



CentraleSupélec

# Where can I find this shirt?

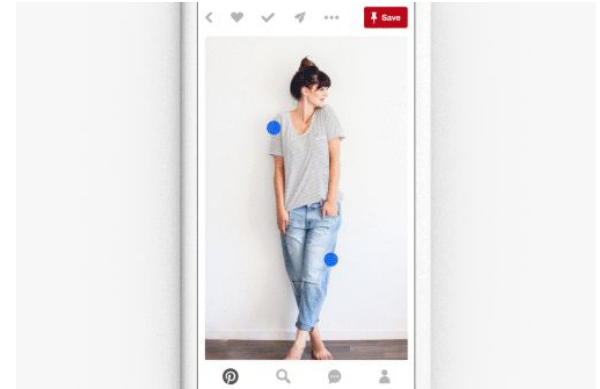
Fatma Moalla & Mohamed Karroumi & Niraj Srinivas & François Le Roux



Visual Computing Final Project

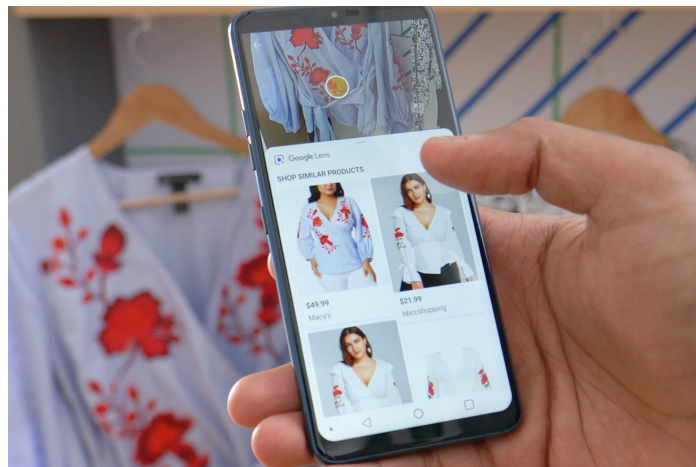
-  
Visual Search

-  
05/03/2020



# Project Motivation

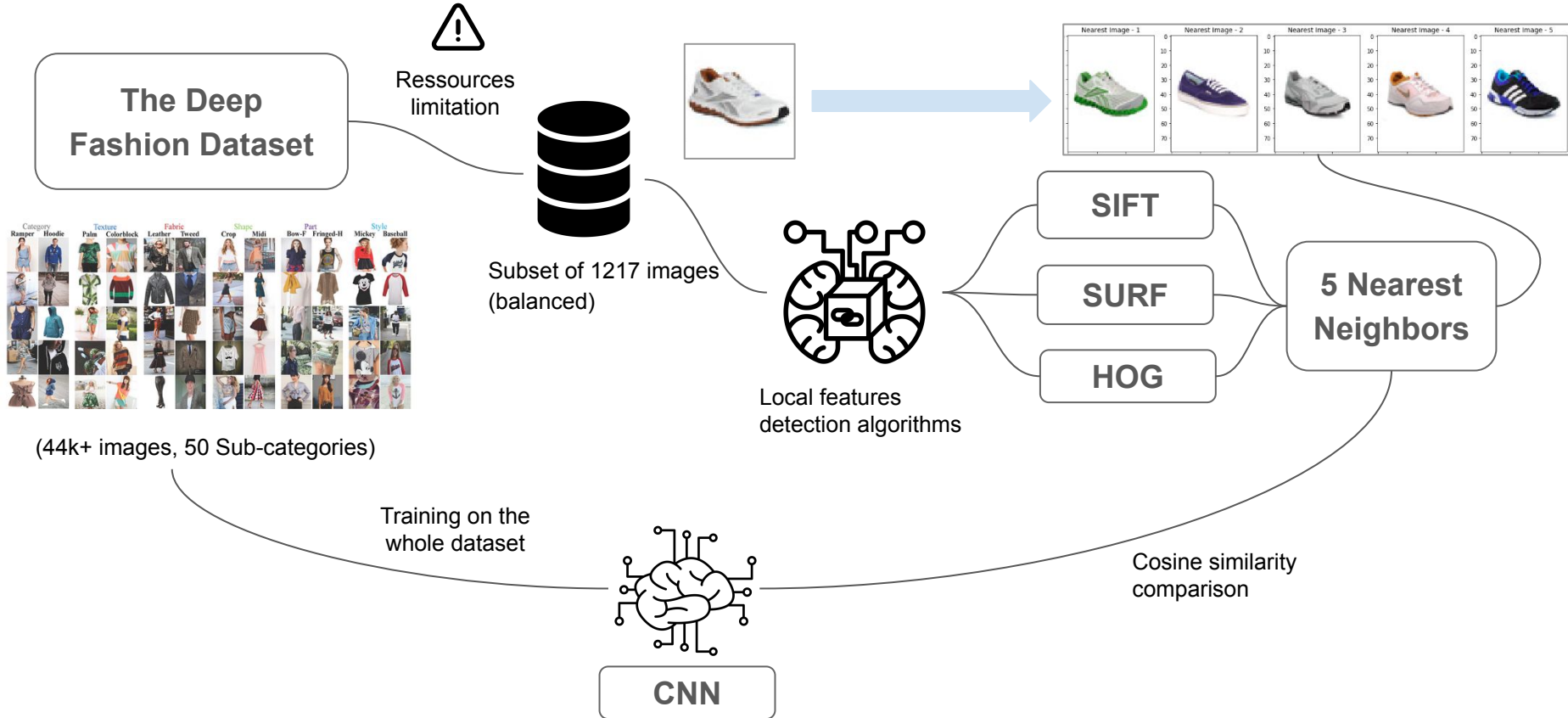
- Year 2000
- Jennifer Lopez and Versace
- “Jennifer Lopez’s green dress”, the most popular search query
- The demand for more than just text
- Birth of Google Image Search
- Fastrack to 2017, Google Lens launched



# Where can I find this shirt?

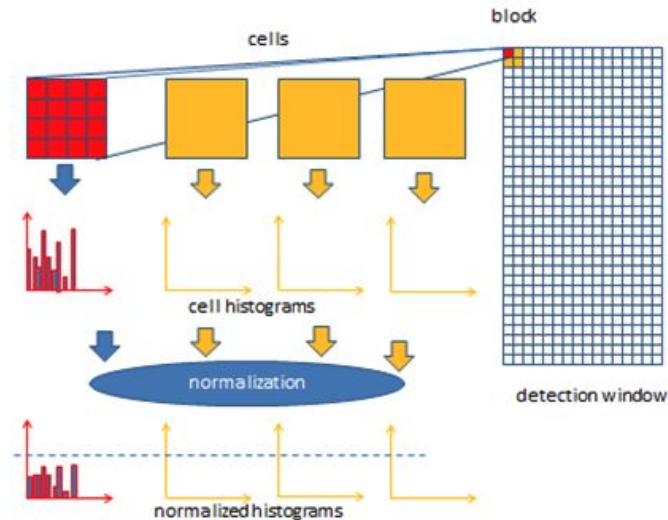
- Growing Mobile and E-Commerce segments in Fashion Industry
- Multiple choices and offers
- But Personalisation = Survival
- Styles, colors, textures and types of dresses contain more information on user's preference than just a few words
- Recommend products based on users' preferences and history of product search.

# Model Pipeline



# Histogram Of Gradients (HOG)

**Main objective:** Converts the image to a feature vector → Important for object recognition



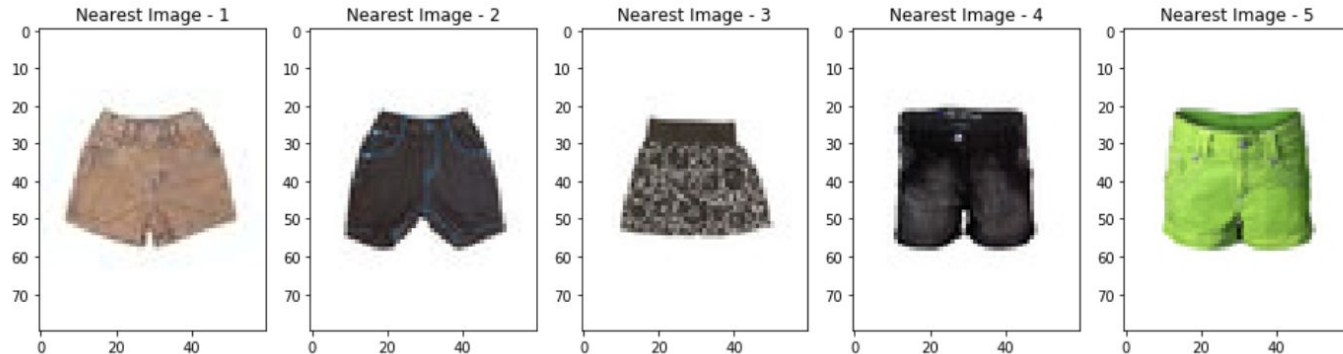
## Keys steps

- 1 **Image preprocessing: patches and cells creation**
- 2 **Gradient (Sobel): magnitude + direction**
- 3 **Histogram: assign a bin (angle) to each cell**
- 4 **16 x 16 Block Normalization**
- 5 **Concatenate blocks: a single feature vector (block\_size x number of positions)**

# HOG results on the Deep Fashion dataset

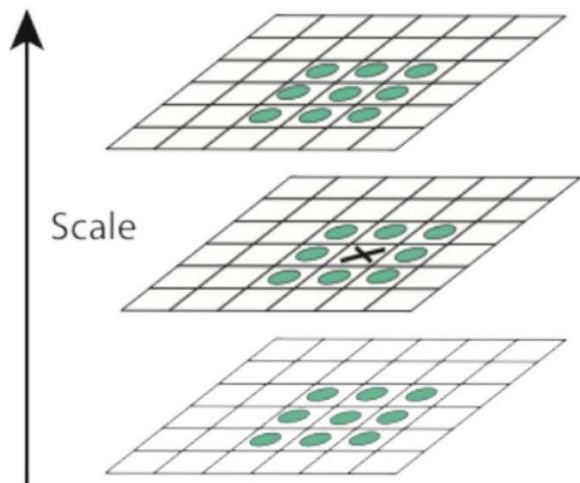


- Cosine similarity = 96% ✓
- Visual Matching ✓
- Detects texture information
- Computationally not intensive



# Scale-Invariant Feature Transform (SIFT)

**Main objective:** building scale invariant image descriptors



Lowe 2004

## Keys steps

- 1 **Key point detection:** LoG
- 2 **Feature point localization:** Difference of Gaussian (DoG)
- 3 **Orientation assignment:** uses Histogram of Orientation
- 4 **Feature descriptor generation**

# SIFT results on the Deep Fashion dataset



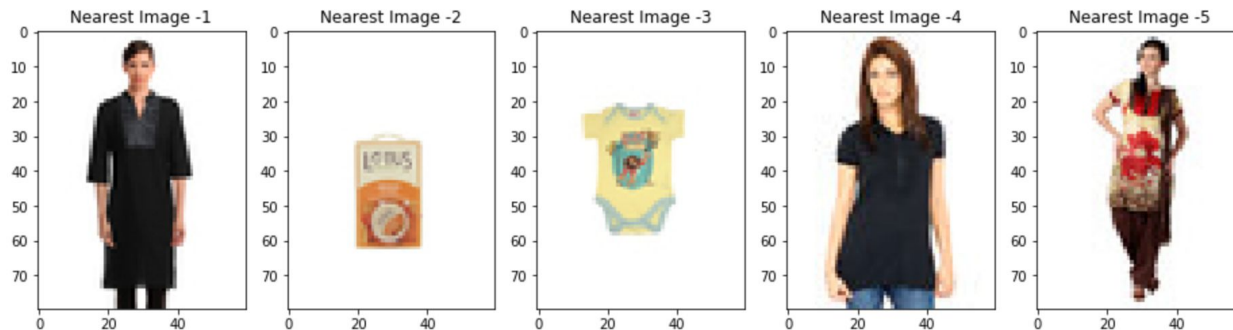
- Cosine similarity = 91.2% ! ✓

- Visual Matching



→ Biased dataset or too small images (80 x 80)

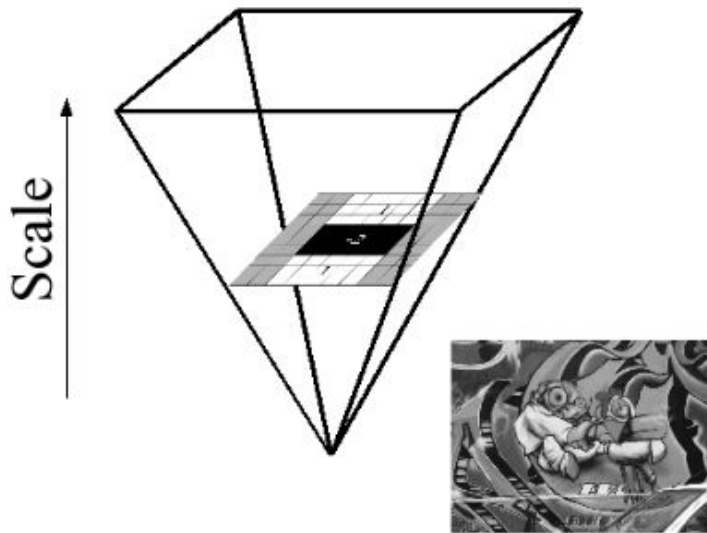
→ Wrong metric





# Speeded Up Robust Features (SURF)

Inspired by SIFT, but designed to be faster



## Keys steps

1

**Key point detection:** Integral image, box filters to approximate Hessian determinant

2

**Selection:** box filters of different sizes for scale, non-max suppression

3

**Orientation assignment:** Haar wavelet response on sliding windows of size  $\pi/3$

4

**Feature descriptor generation:** Haar wavelet responses weighted by Gaussian

# SURF results on the Deep Fashion dataset



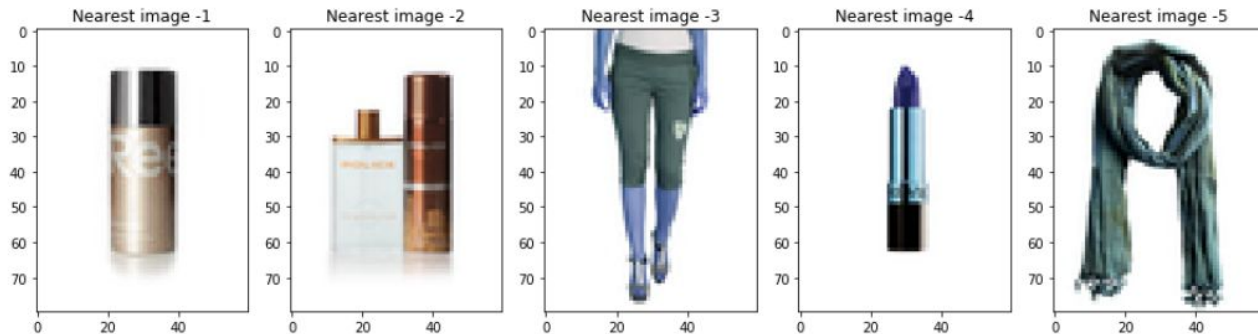
- Cosine similarity = 94.6% ! ✓

- Visual Matching



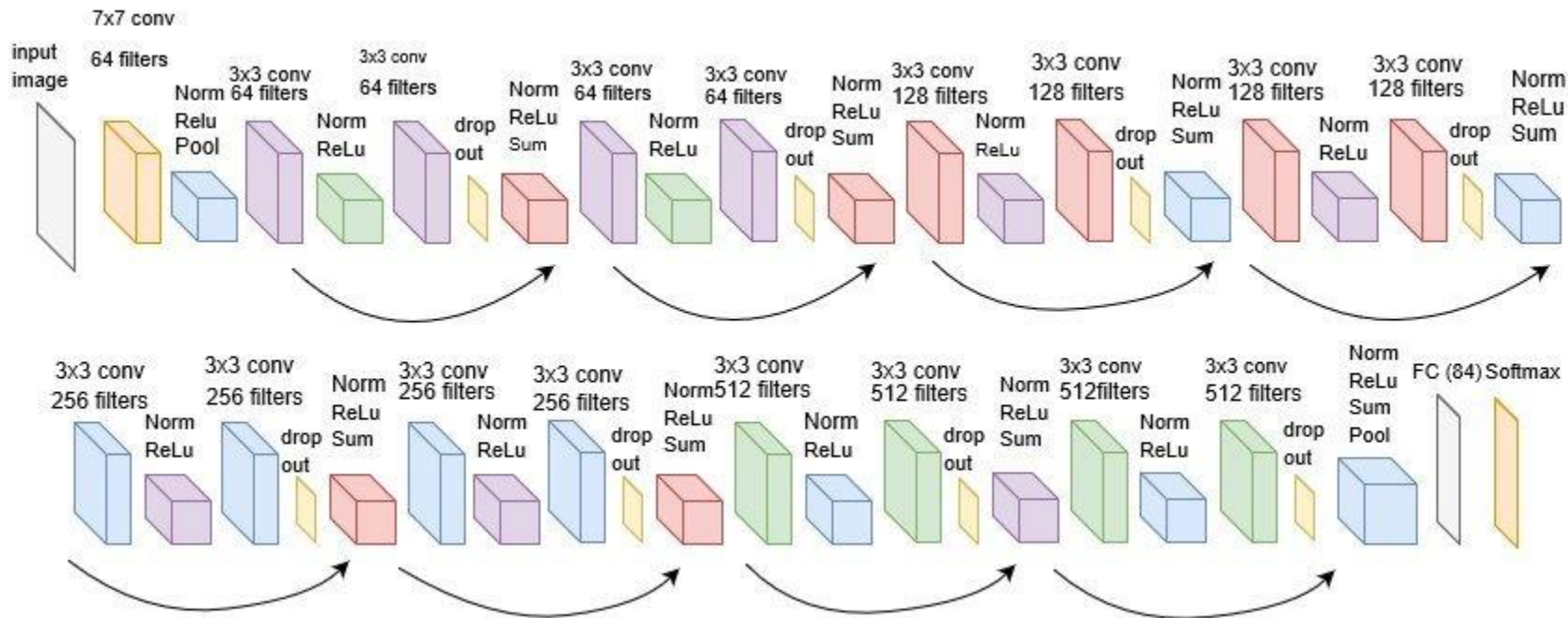
→ Biased dataset or too small images (80 x 80)

→ Not optimal matching method



# Convolutional Neural Networks

- Pretrained model: ResNet\_18



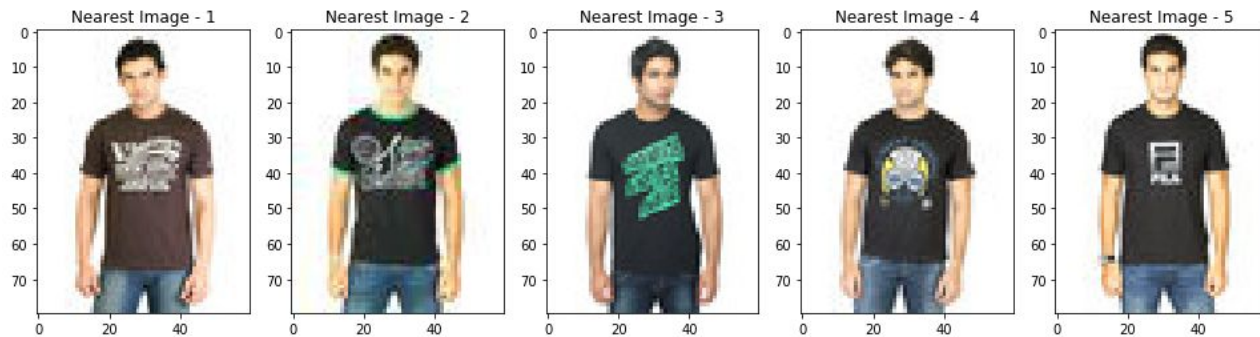
# Convolutional Neural Networks: Approach

- We take a pretrained model: ResNet\_18
- We fine tune the weights of the model to perform Classification on Deep Fashion Dataset.
- For each image extract the second-last layer as a Feature map of the image.
- Use LSHashing on feature maps to find the nearest neighbor.

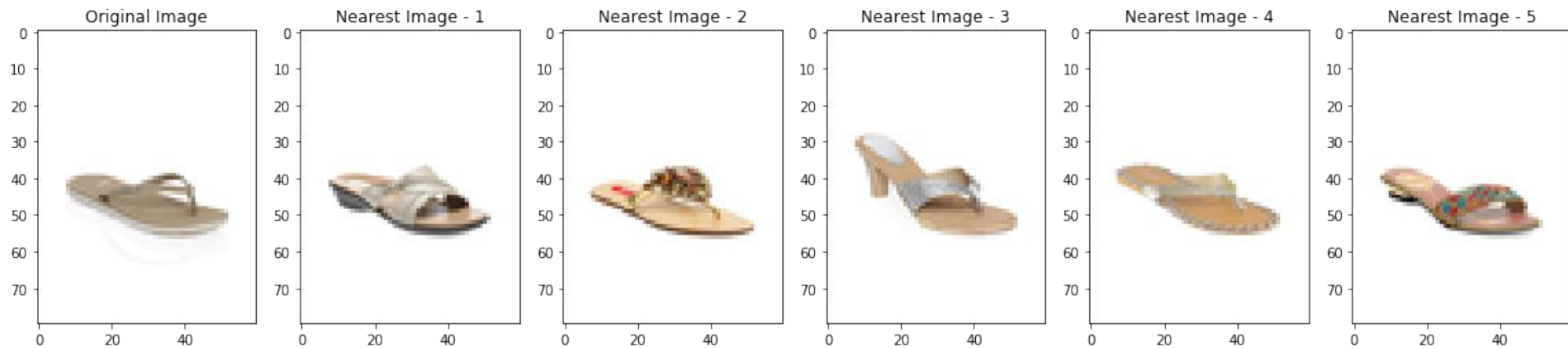
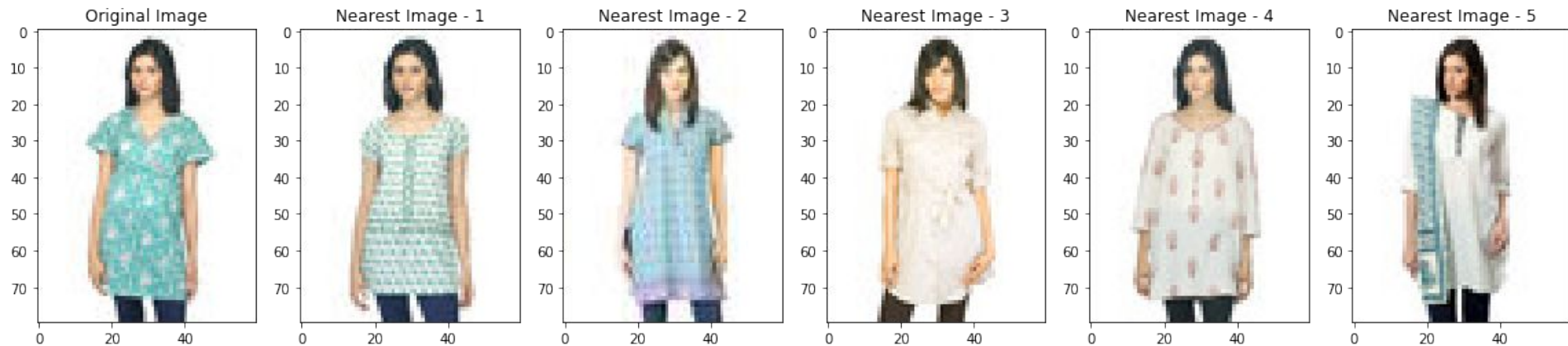
# CNN results on the Deep Fashion dataset



- Cosine similarity = 98.11% ✓
- Visual Matching
- Detects texture information
- **Computationally intensive**



# More Results



# Final results comparison

Approach	HOG	SIFT	SURF	CNN
Average Cosine Similarity	96.3%	93.4%	94.6%	<b>98.11%</b>
Visual Matching	Good	Very Bad	Medium	<b>Perfect</b>

# Final discussion and Conclusion

- **Challenges:** scalability to the whole dataset, accuracy of features for small images
- **Take home messages:** HOG works about as well as CNN for this type of application, SIFT and SURF have some difficulties
- **Next steps:** Try on harder images (non uniform background, more varied situations depicted), try on a larger dataset



**Thank you for your attention**

