Homeland Security

TEMPORAL IDENTIFICATION OF CRIMINAL PROFILES AND ACTION PHASES FROM COMMUNICATIONS METADATA DURING SURVEILLANCE INVESTIGATIONS

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

2024/02 (v5.0) xtractis.ai

PROBLEM DEFINITION

GOAL

Design an AI-based decision system that accurately identifies risky behavior linked to criminal activities by analyzing communication metadata from surveillance investigations, without accessing the content of telephone calls and rationally predicts dangerous Homeland Security situations.

PROS & BENEFITS

- Identify specific metadata characterizing different criminal activities and enhance expert knowledge by helping intelligence specialists understand the causal relationships between the communication profiles and the roles inside criminal organizations.
- Help intelligence services detect attacks as early as possible and understand the underlying strategy of the criminals in order to consider measures to thwart future attacks.
- Avoid many false alarms thanks to transparent diagnosis.

REFERENCE DATA

Source: Confidential data produced by ATOS-BDS-MCS (EVIDEN)

Variable to Predict The model predicts the type of sender profile [**Banal**, **Support**, **Executant**, **Chief**] and the associated temporal phase phase [**P1 Initialization**, **P2 Gathering**, **P3 Planning**, **P4 Execution**] for a total of 10 feasible combinations (10 possible classes):
BNL | SUP_P2 | SUP_P3 | SUP_P3 | EXEC_P2 | EXEC_P3 | EXEC_P4| CHIEF_P2 | CHIEF_P3 | CHIEF_P4

Predictive Variables Each communication is described by 29 to 37 metadata. These metadata are combined and aggregated over time to obtain 321 potential predictors [NUM_SMS_2Days: Number of SMS-type communications over the last 2 days, COMVOLUME: Duration of the call in progress...].

Observations 2,492,273 communications within 7 scenarios. Data are divided into a Learning Dataset for model induction using Training, Validation, and Test Datasets, and an External Test Dataset (involving 6 scenarios) to check the top-model's performance on real data and for benchmarking.

Learning Dataset: 809,554 cases | 32.5% (no duplicates) Training (434,150 | 53.63%), Validation (160,399 | 19.81%), Test (215,005 | 26.56%)									
BNL	SUP_P2	SUP_P3	SUP_P4	EXEC_P2	EXEC_P3	EXEC_P4	CH_P2	CH_P3	CH_P4
57.84%	11.83%	0.95%	0.16%	23.15%	2.19%	0.37%	3.17%	0.30%	0.04%

External Test Dataset: 1,682,719 cases | 67.5% (no duplicates)									
BNL	SUP_P2	SUP_P3	SUP_P4	EXEC_P2	EXEC_P3	EXEC_P4	CH_P2	CH_P3	CH_P4
47.10%	16.23%	0.98%	0.12%	28.72%	1.87%	0.37%	4.26%	0.31%	0.04%

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 **12 gradual rules without chaining, each rule uses some of the 24 variables that XTRACTIS identified as predictors.** Moreover, only a few rules are triggered at a time to compute the decision.
- ☑ **High Predictive Capacity** It has a good Real Performance for all 6 External Test Dataset scenarios (on unknown data).
- ☑ **Efficient AI System** 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	Profile type & time phase Automated Decision (identify behavior profile & time phase)
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
v12.2.44349

1. We launch 464 inductive reasoning strategies; each strategy is applied to the same single partition of the learning dataset (53.6% Training / 19.8% Validation / 26.6% 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 464 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: **12 rules sharing 24 predictors**.

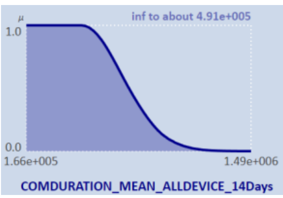
Total number of induced unitary models	Criteria for the induction optimization	Parameter of the top-models selection on validation	Duration of the process (Induction Power FP64)
464 IVEs	Average F_2-Score	Average F_2-Score	35 days (24 Tflops)

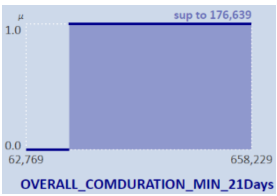
TOP-MODEL STRUCTURE

The top-model has a very good intelligibility as it has 12 rules combining the 24 predictors that XTRACTIS automatically selected out of 321 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

- 24 continuous metadata (out of 321)
- Ranked by impact significance
  (7 strong, 4 medium & 13 weak signals):
  #1 NUM_UNIQUE_USED_DEVICE_SMS_14Days …/…/
  #11 VARPRC_OVERALL_NUM_VOICE_14_21Days …
- Labeled by fuzzy and binary classes
  Examples: **binary interval** "sup to 176,639";
  fuzzy interval "inf to about 4.91e+005"





RULES

- 12 connective fuzzy rules without chaining (aggregated into 10 disjunctive fuzzy rules)
- 3 to 12 predictors per rule (on average, 6.3 predictors per rule)
- Example: **fuzzy rule R6** uses 4 predictors and concludes "EXEC_P2" (Profile *Executant*, Phase *Grouping*). 11 other fuzzy rules complete this model.

IF	COMDURATION_MEAN_ALLDEVICE_14D	IS	inf to ~4.91e+005
AND	NUM_UNIQUE_USED_DEVICE_1D	IS	sup to ~1.99
AND	OVERALL_COMDURATION_MIN_21D	IS	sup to 176,639
AND	VARPRC_OVERALL_NUM_SMS_3_7D	IS	sup to ~-57.0
THEN	Sender Profile_Phase	IS	EXEC_P2

Literally, intercepted communication is that of an EXECUTANT in Gathering Phase if his mean duration of communication, during the last 14 days, is inferior to 8'11'', and his number of different devices used, during the last 24h, is 2 or more, and the group's minimum duration of communication, during the last 21 days, is superior to 2'57'', and the relative change in group's number of SMS, between the last 3 and the last 7 days, is superior to -57%.

TOP-MODEL PERFORMANCE

The top-IVE performances, measured in Training/Validation/Test, then in External Test for each of the 6 scenarios, guarantee the model's predictive and real performances.

Performance	DESCRIPTIVE	PREDICTIVE	REAL	REAL
Dataset	53.6% Training	19.8% Validation	26.6% Test	External Test
Average F_2-Score	92.37%	90.40%	89.82%	87.23%
Classification Error	1.41%	1.56%	1.06%	0.64%

EXPLAINED PREDICTIONS FOR 2 UNKNOWN CASES

Powered by: XTRACTIS® PREDICT v12.2.44349

CASE
(from the External Dataset,
i.e., not included in the Learning Dataset)

DEDUCTIVE INFERENCE OF RULES

AUTOMATED DECISION

ihfgwmqida_2014-05-23 16:17:47.166

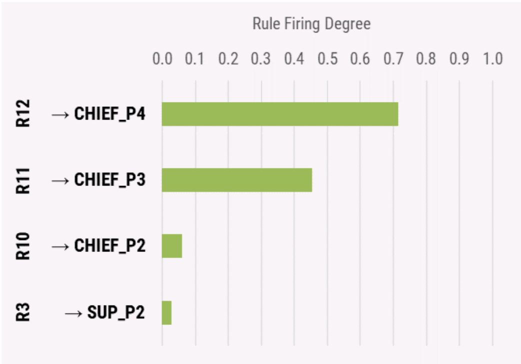
Real Time

actual value = CHIEF_P4	
COMDURATION_MEAN_7D	1.83e+005
NUM_UNIQUE_TMSI _RECEIVER_SMS_3D	Missing Value
NUM_UNIQUE_USED _DEVICE_SMS_14D	6.00
NUM_VOICE_ALLDEVICE_1D	4.0
...	...
OVERALL_COMDURATION _MIN_21D	80,186
VARPRC_NUM_UNIQUE _TMSI_RECEIVER_1_2D	0.0
VARPRC_NUM_VOICE_ALLDE VICE_7_14D	-61.2
VARPRC_OVERALL_NUM _SMS_1_2D	-49.7
VARPRC_OVERALL_NUM _VOICE_7_14D	-50.7

For this communication, 4 rules are triggered:

R12 at 0.715, **R11** at 0.453, **R10** at 0.061 and **R3** at 0.027

The 8 other rules are not activated.



NUMBER OF TRIGGERED RULES
4 / 12

FUZZY PREDICTION
{ CHIEF_P4 | **0.715**,
CHIEF_P3 | **0.453**,
CHIEF_P2 | **0.061**,
SUP_P2 | **0.027** }

FINAL PREDICTION
{ CHIEF_P4 }

The system delivers the correct diagnosis compared to that given by the intelligence expert:

Profile CHIEF, Phase EXECUTION

wavzigquktqy_2013-09-24 21:54:39.903

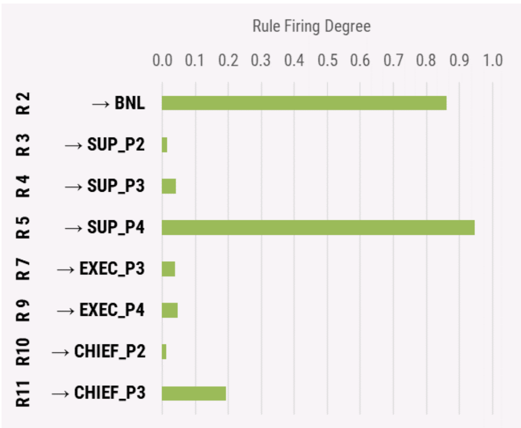
Real Time

actual value = SUP_P4	
COMDURATION_MEAN_7D	3.74E+05
NUM_UNIQUE_TMSI _RECEIVER_SMS_3D	Missing Value
NUM_UNIQUE_USED _DEVICE_SMS_14D	2.00
NUM_VOICE_ALLDEVICE_1D	2.0
...	
OVERALL_COMDURATION _MIN_21D	64,285
VARPRC_NUM_UNIQUE _TMSI_RECEIVER_1_2D	0.0
VARPRC_NUM_VOICE_ALLD EVICE_7_14D	-33.3
VARPRC_OVERALL_NUM _SMS_1_2D	-46.6
VARPRC_OVERALL_NUM _VOICE_7_14D	-50.6

For this communication, 8 rules are triggered:

R5 at 0.946, **R2** at 0.860, **R11** at 0.194...

The 4 other rules are not activated.



NUMBER OF TRIGGERED RULES
8 / 12

FUZZY PREDICTION
{ SUP_P4 | **0.946**
BNL | **0.860**,
CHIEF_P3 | **0.194**,
EXEC_P4 | **0.048**,
SUP_P3 | **0.041**
EXEC_P3 | **0.039**
SUP_P2 | **0.014**
CHIEF_P2 | **0.013** }

FINAL PREDICTION
{ SUP_P4 }

The system delivers the correct diagnosis compared to that given by the intelligence expert, although it considered that it could also be a Banal behavior with a closer possibility:

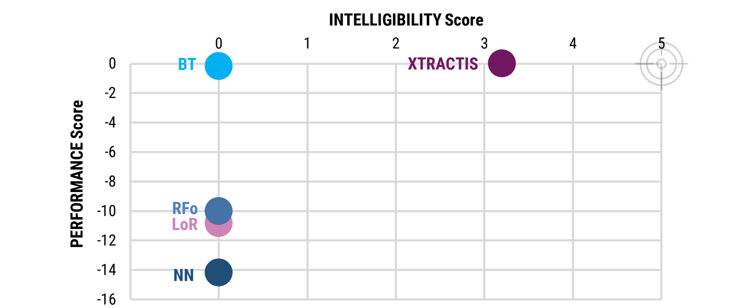
Profile SUPPORT, Phase EXECUTION

TOP-MODELS BENCHMARK

		XTRACTIS	LOGISTIC REGRESSION	RANDOM FOREST	BOOSTED TREES	NEURAL NETWORK
MODELING PARAMETERS	MODELS RELEASE	2023/01	2023/01	2023/01	2023/01	2023/01
	ALGORITHM VERSION	XTRACTIS **REVEAL** 12.2.44349	Python 3.9 | Scikit-Learn 1.3.0	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	All explored strategies for all algorithms use the same single-split of the Learning Dataset: 60% Training | 20% Validation | 20% Test				
	NUMBER OF EXPLORED STRATEGIES(1)	464 induction strategies	1,000 data analysis strategies	1,000 ML strategies	1,000 ML strategies	1,000 ML strategies
	TOP-MODEL SELECTION(2)	Top-IVE among 464 IVEs	Top-IVE among 1,000 IVEs	Top-IVE among 1,000 IVEs	Top-IVE among 1,000 IVEs	Top-IVE among 1,000 IVEs
TOP-MODEL STRUCTURE	NUMBER OF PREDICTORS (out of 321 Potential Predictors)	**24**	**321**	**299**	**313**	**321**
	AVERAGE NUMBER OF PREDICTORS PER RULE / EQUATION	**6.3** per rule	**321.0** per equation	**8.3** per rule	**6.1** per rule	**117.6** per equation
	STRUCTURE OF THE DECISION SYSTEM	**12** fuzzy rules without chaining (aggregated into 10 disjunctive fuzzy rules) Only a few rules are triggered at a time to compute a decision	**10** linear equations	**500** trees without chaining **20,216** binary rules	**10** chains of **309** trees each **49,797** binary rules Tree #N corrects the error of the N-1 previous trees	**2** hidden layers | **22** hidden nodes **32** equations 22 unintelligible synthetic variables

INTELLIGIBILITY × PERFORMANCE SCORES (Performance Score is calculated on all available unknown data)

	Random(3)	XTRACTIS	LoR	RFo	BT	NN
INTELLIGIBILITY Score(4)		**3.20**	**0.00**	**0.00**	**0.00**	**0.00**
IVE Real Perf. (Average F_2-Score) in Test		89.82	78.89	77.83	89.54	84.20
Gap to Leader in Test		**0.00**	**-10.93**	**-11.99**	**-0.28**	**-5.62**
IVE Real Perf. (Average F_2-Score) in External Test	*7.79%*	87.23	76.46	79.19	87.14	64.47
Gap to Leader in External Test		**0.00**	**-10.77**	**-8.04**	**-0.09**	**-22.76**
IVE Average Real Performance		88.53	77.68	78.51	88.34	74.34
PERFORMANCE Score(4)		**0.00**	**-10.85**	**-10.02**	**-0.18**	**-14.19**



(1) For all algos: on the same Learning Dataset. All Models are optimized according to their validation Average F_2-Score.
(2) All top-models are selected according to their validation Average F_2-Score while checking that it remains close to their training Average F_2-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∈[1 ; n] n = number of AI Techniques benchmarked in terms of data-driven modeling = 5
Benchmark #k	B_k	k∈[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

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

Remark:

- 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):

  $$\text{Pen1}(T_i) = \min(0\,, 1 - \log_{10} number\ of\ predictors)$$

  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):

  $$\text{Pen2}(T_i) = \min\left(0\,, 0.01 - \frac{average\ number\ of\ rules\ or\ equations\ per\ modality\ to\ predict}{100}\right)$$

  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):

  $$\text{Pen3}(T_i) = \min\left(0\,, \frac{9 - 3 \times average\ number\ of\ predictors\ per\ rule\ or\ equation}{7}\right)$$

  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):

  $$\text{Pen4}(T_i) = \min(0\,, 1 - number\ of\ chained\ trees)$$

  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):

  $$\text{Pen5}(T_i) = -5$$

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	Average Sensitivity	Min. PPV	Average PPV	**Average F_2-Score**	Weighted Av. F_2-Score	Refusal
RANDOM MODEL								
Nb of Random Permutations (P-value) = 100,000 (0.001%)								
Performance against chance	*81.55%*	*0.37%*	*7.79%*	*0.37%*	*7.79%*	***7.79%***	*18.45%*	
XTRACTIS TOP-MODEL								
Descriptive Performance (Training)	1.41%	74.22%	93.01%	56.22%	92.07%	92.37%	98.59%	0 (0.00%)
Predictive Performance (Validation)	1.56%	51.21%	89.63%	79.06%	94.84%	90.40%	98.42%	0 (0.00%)
Real Performance (Test)	1.06%	60.97%	90.75%	49.44%	90.87%	**89.82%**	98.92%	2 (0.00%)
Real Performance (External Test for 6 scenarios)	0.64%	46.37%	87.48%	54.63%	87.85%	**87.23%**	99.36%	0 (0.00%)
LOGISTIC REGRESSION TOP-MODEL								
Descriptive Performance (Training)	0.91%	76.09%	93.11%	91.11%	97.84%	93.93%	99.09%	
Predictive Performance (Validation)	4.21%	54.57%	82.36%	29.04%	82.37%	80.44%	95.74%	
Real Performance (Test)	2.45%	44.69%	84.64%	22.34%	81.36%	**78.89%**	97.52%	
Real Performance (External Test for 6 scenarios)	8.11%	44.91%	80.62%	26.85%	80.06%	**76.46%**	91.75%	
RANDOM FOREST TOP-MODEL								
Descriptive Performance (Training)	0.31%	93.49%	98.29%	80.48%	95.06%	97.58%	99.70%	
Predictive Performance (Validation)	8.42%	30.47%	80.66%	24.15%	73.28%	76.35%	91.82%	
Real Performance (Test)	7.18%	17.76%	85.56%	11.63%	68.95%	**77.83%**	93.14%	
Real Performance (External Test for 6 scenarios)	12.20%	55.29%	86.68%	20.55%	68.28%	**79.19%**	88.29%	
BOOSTED TREES TOP-MODEL								
Descriptive Performance (Training)	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
Predictive Performance (Validation)	2.92%	30.28%	84.92%	66.63%	91.97%	84.91%	96.97%	
Real Performance (Test)	2.08%	42.36%	89.65%	59.03%	94.12%	**89.54%**	97.80%	
Real Performance (External Test for 6 scenarios)	3.93%	49.74%	87.26%	57.03%	92.97%	**87.14%**	95.97%	
NEURAL NETWORK TOP-MODEL								
Descriptive Performance (Training)	0.64%	78.52%	95.67%	82.20%	95.59%	95.55%	99.35%	
Predictive Performance (Validation)	2.90%	56.64%	87.76%	77.30%	89.45%	87.83%	97.06%	
Real Performance (Test)	1.81%	61.68%	87.57%	33.50%	82.59%	**84.20%**	98.16%	
Real Performance (External Test for 6 scenarios)	18.09%	23.19%	69.84%	32.24%	70.28%	**64.47%**	81.43%	