

COREALIS Piraeus Demo/Training Webinar

COREALIS Asset Management Predictor

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June 4th, 2020



Predictive Maintenance



☐ Preventive vs Predictive Maintenance:

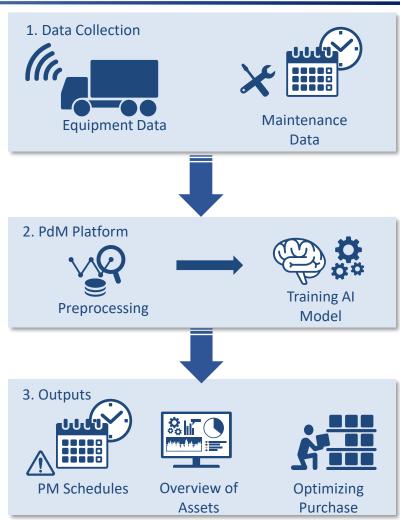
- **Preventive Maintenance**: Engineers inspect vehicles every couple of months. This method is costly and does not capture asset-specific conditions (for e.g. rides per day, occupancy level, weather conditions, etc.).
- **Predictive Maintenance (PdM)** solutions takes into account the operating conditions of vehicles by leveraging data collected from individual assets to predict failures in future.

□ Overview:

- Data Collection: Equipment Data and Maintenance Data
- PdM Platform: Preprocessing and Training Al Model
- Outputs: Schedules, Overview of Assets and Purchase Optimization

☐ Customer Value:

- Reduced Asset Downtime,
- Reduced maintenance and repair costs,
- Optimize spare parts inventory







Market Analysis

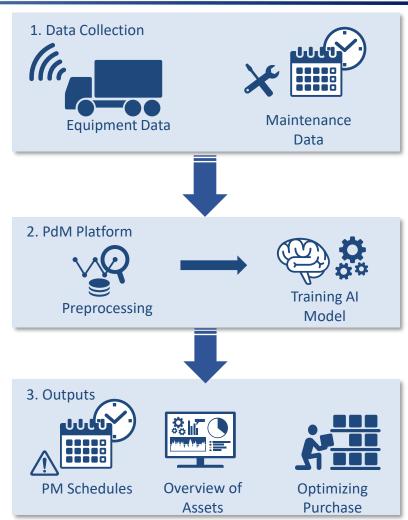


☐ Market Size (General):

 Analysts consensus on growth rate at 25-30% CAGR in 2020-2025 period (Allied Market Research, Market Expert 24, ReportBuyer), but have diverse market size estimates (\$15-30B)

□ PdM Solutions:

- Predictive Maintenance is an imbalanced classification problem where number of part failures is much smaller than predominant normal working parts.
- To the best of our knowledge, PdM solutions (from Bosch, SAP, Huwaei, IBM and SAP) relies on statistical analysis.
- Their solutions does not relies on advanced machine learning algorithms tailored for imbalanced classification tasks.







Technology Description (BRIGHT DAMVI)



■ **BRIGHT** is NEC's Ensemble Learning Technology:

IJCNN 2020

- Combine many weak learners to build a more efficient learner
- Many specialized weak learners can beat a strong one
- That's because "strong" learners (singletons) model the variable in a wide set of conditions, sacrificing memory of rare events to work in general
- Meta-Learning
 - learning how learners perform in which situation
 - A Meta-Learner learns from the behavior of other learners (= base learners)
- **BRIGHT DAMVI***: Meta-learning for imbalanced data classification
 - Learns a diversity-aware weighted majority vote classifier over the base classifiers
 - Delivers benefits in terms of F1-score and Average Precision especially in four main applications: predictive maintenance tasks, credit fraud detection, medical diagnosis and webpage classification.
 - Performs well even for highly imbalanced classification tasks (< 4% positive class examples).

*Diversity-Aware Weighted Majority Vote Classifier for Imbalanced Data

*Anil Goyal and Jihed Khiari, "Diversity-Aware Weighted Majority Vote Classifier for Imbalanced Data", The International Joint Conference on Neural Networks (IJCNN), 2020





Technology Description (BRIGHT DAMVI)

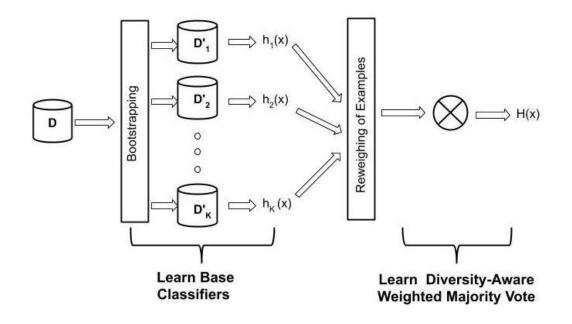


- Base Classifiers: Learn a set of base classifiers corresponding to K bootstrapped samples
- Reweighing of Examples: DAMVI increases the weights of positive examples (minority class) which are "hard" to classify with uniformly weighing of classifiers.
- Learning Diversity-Aware Weighted Majority Vote: Learned base classifiers are combined using diversity-aware weighted majority vote:

$$H(x) = \sum_{k=1}^{K} Q(k).h_k(x)$$

where, $h_k(x)$ is a base learner corresponding to subsampled data D_K and Q(k) is the weight over base learner.









Experimental Results



Datasets

	#Attr	ibutes $\#$ Examples	IR
Webpage	300	34780	3.03
Mammography	6	11183	2.32
Scania	170	60000	1.67
Protein Homo	74	145751	0.9
Credit Fraud	30	284807	0.17
PCT Data	17	816099	0.02

- DAMVI performs best on all datasets in terms of F1-score and for 5 out of 6 datasets in terms of Average Precision.
- DAMVI performs significantly better on PCT dataset with lowest imbalance ratio of 0.02.

F1-score



	Webpage	Mammography	Scania	Protein Homo	Credit Fraud	PCT Data
S-DT	.5062±.028↓	.5198±.009 [↓]	.5848±.011↓	.5278±.005↓	.5610±.016↓	.8793±.011 [↓]
R-DT	.4705±.021↓	$.6053 \pm .043^{\downarrow}$	$.6256 \pm .019^{\downarrow}$	$.7290 \pm .017^{\downarrow}$	$.7556 \pm .013^{\downarrow}$	$.9715 \pm .002^{\downarrow}$
A-DT	.4693±.019 [↓]	$.4978 \pm .034^{\downarrow}$	$.5807 \pm .020^{\downarrow}$	$.5259 \pm .019^{\downarrow}$	$.5653 \pm .027^{\downarrow}$	$.8830 \pm .009^{\downarrow}$
R-BG	$.4620 \pm .016^{\downarrow}$.6145±.026↓	$.6845 \pm .014^{\downarrow}$.7849±.021 [↓]	$.7703 \pm .020^{\downarrow}$	$.9691 \pm .001^{\downarrow}$
S-BG	.6134±.017↓	$.5391 \pm .017^{\downarrow}$	$.6493 \pm .009$	$.6771 \pm .009$	$.6839 \pm .024^{\downarrow}$	$.9430 \pm .006^{\downarrow}$
A-BG	.4804±.021↓	$.5169 \pm .011^{\downarrow}$	$.6269 \pm .007^{\downarrow}$	$.6346 \pm .013^{\downarrow}$	$.6819 \pm .030^{\downarrow}$	$.9312 \pm .004^{\downarrow}$
BB	.3445±.001↓	$.4465 \pm .030^{\downarrow}$	$.4317 \pm .005$.4275±.008↓	$.1376 \pm .006$	$.8014 \pm .006^{\downarrow}$
BRF	.4098±.010↓	$.3659 \pm .014^{\downarrow}$	$.3822 \pm .004^{\downarrow}$	$.4027 \pm .009$	$.1255 \pm .016^{\downarrow}$	$.2943 \pm .007^{\downarrow}$
EE	.4678±.011↓	$.2534 \pm .002^{\downarrow}$	$.4096 \pm .006$	$.3350 \pm .003^{\downarrow}$	$.0922 \pm .007^{\downarrow}$.0881±.001 [↓]
DAMVI	.7996 ±.011	.6661±.023	$.7289 \pm .011$.8067±.009	$.8495 \pm .019$.9816 ±.001

Average Precision

	Webpage	Mammography	Scania	Protein Homo	Credit Fraud	PCT Data
S-DT	.2794±.023↓	$.2919 \pm .010^{\downarrow}$	$.3526 \pm .014^{\downarrow}$	$.3153\pm.005^{\downarrow}$	$.3482 \pm .016^{\downarrow}$.7785±.001 [↓]
R-DT	.3008±.016↓	$.3811 \pm .054^{\downarrow}$	$.3994 \pm .024^{\downarrow}$	$.5347 \pm .025^{\downarrow}$	$.5728 \pm .020^{\downarrow}$	$.9447 \pm .005$
A-DT	.2481±.014 [↓]	$.2740 \pm .034^{\downarrow}$.3483±.023↓	$.3112 \pm .019^{\downarrow}$	$.3516 \pm .030^{\downarrow}$	$.7851 \pm .016^{\downarrow}$
R-BG	.4944±.010↓	$.7011 \pm .021$	$.8097 \pm .016^{\downarrow}$	$.8495 \pm .016$	$.8120 \pm .030^{\downarrow}$	$.9875 \pm .001$
S-BG	.6219±.028↓	$.6971 \pm .025^{\downarrow}$.7275±.019↓	$.8424 \pm .013$.8135±.027 [↓]	$.9863 \pm .001^{\downarrow}$
A-BG	.4400±.024 [↓]	$.6261 \pm .036^{\downarrow}$.6712±.018↓	$.8276 \pm .016$	$.8137 \pm .035^{\downarrow}$	$.9847 \pm .005$
BB	.6302±.034↓	$.6644 \pm .037^{\downarrow}$	$.6745 \pm .024^{\downarrow}$	$.8359 \pm .018$	$.7516 \pm .048^{\downarrow}$	$.9849 \pm .001^{\downarrow}$
BRF	.6930±.022↓	$.6782 \pm .023$.6877±.016↓	$.8549 \pm .014$	$.7615 \pm .047^{\downarrow}$	$.6976 \pm .010^{\downarrow}$
EE	$.6969 \pm .038^{\downarrow}$	$.5967 \pm .043^{\downarrow}$	$.7558 \pm .014^{\downarrow}$	$.8561 \pm .012$	$.7672 \pm .025^{\downarrow}$.0790±.001 [↓]
DAMVI	.8331 ±.013	$.7142 \pm .039$.8335 ±.007	$.8267 \pm .013$	$.8373 \pm .027$.9976 ±.001





Software Development



Web Interface

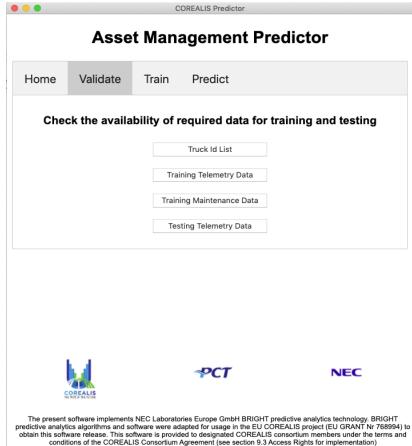
Step 1:

User can check if there exists any learned model for a particular part (from past).

Step 2:

User can validate if the required data for training and testing are stored at desired location or not.









Software Development



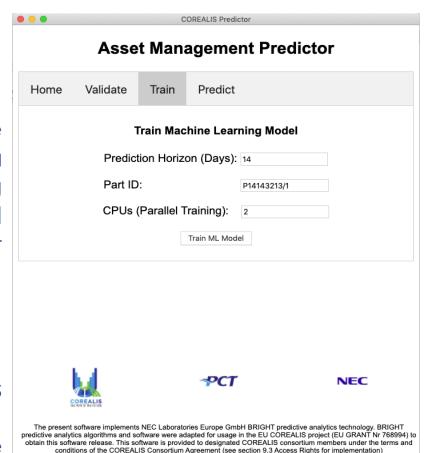
Web Interface

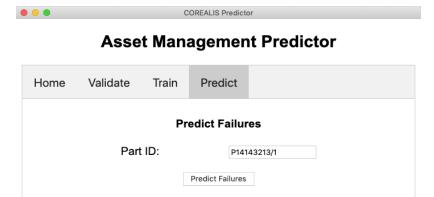
Step 3:

☐ Train the machine learning models for a particular part using prediction horizon and number of CPUs as input tomorrow.

Step 4:

☐ Failures predictions (along with probability) are saved in respective folder in csv file.











The present software implements NEC Laboratories Europe GmbH BRIGHT predictive analytics technology. BRIGHT predictive analytics algorithms and software were adapted for usage in the EU COREALIS project (EU GRANT Nr 768994) to obtain this software release. This software is provided to designated COREALIS consortium members under the terms and conditions of the COREALIS Consortium Agreement (see section 9.3 Access Rights for implementation)







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COREALIS EU Project



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THANK YOU FOR YOUR ATTENTION

NEC

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