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A NEW DEEP LEARNING ALGORITHM FOR VIDEO BASED GAIT BASED RECOGNITION USING HYBRID DEEP CONVOLUTIONAL NEURAL NETWORKS

SWAPNA PAVAN G[1], Dr.N.KANYA[2] and Dr. V.N RAJAVARMAN[3]

[1]Research scholar, Department of Computer Applications, Dr. M. G. R. Educational and Research Institute University, Chennai, India.
[2]Associate Professor, Department of Information Technology, Dr. M. G. R Educational and Research Institute, Chennai, India.
[3]Professor, Department of Computer Science and Engineering, Dr. M. G. R. Educational and Research Institute University, Chennai, India.

Abstract

This paper describes a way to solve the problem of biological recognition based on the patterns of motion made by a person walking. The suggested method uses the data collected by the accelerometer and gyroscope sensors of a smartphone while the user is doing the gait action to improve the design of a recurrent neural network (RNN) to learn the features that best describe each person. The database has 15 people, and the acceleration data is given in a format with three directions (X, Y, and Z). Data are handled ahead of time to determine the motion in the direction of gravity. For person identification, a deep recurrent neural network model is used. This model is made up of LSTM cells that are split into several layers and thick output layers. Most of the time, the end design gives answers that are more accurate than 97%. The suggested design based on deep neural networks is tried in different situations to see how well it works and how well it holds up.

Keywords: Accelerometry; Gait; Walk; Identification; Recognition; Recurrent Neural Network; LSTM; Accuracy; Smartphone

I. INTRODUCTION

Every year, more and more devices are linked to the Internet (IoT), which means that more and more data is being made by these devices [1, 2]. Among these devices, smartphones are important because their features and popularity with users keep getting better and better. So, security must be one of the most important things to think about when making these gadgets. Some of the newest ways to keep people from getting into mobile devices without permission use fingerprints. This is done by looking at and measuring a person's different physical traits or behaviours with the goal of recognizing or identifying them.

The way biometric recognition is done has changed over time and as technology has changed. Fingerprinting, face recognition, eye scans, hand geometry, and voice recognition are some of the most well-known. But new types of biometrics are coming out that try to be less intrusive. One way this happens is when people can be recognised by the way they walk. This way of figuring out who someone is based on how they walk has both pros and cons. Its main benefits are that it allows for automatic, periodic, and non-intrusive identification (following the principles of "calm computing," where the technology doesn't bother the user), since all the user has to do is carry the device (which is usually a smartphone) or be recorded. As a

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drawback, we could say that these biological methods aren't as accurate as others, like fingerprints. This can be fixed with the above-mentioned ongoing and frequent recognition. Methods for identifying people based on their walk can also work well. if the user walks for a long enough time between data samples (for example, 3 seconds, which is what was used in this work), with the goal of always needing as little time as possible to make a correct decision.

In this paper, it is suggested that users can be identified by using recurrent neural networks (RNN). These networks use the acceleration patterns that users make when they walk, which are picked up by a smartphone sensor. These data are collected horizontally, and they will be used to figure out the vertical acceleration (or acceleration over the axis of gravity), which reduces the data and makes it possible to identify each case no matter how the device was put on it. Python 3 is a computer language that is used to do this pre-processing of data and further creation of neural design. The database being used is one that anyone can use [3]. It is a full database made up of 15 people (8 men and 7 women) who do different things while gadgets and sensors (mostly smartphones) are connected to their bodies to track and record data. The people in the database are on average 32 12.4 years old, 1.73 6.9 m tall, and weigh 74.1 13.8 kg on average. The information about database says that the "Samsung Galaxy S4" was used to take the picture. It's also important to note that the activity was done freely, without any limits, and in different places (country, city, street, etc.).

The following points are the most important parts of the paper. First, we try to figure out who the users are based on their accelerometry habits. We do this as accurately as possible and try to make a model that works well in different situations. Second, we create a deep neural network model based on "long-short-term memory" (LSTM) layers that is optimised for handling time series data from worn devices. Third, we try out this model in different situations to see how well it works and how stable it is. So far, the results look good. Gait Recognition Technology gets the information in a number of ways, such as with motion monitors or video cameras. Then, the information is put through a number of complicated recognition steps. Part of the main programme is figuring out how a person walks, processing data, finding outlines and shadows, and sorting different human traits. The method for extracting features is very important if you want to be able to tell one walk from another. There is a chance that these programmes will be different and that their needs will change. Some methods can be used to process video information, while others can be used to process data from devices.

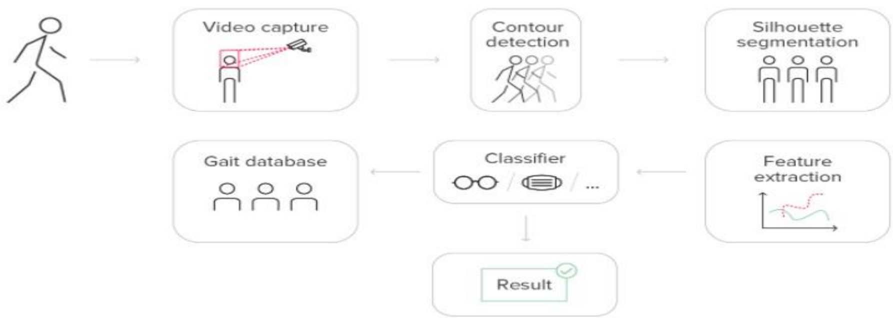

Figure 1: This figure shows the steps of gait recognition algorithm

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II. RELATED WORK

In the past, different processes and methods have been suggested and tested to be able to recognise a person based on the way he or she walks. Based on the technology used to track and describe gait, the systems could be put into three main groups: those based on vision, floor sensors, and external sensors [4]. Wearable sensors don't have problems like occlusions, camera field of view/angle, or poor lighting, which can mess up computer vision methods. They are now commonly built into a wide range of mobile devices, which makes it possible for gait recognition systems to work without cameras or special floors [4].

Marsico et al. [5] did a thorough look at how people can be identified based on walking data taken from worn devices. The writers divide biological traits that can be used to identify a person into hard and soft traits. Most hard ones let you recognise the subject with enough accuracy, but they have problems with certain traits. Soft traits either apply to whole groups of people or don't last long enough. Even though motion is thought of as a soft trait, the algorithms have become much more accurate over the past ten years. [6] Gives a second review of how personal sensors can be used to track how people walk and identify people. The writers talk about different ways to categorise human walking and how it can be used in clinical evaluation, care for the elderly, sports, statistics, therapy, and industry. There is also a list of accessible samples and machine learning methods for movement research.

In the past, researchers have tried different ways to solve the problem of figuring out who a person is based on the time series collected by wearing sensors like accelerometers and gyroscopes. Deb et al. [7] came up with a gait-based recognition method based on finding patterns in the data from worn sensors using a new time-warped similarity. By comparing the way the recorded sensor readings change over time with previously labelled data, the person with the most similarities could be suggested as the user to be identified. There are several ways to find these kinds of connections. In [8], the authors suggested a solution based on signal similarities based on correlation, frequency domain, and statistical distributions of the data collected from a three-dimensional accelerometer that was put on the waist of the subject. In the study [9], absolute peak distance analysis, correlation, histogram, and first-order moments were used to come up with a way to identify something. Thang et al. [10] used data from the time domain to do "dynamic time warping" (DTW), which is a method for comparing two things. The estimates for likeness have been optimised for devices with limited processing power [11] and made more specific for groups of users with specific needs, like older people [12].

A different method for identifying users based on data from personal sensors uses machine learning to find trends and traits that are unique to each user. The writers of [10] took data from accelerometers and pulled frequency components. They then used support vector machines (SVM) to sort people into groups. In [13], a different method was shown that used SVM with radial estimate. The writers of [14] also suggested using SVM to identify a person based on data from personal sensors. There have also been ideas for and tests of other machine learning methods. The paper [15] used a Hidden Markov model for accelerometer-based gait recognition, while the paper [16] suggested using the k-NN (k Nearest Neighbour) method to

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find the closest user in the space of computed features compared to previous tracks recorded in the dataset. There have also been ideas to improve the results by using a majority vote at the end after joining several methods, such as [17].

The goal of machine learning models is to be able to find specific trends in data that vary little from user to user and a lot between users. Deep learning algorithms have also recently been used with worn sensor data to identify users. These algorithms look for complex trends in the sensor data. In [18], the writers look at how a convolution neural network (CNN) can be used to pull out features from data that are then used to verify users with a one-class support vector machine (OSVM). In [19], Giacomo et al. also use a deep CNN structure with a couple of fully linked layers and a softmax function to give each person in the dataset a chance of discovery. The research paper [20] gives a detailed look at how to build and train a recurrent convolutional neural network using a real collection of gait readings from five body sensors. The time series from five body sensors are put into a convolutional neural network with two 1D convolutional layers and a recurrent neural network with gated recurrent units (GRU). The result is sent to two pooling layers for feature subsampling, and a final softmax function is used to predict how likely each data sample is to capture the walk of a specific person. In [21], the writers also use a deep neural network that is a combination of convolutional neural networks (CNN) and recurrent neural networks (RNN). Aside from the structure of learning, the study focuses on analysing the data of the subjects' free walking parts (where they were not forced to do a certain task in a predetermined situation). Recurrent neural networks (RNN) can model complex patterns that change over time. They have also been used in [22] to find the best way to extract features for characterising walking and recognising users. But there were a lot of hand tuning tools used, which makes it hard to generalise the findings.

In this study, we look at RNN structures for gait recognition for people walking freely in the wild and try to find the best ones. We can improve the precision of the results by almost 4% compared to the study in [21] that looks at deep learning techniques for free-form walking segments. Researchers are becoming more and more interested in gait recognition, but there is currently no standard way to compare how well different gait recognition systems work. In this study, a method is given to try to solve this problem. The structure is made up of large motion files, a number of well-designed studies, and evaluation tools. There are 124 people in the database, and 11 of them gave information about their walk. The database takes into account the point of view, the clothes, and how the person is holding. When it comes to the size of the collection, this is one of the largest. The framework has 363 trials, which are grouped into three sets. Several ways can be used to measure how well gait recognition systems work.

Summary of Literature Survey

One of the most interesting things about human-computer contact and smart monitoring is figuring out how people move. Tsushita H and Zin T-T, 2018, looked into strange behaviour caught on camera footage. Right now, it is 2019. The writers have suggested making a set of actions for a drone that is hovering in the air. One of the biggest problems we found with drone monitoring was that it was hard to tell when a person was doing something far away from the drone. This was done with the help of data from three sensors: an accelerometer, a gyroscope,

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and a magnetic field monitor, which is also called a magnetometer. 3D CNNs were used to look at the movies and pull out spatial and temporal information, which was then put through LSTMs design for further processing. We've also made a new system for recognising walking patterns that uses an evolutionary algorithm (GWO). A simple and flexible recurrent neural network can be used to group and find tasks. Several different designs and choices have been tried out to get the most out of the movie collection. System parts include (1) Deep Learning, which identifies people and their actions, (2) Pixel2GPS, which guesses the GPS position of humans based on picture processing, and (3) PAL, which shows recognised people and actions on a map. Even though the low computing power of the UAV was thought to be a big problem for the Deep Learning model, the PeopleAction-Locator (PAL) system worked well. So, you don't need a strong contact system, which isn't always there in disaster or spying situations. In the future, we will be able to improve our goods by adding new hardware. UWB radar, which has a wide range of precision, can find the places in the body where waves spread out. But even though radar-based HAR methods haven't caught on yet, we shouldn't lose hope because radar has its own advantages, like not being affected by the surroundings and being safer. In any case, people who can't move around on their own are still likely to make mistakes when counting. Think about how to understand the difficulty and scale of moving things that aren't people in your future study.

Existing System

Some static or mobile monitoring systems can't find people or figure out where they are in settings that are too complicated for the technology they use. Authorities in the modern city use video tracking to keep an eye on daily activities for safety reasons.

Problem Statement

Safety is a top concern in every business in the modern world, from the military and security to crowded public places. In these places, it's almost impossible to keep an eye out for anything strange. Some static or mobile monitoring systems can't find people or figure out where they are in settings that are too complicated for the technology they use. For example, a static monitoring system that uses the "background subtraction" method would fail if the camera was moving. In a mobile monitoring system, the object's point of view moves from frame to frame. This makes it hard to get an accurate detection, and some current methods for action recognition don't include human localization when identifying actions in a continuous video stream. Gait recognition is a reliable and effective tool that can be used to make sure the public is safe. If the background and settings are complicated, it might be hard to find people.

Proposed Solution

Gait recognition is a beautiful biometric method that can be used to identify people by the way they walk. Since they were first made, algorithms that use deep learning to identify gait have taken the lead in the field and been used in a number of useful ways. Deep Convolution Neural Network is used to figure out how a person walks by training the design of the neural network with images of the person's gait. The Convolution neural network is built on the specific part of the visual brain that does the job of figuring out what things are as the function of nerve

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cells. A convolutional neural network is an artificial neural network that works like a fast feed-forward network. People can be found and found by the law in a single deep learning workflow with the help of proposed systems. The network can deal with a television stream.

Objectives

- To acquire the required dataset.
- To apply efficient pre-processing techniques.
- To instigate and apply segmentation.
- To identify and extract gait features.
- To develop a deep learning model that identifies the person's gait.

III. Proposed Methodology

a) System Design

Deep Convolutional Neural Networks (DCNs) are used in this study to develop an effective system for recognising human gait. Gait is characterised by a gait signature generated directly from the series of silhouettes in the proposed gait detection system. As a general-purpose pattern recognizer, the system is made up of three primary parts, namely,

i. Human detection and tracking.
ii. Training using CNN.
iii. Human recognition.

Initial segmentation and tracking of moving objects (humans) is done in each frame of the video stream (tracking module). It is then used to train and validate the retrieved feature vectors to identify an individual (pattern recognition module). Proposed Gait Recognition System Block Diagram Fig.

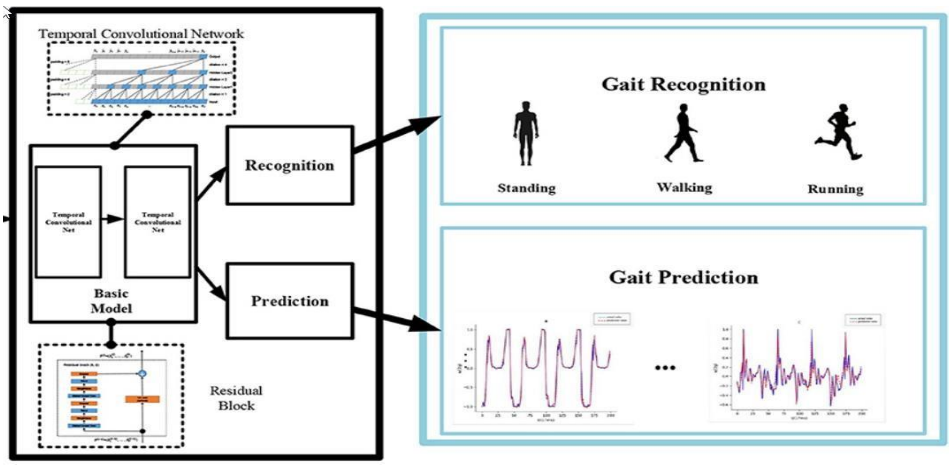

Figure 2: System Architecture overview

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b) Proposed Methodology

1) Data Acquisition, Pre-processing and Standardisation Dataset:

All videos are captured from DJI Mavic mini Drone with video capture resolution 2.7K 1530P. Later all the videos are edited and trimmed. The video format is changed into .avi format or any other formats supported by Matlab. Dataset is created with different individuals in different illusions, different positions, different situations and different conditions. All the videos are stored in a single folder where the main code of the program is stored.

Figure 3: Standard Dataset

Frame Conversion

The selected input video will be converted into number of frames based on length of the video and stored in separate folder named Frames for future use. For the code to get run only required number of frames are considered.

Resizing Frames

Each and every converted frames in the folder will be of different sizes, which makes image processing difficult. Hence all the frames will be resized into default size to make the operations such as multiplying, comparison etc., easier in programming.

Background Subtraction

Computer vision and image processing use a method called "background subtraction" or "foreground detection" to find the most important parts of a picture. Most of the time, an image's attention is drawn to what's in the centre. Background removal is a popular way to find moving things in pictures where the camera was still. The approach works because it is based on the difference between the present frame and a reference frame, also called a background picture or background model. This difference is used to find moving items.

Taking out the background is the first step in video monitoring. Background removal will be used as a part of these more advanced steps in video tracking. Surveillance systems need to do math in real time, so the background reduction method is very important. Taking the

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background out of moving pictures in a dynamic setting is one of these hard jobs. Researchers in the fields of applied picture analysis and computer vision are working on it. TTD for BGS can handle hard conditions like sudden or gradual changes in lighting, slow changes in lighting, long-term scene changes, periodic movements from a crowded background, repeated motions in the clutter, and so on. Tests in a variety of settings have shown that the suggested methods work well and can handle a changing environment. They may also be very accurate. Background results of subtraction.

Using video surveillance, you can find things that are moving by making a model of the background. Any big change in the background model shows that something is moving. Often, an open model of the world is used to do background removal. To figure out what's in the centre, you look at the difference between the current frame and this background model. To make a binary foreground mask, a pixel that stands out more than a certain level will be labelled as coming from an object in the foreground. Pixels are classified as background or centre based on the brightness difference between this picture and the one in the background.

Frame Filtrations

Some of the pictures or frames in the folder may have noise. The flow of work could be slowed down by that noise. So, this noise shouldn't be in the frames that were changed. Matlab has many types of filters, such as the median, the salt-and-pepper, and the Gaussian filters. The Gaussian filter was found to be the best filter for getting rid of noise in frames and pictures.

The Gaussian method is a linear way to filter. Only the Gaussian filter will soften the edges and lower the brightness. Isotropic means that the standard deviation of a Gaussian filter is the same in all directions. A picture can have an isotropic Gaussian filter put on it by giving a numeric number for sigma. Low-pass filter: Gaussian blur uses a Gaussian function to get rid of the high-frequency parts of an image. Since multiplying and adding are both faster than sorting, the Gaussian filter has a speed advantage over other filters.

Binary Conversion

The frames that have been screened will then be turned into binary pictures. All of the pictures will be turned into strings of 0s and 1s. All of the binary pictures will be kept in a different folder called "Binary," which is also where the main code is. When all of the code is run, the binary pictures are saved and then updated.

DCT Frames Conversion

Photos are changed into Discrete Cosine Transform frames and saved in a different folder. The discrete cosine transform (DCT) shows a set of data points as the sum of cosine functions that oscillate at different frequencies. Discrete cosine transform is used in many areas of science and industry, such as lossy music compression (MP3) and picture compression (JPEG), as well as spectral methods for solving partial differential equations. For compression, cosine functions are more important than sine functions because fewer cosine functions are needed to model a normal signal. However, in differential equations, cosines describe a specific set of boundary conditions.

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It is a transform that has to do with Fourier, but unlike the discrete Fourier transform (DFT), the discrete cosine transform only uses real numbers. This is a more important difference because the Fourier series of an extended, periodic sequence is more closely related to the discrete cosine transforms than the Fourier series of an extended, continuous sequence. Discrete Cosine transforms can be used in the same way as Discrete Fourier transforms, but sometimes the input and/or output data are moved by half a sample. There are eight standard versions of the discrete cosine transform, with four being the most common.

Type-II discrete cosine transforms are often called discrete cosine transforms, while type-III discrete cosine transforms are called either the inverse discrete cosine transform or the discrete cosine transform, based on how they are used. Two transforms that are related to each other are the discrete sine transform and the modified discrete cosine transform. When working with data that have more than one dimension, the discrete cosine transform must be changed to include more than one dimension. There are many ways to figure out how to determine the Multidimensional Discrete Cosine Transform. New fast methods are making it easier for computers to do discrete cosine transforms, which used to be hard to do.

Feature Identification and Feature Extraction

Human gait contains many features like walking speed, distance between two legs etc. all these features are identified, extracted and stored in Matlab file format. For extracting the human gait features we use LBP (Local Binary Patterns) technique.

Local Binary Patterns

- Mainly designed for monochrome still images – Have been extended for color Videos.
- A comparative study of texture measures with classification based on feature distributions, Pattern Recognition.
- The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image.
- These labels directly or their statistics are used for further analysis.
- It is assumed that a texture has locally two complementary aspects, a pattern and its strength .
- Generally local binary pattern operator works in a 3×3 pixel.

Deep CNN Algorithm Steps

 # Define the layers of the CNN

ConvolutionalLayer(filters, kernel_size, activation, input_shape)

PoolingLayer(pool_size)

ConvolutionalLayer(filters, kernel_size, activation)

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```
PoolingLayer(pool_size)
ConvolutionalLayer(filters, kernel_size, activation)
FlattenLayer()
DenseLayer(units, activation)
DropoutLayer(dropout_rate)
DenseLayer(units, activation)
OutputLayer(units, activation)

# Define the hyperparameters of the CNN
learning_rate = 0.001
batch_size = 32
epochs = 10

# Compile the CNN model
model.compile(optimizer=Adam(learning_rate),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Train the CNN model
model.fit(X_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          validation_data=(X_val, y_val))

# Evaluate the CNN model
test_loss, test_accuracy = model.evaluate(X_test, y_test)

# Make predictions with the CNN model
predictions = model.predict(X_new_data)
```

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IV. RESULTS & SIMULATIONS

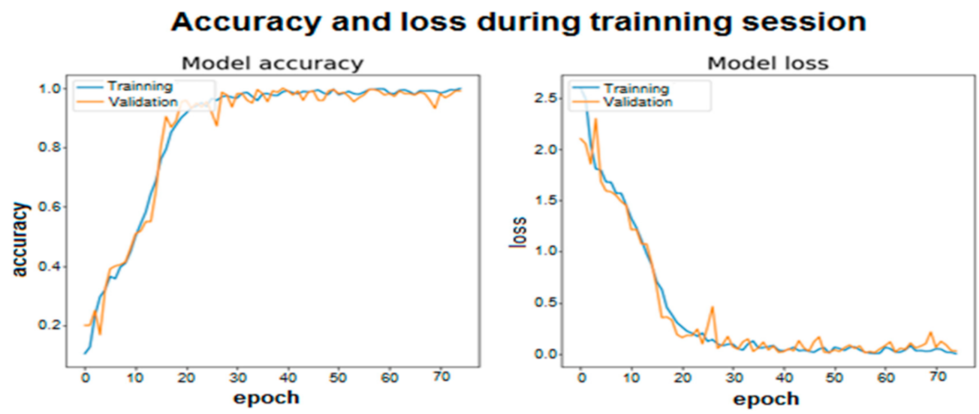

Figure 4: Accuracy Graph

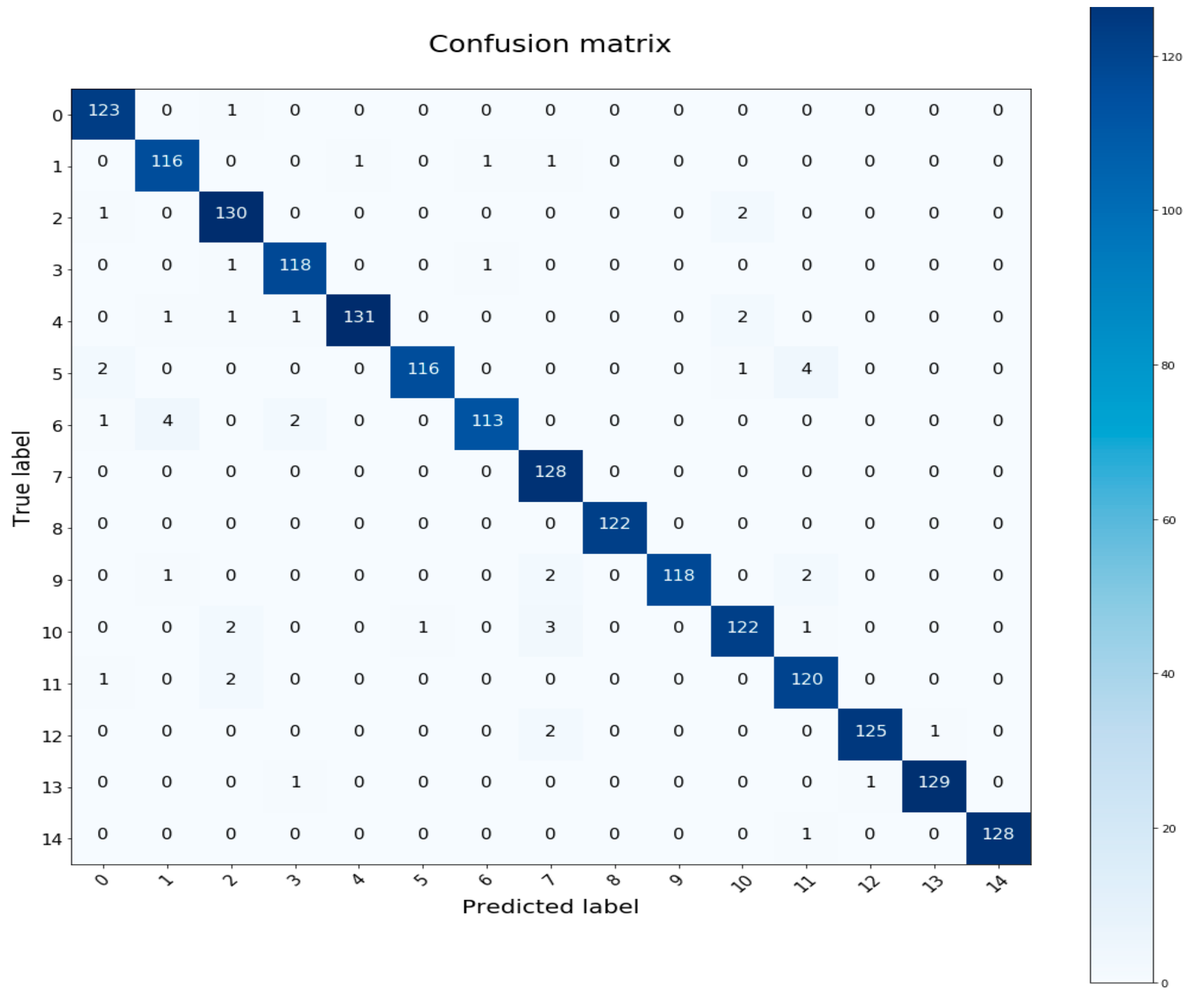

Figure 5: Confusion matrix with architecture. Execution with 97.4% test accuracy

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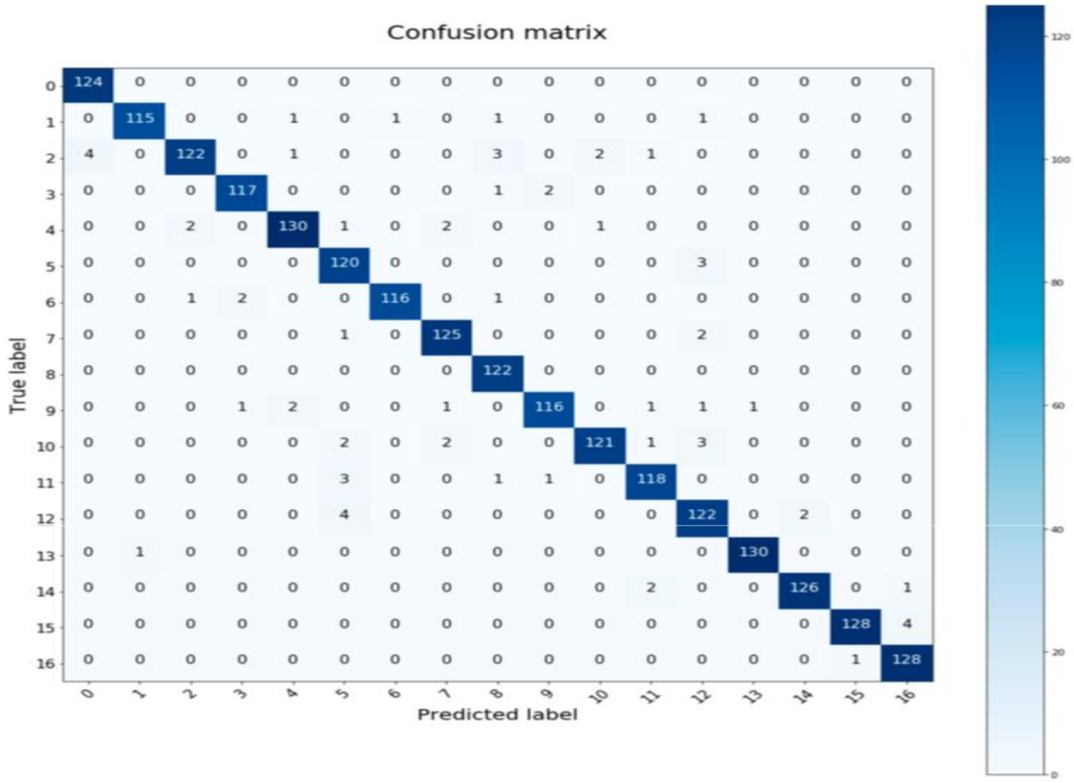

Figure 6: Confusion matrix for a test set. Extended case with two new subjects 15 and 16

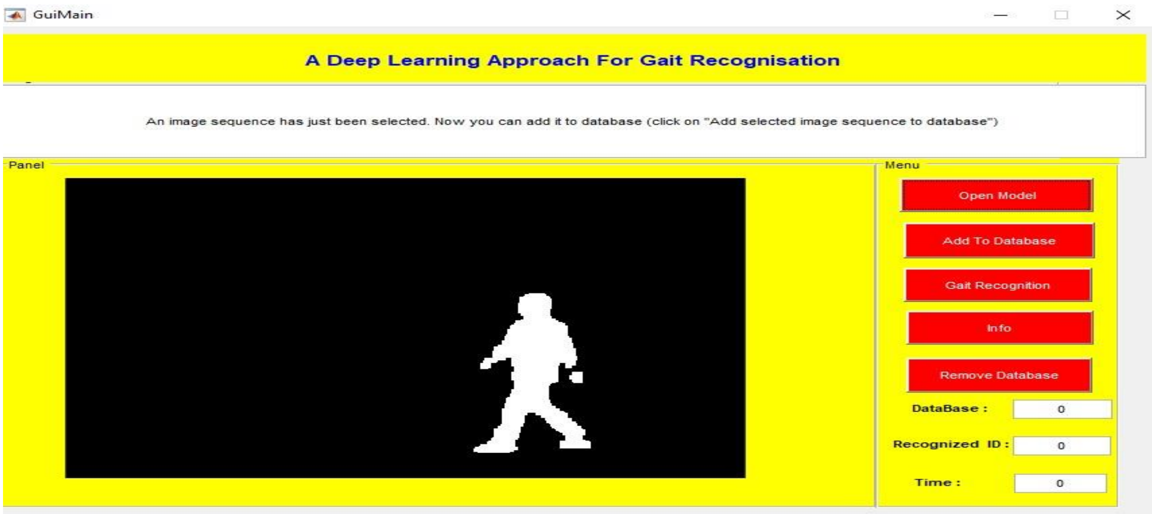

Figure 7: Silhouette of person is displayed

Description: An image sequence has just been selected and then it can be added to the database by giving the respective class label.

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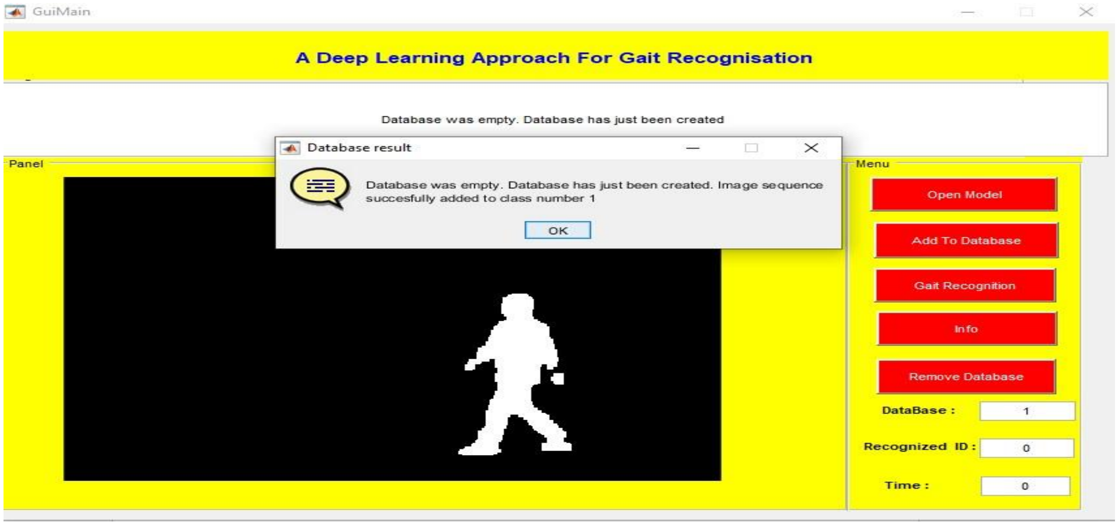

Figure 8: Database created

Description: Earlier database was empty. By clicking on add to database button, image sequence gets added to the database with respective class label successfully.

Figure 9: Setup Recognition Terminated window

Description: Above window pops up when testing is completed and displays recognition ID of the human gait.

V. CONCLUSION AND FUTURE WORK

Drone surveillance may be used to accurately mimic human gait, as shown in this study. Human gait identification using deep CNNs was better understood after doing a literature study. Drone surveillance systems, deep learning, convolutional neural networks and biometrics and image processing are introduced in this phase. The results presented in this manuscript show that deep recurrent networks are able to automatically characterize the gait properties and particularities

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for users when walking in the wild (without the need of a predefined setting) with accuracies higher than 0.97. The results outperform previous studies for gait characterization in unconstrained conditions [21] in which the accuracy values are below 0.94 using a hybrid deep neural architecture and previous RNN-based architectures for gait inspection [22] in which the authors achieve accuracy values below 0.93. Although the accuracy of the proposed method in this manuscript only slightly outperforms other previous studies in controlled settings, it allows the walking activity to be freely executed by each user. The authors in [19] reported a 95% accuracy when the data are collected from six predefined walking segments.

The authors in [20] obtained similar accuracy values from the ones presented in this manuscript but also using the same dataset in the same controlled environment for data capturing. The manuscript shows the optimization process for some of the major parameters in the architecture which provides optimal results for two RNN layers based on LSTM cells with 100 memory cells. The proposed architecture has also shown good generalization properties when including the information of new users recorded in sort of similar conditions. The results also show a slight improvement of results when using both the acceleration and the gyroscope sensors together, although the complexity of the algorithm and the required time for training also increase when adding the gyroscope data. The proposed network has also been trained for other activities such as running and jumping but the results for user identification are worse than for the case of walking (showing that the way we walk better characterize each person than the way we run, jump or climb up stairs).

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