Achieving Perfect Score in Pattern Recognition Systems

Dr. Ching Y. Suen
Director, CENPARMI
Concordia University
Montreal, Canada

PATTERN RECOGNITION

THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY

3.1

EDITOR-IN-CHIEF:

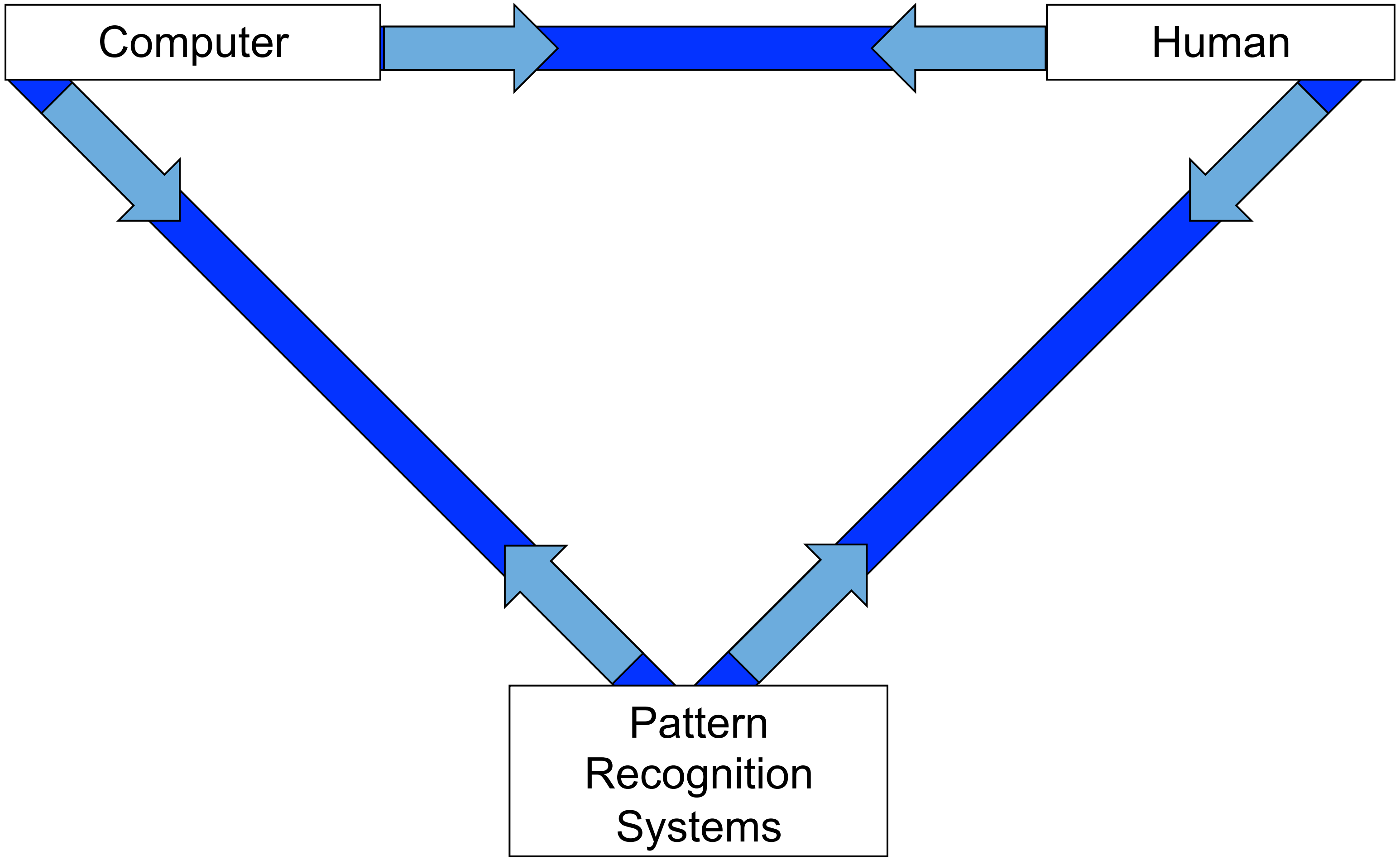
Ching Y. Suen *Concordia University , Montréal, Canada*

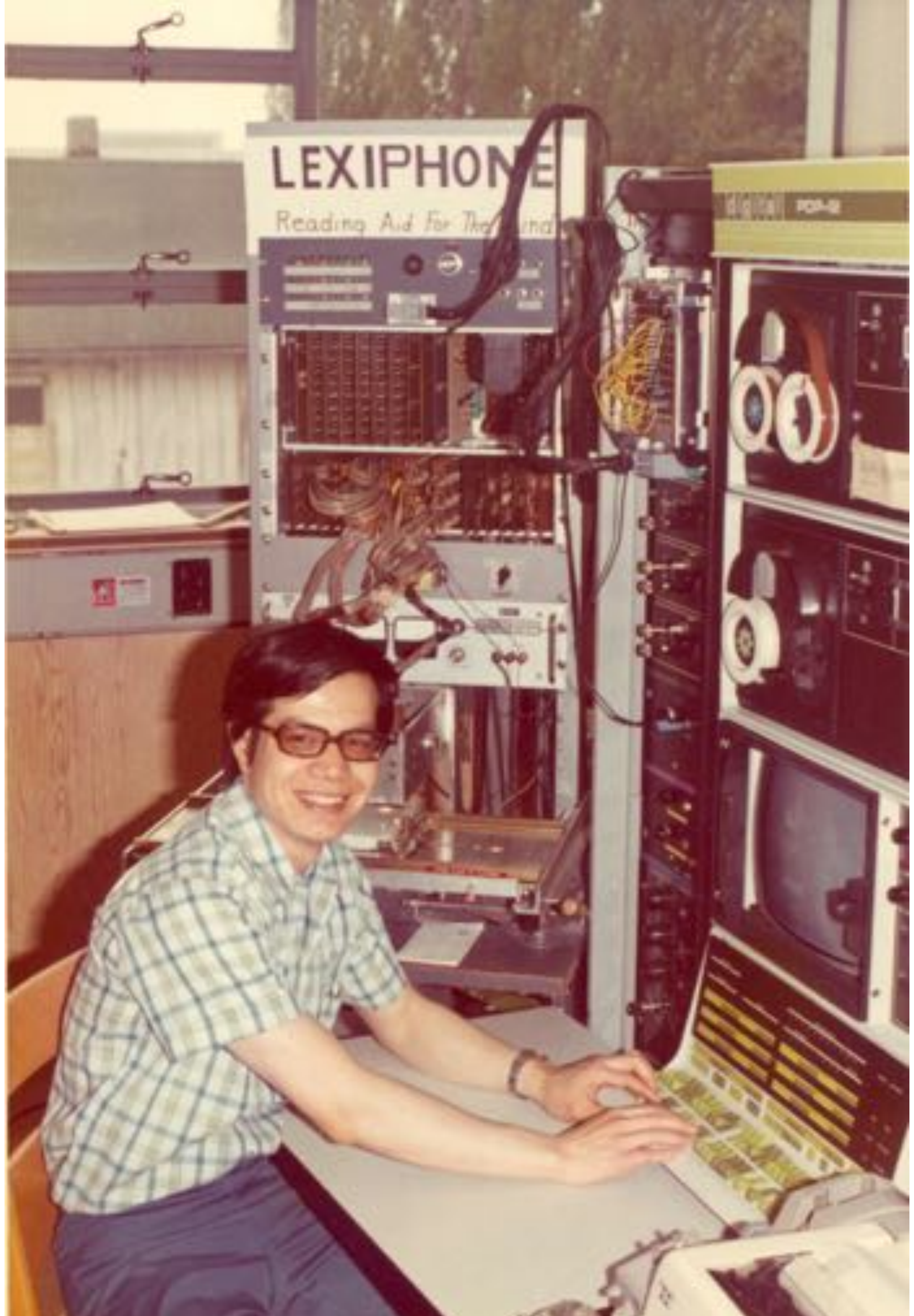
Pattern Recognition is the official journal of the Pattern Recognition Society. The Society was formed to fill a need for information exchange among research workers in the pattern recognition field. Up to now, we "pattern-recognitionophiles" have been tagging along in computer science, information theory, optical processing techniques, and other miscellaneous fields. Because this work in pattern recognition presently appears in widely spread articles and as isolated lectures in conferences in many diverse areas, the purpose of the journal Pattern Recognition is to give all of us an opportunity to get together in one place to publish our work. The journal will thereby expedite communication among research scientists interested in pattern recognition.

www.elsevier.com/locate/pr

Computer Science

Dr. Ching Y. Suen
CENPARMI
Concordia University




LEXIPHONE

PROCEEDINGS OF
THE FOURTH INTERNATIONAL
JOINT CONFERENCE ON

PATTERN RECOGNITION

Invited Survey

Advances in Recognition of Handprinted Characters

Ching Y. Suen

Department of Computer Science
Concordia University
Montreal, Canada H3G 1M8

Marc Berthod

Institut de Recherche d'Informatique et d'Automatique
Rocquencourt, 78150 Le Chesnay
France

Shunji Mori

Electrotechnical Laboratory
Nagata-cho, Chiyoda-ku
Tokyo, Japan

November 7-10, 1978, Kyoto, Japan

PROCEEDINGS OF THE IEEE, VOL. 68, NO. 4, APRIL 1980

Automatic Recognition of Handprinted Characters—The State of the Art

CHING Y. SUEN, SENIOR MEMBER, IEEE, MARC BERTHOD, AND SHUNJI MORI

Abstract–Based on a study of the extensive literature in handprint recognition, this paper presents a survey in this challenging field. Recognition algorithms, data bases, character models, and handprint standards are examined. Achievements in the recognition of hand-

4-percent mistakes when reading in the absence of context [205]. Errors in reading handprints are caused by infinite variations of shapes resulting from the writing habit, style,

手写体字符

自动识别技术的现状综述

1980.3

邮电部第三研究所
科技情报室

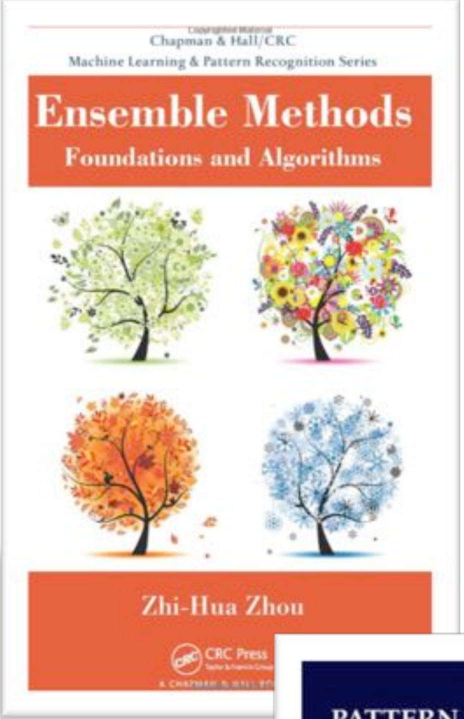
Introduction to Pattern Classification

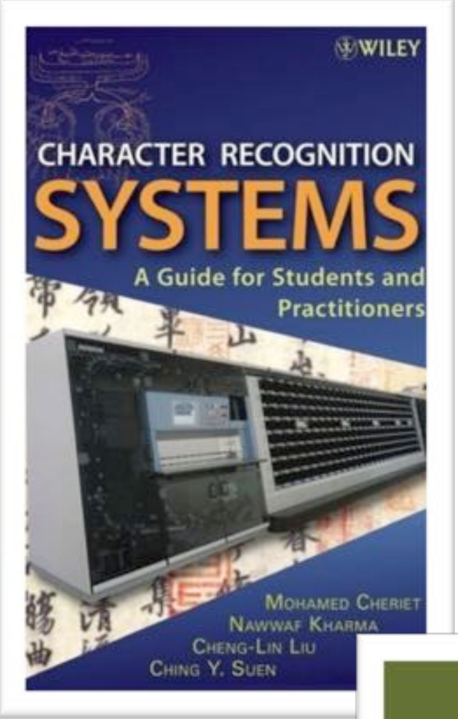
1.1 Pattern Classification . . . .
1.2 Induction Algorithms . . . .
1.3 Rule Induction . . . .
1.4 Decision Trees . . . .
1.5 Bayesian Methods . . . .

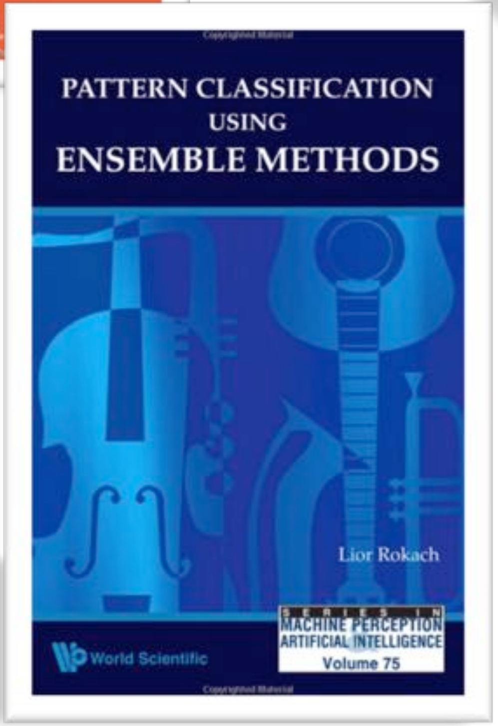
Other Induction Methods . . . . .
1.6.1 Neural Networks . . . . . .
1.6.2 Genetic Algorithms . . . . .
1.6.3 Instance-based Learning . .
1.6.4 Support Vector Machines .

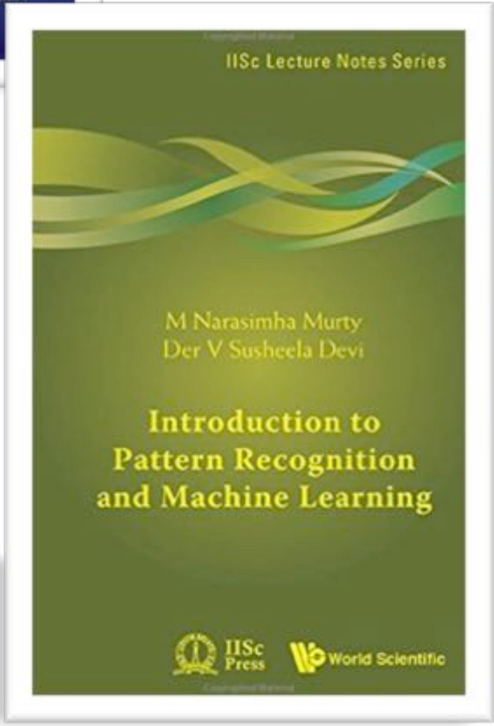
Methods . . . .
Bagging . . . .
Wagging . . . .
Random Forest and Random Subspace
Projection . . . .
Non-Linear Boosting Projection (NLBP)
Cross-validated Committees . . . .
Robust Boosting . . . .

Methods . . . .
Weighting Methods . . . . .
Majority Voting . . . .
Performance Weighting . .
Distribution Summation . .
Bayesian Combination . . .
Dempster–Shafer . . . . . .
Vogging . . . .
Naïve Bayes . . . .
Entropy Weighting . . . . .
Density-based Weighting .
DEA Weighting Method . .
Logarithmic Opinion Pool .


Chapman & Hall/CRC
Machine Learning & Pattern Recognition Series
Ensemble Methods
Foundations and Algorithms
Zhi-Hua Zhou
CRC Press


WILEY
CHARACTER RECOGNITION
SYSTEMS
A Guide for Students and Practitioners
Mohamed Cheriet
Nawwaf Kharma
Cheng-Lin Liu
Ching Y. Suen


PATTERN CLASSIFICATION
USING
ENSEMBLE METHODS
Lior Rokach
World Scientific
SERIES IN
MACHINE PERCEPTION
ARTIFICIAL INTELLIGENCE
Volume 75


IISc Lecture Notes Series
M Narasimha Murty
Der V Susheela Devi
Introduction to
Pattern Recognition
and Machine Learning
IISc Press
World Scientific

Neural Networks and Deep Learning

By Michael Nielsen / Aug 2015

Neural Networks and Deep Learning is a free online book. The book will teach you about:

1. Neural networks, a beautiful biologically-inspired programming paradigm which enables a computer to learn from observational data

2. Deep learning, a powerful set of techniques for learning in neural networks

Neural networks and deep learning currently provide excellent solutions to many problems in image recognition, speech recognition, and natural language processing.

Neural Networks and Deep Learning

by Michael Nielsen - Determination Press, Aug. 2015

- Using neural nets to recognize handwritten digits
- How the backpropagation algorithm works
- Improving the way neural networks learn
- A visual proof that neural nets can compute any function
- Why are deep neural networks hard to train?
- Deep learning
- Appendix: Is there a simple algorithm for intelligence?

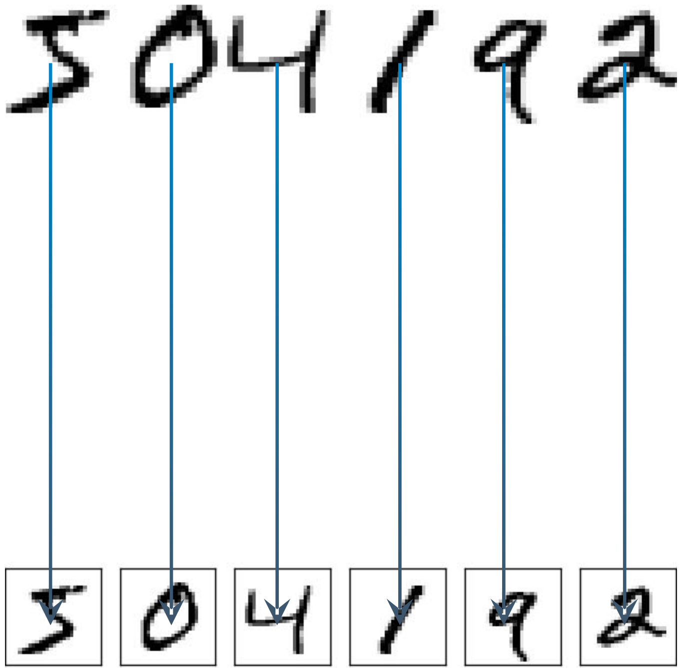
CHAPTER 1

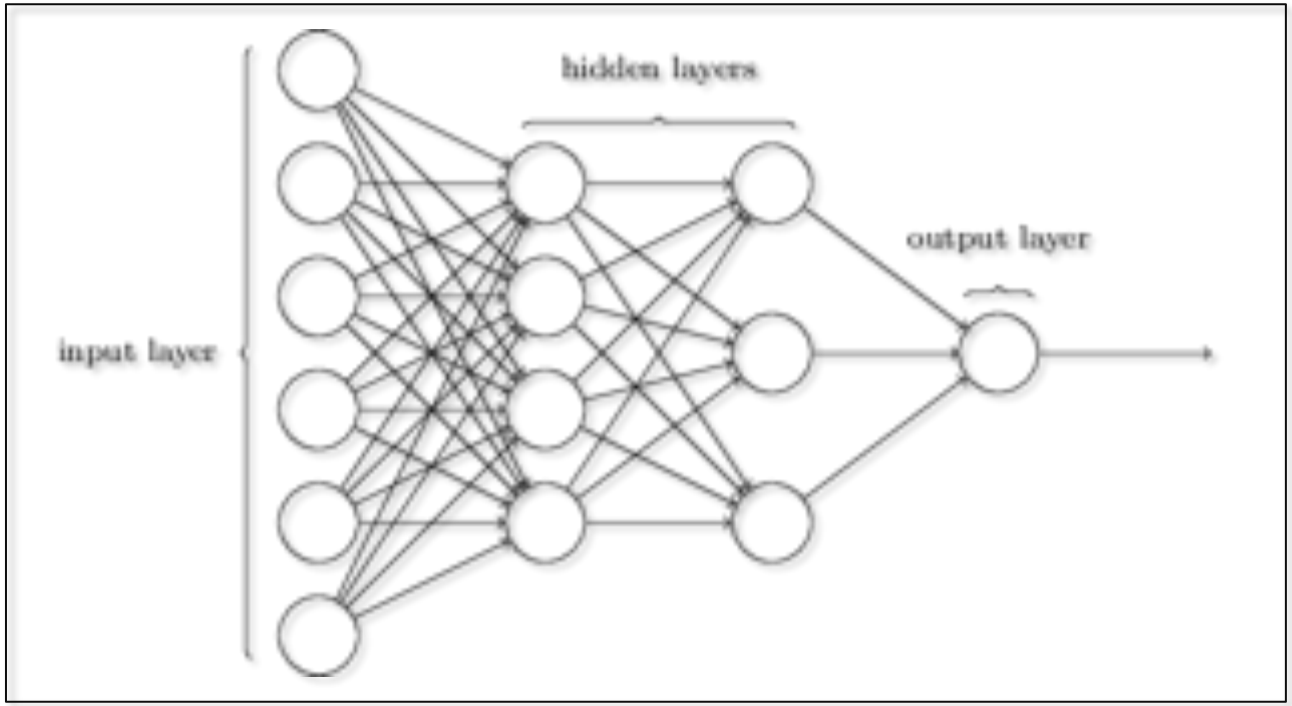
Using neural nets to recognize handwritten digits

The human visual system is one of the wonders of the world. Consider the following sequence of handwritten digits:

Most people effortlessly recognize those digits as 504192. That ease is deceptive. In each hemisphere of our brain, humans have a primary visual cortex, also known as V1, containing 140 million neurons, with tens of billions of connections between them.

Using Neural Nets to Recognize Handwritten Digits



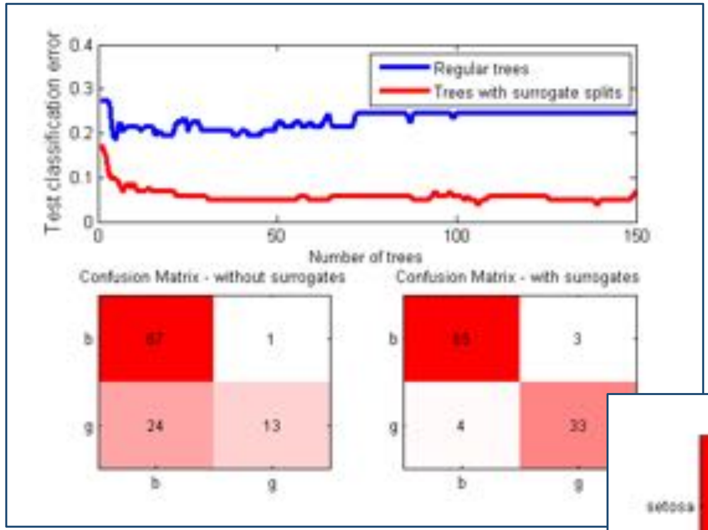

hidden layers
output layer
input layer

MATLAB for Machine Learning

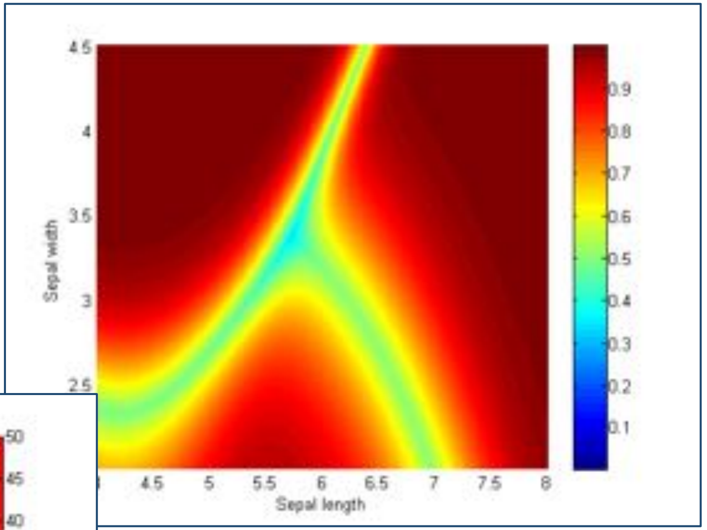
Explore and share user-generated examples or toolboxes,
and view MATLAB Answers for solutions to your questions.

From File Exchange:

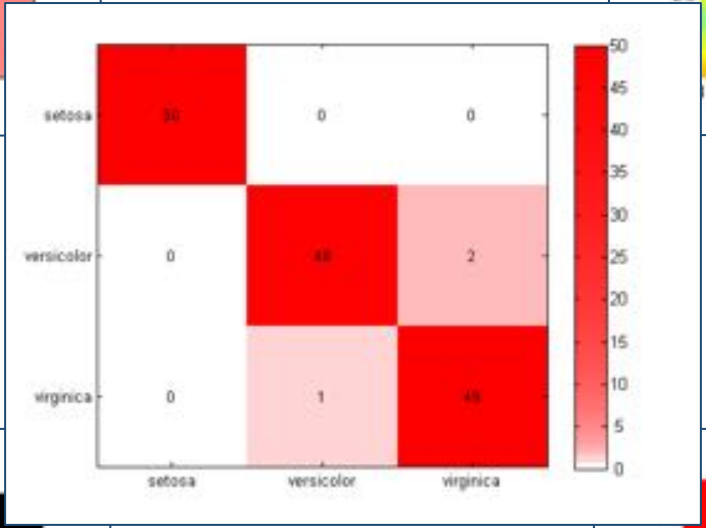
- MatConvNet: CNNs for MATLAB
- Deep Learning Toolbox by Rasmus Berg Palm
- Deep Neural Network by Masayuki Tanaka



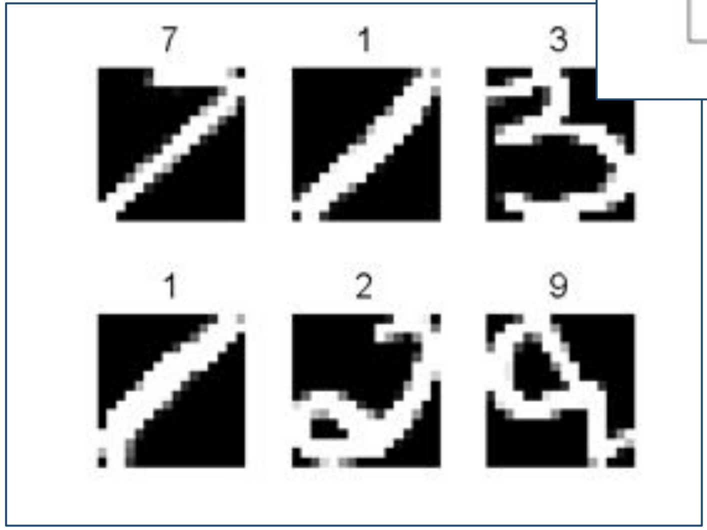
Classification in the Presence of Missing Data



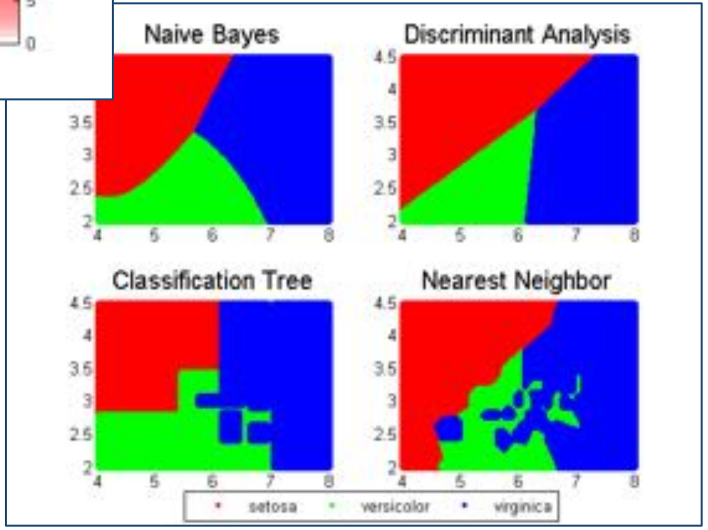
Classification Probability



Confusion Matrix



Handwriting Recognition Using Bagged Classification Trees



Visualize Decision Surfaces for Different Classifiers

ELSEVIER

Pattern Recognition 40 (2007) 1816–1824

PATTERN RECOGNITION

THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY

www.elsevier.com/locate/pr

A trainable feature extractor for handwritten digit recognition

Fabien Lauer[a,*], Ching Y. Suen[b], Gérard Bloch[a]

[a]*Centre de Recherche en Automatique de Nancy (CRAN UMR 7039), Nancy-Univerity, CNRS CRAN–ESSTIN, Rue Jean Lamour, 54519 Vandœuvre Cedex, France*

[b]*Center for Pattern Recognition and Machine Intelligence (CENPARMI), Concordia University, 1455 de Maisonneuve Blvd West, Suite EV003.403, Montréal, QC, Canada, H3G 1M8*

Received 17 November 2005; received in revised form 27 June 2006; accepted 6 October 2006

Abstract

This article focuses on the problems of feature extraction and the recognition of handwritten digits. A trainable feature extractor based on the LeNet5 convolutional neural network architecture is introduced to solve the first problem in a black box scheme without prior knowledge on the data. The classification task is performed by support vector machines to enhance the generalization ability of LeNet5.

A Hybrid Multiple Classifier System of Unconstrained Handwritten Numeral Recognition[1]

C. L. He and C. Y. Suen

Centre for Pattern Recognition and Machine Intelligence, Concordia University, Montreal, Quebec, Canada H3G IM8

e-mail: {cl_he, suen}@cenparmi.concordia.ca

Abstract—o raise the reliability, a hybrid multiple classifier system is proposed by integrating the cooperation and combination of three classifiers: SVM [1], MQDF [3], and leNet5 [2]. In combination, we apply the total probability theorem to the classifiers at the rank level. Meanwhile, differential measurement and probability measurement are defined for the rejection option on different types of classifiers. Considerable improvement has been observed, and the final recognition rate of this system ranges from 95.54 to 99.11% with a reliability of 99.54 to 99.11%.

Many psychological experiments have been performed, e.g.

1. Studied the handwriting of 1,500 students,

2. Studied the characteristics of characters written by right-handed and left-handed people,

3. Finding the legibility of all alphanumeric characters, using the tachistoscope,

4. Finding the relative importance of different portions of the characters,

5. Asked both OCR experts and naïve subjects to write down their criteria in determining the identity of confusing characters,

6. Finding the differences between naïve subjects and accountants in recognizing handwritten numbers,

7. Determining the boundaries between confusing pairs of characters, e.g. 4 - 9, 2-7.

3. source: Liu C.L., Nakashima K., Sako H., Fujisawa H., "Handwritten digit recognition: benchmarking of state-of-the-art techniques", Pattern Recognition, Vol.36, pp.2271-2285, **2003**

=>This Paper's Recognition Rate : for CENPARM I DB = **99.05%** -by SVC-rbf
for CEDAR DB = **99.46%** -by SVC-rbf
for MNIST DB = **99.39%** -by SVC-rbf

Table 1 Previous results on CENPARMI database

Method	Correct (%)	Error (%)	Reject (%)
*Suen et al. [26]	93.05	0	6.95
*Franke et al. [32]	98.50	1.50	0
Lee [33]	97.80	2.20	0
*Gader et al. [34]	98.30	1.70	0
Liu et al. [9]	98.00	2.00	0
Hwang et al. [35]	97.90	2.10	0
Franke [36]	97.60	2.40	0
*Suen et al. [37]	**98.85**	1.15	0
Oh et al. [38]	97.85	2.15	0
Liu et al. [39]	**98.45**	1.55	0

*Multiple classifiers.

Table 2 Previous results on CEDAR database

Method	Correct (%)	Error (%)	Reject (%)
Lee et al. [8]	**98.87**	1.13	0
*Ha et al. [40]	99.09	0.91	0
*Suen et al. [37]	**99.77**	0.23	0
*Filatov et al. [41]	99.54	0.46	0
Cai et al. [42]	98.40	1.60	0
Oh et al. [38]	98.73	1.27	0

*Multiple classifiers.

Table 3 Previous results on MNIST database

Method	Correct (%)	Error (%)	Reject (%)
LeNet-4 [1]	98.90	1.10	0
LeNet-5 [1]	99.05	0.95	0
*Boosted LeNet-4 [1]	99.30	0.70	0
SVC-poly [43]	98.60	1.40	0
Virtual SV [43]	99.00	1.00	0
Pairwise SVC [44]	98.48	1.52	0
Dong et al. [45]	99.01	0.99	0
Mayraz et al. [48]	98.30	1.70	0
Belongie et al. [47]	99.37	0.63	0
Teow et al. [46]	**99.41**	0.59	0

*Multiple classifiers.

2. source: C.Y. Suen, J. Kim, K. Kim, Q. Xu, L. Lam, "Handwriting recognition-the last frontiers", Proceedings of the Fifteenth International Conference on Pattern Recognition, Vol. 4, Barcelona, Spain, pp. 1-10, 2000.

Table 1. Recognition rates of isolated handwritten numerals.(%)

Authors	Database	Error	Reliability	Recognition
'96 S.W.Lee [12]	CENPARMI	2.90	97.10	97.10
'97 T.M.Ha [11]	CEDAR	0.91	99.09	99.09
'92 IBM [13]	NIST	3.49	96.51	96.51
'92 AT&T [13]	NIST	3.16	96.84	96.84
'97 T.M.Ha [11]	NIST	2.90	97.10	97.10
'98 CENPARMI [14]	NIST	0.93	99.07	99.07

Table 2. Recognition rates of isolated handwritten numerals by combined classification methods.

Authors	Database	Error	Reliability	Recognition
'93 AEG-CENPARMI [45]	CENPARMI	1.50	98.50	98.50
'93 CENPARMI [46]	CENPARMI	0.00	100.00	93.05
'97 S.B.Cho [15]	CENPARMI	3.95	96.05	96.05
'99 CENPARMI [34]	CENPARMI	1.15	98.85	98.85
'93 D.S.Lee [47]	CEDAR	1.13	98.87	98.87
'98 Parascript [48]	CEDAR	0.46	99.54	99.54
'99 CENPARMI [34]	CEDAR	0.23	99.77	99.77

Table 2
Comparison of the recognition rate on the test set between a full neural network (NN) and SVM classifiers using the outputs of the last convolutional layer of the same network as input features.

Classifier	training set size	test rec. rate
NN	15000	98.45
SVM poly5	15000	98.57
NN	30000	98.63
SVM poly5	30000	98.86
NN	60000	98.70
SVM linear	60000	98.94
SVM poly5	60000	98.96
SVM rbf	60000	99.17

Table 3

Comparison between the elastic distortions and the affine transformations (translations) for the expansion of the training set. The lines "none" correspond to the original training set before the generation of new samples.

distortion	training set size	test rec. rate
none	15000	98.45
elastic	150000	**98.99**
affine	135000	98.95
none	30000	98.63
elastic	300000	**99.22**
affine	270000	99.15
none	60000	98.70
elastic	600000	99.28
affine	540000	**99.32**

Comparison of the Performance in Different Classifiers with Different Strategies

Classifiers		Recognition Rate, %	Rejection Rate, %	Reliability Rate, %
SVM		99.23	0	99.23
MQDF		98.44	0	98.44
leNet5		98.02	0	98.02
Cooperation		94.86	5.12	99.93
Combination		99.00	0	99.00
Hybrid System	High reliability	95.54	4.39	99.93
	High accuracy	99.11	0	99.11
	High reliability and high accuracy	98.34	1.21	99.54

Table 4
Published results of other methods on the MNIST database. The *distortion* column indicates the type of distortion used to expand the training set.

Classifier	distortion	reference	test error (%)
SVM		[18]	1.4
LeNet5		[2]	0.95
TFE-SVM		**this paper**	**0.83**
VSVM	affine	[18]	0.8
LeNet5	affine	[2]	0.8
LeNet5	**elastic**	**this paper**	**0.72**
boosted-LeNet4	affine	[2]	0.7
LeNet5	**affine**	**this paper**	**0.68**
VSVM2	affine	[18]	0.68
K-NN		[19]	0.63
VSVM2+deskewing	affine	[18]	0.56
TFE-SVM	**elastic**	**this paper**	**0.56**
TFE-SVM	**affine**	**this paper**	**0.54**
convolutional NN	elastic	[7]	0.4

Fig. 4. The 54 patterns of the test set misclassified by the TFE-SVM trained on the training set extended by affine transformations. The labels appear above the image (`target->output`) and the sample index below.

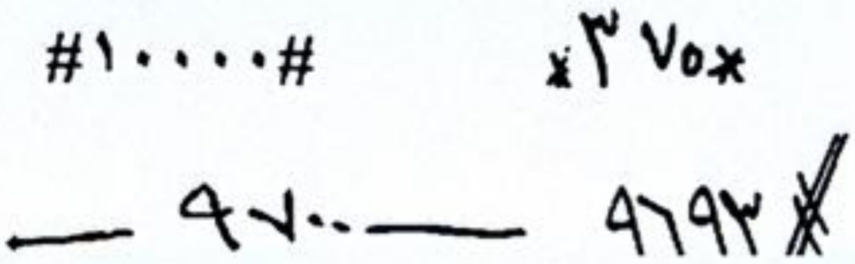


Fig. 10.6. Few samples of Arabic courtesy amounts.

Fig. 10.7. A sample of Indian digits.

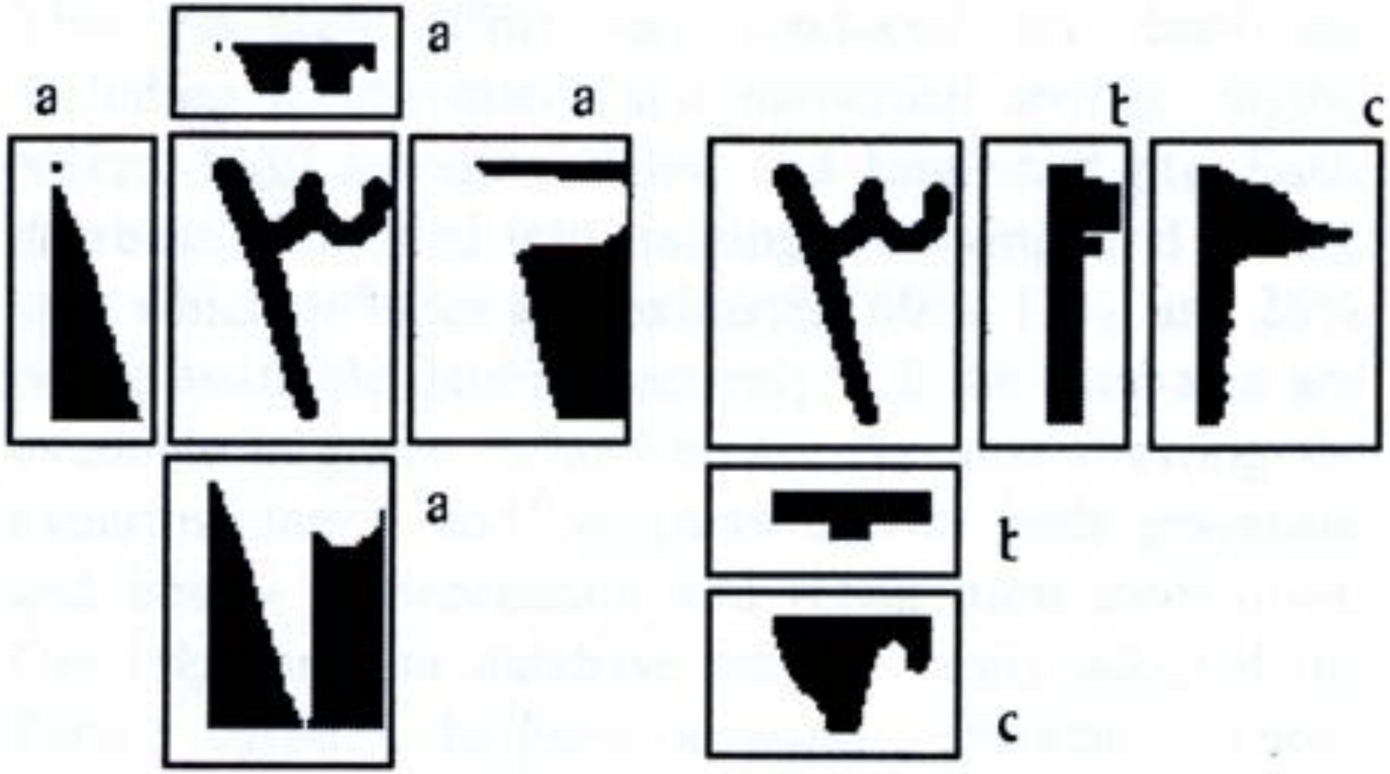
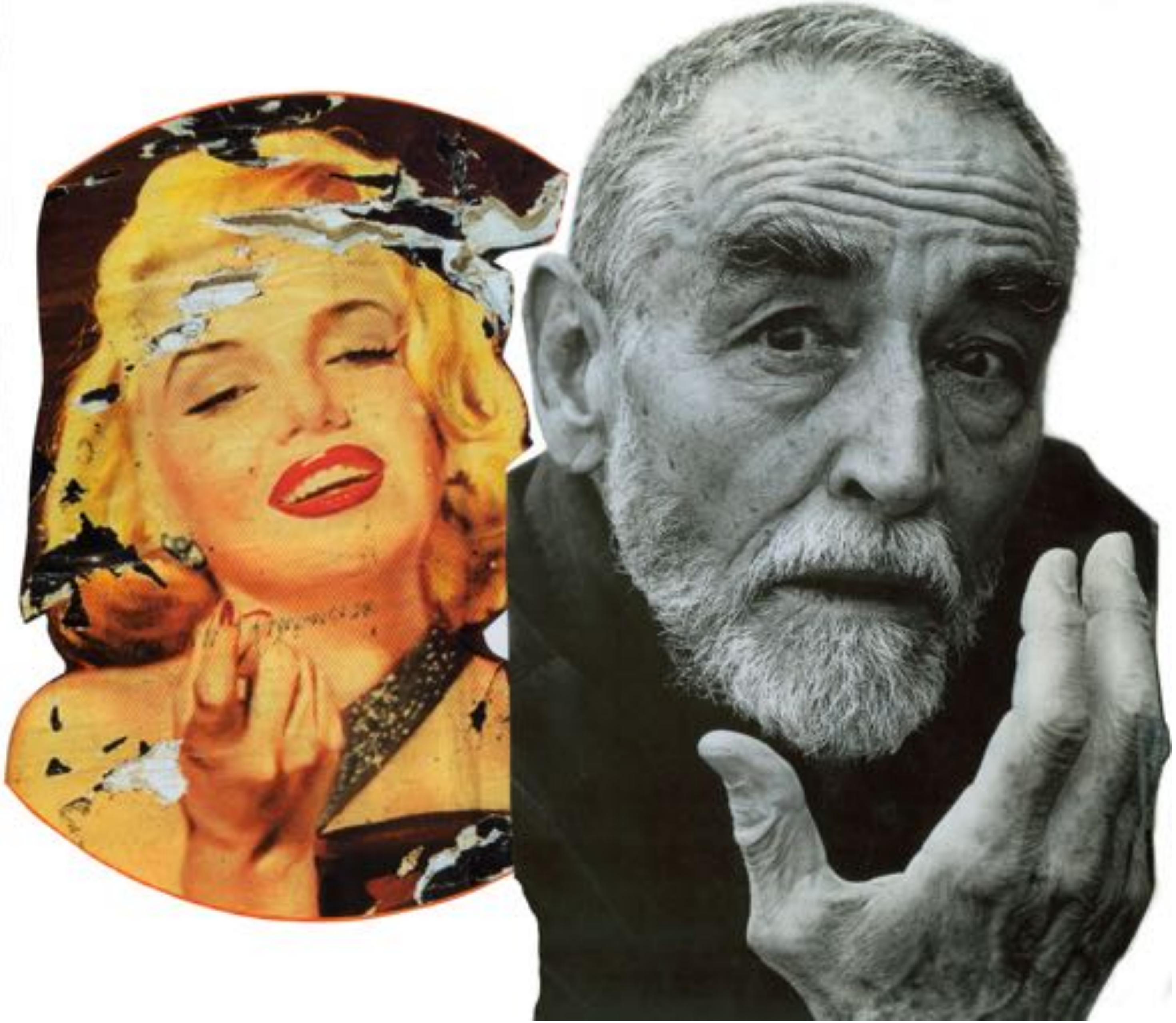


Figure 4. A sample of the features. a: outer profiles, b: crossing counts, c: projection histogram.



ELSEVIER

Pattern Recognition Letters 26 (2005) 369–379

Pattern Recognition Letters

www.elsevier.com/locate/patrec

Analysis of errors of handwritten digits made by a multitude of classifiers

Ching Y. Suen *, Jinna Tan

Centre for Pattern Recognition and Machine Intelligence, Concordia University, CENPARMI, Suite GM 606, 1455 de Maisonneuve Blvd. West, Montréal, Québec, Canada H3G 1M8

Received 5 July 2004; received in revised form 18 October 2004
Available online 19 December 2004

Abstract

In this paper we describe an in-depth study on some data misclassified by a collection of classifiers produced by different authors. First of all, we divide the errors into three categories based on their quality and analyze their distributions according to category. Common errors made by three or more classifiers out of five have been identified and analyzed to deduce the reasons of misclassification. Finally, based

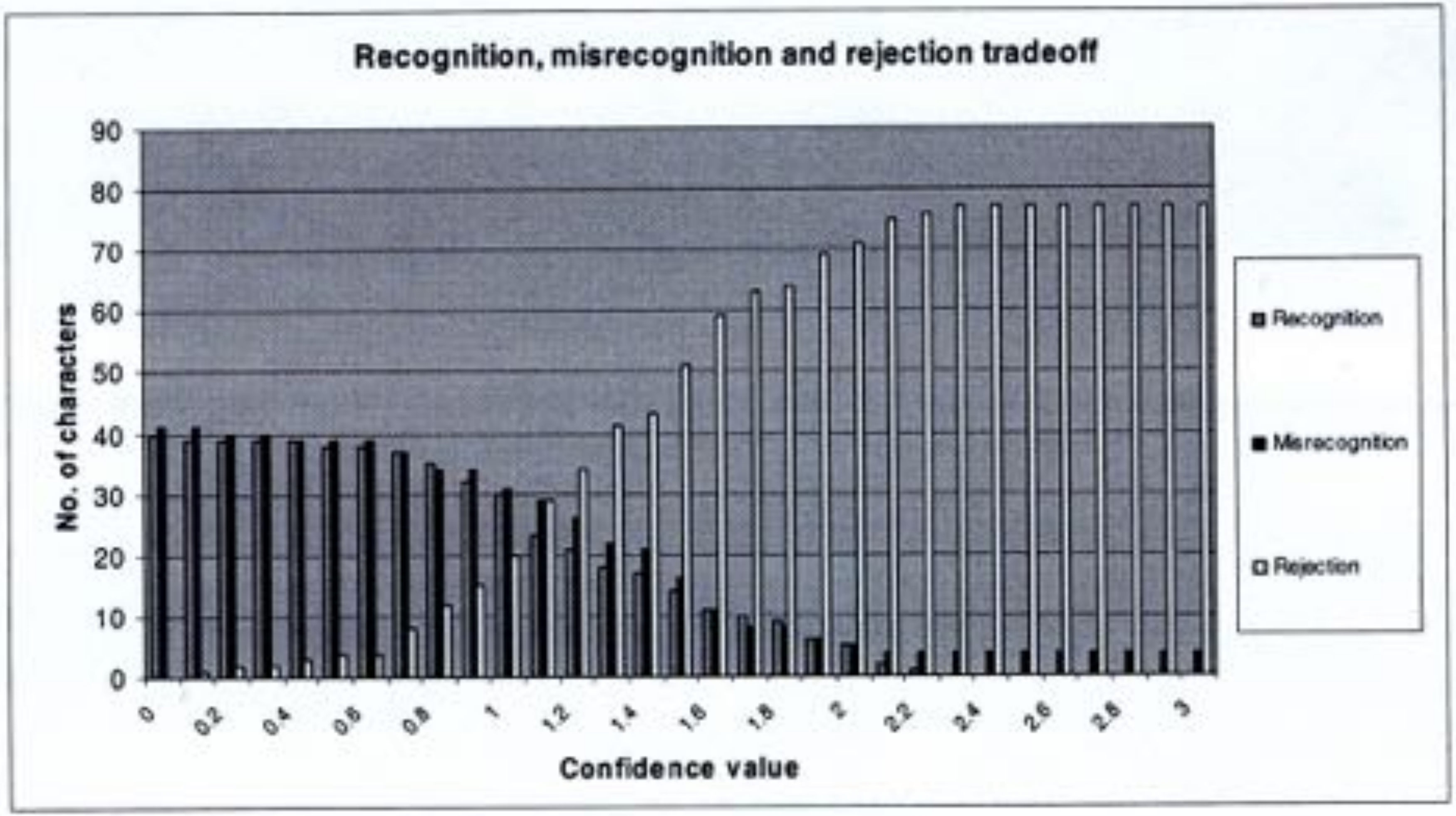


Fig. 7 Trade-off among the recognition, error and rejection rates in the sum voting scheme

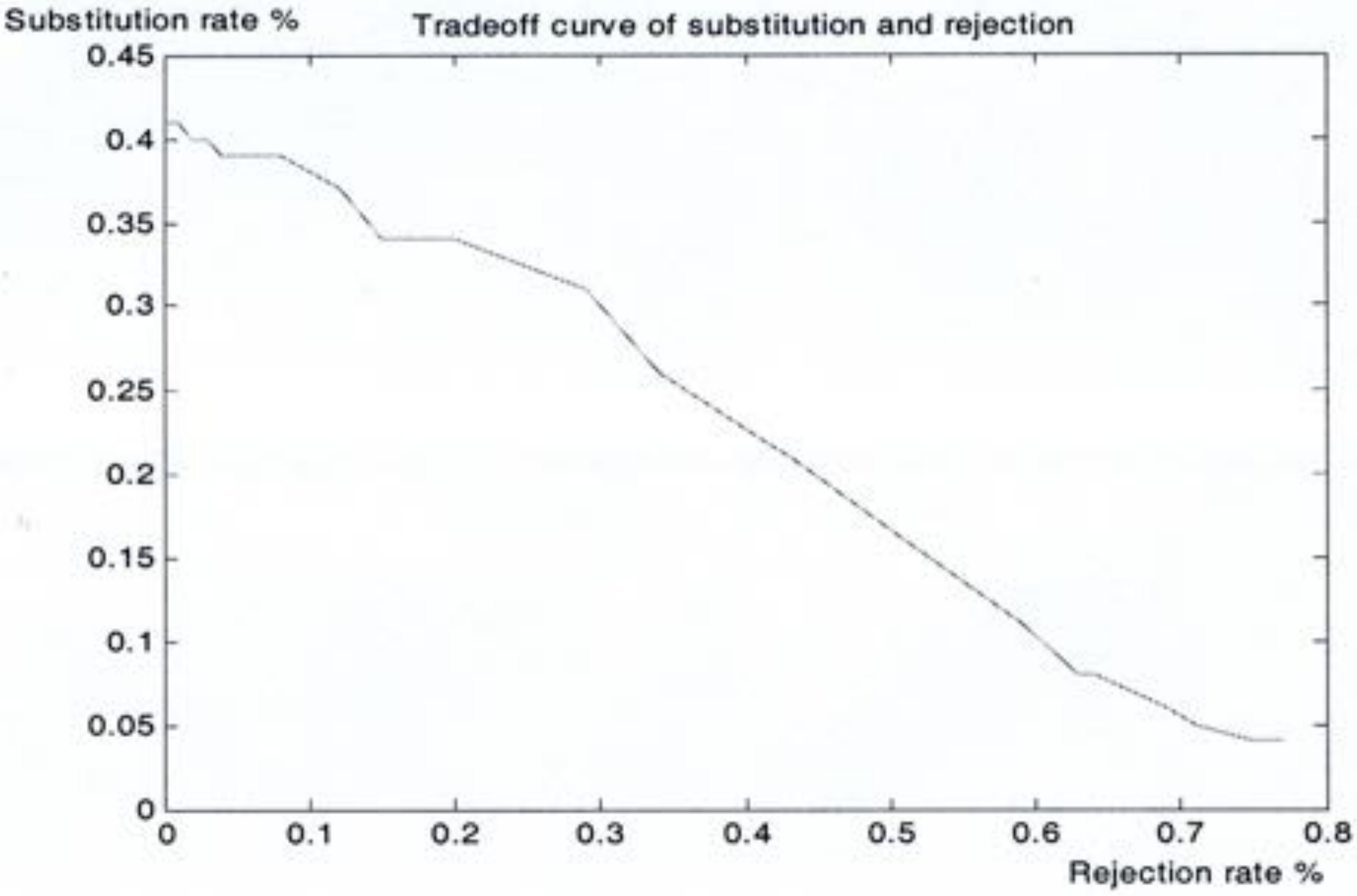


Fig. 8 Trade-off curve between the rejection rate and substitution rate

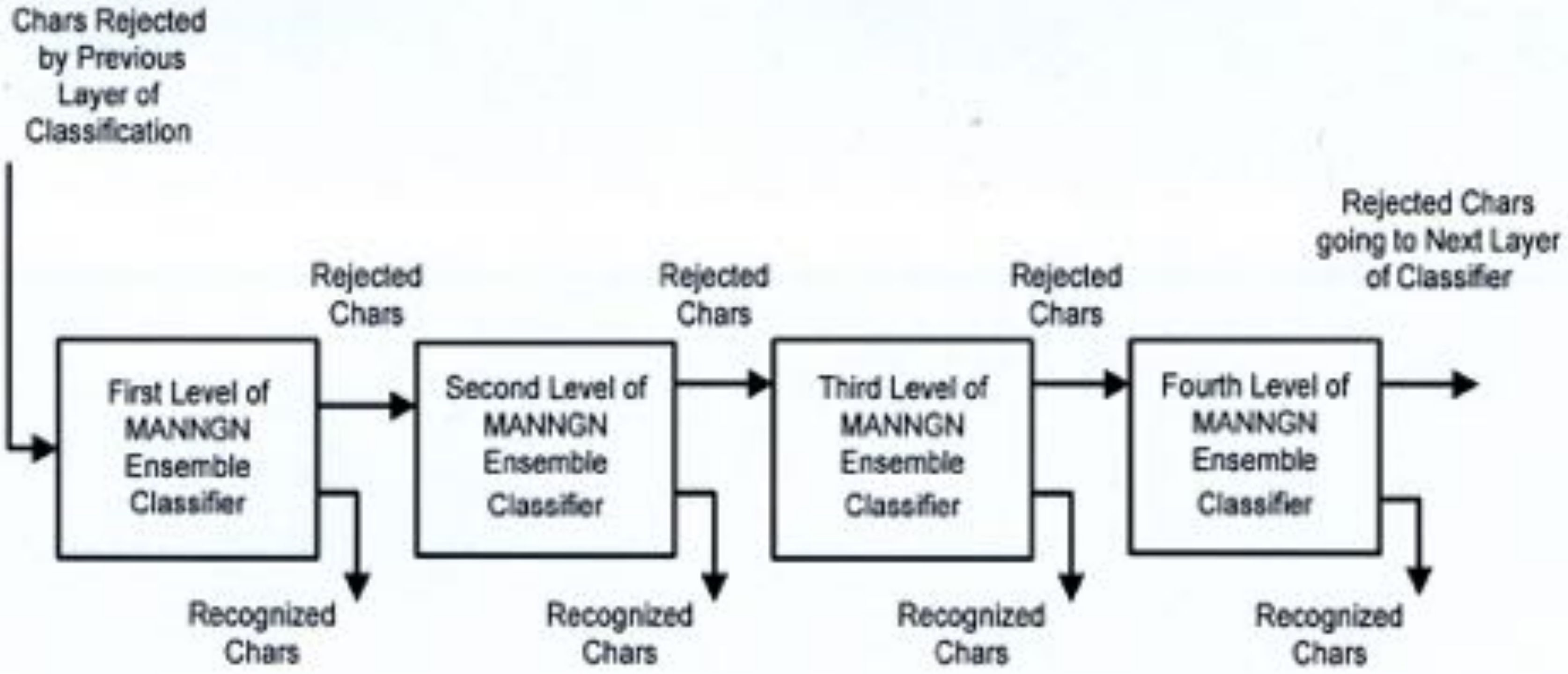


Fig. 5 Schematic diagram of one layer of classification in a cascade classification structure

Fig. 6 shows the schematic diagram of an MANNGN ensemble classifier.

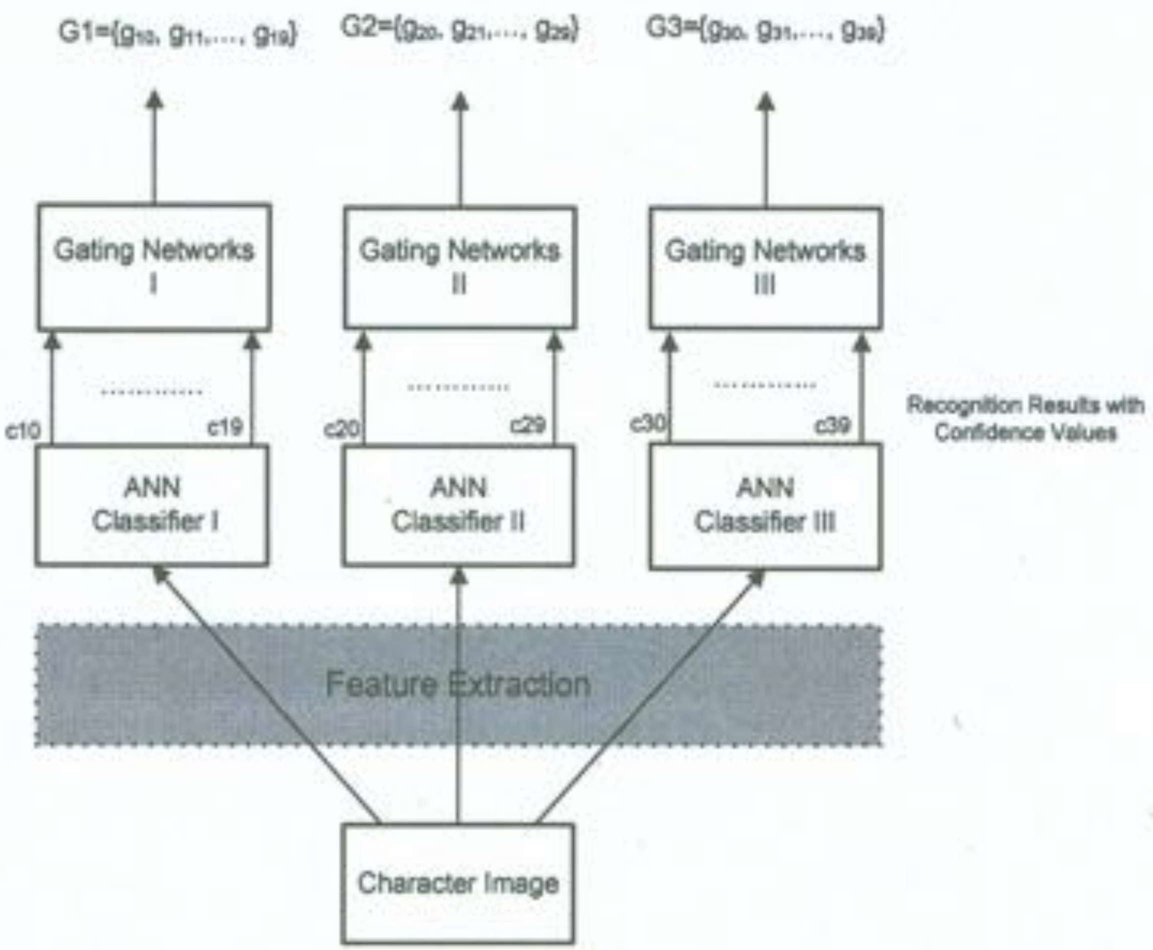


Fig. 6 Schematic diagram of an MANNGN ensemble classifier

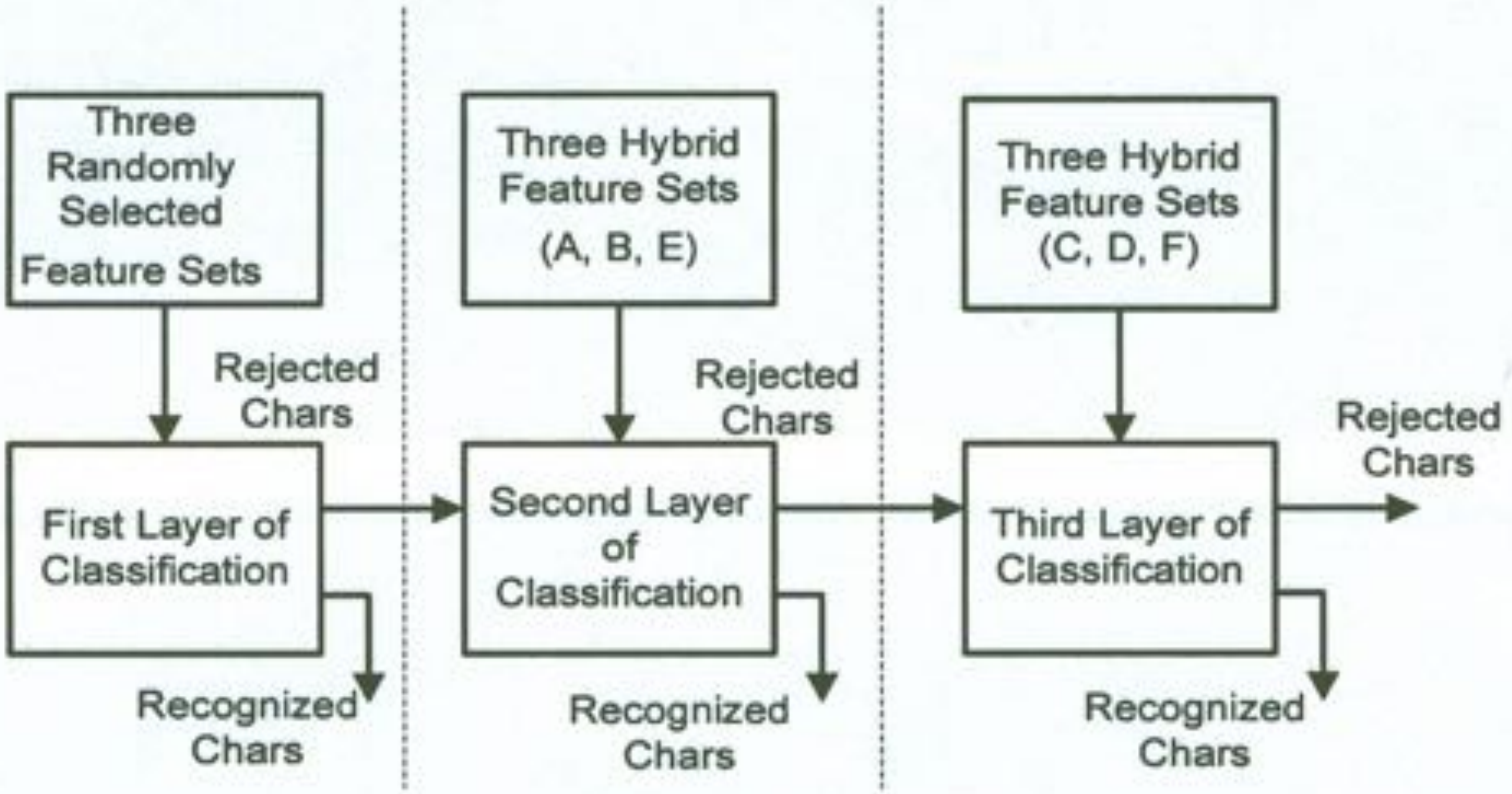


Fig. 4 Cascade recognition structure with rejection strategy

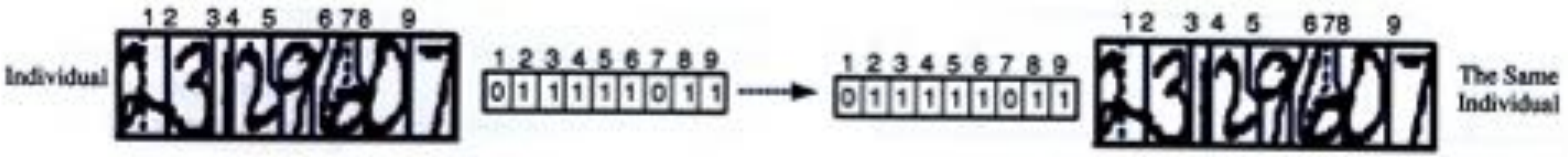


Fig. 14. Selection: very high fitness chromosomes are given a higher chance to reproduce themselves, and to be present in the new generations.

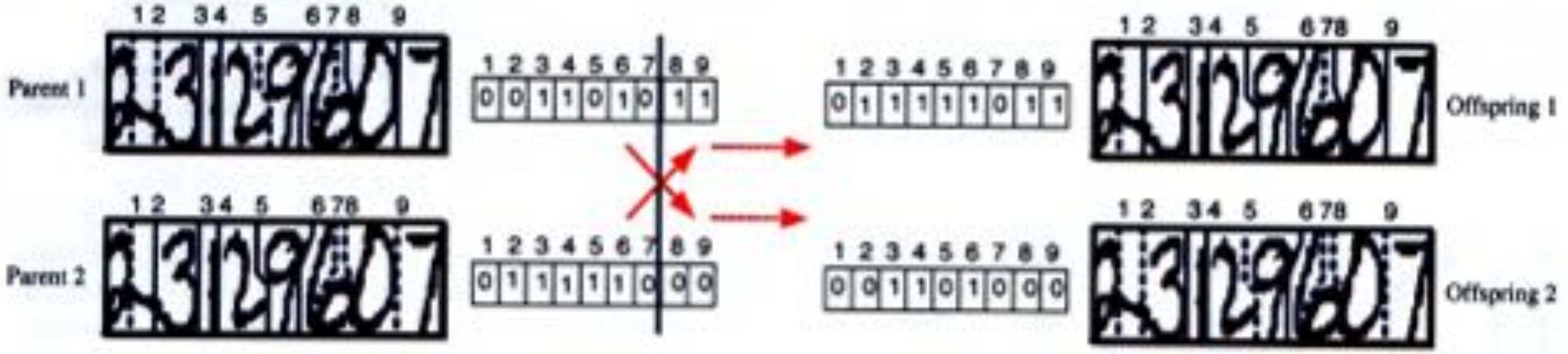


Fig. 15. Crossover: pairs of chromosomes are selected based on their relative fitness in order to perform crossover at a random position. In this example, crossover happens between the locations of the seventh and eighth genes in the two parent chromosomes, and it produces two new offsprings.

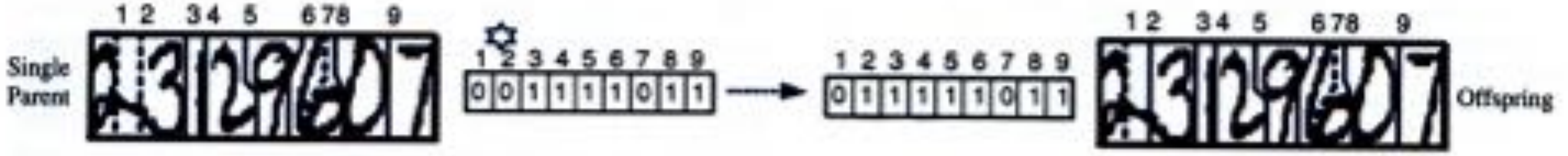


Fig. 16. Mutation: single chromosomes are selected based on their relative fitness in order to be mutated at a single random position. In this example, mutation happens on the second cutting path (second gene in the parent chromosome), and it produces one new offspring.

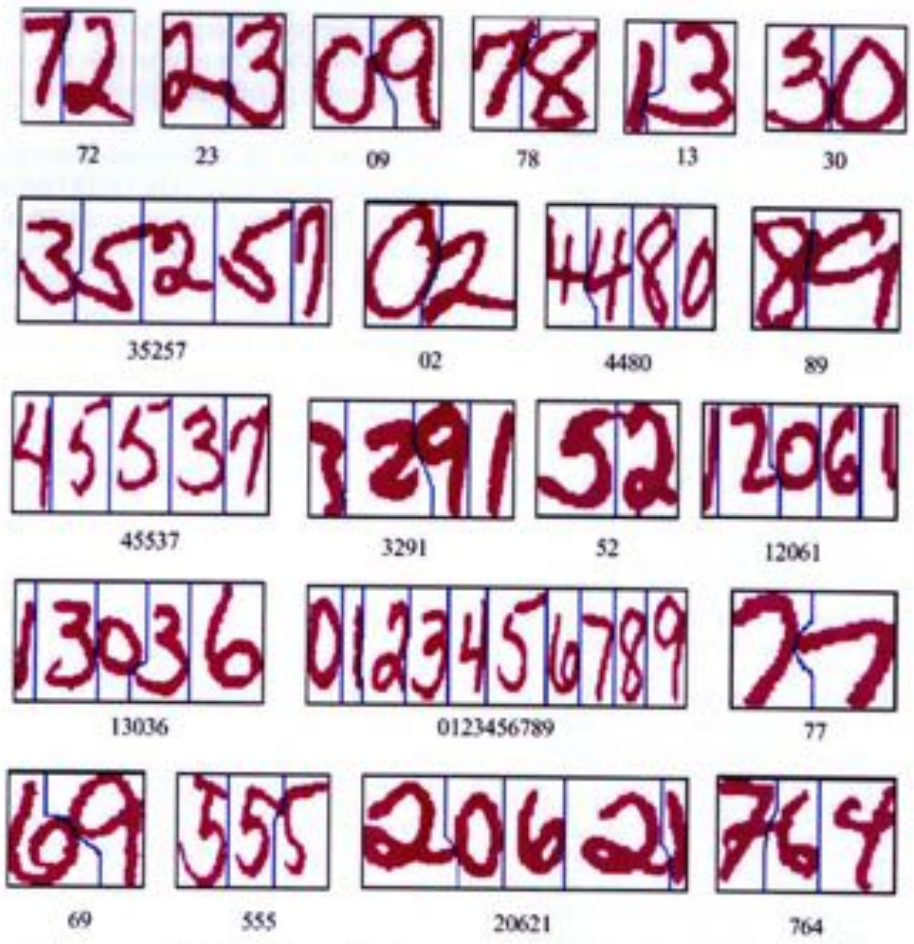


Fig. 26. Successful examples of segmentation/recognition produced by our system. Numeral strings are taken from the NSTRING SD19 Database.

Fig. 27. Unsuccessful examples of segmentation/recognition produced by our system. (a) and (b) Wrong segmentation–wrong recognition; (c) correct segmentation–wrong recognition. (d) and (e) wrong segmentation–correct recognition.

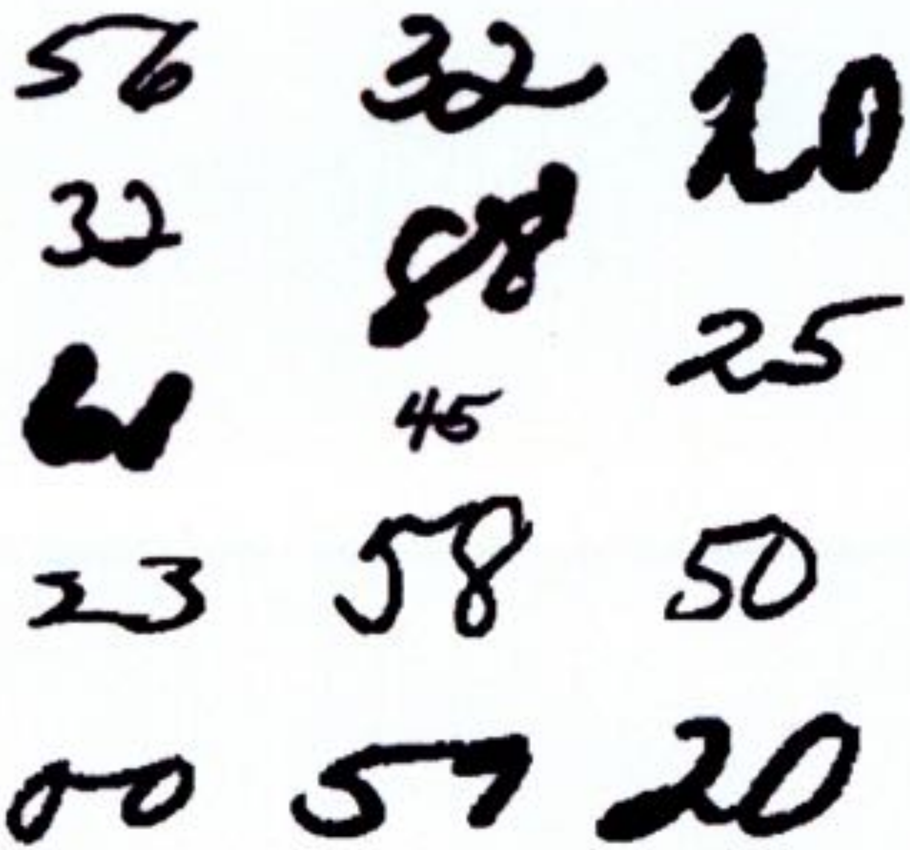
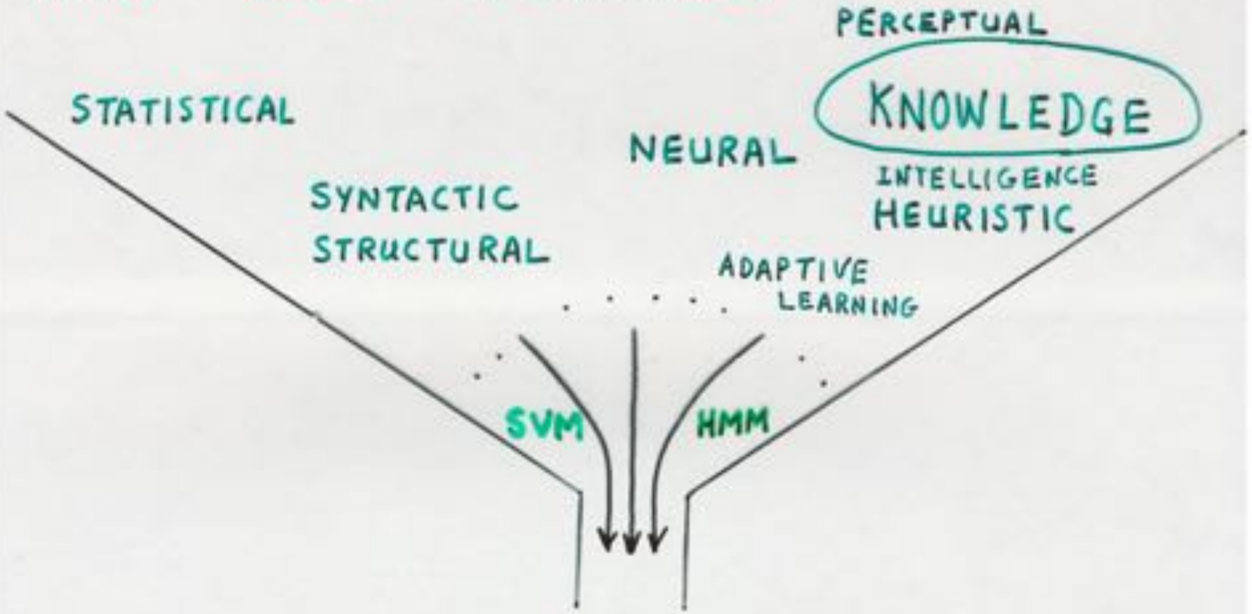


Figure 4 Examples of touching numeral pair images.

Some think ***CENPARMI***
comes only one way.

But don't count on it.

THE BIG FUNNEL

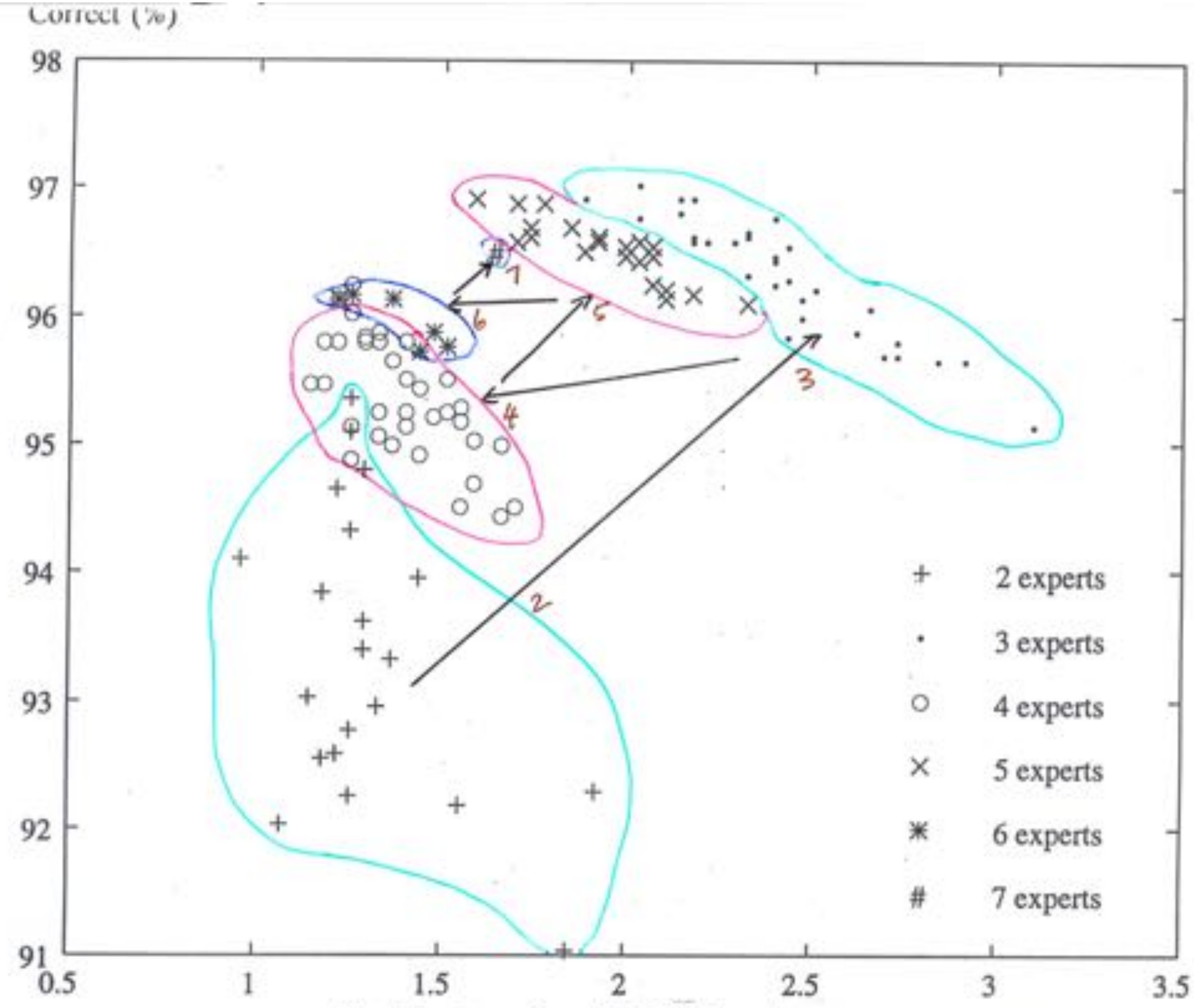


MULTIPLE APPROACHES

REMOVAL OF FUZZINESS

ACCURACY & SPEED & POWER
& FLEXIBILITY

TRADE - OFFS WITH COST



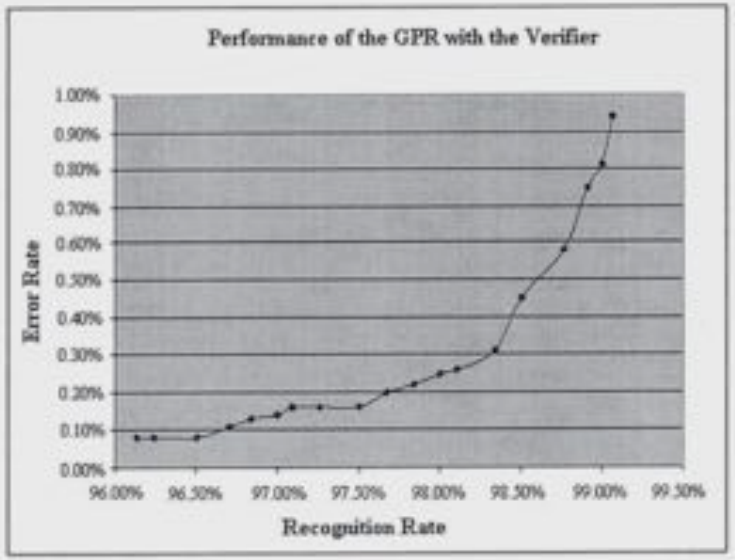
Combined results of 7 OCR algorithms

RECOGNITION RATES

1.	Correlation	99.42%
2.	n-tuples	97.68%
3.	Moments	93.16%
4.	Character Loci	99 %
5.	Transforms	99.71%
6.	Edges and stroke detection	99.5 %
7.	Contour tracing	97.75%
8.	Centre-line (Skeleton)	97 %

Experiment

Performance of the GPR with the verifier



Fast SVM Training Algorithm with Decomposition on Very Large Data Sets

Jian-xiong Dong, Adam Krzyżak, *Senior Member, IEEE*, and Ching Y. Suen, *Fellow, IEEE*

Abstract—Training a support vector machine on a data set of huge size with thousands of classes is a challenging problem. This paper proposes an efficient algorithm to solve this problem. The key idea is to introduce a parallel optimization step to quickly remove most of the nonsupport vectors, where block diagonal matrices are used to approximate the original kernel matrix so that the original problem can be split into hundreds of subproblems which can be solved more efficiently. In addition, some effective strategies such as kernel caching and efficient computation of kernel matrix are integrated to speed up the training process. Our analysis of the proposed algorithm shows that its time complexity grows linearly with the number of classes and size of the data set. In the experiments, many appealing properties of the proposed algorithm have been investigated and the results show that the proposed algorithm has a much better scaling capability than Libsvm, SVM^{light}, and SVMTorch. Moreover, the good generalization performances on several large databases have also been achieved.

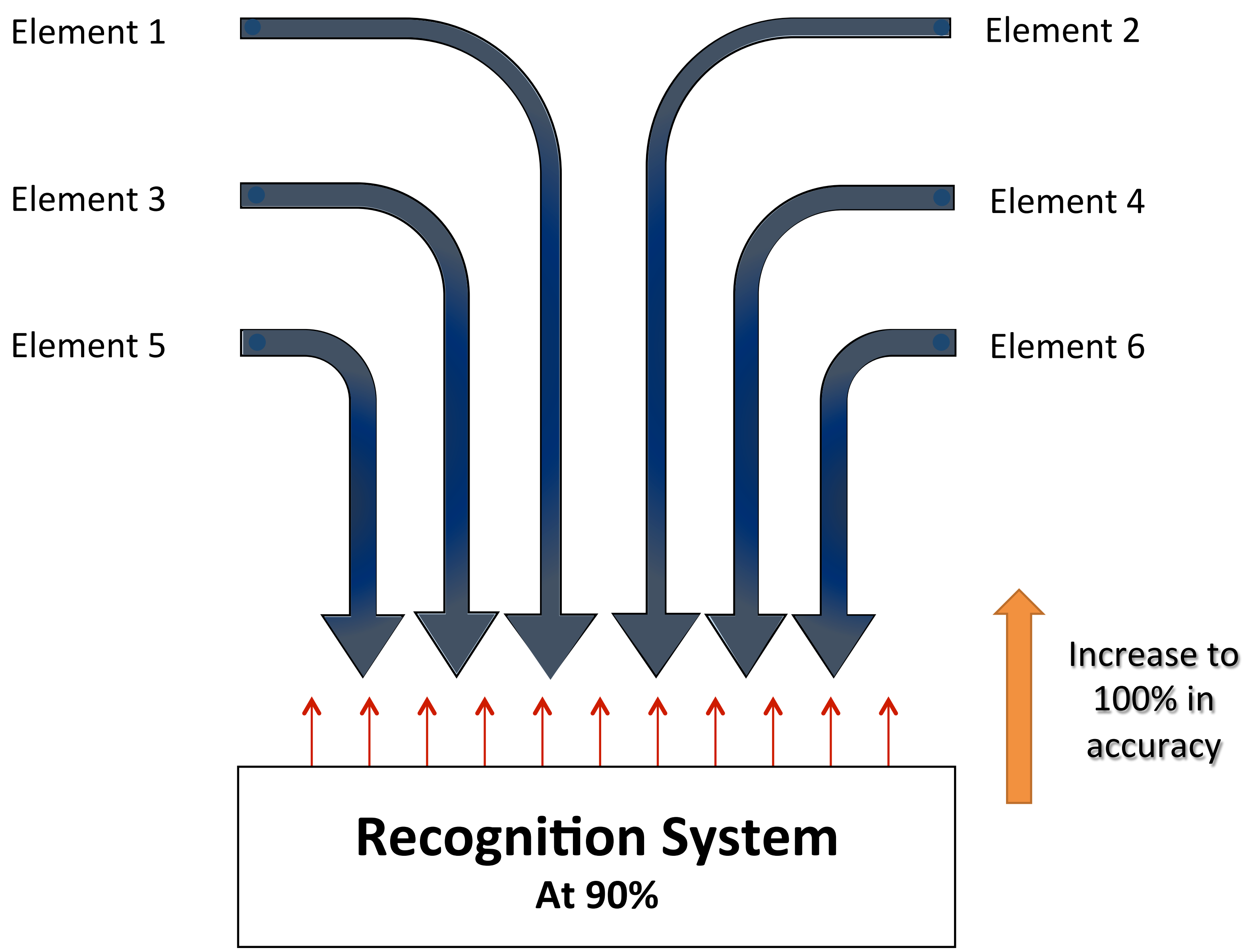
There are 3036 classes for ETL9B. In order to reduce the computational cost and speed up the classification, a pre-classifier is required. The goal of a pre-classifier is to obtain a high cumulative recognition rate so that a small number of selected candidates include the true class label.

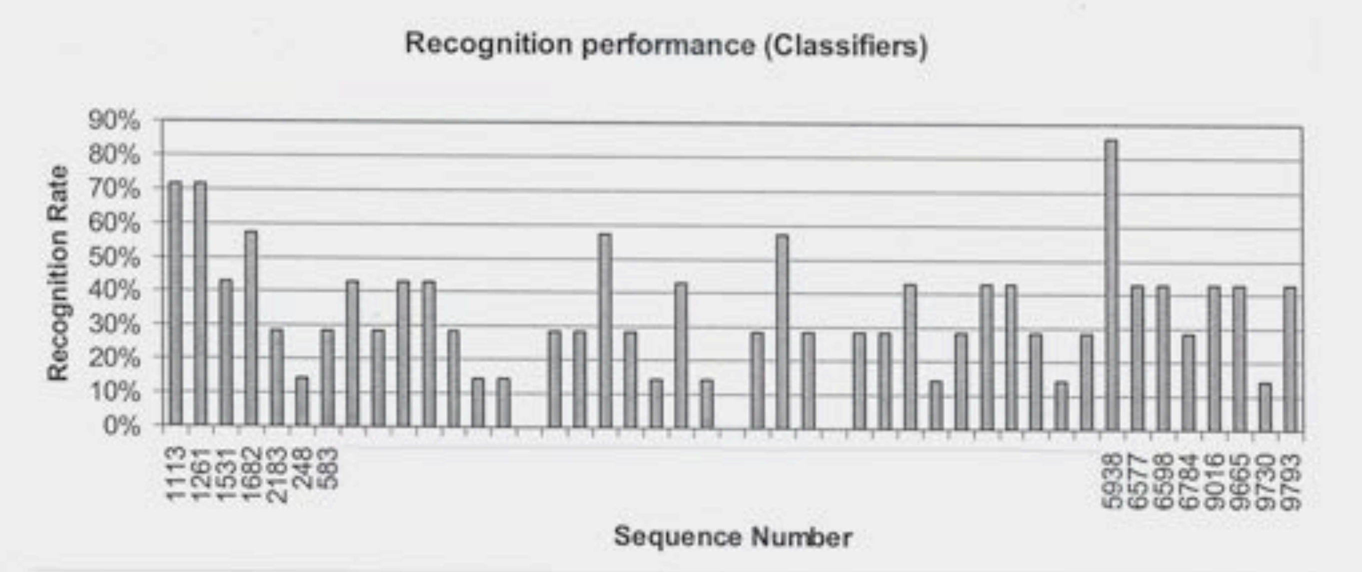
For a gray-scale image, we calculate directional histograms based on image gradients. The procedure for feature extraction is given as follows:

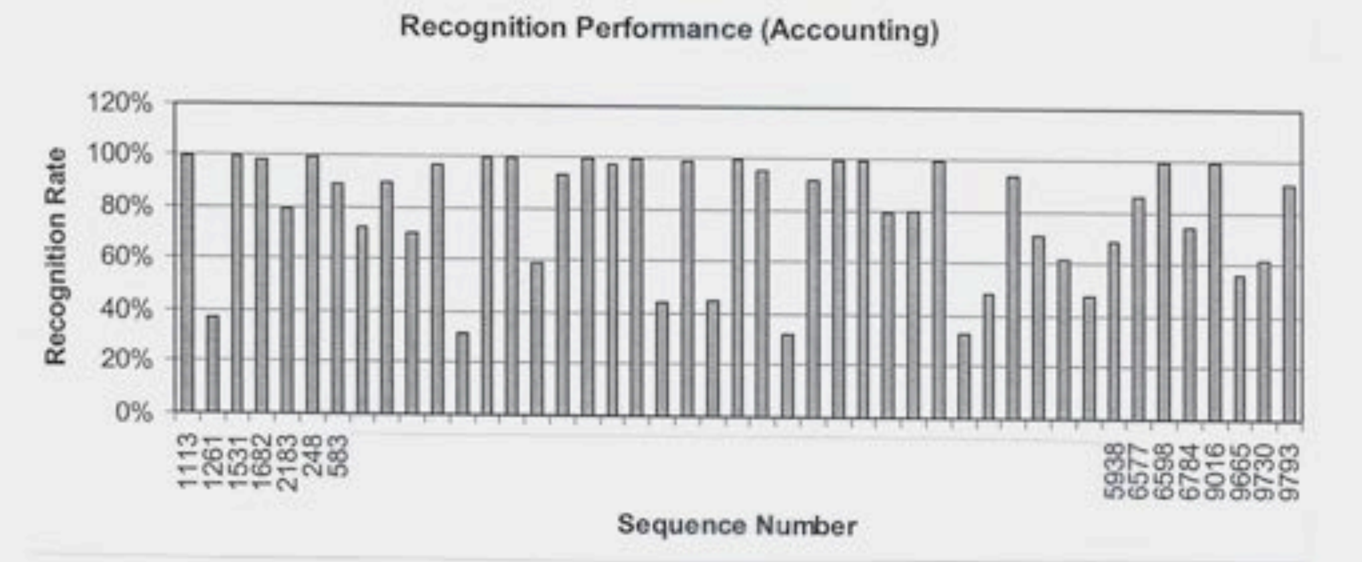
- The gray-scale normalized image is standardized such that its mean and maximum values are 0 and 1.0, respectively [65].
- Center a 64×64 normalized image into an 80×80 box in order to efficiently utilize the information in the four peripheral areas[1]
- Robert edge operator [117] is applied to calculate gradient strengths and directions.

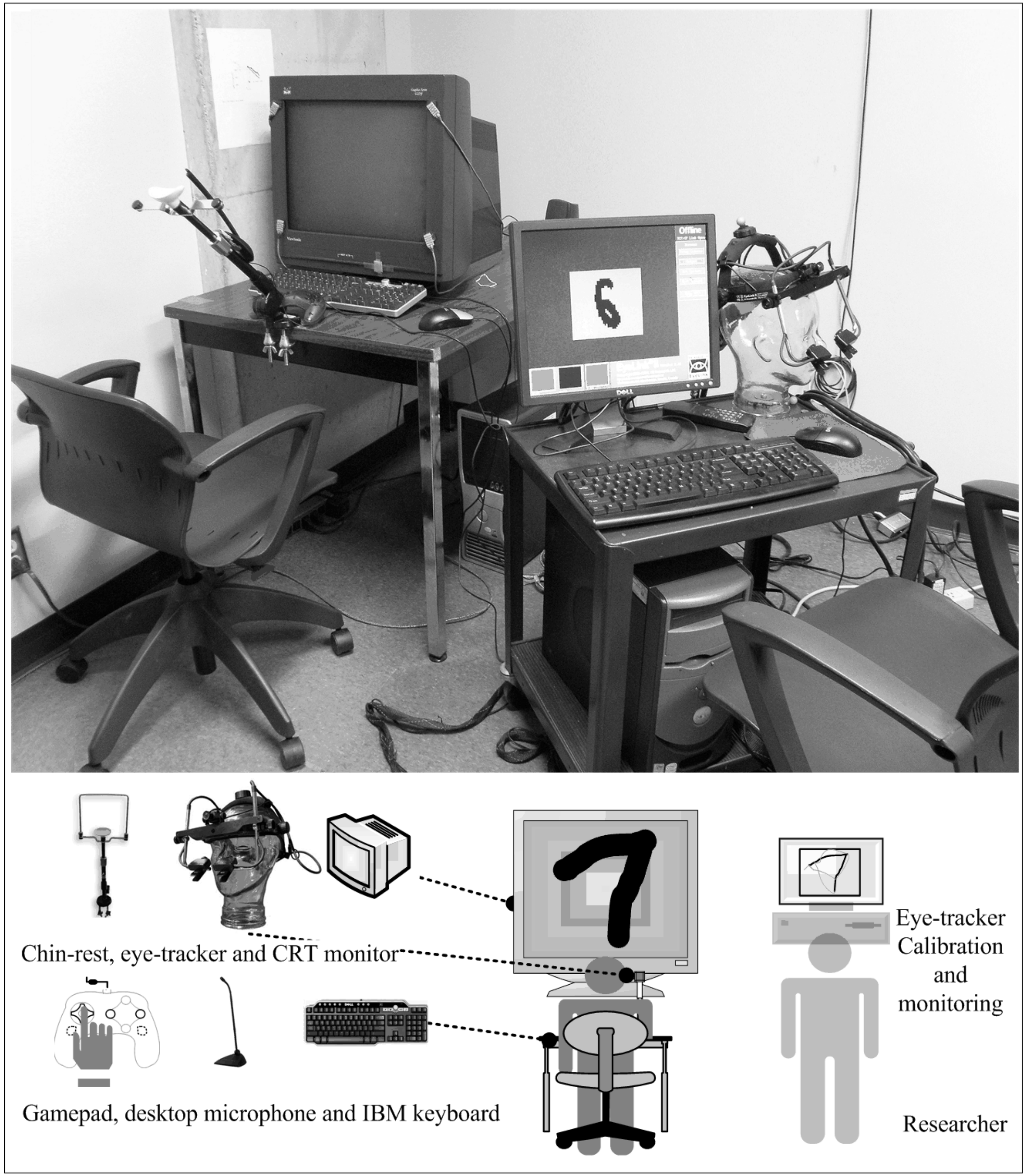
Table 13: Training time and recognition accuracy of SVM on ETL9B

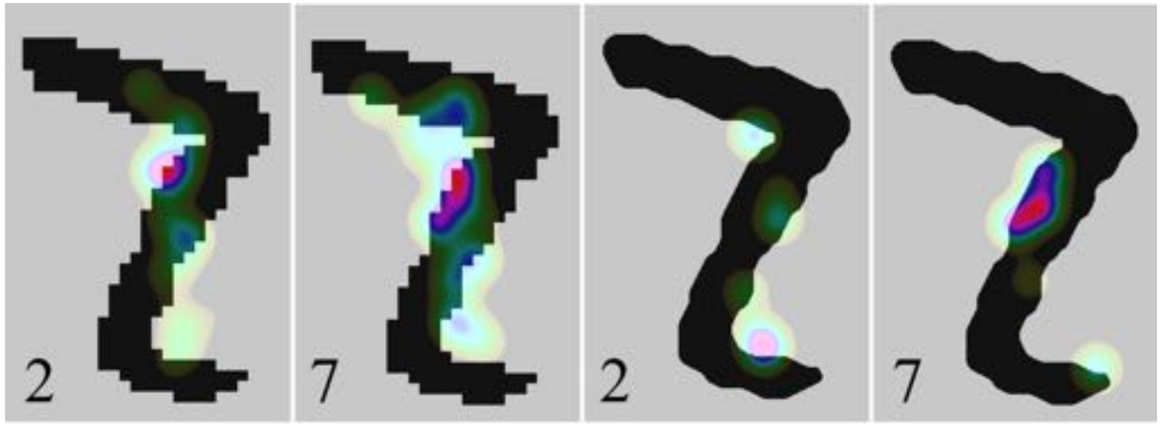
classifiers	size of training set	Total training time (hours)	substitution error (%)
SVM[a]	485760	9.3	1.1%
SVM[b]	2,428,000	54.0	1.0%
Nearest neighbor	485760	—	2.9%
MQDF[21]	—	—	0.95%


Element 1
Element 2
Element 3
Element 4
Element 5
Element 6
Increase to 100% in accuracy
Recognition System
At 90%


Recognition performance (Classifiers)
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Recognition Rate
1113
1261
1531
1682
2183
248
583
5938
6577
6598
6784
9016
9665
9730
9793
Sequence Number

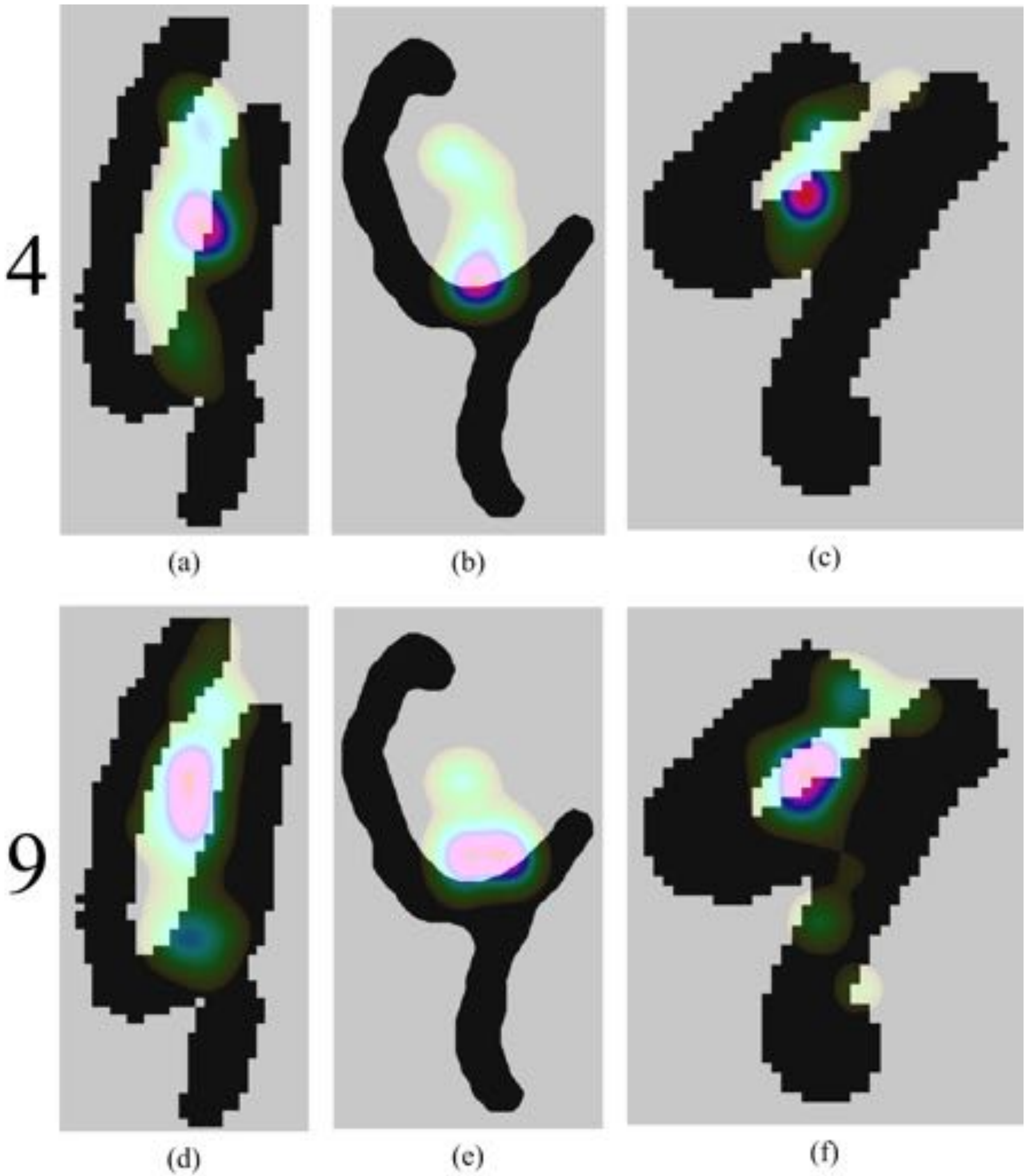

Recognition Performance (Accounting)
120%
100%
80%
60%
40%
20%
0%
Recognition Rate
1113
1261
1531
1682
2183
248
583
5938
6577
6598
6784
9016
9665
9730
9793
Sequence Number


Chin-rest, eye-tracker and CRT monitor
Gamepad, desktop microphone and IBM keyboard
Eye-tracker
Calibration
and
monitoring
Researcher



(a) (b) (c) (d)

Four duration-based heat maps showing gaze density during 1-second period preceding verbal identification of 7-digit no. 9506 as 2 and 7. Heat maps were generated based on: (a) 25 fixations in 10 trials, (b) 26 fixations in 10 trials, (c) 6 fixations in 3 trials, and (d) 7 fixations in 3 trials.


4
9
(a)
(b)
(c)
(d)
(e)
(f)

Recent Publications in Journals (partial listing)

For a more detailed listing, visit www.cenparmi.concordia.ca.

J. Zhou, H. Peng and C.Y. Suen, "Data-driven decomposition for multi-class classification," vol. 41, 67-76, 2008.

P. Zhang, T. D. Bui and C. Y. Suen, "A novel cascade ensemble classifier system with a high recognition performance," Pattern Recognition, vol. 40, 3415-3429, 2007.

F. Lauer, C. Y. Suen and G. Bloch, "A trainable feature extractor for handwritten digit recognition," Pattern Recognition, vol. 40, 1816-1824, 2007.

J. Sadri, C. Y. Suen and T. D. Bui, "A genetic framework using contextual knowledge for segmentation and recognition of handwritten numeral strings," Pattern Recognition, vol. 40, 898-919, 2007.

Z. Yang, L. Yang, D. Qi and C. Y. Suen, "An EMD-based recognition method for Chinese fonts and styles," Pattern Recog. Letters, vol. 27, 1692-1701, 2006.

Y. Fataicha, M. Cheriet, J. Y. Nie and C. Y. Suen, "Retrieving poorly degraded OCR documents," Int. J. Document Analysis & Recognition, vol. 8, 15-26, 2006.

Refereed Conference Papers (partial listing)

For a more detailed listing, visit www.cenparmi.concordia.ca.

C. Y. Suen, "Narrowing the gap between computers and humans in handwriting recognition," In press, Proc. Chinese conference on Pattern Recognition, Beijing, Dec. 2007. Keynote Paper.

C. Y. Suen, A. Zaryabi, C. Feng and Y. Mao, "A survey of techniques for face reconstruction," Proc. IEEE Int. Conf. on SMC, pp. 3554-3560, Montreal, Oct. 2007. Invited Paper.

C. Y. Suen, A. Krzyzak and J. Rokita, "Face recognition from cell phone images," Int. Conf. on Image Analysis and Recognition, Montreal, Aug. 2007. Keynote Paper.

F. Solimanpour, J. Sadri and C. Y. Suen, "Standard databases for recognition of handwritten digits, numerical strings, legal amounts, letters and dates in Farsi language," Proc. Int. Workshop on Frontiers in Handwriting Recognition, pp. 3-7, Labaule - France, Oct. 2006.

C. Y. Suen, S. Izadi et al., "Farsi script recognition: a survey," Proc. SACH '06, Summit on Arabic and Chinese Handwriting, pp.101-110, College Park, Maryland, Sept. 2006, Invited Paper..

J. Sadri, C. Y. Suen and T. D. Bui, "A new clustering method for improving plasticity and stability in handwritten character recognition systems," Proc. 18th Int. Conf. on Pattern Recognition, vol. 2, pp. 1130-1133, Hong Kong, Aug. 2006.

C. Y. Suen, "From humans to handwriting to computer and back," Proc. ICDAR, p. 2, Seoul, Korea, Aug. 2005. Keynote Paper.

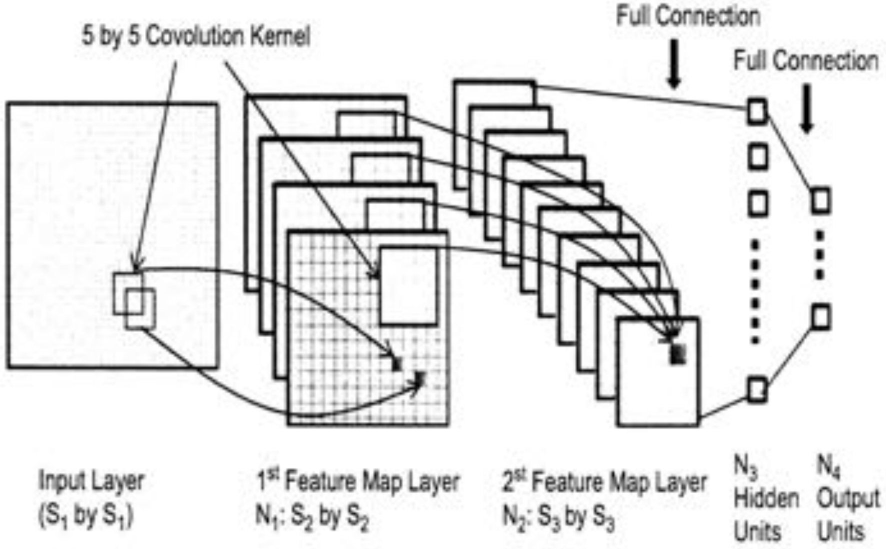
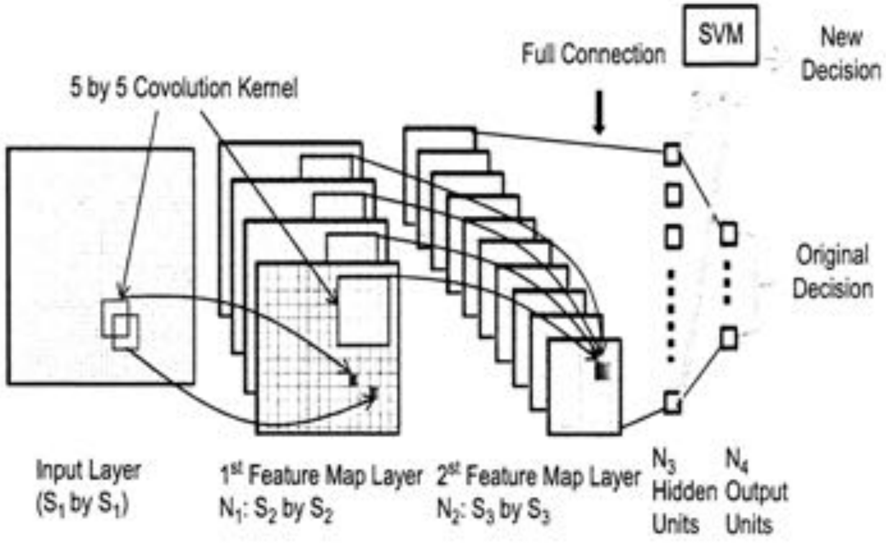
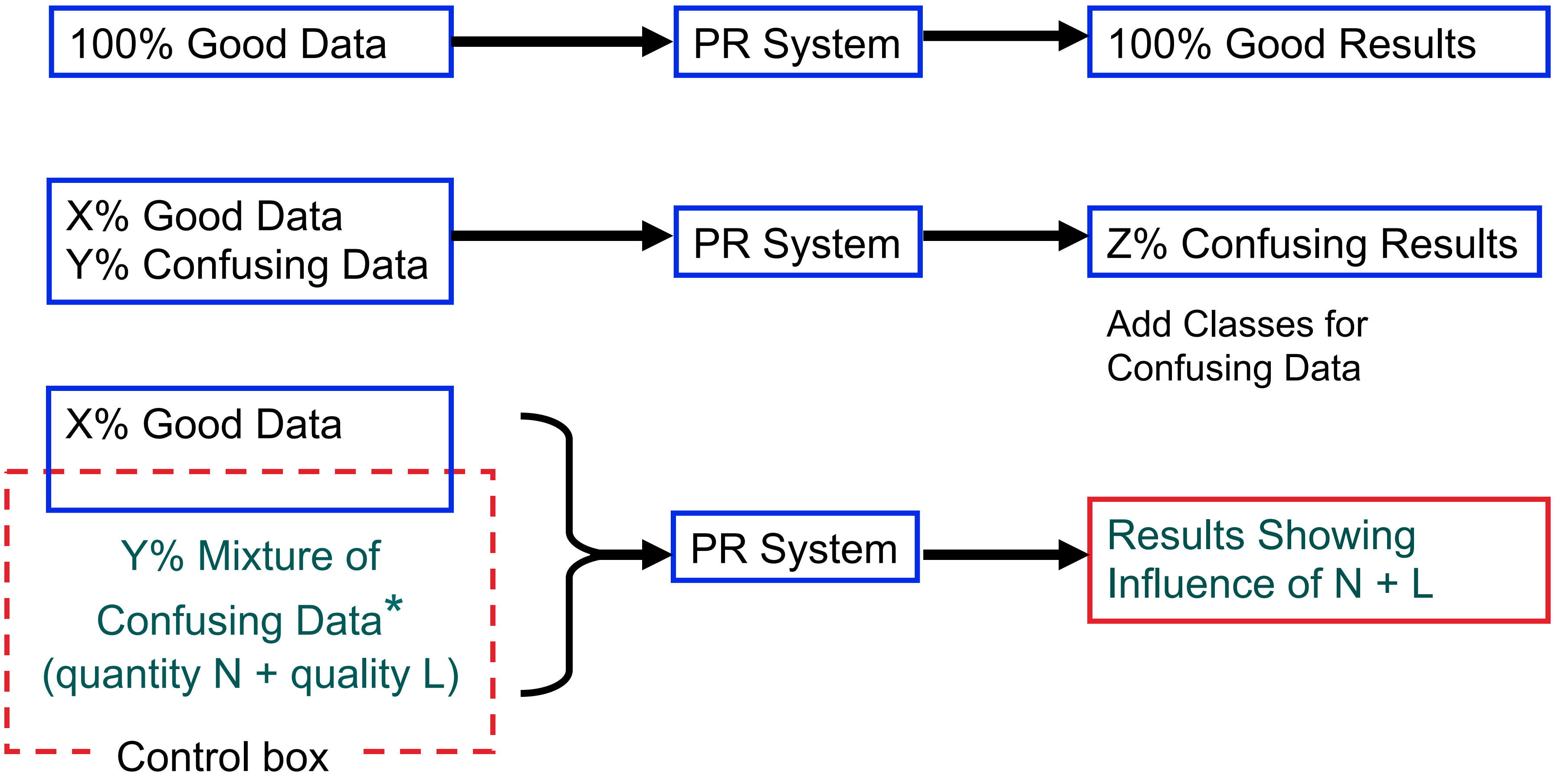


Fig. 1. Structure of the adopted CNN.

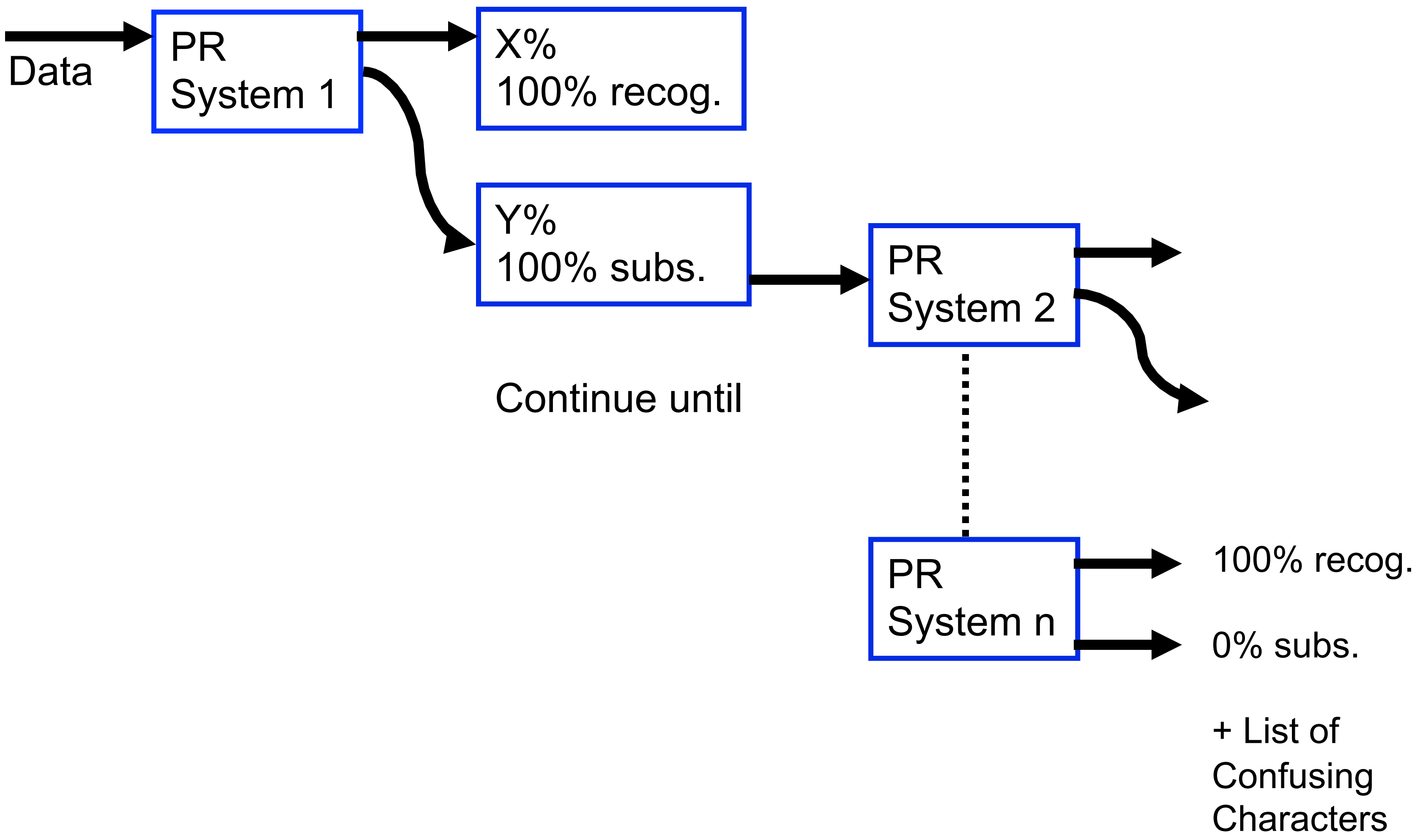


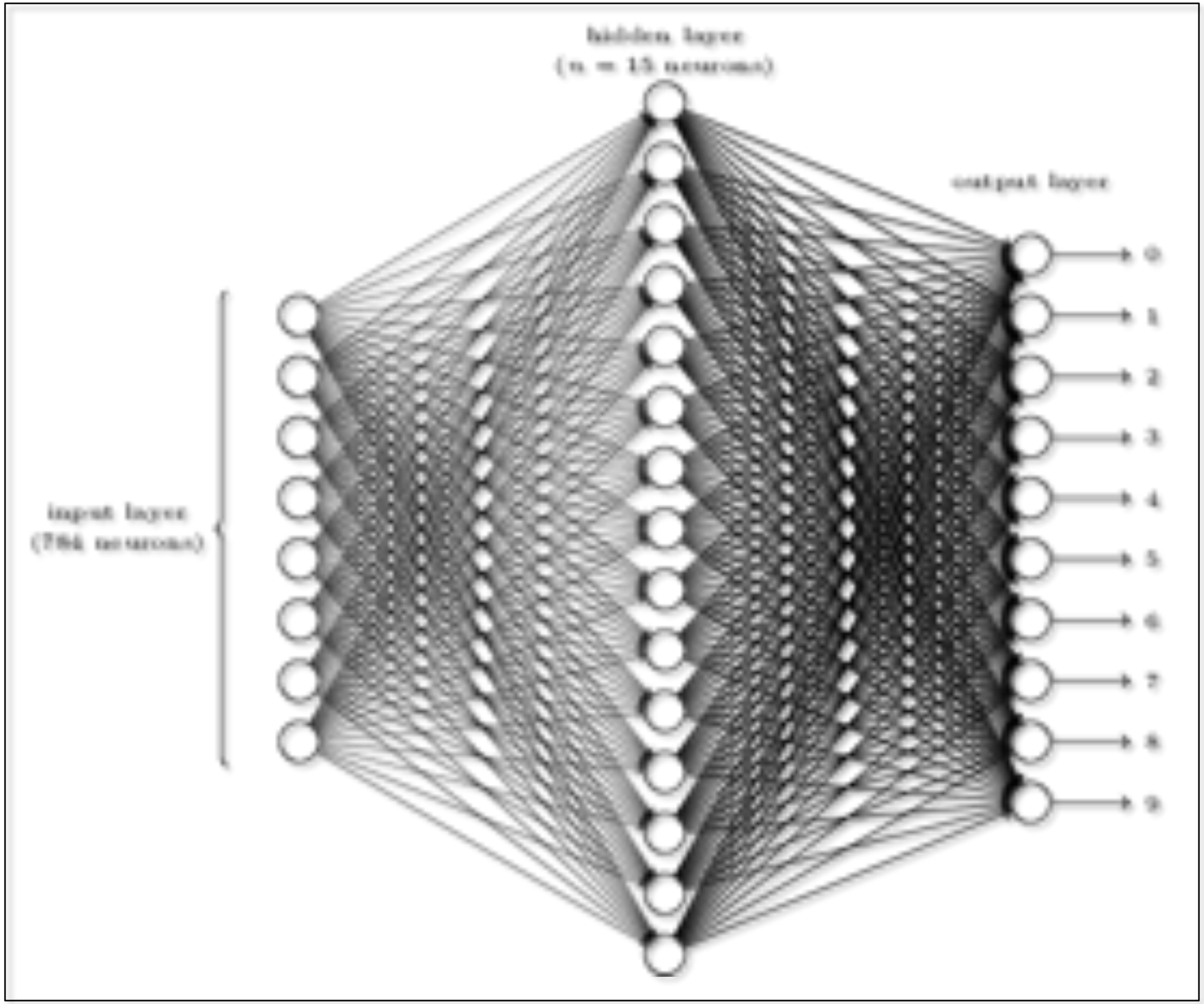
Influence of Training Data



*1 type of data has shapes that are similar to the good data,
1 type of data has shapes that are dissimilar to the good data.

Error-Reduction in Training Mode




hidden layer
(n = 15 neurons)
output layer
input layer
(784 neurons)
0
1
2
3
4
5
6
7
8
9