ADAS / Autonomous Vehicle

EMERGENCY DETECTION FOR AN AUTOMATIC BRAKING ASSIST

Benchmark vs. Random Forest, Boosted Tree & Neural Network

UC#01 — 2024/03 (v2.1)

xtractis.ai

PROBLEM DEFINITION

GOAL

Design an AI-based decision-making system that makes an accurate and instantaneous diagnosis of driving situations based solely on the car's recordings without cameras, radar or lidar, in order to make a rational decision on whether to activate the EBA.

PROS & BENEFITS

- Identify the car parameters involved in the driving situation diagnosis and enhance technical knowledge by helping engineers understand the causal relationships between specific parameters, their combination, and the occurrence of an emergency.
- Help engineers design reliable intelligible autonomous vehicles that assist the driver efficiently according to their driving style. *Intelligible* means that the internal decision logic of the decision system is explicit.
- Enforce the use of stable and transparent models audited by the domain expert and certified by the regulator before embedding them in the vehicle.
- Challenge XTRACTIS to find better models than those we initially crafted "by hand" (see Appendix #3).

REFERENCE DATA

Source:
RENAULT
Patent #WO02057123
(P. Romieu, C. Lorel,
Z. Zalila, J. Benizri, 2001)

Variable to Predict: The model diagnoses the driving situation as **STANDARD** | **EMERGENCY** to activate or not the Emergency Brake Assist (EBA).

Potential Predictors: 17 variables characterize each driving situation, such as the driver gender and recordings from the car's sensors [throttle angle, membrane stroke, pedal stroke, rod effort, longitudinal deceleration, right rear pressure, ...].

Observations: 108 driving trials resulting in over 1,200,000 driving situations, with and without EBA sequences, from experimental R&D campaigns conducted by RENAULT, on test track or open road and led by 13 different drivers.

52 trials compose a Learning Dataset for model induction using Training , Validation and Test Datasets. 56 other trials are used as a 2 kind-External Test Dataset (by points and by trials*) to check the top-model's performance on real unknown data and for benchmarking.

**As the system is dynamic, the performances by points do not secure against a possible instability in decision-making. If, for example, during an emergency braking sequence, the model alternately concludes EMERGENCY and STANDARD over successive time lapses, this would cause flaws in the system. For this reason, we need to evaluate the model's performance on driving sequences by trials.*

Learning Dataset: : 52 trials | 508,696 situations 70% for Training, 15% for Validation, 15% for Test	
STANDARD	EMERGENCY
485,153 | 95.37%	23,543 | 4.63%

External Test Dataset: 56 trials | 732,000 situations	
STANDARD	EMERGENCY
686,799 | 93.82%	45,201 | 6.18%

MODEL TYPE Regression | Multinomial Classification | **Binomial Classification** | Scoring

XTRACTIS-INDUCED DECISION SYSTEM

☑ **Intelligible Model, Explainable Decisions**

- The top-model is a decision system composed of 25 gradual rules without chaining aggregated into 2 disjunctive rules.
- Each rule uses from 2 to 6 predictors among the 11 variables that XTRACTIS automatically identified as significant (out of the 17 features describing each driving situation).
- Only a few rules are triggered at a time to compute the decision.

☑ **High Predictive Capacity** It has a very good Real Performance (on unknown data).

☑ **Ready to Deploy** It computes real-time predictions up to 70,000 decisions/second, offline or online (API).

XTRACTIS PROCESS

STEPS	Reference Data	INDUCTION	XTRACTIS Top-Model	New Cases	DEDUCTION	STANDARD / EMERGENCY Automated Decision (activate EBA or not)
SOFTWARE ROBOTS	XTRACTIS® **REVEAL** Delivers the decision system + its Structure & Performance Reports			XTRACTIS® **PREDICT** Delivers the decision + the Prediction Report explaining its reasoning		

TOP-MODEL INDUCTION

INDUCTION PARAMETERS

Powered by:
XTRACTIS® REVEAL v11.3.40047

1. We launch 1,500 inductive reasoning strategies; each strategy is applied to the same single partition of the learning dataset (70% Training / 15% Validation / 15% Test) to get a reliable assessment of the descriptive and predictive performances, respectively from Training and Validation Datasets.
2. Each strategy thus generates one unitary model called **Individual Virtual Expert** (IVE).
3. Among the 1,500 induced models, the top-IVE is the one that has the best predictive performance, close to its descriptive performance, and with the fewer predictors and rules.

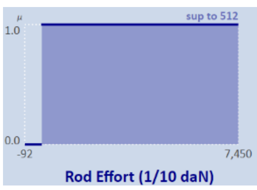
Total number of induced unitary models	Criterion for the induction optimization	Validation criterion for the top-model selection	Duration of the process (Induction Power FP64)
1,500 IVEs	F_1-Score	F_1-Score	~18 hours (24 Tflops)

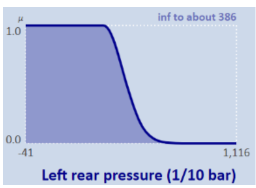
TOP-MODEL STRUCTURE

The top-IVE model has a very good intelligibility for a complex phenomenon as it combines the 12 predictors into 25 rules with 3.5 predictors per rule on average. Its Structure Report reveals all the internal logic of the decision system and ensures that the model is understandable by the human expert. It is a transparent model that can be audited and certified before deployment to end-users.

PREDICTORS

- 12 features out of 17
  11 are continuous vehicle data and 1 is nominal (driver's gender).
- Ranked by individual contribution (3 strong, 6 medium & 3 weak signals):
  #1 Longitudinal deceleration
  #2 Rod Effort; #3 … #12
- Labeled by or binary or fuzzy classes and modalities for the gender
  Examples: **binary interval** "sup. to 512"
  fuzzy interval "inf. to about 386"





RULES

- 25 conjunctive fuzzy rules without chaining (aggregated into 2 disjunctive fuzzy rules)
- 2 to 6 predictors per rule (on average, 3.5 predictors per rule)
- Example:
  fuzzy rule **R20** uses 2 predictors and concludes EMERGENCY.
  25 other rules complete this model.

IF	Longitudinal deceleration (1/100 m/s²)	IS	sup. to about 62
AND	Rod Effort (1/10 daN)	IS	sup. to 512
AND	Left rear pressure (1/10 bar)	IS	inf. to about 386
AND	Longitudinal speed (1/10 km/h)	IS	sup. to about 826
THEN	Driving Situation	IS	EMERGENCY

Literally, the Driving situation is an Emergency (and thus the system activates the EBA) if the Longitudinal deceleration is over around 0.62 m/s², and the Rod effort is superior to 51.2 daN, and the Left rear pressure is under about 38.6 bar, and the Longitudinal speed is over approximately 82.6 km/h.

TOP-MODEL PERFORMANCE

The top-IVE performances, measured in Training / Validation / Test, then in External Test by points on reference data, guarantee the model's predictive and real performances.

Performance	DESCRIPTIVE	PREDICTIVE	REAL	REAL
Dataset	70% Training	15% Validation	15% Test	External Test
F_1-Score	99.04%	99.04%	98.85%	96.28%
Classification Error	0.09%	0.09%	0.11%	0.45%

EXPLAINED PREDICTIONS FOR 3 UNKNOWN CASES

Powered by: XTRACTIS® PREDICT v11.3.40047

CASE (from the External Dataset, i.e., not included in the Learning Dataset)	DEDUCTIVE INFERENCE OF RULES	AUTOMATED DECISION

SITUATION #Janickfrein68 78.01s

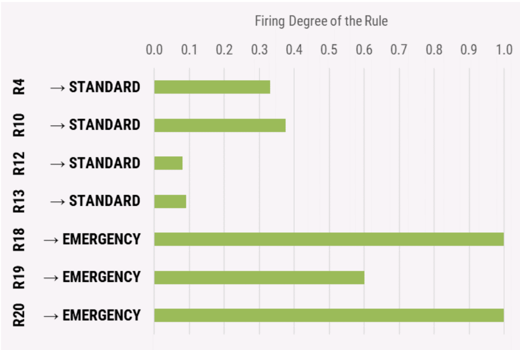
actual value = EMERGENCY	
Membrane Stroke (1/100 mm)_IT	1,534
Longitudinal deceleration (1/100m/s2)	244
Rod Effort (1/10 daN)	882
Left rear pressure (1/10 bar)	256
Master Cylinder 1 pressure (1/10 bar)	595
Master Cylinder 2 pressure (1/10 bar)	M.V.*
Manifold pressure (mbar)	M.V.*
Pressure in mastervac (mbar)	M.V.*
Engine speed	3,395
Longitudinal speed (1/10 km/h)	897
Membrane speed (mm/s)_IT	123
Driver Gender	man

Real Time

For this driving situation, 7 rules are triggered:

R18 and **R20** at 1.000, **R19** at 0.600, **R10** at 0.375, **R4** at 0.331, **R13** at 0.091 and **R12** at 0.081

All other 18 rules are not activated.



NUMBER OF TRIGGERED RULES
7 / 25

FUZZY PREDICTION
{ EMERGENCY | 1.000,
STANDARD | 0.375 }

FINAL PREDICTION
{ EMERGENCY }

The system delivers a correct diagnosis of the driving situation compared to the actual situation in the experiment:

EBA activation

SITUATION #Jean-Pierre frein78 99.94s

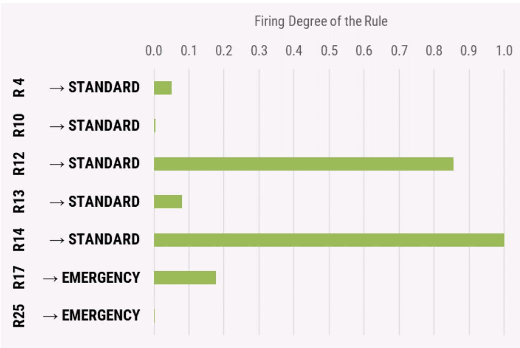
actual value = STANDARD	
Membrane Stroke (1/100 mm)_IT	**273**
Longitudinal deceleration (1/100m/s2)	**67**
Rod Effort (1/10 daN)	**21**
Left rear pressure (1/10 bar)	**3**
Master Cylinder 1 pressure (1/10 bar)	**0**
Master Cylinder 2 pressure (1/10 bar)	M.V.*
Manifold pressure (mbar)	M.V.*
Pressure in mastervac (mbar)	M.V.*
Engine speed	**694**
Longitudinal speed (1/10 km/h)	**196**
Membrane speed (mm/s)_IT	**-51**
Driver Gender	man

Real Time

For this driving situation, 7 rules are triggered:

R14 at 1.000, **R12** at 0.856, **R17** at 0.176 **R13** at 0.080, **R4** at 0.051, **R10** at 0.004 and **R25** at 0.003

All other 18 rules are not activated.



NUMBER OF TRIGGERED RULES
7 / 25

FUZZY PREDICTION
{ STANDARD | 1.000 ,
EMERGENCY | 0.176 }

FINAL PREDICTION
{ STANDARD }

The system delivers a correct diagnosis of the driving situation compared to the actual situation in the experiment:

No EBA activation

SITUATION # Marie-F.frein150 114.85s

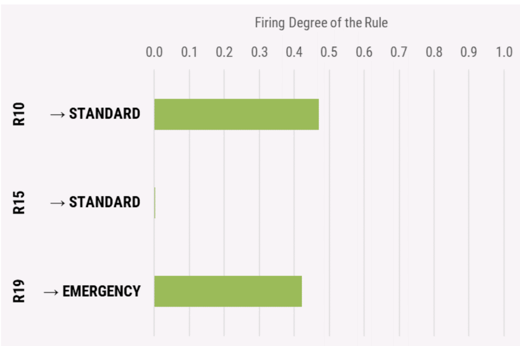
actual value = STANDARD	
Membrane Stroke (1/100 mm)_IT	2,398
Longitudinal deceleration (1/100m/s2)	220
Rod Effort (1/10 daN)	993
Left rear pressure (1/10 bar)	895
Master Cylinder 1 pressure (1/10 bar)	915
Master Cylinder 2 pressure (1/10 bar)	M.V.*
Manifold pressure (mbar)	M.V.*
Pressure in mastervac (mbar)	M.V.*
Engine speed	694
Longitudinal speed (1/10 km/h)	12
Membrane speed (mm/s)_IT	-7
Driver Gender	woman

Real Time

For this driving situation, 3 rules are triggered:

R10 at 0.470, **R19** at 0.422, and **R15** at 0.003

All other 22 rules are not activated.



NUMBER OF TRIGGERED RULES
3 / 25

FUZZY PREDICTION
{ STANDARD | 0.470,
EMERGENCY | 0.422 }

FINAL PREDICTION
{ STANDARD }

The system delivers a correct diagnosis of the driving situation despite hesitation (conflicting rules with close degrees):

No EBA activation

During this recording, the system in fact just switched from an "emergency" to a "standard" state, no longer requiring additional EBA. It is an evolutionary temporal process, where we gradually pass from one state to another. However, the system should have made this change of state 18 records ago, i.e., 0.06s earlier.

**M.V. = Missing Values. These parameters were not measured during the External Test campaign.*

TOP-MODELS BENCHMARK: DECISION STRUCTURE & INTELLIGIBILITY × PERFORMANCE SCORES

MODELING PARAMETERS

	XTRACTIS	RANDOM FOREST	BOOSTED TREE	NEURAL NETWORK
MODELS RELEASE	2021/11	2021/11	2021/11	2021/11
ALGORITHM VERSION	XTRACTIS **REVEAL** 11.3.40047	Python 3.6 | LightGBM 2.2.2	Python 3.6 | LightGBM 2.2.2	Python 3.6 | TensorFlow 2.7 | Keras 2.1.4
CROSS-VALIDATION TECHNIQUE	All explored strategies for all algorithms use the same single-split of the Learning Dataset: 70% Training | 15% Validation | 15% Test			
NUMBER OF EXPLORED STRATEGIES(1)	500 induction strategies	500 ML strategies	500 ML strategies	500 ML strategies
TOP-MODEL SELECTION(2)	Top-IVE among 500 IVEs	Top-IVE among 500 IVEs	Top-IVE among 500 IVEs	Top-IVE among 500 IVEs

TOP-MODEL STRUCTURE

	XTRACTIS	RANDOM FOREST	BOOSTED TREE	NEURAL NETWORK
NUMBER OF PREDICTORS (out of 17 Potential Predictors)	**12**	**17**	**17**	**17**
AVERAGE NUMBER OF PREDICTORS PER RULE OR EQUATION	**3.5** per rule	**5.0** per rule	**5.7** per rule	**20.8** per equation
STRUCTURE OF THE DECISION SYSTEM	**25** fuzzy rules without chaining (aggregated into 2 disjunctive fuzzy rules) Only some rules are triggered at a time to compute a prediction	**12** trees without chaining **851** binary rules	**1** chain of **169** trees **7,415** binary rules Tree #N corrects the error of the N-1 previous trees	**4** hidden layers | **88** hidden nodes **89** equations 88 unintelligible synthetic variables

TOP-MODEL SCORES

	XTRACTIS	RFo	BT	NN
INTELLIGIBILITY Score(4)	**4.59**	**0.00**	**0.00**	**0.00**
IVE Real Performance (F_1-Score) in Test	98.85	98.06	99.75	93.52
Gap to IVE Leader in Test	-0.90	-1.69	0.00	-6.23
IVE Real Performance (F_1-Score) in External Test	96.28	94.45	94.44	89.16
Gap to IVE Leader in External Test	0.00	-1.83	-1.84	-7.12
IVE Real Performance (F_1-Score) in External Test	100.00	98.25	97.39	100.00
Gap to IVE Leader in External Test	0.00	-1.75	-2.61	0.00
Average Real Performance	98.38	96.92	97.19	94.23
PERFORMANCE Score(4)	**-0.30**	**-1.76**	**-1.48**	**-4.45**

(1) For all algos: on the same Learning Dataset. All Models are optimized according to their Validation F_1-Score.
(2) All top-models are selected according to their Validation F_1-Score while checking that it remains close to their Training F_1-Score.
(3) Baseline performances that models must exceed to perform better than chance (P-value = 0.001; 100,000 models generated by random permutation of the output values). The value of each performance criterion is generally achieved by a different random model.
(4) See Appendices 4 & 5 for explanations and detailed results. Performance Scores are calculated on all available unknown data.

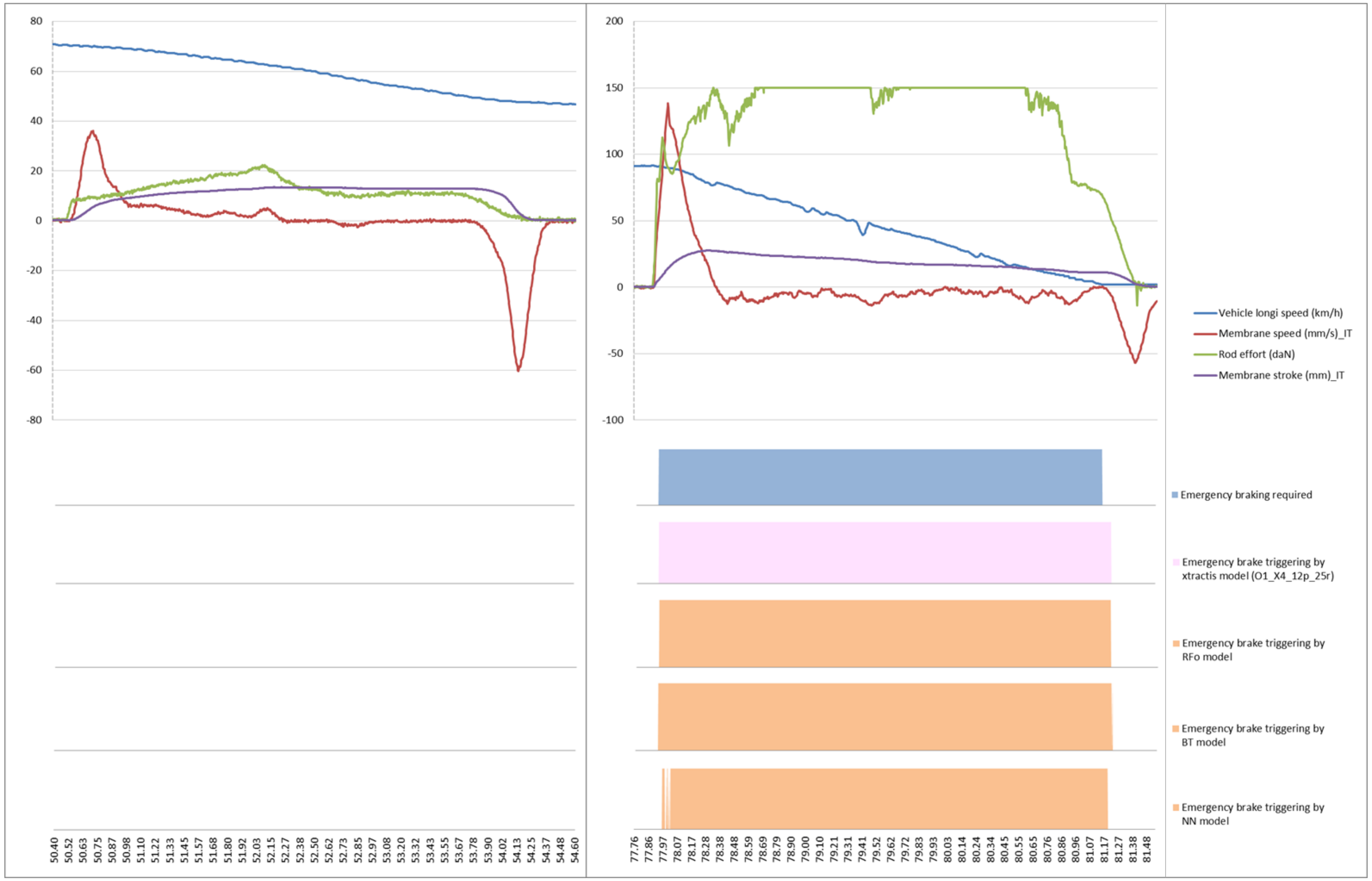
More Use Cases:
xtractis.ai/use-cases/

APPENDIX 1 — Examples of Right and Wrong Diagnoses (from External Test trials)

The following graphs show driving situations over 4-5 seconds, either with a standard braking sequence or requiring emergency braking (blue band). Wrong diagnoses are taken from the problematic cases identified above.

1/ Situations with correct diagnosis from the models

The 4 decisional systems correctly diagnose standard braking, as there is no untimely activation of the EBA. When emergency braking is requested, the NN top-IVE hesitates at the beginning of the sequence, while the XTRACTIS, RFo, and BT top-IVE react perfectly.



Trial #68 — Standard braking situation **with no** expected triggering

Trial #68 — Emergency braking situation **with** expected triggering

2/ Situations with problematic diagnosis from the models

During Trial #71, standard braking is well diagnosed by the XTRACTIS and NN top-IVE, while the RFo and BT top-IVE unexpectedly activate EBA.

During Trial #103, when the driver stops braking for a short time (dip in the green curve) and then brakes again, the 4 decisional systems react poorly and lead to the EBA disconnection. The disconnection is more prolonged for the RFo and BT models.

During Trial #93, when the driver continues to brake whereas there is no more emergency, the XTRACTIS and RFo models react perfectly by disconnecting EBA. The BT model also triggers deactivation but decides to reactivate EBA after 2 seconds without any need. The NN model does not disconnect EBA at all.

Trial #71 — Standard braking situation with no expected triggering

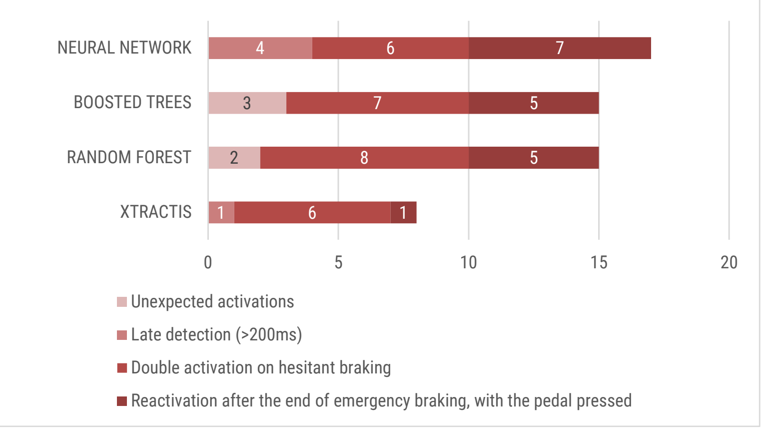
Trial #103 — Emergency braking situation with expected triggering

Trial #93 — Reactivation after end of emergency braking with pedal pressed

APPENDIX 2 — Problematic Cases (from External Test trials)

Each trial consists of driving data that include at least one normal situation and sometimes an emergency. We count the emergency braking sequences detected, and the delay between detection and actual emergency. If the model does not detect an emergency, we count an unfortunate non-triggering. Alternatively, for standard driving or braking sequences, if the model detects an emergency wrongly, we count an unexpected activation. Besides, we notice 2 other types of problematic cases related to specific driving situations:

1. Hesitant braking: the driver hesitates and brakes in 2 steps. If the system disconnects between the 2 steps, we count a double activation.
2. Reactivation after the end of emergency braking, with the pedal pressed: the driver keeps pressing the brake pedal after the vehicle has stopped, sometimes placing the model in a new emergency situation while the vehicle is stationary.



APPENDIX 3 — XTRACTIS vs. Classic Fuzzy Expert Systems

Data from this study was originally used in 1999 to help develop "by hand" a decision support system based on fuzzy rules: an auto-adaptive emergency braking assistance system had been invented by Z. Zalila & INTELLITECH for RENAULT in early 2000. It was subsequently patented [WO02057123] (2001) by RENAULT.

This system was designed using the "traditional" fuzzy logic approach, i.e., the manual design of the fuzzy decision rules, reproducing the human expertise, thanks to our expertise as drivers.

It is, therefore, interesting to compare the two approaches, their main features, and their results. Even if both are fuzzy logic-based approaches, leading to intelligible models (thus auditable and certifiable), we highlight the limitations of traditional Fuzzy Symbolic AI compared to the XTRACTIS Augmented Fuzzy Symbolic AI.

And even if the XTRACTIS top-IVE is perfectible by injecting new data, for example, by merging with data from new sensors, to eliminate the identified problematic cases and further improve its performances, we can affirm that XTRACTIS has met the challenge!

Benefits of XTRACTIS AI vs. classic Fuzzy AI:

- ☑ Overcoming human cognitive limitations: more parameters and driving situations could be considered.
- ☑ Much higher performances: greater reliability of the decision-making strategy.
- ☑ Much faster and less expensive design

	Classic Fuzzy Expert System	XTRACTIS System
Design Approach	Human induction	Automatic induction
Design Time	24-man months	Max. 1 day with a 24 Tflops HPC server
Number of Rules	25 fuzzy rules for short time diagnosis + 2 fuzzy rules for braking behavior + 1 Fuzzy Relation of order 3	25 fuzzy rules
Number of Predictors	4 (cognitive limitation of the human modeler)	12 (selected automatically)
Performance	Descriptive model only: incremental performance by trial/error	Robust predictive model: systematic estimation of descriptive and predictive performance by cross-validation

APPENDIX 4 — Calculation of the Intelligibility × Performance Scores

AI Technique #i	T_i	$i \in [1 ; n]$ n = number of AI Techniques benchmarked in terms of data-driven modeling = 5
Benchmark #k	B_k	$k \in [1 ; p]$ p = number of Benchmarks for the Use Case $\in$ {1, 2, 3}

Remarks:

- In case of a small number of reference data, a CVE model (College of Virtual Experts) is generated by each explored strategy of T_i, generally via an N×K-fold cross validation. In this case, a Benchmark is led with the top-CVE on the External Test Dataset (ETD, composed of unknown reference cases). Then, a top-IVE model (Individual Virtual Expert) is generated from the top-CVE, through the XTRACTIS® reverse-engineering process, or for the other T_i, by applying the top-strategy, which has generated the top-CVE, on the Training and Validation Datasets. And a second Benchmark is led with this top-IVE on the same ETD.
- In case of a huge number of reference data, an IVE is generated by each explored strategy of T_i, via a 1-split validation. In this case, Benchmarks are led with the top-IVE on the Test Dataset (TD, composed of unknown reference cases) and on the available ETDs.
- Each Benchmark uses the latest versions of the following algorithms available at the date of the benchmark. XTRACTIS®: REVEAL; Logistic Regression: Python, Scikit-Learn; Random Forest & Boosted Tree: Python, LightGBM; Neural Network: Python, TensorFlow, Keras.
- Each B_k uses exactly the same TD and ETD for each T_i model.
- No Regression models can be obtained by Logistic Regression. So, this Data Analysis technique is benchmarked only for Classification or Scoring problems.
- The Holy Grail for critical AI-based decision systems is to obtain a model with the highest Performance and the highest Intelligibility scores (top-right corner of the graph).

PERFORMANCE Score

For each B_k, we calculate the values of the Performance Criterion (PC) on the same ETD for all the T_i top-CVEs; and on the same TD and ETDs for all the T_i top-IVEs. The PC is: RMSE in percentage for a Regression; F_1-Score for a Binomial Classification; Average F_1-Score or Average F_2-Score for a Multinomial Classification; Gini index for a Scoring.
Then, we compare the value of the PC of each T_i top-CVE (resp. top-IVE) to the best value of this PC reached by the best T_i top-CVE (resp. top-IVE) on ETD (resp. on TD and ETDs).

For Regression, we calculate for each T_i top-model (CVE and IVE): $PS(T_i, B_k) = Best\_PC(B_k) - PC(T_i, B_k)$.

For Classification and Scoring, we calculate for each T_i top-model: $PS(T_i, B_k) = PC(T_i, B_k) - Best\_PC(B_k)$.

Performance Score of T_i

$$\boxed{PS(T_i) = \text{Mean}\left(PS(T_i, B_k)\right)_{k \in [1 ; p]}}$$

<u>Remark:</u>

- Each PS varies theoretically from -100 (Lowest Score) to 0 (Highest Score), but practically between -50 and 0.

INTELLIGIBILITY Score

We consider the T_i top-IVE. Its Intelligibility Score $IS(T_i)$ is valued from 0.00 to 5.00 regarding the structure of the model: number of predictors, classes, rules, equations, trees, synthetic variables, modalities to predict for classifications (or numeric variables to predict for regressions or scoring). The more compact the model, the higher its IS.

The IS of each T_i is obtained by accumulating the following five penalty values to the ideal IS value of 5.00 (each penalty has a null or a negative value):

- Penalty 1 (logarithmic penalty regarding the number of predictors):
  $Pen1(T_i) = \min(0 , 1 - \log_{10} number\ of\ predictors)$
  Examples: *Pen1 = 0.00 for up to 10 predictors*
  Pen1 = −3.00 for 10.000 predictors

- Penalty 2 (linear penalty regarding the average number of rules or equations per modality to predict):
  $Pen2(T_i) = \min\left(0 , 0.01 - \frac{average\ number\ of\ rules\ or\ equations\ per\ modality\ to\ predict}{100}\right)$
  Examples: *Pen2 = 0.00 for 1 rule or equation per modality to predict on average*
  Pen2 = −3.00 for 301 rules or equations per modality to predict on average

- Penalty 3 (linear penalty regarding the average number of predictors per rule or equation):
  $Pen3(T_i) = \min\left(0 , \frac{9 - 3 \times average\ number\ of\ predictors\ per\ rule\ or\ equation}{7}\right)$
  Examples: *Pen3 = 0.00 for up to 3.0 predictors per rule or equation on average*
  Pen3 = −3.00 for 10.0 predictors per rule or equation on average

- Penalty 4 (linear penalty regarding the number of chained trees, here for BT only):
  $Pen4(T_i) = \min(0 , 1 - number\ of\ chained\ trees)$
  Examples: *Pen4 = 0.00 for 1 tree*
  Pen4 = −3.00 for 4 chained trees

- Penalty 5 (maximum penalty due to unintelligibility of synthetic variables, here for NN only):
  $Pen5(T_i) = -5$

Intelligibility Score of T_i

$$\boxed{IS(T_i) = \max(0.00 , 5.00 + (Pen1+Pen2+Pen3+Pen4+Pen5))}$$

<u>Remarks:</u>

- For the difference between the Intelligibility and the Explainability of a model, please see the XTRACTIS® Brochure, page 7.
- The real complexity of the process/phenomenon under study is intrinsic, i.e., it could not be reduced or simplified, but only discovered; thus, the top-model will be complex if the process/phenomenon turns out to be complex [Zalila 2017]. Consequently, for some complex process/phenomenon, IS can be equal to 3.00 or less, even if Ti natively produces intelligible models (XTRACTIS, Random Forest).
- For similar structures, the Boosted Tree model is always less intelligible than the Random Forest one, as it is composed of chains of trees, instead of a college of trees (see Penalty 4).
- Neural Network model has always the lowest IS of 0.00, because it uses synthetic unintelligible variables (hidden nodes) in addition to all the potential predictors (see Penalty 5).

APPENDIX 5 — Use Case Results (all Performance criteria of all Top-Models)

Performance Criterion	Classification Error	Min. Sensitivity Specificity	Sensitivity	Specificity	PPV	NPV	**F_1-Score**	Refusal
XTRACTIS TOP-MODEL								
IVE - Descriptive Performance (Training)	0.09%	99.18%	99.18%	99.95%	98.91%	99.96%	99.04%	311 (0.09%)
IVE - Predictive Performance (Validation)	0.09%	98.75%	98.75%	99.97%	99.34%	99.94%	99.04%	75 (0.10%)
IVE - Real Performance (Test)	0.11%	98.89%	98.89%	99.94%	98.81%	99.95%	98.85%	67 (0.09%)
IVE - Real Performance (External Test by points)	0.45%	94.37%	94.37%	99.89%	98.26%	99.63%	96.28%	400 (0.05%)
IVE - Real Performance (External Test by trials)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0 (0.00%)
RANDOM FOREST TOP-MODEL								
IVE - Descriptive Performance (Training)	0.17%	97.75%	97.75%	99.94%	98.66%	99.89%	98.20%	
IVE - Predictive Performance (Validation)	0.11%	99.57%	99.57%	99.96%	99.83%	99.91%	99.70%	
IVE - Real Performance (Test)	0.18%	97.54%	97.54%	99.93%	98.60%	99.88%	98.06%	
IVE - Real Performance (External Test by points)	0.66%	91.12%	91.12%	99.89%	98.04%	99.42%	94.45%	
IVE - Real Performance (External Test by trials)	0.88%	98.82%	100.00%	98.82%	96.55%	100.00%	98.25%	
BOOSTED TREE TOP-MODEL								
IVE - Descriptive Performance (Training)	0.00%	100.00%	100.00%	100.00%	99.98%	100.00%	99.99%	
IVE - Predictive Performance (Validation)	0.01%	99.83%	99.83%	100.00%	99.97%	99.99%	99.90%	
IVE - Real Performance (Test)	0.02%	99.72%	99.72%	99.99%	99.77%	99.99%	99.75%	
IVE - Real Performance (External Test by points)	0.67%	92.55%	92.55%	99.77%	96.41%	99.51%	94.44%	
IVE - Real Performance (External Test by trials)	1.33%	98.23%	100.00%	98.23%	94.92%	100.00%	97.39%	
NEURAL NETWORK TOP-MODEL								
IVE - Descriptive Performance (Training)	0.56%	90.65%	90.65%	99.87%	97.03%	99.55%	93.73%	
IVE - Predictive Performance (Validation)	0.54%	90.71%	90.71%	99.88%	97.44%	99.55%	93.96%	
IVE - Real Performance (Test)	0.58%	90.46%	90.46%	99.85%	96.79%	99.54%	93.52%	
IVE - Real Performance (External Test by points)	1.27%	84.78%	84.78%	99.64%	94.01%	99.00%	89.16%	
IVE - Real Performance (External Test by trials)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	