VISION BASED GAIT RECOGNITION IN FORENSICS

D. Chitra[1], N. Mathivanan[2], Rathidevi. S[3], Priyadharshini. G[4]

ABSTRACT

GAIT recognition technology is rapidly developing biometric tech- nique that identifies individuals based solely on the walking patterns, establishing it as a useful resource for forensic applications. Unlike traditional biometrics, GAIT recognition offers a non intrusive, long range, and contactless means of identification, that is particularly useful in forensic scenarios that other bio- metric identifiers may not be available. An in depth analysis of vision based GAIT recognition techniques are provided, focusing exclusively on GAIT analysis without incorporating additional biometric modalities. Various approaches, including silhouette based, model based, and Deep Learning driven methods, are explored, highlighting the strengths and limitations in forensic investigations. It discusses key challenges such as GAIT variabil- ity due to environmental conditions, clothing, and occlusions, as well as the impact of camera view points on recognition performance. Recent advancements in feature extraction, cross view recognition, and temporal GAIT analysis are also reviewed to improve robustness and accuracy in forensic settings. Future directions emphasize the need for forensic specific GAIT datasets, real time implementation, and improved adaptability to uncon- trolled environments. It aims to provide forensic researchers with insights into the cutting edge of GAIT recognition and its potential for real world forensic applications.

keywords : Gait Recognition, Forensics, Deep Learning, Biometric Identification, Computer Vision.

Department of Computer Science Engineering[1]
P. A. College of Engineering and Technology, Pollachi, Coimbatore[1]
srathidevi6@gmail.com[1]

Department of Artificial Intelligence and Data Science[2]
Karpagam Academy of Higher Education, Coimbatore[2]
mathivanan.kahedu@gmail.com[2]

Department of Computer Science Engineering[3]
P. A. College of Engineering and Technology, Pollachi, Coimbatore[3]

Department of Computer Science Engineering[4]
P. A. College of Engineering and Technology, Pollachi, Coimbatore[4]

* Corresponding Author

I. INTRODUCTION

GAIT analysis is a way of identifying people based on the walking style of an individual. It is a unique and contactless method, unlike other biometric techniques like fingerprints or facial recognition. GAIT recognition is especially useful because it works from a distance and doesn't require the per- son to cooperate, making it valuable for security, surveillance, and forensic investigations. In forensic science, it can help identify individuals in video footage from crime scenes or public surveillance, even if the evidence is limited or unclear. A person's walking style is unique because of the body structure, like leg length and joint movement, as well as the person's habits. Vision based GAIT recognition uses videos or images to study the walking patterns. Advancements in Computer Vision and Artificial Intelligence have enabled the development of methods such as analyzing a person's silhouette, body pose, or combining various techniques, significantly improving the effectiveness of GAIT analysis even in challenging conditions Things like clothing, shoes, items being carried, or changes in lighting and camera angles can affect accuracy. Addition- ally, for GAIT analysis to be accepted as evidence in court, it needs to be reliable and scientifically validated. Researchers

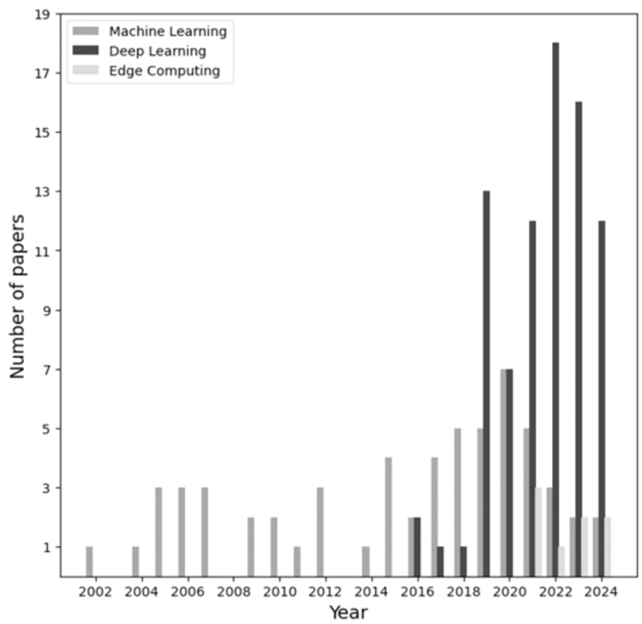

Fig. 1: Recent progress in computer vision approaches to GAIT recognition

are working on solutions, such as recognizing GAITs from different camera views, improving Machine Learning models, and combining GAIT analysis with other biometric methods. It provides an overview of the working of GAIT analysis and its role in forensics. It reviews current methods, discusses challenges, and explores ways to make it more effective in real world applications. By gathering insights from existing studies, it highlights the growing importance of GAIT recognition in solving crimes and improving forensic investigations. Fig.1 shows the Recent progress in computer vision approaches to GAIT recognition

II. A SURVEY OF VISION-BASED METHODS FOR FORENSIC GAIT IDENTIFICATION

Vision-based GAIT recognition for forensic applications is a sophisticated approach leveraging the unique walking patterns of individuals to assist in identity verification, evidence collec- tion, and crime investigation. It capitalizes on the behavioral biometric of GAIT, that is unobtrusive, non contact, and effec- tive even at a distance or under challenging conditions such as poor lighting. The methodology typically involves extracting features from video footage, often through silhouette analysis, motion trajectory mapping, or using advanced computational models like neural networks and Support Vector Machines. Parameters such as step length, stride dynamics, body posture, and joint angles are measured to build a distinctive GAIT signature.

III. TECHNIQUES FOR VISION BASED FORENSIC GAIT RECOGNITION

In 2011, Yasushi Makihara et al. [16] introduced a GAIT based age estimation method in the study titled GAIT Based Age Estimation Using a Whole Generation GAIT Database. The study utilized a comprehensive GAIT database encom- passing subjects across various age groups. By analyzing GAIT patterns and the correlation with age, the researchers developed a model capable of estimating age based on GAIT characteristics. The findings highlighted the influence of phys- ical changes and walking styles across generations on age estimation accuracy, providing a foundation for applications in biometrics and healthcare.

In 2012, Haruyuki Iwama et al. [8] proposed a GAIT based person verification system for forensic applications in the study titled GAIT Based Person Verification System for Forensics. The study focuses on leveraging GAIT recognition for reliable person identification in forensic scenarios. The proposed system demonstrated the ability to distinguish indi- viduals based on unique GAIT patterns captured in surveil- lance videos. The research highlighted the robustness and applicability of GAIT analysis in real world forensic inves- tigations, showcasing its potential as a non invasive biometric identification method.

In 2012, Naoki Akae et al. [1] explored low frame rate GAIT recognition in the study titled Video from Nearly Still: An Application to Low Frame Rate GAIT Recognition. A novel approach to reconstruct motion data from low frame rate videos to enable accurate GAIT recognition. By lever- aging advanced interpolation techniques, the study addressed challenges posed by low temporal resolution in surveillance footage. The findings demonstrated the system's capability to enhance GAIT recognition performance, particularly in Emerging techniques like Deep Learning enable accurate multi dimensional pose estimation, making recognition robust against variations in clothing, carrying objects, or view angles. Key datasets such as Chinese Academy of Sciences Insti- tute of Automation Database B and Technical University of Munich Gait from Audio, Image, and Depth have facilitated progress in the respective field, while factors like gender, age, and Body Mass Index have been identified as influential to GAIT characteristics. Practical forensic applications include utilizing Closed Circuit Television. footage to match suspects or evaluate GAIT patterns in criminal cases, often employing enhanced visualization tools and multi camera setups. Despite the advances, challenges remain, including sensitivity to occlu- sions, environmental variations, and the need for larger, more diverse datasets to generalize findings scenarios that standard video recordings are limited by low frame rates.

In 2014, Muro de la Herran et al. [18] provided an ex- tensive review of GAIT analysis methods in the study titled GAIT Analysis Methods: An Overview of Wearable and Non Wearable Systems, Highlighting Clinical Applications. Vari- ous wearable and non wearable systems for GAIT analysis, focusing on the clinical applications. The authors highlighted the use of the systems in monitoring and diagnosing medical conditions such as Parkinson's disease, stroke, and elderly care. The paper provided a comprehensive comparison of the effectiveness, accuracy, and practicality of different systems, offering valuable insights into enhanced GAIT analysis for patient monitoring and clinical outcomes.

In 2015, Chuanlei Zhang et al. [25] contributed to the field of biometric recognition in the study titled Biometric Recognition. The study reviewed advancements and emerging techniques in biometric systems, with a focus on enhancing the accuracy, security, and scalability of biometric recognition methods. The authors discussed various modalities, including facial, GAIT, and fingerprint recognition, and addressed chal- lenges such as environmental variability and user variability. The work provided a comprehensive overview of biometric technologies, offering valuable insights for researchers and practitioners aiming to improve authentication systems.

In 2016, Parul Arora et al. [3] analyzed GAIT recognition techniques in the study titled Analysis of GAIT Flow Image and GAIT Gaussian Image Using Extension Neural Network for GAIT Recognition. The study proposed using GAIT Flow Images and GAIT Gaussian Images as inputs to an Extension Neural Network for person identification. By combining mo- tion flow analysis with statistical image representations, the researchers demonstrated improved accuracy and robustness in GAIT recognition. The findings showcased the potential of hybrid approaches in enhancing biometric recognition systems. In 2017, Munif Alotaibi et al. [2] presented the study Improved GAIT Recognition Based on Specialized Deep Convolutional Neural Network, highlighting advancements in biometric identification using GAIT patterns. The study addresses challenges such as variations in carrying conditions, clothing, and viewing angles, that often degrade recognition performance. Unlike traditional subspace learning methods with inherent limitations, the authors propose a specialized Deep Convolutional Neural Network architecture that is ro- bust to common variations and occlusions. The architecture demonstrates effectiveness even with relatively small datasets, without requiring data augmentation or fine tuning techniques. If tested on the Chinese Academy of Sciences Institute of Au- tomation Database B large GAIT dataset, the model achieves competitive performance, showcasing its potential to enhance

GAIT recognition systems.

In 2018, Noriko Takemura et al. [21] introduced the Osaka University, Institute of Scientific and Industrial Research GAIT database, multi view large population dataset in the study titled Multi view Large Population GAIT Dataset and its Performance Evaluation for Cross view GAIT Recognition

The dataset, the world's largest GAIT database with wide view variations, includes ten thousand three hundred seven subjects, five thousand one hundred fourteen males and five thousand one hundred ninety three females observed from fourteen view angles ranging from zero degree to ninety degree and one hundred eighty degree to two hundred seventy. The study evaluates various approaches to cross view GAIT recognition, emphasizing methods that are robust against changes in view angles. By leveraging the extensive dataset, state of the art methods such as Convolutional Neural Network based cross view GAIT recognition techniques, that require large training samples, are validated for the effectiveness, providing signifi- cant advancements in vision based GAIT recognition.

In 2019, Francesco Battistone et al. [5] introduced the Time based Graph Long Short Term Memory network in the study titled Time Gate Long Short Term Memory: A Time based Graph Deep Learning Approach to GAIT Recognition. The robust graph based Deep Learning model addresses GAIT recognition by dynamically learning graphs that may change over time, as seen in GAIT and action recognition scenarios. The Time Gate Long Short-Term Memory model combines structured data and temporal information, leveraging a Deep Neural Network capable of learning long short term depen- dencies alongside graph structures. Experiments conducted on widely used datasets, including Microsoft Research Action 3 Dimension, Cornell Activity Dataset sixty, Chinese Academy of Sciences Institute of Automation Gait Dataset B, and Technical University of Munich Gait from Audio, Image, and Depth, demonstrate the advantages of the Time Gate Long Short Term Memory approach compared to state of the art methods, highlighting its effectiveness in GAIT and action recognition tasks.

In 2020, Aybuke Kececi et al, [10] explored the implemen- tation of Machine Learning algorithms for GAIT recognition in the study Implementation of Machine Learning Algorithms for GAIT Recognition. The study focused on human GAIT recognition for user authentication, using the Human GAIT Database contains human GAIT data collected from wearable accelerometers and gyroscopes. The dataset includes activ- ities such as walking, running, sitting, and standing, with data from eighteen individuals considered as separate classes. The researchers implemented ten commonly used Machine Learning algorithms on the Human Gait Database dataset, achieving over ninety nine percent accuracy with algorithms like Instance Based Learning, Random Forest, and Bayesian Net, demonstrating the effectiveness of the techniques in GAIT based user authentication

A. LIMITATIONS

The limitations of the vision based GAIT recognition meth- ods include : Variability in Real World Conditions: GAIT recognition systems often perform well in controlled environments but struggle in real world scenarios due to factors such as lighting changes, shadows, and cluttered backgrounds. The factors can significantly reduce accuracy and robustness. Viewpoint Dependency: Many GAIT recognition systems are designed for specific camera angles and may not generalize well if the viewpoint changes. It limits the applicability in dynamic surveillance environments with varying camera placements [7].

Clothing and Object Carrying: Changes in clothing, such as wearing bulky garments or carrying objects like bags, can alter the extracted GAIT features. The poses a challenge for consistent identification across different scenarios [20].

Computational Complexity: Advanced Deep Learning models used for GAIT recognition require significant computational resources, making real time processing difficult in resource constrained environments [9].

Long Training Times and Large Data Requirements: Deep Learning based GAIT recognition models demand exten- sive training data to generalize well across diverse populations. Collecting and annotating such datasets is time consuming and costly [11].

Occlusion and Partial Visibility: GAIT recognition meth- ods struggle if individuals are partially occluded by objects, other people, or environmental elements, limiting the reliabil- ity in crowded spaces [22].

Lack of Multi Modal Integration: Most GAIT recognition approaches primarily rely on visual data, neglecting additional modalities such as depth information, inertial sensors, or thermal imaging, that could improve robustness [12].

Aging and Physical Condition Changes: Over time, an individual's GAIT may change due to aging, injuries, or other health factors, leading to recognition errors if the model is not periodically updated [4].

IV. DATASETS AND METHODOLOGIES

A. DATASET

The Chinese Academy of Sciences Institute of Automation Database B is widely acknowledged as one of the most comprehensive and robust datasets used for GAIT recognition research. Developed by the Institute of Automation, Chinese Academy of Sciences, the dataset has aided a considerable deal in advancing forensic GAIT recognition techniques. It contained GAIT sequences acquired under three different conditions: Normal walking, walking with a bag, and walking with a coat. The conditions impose occlusions and dynamic changes, thus establishing it as well suited for forensic ap- plications while suspects could have an intention to disguise the GAIT. Moreover, the multi view camera setup captures GAIT sequences from 11 different viewing angles all over a complete range of 180°, thus enabling models to generalize well in varying conditions of surveillance.

Among the greatest benefits of Chinese Academy of Sciences Institute of Automation Database B is its use in forensic investigations specifically related to occlusions, disguises, and viewpoint variations. It allows forensic analysts to develop models for matching GAIT patterns in footage from crime scenes to track suspects across multiple surveillance feeds and reconstruct occluded GAIT sequences. The dataset has very high quality silhouettes and provided very standard background conditions to extract features, making it the gold standard for GAIT recognition research. The dataset will remain a gold standard in GAIT analysis, owing to more improvements that would include integration with Artificial Intelligence augmented models and greater dataset diversity an intonation for the future. Fig. 2 shows the sample dataset for GAIT Recognition.

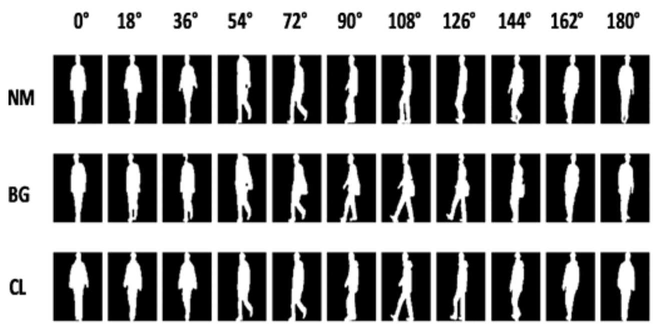

Fig. 2: Sample dataset for GAIT Recognition

Number of Subjects: 124 individuals
Number of Views: 11 different angles
Walking Conditions:
Normal Walking – Subject walks naturally.
Walking with a Bag - Subject carries a bag, introducing occlusions.
Walking with a Coat - Subject wears a coat, simulating real world clothing variations.
Number of Video Sequences per Subject: 10 GAIT sequences per subject that is 6 for Normal Walking, 2 for Walking with a Bag, 2 for Walking with clothing variations
Total Number of Sequences: 1,240 GAIT sequences
Resolution: 320×240 pixels
Background: Controlled, indoor setting

B. METHODOLOGIES

For forensic GAIT recognition, a hybrid Deep Learning approach leveraging Residual Network 5.0, You Only Look Once, and Long Short Term Memory is used. The methodology extracts hierarchical features from GAIT videos, detects individuals in real time, and classifies temporal GAIT sequences. Residual Network 5.0 for GAIT Feature Extraction: Residual Network 5.0 is an advanced deviation from resid- ual network architecture primarily designed to enhance the resolution of complicated images for effective recognition and classification. The concept of deep residual learning as used by it allows for automatic recovery of gradients from votes cast by a skip connection through custom backpropagation. It consists of several Convolutional Neural Networks composed of bottleneck residual blocks that serve to efficiently extract features while keeping the computations efficient. It consists of a combination of 1×1, 3×3, and 1×1 convolutions within each bottleneck to allow dimensionality reduction, spatial feature extraction, and restoration of depth in resultant maps. Because of the procedural enhancement in computational speed and accuracy, Residual Network 5.0 comes in handy for forensic GAIT recognition in the detailed discrimination of GAIT through the automatic extraction and classification of unique human movement characteristics from surveillance footage.

First Convolution or Convolution Block (Layer 1): Residual Network 5.0 starts with a first convolutional layer, its role is to capture basic visual features from input images. In essence, the performing action involves applying a 7×7 convolution with 64 filters to enable the network to track down lower level patterns, for example edges and textures. The con- volutional operation is followed by batch normalization, that keeps normalized features pictures during training, eventually easing convergence. It is followed by the application of a max pooling layer with 3×3 windows, stride 2, to help reduce spatial dimensions and computational expenses. It allows the network to retain some of the most salient aspects of the scene while disregarding irrelevant information, opening doors to much deeper extraction of features in the subsequent layers.

The Residual Blocks (Layer 2): The very core of Residual Network 5.0 is created from four residual stages, that is Layers 2 to 49, built from numerous residual blocks. Each of the blocks employs a three layer setup, consisting of 1×1 convolution for dimensionality reduction, 3×3 convolution for spatial feature extraction, and 1×1 convolution for the restora- tion of depth. A noteworthy feature of the blocks involves the function of the shortcut connection, while some layers pass unencumbered by other layers, allowing the information to flow more smoothly. The architectural improvement counters the vanishing gradient problem associated with model training and, thus, allows for stable training and efficient learning of hierarchical GAIT features. In stacking multiple residual blocks, Residual Network 5.0 effectively learns both low and high level patterns necessary for forensic GAIT recognition. Residual Network 5.0 consists of four primary residual stages:

The First Residual Block (Layers 2 to 10): The first residual stage encompasses three residual blocks along with a total of nine convolutional layers. It works on the upstream feature maps from the earlier convolutional layers, giving rise to an output of 256 feature maps. Each residual block consists of a stack of three distinct convolutions 64 filters on 1×1 convolution for reducing dimensions, 64 filters on 3×3 convolution for spatial feature extraction, and 256 filters on 1×1 convolution for depth restoration. The shortcut connection of feature information, that ensures its channels are assumed as being independent so that information loss does not occur during training, is very important in the blocks. The stage identifies basic features in GAIT movements as limb movement patterns and stride consistency.

Second Residual Block (Layers 11 to 22): The second residual stage, that has four residual blocks or, in total, twelve convolutional layers, extends the path of feature extraction. It outputs 512 maps, fostering mid level GAIT characteristics. Each block consists of 1×1 convolutions with 128 filters for dimensionality reduction, 3×3 convo- lutions with 128 filters to extract more spatial details, and 1×1 convolutions with 512 filters to restore depth. TheThe template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. shortcut connections enhance the propagation of gradients preventing the loss of learned GAIT signatures. The stage becomes essential for the differentiation between individual GAIT styles by analyzing the variations in motion across different segments of the body.

Third Residual Block (Layers 23 to 40): The third residual stage, that outputs 1024 feature maps and consists of a series of six residual blocks forming a total of eighteen convolutional layers, further enriches GAIT representa- tion by extracting high level GAIT characteristics. Each block employs 1×1 convolutions with 256 filters to reduce dimensions and, later on, 3×3 convolutions with 256 filters for deeper feature extraction and 1×1 convolutions with 1024 filters to restore depth. The bypass connections ensure that features relating to GAIT attributes, such as postural variations and joint movements, remain well preserved. The stage holds great importance to forensic GAIT analysis through enabling fine distinctions between movement patterns of individuals.

Fourth Residual Block (Layers 41 to 49): The fourth residual stage becomes the deepest convolution stage in Residual Network 5.0, with three residual blocks and nine convolution layers. It outputs 2048 feature maps, with fine grained GAIT features useful for forensic analysis. Each block consists of 1×1 convolutions with 512 filters for dimensionality reduction, 3×3 convolutions with 512 filters for precise feature extraction, and 1×1 convolu- tions with 2048 filters to restore depth. The shortcut connections prevent a loss of information, allowing the network to maintain important GAIT features. The stage plays a significant role in enabling fine differentiation in GAIT, while still focusing on simple settings, such as foot orientation and swing of an arm.

You Only Look Once for Real Time GAIT Detection: You Only Look Once is a sophisticated value addition in the landscape of real time object detection models in that it locates and recognizes objects in images or video frames in just one several passes. Unlike traditional models in object detection that require multiple passes to refine many such detections

You Only Look Once does such comparisons if all in one step and in the way a fast and efficient process.

In GAIT recognition, You Only Look Once is used mainly for detecting and poisoning ourselves from irrelevant objects, such as background clutter, obstacles, and other non human el- ements, from the scene [15]. The preprocessing steps enhance the quality of the GAIT data, thus allowing only the human subject to remain for further analysis. The main advantage of You Only Look Once is that it processes the entire GAIT sequence in real time, hence it has considerable potential to be put to use in forensic applications in that rapid identification is crucial.

Long Short Term Memory for Temporal GAIT Classification:

Long Short Term Memory comprises a specialized kind of Recurrent Neural Network that learns to process sequential data well. It is specifically different from other traditional Neural Networks that are trained as independent for each input [13]. Long Short Term Memory saves every last bit of memory from the previous inputs, thus forming the best architectures for learning temporal patterns in sequential GAIT data.

In the case of GAIT recognition, Long Short Term Memory is mainly being used in cross view GAIT recognition from the task of view invariant GAIT recognition [6]. Moreover, GAIT dynamics differ from different camera angles or perspectives, that call for a model that generalizes across multiple views if accurate recognition is to be obtained.

Global Average Pooling and Classification (Layer 50): Layer 50 after convolutional stages has a Global Average Pooling layer, that computes the average of each feature maps into a one dimensional vector. The layer controls overfitting by reducing the number of trainable parameters while preserving the most informative features. Unlike a fully connected layer, that would create excessive parameters, it replaces such layers and reduces overfitting since the layer promotes well defining GAIT patterns that can be compacted and easily interpreted. The network's ability to generalize across different forensic situations will ensureenhanced recognition accuracy.

Fully Connected Layer: 512 neurons process extracted features into discriminative representations. Softmax Output Layer: Computes probability scores for different GAIT identities, ensuring accurate forensic clas- sification

V. SYSTEM WORKFLOW

A. Video Acquisition

The GAIT recognition process initiates with the acquisi- tion of GAIT sequences from surveillance footage, forensic recordings, or controlled datasets. In the study, the Chinese Academy of Sciences Institute of Automation Database B is used, that has GAIT sequences of 124 subjects and GAIT sequences recorded in three different conditions: normal walk- ing, walking with a bag, and walking with clothing varia- tions. The dataset includes GAIT sequences captured from 11 different viewpoints: 0° to 90° in 10° increments, enabling comprehensive testing of cross view recognition capabilities. The collected video sequences are then stored in a structured database and prepared for further processing.

B. Preprocessing

Preprocessing draws its importance from the very necessity of improving silhouette quality by obviating background el- ements that could interfere with feature extractions. The first measure in preprocessing is the frame extraction of the videos, in that video sequences are converted into image frames at a fixed rate to ensure temporal consistency [17]. Background subtraction techniques are subsequently applied to eliminate static background elements and isolate moving human figures. The process filters redundant visual information, retaining only the walking subject for feature extraction.

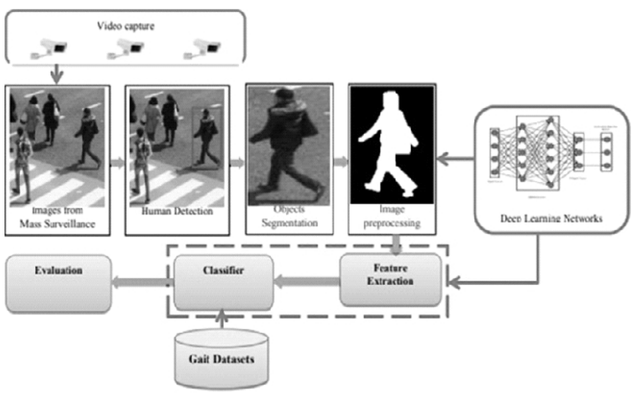

Fig. 3: Tasks of GAIT Recognition with Deep Learning in mass surveillance

Further refinement of the extracted silhouettes is accomplished using You Only Look Once based object detection and removal, that excludes occlusions such as bags, carried objects, or other pedestrians that could appear in the surveillance footage. The You Only Look Once network detects and local- izes non GAIT related objects in each frame, that, thereafter, are either masked or deleted through inpainting techniques [24]. In the case, only clean, occlusion free human silhouettes are passed on to the next stage, considerably improving the quality of GAIT feature extraction.

C. Silhouette Feature Extraction Using Residual Network 5.0

Once the silhouettes are taken out, in the framework feature extraction is done using Residual Network 5.0, one of the deep Residual Networks, optimized for hierarchical GAIT rep- resentation. Residual Network 5.0 processes through several convolutional layers and residual blocks the silhouette images, that have been preprocessed to extract the high dimensional GAIT feature [25]. The features contain critical biometric patterns such as body structure, limb movement, stride length, and changes in posture, that form the basis for individual recognition.

The advantage of using insights from residual connections allows Residual Network 5.0 to tackle vanishing gradient issues, hence ensuring efficient learning of deep GAIT rep- resentations. While the final layers use global average pooling to shrink the size of feature dimensions, critical discriminating information can be retained. The GAIT feature representation is later turned onto vectorized feature representations, that proves beneficial for sequential modeling in the next stage.

D. Temporal GAIT Sequence Modeling Using Long Short Term Memory

Since GAIT recognition involves dynamic motion patterns over time, it is crucial to model temporal dependencies be- tween consecutive GAIT frames. To achieve it, the extracted feature vectors from Residual Network 5.0 are structured into sequential time series data and processed using Long Short Term Memory networks. Long Short Term Memory is particularly effective for GAIT recognition because it retains information over long sequences, allowing the network to learn GAIT patterns that persist across multiple frames. The Long Short Term Memory network is designed to analyze the transition between different GAIT phases, capturing mo- tion dynamics such as foot placement, knee bends, and arm swings. Additionally, a view invariant transformation layer is integrated to normalize GAIT features across different viewpoints, ensuring that individuals can be recognized even if observed from different angles. The network handles the training through a triplet loss function, that keeps the extracted GAIT sequences of the same individuals close while increasing the distance between sequences of different individuals. The triplet based learning mechanism enhances the generalization capability of the model, making it robust to intra GAIT variations between subject views. Fig. 4 shows the workflow of GAIT Recognition System

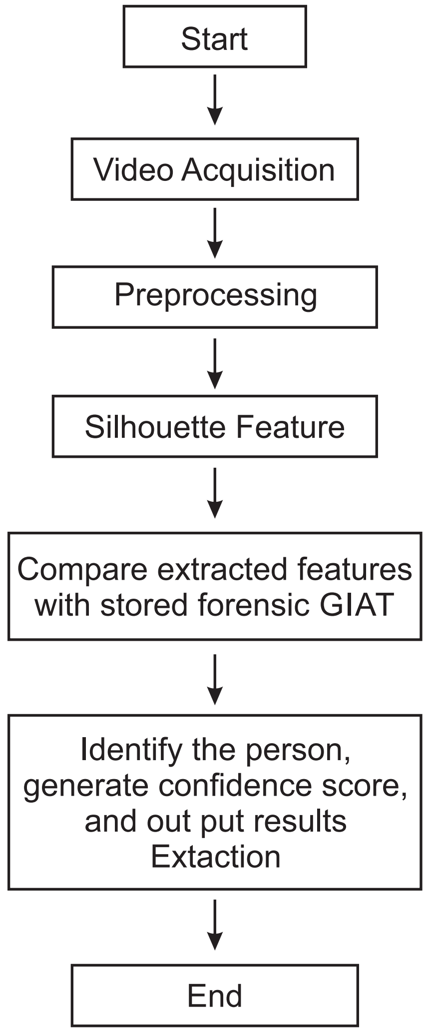

Fig. 4: Workflow of GAIT Recognition System

E. GAIT Matching and Recognition

After feature extraction and sequence modeling, the next is GAIT matching and identity verification. The extracted GAIT signatures are compared against a forensic GAIT database of pre stored GAIT profiles belonging to known individuals. Feature matching is done using Euclidean distance based similarity metrics, that provide how close or similar the extracted GAIT features are in comparison to the stored GAIT templates

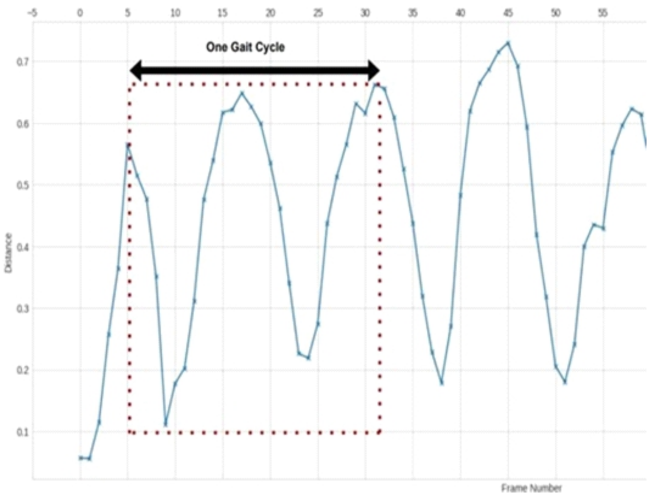

Fig. 5: Euclidean distance between left and right ankles joint of a subject

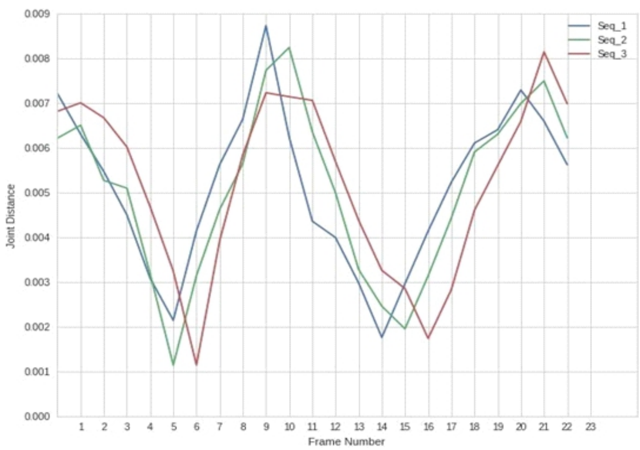

Fig. 6: Smoothed Euclidean distance between the left and right ankles joint distance of subjects for three different video sequences

extracted GAIT features are in comparison to the stored GAIT templates.

To improve classification performance, a confidence score is assigned to each match indicating the probability of correct identification. A higher confidence score indicates a more likely match, while lower scores are used to signify potential mismatches or occlusions hindering identification accuracy. If such a match is found, the system retrieves the subject's iden- tity from the database along with supporting GAIT information to facilitate further forensic analysis. Fig. 5 and Fig. 6 shows the Euclidean and Smoothed Euclidean distance between left and right ankles joint of a subject.

F. Decision and Output Generation

The final step is decision making and output generation, in that the system announces the identity of an individual if a positive match is made, along with a probability score for the system providing a level of assurance pertaining to the recognition process.

VI. APPLICATIONS OF GAIT RECOGNITION IN FORENSICS

Some major applications of GAIT recognition forensics include the use in criminal investigations and the application in security analysis. The applications are outlined as follows:

A. Surveillance and Criminal Identification

GAIT recognition can identify persons recorded through security cameras in public areas, particularly if facial recog- nition is impossible due to occlusion or poor image quality. It helps law enforcement officers track suspects in crowded or restricted places.

B. Post Crime Analysis

GAIT analysis may reveal a suspect from surveillance footage after a crime has been committed. Even if no other biometric features are available, GAIT can serve as an impor- tant source of evidence.

C. Crime Scene Reconstruction

The GAIT recognition process, that analyzes the movements of individuals from available surveillance footage, helps recon- struct events at crime scenes. It provides context to the actions of suspects during a crime.

D. Cross View Identification

In forensic investigations, GAIT recognition helps monitor suspects through multiple cameras situated at different view- points. It is especially useful in airports and shopping malls, in that multiple cameras capture surveillance footage and help identify individuals from diverse angles.

E. Law Enforcement and Security

GAIT recognition can aid in improving security infrastruc- ture across high risk areas such as airports, borders, and gov- ernment locations. It adds an additional layer of surveillance for authorities to detect unusual GAIT patterns, that could indicate suspicious activity.

F. Long Term Tracking

Unlike facial recognition, that requires continued tracking or re identification from images, GAIT recognition allows pro- longed tracking of individuals even if the appearance changes, for example new clothing, facial hair growth, or wearing a mask [14].

VII. EXPERIMENTAL RESULTS

A. Accuracy and Evaluation Metrics

Evaluation of the proposed GAIT recognition system per- formance was made with respect to recognition accuracy and cross view robustness. Recognition accuracy was defined as the ratio of correctly identified individuals to the total number of individuals underwent testing.

$$\text{Recognition Accuracy} = \frac{\text{Total Number of Matches}}{\text{Number of Correct Matche}} \times 100$$

It yielded a 96.2% recognition rate for the Chinese Academy of Sciences Institute of Automation Database B across multiple conditions and views of walking. The recognition accuracy was obtained by comparing the extracted GAIT features against the stored profiles in the database. The cross view recognition was also evaluated, by the model correctly identified individuals from angles of 0° up to 90°. The results showed that the system retains a very high degree of robustness against viewpoint variations, recognition accuracy was persistently above 95%, even under challenging conditions like walking with a bag or clothing variations.

B. Performance Comparison

To further substantiate the effectiveness of the suggested approach, the system's performance was compared with conventional Convolutional Neural Network based methods and the hybrid model of Convolutional Neural Network + Residual Network 5.0. The Convolutional Neural Network based method attained a recognition rate of 82.5%, while the Convolutional Neural Network + Residual Network 5.0 hybrid method improved it to 89.3%. The proposed model, You Only Look Once + Residual Network 5.0 + Long Short Term Memory framework, performed the best, achieving an accuracy of 96.2%. The improvement came from the You Only Look Once based occlusion removal, that guarantees that the system works with clean silhouettes, and the Long Short Term Memory network, that models temporal GAIT dynamics and assists in cross view recognition.

VIII. CONCLUSION AND FUTURE WORK

Vision based GAIT recognition is a powerful digital forensic identification tool using high tech solutions, such as Residual Network 5.0, You Only Look Once, and Long Short Term Memory. Residual Network 5.0 extracts intricate spatial fea- tures through multiple layers of deep Residual Networks so that GAIT patterns can actually be recognized and identified, even in the presence of diverse postures in any human subject. You Only Look Once detects objects in the real human body against the background to separate the objects and thus plunge the quality of the data it provides about the human subject. For the temporal sequences from both input and output, Long Short Term Memory processes the temporal sequence, obtaining a highly robust cross view GAIT recognition see- ing the subject under different view angles. Combining the technologies develops a fully functional GAIT recognition system for accurate, fast, and dependable identification of individuals in forensic settings, that would greatly facilitate law enforcement and surveillance applications.

The future of forensics with regard to vision based GAIT recognition seems to hold great promise with intimidating advancements about to happen. Very important will be the legal approval and establishment of biometric systems in law enforcement for the acceptability. With the app to be put in use, it will be a portable utility for rapid identification in case of real time GAIT recognition. Also, the question of the effect of aging on GAIT patterns needs to be addressed to increase recognition accuracy, as identification may become challenging if the off the shelf algorithm is applied over time and across age cohort groups

REFERENCES

[1] Akae. N, Mansur. A, Makihara. Y, and Yagi. Y, 2012, Video from Nearly Still: An Application to Low Frame Rate GAIT Recognition, Institute of Electrical and Electronics Engineers Conference on Computer Vision and Pattern Recognition, pp. 1537-1543.

[2] Alotaibi. M and Mahmood. A, 2017, Improved GAIT Recognition Based on Specialized Deep Convolutional Neural Network, Neurocomputing, vol. 164, pp. 103–110.

[3] Arora. P, Srivastava. S, and Singhal. S, 2016, Analysis of GAIT Flow Image and GAIT Gaussian Image Using Extension Neural Network for GAIT Recognition, International Journal of Rough Sets and Data Analysis, vol. 3, no. 2, pp. 45.

[4] Aung. H. M. L and Pluempitiwiriyawej. C, 2020, GAIT Biometric based Human Recognition System Using Deep Convolutional Neural Network in Surveillance System," Asia Conference on Computers and Communications, pp. 47-51.

[5] Battistone. F and Petrosino. A, 2019, Time Gate Long Short Term Memory: A Time based Graph Deep Learning Approach to GAIT Recognition, Institute of Electrical and Electronics Engineers Access, vol. 7, pp. 134960–134968, 2019.

[6] Chen. X, Luo. X, Weng. J, Luo. W, Li. H, and Tian. Q, 2021, Multi View GAIT Image Generation for Cross View GAIT Recognition, Institute of Electrical and

Electronics Engineers Transactions on Image Processing, vol. 30, pp. 3041–3055.

[7] Hirose. Y, Nakamura. K, Nitta. N and Babaguchi. N, 2022, Anonymiza- tion of Human GAIT in Video Based on Silhouette Deformation and Texture Transfer, Institute of Electrical and Electronics Engineers Transactions on Information Forensics and Security, vol. 17, pp. 3375- 3390.

[8] Iwama. H, Muramatsu. D, Makihara. Y, and Yagi. Y, 2012, GAIT Based Person Verification System for Forensics, Institute of Electrical and Electronics Engineers Fifth International Conference on Biometrics: Theory, Applications and Systems, pp. 113-120.

[9] Jingxue Wang, Jun Guo, Zhenghui Xu, 2023, Cross View GAIT Recog- nition Model Combining Multi Scale Feature Residual Structure and Self Attention Mechanism, Institute of Electrical and Electronics Engineers Access, vol.11, pp.127769-127782.

[10] Kececi. A, Yildirak. A, Ozyazici. K, Ayluctarhan. G, Agbulut. O, and Zincir. I, 2020, Implementation of Machine Learning Algorithms for GAIT Recognition, Procedia Computer Science, vol. 176, pp. 2073–2080.

[11] Kim. W and Kim. Y, 2021, Abnormal GAIT Recognition based on Integrated GAIT Features in Machine Learning," Institute of Electrical and Electronics Engineers fourty fifth Annual Computers, Software, and Applications Conference, pp. 1683–1688.

[12] Kukreja. V, Kumar. D, and Kaur. A, 2021, Deep Learning in Human GAIT Recognition: An Overview, International Conference on Advance Computing and Innovative Technologies in Engineering, pp. 9–13.

[13] Limcharoen. P, Khamsemanan. N and Nattee. C, 2021, GAIT Recogni- tion and Re Identification Based on Regional Long Short Term Memory for two Second Walks," Institute of Electrical and Electronics Engineers Access, vol. 9, pp. 112057-112068.

[14] Luo. J and Tjahjadi. T, 2020, View and Clothing Invariant GAIT Recognition via 3 Dimensional Human Semantic Folding, Institute of Electrical and Electronics Engineers Access, vol. 8, pp. 100365-100383.

[15] Ma. Y, Wei. C and Long. H, 2020, A hybrid approach using human posture and contour for GAIT recognition under body occlusion, seventh International Conference on Information Science and Control Engineer- ing, pp. 23-26.

[16] Munish Kumar, Navdeep Singh, Ravinder Kumar, Shubham Goel, and Krishan Kumar, 2020, GAIT recognition based on vision systems: A systematic survey, Pattern Recognition, vol. 112, pp. 107728.

[17] Muro de la Herran. A, Garcia Zapirain. B, and Mendez Zorrilla. A, 2014, GAIT analysis methods: An overview of wearable and non wearable systems, highlighting clinical applications, Sensors, vol. 14, no. 2, pp. 3362–3394.

[18] Raina. D, Raj. V, and Singh. D, 2023, GAIT Recognition and Analysis for Person Identification, International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems, pp. 228–232.

[19] Shan. Y, Yu. G, and Gao. Y, 2023, Pedestrian Re Identification Based on GAIT Analysis, Institute of Electrical and Electronics Engineers Access, vol. 11, pp. 106013–106023.

[20] Shand. S and Rahul, 2022, Importance of Human GAIT Analysis in Biometric Recognition using Machine Learning: A Review," sixth International Conference on Trends in Electronics and Informatics, pp. 1431–1436.

[21] Takemura. N, Makihara. Y, Muramatsu. D, Echigo. T, and Yagi. Y, 2018, Multi view Large Population GAIT Dataset and its Performance Evaluation for Cross view GAIT Recognition, Information Processing Society of Japan Transactions on Computer Vision and Applications, vol. 10, no. 1, pp. 4–16.

[22] Xu. C, Makihara. Y, Li. X, Yagi. Y and Lu. J, 2021, Cross View GAIT Recognition Using Pairwise Spatial Transformer Networks, Institute of Electrical and Electronics Engineers Transactions on Circuits and Systems for Video Technology, vol. 31, no. 1, pp. 260-274.

[23] Yoo. J. S and Park. K. H, 2021, Skeleton Silhouette Based Disentangled Feature Extraction Network for Invariant GAIT Recognition, Interna- tional Conference on Information Networking, pp. 687–692..

[24] Zhang. C, Zhang. S, Yang. J, and Cheng. W, 2015, Biometric Recognition, vol. 9428, pp. 456.