Real time diagnosis of cerebral status in traumatic brain injury using neuro-fuzzy networks

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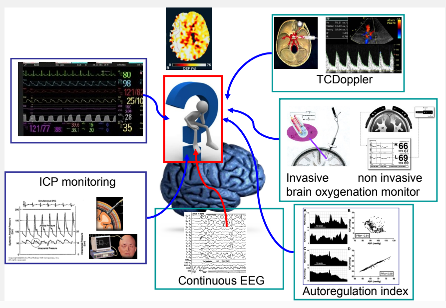
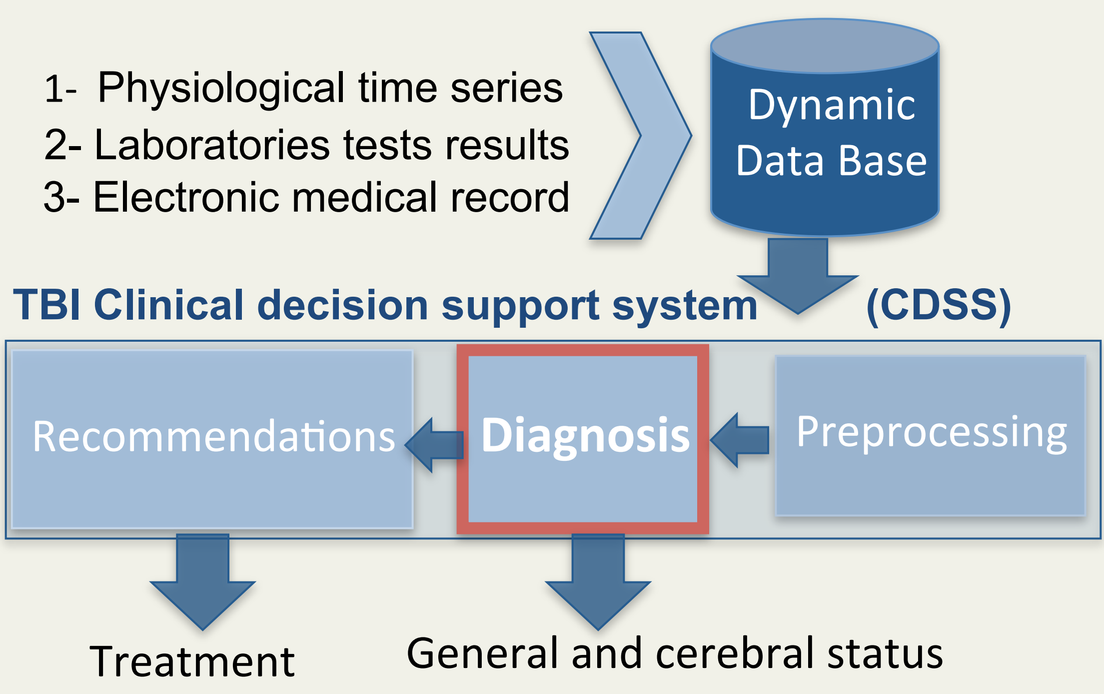
Introduction

- Severe Traumatic brain injury (TBI): main cause of mortality in adolescent and young adults.
- **Rapid and efficient management is required** to minimize secondary injuries, and reduce permanent sequelae risks.
- **Computerized tools can help** intensive care team to improve the management :
  - Inconsistent adherence to guidelines;
  - Overwhelming data flow;
  - Extremely complex and rapidly changing condition.

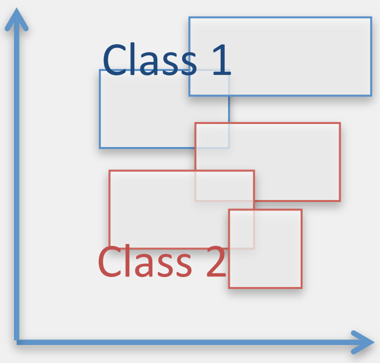




Methods

Improved fuzzy min-max neural network (FMMN) supervised classifier

- Fuzzy logic (human intuition) + neural network (automatic learning).
- Fast training , online learner , simple architecture.



- **Improvements :** Simple interclass overlap management and online data adaptation.
- Performances compared to a similar classifier with a different overlap management method: Data-Core FMMN classifier (DCFMMN)

Model training dataset

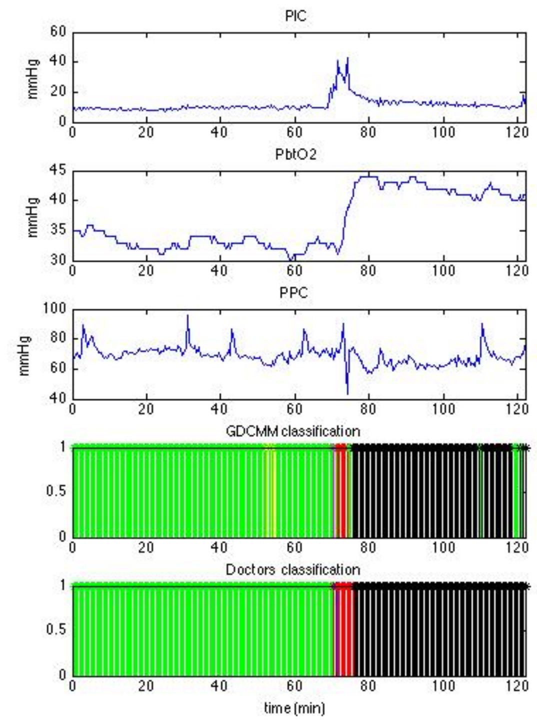
- 4-hour recordings diagnosed by specialists, including at least : Intracranial pressure (ICP), brain tissues oxygenation (PbtO2) and cerebral perfusion pressure (CPP).
- **Diagnosis: 6 possible cerebral conditions :**
  - Controlled condition,
  - Mild intracranial hypertension (ICH),
  - ICH with ischemia or with hyperemia,
  - Brain ischemia/hyperemia without ICH.
- Classifier output compared to specialists' diagnosis.

Results

Algorithm performances on training data set

Classification accuracy (%)						
θ	1	0.1	1	0.1	1	0.1
Training size (%)	80		50		30	
This Work	90	96	91	95	89	95
DCFMMN	85	91	83	86	80	88
Training time ($T_{ThisWork}/T_{DCFMN}$)						
θ	1	0.1	1	0.1	1	0.1
Training size (%)	80		50		30	
	1	0.8	0.9	0.7	1	0.7

Illustrative example of cerebral status evolution and output in a 2-hour period



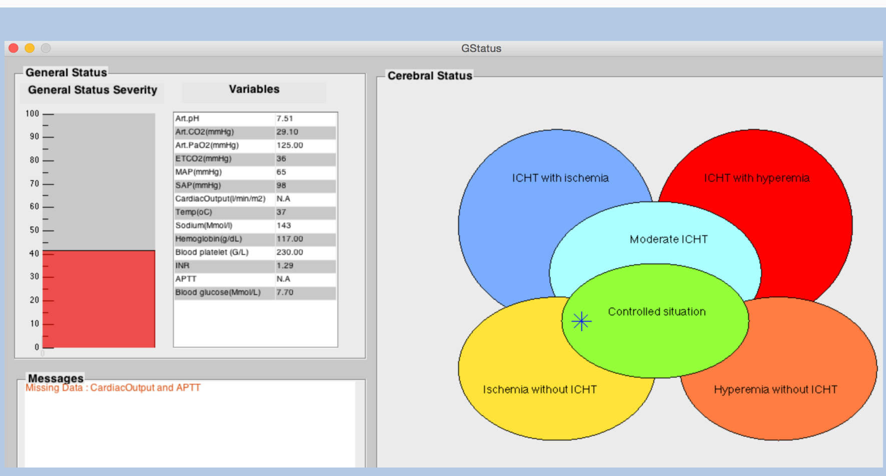
95 % accuracy

Discussion

- Fast training time and high accuracy obtained, even with few training data points.
- Validation is needed with more patients with different conditions to repeatedly cover all possible cerebral conditions.
- Longer period needed to validate online adaptability capacity.
- Missing data not supported yet.

Conclusion

- An efficient improved fuzzy min-max neural network was developed to automatically and continuously categorize the patient brain condition.
- This algorithm could also be used to categorize the general status as well.
- This classification tool will permit to develop easily interpretable graphic interface to facilitate rapid assessment by the team. This is a first step before the implementation of management recommendations in the CDSS.



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