Maintenance

PREDICTION OF THE RUPTURE OF A FLEXIBLE UNDERWATER PIPE

Benchmark vs. Logistic Regression, Random Forests, Boosted Trees & Neural Networks

2024/02 (v3.0)

xtractis.ai

PROBLEM DEFINITION

GOAL

Design an AI-based decision system that accurately predicts the upcoming risk of underwater pipes rupture considering the apparent complexity of the phenomenon, to plan rational and explainable maintenance operations.

PROS & BENEFITS

- Identify the predictors involved in the rupture of a pipe and enhance technical knowledge by helping petroleum industry engineers understand the causal relationships between these predictors, their combination, and the risk of rupture.
- Find the truly influential parameters for assessing the state of the pipe and thus reduce measurement and maintenance costs.
- Carry out maintenance action specific for each pipe in order to avoid critical damage, thanks to rapid and transparent decision-making.

REFERENCE DATA

Source: Technip, FLEXIFRANCE

Variable to Predict The model predicts the Pipe State: **NO-RUPTURE | RUPTURE**.

Predictive Variables 74 Potential Predictors characterize each pipe: composition, loading constraints, physical characteristics: number of layers, material type, measurements …
66 variables are numeric, 8 are nominal.

Observations 1,444 reference cases from 44 experiments, based on testing pipes at various pressures.

Data are divided into a Learning Dataset for model induction using Training and Validation Datasets, and an External Test Dataset to check the top-model's performance on real data and for benchmarking.

Learning Dataset: 1,201 | 84.1% pipes from 37 experiments (25,262 | 28.42% missing values) 80% for Training, 20% for Validation	
NO-RUPTURE	RUPTURE
870 | 72.44%	331 | 27.56%

External Test Dataset: 243 | 15.9% pipes from 7 experiments (17,982 | 31.85% missing values)	
NO-RUPTURE	RUPTURE
206 | 84.77%	37 | 15.23%

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 27 gradual rules without chaining.
- Each rule uses from 1 to 14 predictors among the 20 variables that XTRACTIS identified as significant (out of the 74 ones characterizing each pipe).
- Only a few rules are triggered at a time to compute the decision.

☑ **High Predictive Capacity** It has a 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	Automated Decision (predict rupture): NO-RUPTURE / RUPTURE
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
v13.0.45039

1. We launch 300 inductive reasoning strategies; each strategy is applied to 20 different 5-fold-partitions of the Learning Dataset to get a reliable assessment of the descriptive and predictive performances, respectively from Training and Validation Datasets.
2. Each strategy thus generates 100 unitary models called **Individual Virtual Expert** (IVE), whose decisions are aggregated with 3 possible operators into a **College of Virtual Experts** (CVE).
3. Among the 900 induced CVEs, the top-CVE with the best predictive performance remains complex: 1,228 rules sharing 56 predictors.

Given the small number of reference cases in the reference dataset, the XTRACTIS **CVE→IVE** Reverse-Engineering process is necessary to get a robust AND intelligible model:

4. We build a synthetic dataset composed of 36,030 new cases simulated by deduction from the top-CVE, around the 1,201 original learning cases but distinct from them.
5. We apply 2,000 induction strategies to the same single 34% Training | 33% Validation | 33% Test partition of this new dataset: XTRACTIS induces 2,000 IVEs.
6. The top-IVE selected is as efficient as the top-CVE, but more intelligible: 27 rules sharing 20 predictors.

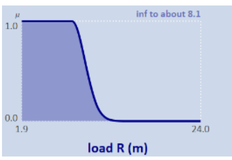
Total number of induced unitary models	Criterion for the induction optimization	Validation criterion for the top-model selection	Duration of the process (Induction Power FP64)
32,000 IVEs	F_1-Score	F_1-Score	~6 days (1 Tflops)

TOP-MODEL STRUCTURE

The top-IVE model has a very good intelligibility as it has 27 rules aggregated into 2 disjunctive rules and combining the 20 predictors that XTRACTIS automatically selected out of 74 variables. The 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

- 20 features out of 74: 18 numeric, 2 nominal.
- Ranked by impact significance (3 strong signal, 11 medium signals, 6 weak signals):
  #1 P (bars) #2 load R (m) #3 …
- Labeled by nominal and fuzzy classes.
  Example:
  binary nominal "{75 × 1,5 RILSAN}"
  fuzzy interval
  "inf to about 8.1"



RULES

- 27 connective fuzzy rules without chaining
- 1 to 14 predictors per rule (on average, 5.4 predictors per rule)
- Example: **fuzzy rule R21** uses 1 nominal predictor, 3 numeric predictors, and concludes "RUPTURE". 26 other fuzzy rules complete this model.

IF	AWT on vault	IS	{75 × 1,5 RILSAN}
AND	load R (m)	IS	inf to ~8.1
AND	P/sEfl (MPa)	IS	inf to ~0.66
AND	P (bars)	IS	sup to ~113
THEN	Pipe State Prediction	IS	RUPTURE

Literally, the pipe is very likely to break if the AWT on vault equals 75 × 1,5 RILSAN, and the load R is under approximately 8.1 m and P/sEfl is under approximately 0.66 MPa and the Pressure is above approximately 113 bars.

PERFORMANCE

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

	Synthetic Data			Reference Data
Performance	DESCRIPTIVE	PREDICTIVE	REAL	REAL
Dataset	34% Training	33% Validation	33% Test	External Test
F_1-Score	99.58%	99.58%	99.30%	91.18%
Classification Error	0.23%	0.23%	0.38%	2.47%

EXPLAINED PREDICTIONS FOR 2 UNKNOWN CASES

Powered by: XTRACTIS® PREDICT v13.0.45039

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

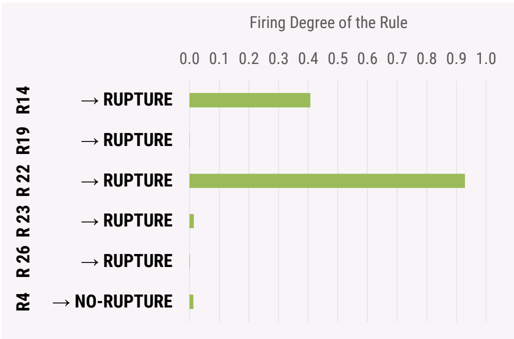
CASE #29b_44

actual value = RUPTURE	
GunderA1 (mm) *	0.000
YMS (MPa) sheet 1	867
UTS (MPa) sheet 1	950
a (deg) sheet 2	30.2
…	…
Mat	Fi09

Real Time

For this pipe, 6 rules are triggered:

R22 is fired at 0.929, **R14** at 0.407, **R23** at 0.014, **R26** at 0.001 and **R19** at 4.79e-5 to conclude {RUPTURE}.
R4 is fired at 0.013 ton conclude {NO-RUPTURE}.



NUMBER OF TRIGGERED RULES
6 / 27

FUZZY PREDICTION
{ RUPTURE | 0.929,
NO-RUPTURE | 0.013 }

FINAL PREDICTION
{ RUPTURE }

The system delivers a correct diagnosis compared to that given by the technician:

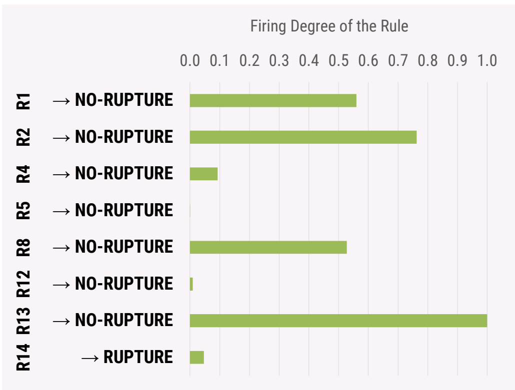
RUPTURE

CASE #29b_6

actual value = NO-RUPTURE	
GunderA1 (mm) *	0.000
YMS (MPa) sheet 1	867
UTS (MPa) sheet 1	950
a (deg) sheet 2	30.2
…	…
Mat	Fi09

Real Time

For this pipe, 8 rules are triggered:
R13 is fired at 1.000, **R2** at 0.763, **R1** at 0.560, **R8** at 0.528, **R4** at 0.093, **R12** at 0.009 and **R5** at 3.16e-04 to conclude {NO-RUPTURE}.
R14 is fired at 0.047 to conclude {RUPTURE}.



NUMBER OF TRIGGERED RULES
8 / 27

FUZZY PREDICTION
{ NO-RUPTURE | 1.000,
RUPTURE | 0.047 }

FINAL PREDICTION
{ NO-RUPTURE }

The system delivers a correct diagnosis compared to that given by the technician:

NO-RUPTURE

**Predictor value outside the variation range of the model but inside the allowed extrapolation range. XTRACTIS will refuse to give a result for an extrapolation far from the allowed extrapolation range. It is one case of the "Refusal" prediction*

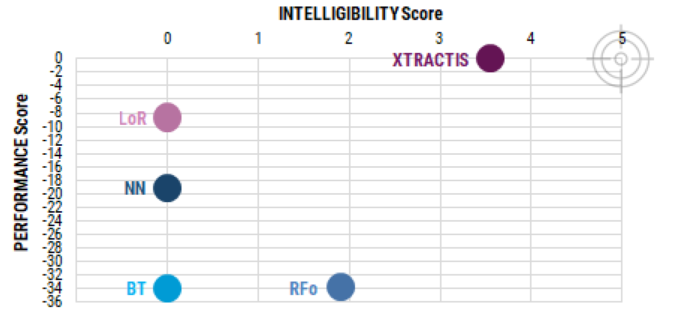
TOP-MODELS BENCHMARK

MODELING PARAMETERS	XTRACTIS	LOGISTIC REGRESSION	RANDOM FOREST	BOOSTED TREES	NEURAL NETWORK
MODELS RELEASE	2023/02	2023/01	2023/01	2023/01	2023/01
ALGORITHM VERSION	XTRACTIS **REVEAL** 13.0.45039	Python 3.9 | Scikit-Learn 1.0.2	Python 3.9 | LightGBM 3.3.2	Python 3.9 | LightGBM 3.3.2	Python 3.9 | TensorFlow 2.10.0 | Keras 2.10.0
CROSS-VALIDATION TECHNIQUE	20×5 folds for each CVE model. Then 1-Split Validation for each IVE model: 34% Training | 33% Validation | 33% Test	For LoR, RFo, BT & NN: 20×5 folds for each CVE model			
NUMBER OF EXPLORED STRATEGIES[1]	300 induction strategies for the CVE on Training / Validation data. 2,000 induction strategies for the IVE on synthetic data	300 data analysis strategies on Training / Validation data	For RFo, BT & NN: 300 ML strategies on Training / Validation data		
TOP-MODEL SELECTION[2]	Top-CVE among 900 CVEs, then Top-IVE among 2,000 IVEs	For LoR, RFo, BT & NN: Top-CVE selected among 300 CVEs, then single model obtained by applying best CVE strategy on 100% of the Learning Dataset			

TOP-MODEL STRUCTURE	XTRACTIS	LOGISTIC REGRESSION	RANDOM FOREST	BOOSTED TREES	NEURAL NETWORK
NUMBER OF PREDICTORS (out of 74 Potential Predictors)	**20**	**24** (out of 97: 6 modal variables are decomposed into 29 binary variables)	**28**	**36**	**95** (out of 97: 6 modal variables are decomposed into 29 binary variables)
AVERAGE NUMBER OF PREDICTORS PER RULE / EQUATION	**5.4** per rule	**24.0** per equation	**4.6** per rule	**5.1** per rule	**61.8** per equation
STRUCTURE OF THE DECISION SYSTEM	**27** fuzzy rules without chaining (aggregated into 2 disjunctive rules) Only a few rules are triggered at a time to compute a decision	**1** linear equation	**13** trees without chaining **394** binary rules	**1** chain of **15** trees **477** binary rules Tree #N corrects the error of the N-1 previous trees	**3** hidden layers | **56** hidden nodes **57** equations 56 unintelligible synthetic variables

INTELLIGIBILITY × PERFORMANCE × VARIABILITY SCORES (Performance and Variability Scores are calculated on all available unknown data)

	Random[3]	XTRACTIS	LoR	RFo	BT	NN
INTELLIGIBILITY Score[4]		**3.55**	**0.00**	**1.91**	**1.17**	**0.00**
CVE Real Performance (F_1-Score) in External Test		92.86	82.50	59.62	68.42	75.95
Gap to CVE Leader in External Test		**0.00**	**-10.36**	**-33.24**	**-24.44**	**-16.91**
IVE Real Performance (F_1-Score) in External Test	*35.14%*	91.18	84.21	56.86	47.62	69.66
Gap to IVE Leader in Test		**0.00**	**-6.97**	**-34.32**	**-43.56**	**-21.52**
Top-IVE Average Real Performance		92.02	83.36	86.98	58.02	72.81
PERFORMANCE Score[4]		**0.00**	**-8.67**	**-33.78**	**-34.00**	**-19.22**



(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 for explanations and detailed results.

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

APPENDIX 1 — Calculation of the Intelligibility × Performance

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 ∈ {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 & Boost Trees: 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 target is to obtain the highest Performance <u>and</u> 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

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

<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 Forests).
- For similar structures, the Boosted Trees model is always less intelligible than the Random Forest one, as it is composed of chains of trees, instead of a college of trees (cf. 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 (cf. Penalty 5).

APPENDIX 2 — 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
RANDOM MODEL								
Nb of Random Permutations (P-value) = 100,000 (0.001%)								
Performance against chance	*19.75%*	*35.14%*					***35.14%***	
XTRACTIS TOP-MODEL								
CVE - Descriptive Performance (Training)	0.17%	99.40%	99.40%	100.00%	100.00%	100.00%	99.70%	0 (0.00%)
CVE - Predictive Performance (Validation)	0.17%	99.40%	99.40%	100.00%	100.00%	100.00%	99.70%	0 (0.00%)
CVE - Real Performance (External Test)	1.71%	89.66%	89.66%	99.51%	96.30%	98.55%	**92.86%**	9 (3.70%)
IVE - Descriptive Performance (Training)	0.23%	99.67%	99.67%	99.81%	99.49%	99.88%	99.58%	0 (0.00%)
IVE - Predictive Performance (Validation)	0.23%	99.56%	99.56%	99.85%	99.59%	99.84%	99.58%	0 (0.00%)
IVE - Real Performance (Test)	0.38%	99.22%	99.22%	99.77%	99.38%	99.71%	99.30%	0 (0.00%)
IVE - Real Performance (1,201 original points)	1.42%	95.77%	95.77%	99.66%	99.06%	98.41%	97.39%	0 (0.00%)
IVE - Real Performance (External Test)	2.47%	83.78%	83.78%	100.00%	100.00%	97.17%	**91.18%**	0 (0.00%)
LOGISTIC REGRESSION TOP-MODEL								
CVE - Descriptive Performance (Training)	2.83%	96.68%	96.68%	97.36%	93.29%	98.72%	94.96%	
CVE - Predictive Performance (Validation)	2.58%	96.68%	96.68%	97.70%	94.12%	98.72%	95.38%	
CVE - Real Performance (External Test)	5.76%	89.19%	89.19%	95.15%	76.74%	98.00%	**82.50%**	
IVE - Descriptive Performance (Training)	2.16%	96.07%	96.07%	98.51%	96.07%	98.51%	96.07%	
IVE - Real Performance (External Test)	4.94%	86.49%	86.49%	96.60%	82.05%	97.55%	**84.21%**	
RANDOM FOREST TOP-MODEL								
CVE - Descriptive Performance (Training)	0.17%	99.40%	99.40%	100.00%	100.00%	99.77%	99.70%	
CVE - Predictive Performance (Validation)	0.17%	99.40%	99.40%	100.00%	100.00%	99.77%	99.70%	
CVE - Real Performance (External Test)	17.28%	82.52%	83.78%	82.52%	46.27%	96.59%	**59.62%**	
IVE - Descriptive Performance (Training)	0.17%	99.70%	99.70%	99.89%	99.70%	99.89%	99.70%	
IVE - Real Performance (External Test)	18.11%	78.38%	78.38%	82.52%	44.62%	95.51%	**56.86%**	
BOOSTED TREES TOP-MODEL								
CVE - Descriptive Performance (Training)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
CVE - Predictive Performance (Validation)	0.08%	99.70%	99.70%	100.00%	100.00%	99.89%	99.85%	
CVE - Real Performance (External Test)	9.88%	70.27%	70.27%	93.70%	66.67%	94.61%	**68.42%**	
IVE - Descriptive Performance (Training)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
IVE - Real Performance (External Test)	13.58%	40.54%	40.54%	94.66%	57.69%	89.86%	**47.62%**	
NEURAL NETWORK TOP-MODEL								
CVE - Descriptive Performance (Training)	0.83%	98.49%	98.49%	99.43%	98.49%	99.43%	98.49%	
CVE - Predictive Performance (Validation)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
CVE - Real Performance (External Test)	7.82%	81.08%	81.08%	94.17%	71.43%	96.52%	**75.95%**	
IVE - Descriptive Performance (Training)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
IVE - Real Performance (External Test)	11.11%	83.78%	83.78%	89.81%	59.62%	96.86%	**69.66%**	