TAMPERE UNIVERSITY OF TECHNOLOGY

AI Solutions for Biomedical and Industrial Data – From Data to Decisions

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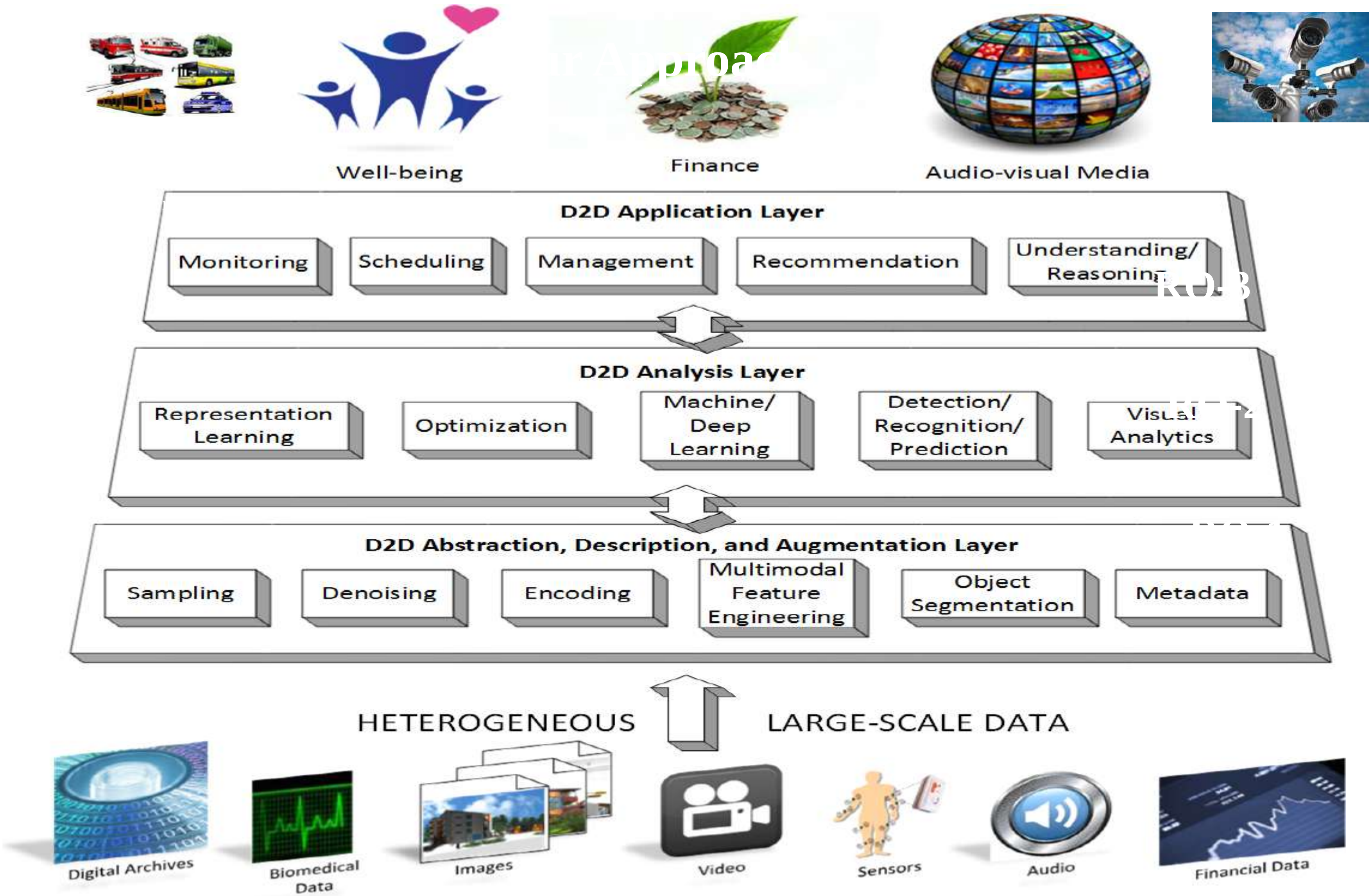
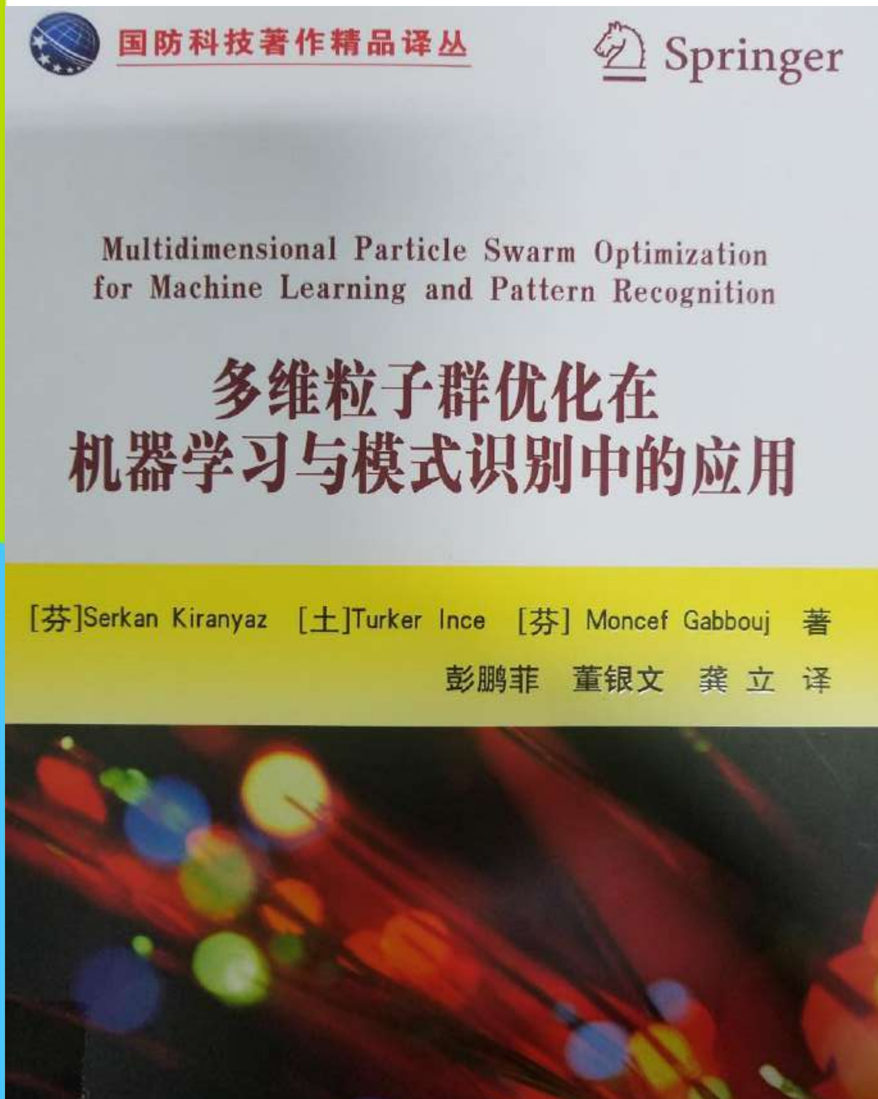
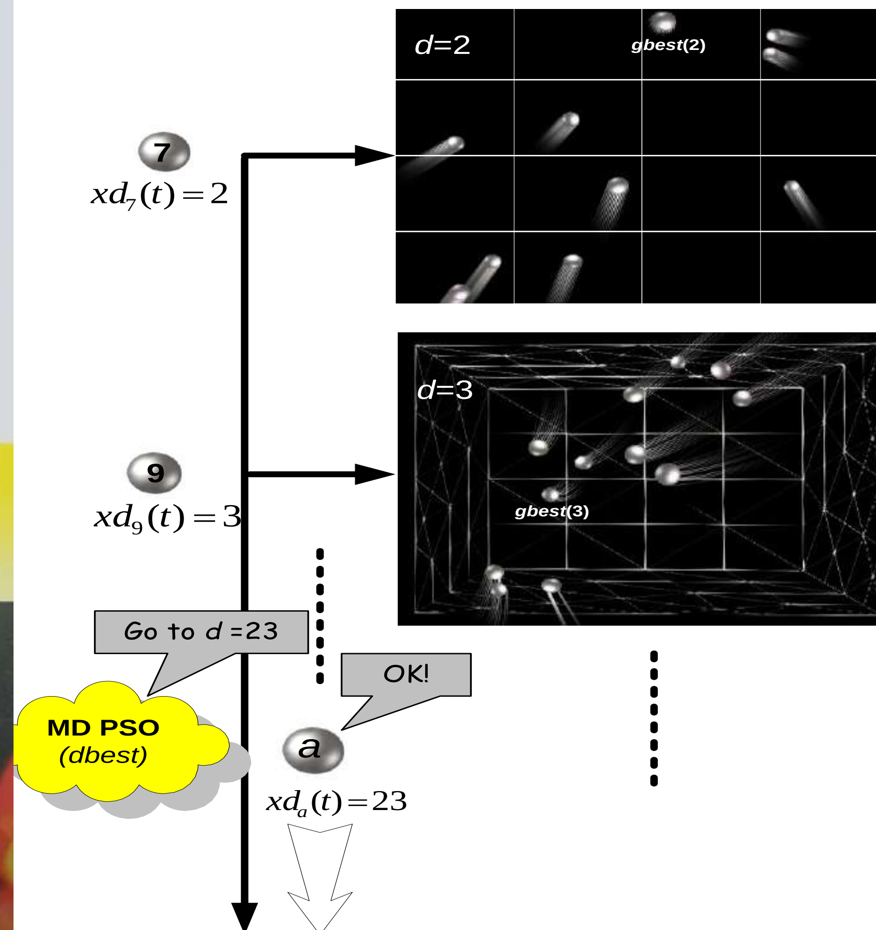
From Data to Decision – Our Approach



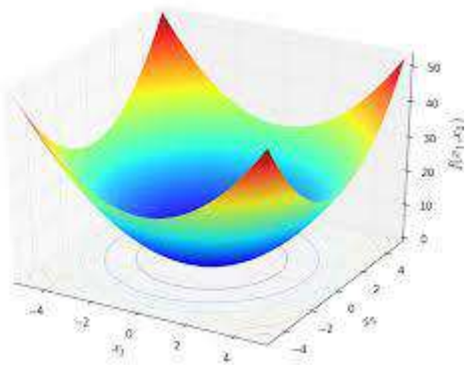
I) Optimization in Machine Learning: Multi-dimensional Particle Swarm Optimization (MD-PSO)



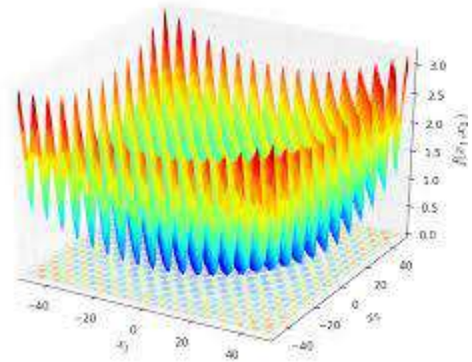


Optimizing over dimensions

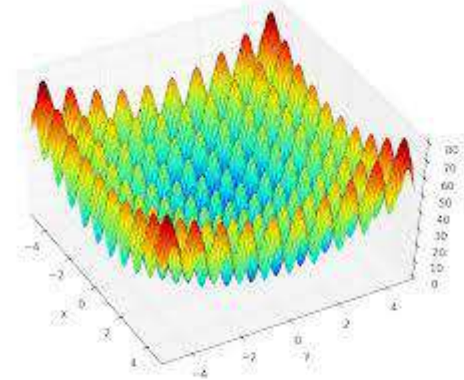
How to deal with such complex functions?



SPHERE

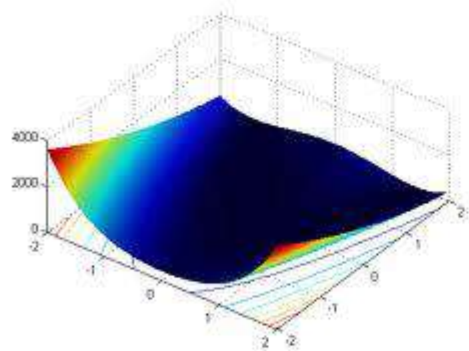


GIUNTA

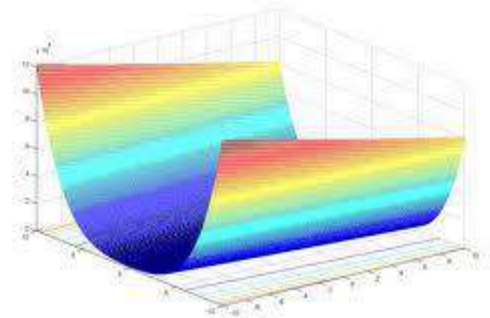


RASTRIGIN

GRIEWANK

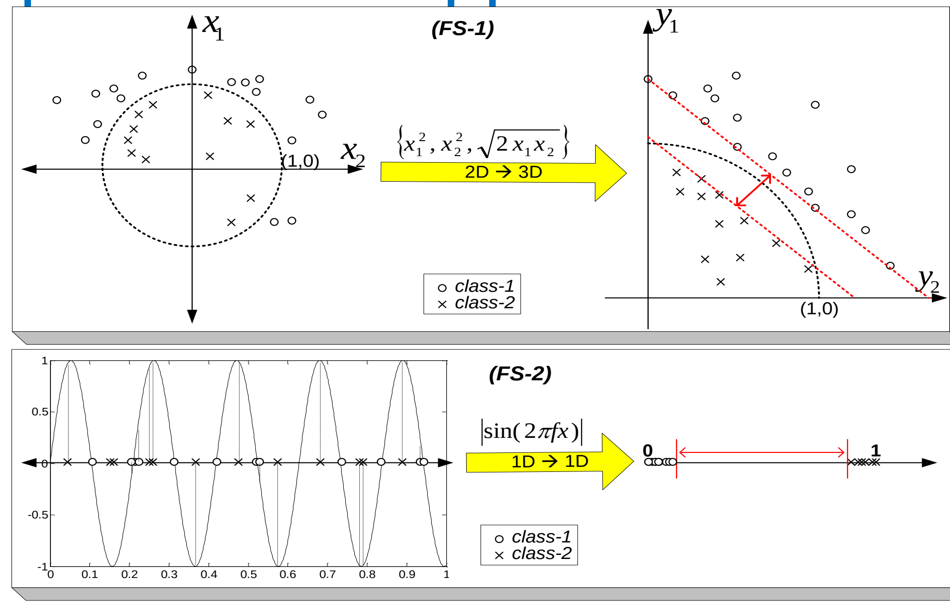


DEJONG



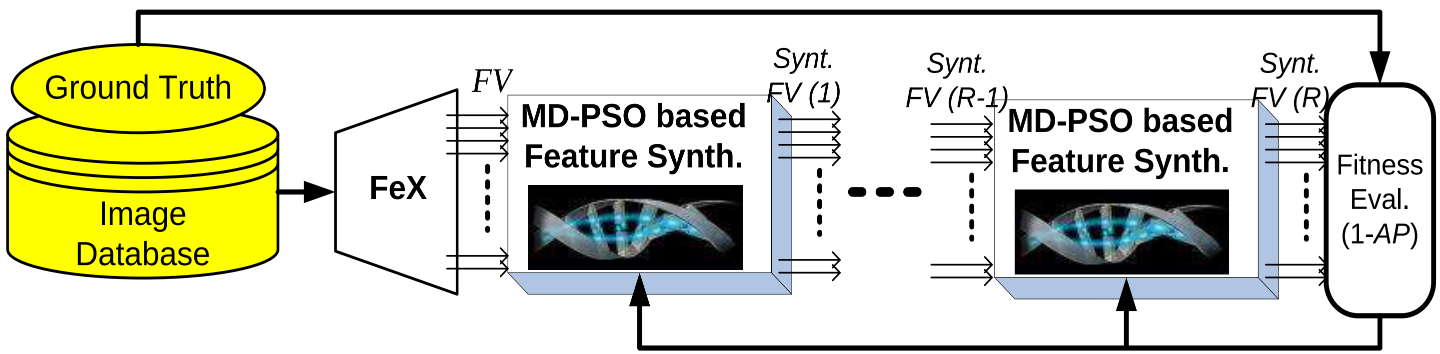
ROSENBROCK

Learn to Synthesize Optimal Features – Signal Processing and Optimization Approach



Feature engineering:

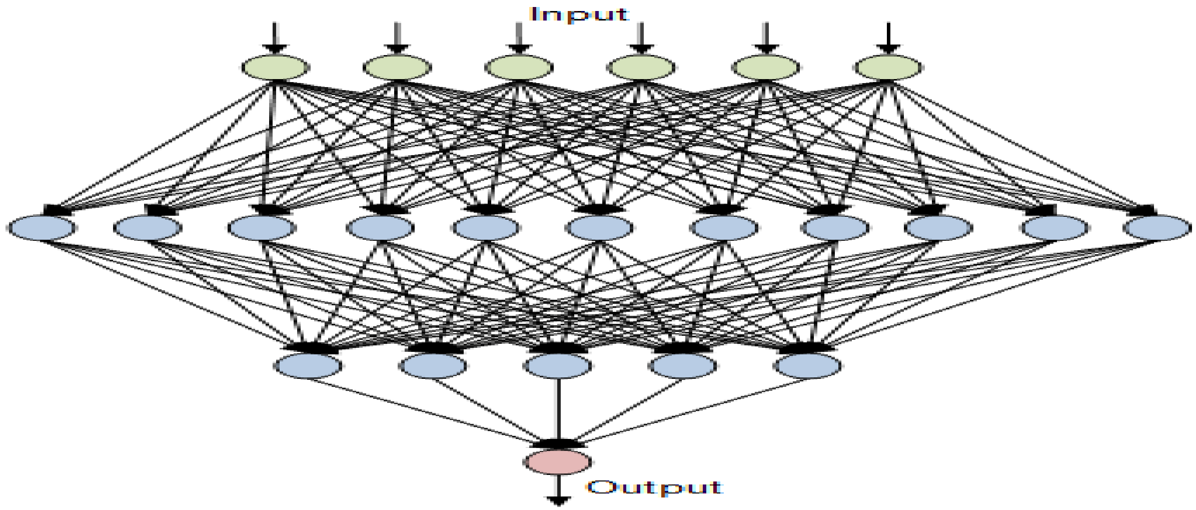
- Feature extraction
- Feature selection
- Feature synthesis



Raitoharju, **Neural Computing and Applications**, 2016.

Network Architecture Design: Evolutionary Artificial Neural Networks

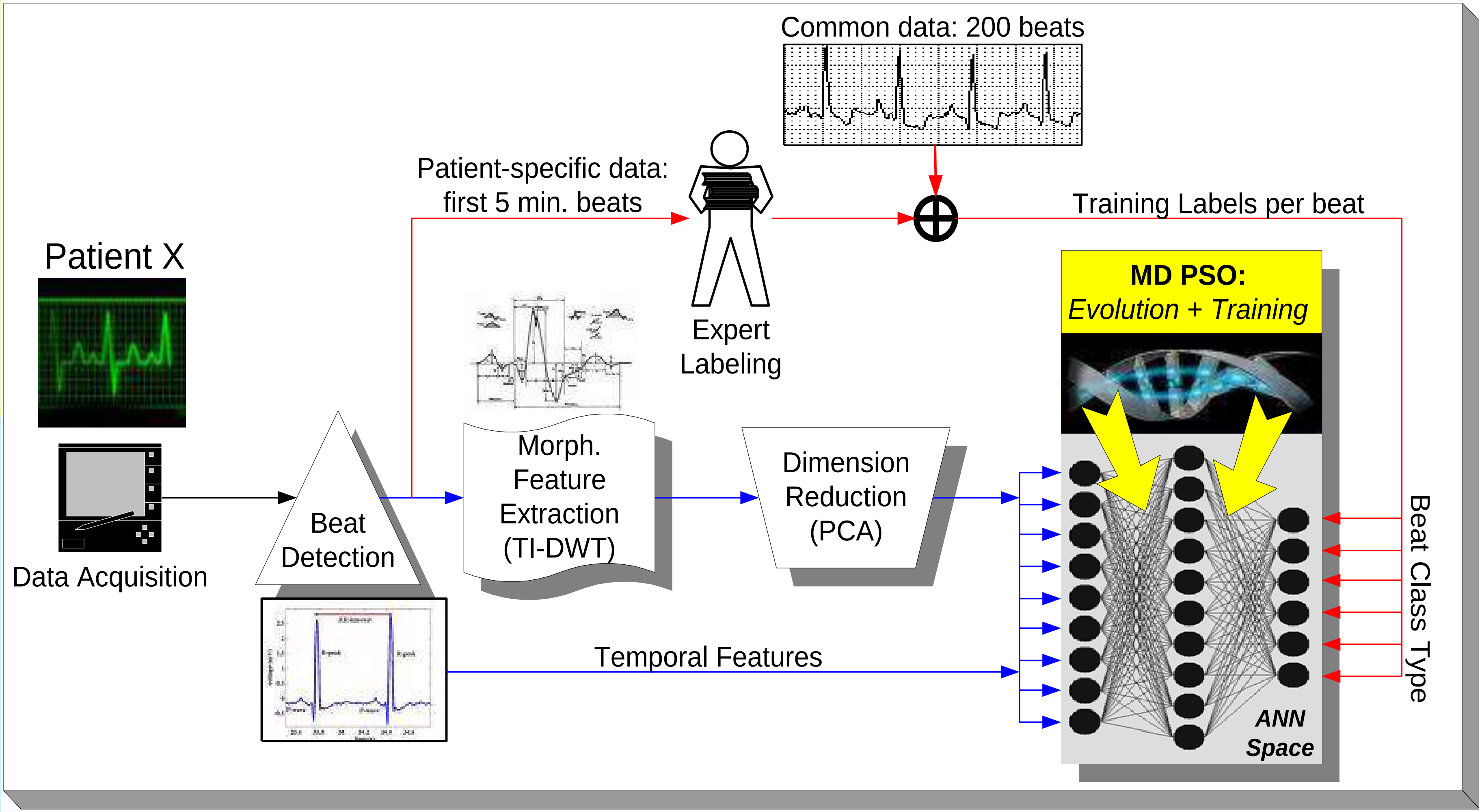
Question: How to design **optimal** neural networks? **MD-PSO**



$$xx_a^{xd_a(t)}(t) = \begin{Bmatrix} \{w_{jk}^0\},\{w_{jk}^1\},\{\theta_k^1\},\{w_{jk}^2\},\{\theta_k^2\} \\ ,\ldots,\{w_{jk}^{O-1}\},\{\theta_k^{O-1}\},\{\theta_k^O\} \end{Bmatrix}$$

Kiranyaz, ***Neural Networks***, 2009. (top 5th downloaded paper from Elsevier Journal)

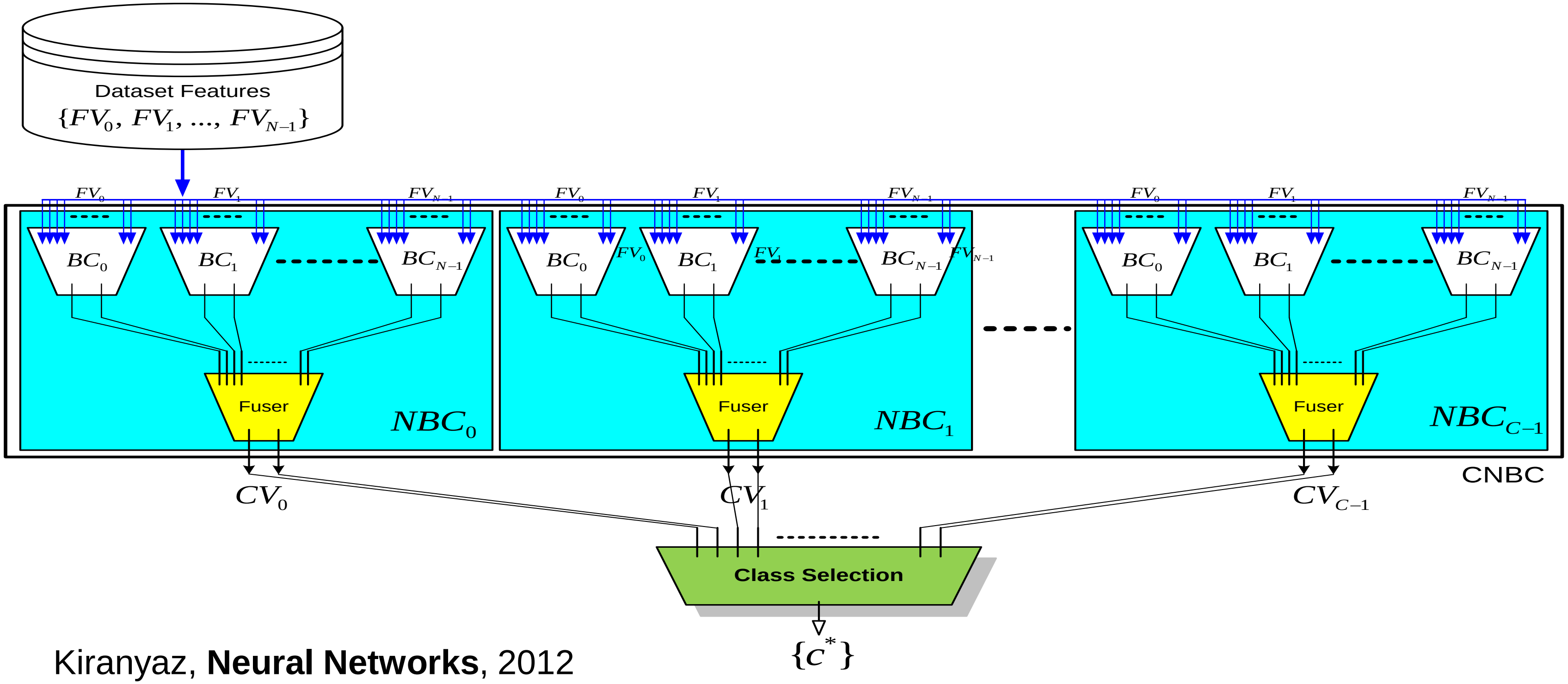
Patient-specific Classification of ECG Data by Evolutionary ANNs



- Ince, *IEEE Transactions on Biomedical Engineering*, 2009.

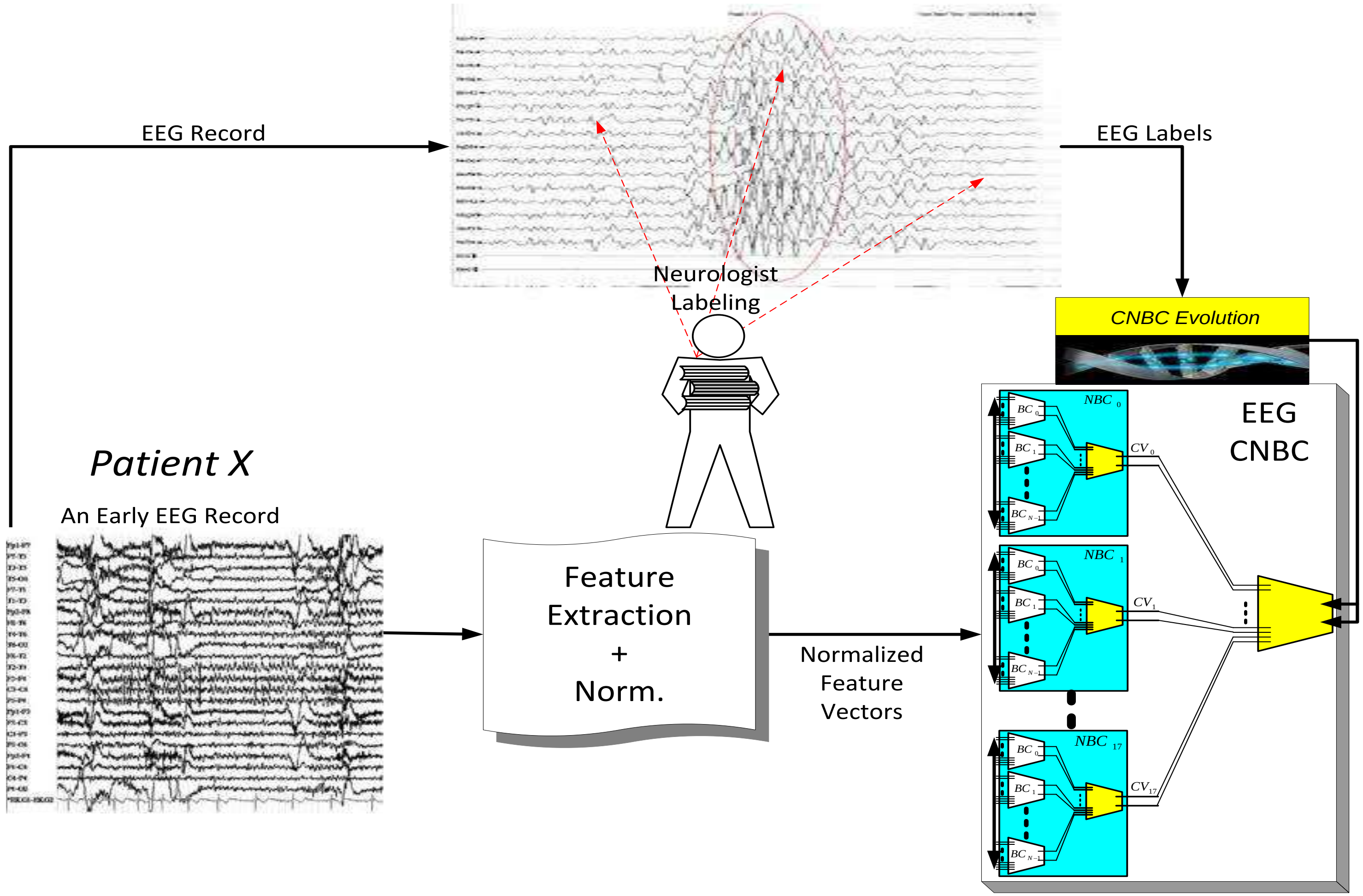
Advanced Patter Recognition and Machine Learning: Collective Network of Binary Classifiers

- Supervised sematic classifier
- Evolutionary classifier (deep rooted in mathematical optimization)
- Scalable wrt both classes and features (suitable for Big Data)
- Incremental as opposed to static classifiers



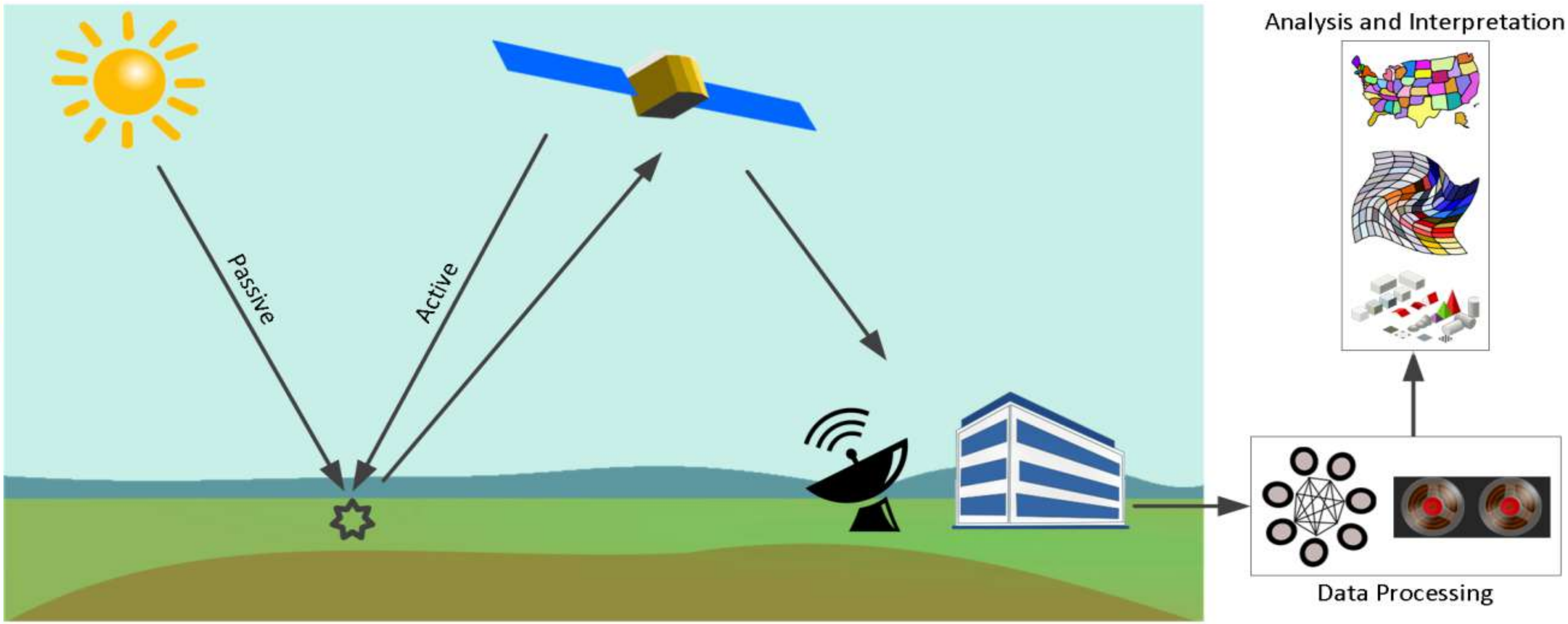
- Kiranyaz, **Neural Networks**, 2012
- Kiranyaz, **IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics**, 2012

EEG Classification by Incremental CNBC Evolution



Kiranyaz, **Journal of Biomedical Informatics**, 2014.

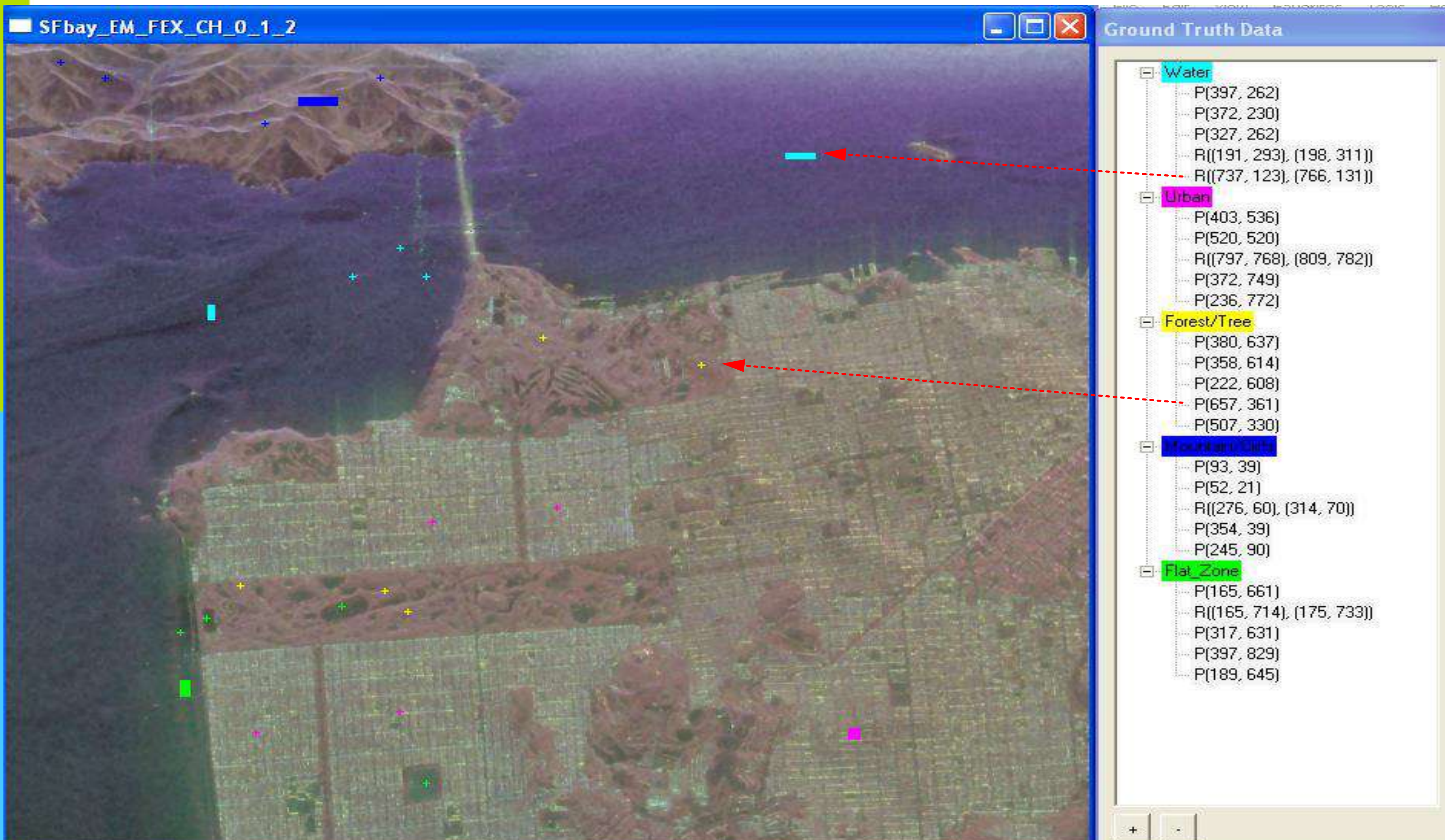
Synthetic Aperture Radar (SAR) Data Analysis and Classification

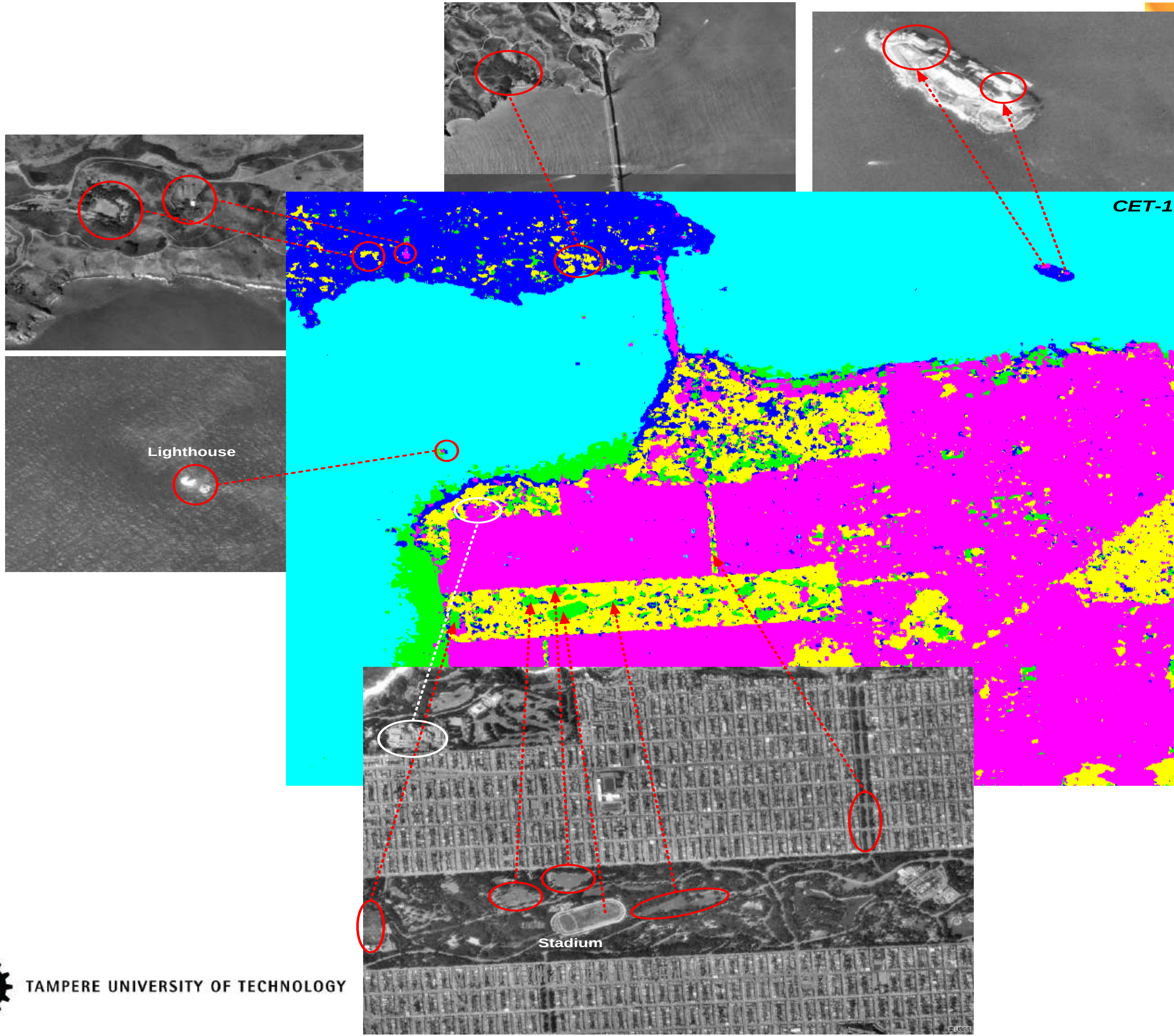


Kiranyaz, ***IEEE Trans. on Systems, Man, and Cybernetics – Part B*****,** 2012.

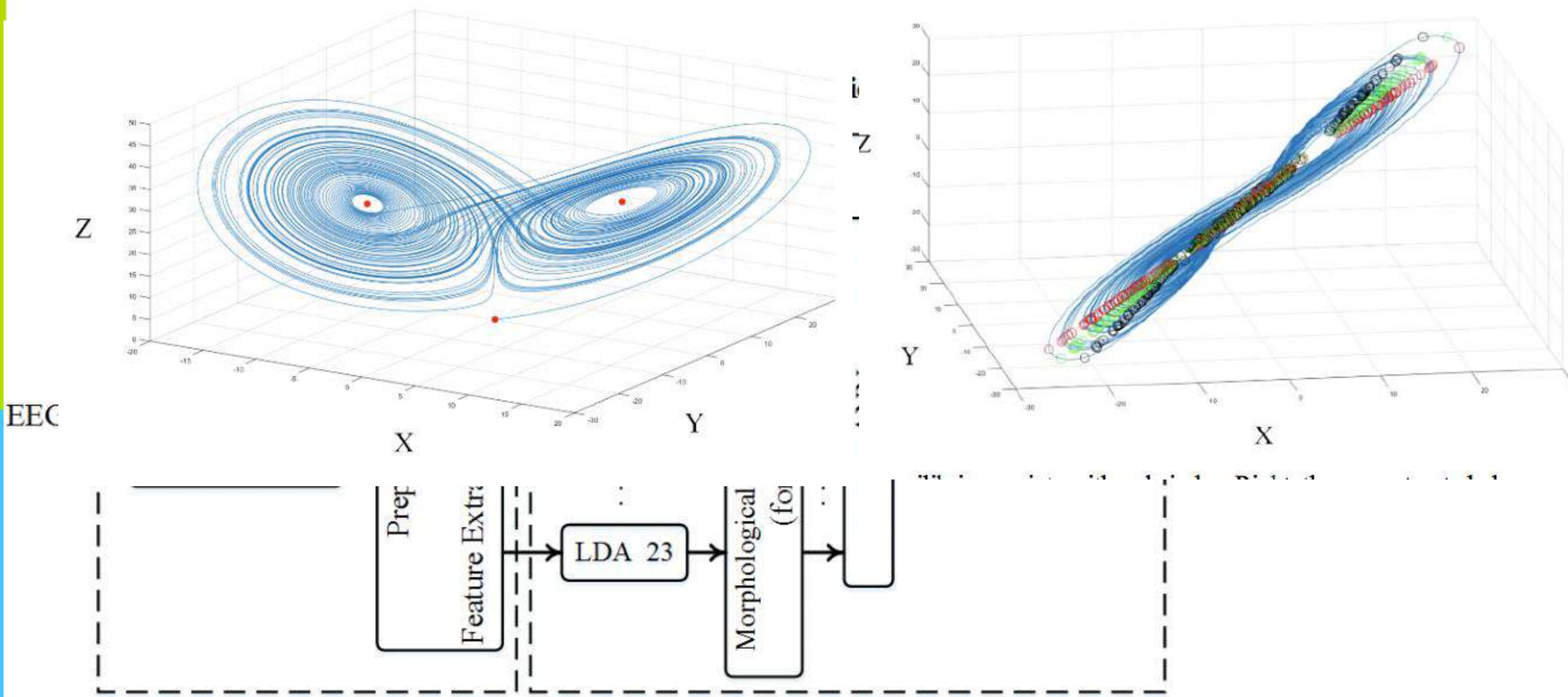
Uhlmann, **IEEE Trans. on Geoscience & Remote Sensing**, 2014.

The CNBC test-bed application GUI showing a sample user-defined ground truth set over San Francisco Bay area.




CET-1
Lighthouse
Stadium

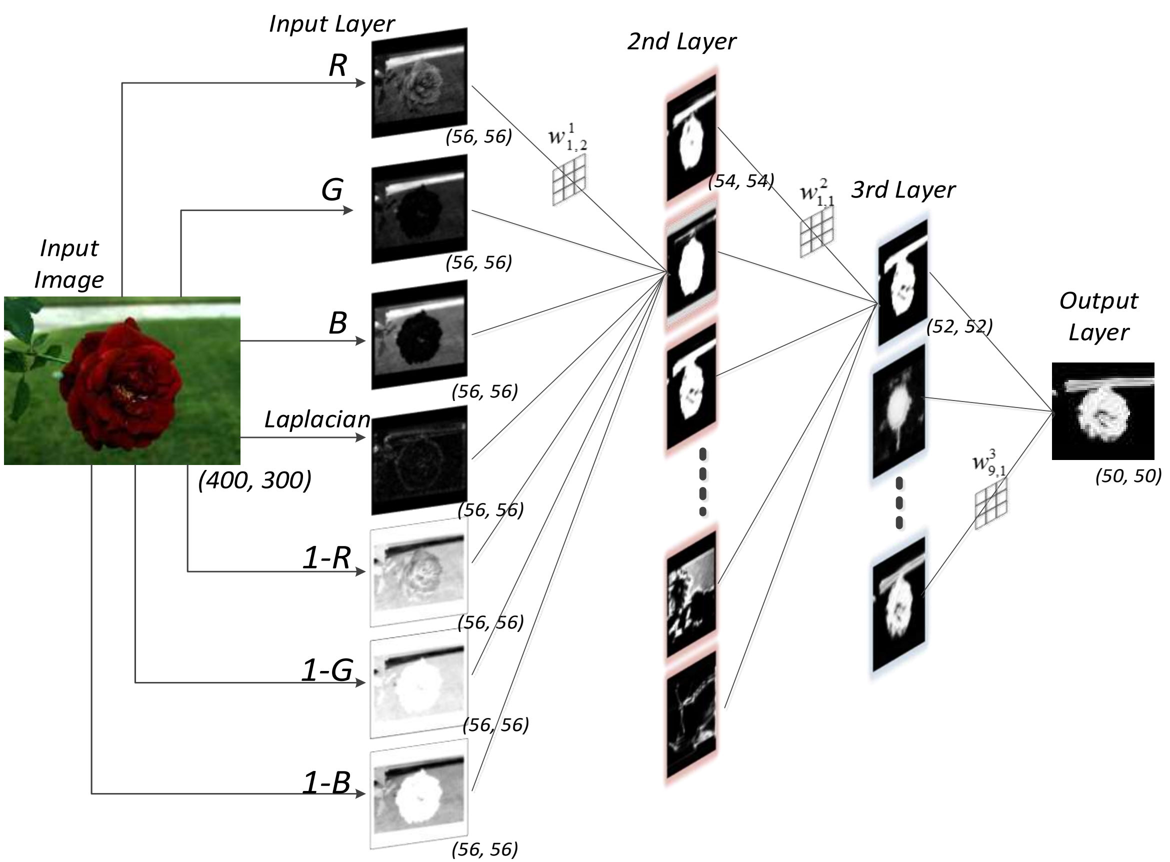
Patient-Specific Seizure Detection Using Nonlinear Dynamics and Nullclides



Average sensitivity 91.15%; average specificity 95.16% on CHB-MIT Database

Zabihi, Journal of Biomedical and Health Informatics, 2018 (under review).

FACE SEGMENTATION IN THUMBNAIL IMAGES BY DATA-ADAPTIVE CONVOLUTIONAL SEGMENTATION NETWORKS



Kiranyaz, **Proc. IEEE ICIP**, 2016, Phoenix, Arizona.

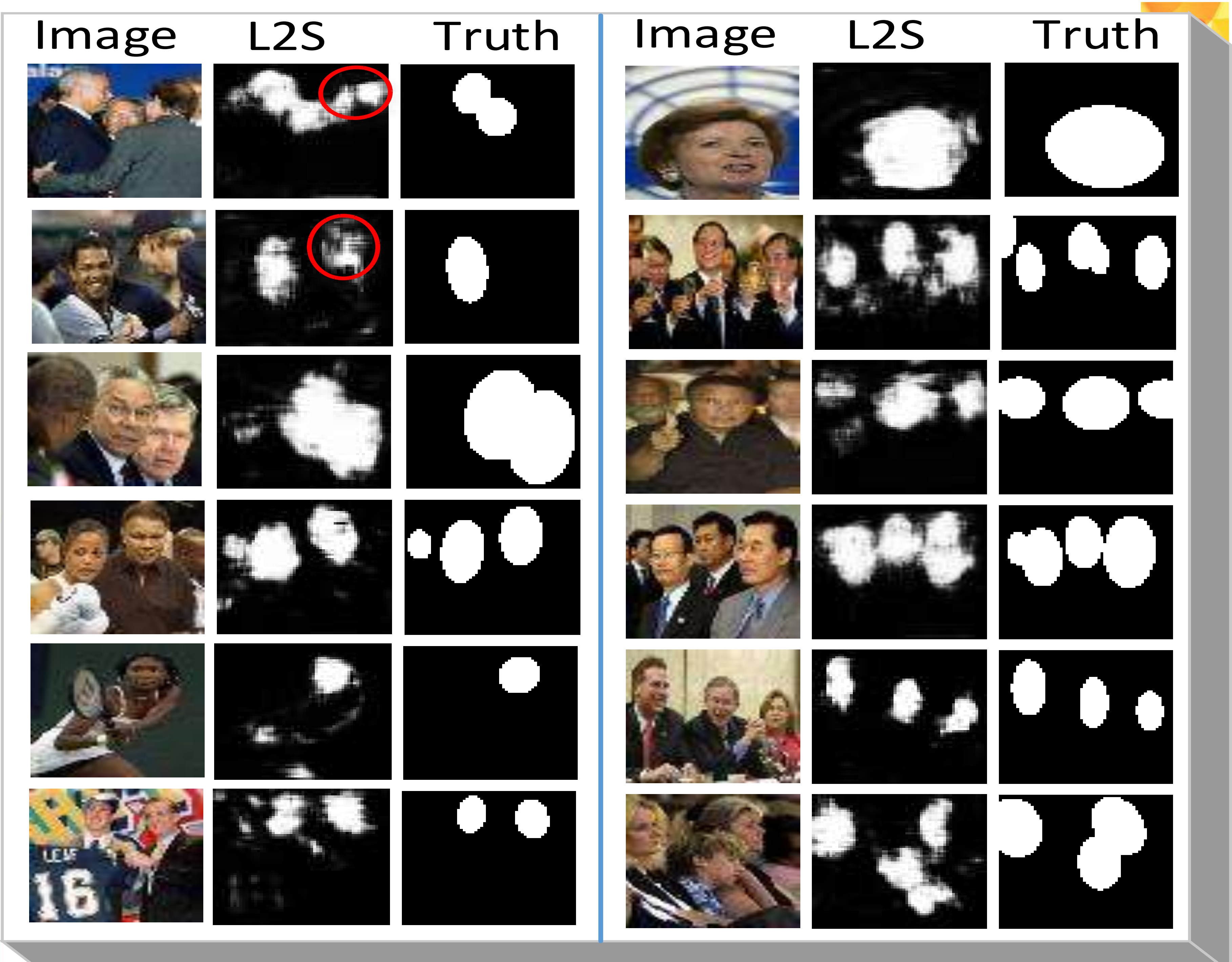


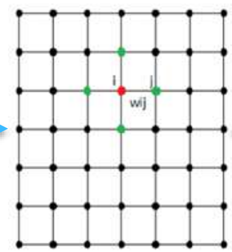
Image
L2S
Truth
Image
L2S
Truth

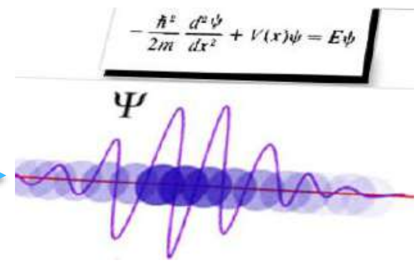
Table 1: Mean performances of the FCN-32s VGG [9] and the proposed L2S with single and 5 CSNs.

	Train (mean %)		Test (mean %)	
Method	Pix. Acc.	F1	Pix. Acc.	F1
L2S (1 CSN)	91.29	70.59	90.23	67.73
L2S (5 CSNs)	**94.38**	**81.05**	91.53	72.02
FCN-32s [9]	94.29	77.91	**93.91**	**76.84**

Kiranyaz, **Proc. IEEE ICIP**, 2016, Phoenix, Arizona.

Combining Quatum Mechanics and Spectral Graph Theory: Quantum-Cut for Salient Object Detection





$$H(i,j) = \begin{cases} V(i) + |N_i|\frac{\hbar^2}{2m} & i = j \\ -\frac{\hbar^2}{2m} & j \in N_i \\ 0 & e.w \end{cases}$$

$$L(i,j) = \begin{cases} \sum_k w_{i,k} & i = j \\ -w_{i,j} & j \in N_i \\ 0 & e.w \end{cases}$$

- Aytekin **Pattern Recognition,** 2016
- Aytekin **Pattern Recognition Letters**, 2016
- Aytekin **ICPR 2014.** IBM Best Paper Award
- Aytekin, Best Nordic Thesis Award, 2017

Object Proposals and Labeling

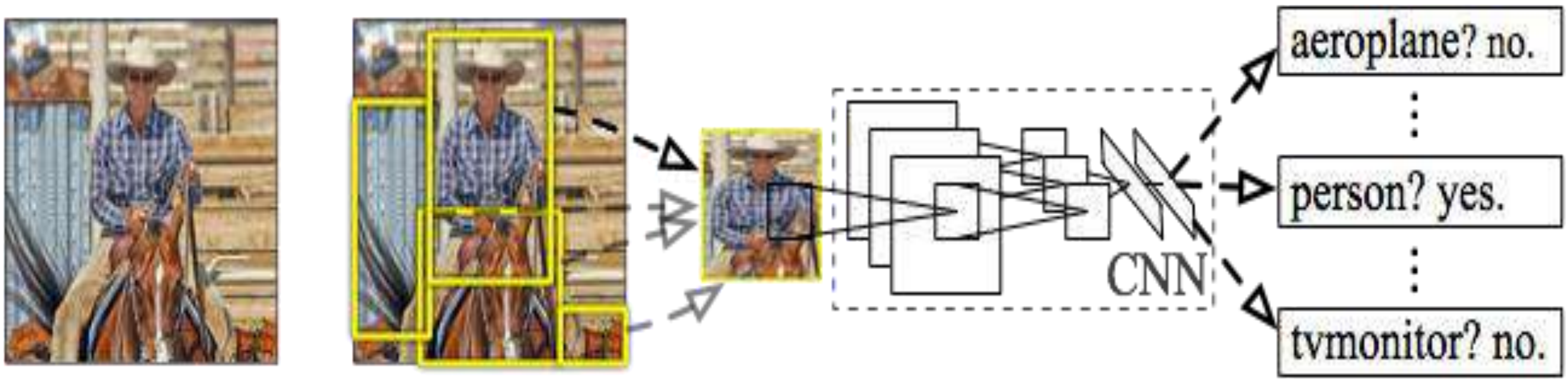
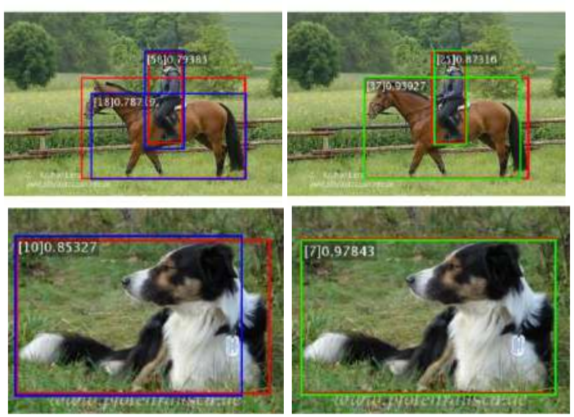
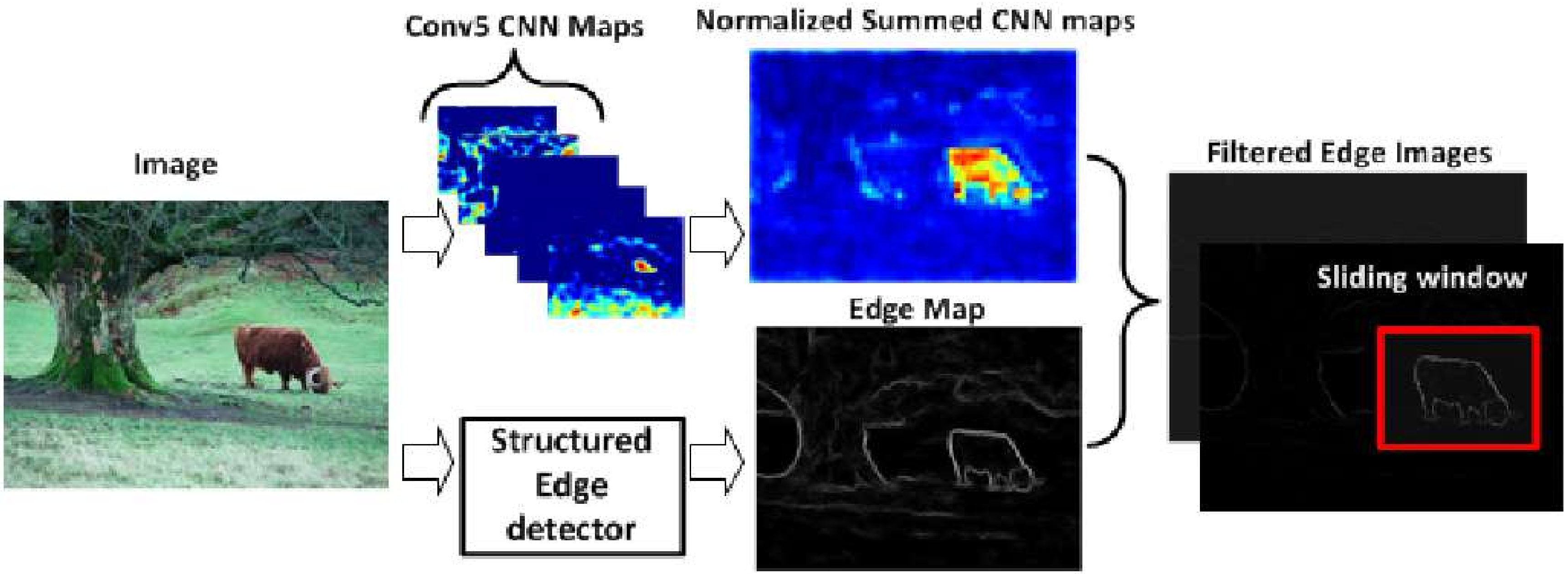


Image Labeling



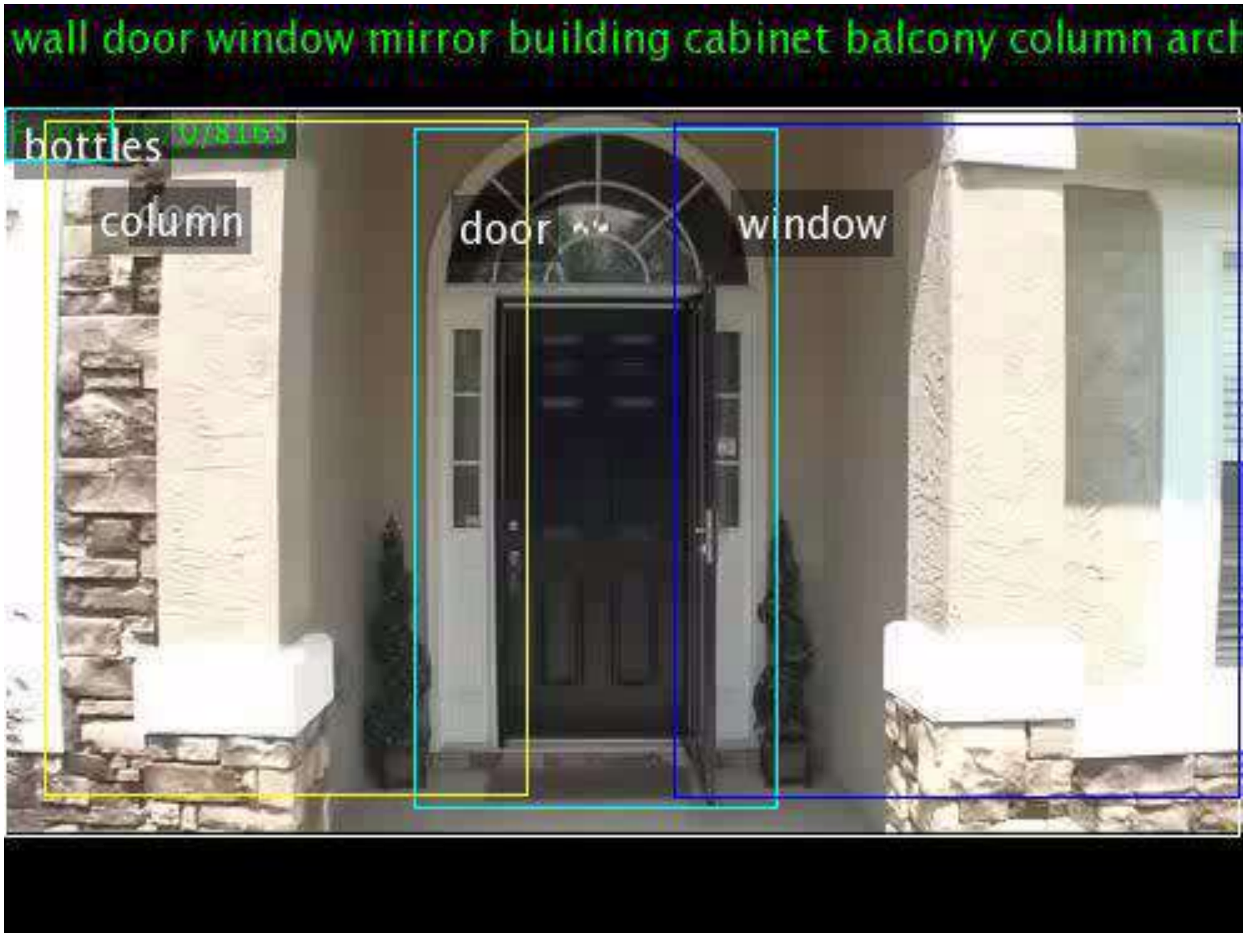
Combining Deep Learning and Signal Processing –

Object Proposals



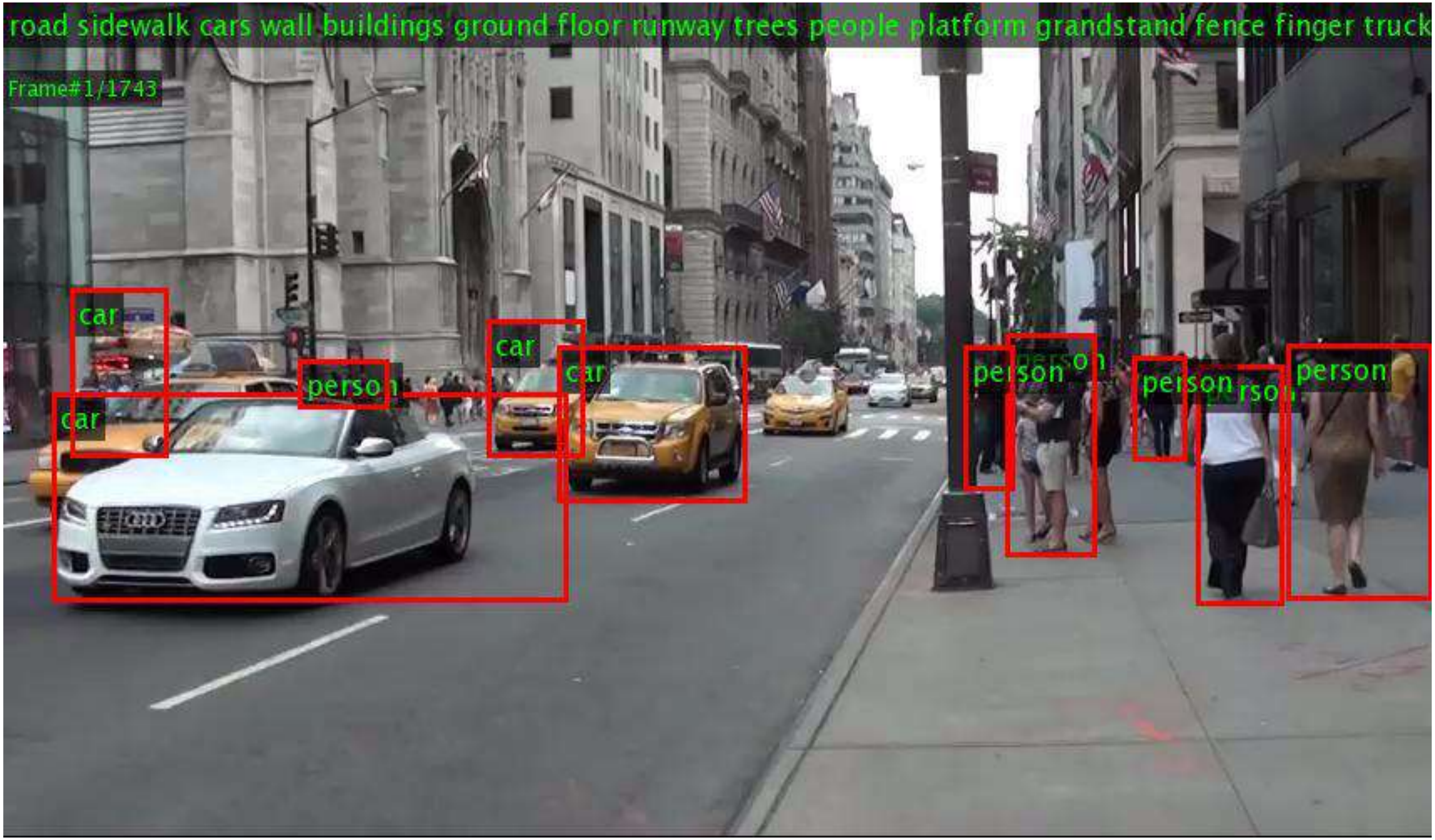
Waris, **Neurocomputing**, 2017.

Object(s) Recognition & Localization

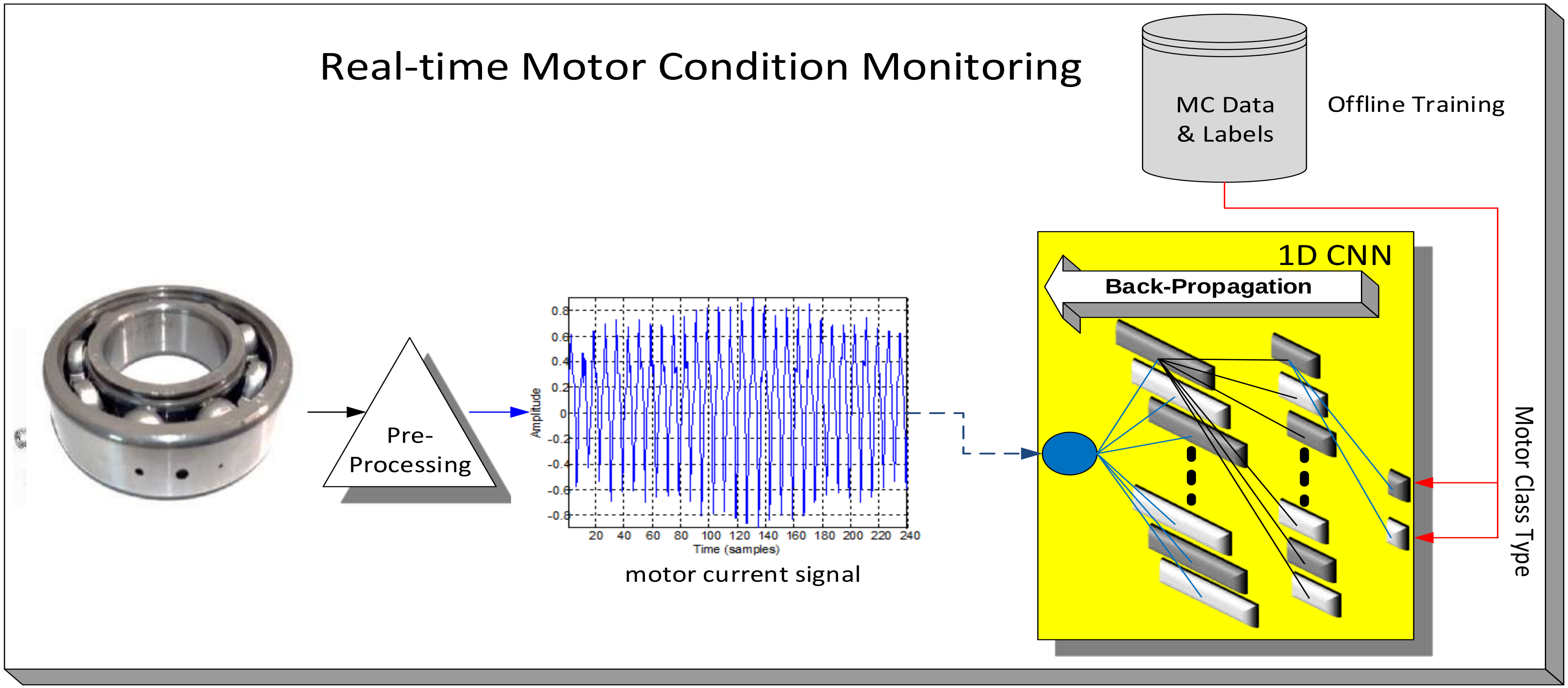


Person Car Bicycle & Bus Detection

Gabbouj/ 12/14/2018

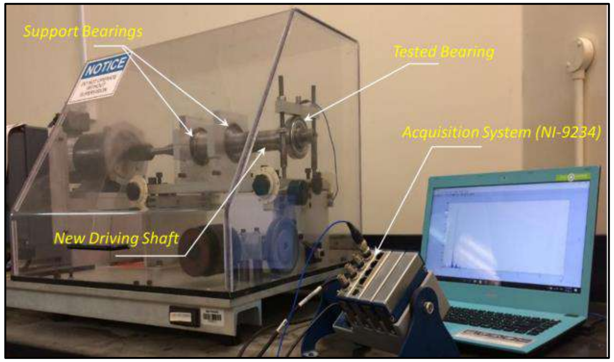


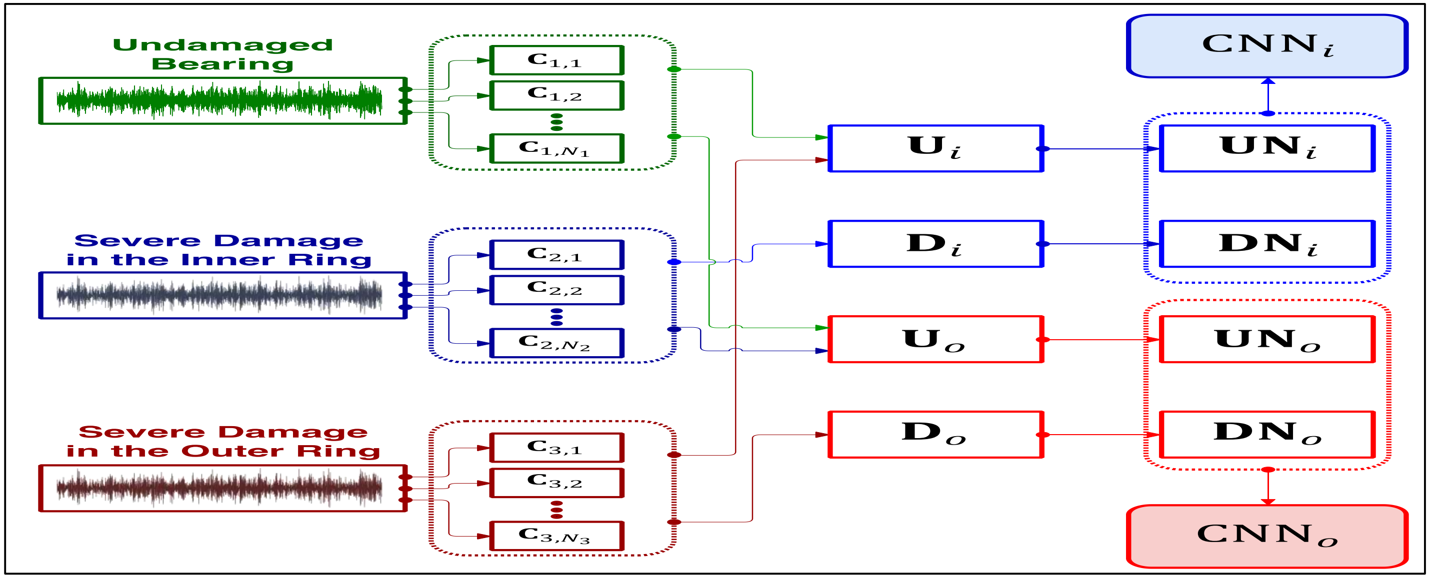
Real-Time Motor Fault Detection by 1-D Convolutional Neural Networks



Kiranyaz, **IEEE Transaction on Industrial Electronics,** 2016.

Real-time Motor Fault Detection by 1D CNN

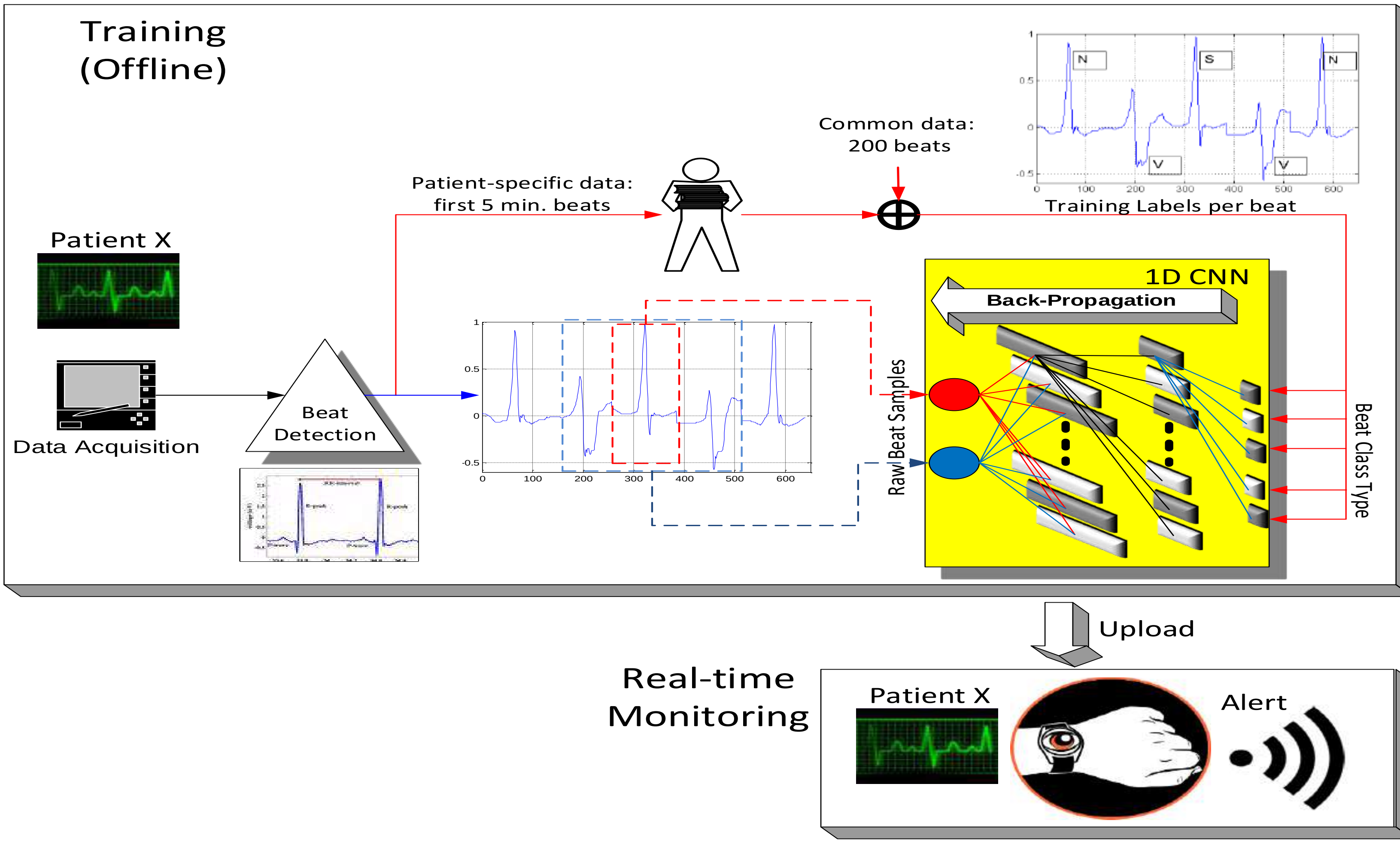




240 msec to detect and classify faults from a 2-sec signal sampled at 12.8kHz (5min for training)

Kiranyaz, **IEEE Transaction on Industrial Electronics,** 2016.

Real-Time Patient-Specific ECG Classification by 1D CNN



Kiranyaz, **IEEE Transactions on Biomedical Engineering**, 2015.

Real-Time Patient-Specific ECG Classification by 1D CNN

Table II: VEB and SVEB classification performance of the proposed method and comparison with the four major algorithms from the literature. Best results are highlighted.

Methods	VEB				SVEB			
	Acc	*Sen*	*Spe*	*Ppr*	*Acc*	*Sen*	*Spe*	*Ppr*
Hu et al. [10] [1]	94.8	78.9	96.8	75.8	N/A	N/A	N/A	N/A
Jiang and Kong [15] [1]	98.8	94.3	99.4	95.8	**97.5**	74.9	98.8	78.8
Ince et al. [16] [1]	97.9	90.3	98.8	92.2	96.1	**81.8**	98.5	63.4
Proposed [1]	**98.9**	**95.9**	**99.4**	**96.2**	96.4	68.8	**99.5**	**79.2**
Jiang and Kong [15] [2]	98.1	86.6	**99.3**	**93.3**	**96.6**	50.6	**98.8**	**67.9**
Ince et al. [16] [2]	97.6	83.4	98.1	87.4	96.1	62.1	98.5	56.7
Proposed [2]	**98.6**	**95**	98.1	89.5	96.4	**64.6**	98.6	62.1
Ince et al. [16] [3]	98.3	84.6	98.7	87.4	97.4	**63.5**	99.0	53.7
Proposed [3]	**99**	**93.9**	**98.9**	**90.6**	**97.6**	60.3	**99.2**	**63.5**

[1] The comparison results are based on 11 common recordings for VEB detection and 14 common recordings for SVEB detection.

[2] The VEB and SVEB detection results are compared for 24 common testing records only.

[3] The VEB and SVEB detection results of the proposed system for all training and testing records.

Kiranyaz, **IEEE Transactions on Biomedical Engineering**, 2016.

SCIENTIFIC REPORTS

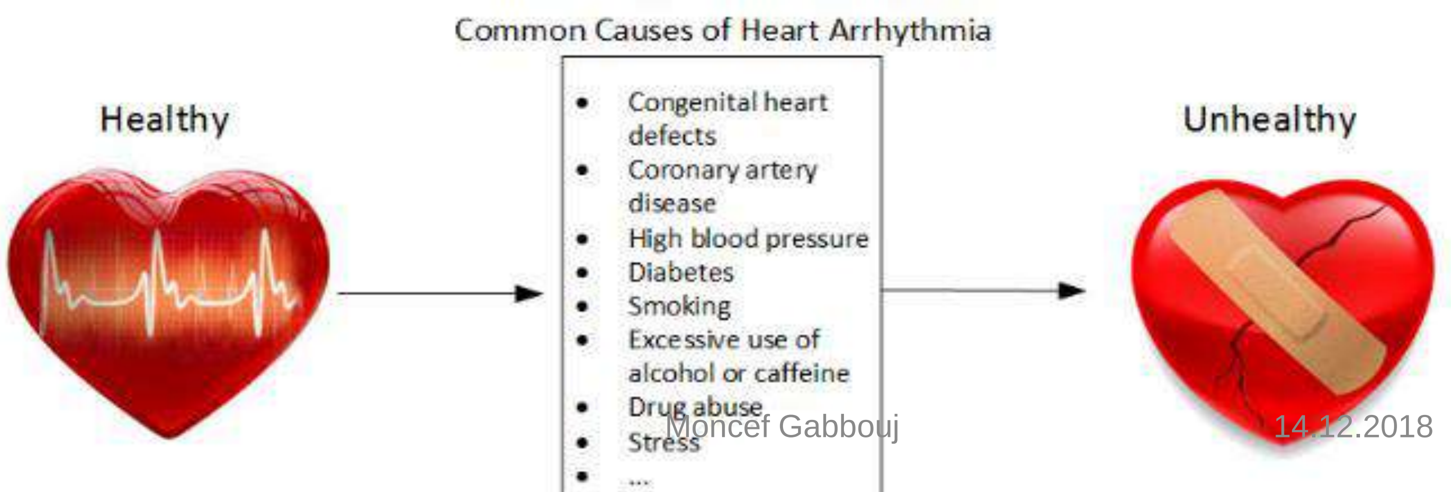
OPEN

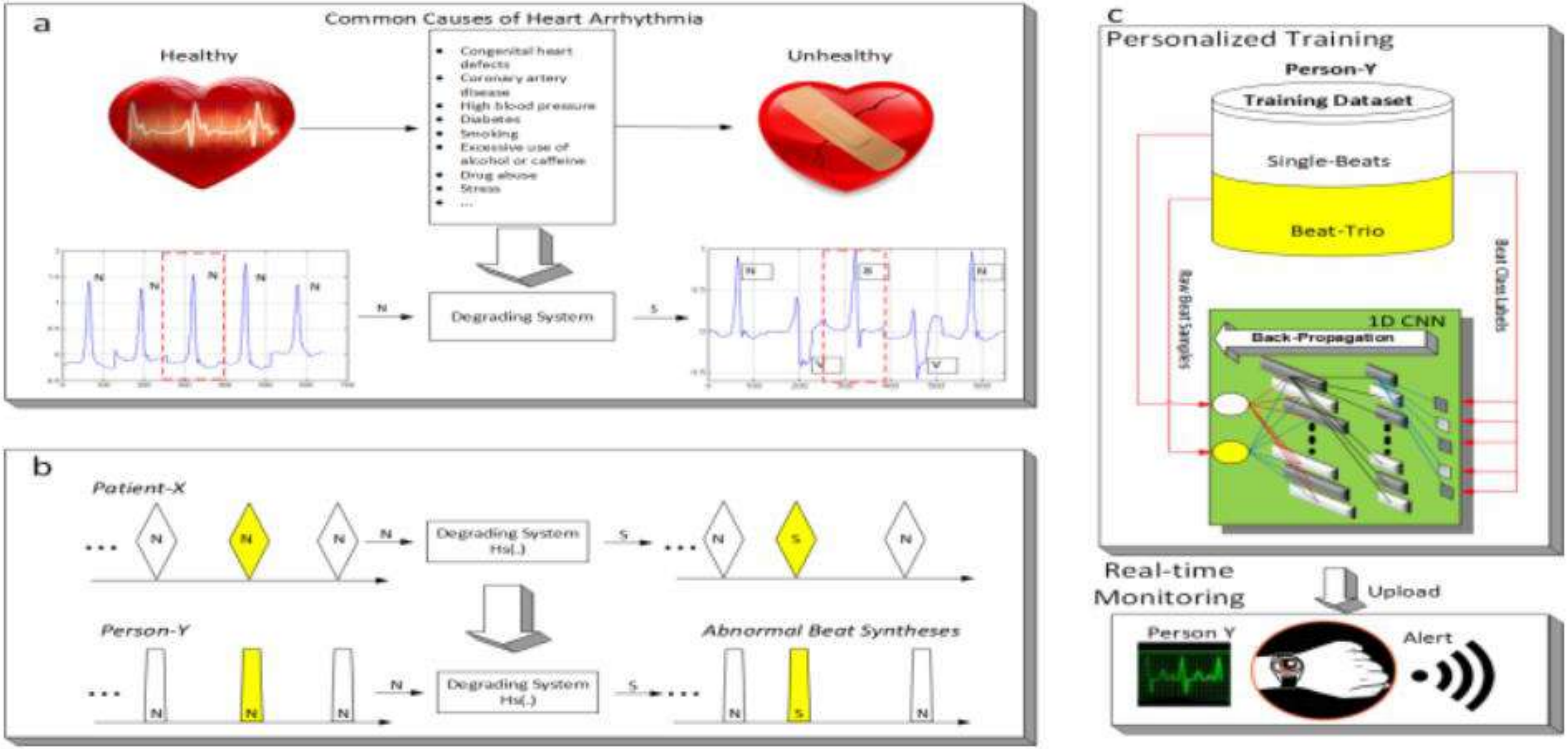
Personalized Monitoring and Advance Warning System for Cardiac Arrhythmias

ed: 30 December 2016

Serkan Kiranyaz[1], Turker Ince[2] & Moncef Gabbouj[3]

Kiranyaz, **Scientific Reports**, 2017. (Springer Nature)





a) Modelling common causes of cardiac arrhythmia in the signal domain.
b) Symbolic illustration of an abnormal S beat synthesis for Person-Y using the degrading system designed from the ECG data of several Patient(s)-X.
c) Illustration of the overall system, where a dedicated CNN is trained by Backpropagation over the training dataset created for Person-Y (top). Once the 1D CNN is trained, it can then be used as a continuous cardiac health monitoring and advance warning system (bottom) for Person-Y.

Results

	Ground Truth					
Real		N	S	V	F	Q
	N	564118	1443	7447	2721	60
	S	1362	12913	9752	447	17
	V	856	217	28145	210	20
	F	224	16	1254	22	3
	Q	120	11	2032	0	0

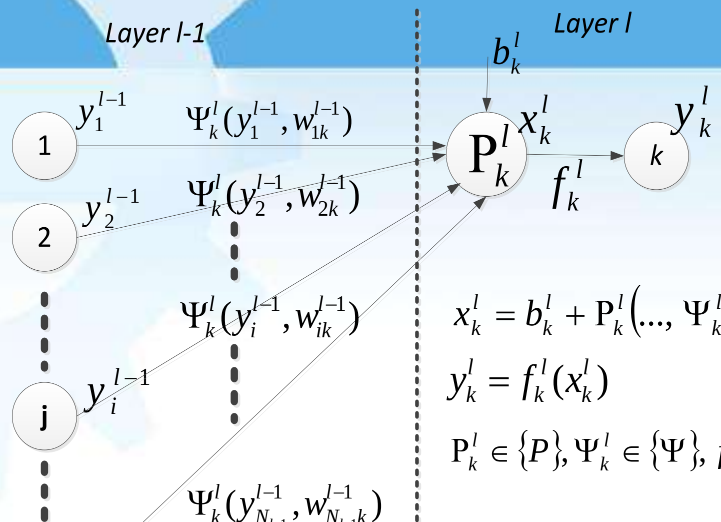
Table 1. Cumulated CM for the test dataset over 10 runs.

	Ground Truth		
Real		N	A
	N	564118	11671
	A	2562	55059

Table 2. 2×2 confusion matrix deducted from the CM in Table 1.

- 34 patient with 63,341 ECG beats were used in the evaluation.
- *Sen* = 82.51%, *Spe* = 99.55%, *Ppr* = 95.55%, *Acc* = 97.75% and *FAR* = 0.45%,
- Average probability of missing the first abnormal beat is 0.174
- The average probability of missing three consecutive abnormal beats is around 0.0053.
- Therefore, detecting one or more abnormal beat(s) among the first three occurrences is highly probable (>99.4%)

Advanced Network Architecture Design: **Generalized Operational Perceptrons (GOPs)**



$$x_k^l = b_k^l + P_k^l\left(\ldots,\ \Psi_k^l(y_i^{l-1}, w_{ik}^{l-1}),\ldots\right)$$

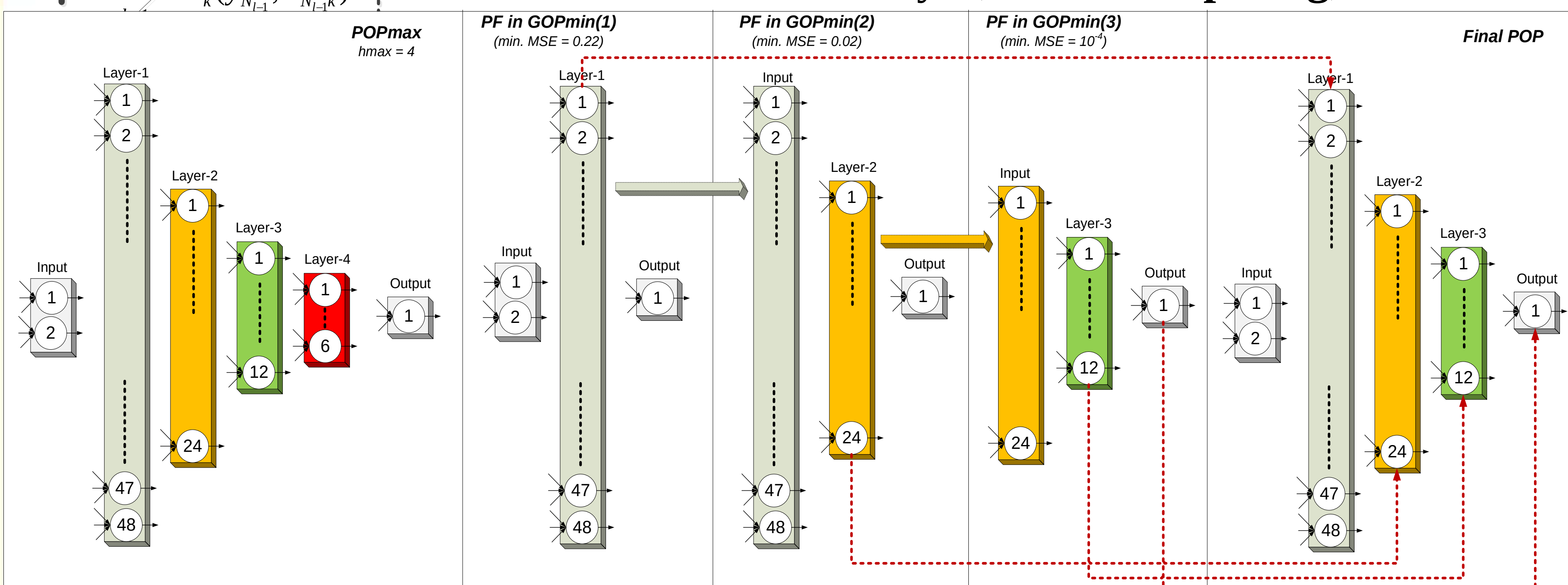
$$y_k^l = f_k^l(x_k^l)$$

$$P_k^l \in \{P\},\ \Psi_k^l \in \{\Psi\},\ f_k^l \in \{F\}$$

We proposed a Progressive Operational Feedforward Neural network learning approach

- Data-driven network's architecture
- Data-driven network's parameters tuning

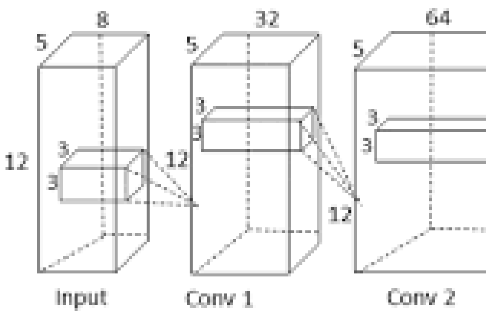
Kiranyaz, **Neurocomputing**, 2017.

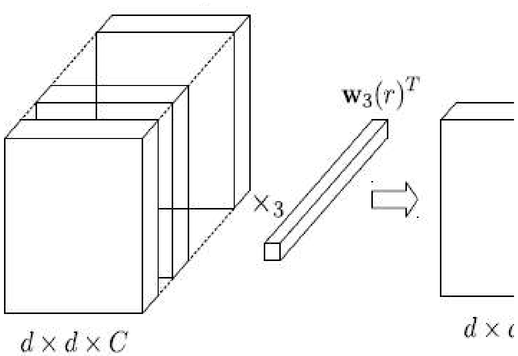


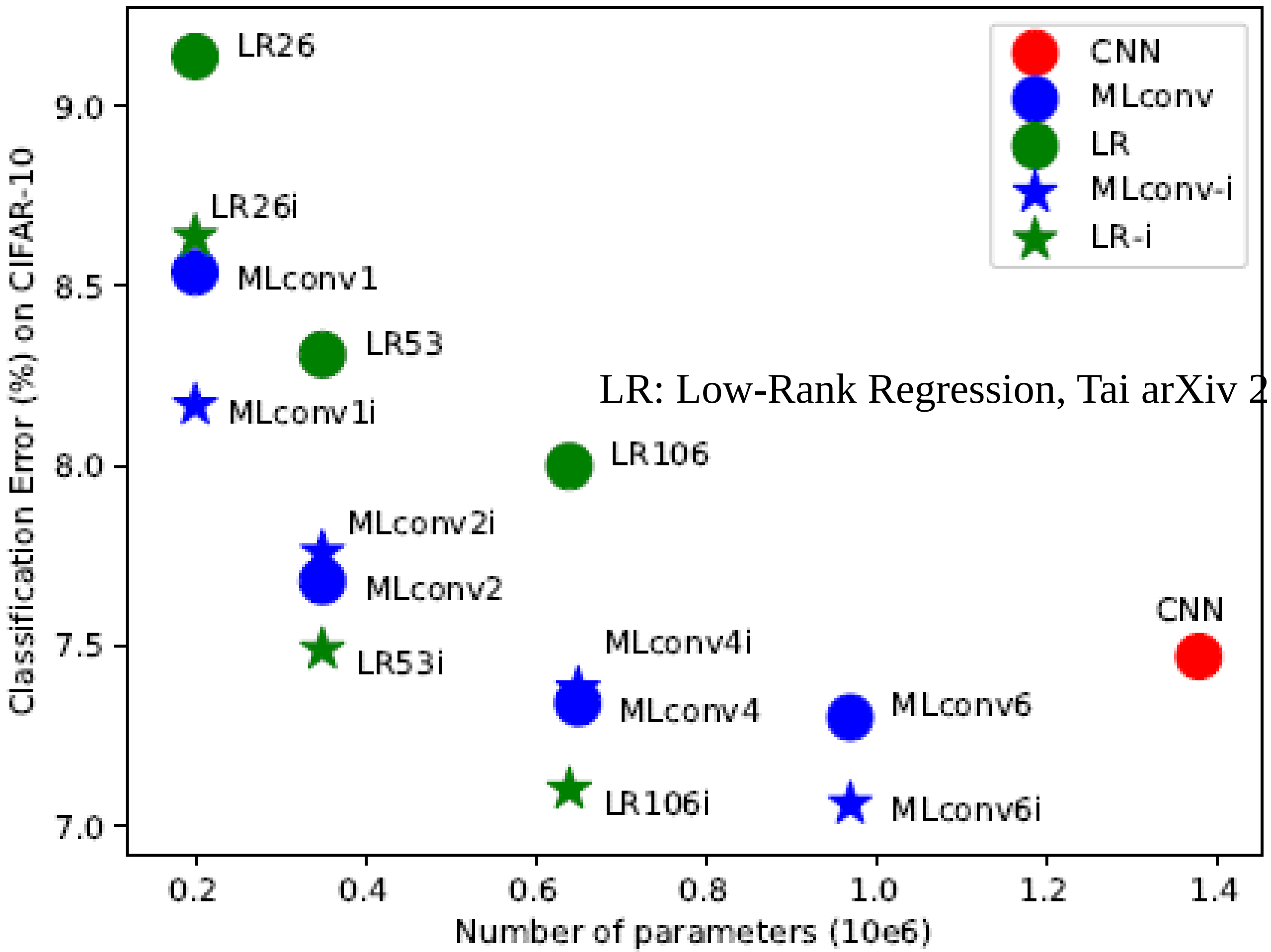
Efficient CNN Design (Deep Learning)

Tensor-based CNN f

› Employing multilinea
› Lower number of ne
› Faster classification







LR: Low-Rank Regression, Tai arXiv 2015

D.T. Thanh, A. Iosifidis and M. Gabbouj, “Improving Efficiency in Convolutional Neural Network with Multilinear Filters”, Neural Networks, 2018 (arXiv 2017)

Long- and Short-memory Neural BoFs

Temporal-aware NN BoF model for time-series data analvsis

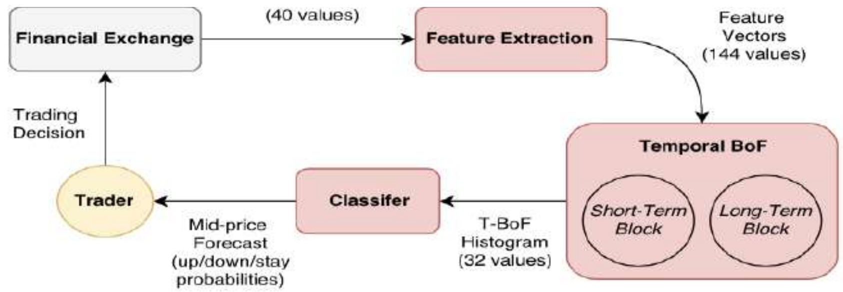
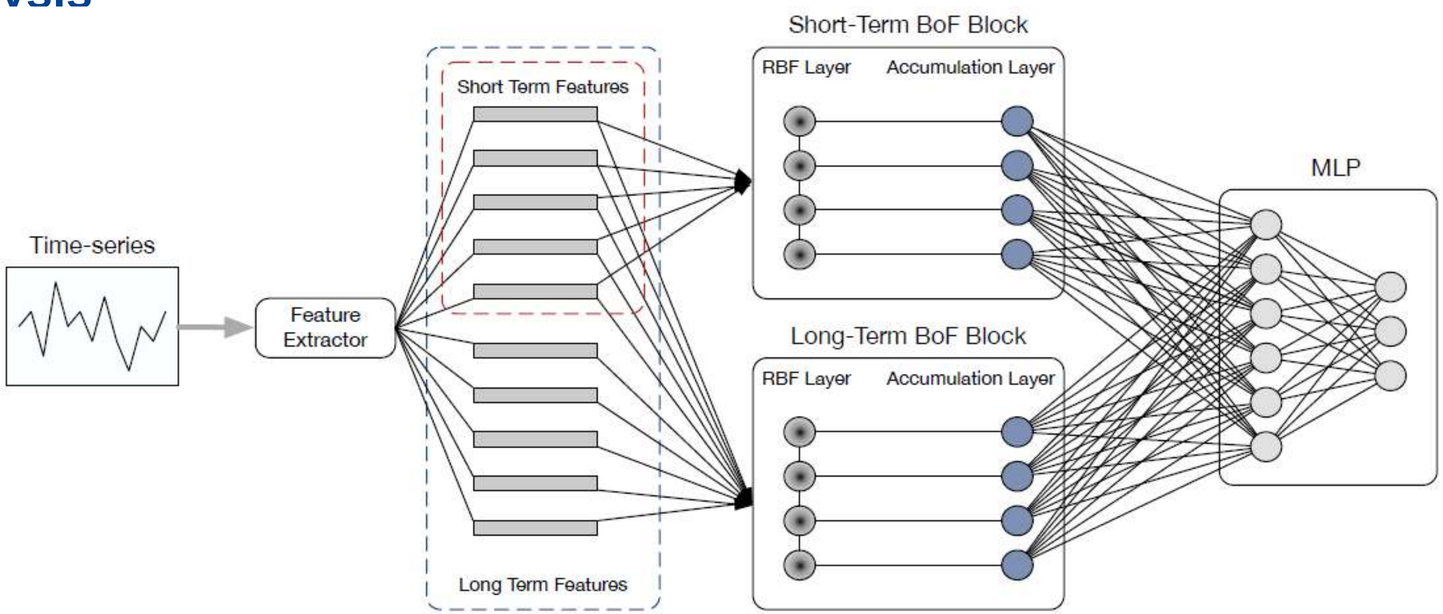


Fig. 1: Pipeline of the proposed financial forecasting model



N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj and A. Iosifidis, “Temporal Bag-of-Features learning for Predicting Mid Price Movements using High Frequency Limit Order Book Data”, IEEE Transactions on Emerging Topics in Computational Intelligence, 2019

Attention in Multi (AMLN)

AMLN architecture incorporates

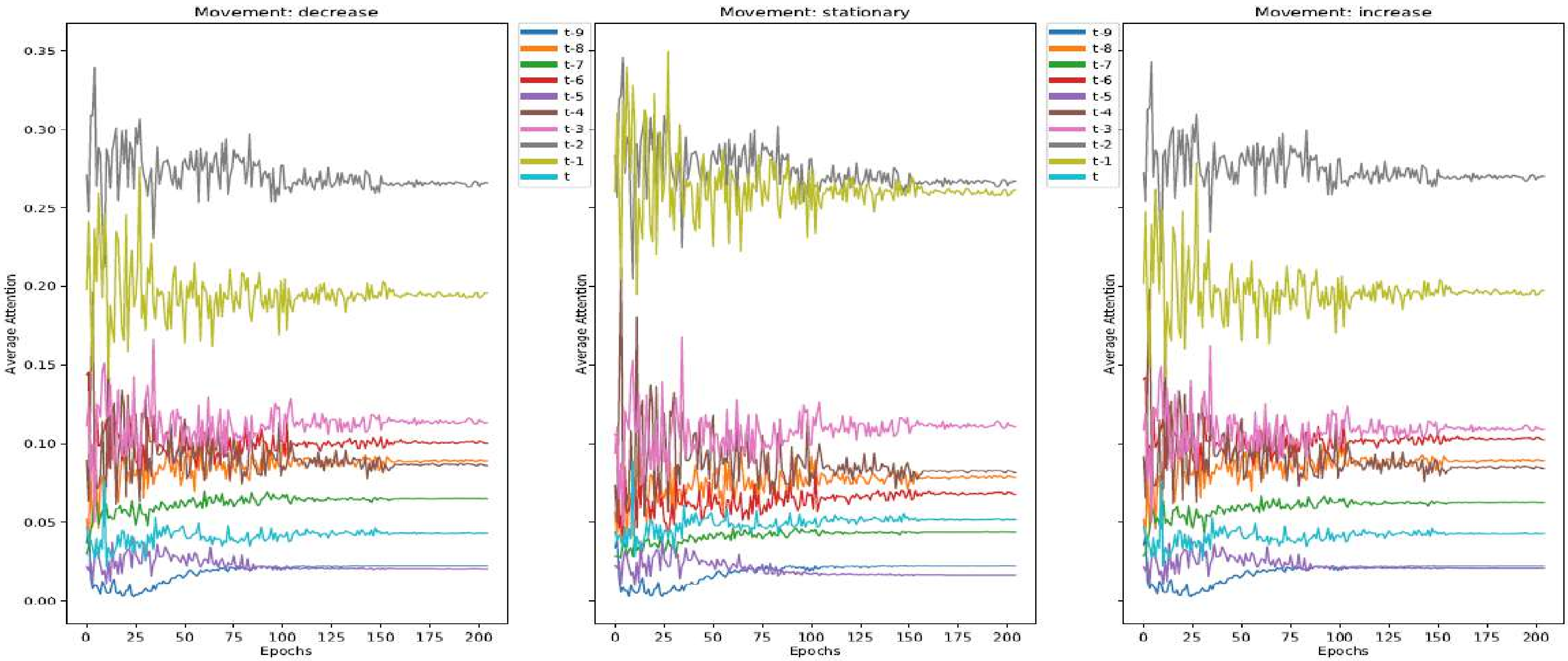
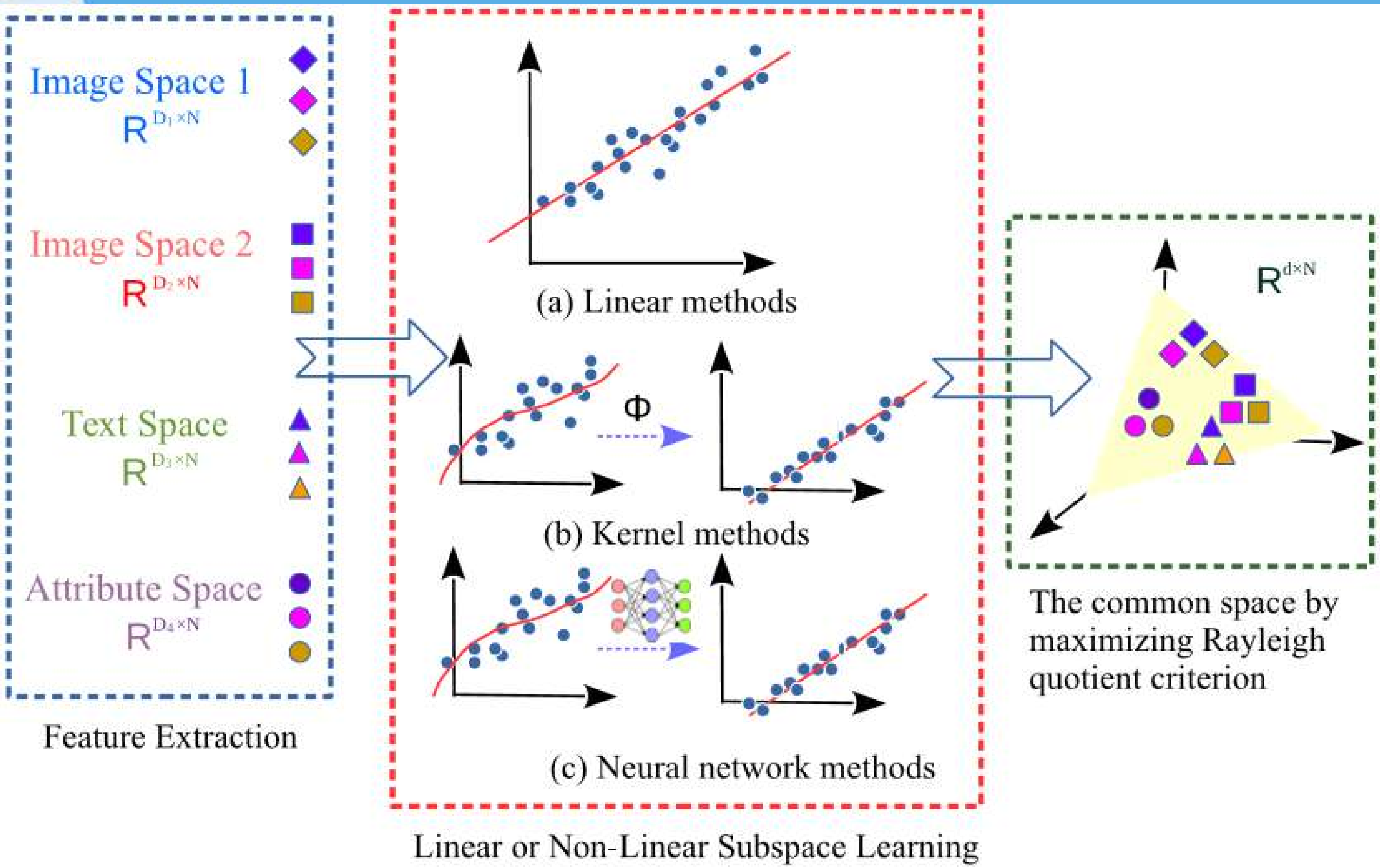


Fig. 3. Average attention of 10 temporal instances during training in 3 types of movement: decrease, stationary, increase. Values taken from configuration A(TABL) in Setup2, horizon $H = 10$

D.T. Tran, A. Iosifidis, J. Kanniainen and M. Gabbouj, "Temporal Attention augmented Bilinear Network for Financial Time-Series Data Analysis", IEEE Transactions on Neural Networks and Learning Systems, 2019

Multimodal and Cross-modal Learning



Gao, **IEEE Transactions on Cybernetics**, 2018.

IEEE NER 2015 BCI CHALLENGE 2015: (3rd PLACE)

OBJECTIVE:

❖P300-Speller is a well-known brain-computer interface paradigm and has great potential to help individuals with neuromuscular disabilities to communicate. The goal of this challenge was to detect errors during the spelling task by analyzing the subjects' EEG recording.

METHODOLOGY:

❖The *BCI challenge@NER2015* dataset is used.

❖56 EEG channels are used.

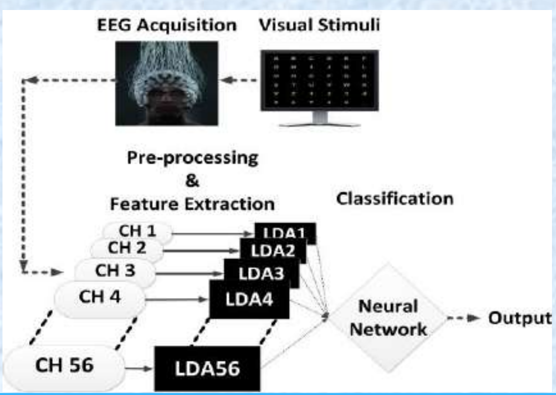
❖13 different features of approximation coefficients of Daubechies 4 wavelets in 5-level decomposition are extracted (base-level features).

❖The base-level features are classified by 56 different linear discriminant analysis (LDA) classifiers (for each channel) to obtain the meta-level features which are the posterior probabilities (of the LDA classifiers).

❖For classification of (56-dimention) feature vectors a feedforward neural network with two hidden layers; 15 neurons in the first and 7 neurons in the second hidden layer is used.

RESULTS:

❖The area under the ROC curve of 0.78 was achieved for the proposed approach (this was 0.69 in the private leaderboard).



PHYSIONET CHALLENGE 2016: (2nd PLACE AMONG 48 TEAMS)

OBJECTIVE:

❖Heart sound has a great potential to be used as a diagnostic test in ambulatory monitoring. The goal was to detect heart anomalies by analyzing the subject's heart sound waves.

METHODOLOGY:

❖The *Physionet challenge 2016 PCG* dataset is used.

❖18 features is selected among 40 features from time, frequency, time-frequency domains.

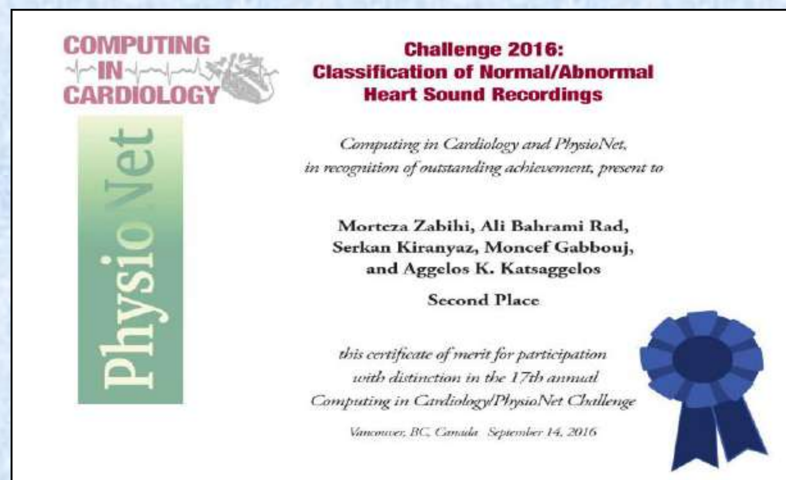
❖Wrapper-based feature selection scheme using sequential forward selection search algorithm is used for feature selection.

❖20 ANN were used with two hidden layers in each, and 25 hidden neurons at each layer.

RESULTS:

Train Dataset 10-fold cross-validation	Evaluation Metrics		
	Sen (%)	Spe (%)	Score (%)
Ave.	94.2	88.8	91.5

Train Dataset 10-fold cross-validation	Evaluation Metrics		
	Sen (%)	Spe (%)	Score (%)
Ave.	94.2	88.8	91.5



PHYSIONET CHALLENGE 2017: (1st PLACE AMONG 75 TEAMS)

OBJECTIVE:

❖The goal of this challenge was to detect Atrial Fibrillation (AF) rhythm using hand-held ECG monitoring devices, in addition to three other classes: normal or sinus rhythm, other rhythms, and too noisy to analyze.

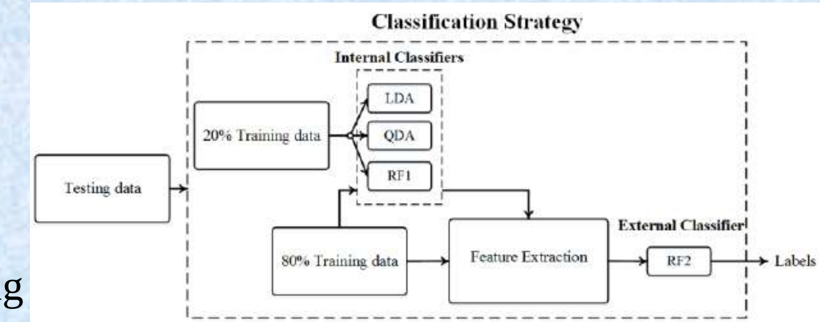
METHODOLOGY:

❖The *Physionet challenge 2017 ECG* dataset is used.

❖491 hand-crafted multi-domain features are extracted.

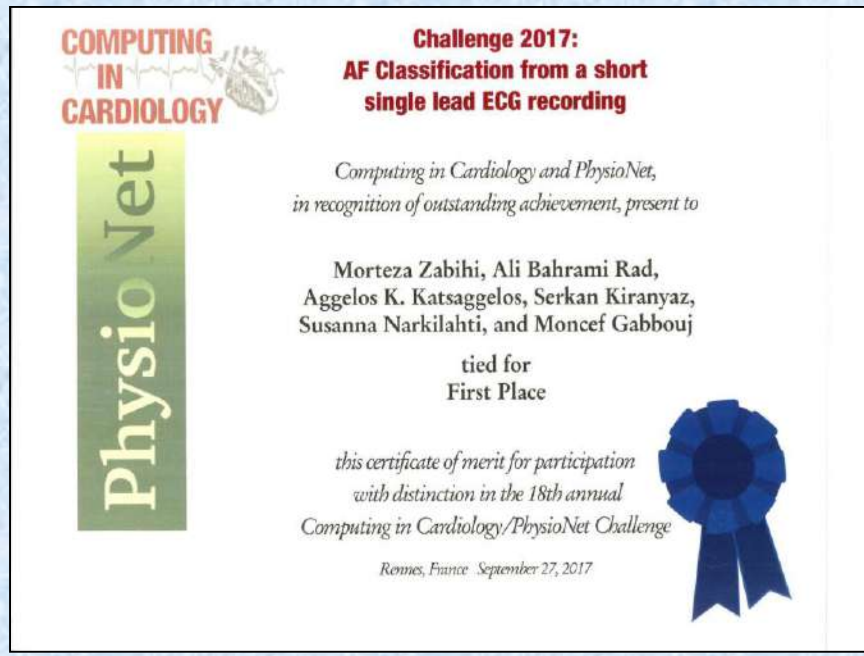
❖150 features are selected using random forest.

❖Hybrid classification (base-level + meta-level) learning



RESULTS:

Evaluation Metrics	Ave. on Train Dataset (%) 10-fold cross-validation	Ave. on Test Dataset (%)
F1n (Normal)	90.49	
F1a (AF)	79.43	
F1o (Other)	75.64	
F1p (Noisy)	61.11	
F1(Total)	81.85	83



NSF-Business Finland-IUCRC-CVDI

CVDI Center for Visual & Decision Informatics

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Areas of Focus

- Visual Analytics
- Predictive Analytics
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- Data Summarization
- Social Media Analytics

Research Projects

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Core and Supplemental Funds, IUCRC Governance

Funding Agencies

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Value Return
- Research Cost Savings
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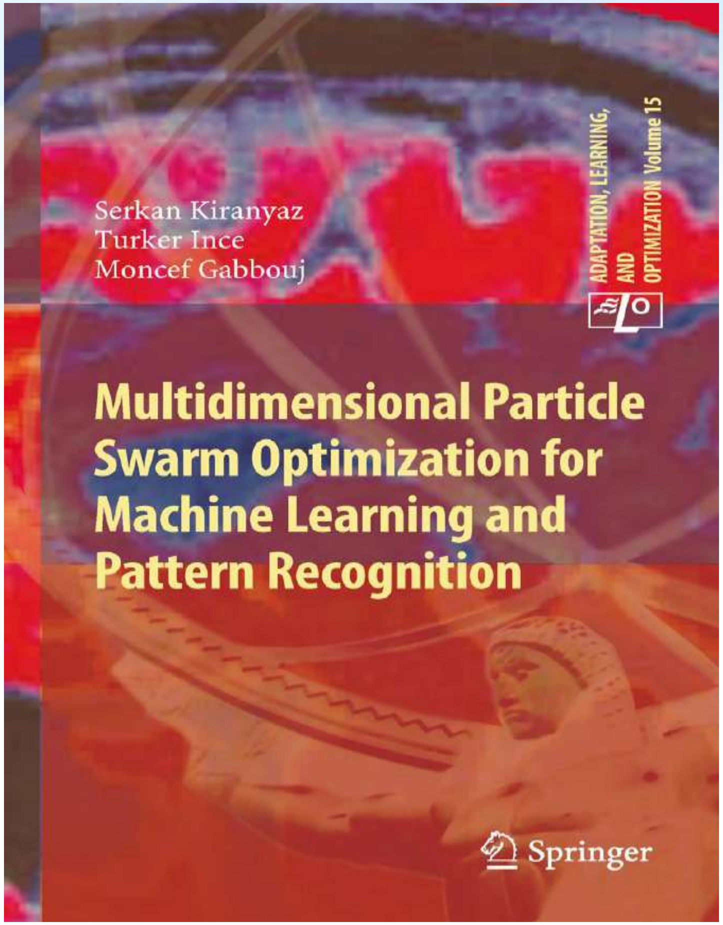
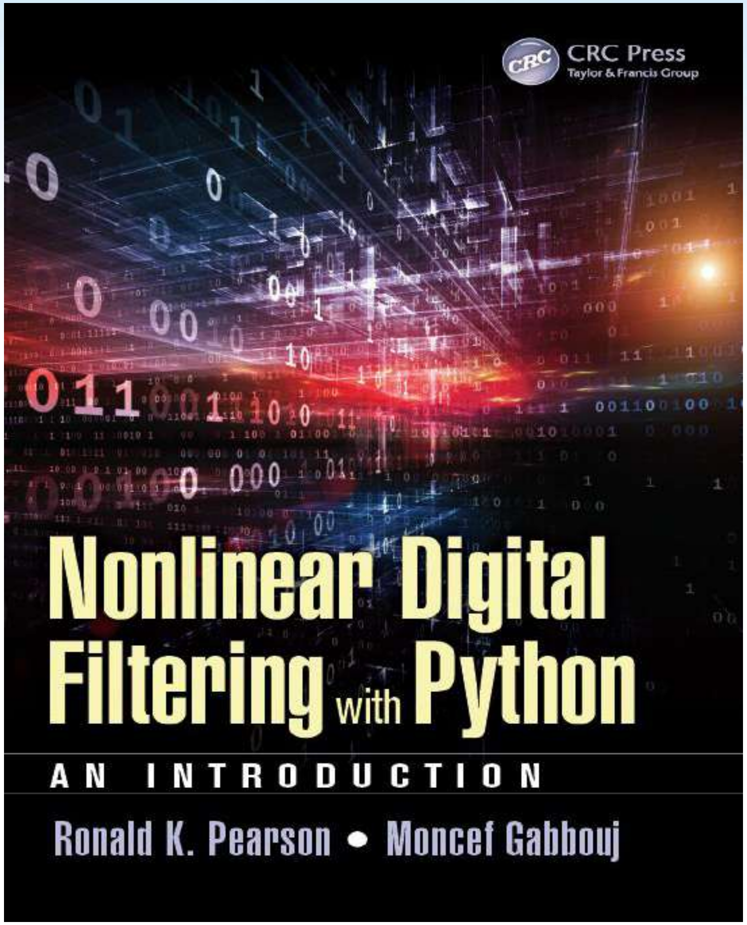
Recent books in the field





Summary

- Novel methods and algorithms for artificial intelligence deeply rooted in signal processing and pattern recognition,
- New machine learning techniques developed based on the specific properties of the problems at hand,
- Data-to-Decision Research Community in TUT gathered a critical mass to make sizeable contributions to the field of AI,