GAIT PATTERN RECOGNITION USING DEEP LEARNING

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ABSTRACT

In this work we investigate the problem of people recognition by their gait. For this task, we implementa deep learning approach using the Neural Networks as the main source of motion information and combine neural feature extraction with the additional embedding of descriptors for representation improvement. To find the best heuristics, we compared several deep neural network architectures, learning and classification strategies. The experiments were made on two popular datasets for gait recognition, so we investigate their advantages and disadvantages and the transferability of consideredmethods.

Keywords: Gait Analysis, Gait Biometrics, Gait Abnormalities, Gait Disorders, Convolution NeuralNetworks (CNN), Feature Selection, Pattern Recognition, Motion Capture during locomotion.

1. INTRODUCTION

Gait pattern recognition, the process of recognizing individuals according to gait patterns, has drawn a lot of attention in recent years. It has become an important research area with applications in various fields such as health, biometrics, surveillance, human-computer interaction. Gait analysis can provide insight into a person's physical health, identify abnormalities or defects, and can also act as a unique biometric identifier.

Gait analysis is the study of human gait, including the movement and interaction of various parts of the body during movement. It provides information about biomechanics, human movement, and performance measurement. Gait analysis, biometrics and identification, sports analysis, human-computer interaction, etc. It has attracted great attention due to its wide application in many fields.

These applications highlight the importance of focusing on healthcare, biomechanics,biometrics, and human-computer interaction. computer network. With the advancement of technology, including deep learning techniques, the focus continues to grow, providing better understanding and innovative solutions for these projects.

There are many advantages to using deep learning to recognize gait patterns. First, deep neural networks will automatically extract hierarchical features from gait sequences bycapturing local and global patterns. This abilityallows them to cope with changes in gait patterns caused by things like walking speed, changes in clothing and mood. Second, deep learning models can learn good representations from big data and reduce reliance on manual and proprietary information. Finally, deep learning models can be adapted and extended to new individuals, making them suitable for real- world applications.

Gait can be defined as the movement of the legsthat allows human movements in a circle. As mentioned earlier, some neurodegenerative diseases, injuries, and aging can affect this group of movements, causing disturbances or abnormalities called gait, but each person has certain metrics of walking, such as walking or long strides. Length and joint can be analyzed so that they can distinguish between normal and abnormal or even what damage has occurred. For gait assessment, it is best practice for a specialist to just look at the patient's cycles and look at parameters such as speed and stridecount or stride length. This method lacks the accuracy and information that can be obtained from the measurement system, which provides quantitative and objective measurements, and may adversely affect the diagnosis and treatment.

1.1 Motivation

This work will review the state of the art concerning the different techniques used to analyze human gait, retrieve gait indicators, and classify between different disorders and normal gait. In this work we can able to identify the people by their silhouette's from some distance to detect the persons gait, which can be useful to identify the person with the help of their respective gait.

1.2 Contributions

These distinctive features are extracted over a large area that is less sensitive to popular images. Most importantly, these properties do not contain static data. The above method demonstrates the ability to identify people using motion only, allowing good recognition for gait data.

1.3: Work Organization

These findings inspired computer vision researchers to extract hidden gait patterns from images to identify individuals. However, it is difficult to find specific gait features in unchallenged characters that are avoided because the character is distracting and is avoided because it does not fit the information.

Gait distinguishing between seemingly similar kinematic patterns associated among people.

2. LITERATURE SURVEY

Gait recognition has always been a difficult task. Medical and physiological research has shown that people who travel have a unique personality. Unlike other biometric indicators such as fingerprint, face, and iris recognition, ithas an important advantage in that it can accurately measure distance without human intervention. This feature provides pedestrian detection suitable for intelligent video surveillance applications such as security. However, the things that affect your performance are your appearance, the different things you can carry, your clothes, your body, and your treatment.

2.2 There are many such things. These factors make motion recognition a challenge for computer vision. The task of expression is like face or fingerprint recognition in principle, but as a strategy, a video sequence is used to shoot a scene where a person is walking from a high place.

2.3 Although this problem can still be considered a test, in practice the way people walk is often closer than the variety of popular activities that exist in literature. It's worth notingthat, unlike many other tasks, this is difficult forhumans as well, because in computer vision the paths are usually the same and there is little difference.

2.4. The main goal of this project is to create a classifier that can solve a specific population problem, as well as a feature extractor that identifies new people not included in the original data. This is important because not all information related to perception is very large.

3. PROPOSED METHODOLOGY

In this we have used CNN method for gait pattern recognition. The model architecture is built using the Keras library with TensorFlow backend. The core components of the model include convolutional layers (`Conv2D`), dropout layers (`Dropout`), max pooling layers (`MaxPooling2D`), and the softmax activation function.

We have taken the CASIA-B data set which contains the silhouettes of different angles of the feet and pose of the person. Where CASIA stand for Institute of automate, Chinese academy of sciences.

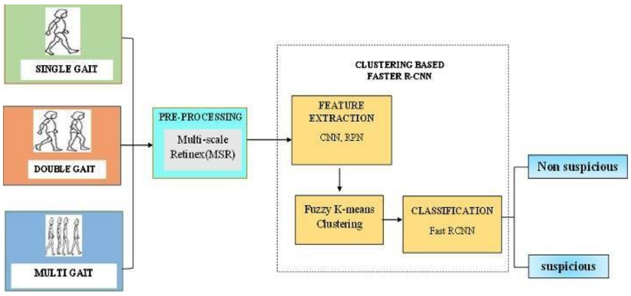

Figure-1

This experiment uses a Convolutional Neural Network with two 2D convolutional layers. CNN is a deep neural network classifier used forimage classification and recognition. Instead of extracting features, can identify featuresdirectly from the data. In the CNN architecture of studies, data is processed by multiple layers for different tasks. The `X_Train` and `Y_train`arrays are converted to NumPy arrays using `np.array` to facilitate further processing. To avoid any bias in the training process, the data is shuffled using the `shuffle` function fromscikit-learn's `utils` module. The shape of the `X_train` array is printed to verify the number of samples and image dimensions.

To split the dataset into training and testing sets, the `train_test_split` function from scikit-learn is used. The data is divided with a test size of 20% and batch size of 32. The labels in the training and testing sets are converted fromcategorical labels to one-hot encoded vectors using the `to_categorical` function from Keras' `utils` module.

The model architecture consists of multiple convolutional layers, max pooling layers, dropout layers, and fully connected layers. Thefirst layer in the model is a `Conv2D` layer with32 filters of size 3x3 and ReLU activation. It takes the input shape of (128, 128, 3) representing the height, width, and channels of the input image. The subsequent layers are stacked `Conv2D` layers with increasing numbers of filters, followed by `MaxPooling2D` layers for down sampling the spatial dimensions.

After pooling layers, the feature maps are flattened using the `Flatten` layer. The flattenedfeatures are then passed through fully connected layers with ReLU activation to learn complex patterns and extract high-level representations. Dropout layers are again added to prevent overfitting. Finally, the output layer consists of a `Dense` layer with a SoftMax activation function.

4. RESULTS

In the model we proposed, we are implementing the Convolution neural network (CNN) on gait pattern images to recognize the pattern of the gait. The dataset used in this contains 20 individuals images whose walking sequences are recorded outdoors in three different views.

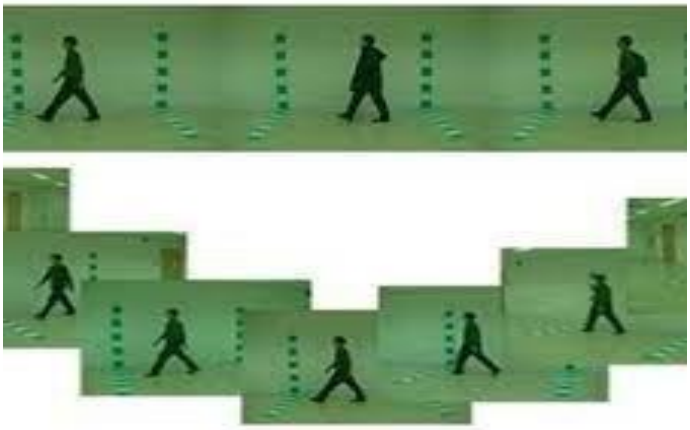

Figure-2

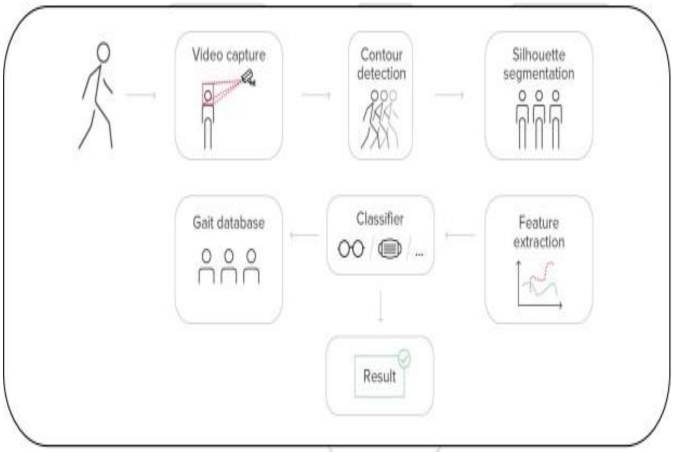

Figure-3

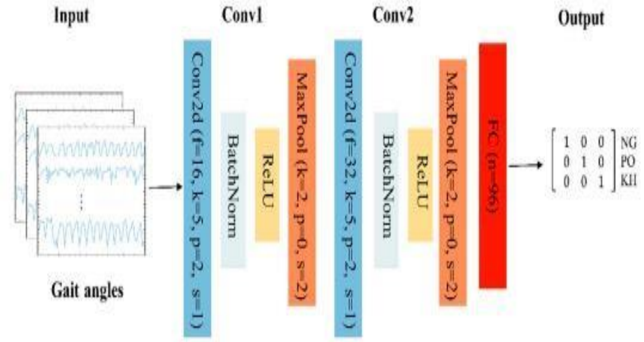

Figure-4

The structure of the proposed CNN is shown in Figure 2. The input of the CNN was the gait angles derived from Kinect; two 2D- convolutional layers were used in the model, and the output of the model was the classification result of the gait pattern. In the first convolutional layer, the number of filters was 16, kernel size 5, padding 2, and stride 1. For the max pooling in the first layer, the kernelsize was 2, padding 0, and stride 2. In the secondlayer, the number of filters was 32, kernel size 5, padding 2, and stride 1. For the max-poolingin the second layer, the kernel size was 2, padding 0, and stride 2.

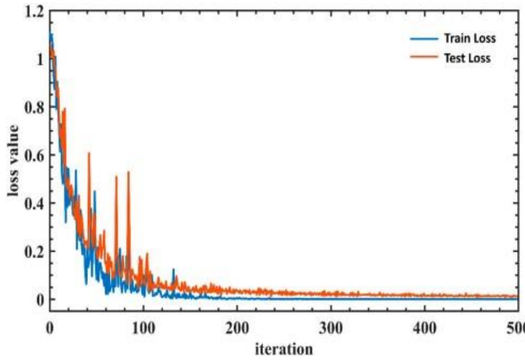

Figure-5

CNN training loss value over iterations. The classic loss curves were found in the CNN model training and model validation. The loss value of the CNN model converges rapidly in the early stage of training. The loss curve plateaus after about 200 iterations, indicating that the model has converged after 200 iterations.

5. CONCLUSION

In this research project, a deep learning model was developed for recognition of gait pattern using CASIA image dataset. The proposed model leverages the power of convolutional neural networks (CNNs) to extract relevant features from the input images and make accurate recognition regarding gait pattern.

The results obtained from the implemented model demonstrate its effectiveness in accurately recognizing gait images. The model achieved a high accuracy rate, showcasing its potential for assisting medical professionals in the diagnosis and recognizing of gait patterns. By automating the gait pattern recognition process, the model can save time and provide valuable support to medical and sports sectors.

The utilization of CNNs in this project enabled the model to learn intricate patterns and featurespresent in gait pattern images. The convolutional layers performed spatial feature extraction, while the pooling layers helped reduce the computational complexity and retainessential data. The inclusion of dropout layers prevented overfitting and enhanced the generalization capability of the model.

The developed model exhibited promising results, showcasing the potential for further advancements in gait pattern recognition. Future research can explore the integration of additional data augmentation techniques, such as rotation, scaling, and flipping, to enhance the model's robustness and improve performance ondiverse datasets.

The proposed work builds a model to recognize a person based upon their gait, which can be implemented further in real-time applications.

The model was trained on CASIA-B dataset in normal walking condition, and it covered 11 different angles. Using a CNN of 8 layers the model was able to achieve acceptable results forboth single view and multi-view data. For single-view dataset, the model was able to achieve an accuracy of 95.45% using ReLU as the activation function.

Below fig shows Comparison of the average classification Comparison of the average classification accuracy of different models.

As we dealt with this gait pattern recognition, which is regarded to deep learning, we considered CNN model which have low average as Compared to other models.

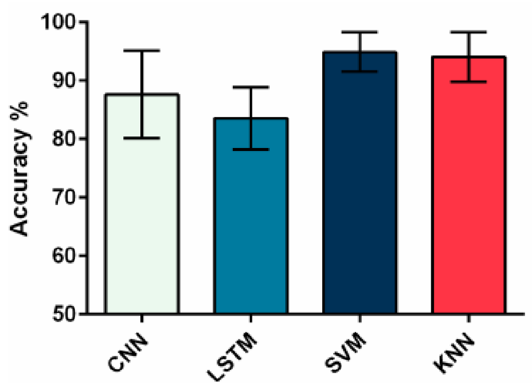

Figure-6

In addition, an accuracy of 91.8% was obtained for multi-view dataset including clothing and baggage scenarios with ReLU activation function. Training for multi-view data is beneficial since all the angles of gait are covered unlike the case of single view, where the modelis trained for all the angles each time separately depending on the angle.

Method	Normal (Without Clothes and Bag)	Normal (With Clothes and Bag)
WideResNet [32]	100.0%	89.4%
VGG+blocks [12]	94.5%	65.1%
Gait with CNN [proposed]	95.45%	91.8%

Figure-7

The above-mentioned table gives a comparison on the accuracy obtained by the proposed work and other researchers using CASIA-B data set.

It is observed from comparing the results obtained by a model that is using WideResNet [32] which presents an accuracy of 100% without clothes and bag and 89.4% with clothesand bag. The other model that is using VGG+Blocks [12], L1 which presents anaccuracy of 94.5% without clothes and bag and65.1% with clothes and bag. The proposed gait recognition system using CNN performs well inboth cases with accuracies of 95.45% and 91.8% respectively and hence with accuracy of above 90% in both cases.

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