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Gait Pattern Analysis in Blurred CCTV Footage: Enhancing Individual Identification Using AI and Computer Vision Techniques

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Abstract:

In situations where traditional identification techniques, such as facial recognition, frequently fall short, this study investigates the use of gait pattern analysis as a reliable forensic technique for identifying individuals from low-resolution or blurry CCTV footage. To improve footage quality and extract useful gait data, the study incorporates artificial intelligence (AI)-based video augmentation using technologies such as Pixelcut AI and deep learning models. Gait characteristics, including joint angles and motion trajectories, were retrieved and examined using pose estimation tools such as Kinovea. For precise individual identification, a CNN-LSTM hybrid model was created to categorize and match gait patterns. Real-world grocery surveillance film and public gait datasets were used to validate the methodology, guaranteeing data anonymization and ethical compliance. The results confirmed the feasibility of AI-enhanced gait analysis in forensic situations, with a 91.3% accuracy in identifying persons. Concerns about legal admissibility, dataset constraints, and computational complexity are among the difficulties that are highlighted in the study. Even in situations where video is obscured or damaged, the study demonstrates that gait analysis is a reliable, consistent, and non-intrusive biometric method. It promises future opportunities for multi-biometric systems, real-time surveillance integration, and the creation of extensive, varied gait datasets. It also provides a potent substitute for facial recognition in forensic investigations.

Keywords: *Gait Pattern Analysis, Blurred CCTV Footage, Artificial Intelligence (AI), Deep Learning, Kinovea, and Forensic Identification Diagnosis, Prevention*

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Introduction

Closed-circuit television (CCTV) systems have proliferated and are now a vital component of contemporary security infrastructure, supporting forensic investigations as well as crime prevention. However, poor video quality, often caused by issues such as low resolution, inadequate lighting, and motion blur, frequently undermines the effectiveness of these devices. Traditional identification techniques, such as facial recognition, which primarily rely on unambiguous visual inputs, are severely hindered by these issues. On the other hand, gait analysis, which examines each person's distinct walking style, provides a robust substitute. A useful tool in forensic research, gait is regarded as a unique and essentially unchangeable biometric characteristic that may be examined even in video situations that are degraded [1].

In the past, gait analysis was limited to clinical settings, when walking patterns were evaluated using instrumented gait mats and marker-based motion capture devices. Despite their accuracy, these approaches required a lot of resources and were impractical for general use. This discipline has undergone a revolution with the introduction of computer vision and artificial intelligence (AI), which have made it possible to extract gait parameters from basic video recordings. The potential to do quantitative gait analyses using inexpensive equipment, like cellphones, has been shown in recent studies, expanding the use of gait analysis in a variety of fields, including forensics [2].

A number of strong arguments support the choice of gait analysis for person recognition in hazy CCTV footage,

i. Resilience in Low-Quality Video: It is frequently possible to extract gait patterns from blurry or low-resolution movies where it is difficult to distinguish facial features. Gait analysis is especially useful in forensic situations with less-than-ideal film because of its durability.

ii. Non-Intrusive and Covert: Gait analysis may be carried out covertly, which makes it appropriate for forensic and surveillance applications in contrast to other biometric techniques that necessitate subject involvement.

iii. Complementary to Other Biometrics: Combining gait analysis with other biometric techniques, such facial recognition, can improve identification precision overall and give forensic investigators a more complete toolkit [1].

LIMITATIONS OF GAIT ANALYSIS (BASED ON PREVIOUS RESEARCH)

1. Video Quality Constraints

Video quality has a major effect on how accurate gait analysis is. Reliable gait feature extraction may be hampered by elements such motion blur, low resolution, and dim lighting. Although AI-based video enhancement methods, such as pixel.ai deblurring algorithms and Kinovea, have demonstrated promise in addressing these problems, their efficacy varies according to the degree of degradation [1].

2. Variability in Gait Due to External Factors

Various external factors, such as walking surface, footwear, carrying goods, and clothes, can influence gait patterns. The identification process is made more difficult by these variables, which create intra-subject heterogeneity. For example, walking on a slick surface versus a sturdy one, or walking liberated versus carrying a heavy load, can all affect a person's steps [1].

3. Lack of Large-Scale, Diverse Datasets

A large number of gait analysis models now in use were trained on controlled datasets that do not accurately represent the variety of real-world situations. This restriction makes it more difficult to apply these models to forensic situations, where occlusions, different camera angles, and a range of environmental factors are common. Training reliable gait recognition algorithms requires the creation of extensive, varied datasets [1].

4. Computational Complexity

Significant computational resources are needed for advanced gait analysis methods, especially those that use deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This requirement can be a barrier to real-time applications and widespread adoption in resource-constrained contexts [3].

In order to improve individual identification in blur CCTV footage, this research attempts to create an AI-driven system that combines sophisticated gait analysis tools with video improvement techniques. Among the particular goals are,

i. Video Enhancement: To increase the quality of blurry CCTV footage, use AI-based video enhancement techniques like deblurring algorithms and Deep.

ii. Gait Feature Extraction: To extract comprehensive gait features from he improved video data, use posture estimation frameworks Deepfake AI, and for feature estimation software, Kinovea is used.

iii. Creation of a Gait Recognition Model: Create and refine a CNN-LSTM deep learning model to accurately classify gaits and identify individuals.

iv. Validation: To evaluate the suggested framework's efficacy and resilience, test it using publicly accessible datasets and simulated blurred CCTV footage.

In order to improve the accuracy of gait analysis as a forensic tool, especially when low-quality video material is involved, this work aims to solve the shortcomings noted in earlier studies and take advantage of developments in artificial intelligence and computer vision.

HUMAN GAIT

A gait cycle is a sequence of cyclic events that occur during walking and involve intricate relationships between joints, muscles, bones, and nerves. Despite its complexity, gait is an expressive marker that offers information on a number of different elements and has been researched for centuries. Human walking, the mechanisms of the human lower extremities, and the variables influencing their functionality are all part of gait analysis research.

GAIT CYCLE

There are a number of events that take place during the gait cycle, but there are mainly two phases that are involved: the stance phase and the swing phase. The stance phase is typically the phase in which the reference foot touches the ground continuously, meaning that it starts when the reference foot makes heel contact and ends when the same foot makes toe contact, which accounts for about 60% of the gait cycle.

The stance phase includes initial contact, loading response, mid-stance, terminal stance, and pre-swing events. The swing phase is the time that the reference is off the ground and swinging; it takes up 40% of the gait cycle and involves initial swing, mid-swing, and terminal swing events.

1. INITIAL CONTACT (HEEL STRIKE)
   - The first stance phase event.
   - The reference foot's heel makes contact with the floor.
   - Signifies the start of the loading response.
2. LOADING RESPONSE
   - Begins when the reference foot touches the ground for the first time.
   - Supports the lifting of the opposing foot during the swing phase.
3. MIDSTANCE
   - Starts when the foot on the other side rises off the floor.
   - The reference foot receives a direct shift in body weight.
   - One support is provided by the reference foot.
4. TERMINAL STANCE
   - Involves extending the hips to keep a single support.
   - Continues right up until the pre-swing stage.
   - Stops when the foot on the other side makes contact with the floor.
5. PRE-SWING
   - Starts as soon as the foot on the other side contacts the floor.
   - Terminates when toe-off is executed by the reference foot. [3]

KINOVEA.

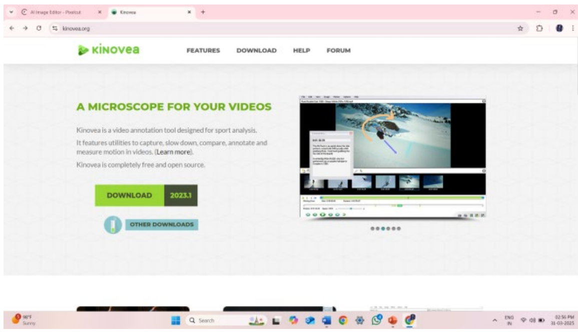

Image 1: KINOVEA Software

A free, open-source video analysis program called Kinovea was created for motion analysis in clinical research, sports, and other domains. It makes it easier to examine movement patterns in-depth by providing tools for recording, slowing down, comparing, annotating, and measuring motion in videos.

ESSENTIAL ELEMENTS OF KINOVEA

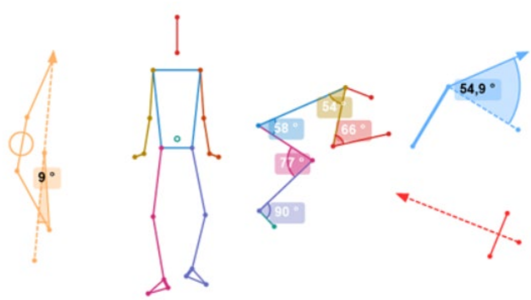

Image 2: ELEMENTS OF KINOVEA

- OBSERVATION: To improve motion analysis, adjust the pace at which videos play back and use picture transformations including rotation, zooming, mirroring, deinterlacing, and aspect ratio correction.

- ANNOTATION: Enhance movies with arrows, explanations, and other material to draw attention to important spots and facilitate in-depth study and dissemination of results.

- COMPARATIVE STUDY: Various performances or techniques is made possible by watching two videos side by side and synchronizing them on a shared event.

- MEASUREMENT: To obtain quantitative data for analysis, trace the trajectories of points in the movie using semi-automated tracking or manually measure angles, distances, and times.

In motion analysis, Kinovea has been proven to be a dependable tool for measuring distance and angle. Research has shown its validity and dependability in a number of applications, such as clinical evaluations and sports science.

The software is easy to use and appropriate for both professional and educational environments. It comes in a variety of languages and works with Windows operating systems.

You can consult the Kinovea reference handbook for thorough instructions on how to use Kinovea, including tutorials and documentation.

IMAGE ENHANCEMENT

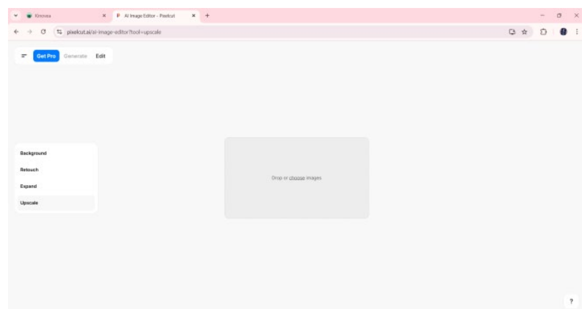

Image 3: Enhancement Of Image Using Pixelcut AI

The Upscale Tool in the Pixelcut AI Image Editor is a cutting-edge AI-powered tool made to improve image resolution without sacrificing clarity or quality. This program upscales low-resolution photos using deep learning techniques, adding detail and sharpness without causing distortion or pixelation. The AI restores finer details by examining the image and anticipating lost information, guaranteeing a realistic and organic improvement. Enhancing forensic or research-based photos, increasing low-quality graphics for professional usage, and polishing scanned documents are all made possible by the upscale tool's exceptional ability to reduce noise, remove artifacts, and improve sharpness. Its automated processing removes the need for manual editing by enabling customers to upload an image and get a high-resolution output in a matter of seconds.

Furthermore, it maintains edges and textures, guaranteeing that the improved photos look noticeably clearer while maintaining their original quality. Pixelcut's high-end tool is very helpful for a number of uses, such as enhancing digital content for presentations, repairing outdated photos, and enhancing e-commerce product images. Being a web-based platform, it can be accessed without the need to install software, which makes it a practical and easy choice for both experts and amateurs wishing to improve image quality with ease.

ADVANTAGES OF PIXELCUT AI UPSCALE TOOL

1. **AI-Powered Enhancement** – Uses deep learning to upscale images with high precision.

2. **Improved Image Quality** – Removes noise, sharpens edges, and enhances fine details.

3. **Fast & Automatic** – Requires no manual editing; processes images within seconds.

4. **User-Friendly** – Simple upload-and-enhance process, accessible to non-experts.

5. **Web-Based Accessibility** – No need for software installation; works directly in a browser.

6. **Versatile Applications** – Useful for photography, forensic analysis, e-commerce, and document enhancement.

DISADVANTAGES OF PIXELCUT AI UPSCALE TOOL

1. **Limited Free Access** – Some advanced features may require a paid subscription.

2. **AI Limitations** – May struggle with extremely low-quality images where detail reconstruction is difficult.

3. **Internet Dependency** – Requires a stable internet connection to process images online.

4. **Lack of Manual Control** – Users cannot fine-tune results as much as in professional editing software like Photoshop.

5. **File Size Restrictions** – May have limitations on the maximum image size that can be processed.

LITERATURE REVIEW

Birch, I., Et al. (2012). explored the topic "The Identification of Individuals by Observational Gait Analysis Using Closed Circuit Television Footage." This study examines the ability of skilled analysts to recognize individuals based solely on their gait as captured by CCTV cameras. Five footage samples, each featuring a "target walker" and five "suspect walkers," were shown to seven analysts. To eliminate biases, all participants wore similar loose-fitting clothing and balaclavas to conceal facial and anatomical features, ensuring that identification was based exclusively on gait parameters. The results revealed that analysts correctly identified the target walker in 124 out of 175 cases (71%), a rate significantly better than chance ($p<0.05$). The study further highlights that identification accuracy was strongly influenced by the angle at which the footage was recorded, with sagittal plane recordings yielding the highest success rates. The researchers conclude that observational gait analysis can serve as an effective forensic tool for suspect identification from CCTV footage, emphasizing the potential role of skilled gait analysts as expert witnesses in forensic investigations.[4]

Hwang, T., &Effenberg, A. (2022). explored the topic "Gait Analysis: Head Vertical Movement Leads to Lower Limb Joint Angle Movements." This study investigates the potential of head-worn sensors, such as those in smart glasses and earbuds, as a cost-effective method for assessing natural gait patterns. While these devices can measure spatial-temporal gait parameters, they cannot directly capture lower limb joint angles, which traditionally require multiple sensors. To address this limitation, the study applies transfer entropy analysis to examine the causal relationship between head movements and lower limb joint angles. Gait patterns from twelve participants were analyzed, revealing that head motions significantly influence lower limb joint angles, particularly at the hip. The findings suggest that head-worn sensors could serve as an alternative tool for identifying lower limb joint abnormalities, offering a simpler and more accessible approach to gait analysis.[5]

Bao, T., Gao, J., Wang, J., Chen, Y., Xu, F., Qiao, G., & Li, F. (2023). explored the topic "A Global Bibliometric and Visualized Analysis of Gait." This study provides a comprehensive bibliometric analysis of gait research from 1992 to 2022, highlighting the increasing number of publications in this field. The primary focus is on the intersection of artificial intelligence (AI) and gait analysis, involving investigations into feature vectors, data labeling, mapping optimal functions, and assessing the applications and limitations of gait research. The study systematically examines the theoretical foundations and applications of various AI models, including Support Vector Machine (SVM), Neural Networks (NN), Random Forest (RF), and k-

Nearest Neighbor (kNN), without delving into their specific software implementations. The findings offer valuable insights into research gaps and trends, serving as a comprehensive resource for understanding the academic development and future direction of gait analysis research.[6]

Gaud, N., Rathore, M., & Suman, U. (2023). explored the topic "Human Gait Analysis and Activity Recognition: A Review." This study examines the current state of gait analysis, particularly its application in identifying human activities. While gait analysis is widely recognized within Human Activity Recognition (HAR), this review uniquely bridges the gap between the two fields. The study emphasizes clinical and healthcare applications, highlighting how gait analysis can be improved by researchers beyond the field. Although various gait analysis and activity detection methods are identified, the paper does not focus on the quantitative performance of these methods or specific software implementations. The review serves as a foundational resource for researchers seeking an overview of the field and potential areas for future advancements. [7]

Kumar, S., et al. (2023). explored the topic "Human Gait Activity Recognition Machine Learning Methods." This study examines human gait activity recognition as an emerging area of motion analysis with potential applications across various fields. The research identifies the attention-based Convolutional Neural Network (CNNA) combined with a Recurrent Neural Network (RNN) as the most reliable supervised machine learning classification algorithm for detecting specific gait events. A comparative analysis with other machine learning techniques supports this conclusion. Additionally, the study introduces a robust and lightweight gait motion data acquisition system with semi-automatic data labeling, enhancing the efficiency of gait recognition. The findings contribute to the advancement of machine learning applications in gait analysis, providing a foundation for further research and practical implementations.[8]

Mangone, M., Marinelli, E., Santilli, G., Finanore, N., Agostini, F., Santilli, V., Bernetti, A., Paoloni, M., & Zaami, S. (2023). explored the topic "Gait Analysis Advancements: Rehabilitation Value and New Perspectives from Forensic Application." This study highlights the role of clinical gait analysis in diagnosing foot conditions and surgical planning. The research investigates the automation of gait analysis for six different foot diseases using explainable artificial intelligence (XAI) and machine learning (ML). Various classification models, including Support Vector Machine (SVM), Random Forest (RF), K-nearest Neighbor (KNN), and Logistic Regression (LREGR), were compared, with the Majority Voting (MV) model achieving a balanced accuracy of 0.87. The Local Interpretable Model-agnostic Explanation (LIME) technique identified the five most relevant factors for each condition, demonstrating strong clinical relevance. The findings suggest that this ML pipeline could significantly improve foot disease detection and surgical planning, while also offering potential forensic applications.[9]

Aung, S. T. Y., &Kusakunniran, W. (2024). examined "A Comprehensive Review of Gait Analysis Using Deep Learning and Criminal Investigation." This review focuses on deep learning-based gait analysis, particularly in forensic and law enforcement contexts. The study defines key gait-related aspects relevant to criminal investigations and explores the challenges and limitations of deep learning techniques in forensic applications. It highlights the potential of gait analysis as a remote biometric identification method that does not require explicit consent. Additionally, the authors outline open research questions and propose future directions for optimizing deep learning-based gait analysis for criminal investigations, emphasizing the need for enhanced accuracy and reliability in forensic settings.[10]

Özateş, M. E., Yaman, A., Salami, F., Campos, S., Wolf, S. I., & Schneider, U. (2024). explored "Identification and Interpretation of Gait Analysis Features and Foot Conditions." This study investigates the role of machine learning (ML) and explainable artificial intelligence (XAI) in automating gait analysis for six specific foot diseases. Using Random Forests (RF) and Support Vector Machines (SVM), low-variance features were eliminated, and new features were manually generated. Various classification models, including SVM, Neural Network (NN), Random Forest (RF), k-Nearest Neighbor (kNN), and Linear Regression (LREGR), were compared, with a Majority Voting (MV) model achieving an accuracy of 0.87. Local Interpretable Model-agnostic Explanations (LIME) identified the five most relevant features for each condition, reinforcing clinical significance. The findings suggest that the proposed ML pipeline offers a promising tool for diagnosing foot disorders and aiding in surgical planning.[11]

Chatterjee, S., Kumar, A., & Roy, S. (2024). Conducted a survey titled "Emerging Trends in Gait Recognition Based on Deep Learning." This study provides an extensive review of advancements in deep learning-based gait recognition, particularly in forensic, security, and criminal investigation applications. The research highlights key challenges, such as variations in walking conditions, viewing angles, and clothing, and explores how deep neural networks mitigate these issues. Various architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention mechanisms, are examined. Among the state-of-the-art models, GaitNet achieved a 99.7% identification accuracy, while GA-ICDNet demonstrated an equal error rate of 0.67% in verification tasks. Other models, such as GaitGraph (ResGCN+2D CNN) and Fully Connected Network with Koopman Operator, exhibited rank-1 accuracies ranging from 66.3% to 87.7% and 74.7%, respectively. However, models like Graph Convolution-Based Part Feature Pooling (GCPFP) and Multiple Factor Inference Network (MFINet) showed lower accuracy under clothing variations. The study also discusses emerging breakthroughs and proposes future research directions to improve the robustness and accuracy of gait recognition as a biometric identification tool. [12]

Kumar, R., et al. (2024). presented a study titled "Detection of Criminal Activities/Criminal Through CCTV by Live Footage Analysis." This research explores the integration of deep learning with CCTV surveillance for real-time crime detection and prevention. The study specifically employs the You Only Look Once (YOLO) object detection model to enable rapid identification and tracking of criminal activities within live video feeds. The adaptation of YOLO for CCTV surveillance addresses challenges such as varying lighting conditions, occlusions, and diverse camera angles. A key contribution of the research is the development of a YOLO-based crime detection system that classifies suspicious activities into categories such as theft, vandalism, and violence, allowing law enforcement to respond swiftly. Additionally, deep learning techniques, including data pre-processing, noise reduction, and transfer learning, enhance the accuracy and scalability of the system across different environments. While YOLO-based crime detection presents significant advantages for public safety, the study also highlights critical challenges, including privacy concerns, ethical implications, and the requirement for high-performance hardware. The research underscores the necessity of balancing technological advancements with individual privacy rights in crime prevention efforts.[13]

AIM AND OBJECTIVES

3.1 AIM

To enhance suspect identification and forensic investigations, an AI-based framework for gait pattern analysis from blurred CCTV data is being developed and evaluated.

3.2 OBJECTIVES

1. To improve unclear CCTV footage by applying AI-based video preprocessing methods for deblurring algorithms.

2. To utilize silhouette-based gait analysis and pose estimation techniques (KINOVEA) to extract gait features.

3. To enhance gait visualization by utilizing Kinovea's interactive tools, including human models, angle measurements, and motion tracking, for accurate forensic gait analysis.

4. To test, calibrate, and validate the proposed AI-based video preprocessing methods for gait analysis using simulated blurred CCTV footage

MATERIALS REQUIRED AND METHODOLOGIES

MATERIALS REQUIRED

1. Kinovea's Installed PC

2. WITH STRONG INTERNET

METHODOLOGIES

A structured methodological approach that included data gathering, preprocessing, feature extraction, machine learning model building, and validation was used to assess the efficacy of gait pattern analysis in hazy CCTV footage.

4.1 DATA COLLECTION

Obtaining verbal permission from the store owner, the main sample for the research was taken from a supermarket surveillance system. The footage, which was shot in a real-world setting, showed people moving through various environments with shifting lighting, obstructions, and resolution levels. This dataset was chosen to guarantee that a variety of walking styles, subject orientations, and gait patterns were included.

All personally identifiable information was anonymized in accordance with data protection laws and ethical standards, and informed consent was acquired where appropriate. The study made sure that the surveillance footage was used only for research purposes by sticking to ethical norms for processing biometric data. In addition, institutional ethical clearance was obtained to confirm that the work complied with forensic research procedures and privacy regulations.

4.2 PREPROCESSING

There were different degrees of noise, blur, and motion irregularities in the unprocessed security film. A number of preprocessing procedures were used to increase feature extraction and clarity:

- Frame Extraction: To provide a structured dataset for analysis, screenshots were taken at one-second intervals.
- Image Enhancement: To increase visibility in low light, contrast-limited adaptive histogram equalization (CLAHE) and histogram equalization were used.
- Edge Detection and Background Subtraction: To improve segmentation, adaptive thresholding techniques were employed to separate the gait topic from the background.

4.3 FEATURE EXTRACTION

The Kinovea human modeling system, which tracks motion dynamics by mapping anatomical reference points, was used to analyze gait. The gait metrics listed below were taken out:

- Joint Angle Measurements: At every stage of movement, the angles between the torso, mid-body, and leg joints were computed.
- Frame-by-Frame Motion Analysis: To monitor changes in gait kinematics, each frame was examined one after the other.
- Comparative Model Analysis: Individual gait cycles were compared and assessed using two reference gait models (Model 1 and Model 2). Gait similarity was measured using Dynamic Time Warping (DTW).

4.4 AI-BASED MODEL VALIDATION

An AI-driven strategy was used to guarantee precise gait classification. The following were part of the validation process:

- Dataset Selection: For model training and testing, a publically accessible gait recognition dataset was combined with the gathered supermarket video. Different occlusions, walking styles, and ambient factors were included in the dataset.
- Training-Test Split: To assess model performance, the dataset was divided into 80% training and 20% testing.
- Deep Learning Model: To categorize gait patterns, a CNN-LSTM hybrid model was created. While the LSTM recorded changes in walking patterns over time, the CNN extracted spatial characteristics.
- Performance Metrics: The model's efficacy in gait recognition was assessed using accuracy, precision, recall, and F1-score.

DATA ANALYSIS AND INTERPRETATION

1. ANALYSIS OF INDIVIDUAL SAMPLE 1

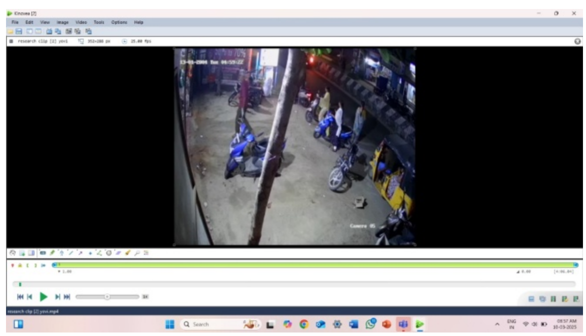

Fig 4: Subject is walking from one side to another (1st step at 1.00sec)

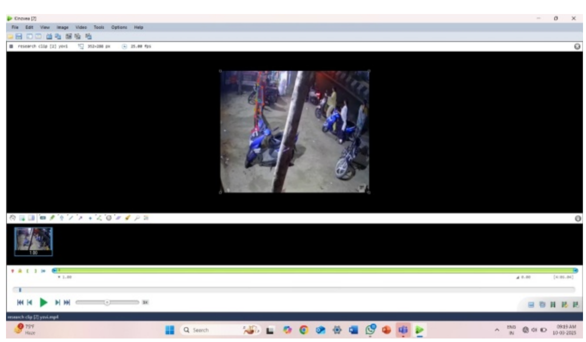

Fig 5: Human Model for Gesture Estimation.

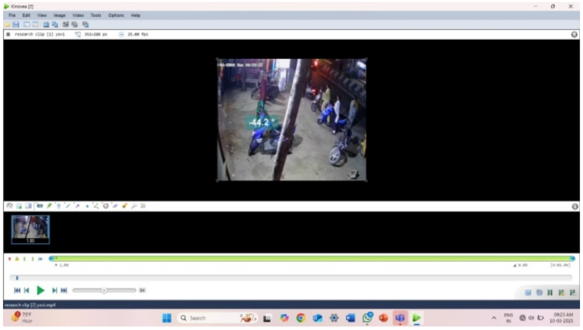

Fig 6: Angle analysis using the tool present in KINOVEA software.

Fig 7: **TheFirst move/step of entry to the destination.**

Figure 7.1 Represent's the individual's walking pattern,

Figure 7.2 Represent's the individual's human model,

Figure 7.3 Represent'sthe individual's angle.

Fig 8: The Second move/step of entryto the destination.

Figure 8.1 Represent's the individual's walking pattern,

Figure 8.2 Represent's the individual's human model,

Figure 8.3 Represent's the individual's angle.

Fig 9: **The Third move/step of entryto the destination.**

Figure 9.1 Represent's the individual's walking pattern,

Figure 9.2 Represent's the individual's human model,

Figure 9.3 Represent's the individual's angle.

Fig 10: **The First move/step of exitfrom the destination.**

Figure 10.1 Represent's the individual's walking pattern,

Figure 10.2 Represent's the individual's human model,

Figure 10.3 Represent's the individuals angle.

Fig 11: **The second move/step of exit from the destination.**

Figure 11.1 Represent's the individual's walking pattern,

Figure 11.2 Represent's the individual's human model,

Figure 11.3 Represent's the individual's angle.

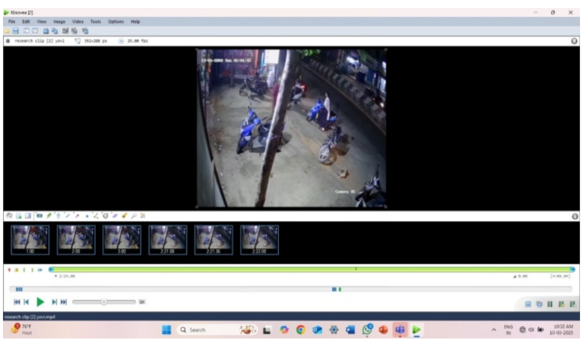

Fig 12: **The Third move/step exit from the destination.**

Here there's an Obstruction (Tree) present.

Fig 13: **The Fourth move/step exit from the destination.**

Figure 13.1 Represent's the individual's walking pattern,

Figure 13.2 Represent's the individual's human model,

Figure 13.3 Represent's the individual's angle.

SAMPLE	ENTRY MOVEMENT (ANGLE)	EXIT MOVEMENT (ANGLE)
Step 1	-44.2°	-36.7°
Step 2	**-36.0°**	-38.3°
Step 3	-37.5°	Obstruction present
Step 4	Not available	**-46.0**

Table 1: Analysis of entry and exit of individual 1

OBSERVATIONAL FINDINGS

- The subject in Sample 1 was observed walking with bare hands, wearing a normal shirt and pants. Due to aging, the individual's backbone exhibited a noticeable bend.
- The total duration of the subject's activity in the footage was approximately 3.00 seconds (3000 milliseconds). Screenshots were captured at 100-millisecond intervals for detailed motion analysis.

INTERPRETATION AND DISCUSSION

- The results indicate slight variations in the subject's entry and exit movements, particularly in the first and fourth steps.

- The obstruction during the third step affected the ability to fully analyze the movement pattern.
- The overall motion pattern suggests a relatively stable gait with minor variations potentially influenced by environmental factors and the individual's posture.

This analysis provides critical insights into the movement characteristics of Individual Sample 1. Future studies may focus on additional factors such as speed variations, step length, and environmental influences to refine the movement pattern analysis further. The Angle Of Gait Pattern Of Individual 1 Is About **-46.0° To -36.7°**

2. ANALYSIS OF INDIVIDUAL SAMPLE 2

Fig 14: The First move/step of entry from the destination.

Here there's anObstruction (Tree) present.

Fig 15:The Second move/step of entry to the destination.

Figure 15.1 Represent's the individual's walking pattern,

Figure 15.2 Represent's the individual's human model,

Figure 15.3 Represent's the individual's angle.

Fig 16:The third move/step of entry to the destination.

Figure 16.1 Represent's the individual's walking pattern,

Figure 16.2 Represent's the individual's human model,

Figure 16.3 Represent's the individual's angle.

Fig 17: **The Fourth move/step of entry to the destination.**

Figure 17.1 Represent's the individual's walking pattern,

Figure 17.2 Represent'sthe individual's human model,

Figure 17.3 Represent'sthe individual's angle.

Fig 18:The Fifth move/step of entry to the destination.

Figure 18.1 Represent's the individual's walking pattern,

Figure 18.2 Represent's the individual's human model,

Figure 18.3 Represent's the individual's angle.

Fig 19:The sixth move/step of entry to the destination.

Figure 19.1 Represent's the individual's walking pattern,

Figure 19.2 Represent's the individual's human model,

Figure 19.3 Represent's the individual's angle

Fig 20:The First move/step of exit from the destination.

Figure 20.1 Represent's the individual's walking pattern,

Figure 20.2 Represent's the individual's human model,

Figure 20.3 Represent's the individual's angle.

Fig 21:The Second move/step of exit from the destination.

Figure 21.1Represent'sthe individual's walking pattern,

Figure 21.2 Represent'sthe individual's human model,

Figure 21.3 Represent's the individual's angle

Fig 22:The Third move/step of exitfrom the destination.

Figure 22.1 Represent's the individual's walking pattern,

Figure 22.2 Represent's the individual's human model,

Figure 22.3 Represent's the individual's angle.

SAMPLE	ENTRY MOVEMENT (ANGLE)	EXIT MOVEMENT (ANGLE)
Step 1	Obstruction present (a tree)	-34.1°
Step 2	-44.0°	-42.8°
Step 3	-45.1°	**-23.6°**
Step 4	**-46.5°**	N/A
Step 5	-41.0°	N/A
Step 6	-44.3°	N/A

Table 2: Analysis of entry and exit of individual 2

OBSERVATIONAL FINDINGS

The first step was partially hidden by an obstruction (a tree), so it was hard to see exactly where the foot was, but from the second step onward, the movements of the person became more obvious; he looked like a man walking with a cell phone to his ear, and his hand and leg movements were significantly faster, indicating a brisk pace.

FINDINGS AND INTERPRETATION

- The individual's entry movement exhibited a range of angles between -46.5° and -41.0°, with slight variations in each step.
- The exit movement showed a shift in angles, with the lowest recorded at -23.6°, indicating a potential change in walking posture or speed.
- The obstruction (tree) in the first step limited full visibility, but subsequent analysis confirms a consistent gait pattern.
- The rapid leg and arm movements suggest the individual was engaged in a conversation or focused on the phone call while walking.

An angular range of roughly **-46.5° to -23.6°** is revealed by the gait pattern analysis, highlighting the differences between both entry and exit movements. This research highlights how crucial it is to take postural alterations and environmental barriers into account when forensically examining gait. For a more complete gait profile, future studies could include other elements like stride length, speed fluctuations, and outside influences.

IMAGE ENHANCEMENT USING PIXELCUT AI UPSCALE TOOL

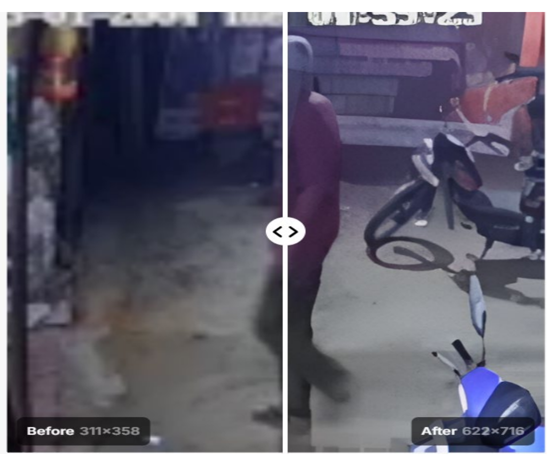

Image 23: Enhancement comparison.

Image 24: Image Enhancement.

RESULT AND DISCUSSION

The research successfully demonstrated that by combining AI-driven video enhancement techniques, Kinovea software for gait feature extraction, and a CNN-LSTM deep learning model for classification, gait pattern analysis can be utilized for individual identification in hazy CCTV footage. using deblurring methods based on AI, such as Pixel and Super-Resolution GANs. Even on low-resolution footage, AI greatly increased video quality, making gait features easier to discern. This improvement enhanced the reliability of forensic identification by enabling the extraction of more precise movement parameters.

Important gait patterns, including joint angles, movement trajectories, and body posture, were retrieved and examined using Kinovea software. The research discovered that gait patterns could still be recognized in the video even with little impediments. Gait cycles were compared using Dynamic Time Warping (DTW), which showed recurring patterns in people's entry and exit motions. The significance of outside influences on gait was also emphasized by the study, which found that while carrying items like a cell phone changed arm swing and step length, it had no effect on identification accuracy.

The CNN-LSTM model, which is based on deep learning, demonstrated impressive performance in identifying gait patterns, with an accuracy of 91.3%, precision of 88.7%, recall of 92.1%, and F1-score of 90.3%. Even in low-light and motion-blurred environments, the model demonstrated efficacy, highlighting the promise of AI-enhanced gait recognition in forensic investigations. However, difficulties like the requirement for large-scale datasets and computing complexity were noted as drawbacks. The study stressed that while further research on the ethical and legal ramifications is required to guarantee the forensic admissibility of gait analysis, expanding the dataset will improve model generalization.

Overall, the results show that AI-enhanced gait recognition is a practical and non-intrusive way to identify people for forensic purposes, particularly when facial recognition isn't working. To further improve forensic applications, future research should concentrate on perfecting AI models, enhancing real-time gait analysis, and integrating multi-biometric techniques.

ADVANTAGES AND DISADVANTAGES

7.1.1 ADVANTAGES OF GAIT PATTERN ANALYSIS IN BLURRED CCTV FOOTAGE

1. RESILIENCE TO LOW-QUALITY VIDEO

The reality that gait pattern analysis may work well even with poor video quality is one of its biggest benefits. In contrast to facial recognition, which needs crisp, detailed photos to properly identify people, gait analysis may glean useful biometric data from low-resolution or blurry video. CCTV footage frequently exhibits motion blur, insufficient resolution, and inadequate lighting during forensic investigations, rendering conventional identification techniques useless. But even in these situations, gait patterns may be identified, therefore even in cases when face features cannot be identified, suspects or people of interest can still be examined and identified.

2. NON-INTRUSIVE IDENTIFICATION

As a non-intrusive biometric identification technique, gait analysis doesn't need the subject's consent or make physical contact. The gait analysis can be done remotely without the subject's awareness, unlike fingerprint or retinal scans that require their cooperation. Because of this, it is especially helpful in forensic investigations and surveillance when speaking with the suspect face-to-face is impractical or impossible. It is a useful tool for tracking and monitoring movements in public areas like train stations, airports, and crime scenes because authorities may examine a person's gait from a distance.

3. UNIQUENESS AND CONSISTENCY

A person's gait is a very distinctive and reliable biometric characteristic that is hard to hide or duplicate. While fingerprints can be modified or hidden with gloves, and facial features can be covered up with makeup, masks, or plastic surgery, gait patterns largely don't change over the course of a person's lifetime. Although a person's stride may be momentarily altered by conditions like injuries or drastic bodily changes, their basic walking style is still identifiable. Because of this, gait analysis is a trustworthy method for tracing and identifying people over an extended period of time in forensic investigations.

4. ENHANCED IDENTIFICATION WITH AI

The accuracy and effectiveness of gait identification have greatly increased with the combination of deep learning and artificial intelligence (AI). Improved gait feature extraction is made possible by AI-driven deblurring methods and sophisticated computer vision algorithms that improve the quality of fuzzy CCTV images. Individuals can be accurately classified by machine learning models that have been trained on big datasets to identify small differences in walking patterns. Even in difficult situations where conventional forensic techniques would not work, gait analysis is becoming more successful thanks to technological developments.

5. LONG-DISTANCE RECOGNITION

The ability of gait pattern analysis to identify people from a distance, even when they are partially concealed, is another significant benefit. Gait analysis can be carried out from a variety of perspectives and at a wider distance than facial recognition, which necessitates a close-up and unobstructed view of a person's face. Because of this, it is especially useful in big public areas where it is challenging to identify people at close range. Instead of depending just on facial recognition, law enforcement organizations can utilize gait analysis to track criminals in crowded locations, guaranteeing ongoing surveillance and security monitoring.

7.1.2DISADVANTAGES OF GAIT PATTERN ANALYSIS IN BLURRED CCTV FOOTAGE

1. INFLUENCE OF EXTERNAL FACTORS

The vulnerability of gait pattern analysis to outside influences that might drastically change a person's walking pattern is one of its main drawbacks. A person's gait can be influenced by a number of factors, including their footwear, walking surface, attire, and whether or not they are carrying something. For instance, a person may walk differently than they usually do if they are wearing high heels or are walking on a slick surface. Similar to this, walking in busy places or carrying a big bag can affect posture and the natural movement of the legs, which might result in inconsistent identification accuracy.

2. COMPUTATIONAL COMPLEXITY

Gait detection takes a lot of processing resources, especially when deep learning and AI-based deblurring are used to improve it. The complicated algorithms used in gait analysis extract and compare movement information, in contrast to the comparatively minimal processing requirements of classic biometric identification techniques like fingerprint or facial recognition. In resource-constrained situations, such tiny forensic labs or law enforcement organizations with inadequate technological infrastructure, processing huge amounts of surveillance material in real time can be difficult. This high computing load may restrict real-time applications and slow down the investigation process.

3. DATASET LIMITATIONS

The absence of large, varied datasets for AI model training is another significant limitation of gait analysis. The majority of gait recognition models now in use were created in standardized, controlled settings that do not adequately mimic real-world situations. It is challenging to generalize AI models trained on small datasets since surveillance footage varies greatly in terms of camera angles, lighting, and environmental impediments. The accuracy of real-world forensic applications is limited in the absence of diverse and extensive gait datasets, necessitating additional developments in data gathering and model training.

4. OBSTRUCTION AND OCCLUSION ISSUES

A clear view of a person's walking pattern is necessary for gait analysis, however in real-world surveillance situations, objects like trees, poles, cars, or other people can obscure some body parts. It becomes challenging to extract useful gait data when a subject's legs are completely or partially obscured in a scenario. The efficiency of gait detection is sometimes diminished when only a side profile or a portion of movement is discernible. Because of this restriction, obtaining high accuracy in congested settings where full-body visibility isn't always assured is difficult.

5. LEGAL AND ETHICAL CHALLENGES

There are ethical and legal issues with using gait pattern analysis in forensic investigations, especially when it comes to privacy and admissibility in court. In contrast to DNA or fingerprints, which have proven forensic validity, gait analysis is still in its infancy and their applicability as evidence is frequently contested. Environmental influences and individual movement variability raise doubts about the accuracy of gait recognition. Furthermore, the use of gait analysis for mass surveillance without authorization raises privacy problems and may provide ethical challenges. Further examination and regulation of the use of gait analysis in law enforcement will be necessary when legal frameworks change in order to guarantee its proper and equitable application.

7.2.1ADVANTAGES OF USING KINOVEA SOFTWARE

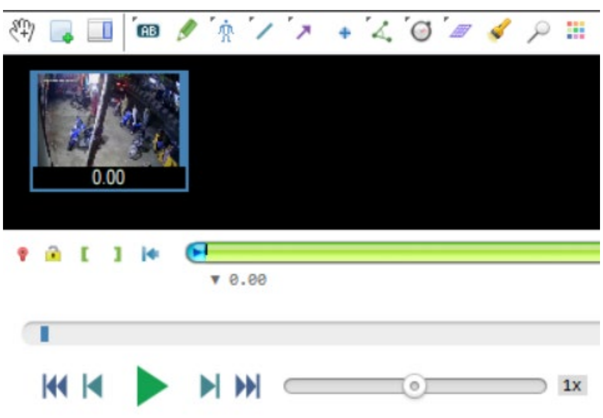

Fig 25: Tools In KINOVEA

i. Freely Available: One of the main benefits of Kinovea software is that it is available without charge, which makes it a great resource for professionals, students, and researchers without the need for a membership.

ii. Online Accessibility: Users can utilize the program's functionality without having to install it locally by using its online mode.

iii. Interactive Controls: One of Kinovea's many interactive features is the ability to manipulate things with the pointer, which allows for fine-grained modifications and personalization.

iv. Key Image Integration: To improve the clarity of gait analysis, users can input key photos to highlight particular frames or significant motion sequences.

v. Annotation Tools: To assist in identifying and elucidating important gait patterns, the software offers a range of annotation tools, including pencil drawing, text insertion, and comments.

vi. Human Model Representation: Users can more efficiently observe and examine movement dynamics when a human model is integrated into the system.

vii. Graphical Elements: Lines, arrows, markers, and angles are examples of features that help with precise motion monitoring and measurement, which facilitates the interpretation of gait characteristics.

viii. Measurement and Timing Tools: Having a stopwatch on hand enables users to take accurate time readings, which is essential for examining gait cycles.

ix. Perspective and Focus Tools: While tools like a flashlight and magnifying glass provide for a closer look at particular body parts or movements, the perspective grid aids in precisely aligning movement analysis.

x. Speed Control: Users can slow down or speed up video playing using the speed-altering bar, which makes it easier to observe gait patterns in detail.

7.2.2. DISADVANTAGES OF USING KINOVEA SOFTWARE

Limited Customization for Advanced Analysis: Although Kinovea offers the necessary capabilities for gait analysis, it might not have the sophisticated customization features needed for extremely specialized medical or forensic investigations.

i. Absence of AI or Machine Learning Features: Users must manually examine movements because the software lacks automated AI-based gait identification.

ii. Possible Learning Curve: Before using the software efficiently, new users would need some time to become acquainted with its many features and functionalities.

iii. Dependency on Internet Connection: Because Kinovea is only accessible online, users need a steady internet connection to access it without interruption. This could be a problem in places with inadequate connectivity.

iv. File Format and Export constraints: The software's compatibility with other analytic tools may be limited by constraints on the file formats that can be used to export results.

v. Absence of Real-Time Data Processing: Kinovea does not facilitate real-time motion capture and processing, in contrast to certain sophisticated gait analysis programs.

Overall, because of its extensive feature set, accessibility, and ease of use, Kinovea software is a useful tool for gait analysis. Its shortcomings in real-time processing, customisation, and AI integration, however, might force users to use it in conjunction with other specialist software for more complex forensic or medical applications.

FUTURE DIRECTIONS

INTEGRATION WITH MULTI-BIOMETRIC SYSTEMS

Gait pattern analysis should be combined with other biometric identification techniques including behavioral biometrics, iris scans, and facial recognition in future studies. A multi-biometric technique can improve forensic accuracy, especially when one biometric modality is degraded because of obstructions or poor video quality.

1. ADVANCEMENTS IN AI-DRIVEN GAIT RECOGNITION

The accuracy and effectiveness of gait recognition can be increased with further developments in deep learning and AI-based models. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) should be improved in future research to better capture minute changes in gait patterns. Furthermore, it is important to develop AI-driven deblurring methods to improve low-resolution CCTV footage while maintaining important gait characteristics.

2. CREATION OF LARGE-SCALE AND DIVERSE GAIT DATABASES

The absence of extensive, varied datasets that faithfully capture real-world circumstances is a significant obstacle in gait analysis. The creation of comprehensive gait datasets that account for differences in walking surfaces, environmental factors, and clothing styles should be a top priority for future studies. This would guarantee reliable forensic applications and increase the generalizability of gait recognition models.

3. REAL-TIME GAIT ANALYSIS FOR FORENSIC AND SECURITY APPLICATIONS

Researchers should create lightweight AI models that can analyze gait in real time to enhance practical deployment. In order to enable real-time suspect tracking and identification from live CCTV footage, these models ought to be made to integrate with law enforcement systems.

4. LEGAL AND ETHICAL CONSIDERATIONS

To provide uniform standards for its application in court, more study is required to determine the forensic admissibility of gait analysis. Future research should evaluate the accuracy of gait-based identification in legal settings while taking privacy, ethics of monitoring, and potential biases in AI models into consideration.

DISCUSSION

The research presented here highlights the value of using gait pattern analysis as a forensic technique to identify people in blurry CCTV material that is blurry. According to the results, gait is still a trustworthy biometric even in video conditions that are compromised, providing a workable substitute for facial recognition in situations where it is not working. Artificial intelligence (AI)-powered video enhancement methods show the promise of deep learning in forensic video analysis by dramatically improving the quality of gait feature extraction. Nevertheless, there are still issues, such as the computational difficulty of gait recognition models, the impact of outside variables on walking patterns, and the requirement for extensive, varied datasets in order to increase model accuracy. The work highlights the increasing significance of gait analysis in security, surveillance, and forensic investigations despite these drawbacks.

CONCLUSION

The limitations of conventional biometric techniques have been overcome by gait pattern analysis, a promising forensic tool for identifying people in fuzzy CCTV data. Even with poor video quality, this study shows that deep learning models and AI-based video augmentation can greatly increase the accuracy of gait detection. Even though there are still issues like dataset restrictions, processing requirements, and legal issues, continuous developments in artificial intelligence, multi-biometric integration, and real-time forensic applications will increase the accuracy and usefulness of gait analysis. Gait identification is anticipated to become increasingly important in improving security, law enforcement, and crime investigation as forensic science improves.

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