Surveillance System to Provide Secured Gait Signatures Using Deep Learning

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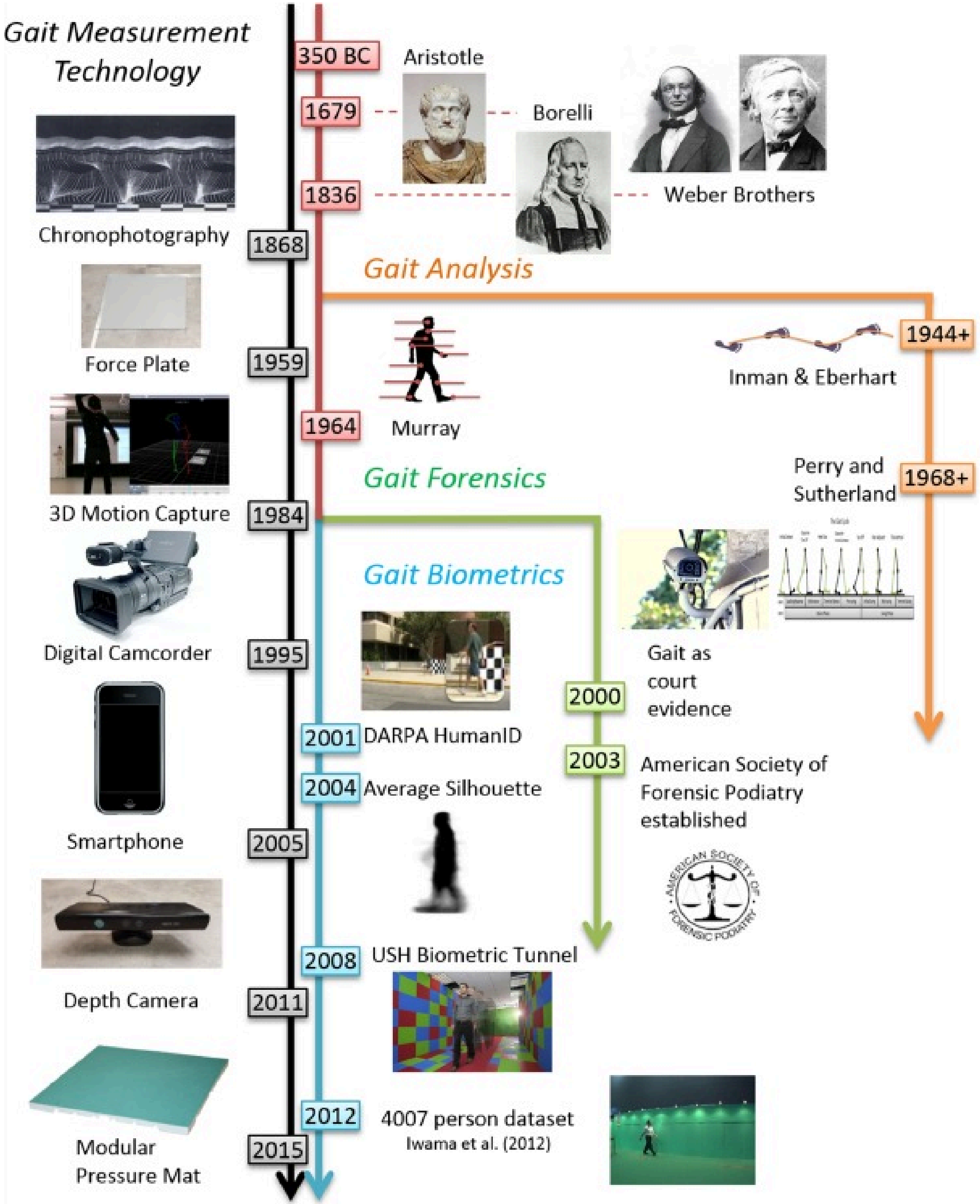
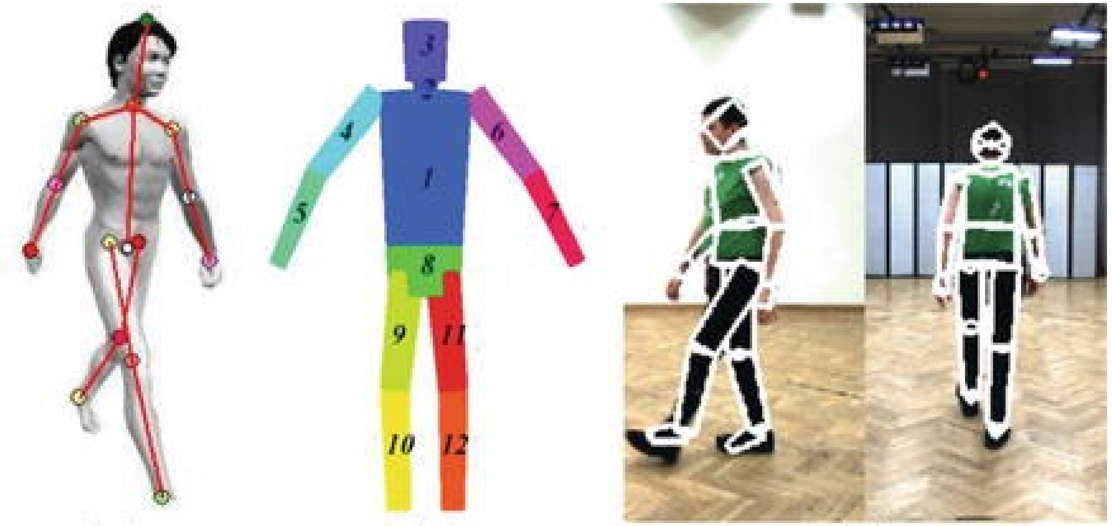
Introduction

- Biometrics is an important technique for uniquely identify the human.
- There are many techniques like face recognition, iris, finger print etc. But all these either need high resolution images or need human intervention.
- Gait is the most efficient and effective biometric when it comes to monitoring individual subjects who are not very cooperative.



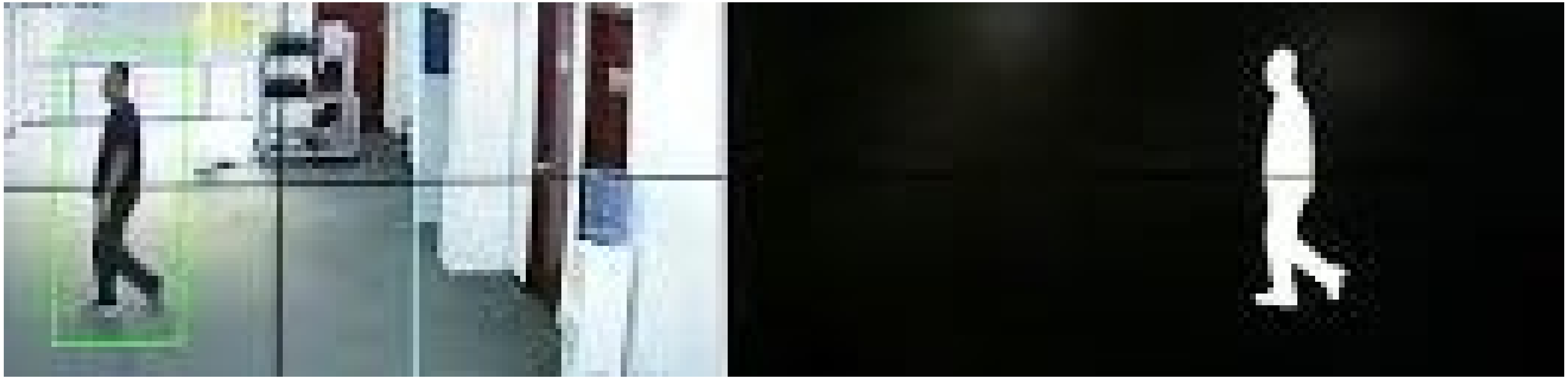
Types of Gait Recognition

Model-based methods



- They have the ability to deal with the various intra-class variations caused by different covariates such as clothing, carrying and view angle which affect the subjects appearance.
- However, the complexity of the models and the extraction of their components from the video stream is not a trivial task.
- Consequently, model-based techniques are preferred in practical applications.

Model-free gait recognition

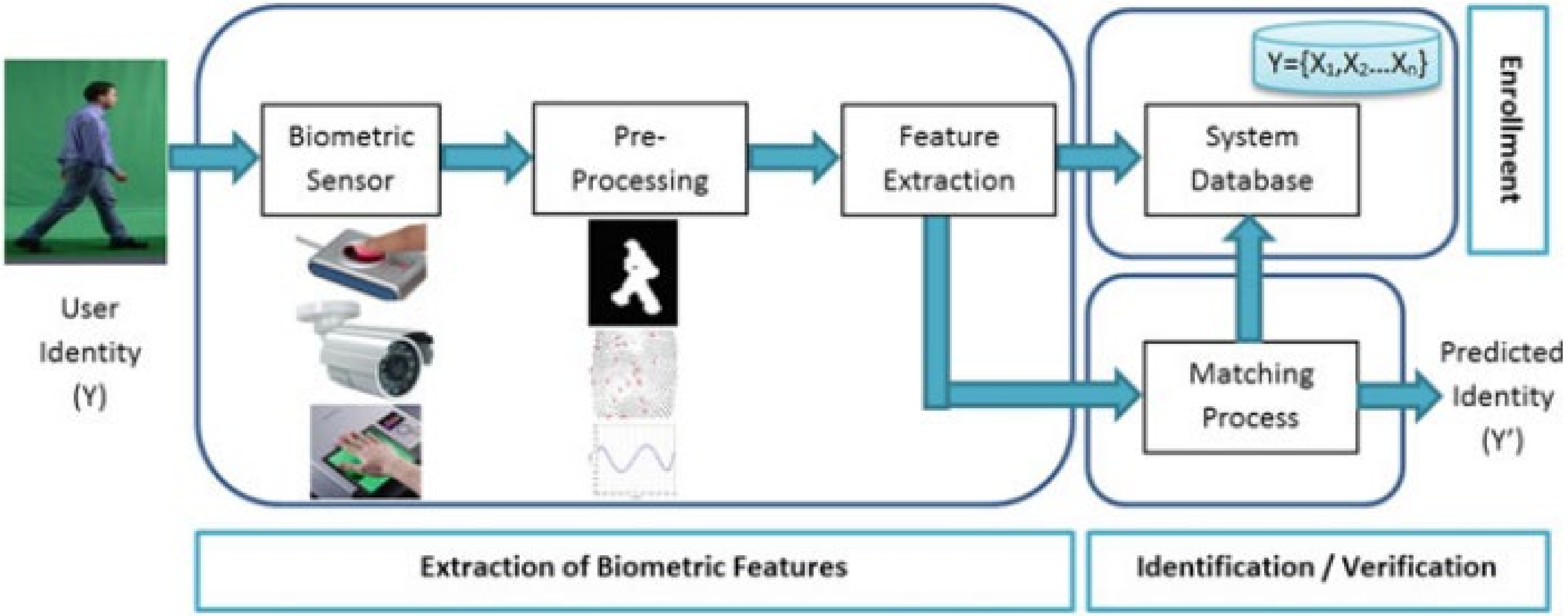


- Model-free approaches, which can be seen as image measurement methods, exploit the moving shape of the subject to derive the gait characteristics.
- Therefore, they do not require to rebuild a model of human walking steps

S.no	Paper	Methodology	Dataset Used	Results	Research gap	Desired Improvements
1.	Ziyuan Zhang, Luan Tran, Feng Liu, On Learning Disentangled Representations for Gait Recognition, IEEE Transactions On Pattern Analysis and Machine Intelligence,2019.	Adaptive outlier detection method to remove the effect of clothing on silhouettes. The proposed method detects the most similar parts of probe and each gallery sample independently and uses these parts to obtain a similarity measure.	Experimental results on OUISIR Gait Database, the Treadmill Dataset B and CASIA Gait Database, Dataset B	96.44%	**They have high computation cost and** need considerable amount of gallery data in various conditions in order to learn the body-parts.	Take spatial and temporal features because they are invariant of all the covariate factors.
2.	Liang Wang, Tieniu Tan Silhouette Analysis-Based Gait Recognition for Human Identification Transactions On Pattern Analysis and Machine Intelligence, Vol. 25, No. 12, December 2018	used pooled segmented statistical features to describe the shape of GEI edge contour.	CASIA B	96.59%	Most of these methods address different covariates **with limited gait views**, mainly using frontal or side view of the gait sequences. In fact, it is difficult for a 2D training dataset to cover all conditions, especially incomplete gait silhouettes and with different carrying that affect the overall body shape directly	Training on all the angles so as to cover all the viewpoints.

S.no	Title with paper	Methodology	Dataset Used	Results	Research gap	Desired Improvements
3.	W. Kusakunniran, "Attribute-based learning for gait recognition using spatio-temporal interest points," Image Vis. Comput., vol. 32, no. 12, pp. 1117–1126, 2014.	The gait data is firstly processed using three gait representation methods as the features sources; Accumulated Prediction Image (API) and two new gait representations namely; Accumulated Flow Image (AFI) and Edge-Masked Active Energy Image (EMAEI).	CASIA B	91%	**single view is imposed by the system setup.** How can they combine (fuse) the result with normal data set with the recognition rate? Until and unless the use Sno.1 paper ie. Removing the cloth from the body. (Clothing-invariant human gait recognition using an adaptive outlier detection method)	Training on all the angles so as to cover all the viewpoints. Make a deep learning model which is best fitted for covariates such as clothing, bag pack etc.
4.	Haung, Y., Wang, L., Wang, X., & Tan, T. A Comprehensive Study on Cross-View Gait based Human Identification with Deep CNNs. Transactions On Pattern Analysis and Machine Intelligence 2017.	The main purpose of the experiments presented in this section is to provide an indication of why previous studies have achieved significantly lower recognition rates over time, by employing similar techniques to this study. The results could be improved if algorithms that are less sensitive to change in clothing are used. However, this paper does not focus on improving performance of recognition approaches but on understanding the effect of time on the performance of the baseline algorithm and a more recent gait representation.	MIT 2001 HumanoID SOTON 2002 UMD SOTON Temporal	89%	A similar recognition performance was achieved over seven different time periods and a CCR of 95% is achieved over period of 9 months. They hypothesize that a CCR of nearly 100% could be achieved if various covariate factors (like clothing, footwear etc.) were controllable. Unfortunately, this situation is unlikely to occur in the real world. **Did not take temporal features therefore less recognition rate**	Taking temporal features because they are invariant of clothing.
5.	Wang, L., Tan, T., Ning, H., Hu, W.: 'Silhouette analysis-based gait recognition for human identification', *IEEE Trans on Patt Anal and Machine Intell*, 2003, 25, (12), pp. 1505–1518 2018.	show how covariates factors can separately affect the walking pattern. Further we assess the contribution and discriminatory significance of the gait dynamics used for recognition. Based on a covariate-based probe dataset of 440 samples, This is to confirm that people identification using dynamic gait features is still perceivable with better recognition rate even under the different covariate factors.	CASIA B	83.33% and 86.67%	**Used model based approach**	Use model-free approach

Methodology



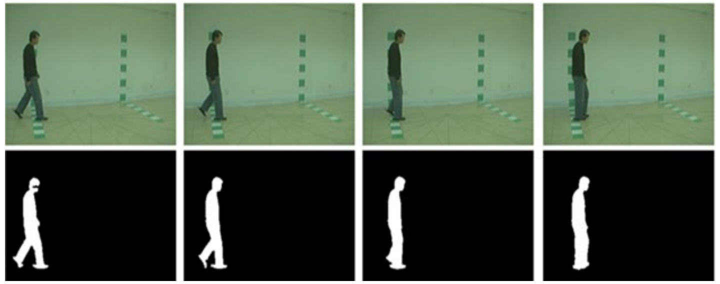
Dataset

- CASIA B consist of multi-view gait database.
- In this dataset there exist 124 subjects and has 11 views
- In order to provide variations in covariate condition, dataset consist of three variants: clothing, view angle, and carrying bag in figure .

(a) Normal walking (b) With a bag (c) With a coat

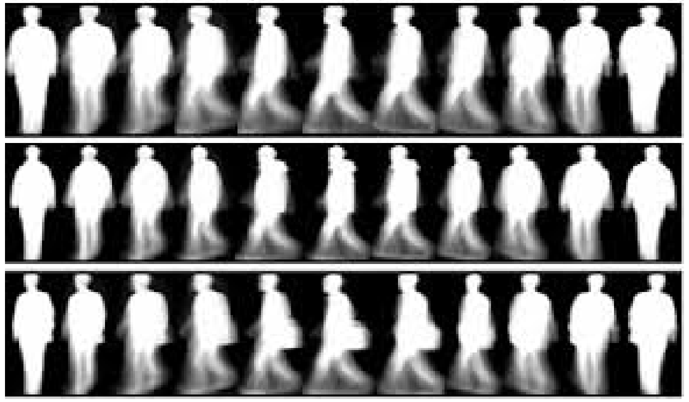
The proposed methodology can be seen, it is divided into five steps

- Videos are converted into frames.
- Background is subtracted.



- Next the gait energy image is created by take the average of frames by given formula:

$$G(a,b) = 1/N \sum_{c=1}^{N} B(a,b,c)$$



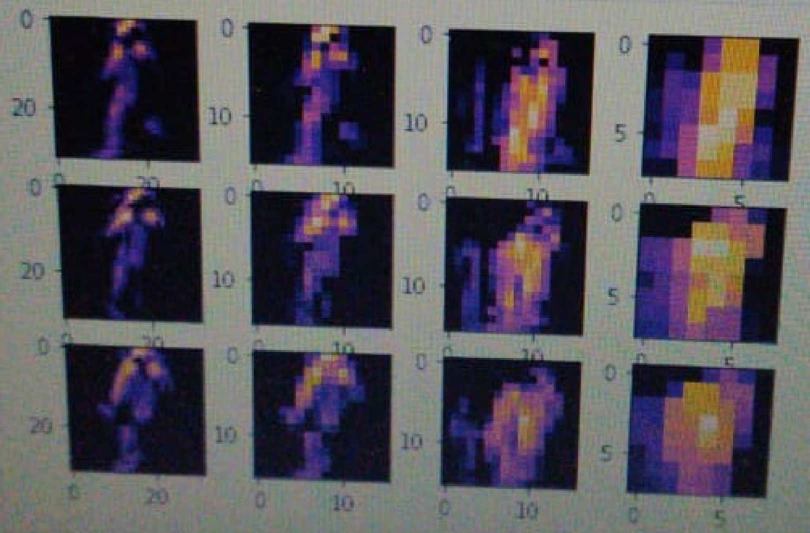
- CNN model is given to extract the spatial and temporal features.
- Finally, fully connected layer is formed to and softmax activation function is used to get the final prediction.

Convolution Neural Network

The network created had 15 layers consisting of:

- Image Input Layer - 1
- Convolution Layer - 3
- Batch Normalization layer - 3
- ReLU Layer - 3
- Max Pooling Layer - 2
- Fully connected Layer - 1
- Softmax Layer - 1
- Classification Layer - 1

```
THIRD_IMAGE=26
CONVOLUTION_NUMBER = 1
from tensorflow.keras import models
layer_outputs = [layer.output for layer in model.layers]
activation_model = tf.keras.models.Model(inputs = model.in
for x in range(0,4):
  f1 = activation_model.predict(test_images[FIRST_IMAGE].re
  axarr[0,x].imshow(f1[0, : , :, CONVOLUTION_NUMBER], cmap=
  axarr[0,x].grid(False)
  f2 = activation_model.predict(test_images[SECOND_IMAGE].r
  axarr[1,x].imshow(f2[0, : , :, CONVOLUTION_NUMBER], cmap=
  axarr[1,x].grid(False)
  f3 = activation_model.predict(test_images[THIRD_IMAGE].res
  axarr[2,x].imshow(f3[0, : , :, CONVOLUTION_NUMBER], cmap=
  axarr[2,x].grid(False)
```



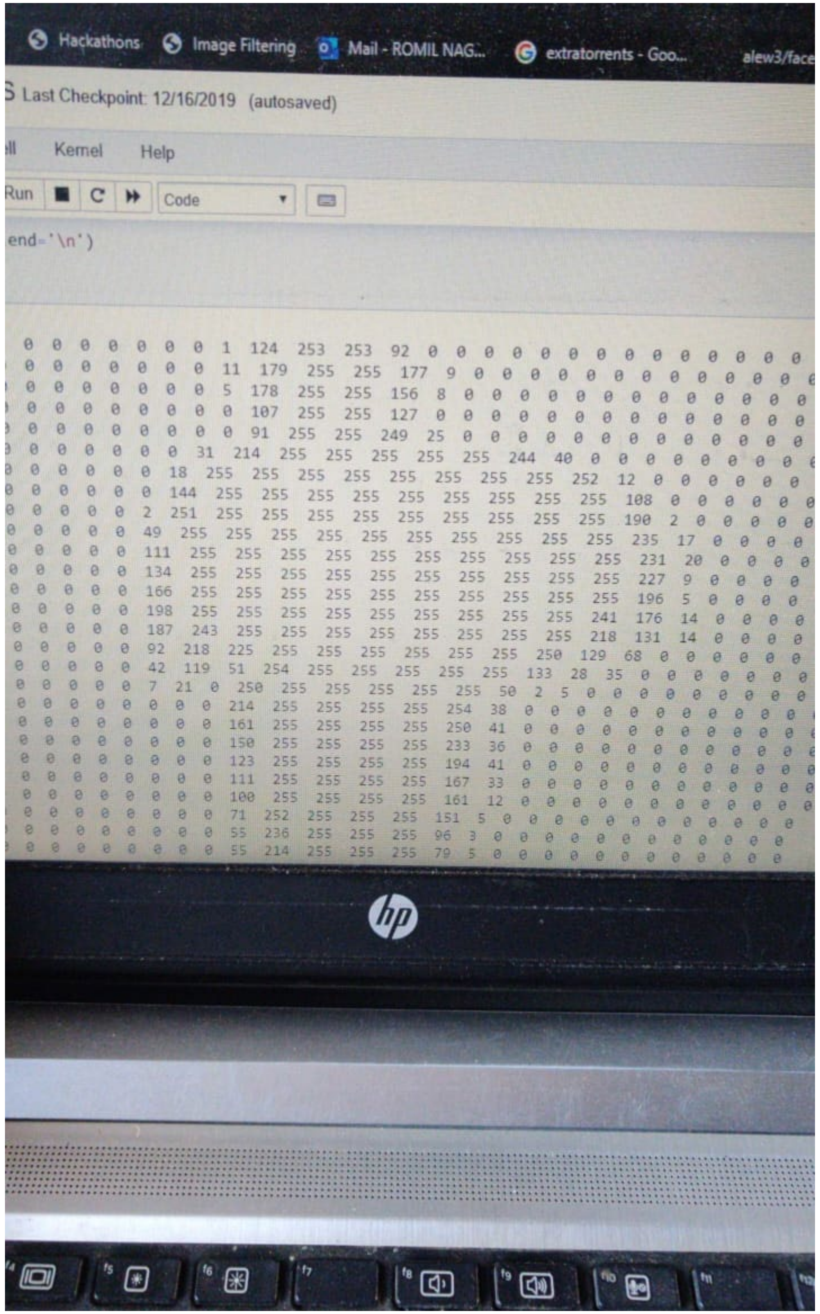


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Image Filtering
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alew3/face
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end='\n')
0 0 0 0 0 0 0 1 124 253 253 92 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 11 179 255 255 177 9 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 5 178 255 255 156 8 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 107 255 255 127 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 91 255 255 249 25 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 31 214 255 255 255 255 255 244 40 0 0 0 0 0 0 0 0
0 0 0 0 0 18 255 255 255 255 255 255 255 255 252 12 0 0 0 0 0 0
0 0 0 0 0 144 255 255 255 255 255 255 255 255 255 108 0 0 0 0 0 0
0 0 0 0 0 2 251 255 255 255 255 255 255 255 255 255 190 2 0 0 0 0 0
0 0 0 0 0 49 255 255 255 255 255 255 255 255 255 255 235 17 0 0 0 0
0 0 0 0 0 111 255 255 255 255 255 255 255 255 255 255 231 20 0 0 0 0
0 0 0 0 0 134 255 255 255 255 255 255 255 255 255 255 227 9 0 0 0 0
0 0 0 0 0 166 255 255 255 255 255 255 255 255 255 255 196 5 0 0 0 0
0 0 0 0 0 198 255 255 255 255 255 255 255 255 255 241 176 14 0 0 0 0
0 0 0 0 0 187 243 255 255 255 255 255 255 255 255 218 131 14 0 0 0 0
0 0 0 0 0 92 218 225 255 255 255 255 255 255 250 129 68 0 0 0 0 0 0
0 0 0 0 0 42 119 51 254 255 255 255 255 255 133 28 35 0 0 0 0 0 0 0
0 0 0 0 0 7 21 0 250 255 255 255 255 255 50 2 5 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 214 255 255 255 255 254 38 0 0 0 0 0 0 0 0 0 0 0
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0 0 0 0 0 0 0 0 150 255 255 255 255 233 36 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 123 255 255 255 255 194 41 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 111 255 255 255 255 167 33 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 100 255 255 255 255 161 12 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 71 252 255 255 255 151 5 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 55 236 255 255 255 96 3 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 55 214 255 255 255 79 5 0 0 0 0 0 0 0 0 0 0 0

```
74  74  74  75  75  75  76  76  76  77  77  77  78  78  78  79  79  79  ...
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```

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```

```
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 86  86  86  87  87  87  88  88  88  89  89  89  90  90  90  91  91  91
 92  92  92  93  93  93  94  94  94  95  95  95  96  96  96  97  97  97
 98  98  98  99  99  99 100 100 100 101 101 101 102 102 102 103 103 103
104 104 104 105 105 105 106 106 106 107 107 107 108 108 108 109 109 109
110 110 110 111 111 111 112 112 112 113 113 113 114 114 114 115 115 115
116 116 116 117 117 117 118 118 118 119 119 119 120 120 120 121 121 121
122 122 122 123 123 123 124 124 124]
```

```
0]: a=[]
for i in range(len(classifications)):
    print(np.argmax(classifications[i]),end='  ')
    a.append(np.argmax(classifications[i]))
```

```
1  1  1  2  2  2  3  26  3  4  4  4  6  50  6  7  7  7  8  8  8  9  9  83  10  10  10
14  14  15  15  15  16  16  16  17  17  17  18  18  18  19  19  19  20  20  20  21  21
25  99  63  26  26  26  55  49  27  28  28  28  29  29  29  30  30  30  31  31  31  32
35  36  36  36  37  37  37  38  38  38  39  39  39  40  40  40  105  41  67  42  42  42
6  46  46  47  47  47  48  48  48  49  49  49  53  50  50  51  51  51  52  52  52  53
56  57  57  57  113  58  58  59  59  59  60  34  60  61  6  61  62  62  62  63  29  63
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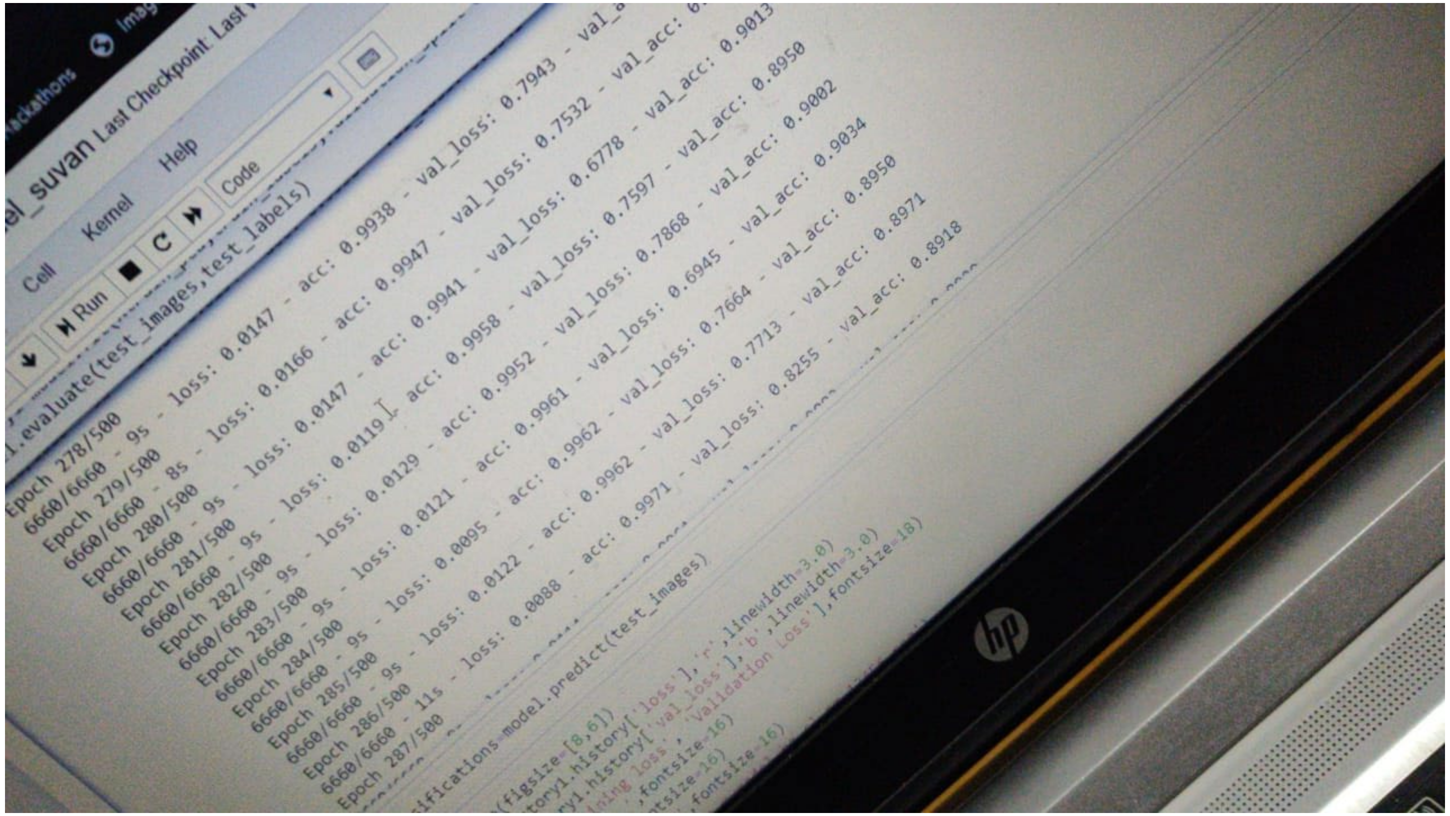
99  99  100  100  100  101  101  101  58  65  102  103  49  103  104  104  104  105  105
8  108  108  109  54  109  101  110  110  111  111  111  112  105  112  113  74  113  114
16  117  117  117  118  118  118  119  93  119  120  120  120  121  121  121  122  122  12
```



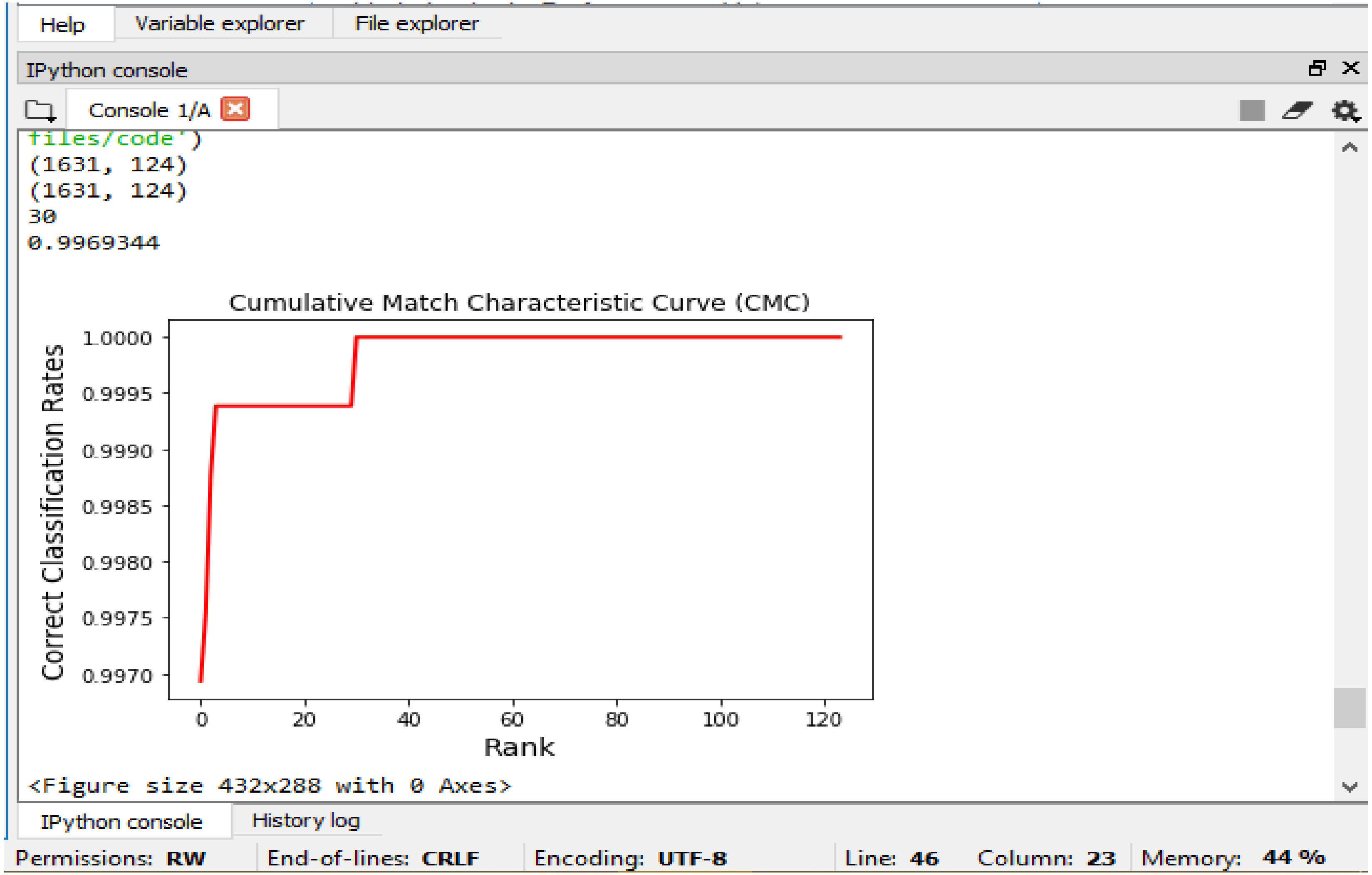
Last Checkpoint
Cell
Kernel
Help
Run
Code
.evaluate(test_images,test_labels)
Epoch 278/500
6660/6660 - 9s - loss: 0.0147 - acc: 0.9938 - val_loss: 0.7943
Epoch 279/500
6660/6660 - 8s - loss: 0.0166 - acc: 0.9947 - val_loss: 0.7532
Epoch 280/500
6660/6660 - 9s - loss: 0.0147 - acc: 0.9941 - val_loss: 0.6778 - val_acc: 0.9013
Epoch 281/500
6660/6660 - 9s - loss: 0.0119 - acc: 0.9958 - val_loss: 0.7597 - val_acc: 0.8950
Epoch 282/500
6660/6660 - 9s - loss: 0.0129 - acc: 0.9952 - val_loss: 0.7868 - val_acc: 0.9002
Epoch 283/500
6660/6660 - 9s - loss: 0.0121 - acc: 0.9961 - val_loss: 0.6945 - val_acc: 0.9034
Epoch 284/500
6660/6660 - 9s - loss: 0.0095 - acc: 0.9962 - val_loss: 0.7664 - val_acc: 0.8950
Epoch 285/500
6660/6660 - 9s - loss: 0.0122 - acc: 0.9962 - val_loss: 0.7713 - val_acc: 0.8971
Epoch 286/500
6660/6660 - 11s - loss: 0.0088 - acc: 0.9971 - val_loss: 0.8255 - val_acc: 0.8918
Epoch 287/500
model.predict(test_images)

Results

Angle	Bag	Overcoat			Normal	
	Our Result	Ziyuan Zhang	Liang Wang	**Our Result**	Deng. Et al.	**Our Result**
0	**87.64**	78.49	75.59	**78.35**	93.59	**98.14**
18	**88.49**	94.74	98.35	**90.30**	95.44	**98.14**
36	**85.49**	98.75	94.34	**98.44**	94.29	**98.14**
54	**88.69**	96.50	96.39	**98.35**	94.14	**98.04**
72	**87.44**	96.40	95.69	**98.06**	95.14	**98.05**
90	**88.59**	96.44	96.59	**97.08**	96.14	**99.05**
108	**83.63**	96.30	90.34	**96.29**	96.44	**99.14**
124	**81.58**	92.39	90.64	**95.30**	97.29	**97.29**
144	**81.63**	94.34	94.64	**94.15**	97.74	**96.14**
162	**88.78**	94.34	90.64	**94.59**	97.59	**95.14**
180	**86.49**	76.37	75.24	**77.44**	95.29	**98.04**

Recognition of human gait while carrying a bag falls under 81–90%. In overcoat clothing recognition rate is 77–100%. For normal gait is in 95–100%.

Performance

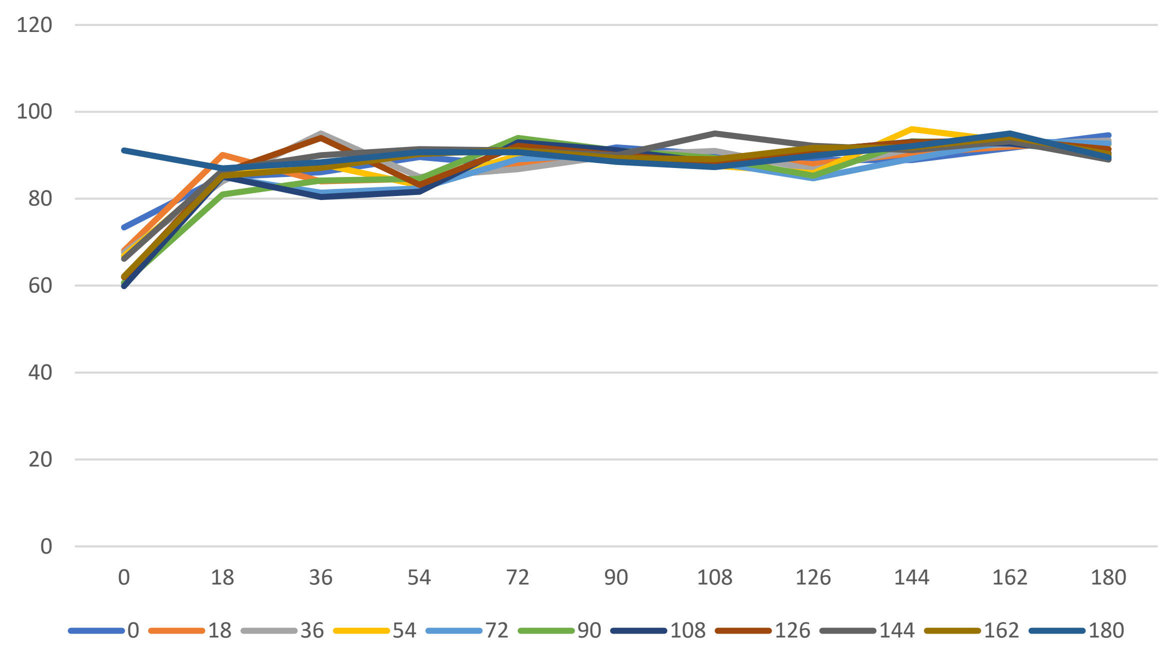


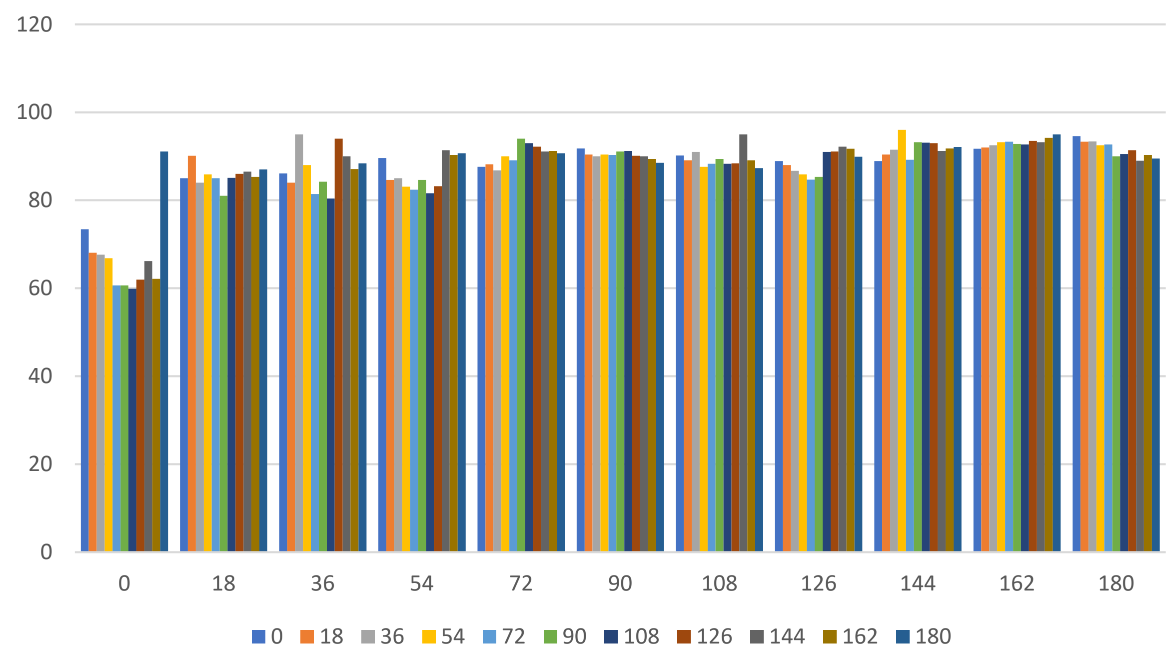
Result Analysis

	0	18	36	54	72	90	108	126	144	162	180
0	73.4	68.05	67.63	66.83	60.64	60.66	59.89	61.96	66.17	62.14	91.11
18	85	90.1	84	85.9	85	81	85.1	86	86.5	85.3	87
36	86.1	84	95	88	81.4	84.2	80.4	94	90	87.1	88.4
54	89.6	84.6	85	83.1	82.4	84.6	81.6	83.2	91.4	90.3	90.7
72	87.6	88.2	86.8	90	89.1	94	93	92.2	91.1	91.2	90.7
90	91.8	90.4	90	90.4	90.3	91.1	91.2	90.1	90	89.4	88.5
108	90.2	89.1	91	87.6	88.3	89.4	88.3	88.4	95	89.1	87.3
126	88.9	88	86.7	85.9	84.7	85.3	91	91.1	92.2	91.7	89.9
144	88.9	90.4	91.5	96	89.2	93.2	93.1	93	91.2	91.8	92.1
162	91.7	92	92.5	93.2	93.3	92.8	92.7	93.5	93.2	94.2	95
180	94.6	93.3	93.4	92.5	92.7	90	90.5	91.4	89	90.3	89.5

When testing on two different datasets the mean accuracy is about 92.83 %

Result Analysis





Conclusion

Experimental result shows the proposed approach is more robust and efficient than previous state of art. Further, it has produced better results than the previous model-free approaches.

The major contributions of this research can be summarized as below:

- Provides efficient multi variant model.
- Proposed methodology gives better result than the existing methods (that is with bag, Overcoat, Normal).
- As the results are good in all the angles this system can actually be used for real surveillance for providing security.

References

[1] Ziyuan Zhang, Luan Tran, Feng Liu, On Learning Disentangled Representations for Gait Recognition, IEEE Transactions On Pattern Analysis and Machine Intelligence,2019.

[2] Liang Wang, Tieniu Tan Silhouette Analysis-Based Gait Recognition for Human Identification Transactions On Pattern Analysis and Machine Intelligence, Vol. 25, No. 12, December 2018

[3] W. Kusakunniran, "Attribute-based learning for gait recognition using spatio-temporal interest points," Image Vis. Comput., vol. 32, no. 12, pp. 1117–1126, 2014.

[4] Haung, Y., Wang, L., Wang, X., & Tan, T. A Comprehensive Study on Cross-View Gait based Human Identification with Deep CNNs. Transactions On Pattern Analysis and Machine Intelligence 2017.

[5] Wang, L., Tan, T., Ning, H., Hu, W.: 'Silhouette analysis-based gait recognition for human identification', *IEEE Trans on Patt Anal and Machine Intell*, 2003, 25, (12), pp. 1505–1518 2018.