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UPPER GAIT ANALYSIS FOR HUMAN IDENTIFICATION USING CONVOLUTIONAL – RECURRENT NEURAL NETWORK

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ABSTRACT

The human gait as a source of biometric data has improved identification at father distance, however it only full body gait data has been explored with deep learning models, which is resource demanding not always available due obstacles as in environment of deployment. In this research, we explored the use of upper gait analysis for identification with deep learning model convolutional recurrent neural network- Long Short Term Memory CRNN-LSTM and evaluate the reliability of using half gait against full gait, primary dataset was collected from 26 subject 12 females and 14 males. The result returns better accuracy with upper half gait than full body gait, hence, lower computation demand.
Keywords: *Gait, Gait Analysis, C-RNN, Human Identification, Computer Visions*

1 INTRODUCTION

Identification is a key element of security for access control, surveillance, etc. digital biometric system such as finger print scanners, retina scan, voice recognition are deployed to identify persons, recent advancements in computer visions solution, researchers have proposed several method of analyzing the human walking behavior to serve as biometrics as it has been established that all humans walk uniquely

The human gait can be captured using visual data or data from other sensors, graphical data is captured using camera, making the gait visual data the farthest biometric data that can be acquired from a person. Several factors can influence the human gait such as health, wears, and luggage. Variation in gait in response to change in aforementioned allows further applications of gait analysis is various fields. Important factors that affect data collected in studying visual gait data are angle of capture, framerate, resolution, color scale, etc.

The human gait is an embodiment of information that can gives insight on person's state of mind [1], medical condition [2] [3] which could guide therapies and mental diseases [4], orthopedic disease [5], psychological disorders and neurological disease; biometrics: gender classification [6, 7], action recognition, surveillance [8]; Robotics [9] [10]: modelling, simulation.

In surveillance, the use of Close Circuit Television CCTV has been adopted unanimously as an essential perimeter monitoring equipment, through computer visions surveillance has been improved to detect objects, person biometrics, behavioral analysis, anomaly detection among others.

Application of gait analysis in area of surveillance will lead to smart surveillance where human is not required to watch video footage at always, object and person detection and identification can be done automatically, however in surveillance a person might not be fully visible from head the toes unlike in medical diagnosis the environment is controlled the physician may ask the patient to walk again. Obstacles such as cars, short fence, tables and many more that may block the lower part of the target.

Computer vision as a field of computer science is aimed giving the computers machine to infer from visual data as humans do, advancement in computing and computational methods such as machine learning encourage further adoption of computer solutions in the area of gait analysis in different fields.

Machine learning methods allows applying computer to solve problems without detailing in algorithm explicitly, it map inputs to output and learn different from historic data for a specific problems. Visual problems can be categorized as fuzzy as even humans do explicitly measure of numerical compute

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visual problems such as identification of object or person.

Researchers focus mostly on the factors influencing gait and models use for the analysis, hence, they used full body gait dataset which challenges adoption in areas with obstacle that full body gait is not obtainable,

In this research we investigated the effect of using upper half body gait and against full body gait. The purpose of this study is to investigate the feasibility of human identification using deep learning on upper gait and measure its implications concerning reliability and accuracy in comparison with full gait.

The rest of the paper is structured as follow: Section 2 describes the human gait, covering factors influencing it and methods of analysis, in section 3 we discussed some of the relevant literature we reviewed and in section 4 we discussed we discussed the method we used, dataset preparation process, model description, in section 5 we briefly show hyper parameters that describe experiment setup. The result was discussed in section 6 followed summary, conclusion and recommendation for future work.

2 THE HUMAN GAIT

Human gait is human behavior of maintaining balance while in motion, it entails relative displacement of body part and weight distribution synchronized as the human walks. The human gait cycle is comprised of left step proceeding the right or vice versa. From the feet perspective, the gait event can be categorized into swing and stance phases as described in Fig 1 below where the swing phase are when the leg is not on the ground. The stance phase is when the feet is contact with the ground covering 60 percent of the gait cycle [11]. The swing covers 40 percent while the feet is off the ground.

At the swing phase the rest of the body balance itself on the other leg at stance position, the adaptation is observe in movement of shoulder, up and down movement of the head, hip angle, belly the and waist twisting, hand swinging etc. variation in the physiology of individuals and environment categorized as internal and external factors [12] of walking influence the gait.

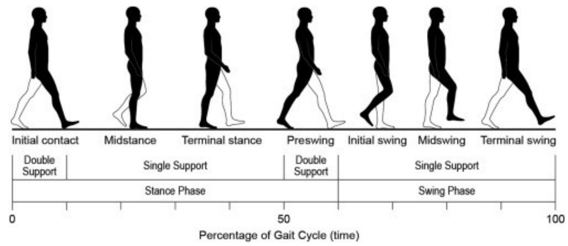

Figure 1: Human Gait Cycle

2.1 Factors Affecting Gait

The human gait adjust to adapt to changes, these factors that influences the gait are categorized into internal and external factors.

2.1.1 Internal Factors

These factor that have to do with the inner condition of the person that can affect his gait such as health condition, state of mind, gender, length of part, body weight, and general built etc. In medical application, most especially orthopedics, physiology, neurology and psychology, they use gait analysis neurological diagnostics of diseases and Alzheimer's disease, Parkinson's disease, in orthopedic and physiology, gait is used in therapy session to monitor recovery of patients, determine size of working aid

2.1.2 External Factors

These are environmental factors a person is in direct or indirect contact with while walking that can influence the gait such as walking surface: friction, sloppiness, fragility; clothing: shoe type, size, level of comfort, length and weight of clothing; Atmospheric conditions: temperature; location: indoors or outdoors; treadmill or direct of the floor etc.

Various changes in the factors may lead an observable change in gait that may vary from human to human due to factors like physical built, level of endurance, however, some measurable data can be derived from the adaptive adjustments on some part, example: a man walking in an uncomfortable left wear will tend to limp a bit on the affected side resulting shorter stance time than the other legs to reduce pressure on the leg, this can also be observe in the upper body rhythm of movement, all variables that can be used to measure the these effect serve as parameters for analyzing gait.

2.2 Methods of Gait Analysis

Visual-based gait analysis makes use of a variety of methodologies, including computer vision algorithm-based and machine learning techniques [11], model-based and model-free methods.

2.2.1 Model based vs model free

For Model-based gait analysis, an abstract representation of the entire body is done using

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mathematical notations or other paradigms showing relationships between parts during gait cycle. A databases of data of interest is created, the data is queried from a database to be matched with video input for identification, prediction, or other analytical purposes [11]. Challenges of Model-based analysis are:

- Identification of modeling parameter
- Representation of modeling parameters
- And high computational demand in storage and processing.

Model-Free Gait analysis approach On the other hand are based on some features extracted from a specific perspective, features change directly to the position of the body as human walk [12] , this could be a visual or sensor based data, unlike the aforementioned this method fewer computations and storage. The main challenge with this approach is identifying the best feature or perspective of gait to extract data for a purpose.

Machine learning approach is categorized model free as no visual modelling of the gait is required

2.2.2 Machine Learning Vs Algorithmic Approach

Machine learning as a black-box method of computation influence wider application in computer visions where specific features and patterns are not explicitly known, hence, attracting researcher in different field to adopt computerized method of gait analysis.

Researchers have proposed various approach to algorithmic-based methods analyze the human gait, In a survey done by Kale et al [9] it identifies the importance of gait analysis to various field and described it as one of the most fascinating and challenging problems in computer visions, these methods deal with the explicit measurement of partial or full parts of the humans with respect to the displacement between parts or spatiotemporal dispositioning of the body.

3 LITERATURE REVIEW

Several approaches to gait analysis ranging from type of data to analysis method and tools, in this research we used the visual data with machine (deep) learning approach, hence, literatures reviewed in this section.

A CNN based model adopted by yeoh et al [13] on OU-ISIR Gait Energy Image GEI treadmill dataset to evaluate identification rate with variation in clothing, sequence of frames were collated together to serve in input into the model. They employed support vector machines SVM and softmax 91.38 and 87.80 accuracies respectively was achieved.

Similarly Yan et al, [14] used CNN base model with single input of GEI for automatic feature engineering like [13] with MLP (multilayer perceptron classifier). CASIA B dataset was used for training and evaluation of the model. 95.88% accuracy was achieved. In the research they considered variation in scene and view using CASIA B section VI-B and VI-C respectively.

Furthermore, Shiraga et al. [15] developed GEINet, a CNN with two consecutive groups. In the training stage, the network input is a single GEI image (from the OU-ISIR database). The dissimilarity between a probing GEI and gallery GEI pair is calculated in the testing stage utilizing the distance between them at the fully connected layer. The result was presented in two categories, the cooperative and non-cooperative settings, each group, evaluation was carried out based on variation in views and gallery, 93.7% accuracy was recorded.

Wang and Yan [16] proposed a CNN based ensemble learning which was evaluated on CASIA and OU-ISIR Gait dataset. An accuracy of 65.93 was achieved with 10 primary classifiers.

Wolf et al. [17] proposed a 3D CNN with a 3D spatiotemporal tensor as input by pilling up sequence of gait frames to form a 3D input, consisting of a grey-scale image for the first channel and optical flow for the second and third channels. CMU MoBo dataset, USF gait dataset and CASIA-B dataset with 66% and 33% partition up to 100% accuracy on CMU MoBo Database, 99.9 on CASIA-B dataset.

Castro et al. [18], like [17], used a spatiotemporal 3D tensor of the optical flow as the CNN's input. With gait situations, clothing, and carrying modifications for each individual, the network was trained and evaluated using the TUMGAID database. Although employing the optical flow rather than silhouette-based input dramatically enhanced network accuracy.

For the purpose of the study, we collected a primary dataset of 26 human gait with variations in features such as age, gender, outfit, load and direction, the gait data preprocessed to create upper gait to overcome the limitation identified and cost using half gait over full for identification problem.

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4 PROPOSED METHOD

Several approaches are explored by researchers for gait analysis, however, the have similarity in objectives that are achieved using different methods and tools. Generally, gait analysis comprises the following: dataset collection: this is where relevant data is collected from a sensor of camera in our case, video files are trimmed and labelled appropriately; preprocessing: dataset may have noise and or needs to be augmented to reduces unnecessary features interfering with the goal of the analysis at the end of this stage the dataset is formatted for implementation in some instances either as GEI of Silhouette (binary image) or cropped extracted sequences of images, Liu et al [19] show silhouette reduces the quality recognition via gait; and model or algorithm design and implementation; this is the processing phase where analysis/measurement of features for comparison with features stored in a database or apply machine learning technique to build a model for identification [20].

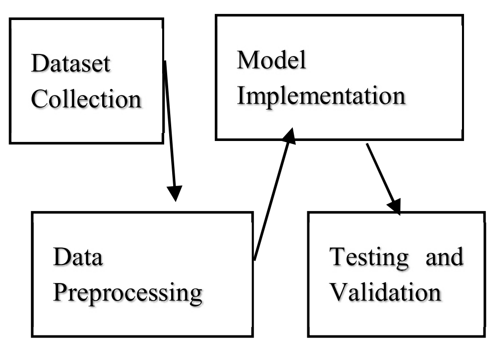

Figure 2 Research Approach

4.1 Dataset:

This research aim to proof a concept that upper body gait can be used for various gait analysis as such to ease extraction of desired feature camera views variation is limited subjects walking parallel to camera (180°) or perpendicular at 90° below is summary of existing datasets

Table 1: Available Dataset

Dataset	Description	Limitation
CASIA A [21]	20 persons, 12 scenarios, varying angle,	Undefined framerate, angles of capture not convenient for half gait extraction.
CASIA B	124 subject ,11 views, varying angles, clothing and load	Undefined framerate, inconvenient angles of capture for the research
CASIA C	Thermal camera, 153 subject, varying load size and speed	Undefined framerate, angle of capture,
CMU MoBo [22]	25 subject, treadmill, varying angles , speed and incline and carrying ball	Undefined framerate, limited variation in clothing
USF [23]	122, subject varying weather condition	Elliptical path + Above
OU-ISIR [24]	Treadmill, 30 fps, 4007 subjects	Environment is too controlled
TUM-IITKGP [25]	35 individuals, 6 configurations each	Outfit variation not inclusive of leg covering outfits
AVAMVG [26]	20 persons,	1 : 4 ratio of male to female

Primary dataset was collected the from 26 persons, 12 female and 14 males, with variation in load, outfit, time of the day and direction of movements, dressing pattern wear covers English, native Nigerian dresses and hijab wears for the female and male covers for English wears and kaftans commonly worn in the northern part of the country.

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With the consideration, in spite of limiting camera views, the dataset was made to be robust with wider variation in clothing, actions while walking like making phone calls, texting holding tea. Dataset was captured at 60 frames per second fps, in earlier work [27] we investigated the effect of lower framerate on accuracy and loss, with 30% of dataset used for validation, we extracted frames at 60, 30 and 15 fps which result not tradeoff with slight in improvement in reliability at 15 fps.

Two set of dataset where prepared with dataset-A: having full gait and dataset-B: half gait capturing from waist level upwards, both dataset were extracted as 15fps

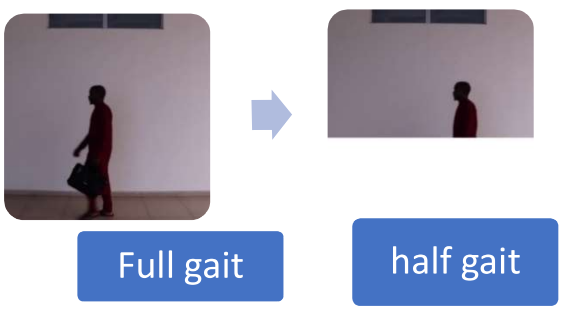

Figure 3: Datasets A (Full) and B (upper half)

4.1.1 Data Preprocessing

4.2 Model Description:

Application of deep learning models such as the convolutional neural network CNN on visual data ease feature engineering for various problems such as classification or prediction. CNN has a celebrated advantage in image feature engineering to extract important feature has made it possible for visual data analysis to be fuzzy based analysis like how humans naturally learn, human identification is naturally done by qualitative fuzzy estimation done by the brain without precise measured guided by experience, as such making challenging for algorithm based solution to achieve optimal solution accommodating diversity.

Features extracted from images by CNN can be used for effective classification or prediction of problems, it comprises of two steps convolutions and pooling as shown in *figure 4.* A CNN consists of one or more convolutional layers, each layer made of multiple filters. The architecture of CNN captures different features such as edges, shapes, and texture by leveraging the 2-dimensional spatial structure of an image using filters.

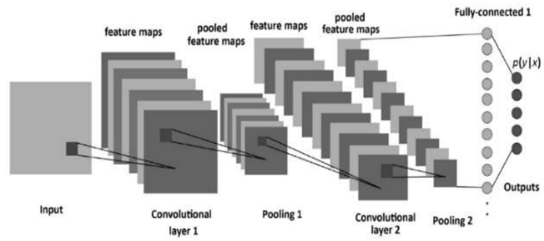

Fig. 4: Convolutional Neural Network CNN

Recurrent Neural Network RNN has a competitive victory analyzing sequential datasets such as sequence of characters to form words and words in sentences, sequence of images from video. Natural Language Processing NLP problems like translation, DNA sequence analysis [28] and video analysis problems like action recognition.

Figure 5 shows RNN model temporal dynamics by mapping input sequences to hidden states, and hidden states to outputs via the following recurrence equations 1 and 2 where *g* is an element-wise non-linearity, such as a sigmoid or hyperbolic tangent, x_t is the input, $h_t \in \mathbb{R}^N$ is the hidden state with N hidden units, and y_t is the output at time *t*. For a length *T* input sequence $<x_1,x_2,\ldots,x_T>$, the updates above are computed sequentially as h_1 (letting $h_0 = 0$), $y_1, h_2, y_2, \ldots, h_T, y_T$.

$$h_t = g(W_{xh}x_t + W_{hh}h_{t-1} + b_h \quad (1)$$

$$y_t = g(W_{hz}h_t + b_z) \quad (2)$$

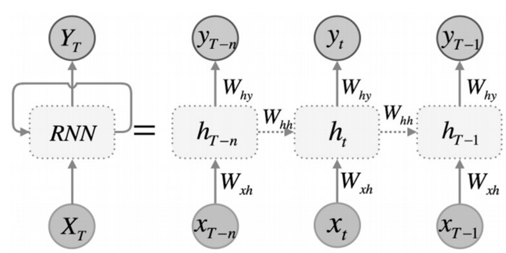

Figure 5: Traditional Recurrent Neural Network RNN

Though RNNs has recorded successes on tasks such as speech recognition and text generation where data is ordered sequentially, it has high storage demand most especially with the sequence of images as input, it can be difficult to train them to learn long-term dynamics, likely due to exploding and vanishing gradient problem that can result from propagating the gradients down through the many

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layers of the recurrent network, each corresponding to a particular time step.

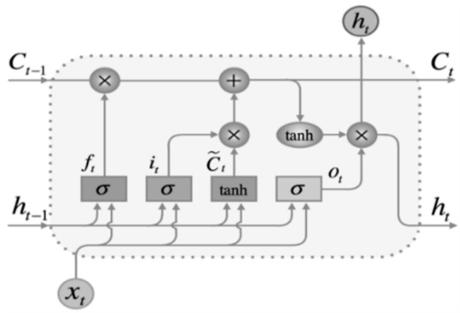

Figure 6: RNN-Long Short Term Memory RNN-LSTM

The Long Short-Term Memory (LSTM) introduces the ability for the network to "forget" previous hidden state when new information is available, hidden units with varying connections within the memory unit have been proposed. We use the LSTM unit as described in Figure 6.

Letting $\sigma(x) = (1 + e^{-x})^{-1}$ be the sigmoid non-linearity which squashes real-valued inputs to a [0,1] range.

Letting $\tanh(x) = \frac{e^x - e^{-e}}{e^x + e^{-x}} = 2\sigma(2x) - 1$ be the hyperbolic tangent nonlinearity, similarly squashing its inputs to a [−1,1] range,

The LSTM updates for time step t given inputs x_t, h_{t-1}, and c_{t-1} are:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i \quad (3)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f \quad (4)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o \quad (5)$$

$$g_t = tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c \quad (6)$$

$$c_t = f_t.c_{t-1} + i_t.g_t \quad (7)$$

$$h_t = o_t.\tanh(c_t) \quad (8)$$

As seen in equations 3 to 8, the LSTM incorporate input gate $i_t \in \mathbb{R}^N$ forget gate $f_t \in \mathbb{R}^N$, output gate $o_t \in \mathbb{R}^N$, input modulation gate $g_t \in \mathbb{R}^N$, and memory cell $c_t \in \mathbb{R}$

The prior memory cell unit ct_{-1} is modulated by f_t, while g_t is a function of the current input and previous hidden state, modulated by the input gate it. Because i_t and f_t are sigmoidal, their values fall between 0 and 1, and they can be regarded of as knobs that the LSTM learns to use to selectively ignore old memories or evaluate current information. The output gate o_t learns how much of the memory cell to transfer to the hidden state in the same way.

The LSTM can now learn complicated and long-term temporal dynamics for a range of sequence learning and prediction tasks thanks to these enhancements. By stacking LSTMs on top of each other, more depth can be added to them, using the hidden state $h(-1)_t$ of the LSTM in layer `−1 as the input to the LSTM in layer.

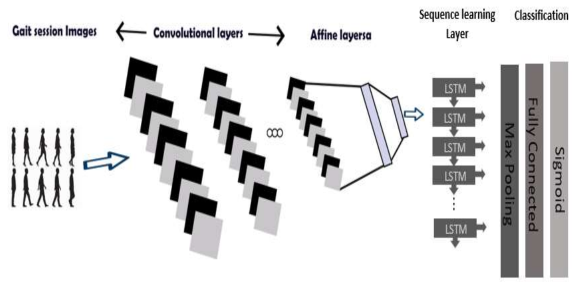

Figure 7: CRNN-LSTM

Loading images on the RNN will be very expensive as storage demanding even with LSTM, however, a concatenation of the two architecture to form the Convolutional Recurrent Neural Network (CRNN-LSTM) will be more efficient, with the convolution as encoders loading extracted feature onto the RNN as decoders to learn patterns in in the sequence of extracted features as shown in figure 7

4.3 Model Implementation

Model implemented using Python and relevant libraries by PyTorch Vision, Numpy, and OpenCV, was executed in anaconda environment with the following hyper parameters:

- Batch size=8,
- Dampening =0.9,
- Learning patience=10,
- Learning rate=0.0001,
- Momentum factor =0.9,
- Number of epochs=100,
- Optimizer = SGD,
- Weight decay=0.001
- Validation set = 30%
- Training set = 70%

4.4 Evaluation Criteria

Gait analysis for recognition performance is often measured through probe and gallery method where the system/model is subjected identify gait that was not use in the training of model or stored in the database where applicable.

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In machine learning the use of validation set

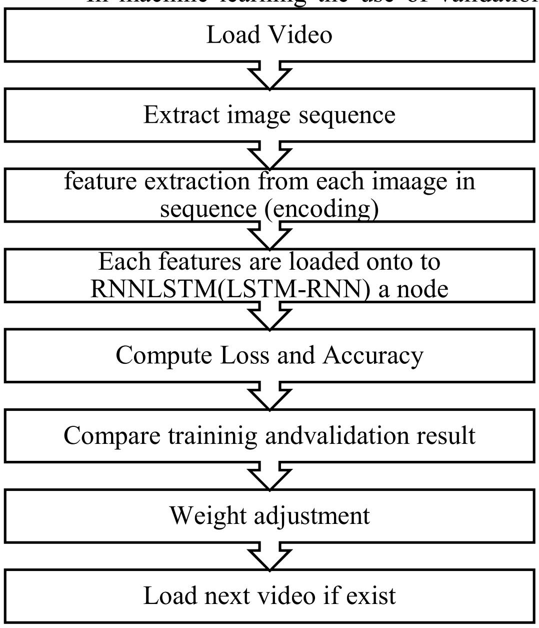

Figure 8: Methodology

along testing measures the reliability of result. Accuracy and loss were the evaluation criteria for the study to measure correctness of model classification and data fitting respectively.

5 EXPERIMENT SETUP

The model as discussed in previous section was implemented with python, for the experiment

Datasets A and B were used to trained exactly the same model on similar computation environment, in each instance, the test and validation accuracy and loss was measure and graph as discussed in the next section

6 RESULT AND DISCUSSION

From the experiment, a maximum accuracy and loss were measured and represented in graphs in figures 6, 7, 8 and 9. In the graphs result from training and validation are represented, the closer they more reliable the result, loss shows how well the data are loaded into the model, the smaller the loss the better, the half gait loss is reduces faster making it more suitable for model, however, the validation loss tend to be slightly less converged compared to full gait in fig 6.

A higher accuracy of 91.5888% was observed for the half gait as against 82.08% from full gait, similarly, the corresponding validation accuracy was better for full gait as shown figures 8 and 9.

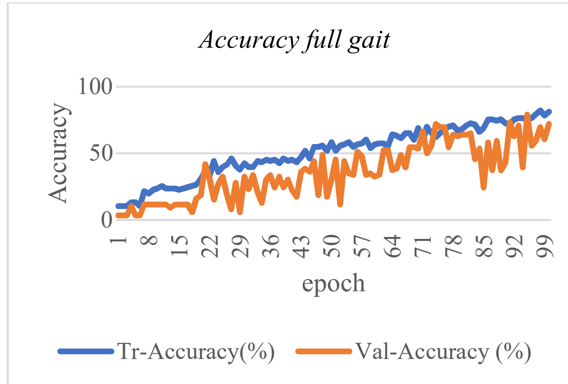

Figure 9: Accuracy Full Gait

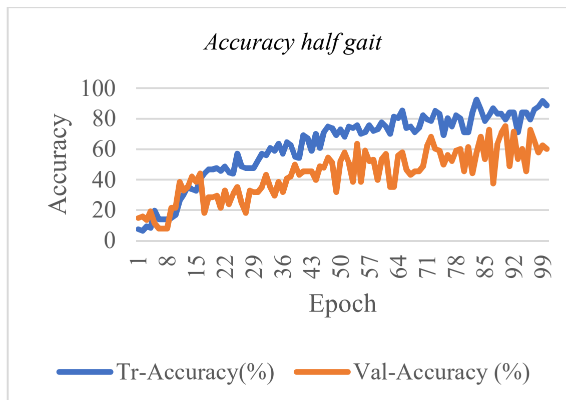

Figure 10: Accuracy Half Gait

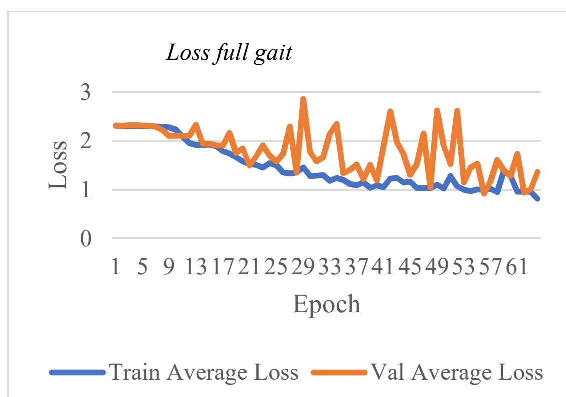

Fig 11: Full gait Loss

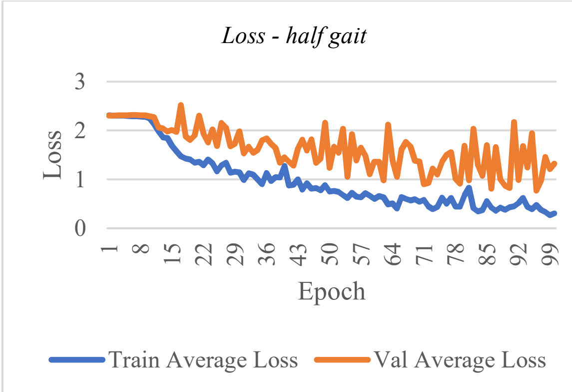

Fig 12: Half Gait Loss

From previous works, which are based on full data

7 SUMMARY AND CONCLUSION

In this research we investigated the possibility of human identification through upper gait analysis and tradeoffs against full gait as used by most researchers. Primary dataset was collected to accommodate native African wears and conventional wears, peculiarity with most West African attire is the legs are not necessarily available, which has not been covered in available dataset. 26 subjects volunteered with variation in wears, load, direction of movement with 12 to 16 gait instances, 315 gait data was collected.

Two dataset were prepared at 15fps, with dataset A of full gait and dataset B half gait. Both were used to train and test a CRNN-LSTM deep learning model.

We observed that half gait performs better with a tradeoff on reliability, the full gait based model result has lesser accuracy but narrower gap with validation accuracy.

In conclusion, the study has shown that upper gait analysis for human identification is feasible and has potential of better accuracy that full gait with wider applicability to environment where full gait is not obtainable, In addition, the research can be extended to cover other area of application such as actions classification,

In future work the below will recommended:

- Inclusion of other evaluation criteria, such as recall, F1 score, and sensitivity can be further explored, in this study we emphasized on loss and accuracy, and a corresponding validation to measure the reliability of the results obtained.
- Several deep learning models have been used on gait data for identification and other problems, applying half gait to candidate models such as 3D-CNN, KNN, investigate variation in performance among deep learning models.
- Different classification problems like action recognition can be explored with upper gait.
- Upper body gait analysis will be explored to cover clinical gait analyst

Other limitations of the research includes:

- Dataset used are based on indoors
- Only CRNN-LSTM was considered among deep learning models.
- Only four camera views were considered to ease cropping process
- The study considered only identification problem, other perspective such as gender classification, race, and disease diagnosis can be explored further using half gait.
- Experiment was carried at 100 epoch

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