GAIT Recognition using Deep Learning

Submitted in partial fulfillment of the requirements for the degree of

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in

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by

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May, 2022

DECLARATION

We hereby declare that the thesis entitled " **GAIT Recognition using Deep Learning** " submitted by us, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of

Dr. Jaisakthi S M.

We further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore

Date : 1st June, 2022

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CERTIFICATE

This is to certify that the thesis entitled "**GAIT Recognition using Deep Learning**" submitted by Utkarsh Singh (18BCE2139), Samar Pratap Singh (18BCE2169), Kriti Chapagain (18BCE2483) & **School of Computer Science & Engineering**, VIT University, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of bonafide work carried out by him under my supervision during the period, 01. 12. 2022 to 30.05.2022, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Signature of the Guide

Date : 1st June, 2022

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Executive Summary

This reports analyzes the silhouette, height, speed, and walking characteristics and identifies the individual from a database. This technique is more convenient than retinal scanners or fingerprints in public places as it is unobtrusive. Moreover, gait recognition is unlikely to be outsmarted — every person's gait has no duplicates.

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List of Abbreviations

PCK	Percentage of Correct Key-Points
HOG	Histogram of Oriented Gradient
LBP	Local Binary Pattern
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units

Symbols and Notations

-None-

1. Introduction:

Gait recognition is a sub-discipline of biometric authentication that focuses on detecting people using private strategies and relationships, including trunk and limb size, in addition to space-time statistics related to inherent behaviors in individuals' motions. Gait recognition is without difficulty sampled from distance, which stands for a massive benefit regarding other methods, especially while the identification isn't assisted by way of the analyzed character, e.g., crook investigations. moreover, since it does now not require excessive-tech gadget for statistics extraction, these strategies are typically less expensive than other techniques, due to the popularization of surveillance systems and the upward push of cellular telephones ready with accelerometers, which translated the weight of extracting information signals into a easy task. furthermore, in comparison to different biometric identity modules, gait recognition structures have a few advantages because hacking such models is tough.

1.1 Objective of the proposed work

The objective is to discover machine learning knowledge of techniques and look at their benefits and cons on employing gait patterns for validating users. This device is one of the particular attributes. using a database which consists of numerous sorts of behaviors including going for walks, strolling, status and sitting.

There are three primary aims:

- To systematically get the most latest and significant works consisting strategies for gait recognition through deep studying strategies; and
- To offer the reader with a qualitied and illustrated theoretical history concerning gait popularity, exploring its roots on biometric recognition and learning the most popular gear employed to gait characteristic extraction and the fashions used to address the respective constraints; and
- To reveal an illustrated, classified, and characterized catalog of the general public datasets to be had for the project of gait recognition.

1.2 Motivation

Despite the simplicity concerning the equipment, figuring out gait with the aid of on foot and moving is a long way from a trivial task. standard gait recogniton techniques, i.e., which comprise facts pre-processing and features extracted in a hand made fashion for similarly recognition, often be afflicted by several constraints and demanding situations imposed by means of the complexity of the mission, such as viewing attitude and huge intra-magnificence variations, occlusions, shadows, and finding the frame segments, amongst others. a new trend on machine learning, known as deep studying, emerged in the last years as a revolutionary device to handle subjects in image and sound processing, pc vision, and speech, overwhelmingly outperforming actually any baseline hooked up till then. the new paradigm exempts the need of manually extracting representative functions from professionals and also gives paramount consequences regarding gait recognition, surpassing present demanding situations and starting room for further research.

1.3 Theoretical Background

Gait recognition is a branch of biometric identity that makes a speciality of detecting individuals the usage of non-public measures and relationships, such as trunk and limb size, in addition to space-time records related to inherent patterns in individuals' motions. within the context of surveillance systems or foggy environment tracking, as an instance, wherein one of a kind factors usually used for biometric identity, along with the fingerprint and face, are hard or not possible to distinguish, such an technique has tested to be quite effective.

2. Project Description and Goals

Many biometrics, e.g., the fingerprint, iris,face, and voice and many others., were implemented commercially. a number of these biometrics are evident to customers as they require the cooperation of users to accumulate the facts. for example, customers are asked to region a finger on a device to have their fingerprints captured or to have a look at a digicam close enough to have their irises imaged. In such cases, a person can also feel angry and without difficulty realizes that his/her identity is being checked. in the meantime, a few biometrics are effortlessly cast and attacked. as an example, face recognition may be cheated with the aid of the usage of an picture or a video of the target face As a end result, much less obvious and greater robust biometrics are currently in exquisite demand. Unobtrusiveness is mainly vital for a biometric system that must paintings in a discrete way, e.g., to recog-nize the identification of a person but now not to allow him/her recognise he/she is being diagnosed. Amongst various biometrics, gait now not simplest satisfies the requirement of being unobtrusive however also is greater tough to hide.

The task stems mostly from the concept's inherent properties, namely, identity primarily based on its mobility, that is especially difficult to breed. The equal can't be said for other techniques, which include disguising one's face from the system. Moreover, gait recognition fashions do now not require excessive-resolution pix or particular gadget, which include iris and fingerprints, for proper identification. furthermore, whilst other techniques require the studied person to interact with the identifying device, gait popularity methods do not require man or woman interplay.

2.1 Introduction and related concepts

To obtain identification authentication, gait recognition mainly leverages the varied postures of each individual. The entire-cycle gait pics are used for feature extraction in previous methods, but there are problems including occlusion and body loss within the actual scene. A full-cycle gait picture is hard to return with the aid of. As a result, the focal point of gait recognition research has shifted to a way to construct a fairly green gait recognition algorithm framework based totally on a small quantity of gait images so that it will decorate recognition efficiency and accuracy.

The CRBM+FC deep neural network is built on this bankruptcy. a way of gaining knowledge of gait identity from GEI to output is supplied based on the houses of nearby Binary sample (LBP) and Histogram of orientated Gradient (HOG) fusion. It is suggested a logo-new gait detection set of rules based on the layered fu-sion of LBP and HOG. This chapter also gives a characteristic mastering network that trains Gait power photos the usage of an unsupervised convolutional restricted Boltzmann gadget (GEI).

3. Technical Specifications

The network takes raw RGB video frames of a pedestrian as an input and produces one-dimensional vector - gait descriptor that exposes as an identity vector. The identity vectors from gaits of every two special people must be linearly separable. Whole network includes two sub-networks connected in cascade - HumanPoseNN and GaitNN.

Spatial features from the video frames are extracted in line with the descriptors that contain pose of the pedestrian. These descriptors are generated from the first sub-network - HumanPoseNN defined in human_pose_nn module. HumanPoseNN can be extensively utilized as a standalone network for everyday second pose estimation trouble from nonetheless pix.

Duty of the second sub-network - GaitNN described in gait_nn module is additional processing of the generated spatial capabilities into one-dimensional pose descriptors with the usage of a residual convolutional network. Temporal features are then extracted throughout those pose descriptors with using the multilayer recurrent cells - LSTM or GRU. All temporal features are in the end aggregated with average temporal pooling into one-dimensional identification vector with excellent discriminatory properties. As already cited within the text above, the human identity vectors are linearly separable with every other and can therefore be categorized with e.g. linear SVM.

3.1 Gait recognition

The dummy code under indicates how to generate the identification vector from the enter facts video_frames. For the good outcomes, all frames ought to include the whole person visible from the profile view. The man or woman have to be located approximately within the middle of each frame.

```
# Initialize computational graphs of both sub-networks

net_pose = HumanPoseIRNetwork()

net_gait = GaitNetwork(recurrent_unit = 'GRU', rnn_layers = 2)

# Load pre-trained models

net_pose.restore('path/to/pose_checkpoint.ckpt')

net_gait.restore('path/to/gait_checkpoint.ckpt')

# Create features from input frames in shape (TIME, HEIGHT, WIDTH, CHANNELS)

spatial_features = net_pose.feed_forward_features(video_frames)

# Process spatial features and generate identification vector

identification_vector = net_gait.feed_forward(spatial_features)
```

3.2 Pose estimation

The first sub-network HumanPoseNN can be also used as a standalone network for 2D pose estimation problem. This can be done in such a way:

```
net_pose = HumanPoseIRNetwork()

# Restore pre-trained model

net_pose.restore('path/to/pose_checkpoint.ckpt')

# input_images should contain RGB images (299 x 299) to be processed.

# The images in batch should be stacked along the first dimension, so the shape of input_images

# has to be (BATCH, 299, 299, 3)

coords_y, coords_x, probabilities = net_pose.joint_positions(input_images)
```

Where coords_y, coords_x and probabilities stores predicted joint coordinates in Y axis, X axis and possibility of every estimate, respectively. some of these tensors have form (BATCH, 16), in which the second size is the body joint. The order of the frame joints inside the second measurement is as follows:

1. right ankle
2. right knee
3. right hip
4. left hip
5. left knee
6. left ankle
7. pelvis
8. thorax
9. upper neck
10. head top *(in human3.6m - head middle)*
11. right wrist
12. right elbow
13. right shoulder
14. left shoulder
15. left elbow
16. left wrist

3.2.1 **Dummy pose estimation**

If you run the script dummy_pose_estimation.py, the pose of a human in the dummy photo /photos/dummy.jpg will be estimated and displayed in a new-created file /photos/dummy_pose.jpg. For doing this you must have the matplotlib package installed and feature pre-trained version MPII+LSP stored in /models/MPII+LSP.ckpt - for getting pre-trained models test the next phase. The generated photo in /images/dummy_pose.jpg must appear like this one:

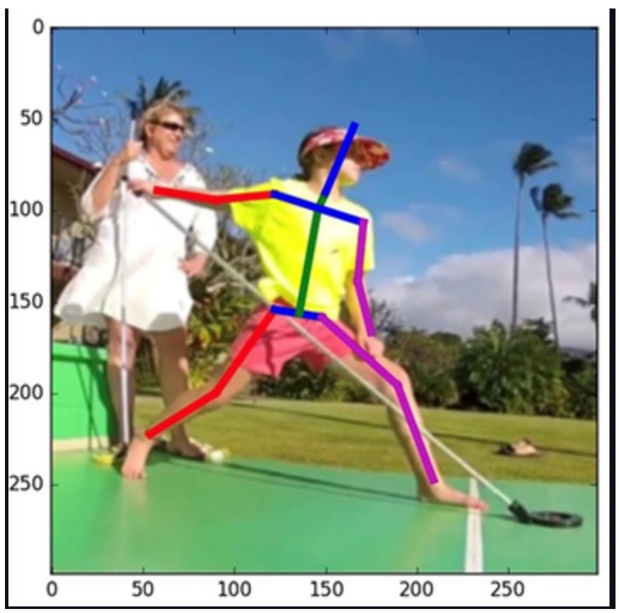


Fig 1: HumanPoseNN: MPII + LSP

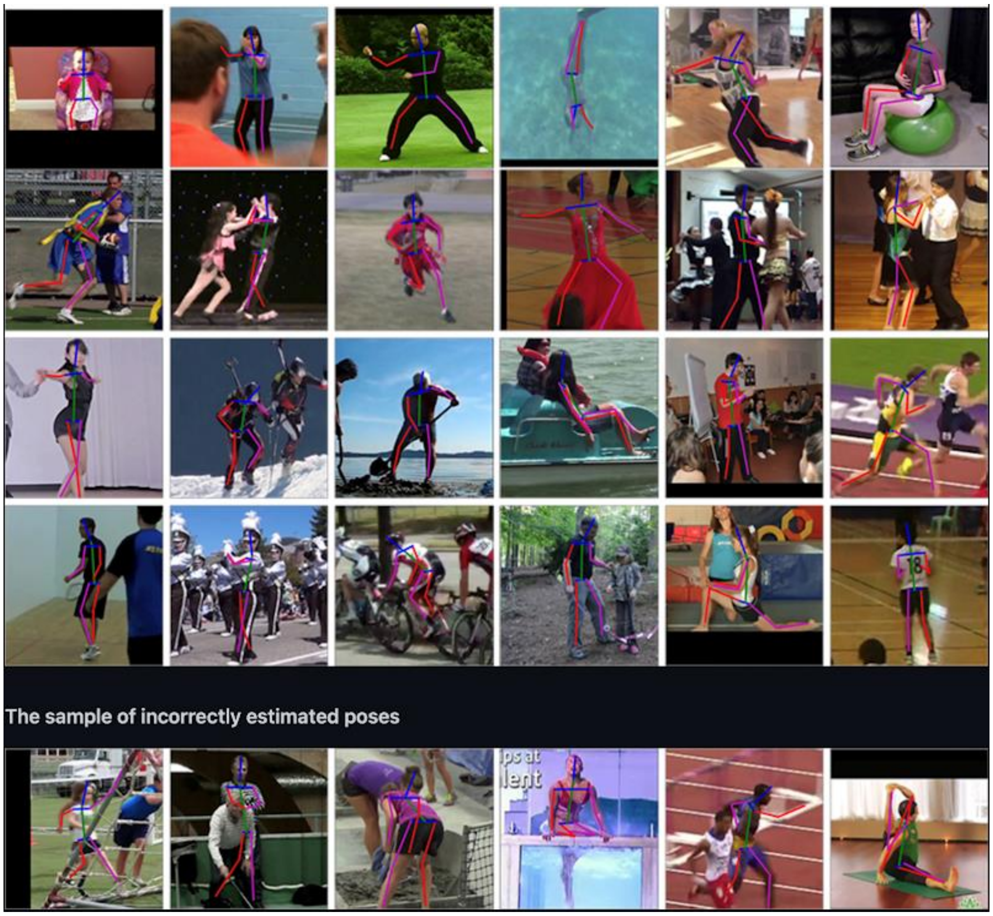


Fig 2: HumanPoseNN: Human 3.6m

The checkpoint Human3.6m.ckpt changed into trained on the database Human 3.6m and handiest on the on foot sequences of peoples S1, S6, S7, S8, S9 and S11 (48 sequences). individual S5 (8 sequences) was used for a validation functions and the average distance between anticipated and desired joints is shown within the following graph. As you may see, mistakes are smaller compared to MPII+LSP. it is because desired poses in Human three.6m was classified more precisely the usage of motion seize machine, so the a skilled network can greater accurately estimate the human pose. The second one motive is that Human 3.6m sequences are very monotonous and thus human pose estimation is less challenging.

3.3 GaitNN

We use the identical general TUM GAID experiments as described e.g. on this paper (segment Experimental effects on TUM GAID) from F.M. Castro et al. that currently reap state of the art consequences. In short, there are 2 important experiments. The goal inside the first one is to perceive 305 human beings (a hundred training, one hundred fifty validation, 155 checking out) the use of 10 gait sequences for all people. these sequences catch character in three one of a kind covariate situations: Normalwalk, walking with backpack and taking walks with coating shoes. however, the human beings on all of these video-sequences wear the equal apparel. To cope with the diverse clothing situations, there's the second one test. The purpose of the second one experiment is to perceive 32 peoples (10 train, 6 validation, 16 trying out) the use of 20 gait sequences for all people – first 10 became taken in January and the opposite 10 in April. The humans have extraordinary garb, standard for respective season.

Fig 3: GaitNN Difference

4. Design Approach and Details

4.1 Materials and Methods

4.1.1 System Requirements

4.1.1.1 H/W Requirements

- CPU (at least intel core i5)
- GPU will speed up process (optional)

4.1.1.2 S/W Requirements

The code was written in Python3.5 and various python packages were used:

Tensorflow (Deep Learning Purpose), numpy (mathematical applications),

Scipy (manipulate the data and visualize wide range of data using high-level python commands,

PIL (modules for image processing).

4.1.2 Proposed system model

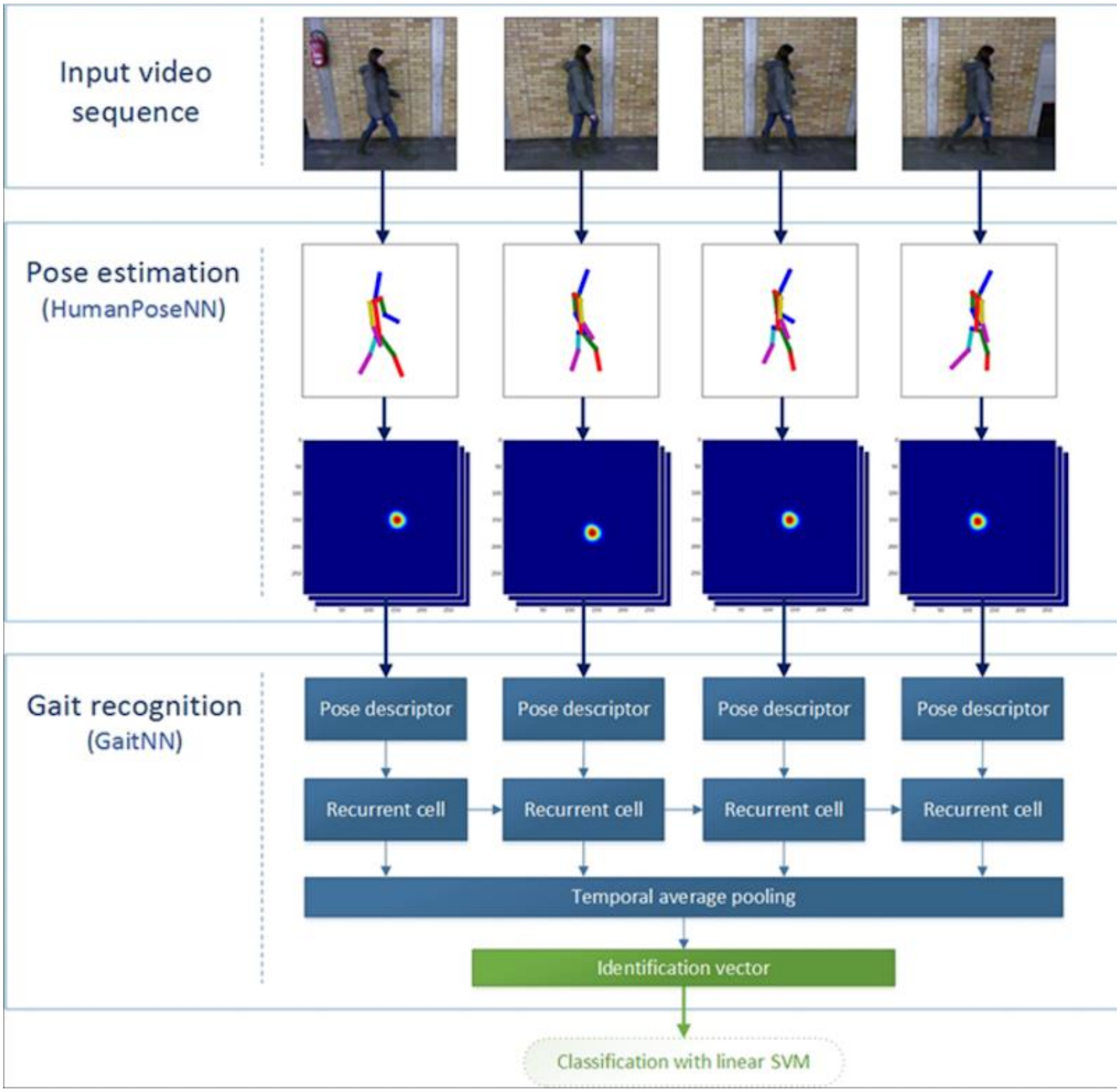


Fig 4: Proposed System Model

4.1.3 Proposed System Analysis and Design

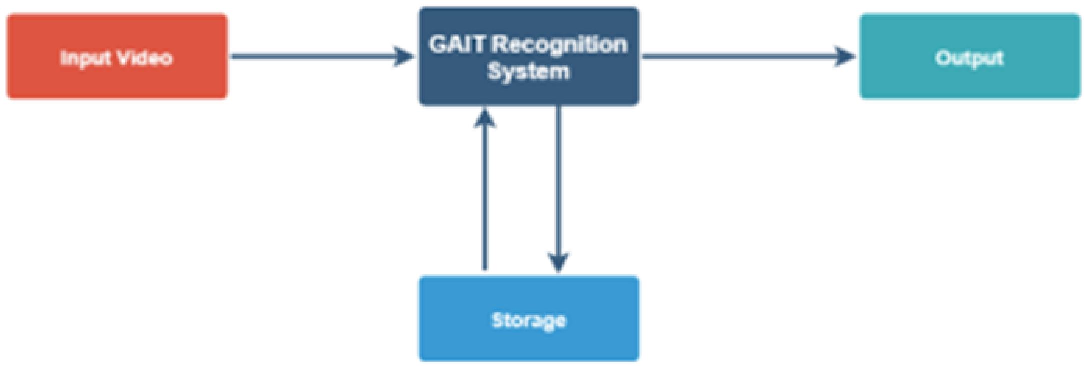


Fig 5: Proposed System Analysis and Design

4.2 Codes and Standards

Wearable Sensors: WS are an obvious approach to collect human gait due to their comfort, efficiency and decrease price. in contrast to different gait capturing structures, WS impose upon the person to cooperate sporting the tool in a non-invasive way to provide gait signals. The advances in digital gadgets and sign processing techniques have extended the packages of WS sensors to produce a dimension of human frame orientation, function and precise pressure in space and time. The inertial size unit (IMU) is a kind of WS system that has been significantly used because of its small size, fee, mild weight, and precise precision traits. a typical IMU affords the most widely used combination of sensing modalities to seize human sports, together with gait. It accommodates of an accelerometer, a gyroscope and regularly a magnetometer, which gives the heading course. extra additives including batteries, microprocessors and verbal exchange modules are arranged to together function an IMU system. Gyroscope sensors measure the angular pace as the rate of exchange of the sensor's orientation, while accelerometer sensors degree the acceleration of the frame resulting from the acting forces in the contrary course. A aggregate of these sensors can create a comprehensive report on the human body orientation, gravitational forces, speed and acceleration.

4.3 Constraints, Alternatives and Tradeoffs

Gait recognition does now not enjoy the benefit of deploying conventional and demonstrated techniques, consisting of harmonic evaluation where functions are represented in a complete and orthogonal base, e.g. as a superposition of sine and cosine functions. Regrettably, a complete and orthogonal feature base for gait is hard to outline, or in other words, the gait primitives are in large part undefined. The gait features normally used in practice neither are absolutely impartial nor do they exhaust all of the viable participants of the set. On this backdrop, the automatic extraction of those gait features which permit to distinguish a positive target case with the first-rate accuracy, e.g. in healthcare or biometrics, seems to be a winning strategy. However, the nature of human gait calls for distinct strategies depending at the person and quantity of the recorded sensor information (sensing modality, availability of datasets, computational value, and so forth.). This causes variations inside the most reliable selections made: the modalities for complementary fusion, the records representations, the superior deep studying fashions, in addition to the way of their usual deployment.

Gait tracking with floor sensors calls for minimum, if any, cooperation or interest by the consumer and is amenable to embodiments for lengthy period, non-stop information seize. This motivates the advances in sensor technology for footsteps taking pictures systems and processing of GRF records to extract different information on gait events, evolution of walking conduct and response to physical and psychological interventions. normal applications of FS are in the fields of biometrics, healthcare, sports activities, safety and security.

5. Schedule, Tasks and Milestones

Jan 2022: Development of project idea and initial searching through references.

Feb 2022: Working on first module of project, ‘Pose Estimation’, resources for development of this module.

Mar 2022: Developing code and acquiring datasets for the model in pose estimation

March End: **MILESTONE: Found ideal datasets for both modules and good compatibility with code**

Apr 2022: Completed ‘Pose Estimation’ and started 2nd module development ‘Gait Recognition’

May 2022: Completed ‘Gait Recognition’ module, with only graph and results generation left.

May end: **MILESTONE: Project completed and outputs, results generated.**

6. Project Demonstration

6.1 Pose Estimation

By running the following code ‘dummy_pose_estimation.py’, we are able to list down the prediction of each of the joints using the model. The dataset is stored in the device folder and is imported by the code.

The code then extracts the ‘demo.jpg’ image and analyzes it.

Output is then generated and stored as a new image file ‘demo_pose.jpg’

dummy_pose_estimation.py | gait_nn.py | initialize.py | human_pose_nn.py

```python
import numpy as np
import matplotlib as mpl
mpl.use('Agg')
import matplotlib.pyplot as plt
from scipy.misc import imresize, imread
from human_pose_nn import HumanPoseIRNetwork

net_pose = HumanPoseIRNetwork()
net_pose.restore('models/MPII+LSP.ckpt')

img = imread('images/demo.jpg')
img = imresize(img, [299, 299])
img_batch = np.expand_dims(img, 0)

y, x, a = net_pose.estimate_joints(img_batch)
y, x, a = np.squeeze(y), np.squeeze(x), np.squeeze(a)

joint_names = [
    'right ankle ',
    'right knee ',
    'right hip',
    'left hip',
    'left knee'
```

Fig 6: Pose Estimation Code

The pictures below show the input and output of the pose estimations for a .jpg format

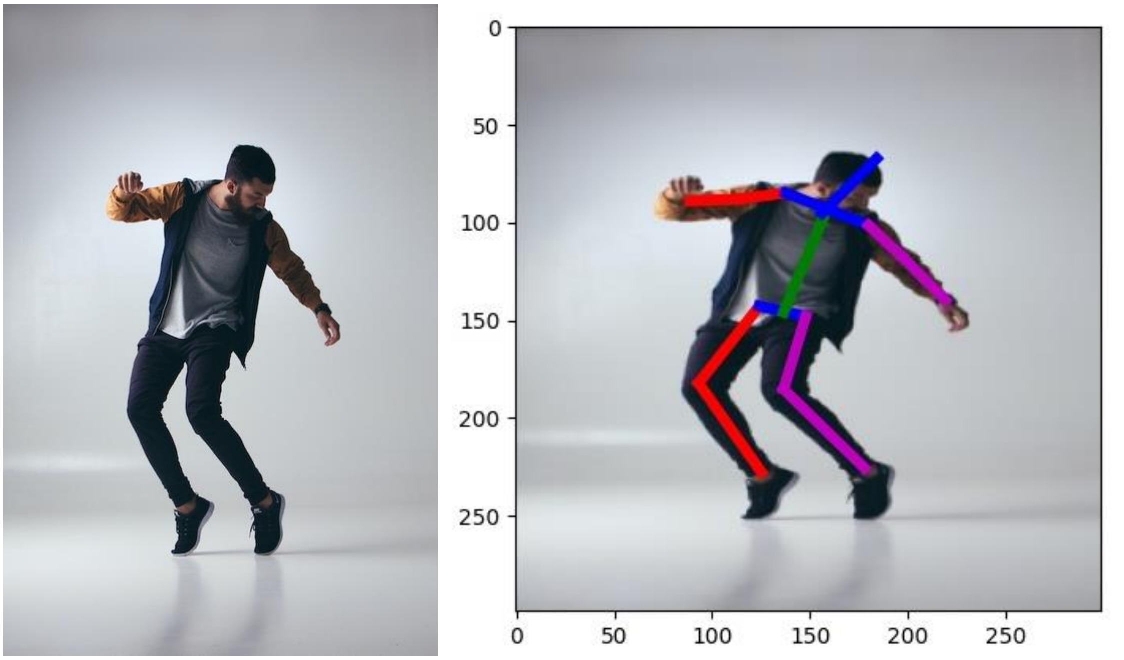


Fig 7: Pose Estimation Image Output

The picture below shows output of the pose estimation, live, with the given input as a .MP4 (video) format file. The code output that gets generated is the prediction for each of the joints shown in the photo

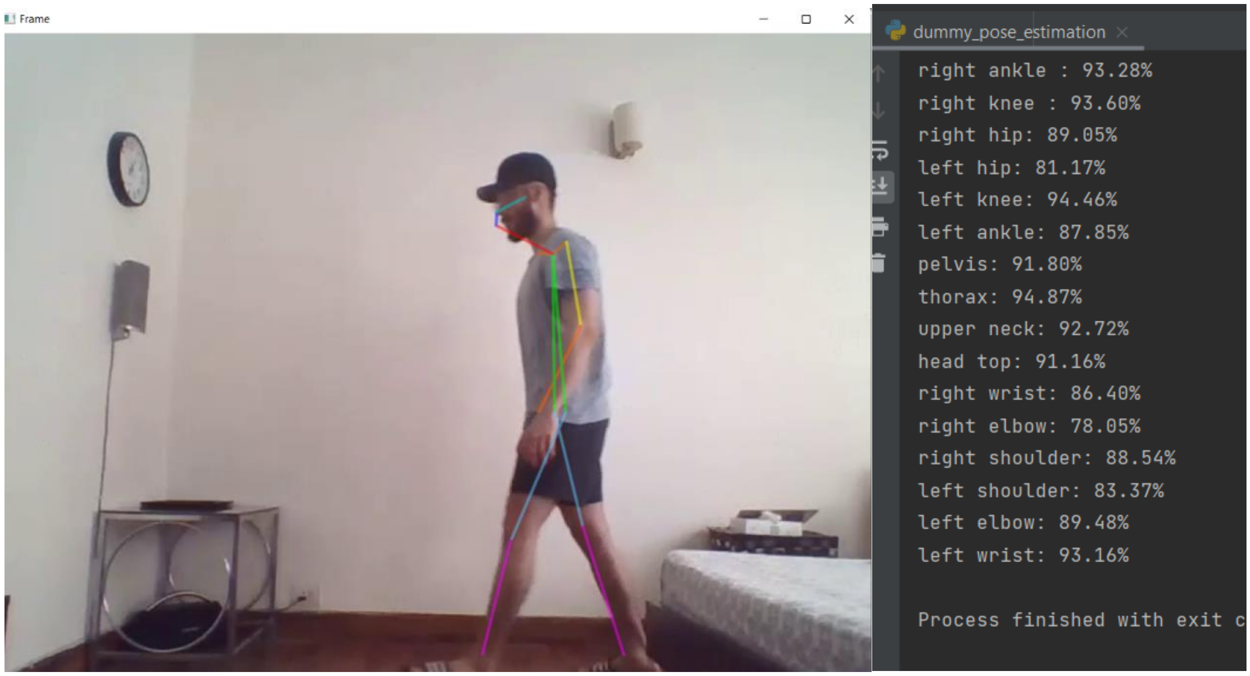


Fig 8: Pose Estimation Live Video Output

6.2 Gait Recognition

The code below runs the gait recognition model for a video file (.MP4), which has been saved in the device folder as 'samar.mp4'

The code then imports the dataset and runs the model to generate a series of coloured points; each representing a different joint/feature.

```
poseDetectVideo.py

# import the necessary packages
import ...

fvs = FileVideoStream('data/samar.mp4', queue_size=1024).start()
time.sleep(1.0)

kernelSize = 7
backgroundHistory = 15

openposeProtoFile = "pose/coco/pose_deploy_linevec.prototxt"
openposeWeightsFile = "pose/coco/pose_iter_440000.caffemodel"
nPoints = 18

# COCO Output Format
keypointsMapping = ['Nose', 'Neck', 'R-Sho', 'R-Elb', 'R-Wr', 'L-Sho', 'L-Elb', 'L-Wr', 'R-Hip', 'R-Knee', 'R-Ank',
                    'L-Hip', 'L-Knee', 'L-Ank', 'R-Eye', 'L-Eye', 'R-Ear', 'L-Ear']

POSE_PAIRS = [[1, 2], [1, 5], [2, 3], [3, 4], [5, 6], [6, 7],
              [1, 8], [8, 9], [9, 10], [1, 11], [11, 12], [12, 13],
              [1, 0], [0, 14], [14, 16], [0, 15], [15, 17],
              [2, 17], [5, 16]]

# index of pafs correspoding to the POSE_PAIRS
# e.g for POSE_PAIR(1,2), the PAFs are located at indices (31,32) of output, Similarly, (1,5) -> (39,40) and so on.
mapIdx = [[31, 32], [39, 40], [33, 34], [35, 36], [41, 42], [43, 44],
          [19, 20], [21, 22], [23, 24], [25, 26], [27, 28], [29, 30],
          [47, 48], [49, 50], [53, 54], [51, 52], [55, 56],
          [37, 38], [45, 46]]

colors = [[0, 100, 255], [0, 100, 255], [0, 255, 255], [0, 100, 255], [0, 255, 255], [0, 100, 255],
```

Fig 9: Gait Recognition Code

The output of the code is shown below. The path of each joint is clearly visible and hence can be used to differentiate between unique features in every individual's walk.

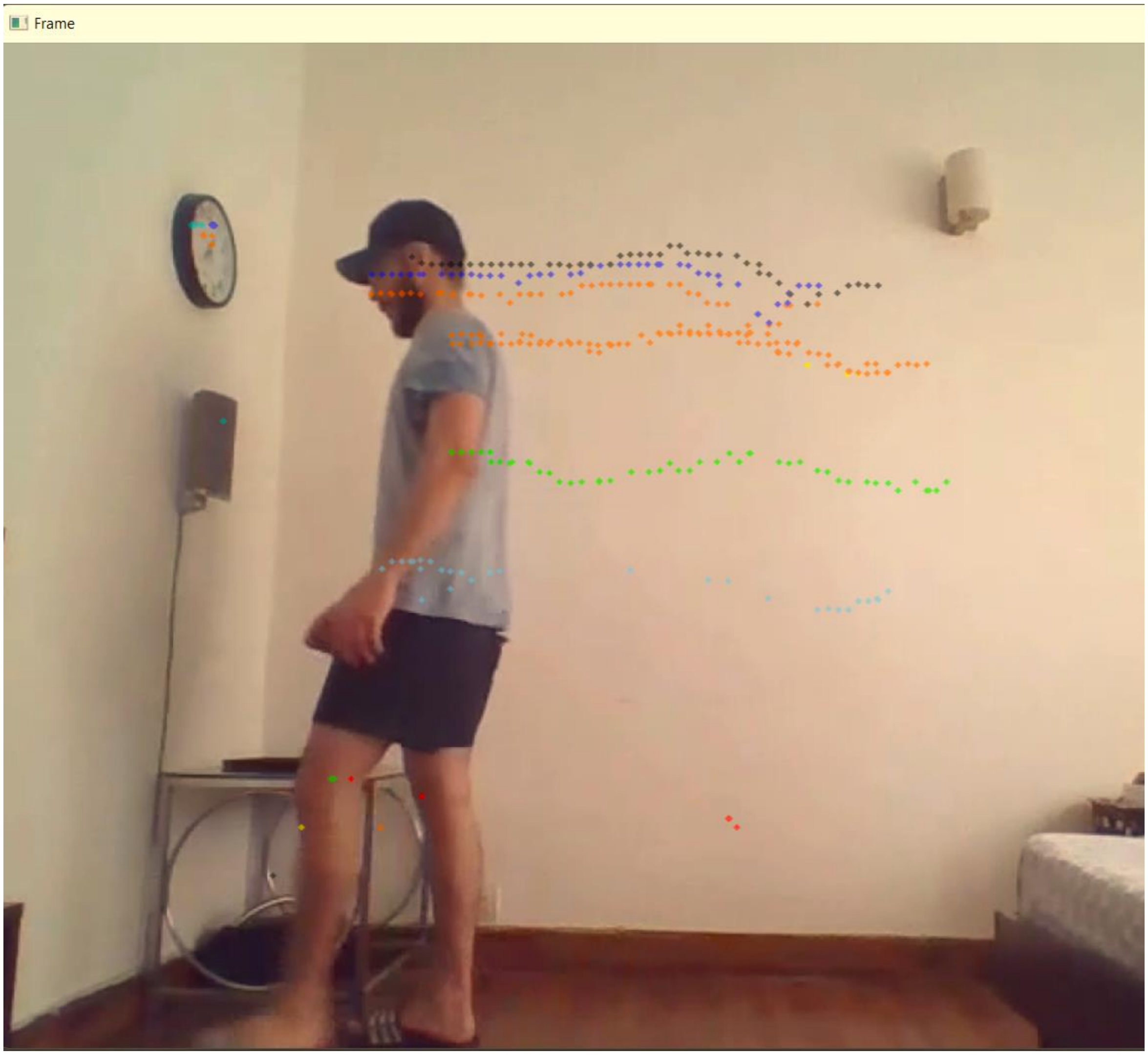


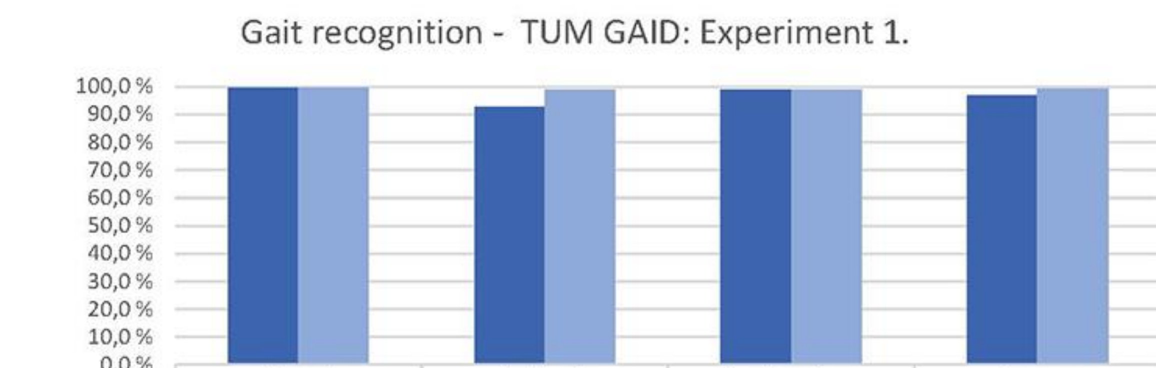
Fig 10: Gait Recognition Live Video Output

7. Results and discussion

Results for gait recognition:

The best model on the primary experiment is H3.6m-GRU-1 and on the second is M+L-GRU-2. The graphs bellow compares the overall performance of those fashions with already mentioned nation of the artwork model PFM from F.M. Castro et al. The model H3.6m-GRU-1 became trained simplest on the first experiment and on the second one graph there's proven, how this version works at the validation set of the second one test. As you can see, both models outperform PFM inside the second experiment with a massive margin. It means that these fashions are a great deal greater sturdy towards clothing and time elapsed factors.

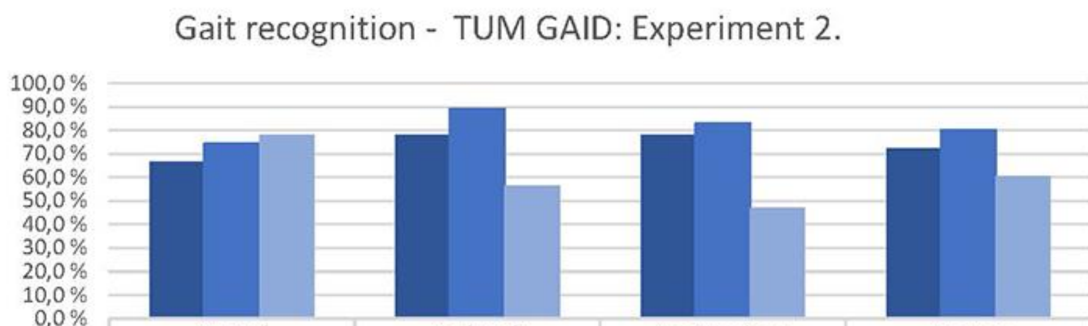
- **Human 3.6m validation set:**



	Normal	Backpack	Coating shoes	Average
H3,6m-GRU-1	99,4 %	92,6 %	98,7 %	96,9 %
PFM	99,7 %	99,0 %	99,0 %	99,2 %

Table 1: Human 3.6m Results

- **MPII + LSP validation set:**



	Normal	Backpack	Coating shoes	Average
M+L-GRU-2	66,4 %	78,1 %	78,1 %	72,3 %
H3.6m-GRU-1	74,2 %	89,1 %	82,8 %	80,1 %
PFM	78,1 %	56,3 %	46,9 %	60,4 %

Table 2: MPII+LSP Results

<u>Result for pose estimation</u>:

The checkpoint MPII+LSP.ckpt became trained on photos from MPII and LSP database. inside the graph below you can see the average distance among anticipated and favored joints on a validtion set of approximately 6 000 pictures.

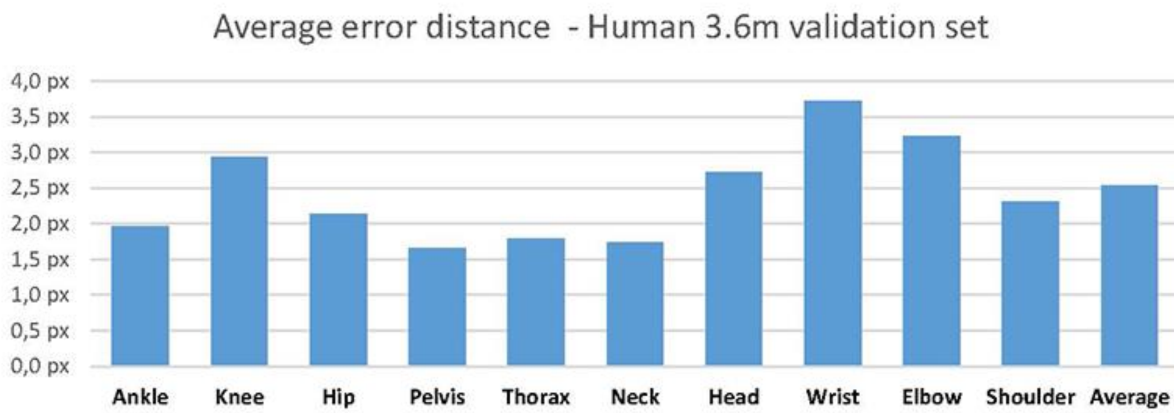


Table 3: Average Error Distance – Human 3.6m

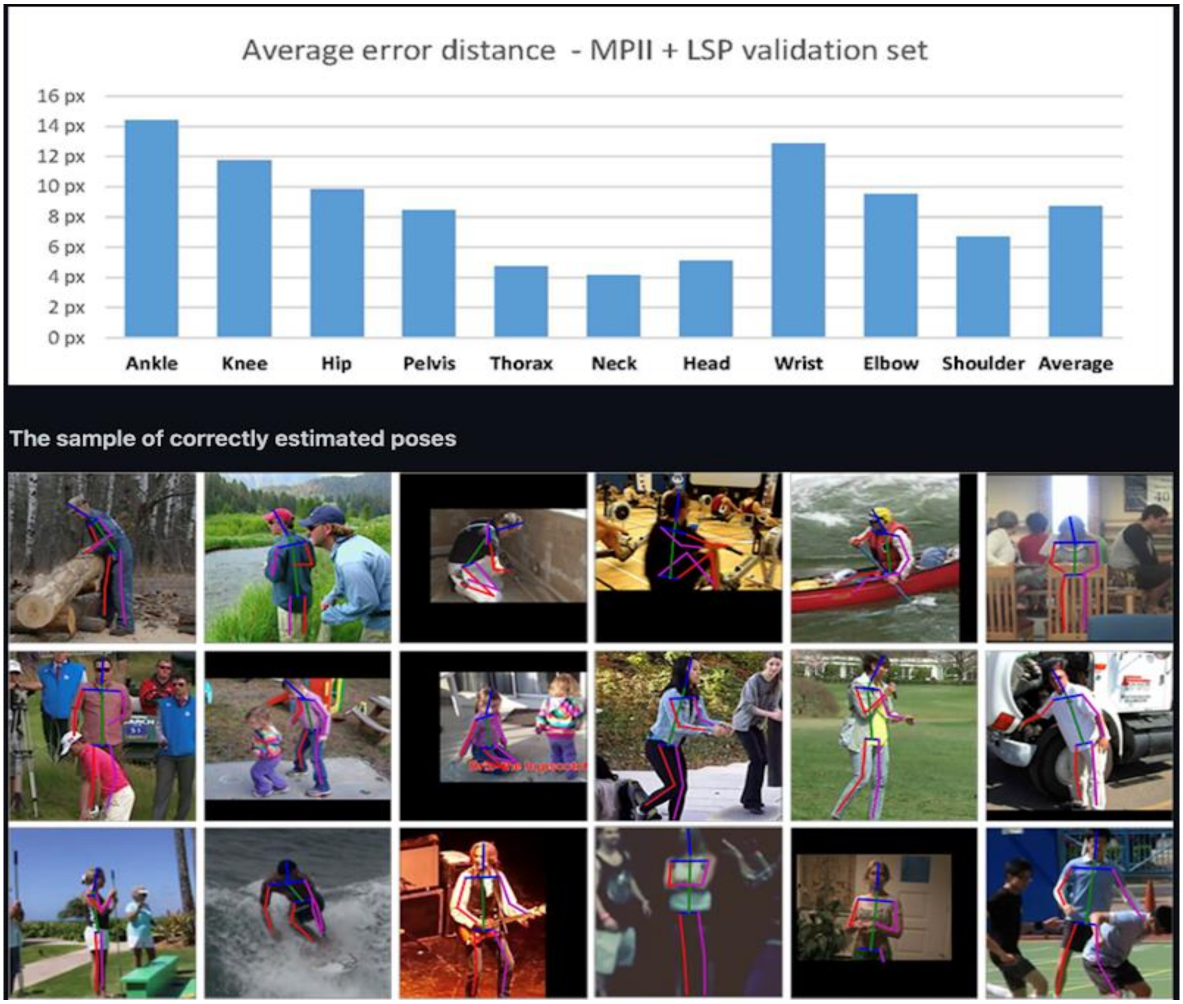


Table 4: Average Error Distance – MPII + LSP

Printed probabilities of each estimate:

right ankle : 85.80%

right knee : 80.27%

right hip: 85.40%

left hip: 80.01%

left knee: 83.32%

left ankle: 92.08%

pelvis: 88.84%

thorax: 96.41%

upper neck: 97.40%

head top: 88.81%

right wrist: 87.90%

right elbow: 88.85%

right shoulder: 91.30%

left shoulder: 93.63%

left elbow: 92.31%

left wrist: 94.24%

Discussion

Gait recognition is a biometric approach that ambitions to decide the identity of people primarily based at the style and way of their walk. in this paper, we evolved a specialised deep CNN version, which consists of many layers, for human gait recognition. The positive of the deep CNN is its capacity to extract discriminative capabilities and better classification, in particular if the available trained dataset is massive. We empirically decided an appropriate structure of the deep CNN for gait recognition. The proposed CNN is able to overcoming many problems associated with gait recognition, particularly while covariate elements are involved, and for this reason leads to higher gait recognition overall performance. Numerous distinctive experimental effects at the databases reveal that the proposed deep CNN version can achieve competitive performance.

8. Summary

Computerized individual recognition based totally on visual cues is a huge studies vicinity in computer vision. Vital applications are surveillance systems in public areas to increase safety. The maximum popular strategies use face, iris or fingerprint facts for detection and popularity. those techniques paintings well in lots of programs, but are now and again impractical. They may be sensitive to occlusion, massive distances or low-resolution information and often require cooperation of the problem. On this work we present a method to address these demanding situations in Gait recognition adapting recently advanced principles in deep mastering. A 3-D Convolutional Neural network (CNN) is offered using spatio-temporal records, searching for a wellknown descriptor for human gait invariant for view angles, coloration and extraordinary on foot situations. a new approach has been offered to tackle the challenges in the field of Gait popularity. View, clothing and strolling velocity invariance make Gait recognition a flexible and hard challenge. A contemporary brand new approach the usage of Convolutional Neural Networks is proposed, extracting spatiotemporal features for category. This illustration consequences in a excessive accuracy across experiments on one of a kind famous databases declaring the high capacity of CNNs for Gait recognition. although, because of the small amount variance and the small database size standard, a unique facts split is implemented and overfitting is a problem. Except using better hardware and larger network structures, possible enhancements can also be visible inside the developing amount of information with larger databases to return. The use of databases inclusive of hundreds of subjects and a massive variance in walking conduct and look can in addition enhance overall performance and reduce overfitting.

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