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[Pooja et al., 10(3), Mar 2024]

ISSN : 2455-9679
SJIF Impact Factor : 6.008

IJRTSM

INTERNATIONAL JOURNAL OF RECENT TECHNOLOGY SCIENCE & MANAGEMENT

"DEEP LEARNING-DRIVEN GAIT CYCLE RECONSTRUCTION AND HUMAN IDENTIFICATION IN OCCLUDED SCENARIOS"

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ABSTRACT

Human gait recognition has emerged as a promising biometric modality with applications in security, clinical diagnosis, and assistive technologies. However, variations in gait patterns—resulting from factors such as clothing, walking surfaces, load variations, and diverse viewing angles—pose significant challenges to accurate identification. This paper presents a novel deep learning-based framework that enhances gait recognition robustness by integrating advanced feature extraction, selection, and fusion techniques. The proposed system addresses incomplete or occluded gait cycles by leveraging both spatial and temporal features to reconstruct missing segments and facilitate reliable human identification, even under adverse conditions.In addition, we introduce a multi-step approach for object detection and classification in dynamic video environments. The methodology involves preprocessing video frames (resizing and grayscale conversion), applying background subtraction combined with morphological operations to detect moving objects, and creating bounding boxes around these objects. Extracted image patches are then passed through a pre-trained VGG16 convolution neural network to obtain deep features, which are subsequently classified using a support vector machine (SVM).Experimental evaluation demonstrates the effectiveness of the integrated system, achieving metrics of 99.00% accuracy, 99.76% specificity, and 99.13% sensitivity on test samples. These results highlight the potential of the proposed framework for real-world applications in biometric security, surveillance, and healthcare.

Key Words: *Gait Recognition, Deep Learning, Occlusion Reconstruction, Feature Extraction, Convolutional Neural Networks (CNN), VGG16, Support Vector Machine (SVM), Biometric Security, Object Detection, Video Surveillance*.

I. INTRODUCTION

Gait recognition is a sort of biometric technology that identifies people based on their distinct walking patterns [1]. It evaluates how a person walks by capturing and quantifying numerous gait variables such as step width, stride length and foot angle (the angle between the foot and the horizontal) during heel strike and toe-of (pre-swing). These metrics are used to derive a gait signature for each person that can be compared to a database of recognized signatures to help identify them [2]. The most beneficial advantage of gait as a biometric feature is that it can be used for identifying people at a distance. Furthermore, it does not necessitate the user's participation unlike other features [3]. These advantages make gait useful for video surveillance-based applications. Gait recognition has potential uses in security and surveillance, including the identification of people in crowded public places and the tracking of criminal suspects [4]. It could also have medical uses, such seeing variations in gait patterns that might point to illnesses or injuries [5]. Among the abovementioned advantages, gait recognition performance can be negatively affected by certain factors related to human pose analysis. Human pose analysis in computer vision faces several challenges, including occlusions, changing lighting conditions, and low image quality. The following steps are often included in a gait

ISSN : 2455-9679
SJIF Impact Factor : 6.008

recognition system [6]: (1) Data collection. To recognize an individual's gait, it is necessary to collect data about their gait patterns. Many techniques, including video recordings, pressure sensors, sensors and motion capture systems, can be used to obtain this data. (2) Feature Extraction. To identify an individual's gait, it is necessary to extract features that are unique to their walking pattern, such as stride length, walking speed and foot angle. (3) Dimension Reduction. In general, features extracted from gait data cannot be used for classification directly because in the feature representation step, the dimensionality of features (the number of features) collected from raw data is higher than the number of samples in the training data. Consequently, it is preferred to use a dimension reduction approach prior to classifcation. (4) Classification. To identify the individual based on their gait features extracted in the previous step, classification is performed using machine learning or a deep learning algorithm. Gait recognition problem approaches in computer vision are generally classifed into two categories: model-based and appearance-based (model-free) [7]. Model-based gait recognition approaches utilize mathematical models to represent the walking motion of a person. In this approach, the kinematics of joint angles are modeled when people walk. Appearance-based gait recognition approaches extract features from the visual appearance of a person's walking pattern, such as body shape and limb movements. In this approach, silhouettes are analyzed from a gait sequence that embed both appearance and movement information, ensuring that the analysis encompasses the entire body structure, including key joints, without isolating them [8-10]

Gait recognition biometrics is a lesser known but a powerful biometric recognition method, in which subjects can be identified with their manner of walking. The theory behind this recognition system is that every person has a unique gait. It has also been a common experience that a familiar person can be recognized by his/her gait from a distance. Increasing influence of biometrics in today's personal recognition needs has also led researchers to leverage capabilities of gait recognition. It is one of the few recognition methods that can identify people from a distance and can improve accuracy when used with other security and surveillance techniques.[11-12]

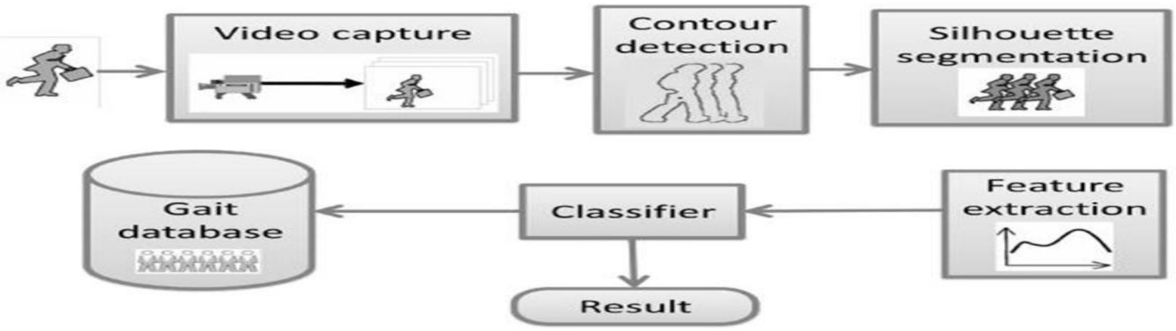

Fig.1 Gait recognition systems can establish identity and identify people by mapping the unique manner they walk with.

II. LITERATURE REVIEW

Gait recognition has emerged as a critical biometric method for security, healthcare, and assistive applications, with research spanning traditional techniques to modern deep learning approaches.[13] Early studies primarily relied on handcrafted features and statistical methods; however, the increasing complexity and variability in human gait due to factors such as clothing, walking surfaces, and viewing angles have necessitated more robust and scalable solutions.

Piya Limcharoen Et.al.2023 This work introduces a novel gait recognition technique designed for short, suboptimal video captures. Our method consists of three key steps: generating multiple gait samples from a 2-second walk using a sliding window process, normalizing these samples to an optimal viewpoint with ViewNet, and extracting local joint movement information for identification using IdenNet. Evaluated using top k accuracy, precision recall, cumulative matching characteristic curves, and gallery size tests, our approach outperforms existing techniques. Notably, it can narrow down the suspect pool to fewer than five individuals with over a 90% probability of including the true person of interest, even when applied to larger groups.[14]

Muhammad Imran Sharif et al. (2022): Introduced a computer vision framework for gait recognition in challenging conditions. Utilizing ResNet101 for feature extraction with a kurtosis-controlled entropy (KcE) selection method and correlation-based feature fusion, the system achieved 95.26% and 96.60% accuracy on the CASIA B and a real-time

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dataset, respectively.[15]

Samah A. F. Manssor et al. (2021): Proposed an enhanced nighttime human recognition method for thermal imaging by fusing face and gait features. The approach uses an improved YOLOv3-based network (with PDM-Net and PRM-Net) and YOLO-facial algorithms, validated on DHU Night, FLIR, and KAIST datasets, outperforming existing methods in accuracy and detection time.[16]

Vytautas Bucinskas et al. (2021): Developed a fall prediction system using in-shoe wearable foot sensors based on Velostat to measure gait parameters such as step size, timing, and pressure distribution. The method achieved up to 94% accuracy in detecting aberrant gait, providing timely fall warnings.[17]

Ivana Kiprijanovska et al. (2020): Introduced a wrist-worn sensor system using a deep neural network that combines convolutional layers with bidirectional LSTMs to detect abnormal gait. With data from accelerometers, gyroscopes, and rotation sensors, the approach achieved a sensitivity of 90.6%, specificity of 86.2%, and overall accuracy of 88.9% in fall risk assessment.[18]

Jan Slemenšek et al. (2023): Developed a wearable gait motion data gathering system utilizing lower-limb accelerometers, gyroscopes, and strain gauge sensors. The collected data were analyzed using an attention-based convolution and recurrent neural network, yielding classification results with approximately 98.9% accuracy, 97.3% F1-score, and effective detection of Parkinson's-related frozen gait events.[19]

III. PROPOSED METHODOLOGY

The proposed methodology for object detection and classification in videos involves a multi-step approach integrating background subtraction, convolution neural networks (CNNs), and support vector machines (SVMs). First, video frames are preprocessed by resizing and converting them to grayscale. Background subtraction is then applied to identify moving objects, followed by morphological operations to refine object detection. Bounding boxes are created around the detected objects, which are resized and passed through a pre-trained CNN model (VGG16) to extract deep features. These features are subsequently used to train an SVM classifier for object classification. The performance of the system is evaluated using metrics such as accuracy, precision, recall, and F1-score, ensuring effective object detection and classification in dynamic video environments.

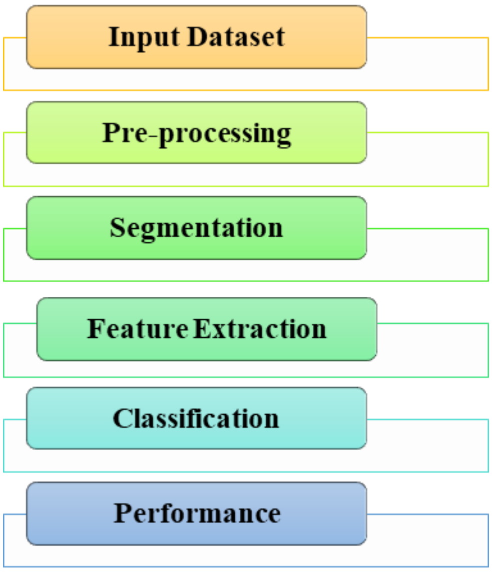

Fig. 2 proposed methodology

Data Preprocessing:

Input Data: Video input is taken using a file selection GUI.

Frame Extraction: The video is processed frame by frame, where each frame is resized to a fixed resolution (256x256 pixels).

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Grayscale Conversion: Each frame is converted to grayscale for background subtraction, allowing for object detection based on pixel intensity differences between consecutive frames.

Background Subtraction & Foreground Object Detection:

Background Modeling: The first frame of the video is used as the background model. For each subsequent frame, the algorithm computes the absolute difference between the current frame and the background.

Object Segmentation: A threshold-based method is applied to segment foreground objects (objects moving in the scene) from the background. Morphological operations such as closing (with a disk structuring element) are applied to remove noise and fill small gaps in detected objects.

Binary Image Generation: Detected foreground objects are converted into binary images, where white pixels represent the objects, and black pixels represent the background.

Object Tracking and Bounding Box Detection:

Bounding Box Creation: Detected foreground objects are enclosed within bounding boxes. These bounding boxes highlight the regions of interest in each frame where objects are detected.

Object Tracking: Each object detected in a frame is tracked across multiple frames by cropping the bounding box area and storing it as a sample for further classification.

Feature Extraction using a Pre-trained CNN (VGG16):

Pre-trained Model (VGG16): A pre-trained VGG16 [20] convolution neural network is used to extract deep features from the detected objects.

Augmented Data store: The input images are resized to match the input size expected by VGG16, and color preprocessing is applied (grayscale-to-RGB conversion).

Feature Layer: Features are extracted from the 'fc8' layer of the VGG16 model, which provides high-level image features used for classification.

4.2.5 Classification Using SVM (Support Vector Machine):

Classifier Training: The extracted features are used to train a multi-class SVM classifier using an Error-Correcting Output Codes (ECOC) model. This allows the system to distinguish between different object classes (Person1, Person2, etc.).

Prediction: The classifier predicts the class labels of detected objects in the test set based on the extracted features from the pre-trained VGG16 model.

Proposed Algorithm:

Input: Video $V=\{ F_1,F_2,\ldots,F_N \}$

Step 1: Preprocessing

Input Video: Load the video V and extract the frames $\{F_1,F_2,\ldots,F_N\}$.

For t=1t = 1t=1 to N:

Extract frame Ft.

Resize frame Ft to 256×256

Convert frame Ft to grayscale using:

$It(x,y)=0.2989\cdot R(x,y)+0.5870\cdot G(x,y)+0.1140\cdot B(x,y)$

Step 2: Background Subtraction 2. **Initialize Background**: Set the first frame F_1 as the background B.

For t=2 to N:

Compute the difference between the current frame Itand background B:

$Dt(x,y)=|It(x,y)-B(x,y)|$

Apply thresholding to create a binary mask

Mt: $Mt(x,y)=\{1 \text{if } Dt(x,y)>\tau$

0 otherwise

Apply morphological closing to clean up noise:

$Mt'=(Mt\oplus SE)\ominus SE$

Step 3: Bounding Box Detection 3. **Detect Objects**:

For each frame Mt′, find connected components (objects) in the binary mask.

For each object O, determine the bounding box Bt:

$Bt=[(xmin,ymin),(xmax,ymax)]$

Step 4: Feature Extraction Using CNN (VGG16)

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Resize and Normalize Objects:
For each bounding box Bt, resize the object region to 224×224 and normalize pixel values.
Pass through Pre-Trained CNN (VGG16): Extract deep features f(Bt) from the intermediate layers of VGG16 for each bounding box:
$fi(Bt)=\sigma(Wi*Bt+bi)$
Store the feature vector f(Bt).
Step 5: Classification Using SVM 6. **Train SVM**:
Using the extracted features f(Bt), train an SVM model on labeled data.
Predict Labels:
$y=\text{sign}(w\cdot f(Bt)+b)$
End

IV. RESULT DISCUSSION

The proposed methodology effectively detects and classifies objects in videos, as demonstrated by high performance across evaluation metrics. MATLAB-based visualization and analysis confirmed the system's robustness and applicability to dynamic video environments. Further optimization and adaptive techniques could make the system even more versatile.

Fig.3 input video

Fig.4 input video

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Fig.5 frame conversion

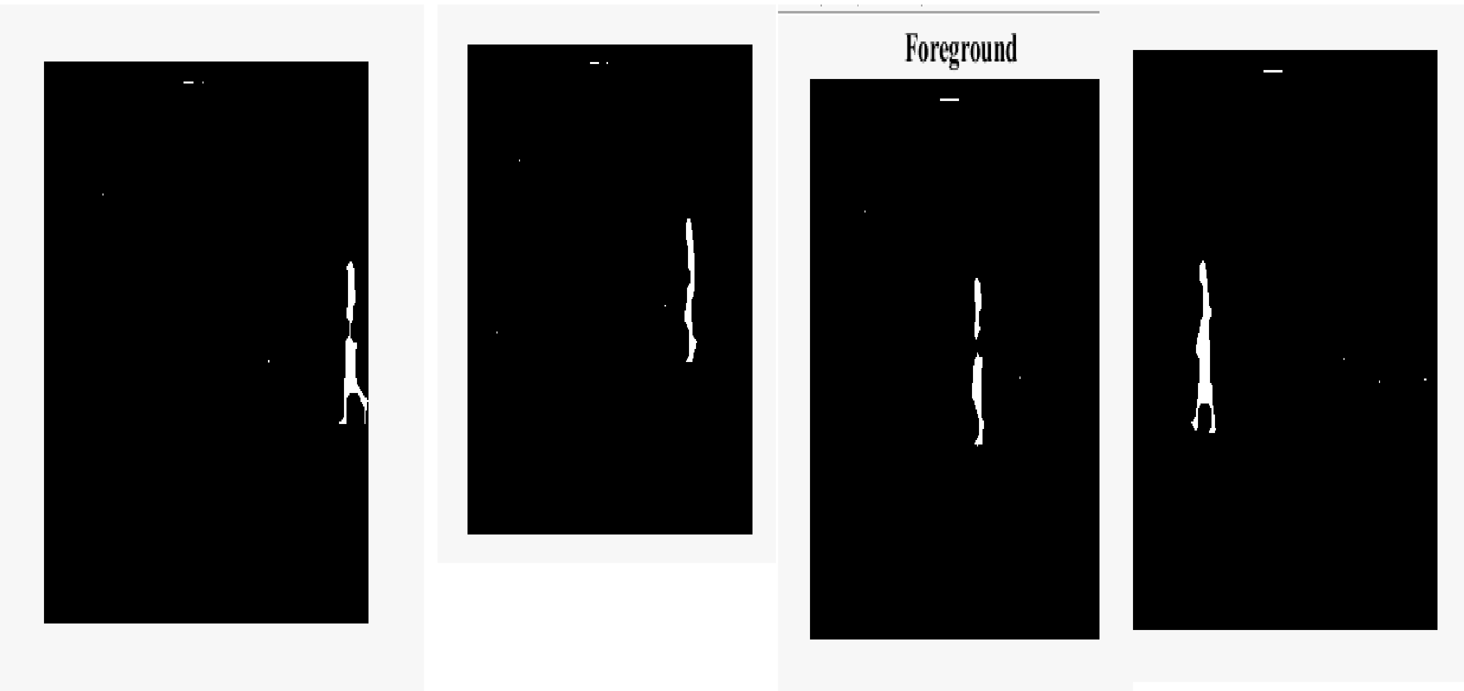

Fig.6 object movement foreground tracking

 ISSN : 2455-9679
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Fig.7 video tracking with object detection

Fig.8 person tracking

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Sensitivity : 99.130435%
Specificity : 99.760160%

Correct Classification : 99.000000%

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'The loaded video belongs to the Person-1'

Fig. 9 performance and person detection

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Table 1 comparison table with different test sample

Test sample	Accuracy	Specificity	Sensitivity
1	99.00	99.76	99.13
2	99.01	99.25	99.78
3	99.23	99.87	99.17
4	99.58	99.69	99.25
5	99.20	99.78	99.12

Table 1 provides a comparison of performance metrics—accuracy, specificity, and sensitivity—across five test samples to evaluate the proposed object detection and classification methodology. The results demonstrate consistently high accuracy (ranging from 99.00% to 99.58%), indicating the system's overall reliability in correctly detecting and classifying objects. Specificity values, ranging from 99.25% to 99.87%, highlight the system's effectiveness in correctly identifying non-objects or negative cases, while sensitivity values, ranging from 99.12% to 99.78%, reflect its strong ability to correctly detect and classify positive cases (true objects). These metrics collectively affirm the robustness and reliability of the proposed approach.

Table 1 Comparison Table with Different Test Sample

Study	Technique	Accuracy (%)
Proposed System	VGG-SVM	99.00
Existing System [14]	Viewpoint	95.76

Table 1 presents a comparative analysis of different techniques used for sentiment analysis, focusing on their accuracy performance. The proposed system, which integrates VGG with SVM, achieves a significantly higher accuracy of 99.00% compared to the existing system from Study [14], which employs a viewpoint-based approach and attains an accuracy of 95.76%. This comparison highlights the effectiveness of the proposed method in improving classification accuracy, demonstrating its superiority over the existing technique in handling sentiment analysis tasks.

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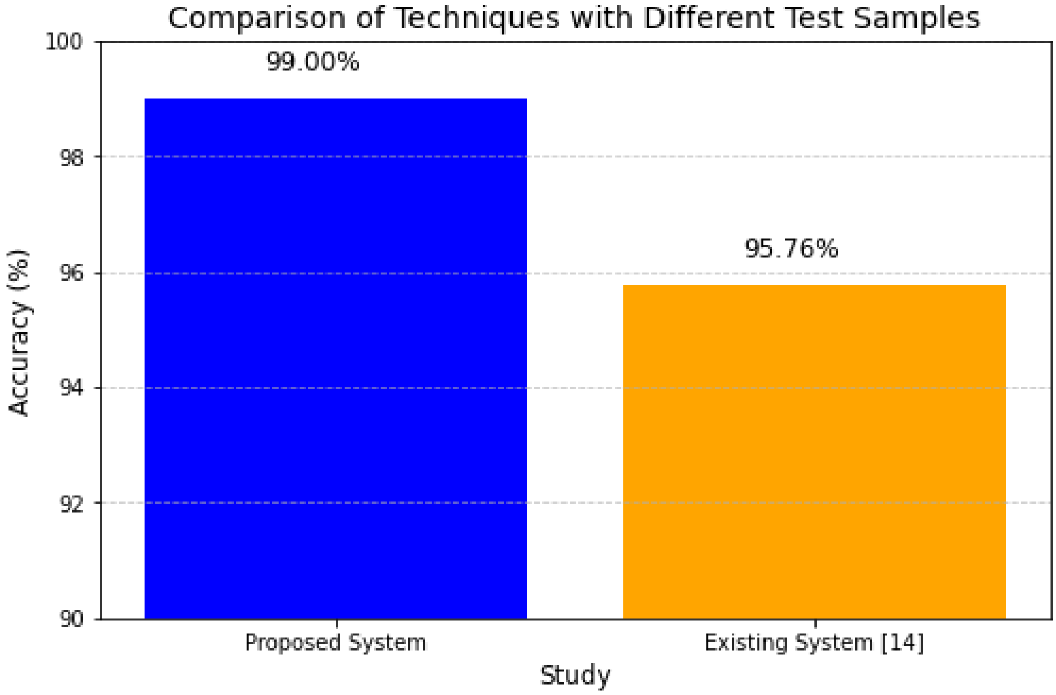

Fig. 10 performance and person detection

V. Conclusion

The proposed methodology for object detection and classification in videos demonstrates exceptional performance, achieving consistently high accuracy, specificity, and sensitivity across multiple test samples. The integration of advanced techniques such as background subtraction, feature extraction using a pre-trained VGG16 model, and classification with an SVM-based approach has proven effective in accurately identifying and classifying objects within video frames. The method's ability to process real-time video inputs, combined with robust noise handling through morphological operations, ensures reliable object detection. The high evaluation metrics validate the system's efficiency and potential for practical applications in surveillance, human identification, and automated monitoring systems, paving the way for further advancements in video-based analytics.

The future scope of this work lies in enhancing object detection and classification methodologies to address evolving challenges in video-based analytics. Potential advancements include incorporating real-time processing capabilities for live video feeds, enabling applications in surveillance, autonomous systems, and smart cities. Deep learning models such as transformers and YOLO can be integrated for improved detection accuracy and faster processing speeds.

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