HIGHER SCHOOL OF ECONOMICS
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Fast Nearest-Neighbor Classifier based on Sequential Analysis of Principal Components

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AIST

Analysis of images, social networks, and texts 2019

Outline

- Image recognition problem
- Proposed recognition method based on sequential analysis of principal components
- Experimental results in face classification
- Concluding comments and future plans

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Problem formulation

The problem is to assign an input set of T feature vectors $x(t) = [x_1(t), \dots, x_D(t)]$ into one of C classes. They are specified by a training set of $R \geq C$ points $x_r = [x_{r;1}, \dots, x_{r;D}], r \in \{1, \dots, R\}$, which class label $c(r) \in \{1, \dots, C\}$ is known. Dimensionality D is rather high

Instance-based learning approach

- k-nearest neighbor (k-NN)

As such feature vectors are high-dimensional, classification speed can be too low for many practical applications

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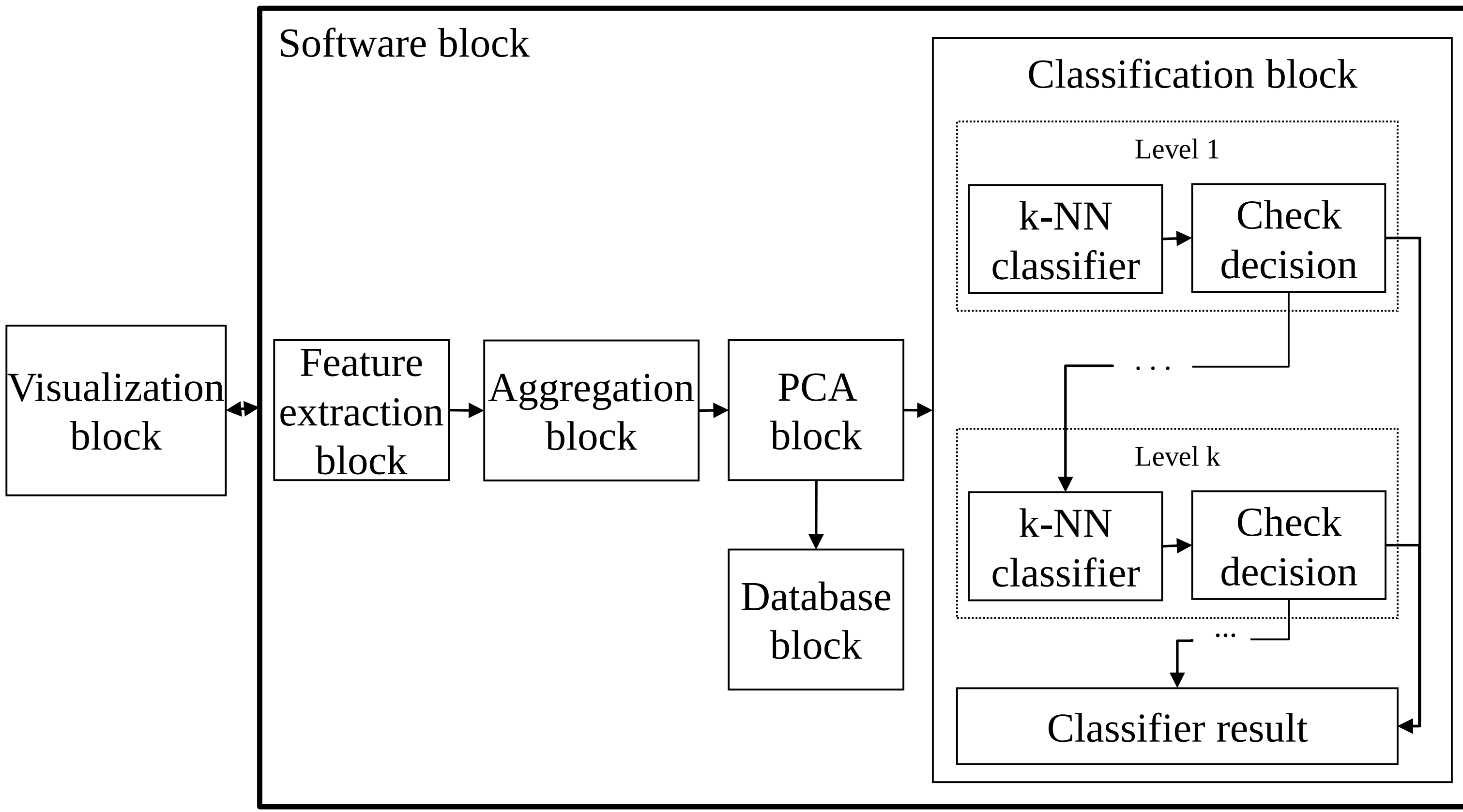
Proposed algorithm



Proposed approach

Feature extraction is implemented using the deep CNNs trained with an external large dataset.

The distance between feature level to speed-up the matching:

$$\rho\left(\tilde{x}^{(l)}, \tilde{x}_r^{(l)}\right) = \rho\left(\tilde{x}^{(l-1)}, \tilde{x}_r^{(l-1)}\right) + \sum_{d=d_{(l-1)}+1}^{d_l} \rho(\tilde{x}_d, \tilde{x}_{r;d}) \quad (1)$$

Nearest neighbor class:

$$\mathrm{c}_l^* = \underset{c \in C_l}{\operatorname{argmin}}\, \rho_{\mathrm{c}}(\tilde{x}^{(l)}) \quad (2)$$

The set of candidates

$$C_{l+1} = \left\{ c \in C_l \,\middle|\, \frac{\rho_{\mathrm{c}}(\tilde{x}^{(l)})}{\rho_{\mathrm{c}_l^*}(\tilde{x}^{(l)})} \leq \delta \right\} \quad (3)$$

Aggregation techniques

Average features vector:

$$\overline{x} = \frac{1}{T}\sum_{t=1}^{T} x(t) \tag{4}$$

Medoid:

$$x^* = \underset{x(t)}{\operatorname{argmin}} \sum_{t'=1}^{T} \rho(x(t), x(t')) \tag{5}$$

Median:

$$x' = [x'_1, \dots, x'_D] \tag{6}$$

x'_i – the median of i-th component of all vectors $\{x(t), t = 1,2, \dots, T\}$

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Datasets

- LFW (Labeled Faces in the Wild)
  - 1680 people
  - 13000 images
  - 1-10 images
- YTF (YouTube Faces)
  - 1595 people
  - 3425 videos
  - 48-6070 frames

Feature extraction

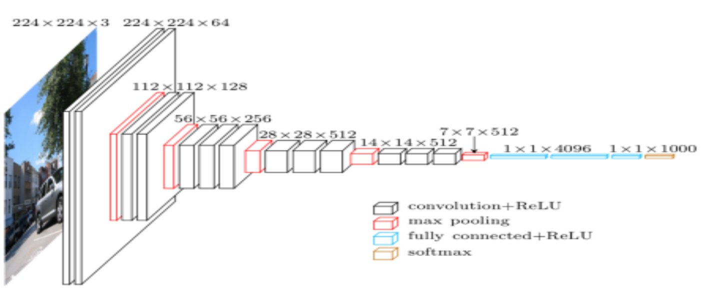
- Lightened CNN (version C)

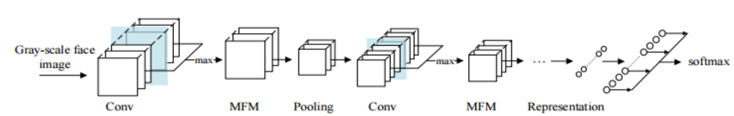
  Out: vector of 256 elements
- FaceNet

  Out: vector of 512 elements
- VggFace2

  Out: vector of 2048 elements
- VggFace

  Out: vector of 4096 elements



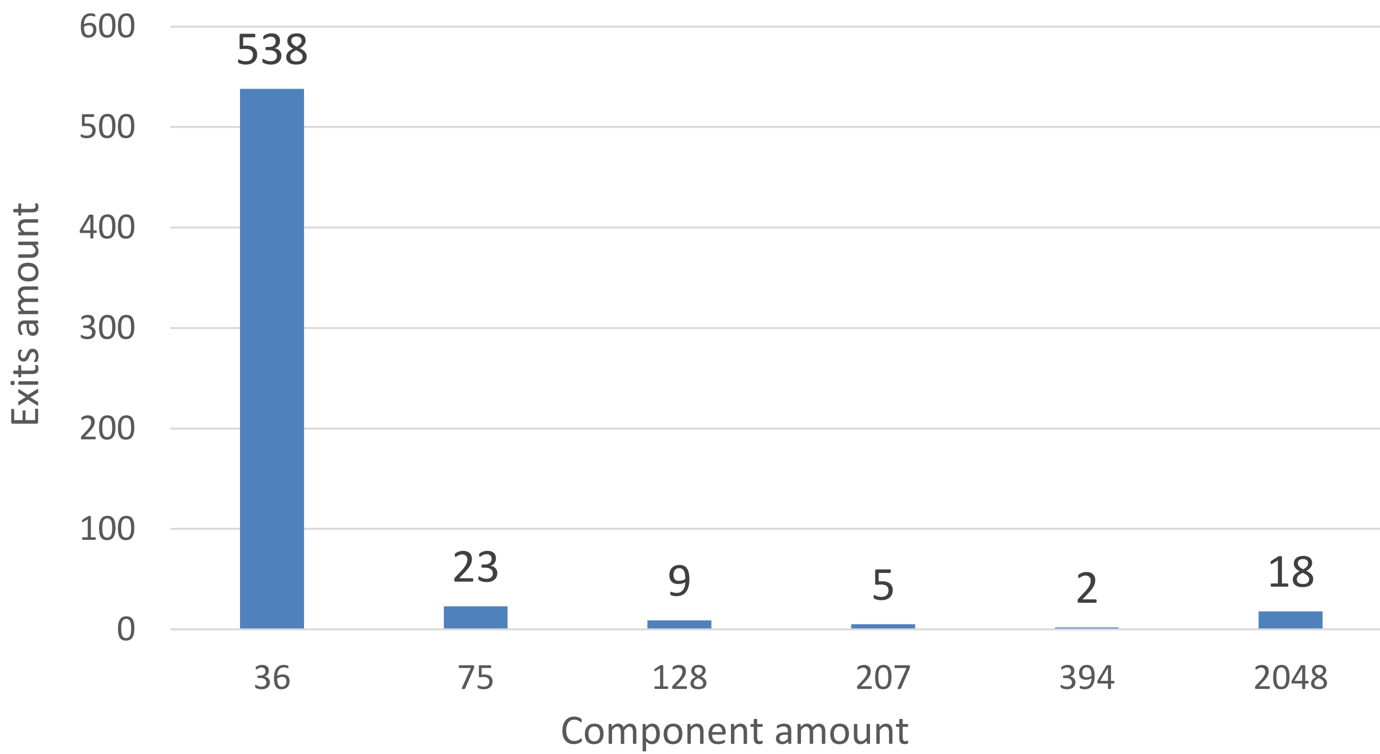


TensorFlow

Face recognition results for the k-NN classifier (LFW)

Metric	Classifier	VGGFace	LCNN	VGGFace2	FaceNet
Accuracy (%)	k-NN, all components	96.31	97.48	98.66	98.15
	k-NN, fixed no. of components	94.10	96.21	96.95	97.36
	sequential k-NN, fixed no. of components	95.97	96.97	98.32	98.15
	sequential k-NN, variable no. of components	95.80	96.81	97.98	97.94
Time (ms)	k-NN, all components	50.39	4.88	34.78	9.37
	k-NN, fixed no. of components	2.53	2.50	2.53	2.52
	sequential k-NN, fixed no. of components	2.92	2.54	2.84	2.69
	sequential k-NN, variable no. of components	3.20	2.23	2.81	1.87

Face recognition results for the k-NN classifier (LFW)



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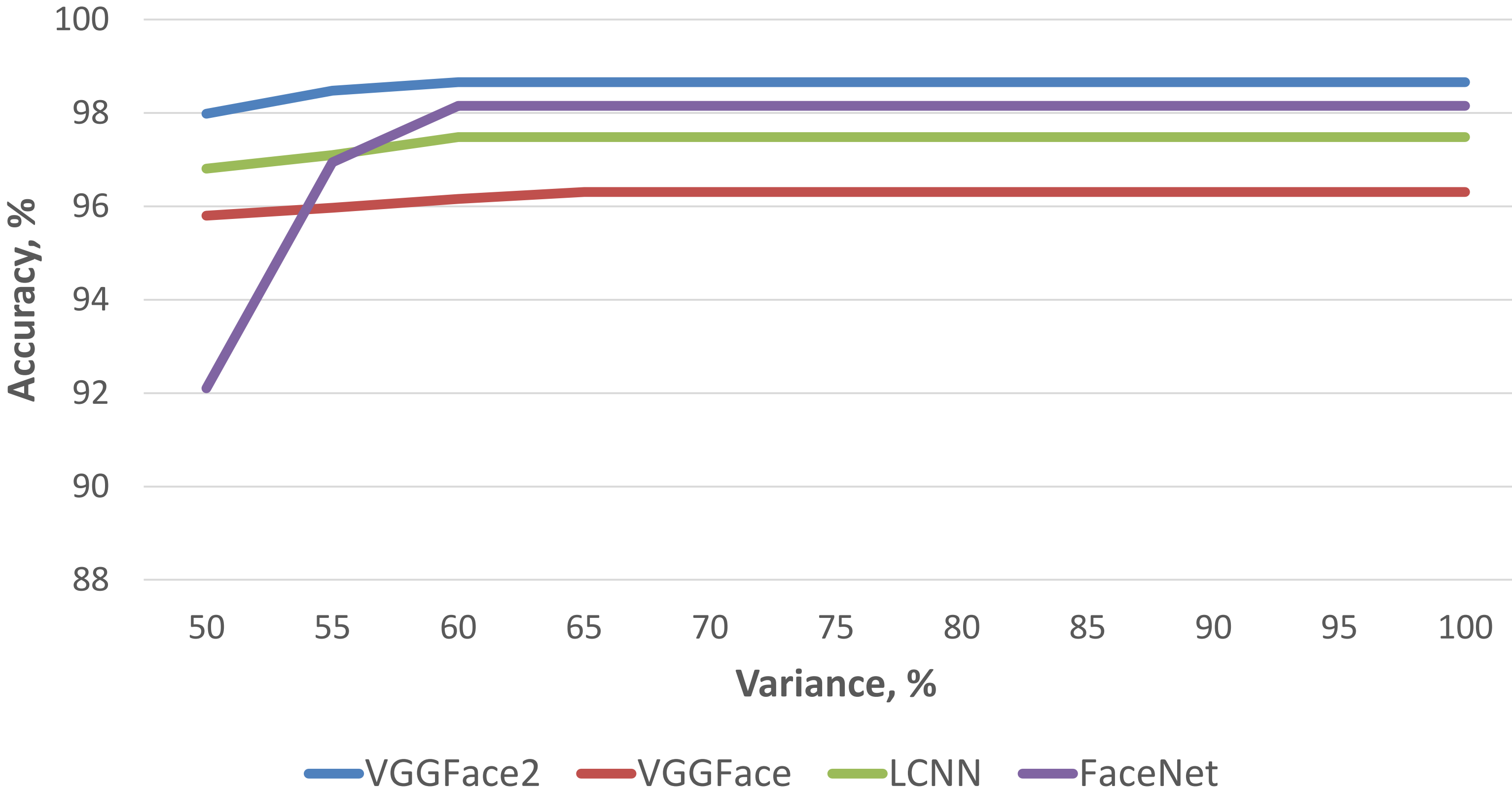
Face recognition results for the k-NN classifier (LFW)



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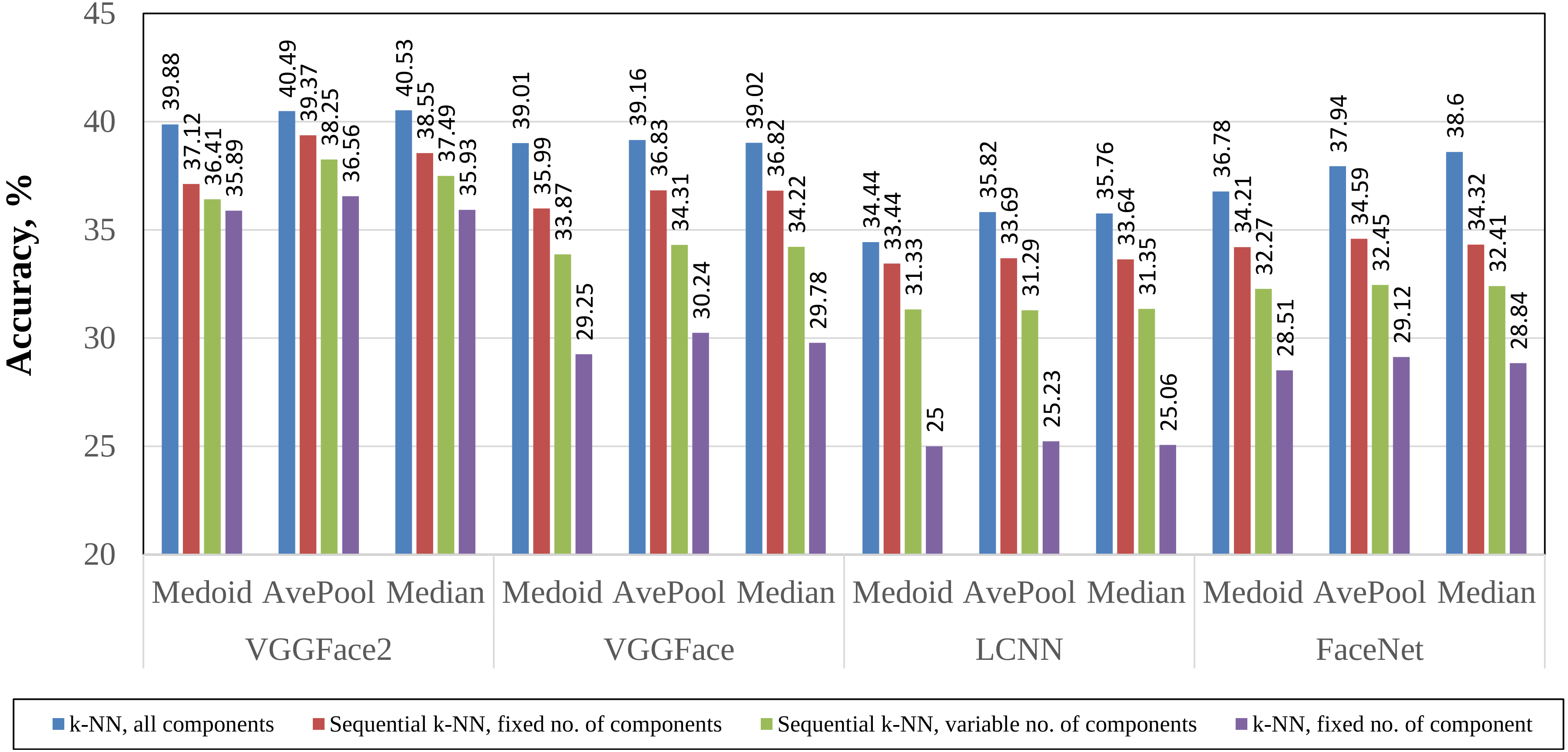
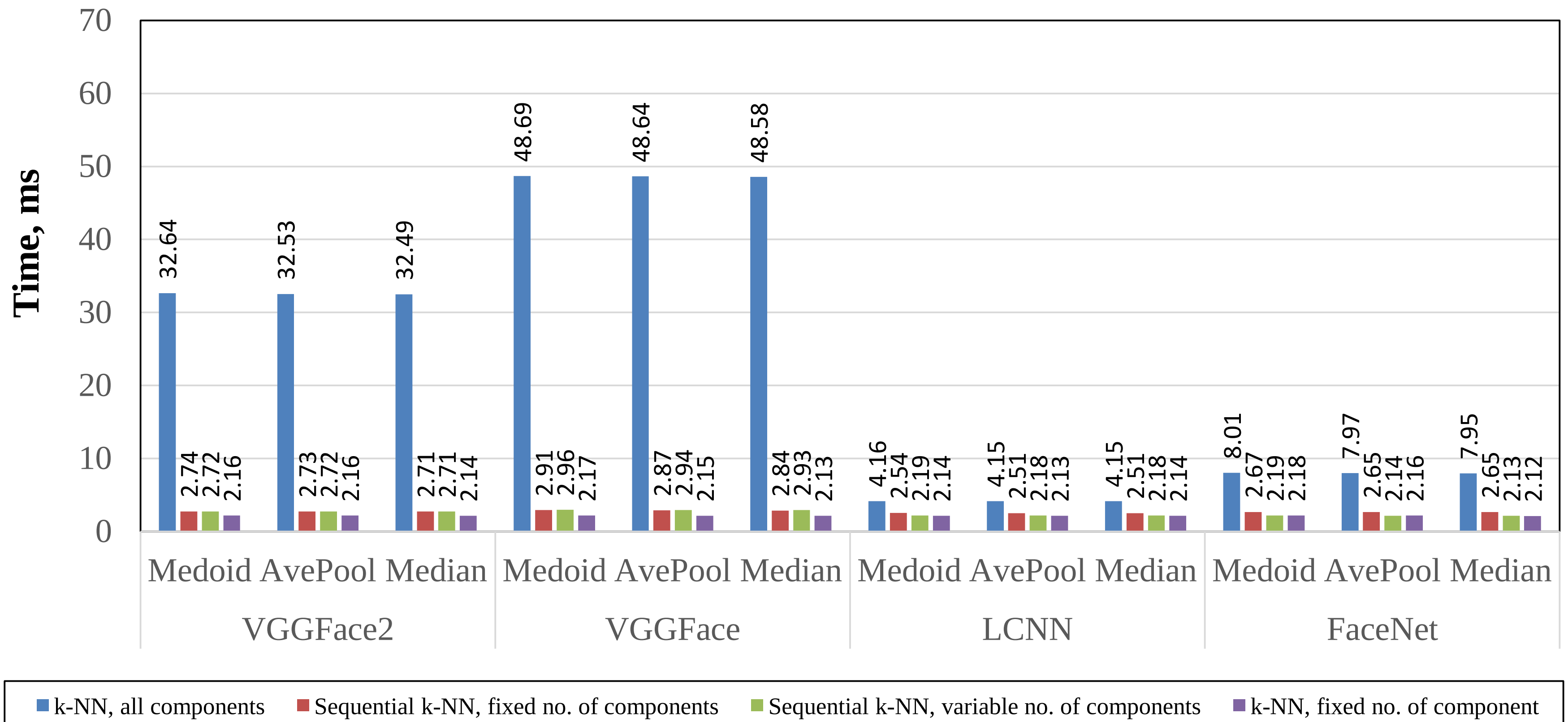
Face recognition results for the k-NN classifier (YTF)



Face recognition results for the k-NN classifier (YTF)



Conclusion

- We proposed the modification of the k-NN classification method based on sequential analysis of high-dimensional features
- The proposed approach is up to 8-10 times faster when compared to the original k-NN method, while the accuracy decreases only by 0.1-0.9%

Future work

- To examine sophisticated classifiers in order to increase the recognition accuracy
- To use more difficult dissimilarity measures
- To study contemporary aggregation techniques instead of simple averaging of individual features

Thank you for attention!