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Optimal Hyperbox shrinking in Dendritic Computing applied to Alzheimer’s Disease detection in MRI

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Content

- Introduction
- Dendritic Computing
- Experimental results
- Summary and Conclusions

Introduction

Dendritic Computing

- simple and fast
- based on biology
- binary class problems
- based on lattice theory

Introduction

Has been proved to compute a **perfect** approximation to **any data distribution.**

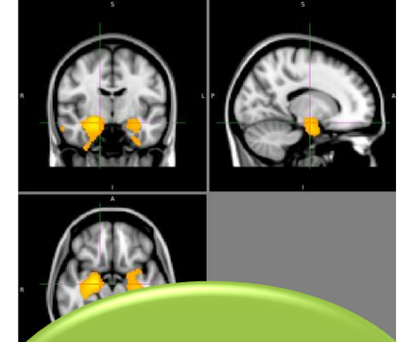
The results of cross-validation experiments give very poor performance: **high sensitivity and very low specificity**.

We attribute this to the fact that the **DC learning algorithm** always tries to **guarantee** the good classification of the class 1 samples.

We propose to apply a **reduction factor** on the size of the hyperboxes

OASIS subjects →

VBM Analysis →

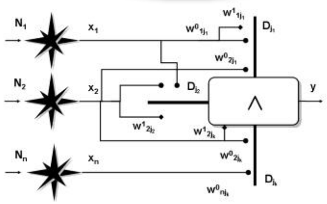


SPM

↓

Compute Feature Vectors ←

Mean and standard Deviation ←



DC

↓

Result

α	Accuracy	Sensitivity	Specificity
0	58	94	23
0.5	60	81	40
0.53	59	77	42
0.55	64	85	44
0.57	63	83	43
0.6	62	81	44
0.63	64	83	45
0.65	**69**	**83**	**54**
0.67	64	78	49
0.7	64	79	49
0.73	65	79	52
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0.87	63	74	52
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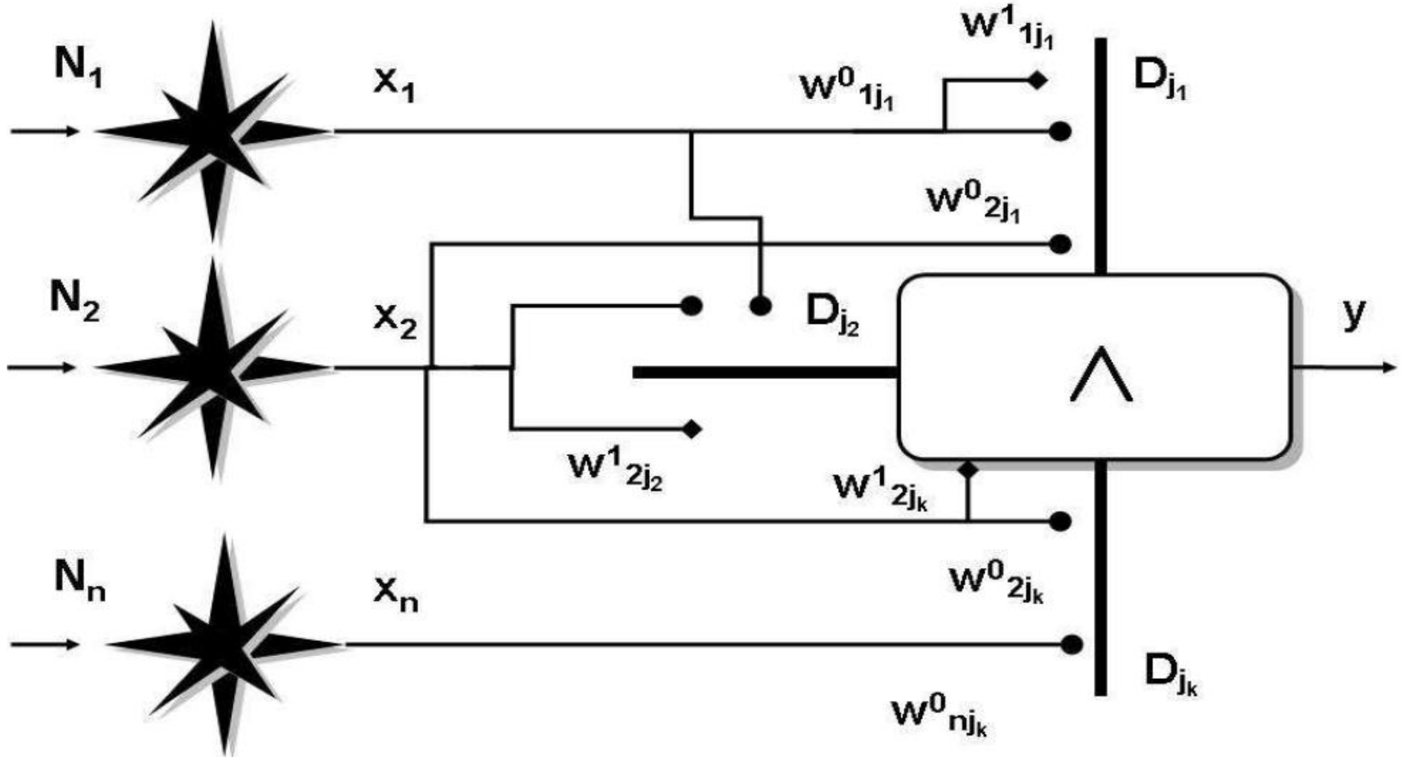
0.97	61	69	53

Dendritic Computing

Structure of a single output class single layer Dendritic Computing system



Algorithm 1 Dendritic Computing learning based on elimination

Training set $T = \left\{ \left(\mathbf{x}^{\xi}, c_{\xi} \right) \mathbf{x}^{\xi} \in \mathbb{R}^{n}, c_{\xi} \in \{0,1\}; \xi = 1, \ldots, m \right\}$, $C_1 = \{\xi : c_{\xi} = 1\}$, $C_0 = \{\xi : c_{\xi} = 0\}$

1. Initialize $j = 1$, $I_j = \{1, \ldots n\}$, $P_j = \{1, \ldots, m\}$, $L_{ij} = \{0,1\}$,

$$w_{ij}^{1} = -\bigwedge_{c_{\xi}=1} x_i^{\xi};\ w_{ij}^{0} = -\bigvee_{c_{\xi}=1} x_i^{\xi}, \forall i \in I$$

Construct a basic hyperbox

2. Compute response of the current dendrite D_j, with $p_j = (-1)^{\operatorname{sgn}(j-1)}$:

$$\tau_j\left(\mathbf{x}^{\xi}\right) = p_j \bigwedge_{i \in I_j} \bigwedge_{l \in L_{ij}} (-1)^{1-l} \left(x_i^{\xi} + w_{ij}^{l} \right), \forall \xi \in P_j.$$

3. Compute the total response of the neuron:

$$\tau\left(\mathbf{x}^{\xi}\right) = \bigwedge_{k=1}^{j} \tau_k\left(\mathbf{x}^{\xi}\right); \xi = 1, \ldots, m.$$

4. If $\forall \xi \left(f\left(\tau\left(\mathbf{x}^{\xi}\right)\right) = c_{\xi} \right)$ the algorithm stops here with perfect classification of the training set.
5. Create a new dendrite $j = j+1$, $I_j = I' = X = E = H = \emptyset$, $D = C_1$
6. Select $\mathbf{x}^{\gamma}$ such that $c_{\gamma} = 0$ and $f(\tau(\mathbf{x}^{\gamma})) = 1$.
7. $\mu = \bigwedge_{\xi \neq \gamma} \left\{ \bigvee_{i=1}^{n} \left| x_i^{\gamma} - x_i^{\xi} \right| : \xi \in D \right\}$.
8. $I' = \left\{ i : \left| x_i^{\gamma} - x_i^{\xi} \right| = \mu, \xi \in D \right\}$; $X = \left\{ \left(i, x_i^{\xi} \right) : \left| x_i^{\gamma} - x_i^{\xi} \right| = \mu, \xi \in D \right\}$.
9. $\forall \left(i, x_i^{\xi} \right) \in X$
   a. if $x_i^{\gamma} > x_i^{\xi}$ then $w_{ij}^{1} = -(x_i^{\xi} + \alpha \cdot \mu)$, $E_{ij} = \{1\}$
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Hard-limiter function

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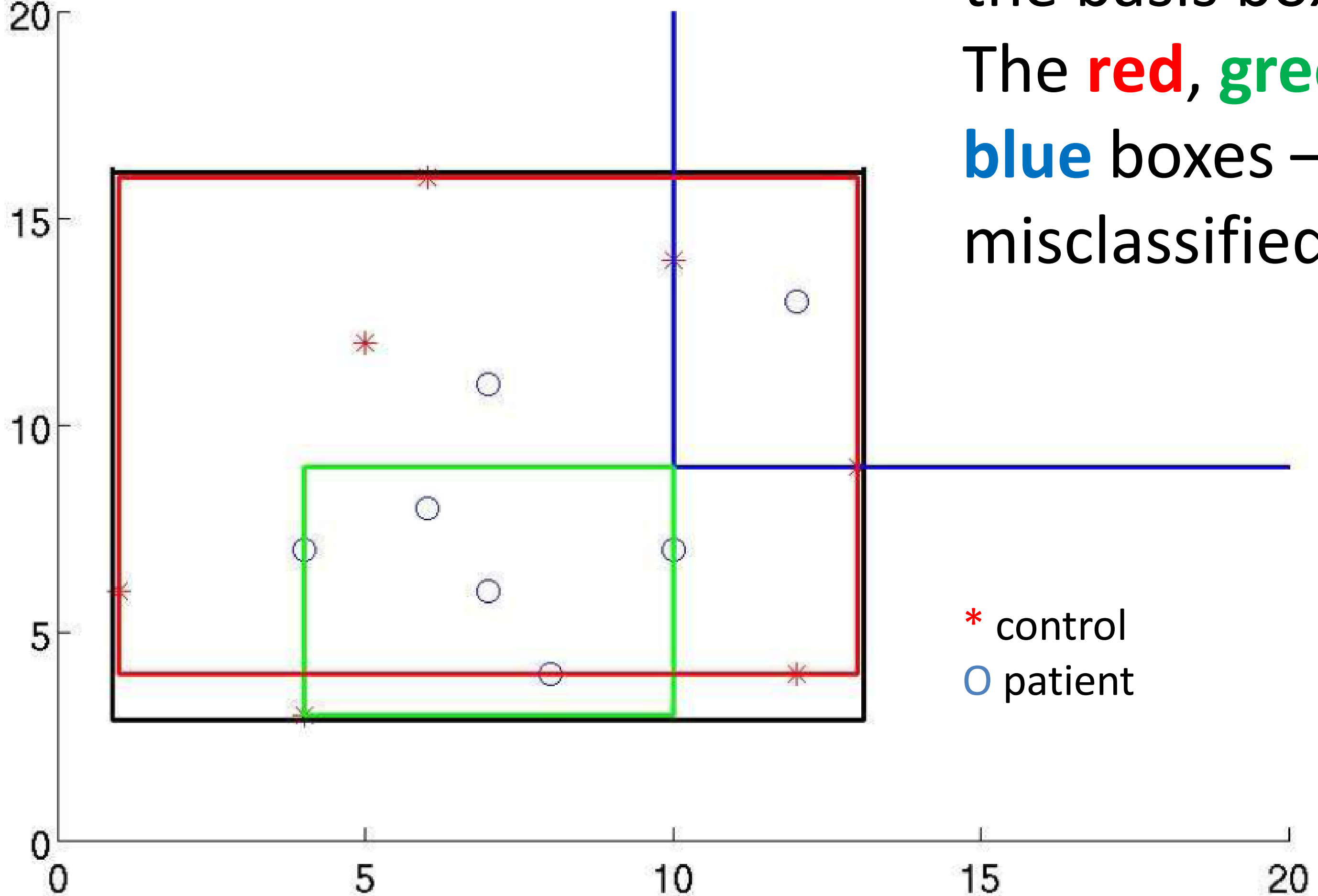
Adding of dendrites to remove misclassified patterns of class 0 that fall inside this hyperbox

Dendritic Computing

Synthetic 2D dataset.

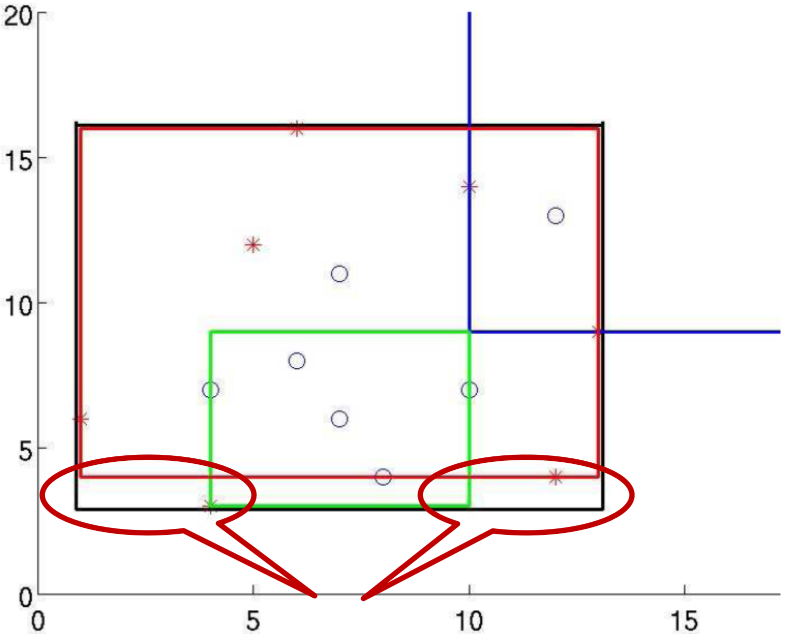


The **black** hyperbox is the basis box.
The **red**, **green** and **blue** boxes – to remove misclassified controls

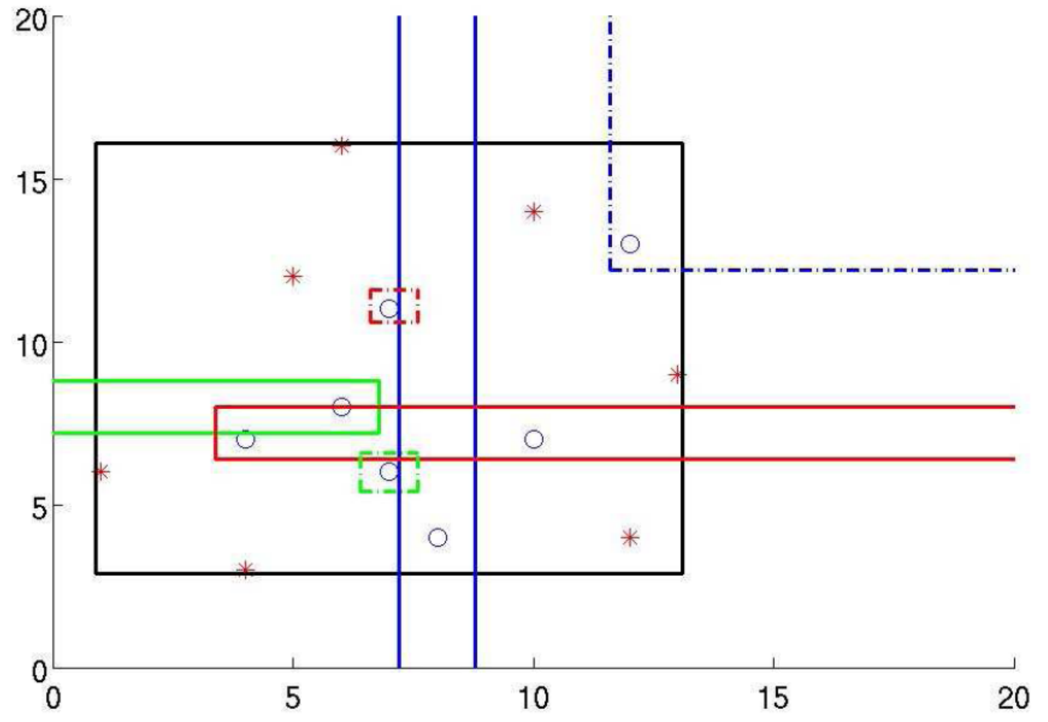
* control
O patient

Dendritic Computing

- To establish specificity and sensitivity we propose shrinking the boundaries of the hyperbox.
- Exclude the region occupied by a misclassified item of control

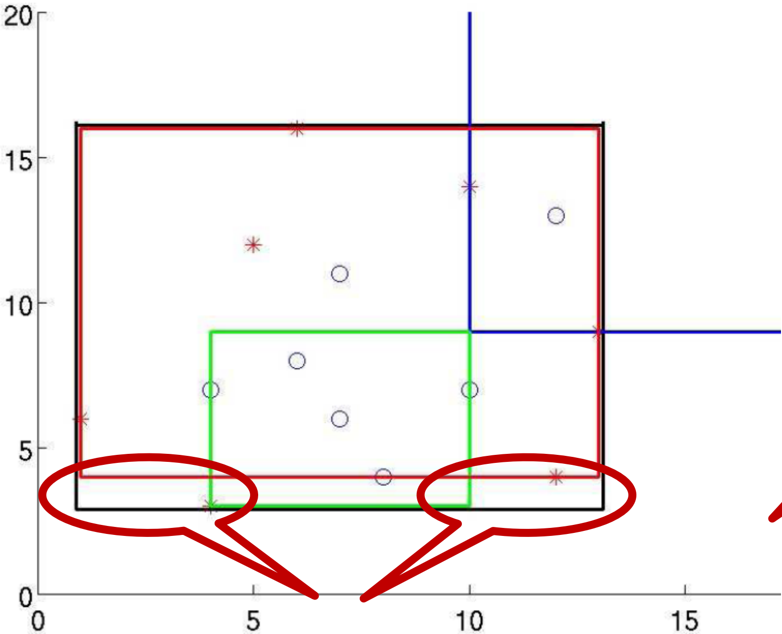


Generalization for patient

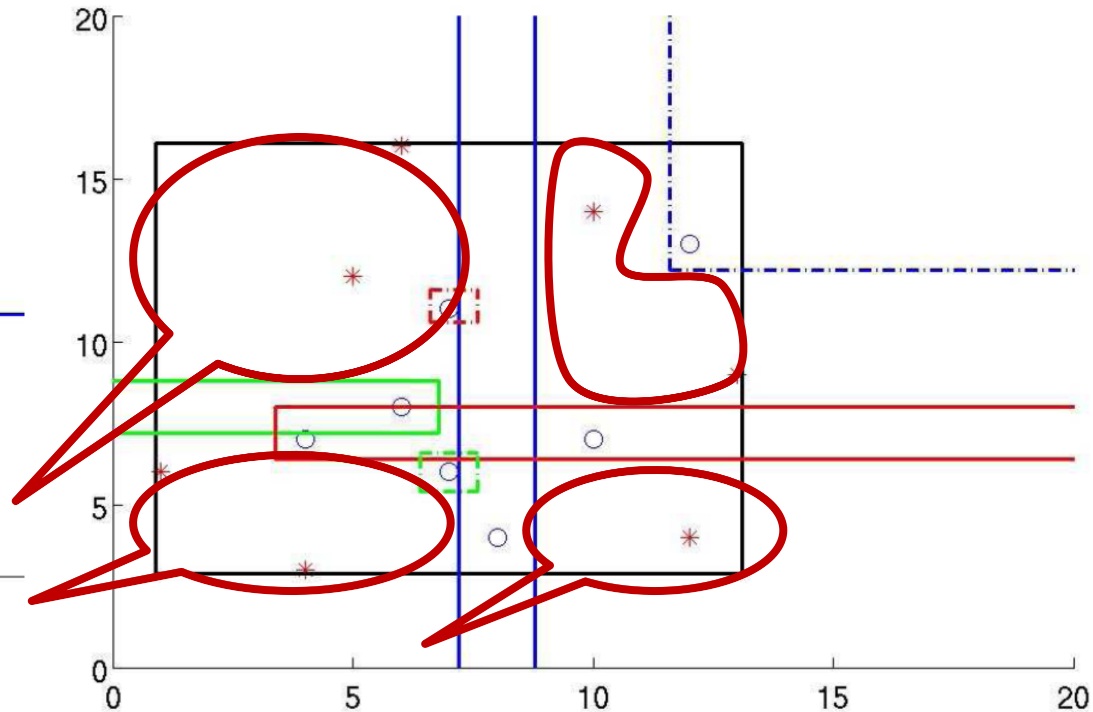


Dendritic Computing

- To balance specificity and sensitivity we propose shrinking the boundaries of the hyperbox corresponding to each dendrite
- Exclude the region occupied by a misclassified item of control



Generalization for patient



Results on Alzheimer Detection

α	Accuracy	Sensitivity	Specificity
0	58	94	23
0.5	60	81	40
0.53	59	77	42
0.55	64	85	44
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0.97	61	69	53

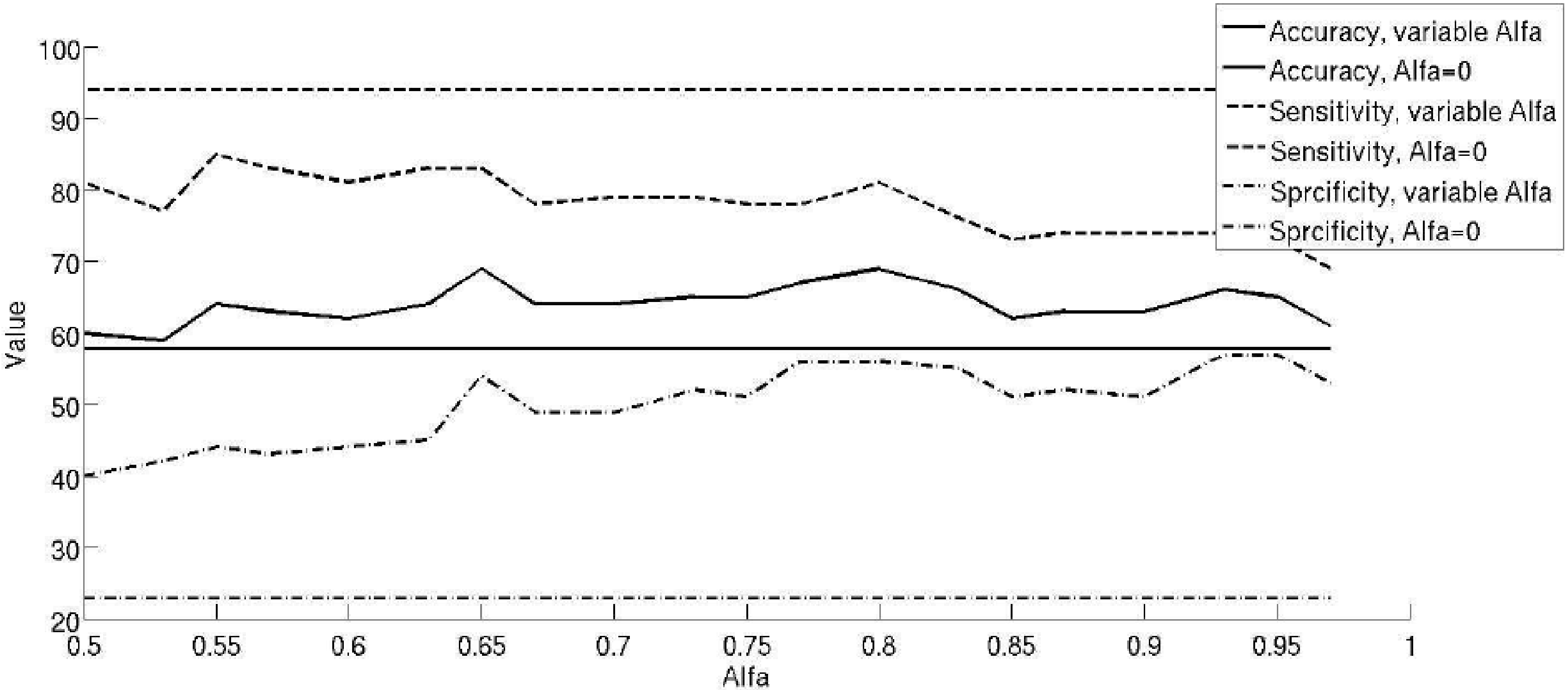
First row – **baseline DC**

We defind Shrinking parameter of the box *αϵ[0,1).*

For each shrinking parameter we have performed 10 –fold cross validation

The best result:
Sensitivity worse
Specificity **increase** – the best balance which gives the best Accuracy

Results on Alzheimer Detection



- **Specificity** (at the bottom) – control classification:

For 0.5 increase very fast and still increase

- **Sensitivity** (at the top) – patient classification:

Shows the better results for baseline DC

- But the **Accuracy** (in the middle)

Shows the best result for *α=0.8*

Conclusions

We found empirically, performing **cross-validation** on an **Alzheimer's Disease database** of features computed from **MRI** scans, that a single layer neuron model endowed with **Dendritic Computing** has poor generalization capabilities.

The model shows **high sensitivity** but **poor specificity**. In this paper we have proposed a **simple change** in the learning algorithm

- that produces a significative **increase** in performance in terms of accuracy,
- obtaining a better trade-off between sensitivity and specificity.

Thank you for your attention!

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