Deep Learning Based Gender Determination Using Fingerprints

Roy Amante Salvador   Megan Villanueva

Department of Computer Science
College of Engineering, University of the Philippines Diliman

May 12, 2016

Outline

1. Introduction
2. Related Work
3. Methodology
   - Dataset
   - CNN Architectures
4. Experiment Results
   - Selection of CNN Architecture
   - Dealing with Imbalanced Dataset
   - Effect of Finger Class to Gender Determination
5. Conclusion

Introduction

Fingerprints

- unique
- can provide information such as gender

Related Work

- Females have a higher ridge density compared to male

Related Work

- Females have a higher ridge density compared to male
- (Gnanasivam et al. 2012)
  - Combining analysis of its frequency domain and spatial domain. Classify by K-Nearest Neighbour

Related Work

- Females have a higher ridge density compared to male
- (Gnanasivam et al. 2012)
  - Combining analysis of its frequency domain and spatial domain. Classify by K-Nearest Neighbour
- (Gornale et al. 2015)
  - SVM while employing 10 fold cross validation technique.
  - Classification Rate: 88.28%

Related Work

- Females have a higher ridge density compared to male
- (Gnanasivam et al. 2012)
  - Combining analysis of its frequency domain and spatial domain. Classify by K-Nearest Neighbour
- (Gornale et al. 2015)
  - SVM while employing 10 fold cross validation technique.
  - Classification Rate: 88.28%
- (Ganesh et al. 2015)
  - Applied thresholding on Fast Fourier Transform(FFT), Discrete Cosine Transform(DCT) and Power Spectral Density(PSD).
  - Classification Rate (Male): 78%
  - Classification Rate (Female): 88%

Outline

Data Set

National Institute of Standards and Technology (NIST) Special Database 4

- 4000 fingerprint images from 2000 individuals
- 8-bit grayscale
- 512 x 512 pixels

Table: NIST Special Database 4 Class Counts

	Male	Female	Total
Right Thumb	314	70	384
Right Index	360	82	442
Right Middle	332	72	404
Right Ring	328	68	396
Right Little	292	60	352
Left Thumb	328	68	396
Left Index	352	86	438
Left Middle	344	88	432
Left Ring	322	74	396
Left Little	284	72	356
Total	3250	750	4000

Data Set
Breakdown

- Training set: 50% of the samples of each finger class in each gender
- Test set: Remaining 50%

Outline

LeNet

Layer	1	2	3	4	5	Output
Stage	Conv	Max Pool	Conv	Max Pool	Full	Full
Spatial Input	256x256	252x252	126x126	122x122	61x61	1x1
# of Channels	20	20	50	50	500	2
Filter Size	5x5	2x2	5x5	2x2		
Stride	1	2	1	2		
Activation Function					ReLU	Softmax

Table: LeCun et al. 1998. It was successfully used for hand and machine written character recognition.

AlexNet

Layer	1	2	3	4	5	6	7	8	9	10	Output
Stage	Conv	Max Pool	Conv	Max Pool	Conv	Conv	Conv	Max Pool	Full + Dropout	Full + Dropout	Full
Spatial Input	256x256	62x62	31x31	31x31	15x15	15x15	15x15	15x15	7x7	1x1	1x1
# of Channels	96	96	256	256	384	384	256	256	4096	4096	2
Filter Size	11x11	3x3	5x5	3x3	3x3	3x3	3x3	3x3			
Stride	4	2	2	2	1	1	1	2			
Padding Size			2		1	1	1				
Group			2			2	2				
Activation Function	ReLU		ReLU		ReLU	ReLU	ReLU		ReLU	ReLU	Softmax
Normalization	LRN		LRN								

Table: Krizhevsky et al. 2012. Won the Imagenet Large Scale Visual Recognition Challenge (ILSVRC) by a huge margin

Maxout Network

Layer	1	2	3	4	5	6	7	8	9	10	Output
Stage	Conv	Max Pool	Conv	Max Pool	Conv	Conv	Conv	Max Pool	Full + Dropout	Full + Dropout	Full
Spatial Input	256x256	62x62	31x31	31x31	15x15	15x15	15x15	15x15	7x7	1x1	1x1
# of Channels	96	96	256	256	384	384	256	256	4096	4096	2
Filter Size	11x11	3x3	5x5	3x3	3x3	3x3	3x3	3x3			
Stride	4	2	2	2	1	1	1	2			
Padding Size			2		1	1	1				
Group			2			2	2				
Activation Function	Maxout		Maxout		Maxout	Maxout	Maxout		Maxout	Maxout	Softmax

Table: Goodfellow and Bengio 2013

Network In Network (NIN)

Layer	1	2	3	4	5	6	7	8	Output
Stage	MLPConv	Max Pool	MLPConv	Max Pool	MLPConv	Max Pool	MLPConv	Ave Pool	Full
# of Channels	96	96	256	256	384	384	1024	1024	2
Filter Size	11x11	3x3	5x5	3x3	3x3	3x3	3x3	6x6	
Stride	4	2	1	2	1	3	1	1	
Padding Size			2		1		1		
Activation Function	ReLU		ReLU		ReLU		ReLU		Softmax

Table: Lin et al. 2014.

Exponential Linear Unit (ELU) Network

Layer	1	2	3	4	5	6	7	8	9	10	Output
Stage	Conv	Max Pool	Conv	Max Pool	Conv	Conv	Conv	Max Pool	Full + Dropout	Full + Dropout	Full
Spatial Input	227x227	62x62	31x31	31x31	15x15	15x15	15x15	15x15	7x7	1x1	1x1
# of Channels	96	96	256	256	384	384	256	256	4096	4096	2
Filter Size	11x11	3x3	5x5	3x3	3x3	3x3	3x3	3x3			
Stride	4	2	2	2	1	1	1	2			
Padding Size			2		1	1	1				
Group			2			2	2				
Activation Function	ELU		ELU		ELU	ELU	ELU		Maxout	Maxout	Softmax

Table: Clevert et al. 2016. Yielded the best published result on CIFAR-100, without the use of multi-view evaluation or model averaging

Tools

- CAFFE Deep Learning Framework
- NVIDIA GeForce GTX 970M

Outline

1. Introduction
2. Related Work
3. Methodology
   - Dataset
   - CNN Architectures
4. Experiment Results
   - Selection of CNN Architecture
   - Dealing with Imbalanced Dataset
   - Effect of Finger Class to Gender Determination
5. Conclusion

Accuracy

Table: Performance of CNN Models with Imbalanced Training Set

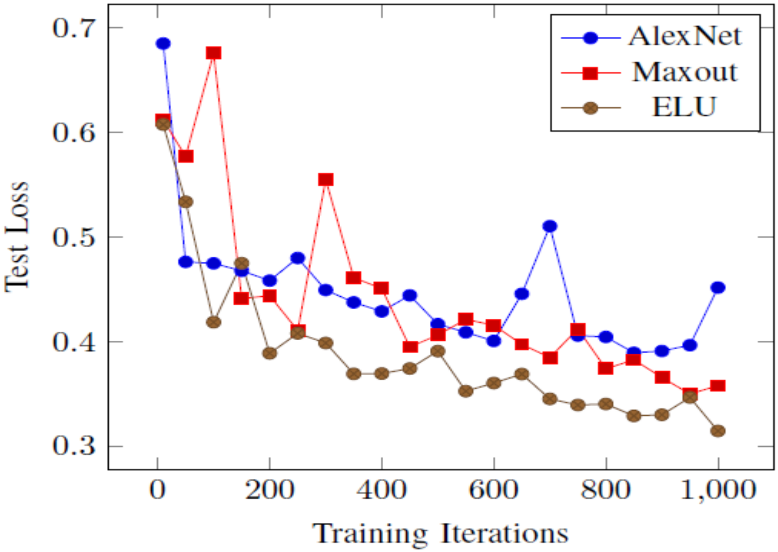
	Average Accuracy (%)		
	Male	Female	Overall
LeNet	95.50	47.50	86.07
AlexNet	94.84	58.93	88.12
Maxout Network	94.98	59.64	88.45
ELU Network	94.91	61.06	88.48

Speed

Table: Training Time of CNN Models for 10,000 iterations

	Average Training Time (minutes)
AlexNet	25.67
Maxout Network	31.00
ELU Network	31.00

Test Loss



AlexNet
Maxout
ELU
Test Loss
0.7
0.6
0.5
0.4
0.3
0
200
400
600
800
1,000
Training Iterations

Outline

Dealing with Imbalanced Dataset

- Undersampling

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances
  - Reduces the training examples by about 4 times

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances
  - Reduces the training examples by about 4 times
- Oversampling

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances
  - Reduces the training examples by about 4 times
- Oversampling
  - Used out-of-the-box mirroring and cropping feature in the data layer in CAFFE

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances
  - Reduces the training examples by about 4 times
- Oversampling
  - Used out-of-the-box mirroring and cropping feature in the data layer in CAFFE
  - Random crops and flips

Dealing with Imbalanced Dataset

- Undersampling
  - Randomly remove training instances from the Male class so that the two classes have the same number of instances
  - Reduces the training examples by about 4 times
- Oversampling
  - Used out-of-the-box mirroring and cropping feature in the data layer in CAFFE
  - Random crops and flips
  - Patches of size 227 x 227 are randomly extracted from 256 x 256 training images

ELU with Data Augmentation Comparison

Table: Performance of ELU Network with Different Training Sets

	Accuracy (%)		
	Male	Female	Overall
Imbalanced Data	94.91	61.06	88.48
With Undersampling	58.56	84.40	63.04
With Data Augmentation	94.28	72.00	90.10

Outline

Effect of Finger Class to Gender Determination

Table: Accuracy of Data Augmented ELU Network Per Finger Class

	Accuracy (%)		
	Male	Female	Overall
Right Thumb	98.09	34.29	86.46
Right Index	92.22	65.86	87.33
Right Middle	99.40	80.56	96.04
Right Ring	95.03	79.49	92.00
Right Little	91.78	80.00	89.77
Left Thumb	96.95	47.06	88.38
Left Index	92.04	81.39	89.95
Left Middle	98.26	79.54	98.26
Left Ring	94.41	78.38	91.41
Left Little	83.10	88.89	84.27
Overall	94.28	72.00	90.10

Conclusion

- Among the models LeNet, AlexNet, Maxout and ELU, ELU classifies best the gender of the person through its fingerprint which scored 88.48% overall.
- The middle finger best determines the gender of the fingerprint owner which scored 98.26% and 96.04% for left and right fingers respectively.