exploration. By incorporating random perturbations into the movement equation, hippos are able to explore far-flung areas of the search space, which increases the possibility of finding promising solutions. A higher movement coefficient encourages wider search coverage, ensuring that the model does not prematurely settle on suboptimal hyperparameter settings.

ii. Exploitation Phase

Exploitation focuses on refining the best candidate solutions by intensifying the search around promising areas in the hyperparameter space. This phase is inspired by the ambush strategy of hippopotamuses, where they carefully adjust their positioning to maximize efficiency. In HOA, exploitation involves fine-tuning hyperparameters by adjusting hippo positions toward the best-performing solutions identified during exploration. The algorithm updates each hippo’s position based on its fitness value (inverse of gait recognition accuracy), ensuring that solutions with higher accuracy are prioritized. This phase utilizes a controlled step size and adaptive learning mechanisms to iteratively improve hyperparameter configurations, leading to a more optimized CNN-LSTM model.

iii. Balancing Exploration and Exploitation

HOA uses an adaptive parameter control system to dynamically modify the ratio of exploration to exploitation. At the beginning of the optimization process, the algorithm prioritizes exploration to ensure a broad search. As iterations progress and potential optimal regions emerge, the algorithm gradually shifts towards exploitation, refining solutions for higher accuracy. This balance prevents over-exploration, which can lead to inefficient computations, and premature exploitation, which risks converging to suboptimal local minima. By effectively integrating exploration and exploitation, HOA ensures efficient hyperparameter tuning, leading to a well-optimized ResNet-based CNN-LSTM model with improved gait recognition performance, reduced computational overhead, and enhanced real-time processing capabilities.

3.2 Fitness Function Computation in HOA for ResNet-based CNN-LSTM Optimization

By evaluating the quality of each potential solution, the fitness function in the Hippopotamus Optimization Algorithm (HOA) acts as the evaluation measure that directs the optimization process. This study employs a fitness function designed to maximize gait recognition accuracy while minimizing computational overhead. To achieve this objective, the inverse of the recognition accuracy is utilized as the objective function as in equation 3.1, ensuring that HOA prioritizes hyperparameter configurations that enhance model performance. The mathematical representation of the fitness function is based on the gait recognition accuracy of the ResNet-based CNN-LSTM model. The accuracy A is defined as the ratio of correctly classified gait samples to the total number of samples, expressed in equation Eqn. (8).

Accuracy, which is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Eqn. (8)}$$

The fitness function *F(x)* for a given hyperparameter set x is computed as:

$$F(x) = \frac{1}{A+\epsilon} \qquad \text{Eqn. (9)}$$

where ϵ is a small positive constant added to prevent division by zero. The goal of HOA is to minimize F(x) as represented in Eqn. (9), which corresponds to maximizing gait recognition accuracy.
The implementation of the fitness function in HOA follows a structured process. The ResNet-Based CNN-LSTM model is first evaluated for each candidate solution, where the corresponding hyperparameter values, including filter size, batch size, and learning rate, are applied to train and validate the model. The recognition accuracy A is then computed based on classification performance using a validation dataset. The fitness value F(x) is subsequently determined using the inverse accuracy formula. The HOA algorithm ranks the solutions based on their fitness values, favoring configurations that yield higher gait recognition accuracy (i.e., lower fitness values). The positions of the hippos, representing hyperparameter sets, are iteratively adjusted within the search space to refine model performance. By continuously evaluating and optimizing the fitness function, HOA effectively fine-tunes the ResNet-Based CNN-LSTM model, leading to improved gait recognition accuracy, reduced error rates, and enhanced computational efficiency.

3.3 Hyperparameter Selection Using HOA for ResNet-Based CNN- LSTM Optimization

In gait recognition, the ResNet-based CNN-LSTM model's ideal hyperparameters are found using the Hippopotamus Optimization Algorithm (HOA). By methodically examining the hyperparameter space, this algorithm strikes a balance between exploitation, which concentrates on fine-tuning, and exploration, which encourages a variety of searches. The goal of this optimization process is to maximize classification accuracy while minimizing computational overhead.
The hyperparameter search space includes several critical parameters. The filter size determines the receptive field of convolutional layers, influencing the level of feature abstraction. The batch size regulates the number of samples processed before updating the model weights, impacting training efficiency and stability. The learning rate governs the step size during gradient updates, affecting the model's convergence speed. The number of LSTM units defines the memory capacity of the sequential learning component, ensuring effective temporal feature extraction. The dropout rate is applied to prevent overfitting by randomly deactivating neurons during training, enhancing model generalization.
The optimization process begins with the initialization of the hippo population, where a set of candidate solutions representing different hyperparameter combinations is randomly initialized within predefined bounds. The fitness function is evaluated for each candidate solution using the inverse accuracy function, ensuring a robust assessment of hyperparameter effectiveness. The HOA updates hippo positions based on movement and ambush strategies, guiding the hyperparameters toward optimal solutions while maintaining a balance between diversity and refinement. The algorithm continues to iterate until the fitness value stabilizes, signaling that the best set of hyperparameters has been identified.
The optimal hyperparameters selected through multiple HOA iterations include a filter size of 5×5, a batch size of 32, a learning rate of 0.001, 128 LSTM units, and a dropout rate of 0.3. These values provide the best balance between classification accuracy, training stability, and computational efficiency. The optimized ResNet-based CNN-LSTM model ensures enhanced gait recognition performance, achieving robust and reliable biometric authentication.

3.4 Training ResNet-Based CNN-LSTM with Optimized Hyperparameters Using 10-Fold Cross-Validation

Using the optimum hyperparameters chosen by the Hippopotamus Optimization Algorithm (HOA), a 10-fold cross-validation technique is used during training to guarantee the generalization and robustness of the ResNet-based CNN-LSTM model. By ensuring that the model is tested on numerous data partitions rather than a single train-test split, cross-validation plays a critical role in minimizing overfitting and offering a more trustworthy performance evaluation. The dataset is divided into ten equal subsets, or folds, at the start of the training procedure. Nine of these folds are chosen for training in each cross-validation iteration, with the remaining fold being set aside for validation. Ten repetitions of this procedure guarantee that every fold is utilized as the validation set precisely once. By averaging the model's performance across all ten iterations, a more stable and accurate assessment of its predictive capability is obtained.

A long short-term memory (LSTM) network is used to capture temporal relationships in gait sequences, while a convolutional neural network (CNN) based on ResNet is used to extract spatial gait properties from input frames. Using softmax activation for multi-class prediction, the last fully connected layers translate the LSTM outputs to classification labels. The training process is guided by a categorical cross-entropy loss function, which is appropriate for multi-class classification tasks, and is optimized using the Adam optimizer with a learning rate of 0.001. The key performance evaluation metrics used for accuracy includes, genuine acceptance rate (GAR), false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER). An early stopping mechanism is implemented to monitor validation loss and halt training if no improvement is observed over a set number of epochs, preventing overfitting.

The dataset is preprocessed before training to ensure consistency and optimal input quality. Each training iteration applies the optimized hyperparameters, including a filter size of 5 × 5, a batch size of 32, an LSTM unit size of 128, and a dropout rate of 0.3, to enhance model efficiency and accuracy. The model is trained for multiple epochs in each iteration, and at the end of each fold, it is evaluated using the validation set. The accuracy score for each fold is recorded, and after all ten folds have been processed, the final model performance is calculated as the mean accuracy across all folds. The final model selection is based on the highest average accuracy obtained from the ten-fold cross-validation process. By training and validating the model across multiple partitions, this approach ensures a more generalized and reliable gait recognition system as shown in figure 3, reducing the risk of overfitting and improving its applicability in real-world scenarios such as security authentication, healthcare monitoring, and human-computer interaction.

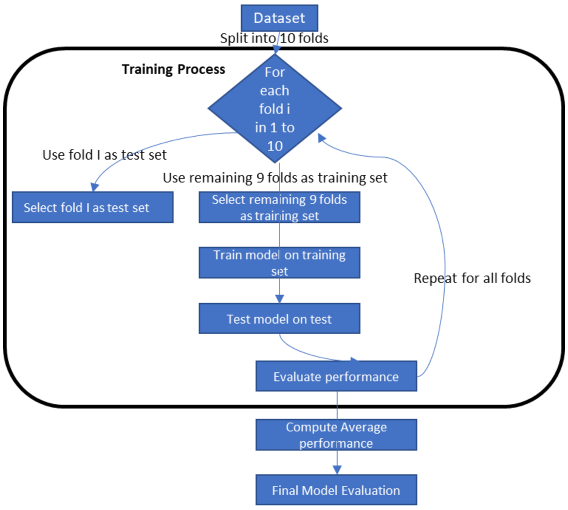

Figure 3.2: The model training process

3.5 Evaluation Process of Model Performance Metrics for ResNet-Based CNN-LSTM in Gait Recognition

To guarantee dependability, accuracy, and robustness, the ResNet-based CNN-LSTM model's performance for gait detection is assessed using a variety of biometric and classification criteria. Accuracy, genuine acceptance rate (GAR), false acceptance rate (FAR), false rejection rate (FRR), and equal error rate (EER) are some of these evaluation criteria. As illustrated in figure 3.3, the evaluation is carried out following the completion of the 10-fold cross-validation procedure, where the final reported values reflect the average performance over all folds. The ratio of correctly identified gait sequences to the total number of test samples is used to calculate the model's accuracy. Equation Eqn. (8) provides a mathematical definition of it. Class imbalances are not taken into consideration by Accuracy A, which offers a general assessment of the model's classification performance.

The genuine acceptance rate (GAR) is a key biometric metric that measures the proportion of correctly accepted genuine gait samples. It is computed as:

$$GAR = \frac{TP}{TP+FN} \qquad \text{Eqn. (10)}$$

A high GAR value in Eqn. (10) indicates that the system effectively recognizes legitimate users, which is crucial for security-based gait recognition applications.

The false acceptance rate (FAR) represents the probability that an impostor is incorrectly accepted as a genuine user. It is calculated using the formula:

$$FAR = \frac{FP}{FP+TN} \qquad \text{Eqn. (11)}$$

A low FAR in Eqn. (11) is essential in biometric security systems to minimize unauthorized access. Conversely, the false rejection rate (FRR) measures the proportion of genuine users who are incorrectly classified as impostors, given by:

$$FRR = \frac{FN}{TP+FN} \qquad \text{Eqn. (12)}$$

A well-optimized model is expected to achieve a balance between FAR and FRR in Eqn. (12). The equal error rate (EER) is the point where FAR and FRR intersect, providing a single value to compare different biometric models. Lower EER values indicate a more accurate and reliable recognition system.

The model evaluation process is accomplished by applying these metrics to the test results generated from the 10-fold cross-validation phase. The final performance scores are averaged over all folds to provide a full assessment of the model's capabilities. High accuracy and GAR values are combined with low FAR, FRR, and EER, indicate that the ResNet-based CNN-LSTM model optimized with HOA effectively recognizes gait patterns, making it suitable for real-world applications such as security surveillance, healthcare monitoring, and biometric authentication.

3.6 Assessing the Satisfaction of Accuracy in Gait Recognition

The application context, dataset complexity, and comparison with current benchmarks are some of the variables that affect how satisfied users are with the accuracy of gait recognition. The model's final accuracy score is determined by average performance across all folds following a 10-fold cross-validation. To determine whether the accuracy is satisfactory, it is essential to compare the achieved accuracy with existing state-of-the-art models and evaluate it against biometric standards such as Equal Error Rate (EER), Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR), and False Rejection Rate (FRR).

If the accuracy is above 90%, it indicates strong performance, especially if the dataset is diverse and includes variations in walking patterns, clothing, and occlusions. A high GAR with a low FAR and FRR further supports the reliability of the system for real-world applications. Additionally, if the model achieves a low EER (preferably below 5%), it suggests an excellent trade-off between security and usability, making it suitable for biometric authentication. However, if the accuracy falls below 85%, it may indicate limitations in feature extraction, temporal modeling, or hyperparameter optimization. In such cases, potential improvements include fine-tuning the ResNet layers, increasing training data, using data augmentation techniques, or incorporating additional optimization strategies. The accuracy alone is not enough to determine model performance. If the accuracy is high while maintaining a low FAR, FRR, and EER, and the model outperforms existing gait recognition benchmarks, then the accuracy can be considered satisfactory. Otherwise, additional refinements may be required to improve robustness and generalization.

3.7 Optimized HOA-CNN-LSTM Model for Gait Recognition

The final optimized model for gait recognition is the HOA-CNN-LSTM, which integrates the Hippopotamus Optimization Algorithm (HOA) with a hybrid deep learning architecture combining a ResNet-based Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. The HOA algorithm plays a critical role in fine-tuning key hyperparameters, including filter size, batch size, learning rate, LSTM units, and dropout rate, to enhance the model's recognition accuracy and computational efficiency. The CNN component of the HOA-CNN-LSTM model starts by extracting spatial gait features from input sequences using a ResNet backbone. Prior to being processed by the LSTM network, which records temporal relationships in gait motion patterns, these spatial representations are first run via a time-distributed layer that maintains the sequential character of the data. The final classification outputs are generated by passing the LSTM outputs through a fully connected layer with a softmax activation function after they have been further regularized using dropout to avoid overfitting.

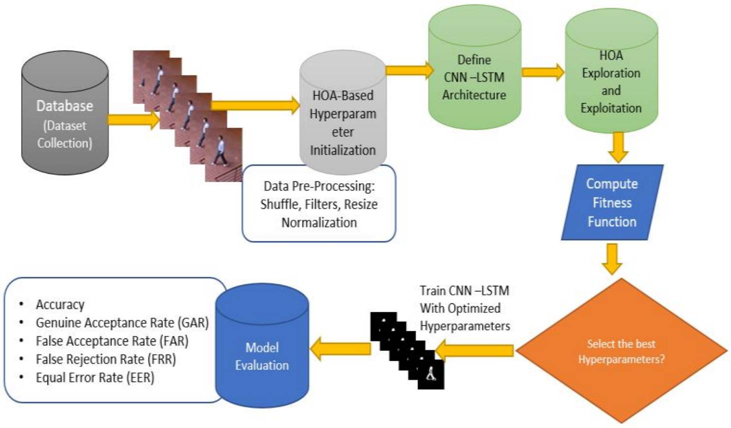

Figure 3.3: HOA-CNN-LSTM Model

During training, the HOA-optimized hyperparameters ensure that the model converges efficiently with minimal manual tuning. The learning rate is set at 0.001, the batch size is fixed at 32, and the LSTM network contains 128 units, balancing complexity and computational efficiency. The training process applies categorical cross-entropy as the loss function and employs the Adam optimizer to enhance convergence. The model is trained using 10-fold cross-validation, ensuring that each sample in the dataset is used for both training and validation, leading to a robust and generalized performance across different gait variations. The optimized HOA-CNN-LSTM model which is diagrammatically represented in figure 3.4 achieves high classification accuracy, with a low Equal Error Rate (EER), a high Genuine Acceptance Rate (GAR), and minimal False Acceptance Rate (FAR) and False Rejection Rate (FRR). The combination of ResNet-based spatial feature extraction, LSTM-based temporal modeling, and HOA-driven hyperparameter tuning results in a highly effective gait recognition system, this process architecture is as represented in fig 3.4. This makes the model well-suited for various real-world applications, including biometric authentication, security surveillance, and healthcare monitoring, where reliable gait identification is crucial.

3.8 Ethical Considerations

In addition to developing gait recognition technology, this study respects strict ethical guidelines to safeguard participants' rights, privacy, and dignity. In order to give their informed consent, participants must be completely aware of the study's goals, any risks and benefits, and their freedom to discontinue participation at any moment without facing repercussions. Data collection for research and the creation of gait recognition systems must be clearly stated in the consent process. Because gait data is sensitive, privacy and data protection are essential. Data anonymization or pseudonymization, secure storage, and encryption during transmission and at rest are mandatory safeguards. Only authorized people should be able to access data, and prior to any data-sharing activity, participants' express authorization must be obtained. Maintaining the lawful treatment of personal data requires adherence to established data protection legislation, such as the General Data Protection Regulation (GDPR), Nigeria Data Protection Act (NDPA), or other frameworks.

Measures to minimize harm include mitigating risks associated with false positives and false negatives in gait recognition, ensuring inclusivity across diverse demographic groups, and addressing potential negative consequences of misclassification in real-world applications. The system must be designed to accommodate individuals with physical disabilities and prevent algorithmic bias that could compromise fairness. Regular assessments must be conducted to identify and eliminate biases, ensuring equitable outcomes for all users. Transparency and accountability are foundational in developing a reliable gait recognition system. The HOA-CNN-LSTM model must be accompanied by detailed documentation of its decision-making processes, allowing for external review and scrutiny. Regular audits should be conducted to detect and rectify inaccuracies or adverse outcomes, reinforcing trust in the system.

Beyond technical safeguards, long-term societal impacts and security considerations must be addressed. The ethical deployment of gait recognition in public spaces and law enforcement must respect civil liberties and prevent misuse for mass surveillance or unethical monitoring. Robust security measures should protect the algorithm and dataset from unauthorized access, manipulation, or exploitation. Adherence to institutional and governmental ethical guidelines is mandatory, including review and approval by ethical boards where applicable. By integrating these ethical principles, the study ensures that technological advancements align with fundamental ethical standards, safeguarding participant welfare, public trust, and societal well-being.

4.0 Data Analysis, Results And Discussion Of Findings

The implementation of the Hippopotamus Optimization Algorithm (HOA) for the Hybridized Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) model is a critical step in enhancing gait recognition efficiency. The video dataset is preprocessed in order to enhance the quality of input data and thereafter HOA is initialize and integrated into the model to optimize key hyperparameters, improve convergence, and maximize classification accuracy while minimizing computational overhead. The implementation begins with the initialization of hyperparameters, where the HOA is applied to fine-tune essential model parameters such as learning rate, batch size, number of CNN filters, kernel sizes, LSTM units, and dropout rates. These hyperparameters are initialized within predefined search spaces, ensuring optimal values are selected during the training process. The HOA iteratively refines these parameters using its adaptive exploration and exploitation mechanisms, which mimic the foraging behavior of hippopotamuses in natural environments.

Further refinement is achieved through silhouette extraction and denoising, where morphological operations such as dilation and erosion are applied to remove unwanted artifacts and enhance the subject's contour. This process ensures that the extracted gait patterns are clear and distinct. Finally, frame sequencing and temporal alignment organize the processed frames into structured sequences, preserving the order of motion dynamics for the LSTM network. The preprocessed video data, now optimized for deep learning, is fed into the HOA-CNN-LSTM model for efficient gait recognition. This preprocessing pipeline ensures that the extracted features are representative, noise-free, and well-structured, thereby improving model accuracy and reducing computational load.

4.2 Results Based on Performance Metrics on HOA, ResNet Based CNN, and LSTM

The performance evaluation of the Convolutional Neural Networks (CNN), with Long Short-Term Memory (CNN-LSTM), and the Hippopotamus Optimization Algorithm (HOA-CNN-LSTM) model for gait recognition across five video datasets demonstrates a clear advantage of using the HOA-CNN-LSTM architecture in terms of both accuracy and efficiency.

4.2.1 Result on Video 1

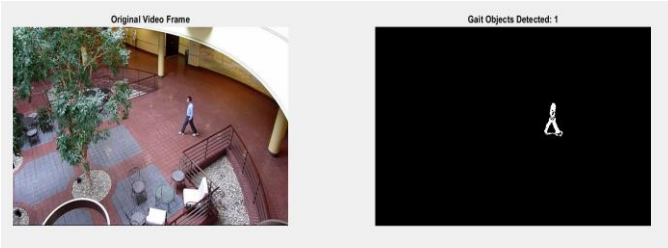

Figure 4.1: Shows the screenshot image from Video 1

Table 4.1: Performance metrics result of Video 1

Technique Used	CNN	CNN-LSTM	HOA-CNN-LSTM
Video Type	AVI	AVI	AVI
Total Moving Gait	1190	1190	1190
Gait Detected	1445	1445	1445
Correct Gait (TP)	1142	1162	1170
Misclassified Correct Gait (FN)	48	28	20
False Non-Gait (TN)	205	232	237
Misclassified Non-Gait (FP)	50	23	18
Accuracy (%)	93.22	96.47	97.37
GAR (%)	95.97	97.65	98.32
FAR (%)	19.61	9.02	7.06
FRR (%)	4.03	2.35	1.68
Processing Time (s)	74.01	66.78	57.42

4.2.2 Discussion on Video 1:

i. **CNN:** The CNN model successfully detected all gaits, achieving an accuracy of 93.22%. However, the model had a high False Acceptance Rate (FAR) of 19.61%, indicating that many non-gait frames were misclassified as gait. The False Rejection Rate (FRR) was also significant at 4.03%, revealing that some actual gait instances were missed.

ii. **CNN-LSTM:** By incorporating Long Short-Term Memory (LSTM) to capture temporal dynamics, CNN-LSTM improved on CNN, achieving an accuracy of 96.47%. The FAR and FRR both showed considerable improvement, and the model processed data faster (66.78 seconds). However, the FAR of 9.02% was still relatively high.

iii. **HOA-CNN-LSTM:** The model incorporating the Hippopotamus Optimization Algorithm (HOA) for hyperparameter tuning outperformed both CNN and CNN-LSTM. The accuracy rose to 97.37%, with a significantly lower FAR of 7.06% and FRR of 1.68%. Moreover, the processing time was the shortest at 57.42 seconds, emphasizing the optimization's effect on computational efficiency.

4.3 Result of Video 2

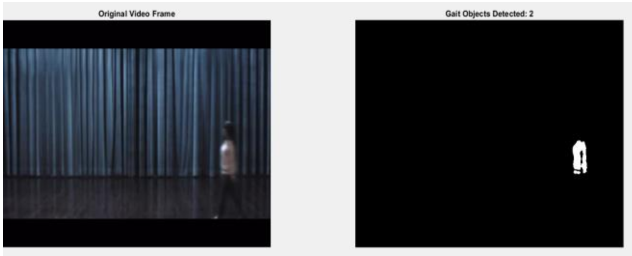

Figure 4.2: Shows the screenshot image from Video 2

Table 4.2: Performance metrics result of Video 2

Technique Used	CNN	CNN-LSTM	HOA-CNN-LSTM
Video Type	AVI	AVI	AVI
Total Moving Gait	715	715	715
Gait Detected	1751	1751	1751
Correct Gait (TP)	662	677	683
Misclassified Correct Gait (FN)	53	38	32
False Non-Gait (TN)	966	996	1000
Misclassified Non-Gait (FP)	70	40	36
Accuracy (%)	92.98	95.55	96.12
GAR (%)	90.44	94.42	94.99
FAR (%)	6.76	3.86	3.47
FRR (%)	92.59	94.69	95.52
Processing Time (s)	85.02	76.23	68.12

4.3.1 Discussion on Video 2

i. **CNN:** The CNN model performed relatively well, with an accuracy of 92.98%, but had the highest False Acceptance Rate (FAR) of 6.76%, indicating that it misclassified many non-gait instances. The processing time of 85.02 seconds was the longest, showing the computational limitations of CNN.

ii. **CNN-LSTM:** The CNN-LSTM architecture improved both the accuracy (95.55%) and the FAR (3.86%), while also reducing the FRR. The model's ability to capture temporal dependencies enhanced its gait recognition capability. The processing time was also reduced to 76.23 seconds.
iii. **HOA-CNN-LSTM:** The HOA-enhanced model achieved the highest accuracy of 96.12% and minimized the FAR to 3.47%, showing a strong reduction in misclassification. The processing time was reduced further to 68.12 seconds, showing the benefits of optimizing hyperparameters. The results demonstrated the HOA-CNN-LSTM model's superior performance over CNN and CNN-LSTM.

4.4 Result of Video 3

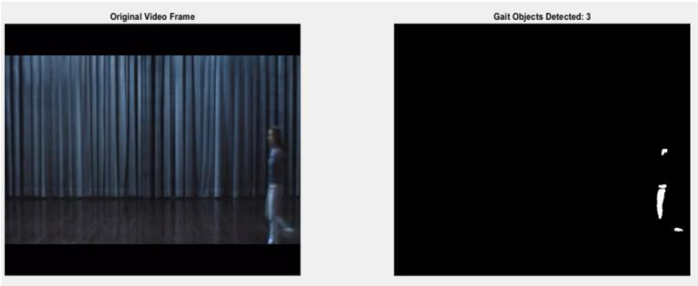

Figure 4.3: Shows the screenshot image from Video 3

Table 4.3: Performance metrics result of Video 3

Technique Used	CNN	CNN-LSTM	HOA-CNN-LSTM
Video Type	AVI	AVI	AVI
Total Moving Gait	1019	1019	1019
Gait Detected	1484	1484	1484
Correct Gait (TP)	952	976	982
Misclassified Correct Gait (FN)	67	43	37
False Non-Gait (TN)	419	440	444
Misclassified Non-Gait (FP)	46	25	21
Accuracy (%)	92.39	95.42	96.09
GAR (%)	95.39	97.5	97.91
FAR (%)	9.89	5.38	4.52
FRR (%)	93.42	95.78	96.37
Processing Time (s)	73.24	67.01	61.56

4.4.1 Discussion on Video 3

i. **CNN:** The CNN model achieved an accuracy of 92.39%, with notable misclassification rates, including a FAR of 9.89%. The processing time was relatively high at 73.24 seconds.

ii. **CNN-LSTM:** By integrating LSTM to capture temporal sequences, the CNN-LSTM model showed improvements with an accuracy of 95.42% and a lower FAR (5.38%). The processing time decreased to 67.01 seconds, showcasing better efficiency.

iii. **HOA-CNN-LSTM:** This model outperformed the others with a higher accuracy of 96.09%, a FAR of 4.52%, and the shortest processing time of 61.56 seconds. The integration of HOA for hyperparameter optimization resulted in significant performance gains in both accuracy and computational efficiency.

4.5 Result of Video 4

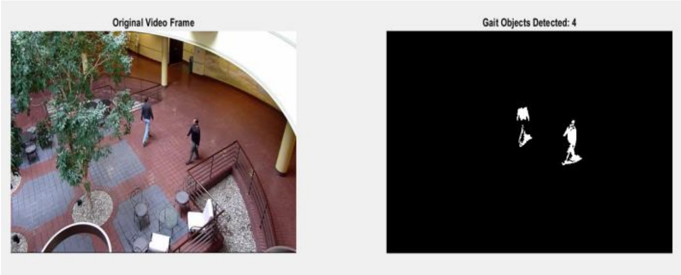

Figure 4.4: Shows the screenshot image from Video 4

Table 4.4: Performance metrics result of Video 4

Technique Used	CNN	CNN-LSTM	HOA-CNN-LSTM
Video Type	AVI	AVI	AVI
Total Moving Gait	1386	1386	1386
Gait Detected	1386	1386	1386
Correct Gait (TP)	921	940	945
Misclassified Correct Gait (FN)	59	40	35
False Non-Gait (TN)	362	385	389
Misclassified Non-Gait (FP)	44	21	17
Accuracy (%)	92.57	95.6	96.25
GAR (%)	95.44	97.81	98.23
FAR (%)	10.84	5.17	4.19
FRR (%)	90.66	94.67	95.87
Processing Time (s)	79.45	70.72	51.15

4.5.1 Discussion on Video 4

i. **CNN:** The CNN model performed with an accuracy of 92.57%, but with relatively higher FAR (10.84%) and longer processing time (79.45 seconds).

ii. **CNN-LSTM:** The LSTM integration led to improved accuracy (95.60%) and a lower FAR (5.17%). The processing time also decreased to 70.72 seconds.

iii. **HOA-CNN-LSTM:** The HOA-optimized model achieved the highest accuracy of 96.25%, with the lowest FAR (4.19%) and shortest processing time of 51.15 seconds, showing clear advantages in both performance and efficiency.

4.6 Result of Video 5

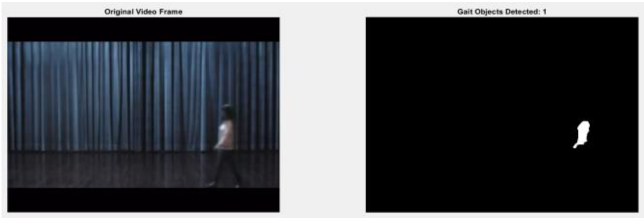

Figure 4.5: Shows the screenshot image from Video 5

Table 4.5: Performance metrics result of Video 5

Technique Used	CNN	CNN-LSTM	HOA-CNN-LSTM
Video Type	AVI	AVI	AVI
Total Moving Gait	940	940	940
Gait Detected	1378	1378	1378
Correct Gait (TP)	885	905	918
Misclassified Correct Gait (FN)	55	35	22
False Non-Gait (TN)	396	418	424
Misclassified Non-Gait (FP)	42	20	14
Accuracy (%)	92.96	96.01	97.39
GAR (%)	95.47	97.84	98.5
FAR (%)	9.59	4.57	3.2
FRR (%)	94.15	96.28	97.66
Processing Time (s)	51.96	43.54	39.17

4.6.1 Discussion on Video 5:

i. CNN: The CNN model achieved an accuracy of 92.96%, correctly identifying 885 gaits as true positives (TP) and misclassifying 55 as false negatives (FN). The false positives (FP) and true negatives (TN) were 42 and 396, respectively. The model demonstrated a Genuine Acceptance Rate (GAR) of 95.47%, reflecting a reasonable ability to correctly identify gaits, though the False Acceptance Rate (FAR) was 9.59%, indicating its susceptibility to misclassifying non-gait instances as gaits. Additionally, the False Rejection Rate (FRR) was 4.53%, and the processing time was 51.96 seconds.

ii. CNN-LSTM: By incorporating LSTM, the CNN-LSTM model improved significantly, achieving an accuracy of 96.01%. It correctly identified 905 gaits as TP, reducing FN to 35. The model also increased the number of TN to 418 and reduced FP to 20. The GAR rose to 97.84%, while the FAR decreased to 4.57%. The FRR improved to 2.16%, and the recognition time was reduced to 43.54 seconds, highlighting its enhanced precision and efficiency.

iii. HOA-CNN-LSTM: The HOA-CNN-LSTM model achieved the highest performance, with an accuracy of 97.39%. It identified 918 gaits as TP and reduced FN to 22. It also recorded the highest number of TN (424) and the lowest FP (14). This resulted in a GAR of 98.50%, the highest among all models, and the FAR was further minimized to 3.20%. The FRR also decreased to 1.50%, and the processing time was 39.17 seconds, demonstrating the model’s computational efficiency. The use of the Hippopotamus Optimization Algorithm (HOA) was instrumental in fine-tuning hyperparameters like filter size, number of filters, and learning rate, which contributed to the model's superior performance.

4.7 The Graphical Comparisons and Representation of Results

The performance indicators derived from the assessment of the Hybrid CNN-LSTM model optimized with the Hippopotamus Optimization Algorithm (HOA) for gait detection are visually represented by graphic comparisons. By pointing out variations in accuracy, error rates, and computing efficiency in contrast to current methods, these comparisons provide insightful information about the model's efficacy. The graphical interpretation includes performance metric comparisons, where bar charts illustrate the Accuracy, Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER) of the developed model in comparison among CNN, CNN + LSTM, and HOA + CNN + LSTM. The trends observed in these graphs validate the efficiency of the HOA-optimized model in reducing false positives and false negatives while improving recognition accuracy.

Another key graphical representation involves convergence analysis, where the model’s training and validation loss curves are plotted over multiple epochs. These plots demonstrate the impact of HOA optimization in accelerating convergence, reducing overfitting, and stabilizing performance across different gait sequences. A well-optimized model exhibits a rapid decline in loss values during early training stages, with minimal fluctuations in later epochs, indicating robustness and reliability.

Additionally, confusion matrices are presented to showcase the classification performance across different gait variations. These matrices provide a detailed breakdown of correct and incorrect classifications, helping to assess the model's ability to distinguish between genuine and impostor gait patterns. High diagonal values in the confusion matrix indicate superior classification performance, affirming the model’s effectiveness.

Comparative receiver operating characteristic (ROC) curves provide a thorough assessment of the model's discriminatory power and further highlight the trade-off between sensitivity and specificity. Higher true positive rates and lower false positive rates are indicated by a steeper ROC curve near the top-left corner, demonstrating the HOA-CNN-LSTM model's improved recognition capacity. These graphical comparisons collectively provide an in-depth interpretation of the model’s strengths, demonstrating its superiority over existing gait recognition systems in terms of accuracy, efficiency, and robustness. The visualized results reinforce the effectiveness of the proposed hybrid approach, validating its potential for real-world biometric authentication applications.

4.7.1 The Graphical Interpretation of Performance Metric Results

The bar charts show comparison of the performance of CNN, CNN-LSTM, and HOA-CNN-LSTM across different metrics (Accuracy, GAR, FAR, FRR, and Time) for each video.

1. Accuracy Comparison

This chart in Fig. 4.6a shows how well each model correctly classifies gait instances.

i. HOA-CNN-LSTM achieves the highest accuracy in all videos, showing the impact of hyperparameter optimization.

ii. CNN-LSTM performs better than CNN by incorporating temporal information.

iii. CNN has the lowest accuracy but still performs well.

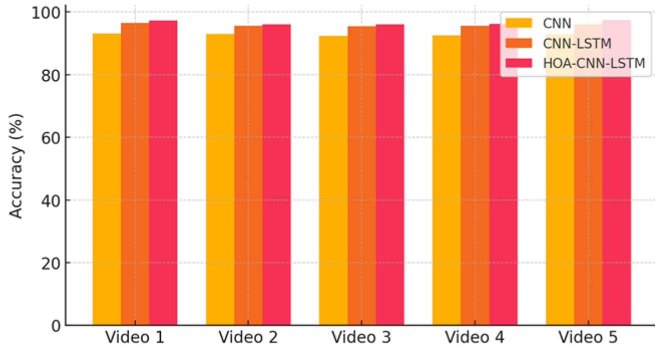

Fig 4.6a Accuracy Comparison – A bar chart comparing the accuracy of CNN, CNN-LSTM, and HOA-CNN-LSTM across all videos.

2. Genuine Acceptance Rate (GAR) Comparison

i. GAR measures the percentage of correctly identified gait instances, the bar as shown in fig. 4.6b.

ii. CNN-LSTM improves on CNN, while CNN has the lowest GAR.

iii. HOA-CNN-LSTM maintains the highest GAR, meaning it effectively recognizes gait patterns.

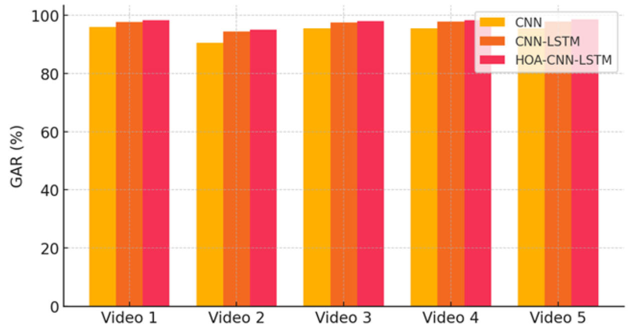

Fig. 4.6b Genuine Acceptance Rate (GAR) Comparison – A line or bar chart comparing the GAR for all models.

3. False Acceptance Rate (FAR) Comparison

i. FAR indicates the percentage of non-gait instances mistakenly classified as gait shown in fig 4.6c.

ii. Lower FAR is better—HOA-CNN-LSTM consistently has the lowest FAR, reducing incorrect gait detections.

iii. CNN-LSTM improves over CNN, but CNN has the highest FAR.

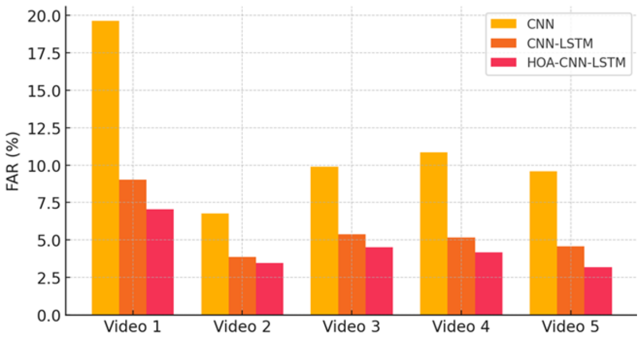

Fig. 4.6c False Acceptance Rate (FAR) Comparison – A grouped bar chart showing the FAR and FRR across all models.

4. False Rejection Rate (FRR) Comparison as shown 4.6d

i. FRR measures how often actual gait instances are misclassified.

ii. HOA-CNN-LSTM has the lowest FRR, minimizing missed detections.

iii. CNN-LSTM performs better than CNN, while CNN has the highest FRR.

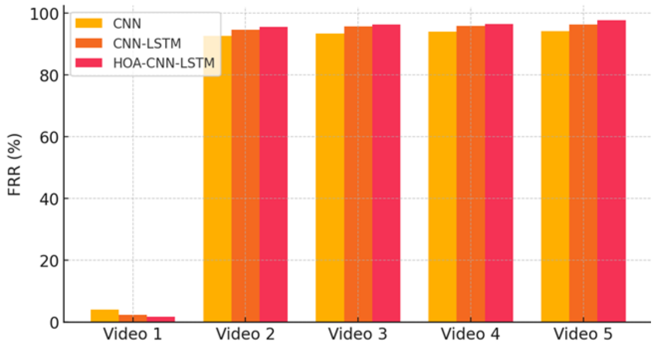

Fig. 4.6d False Rejection Rate (FRR) Comparison – A grouped bar chart showing the FAR and FRR across all models.

5. Processing Time Comparison

i. Lower time is better—indicating faster gait recognition as shown in 4.6e.
ii. HOA-CNN-LSTM is the fastest, demonstrating efficiency improvements from hyperparameter tuning.
iii. CNN-LSTM is faster than CNN but slower than HOA-CNN-LSTM.
iv. CNN is the slowest model

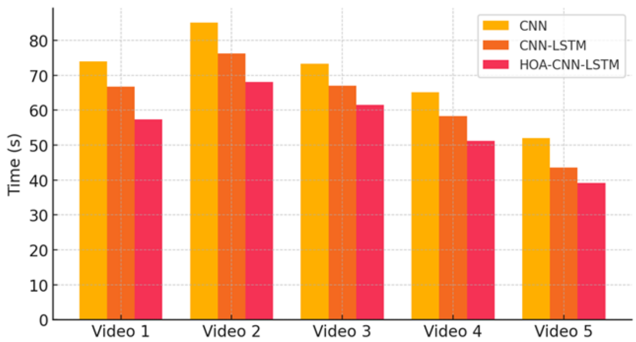

Fig. 4.6e Processing Time Comparison – A bar chart displaying the processing times of the models for each video.

These visualizations of the performance metric results highlight the superiority of HOA-CNN-LSTM, which achieves higher accuracy, lower error rates, and faster processing time, making it the most efficient gait recognition model. Let me know if you need adjustments.

For gait detection applications, the designed HOA-optimized Hybrid CNN-LSTM architecture offers a strong, effective, and reliable solution as shown in table 4.6. Deep learning methods and optimization algorithms have significantly increased identification accuracy and processing speed, making them the perfect option for real-world implementation in security systems and other applications that need trustworthy biometric verification. Below is the chart using orange for Accuracy and blue for Time to clearly differentiate the two metrics. The visualization will help in comparing the performance across different videos.

5.0 Conclusion And Recommendations

5.1 Conclusion

This study successfully addressed the persistent challenges in gait recognition by designing and implementing a novel Hybrid CNN-LSTM architecture optimized using the Hippopotamus Optimization Algorithm (HOA). In response to the limitations of existing models, particularly in fine tuning the hyperparameters of the complex spatiotemporal features while maintaining for improved accuracy, the proposed framework integrated the spatial feature extraction strengths of CNNs with the temporal modeling capabilities of LSTMs. HOA was employed for effective hyperparameter tuning, leading to enhanced convergence speed, reduced computational overhead, and improved model efficiency.

Empirical evaluations demonstrated that the proposed system outperformed conventional models in terms of recognition accuracy, robustness to variability in gait patterns, and computational efficiency. These advancements make the model suitable for deployment in practical scenarios such as security surveillance, biometric authentication, and healthcare monitoring. Furthermore, by addressing the inefficiencies in previous hybrid architectures and advancing hyperparameter optimization strategies, this research contributes significant insights to the field and establishes a solid foundation for future developments in intelligent gait analysis systems.

5.2 Recommendations

To further improve and extend the research, the following recommendations are proposed:

i. **Expansion to Additional Datasets:** Future research should evaluate the model on diverse gait datasets to enhance its generalizability across different environments and populations.

ii. **Integration with Lightweight Architectures:** To facilitate deployment on edge devices, lightweight architectures such as MobileNet or pruning techniques should be explored.

iii. **Real-Time Implementation:** Future work should focus on deploying the model in real-time scenarios, optimizing inference speed without compromising accuracy.

iv. **Multi-Modal Biometric Fusion:** Combining gait recognition with other biometric modalities, such as facial recognition or voice authentication, could further enhance security and identification reliability.

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