LA-UR-21-28939
Approved for public release; distribution is unlimited.

Title: LUNA Condition-Based Monitoring Update: Random Forest and Mahalanobis Ensemble Accuracy Crossover Point

Author(s): Green, Andre Walter

Intended for: Progress report to sponsor.

Issued: 2021-09-10

Disclaimer:
Los Alamos National Laboratory, an affirmative action/equal opportunity employer, is operated by Triad National Security, LLC for the National Nuclear Security Administration of U.S. Department of Energy under contract 89233218CNA000001. By approving this article, the publisher recognizes that the U.S. Government retains nonexclusive, royalty-free license to publish or reproduce the published form of this contribution, or to allow others to do so, for U.S. Government purposes. Los Alamos National Laboratory requests that the publisher identify this article as work performed under the auspices of the U.S. Department of Energy. Los Alamos National Laboratory strongly supports academic freedom and a researcher's right to publish; as an institution, however, the Laboratory does not endorse the viewpoint of a publication or guarantee its technical correctness.

LUNA Condition-Based Monitoring Update: Random Forest and Mahalanobis Ensemble Accuracy Crossover Point

Presented 9/8/2021

Andre Green

Feature Performance for each Dataset

[Mahalanobis Ensemble v. Random Forest]

An isolation forest was used to remove potentially anomalous/outlier points (points possibly between changing between damage type/severities); approximately 10% for Board 401 and Multi-Actuator, 20% for Philadelphia dataset.

Uniformly Selected* Features [Variable number of features]	Ali's Features [13 features]
1 out of 100 samples was used. This is the same 'feature vector' which was used in the previous report for the random forest.	['Var_of_Accel_1', 'Var_of_Accel_2', 'Var_of_Accel_3', 'Mean_of_PG_1', 'Mean_of_PG_2', 'Mean_of_PG_3', 'Var_of_PG_1', 'Var_of_PG_2', 'Var_of_PG_3', 'Slope_of_Angle', 'Pressure_Diff_Sum', 'Diff_Temp_Var', 'Pressure_Max']

Random Forest

~92% for Board 401 Dataset
~90% for Multi-Actuator Dataset
~100% for Philadelphia Dataset

Mahalanobis Ensemble

The covariance matrix was always singular, so the Mahalanobis ensemble doesn't work for this set of features (on any of the datasets).

Random Forest

~86% for Board 401 Dataset
~75% for Multi-Actuator Dataset
~98% for Philadelphia Dataset

Mahalanobis Ensemble

~87% for Board 401 Dataset
~83% for Multi-Actuator Dataset
~99% for Philadelphia Dataset

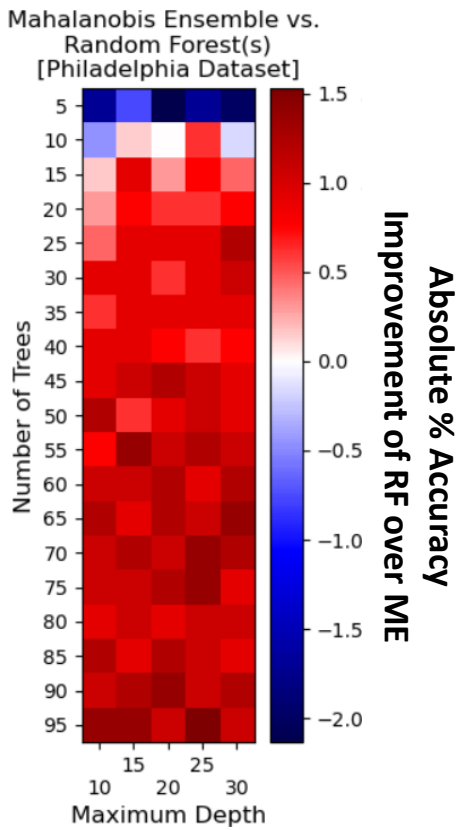
The random forest of size 16 with maximum depth 10 does comparably well (the means, mins, maxes, and medians of accuracy across the 9 folds are similar) to the Mahalanobis Ensemble when used with Ali's features.

The random forest gets better performance using the uniformly-down-sampled 'features' (1 out of every 100 samples) regardless of the dataset: the only downside is the results may not be as easily interpretable.

Performance Maps for each Dataset [Using Ali's Features]

[Mahalanobis Ensemble v. Random Forest] **% Improvement of RF over ME shown by color.**

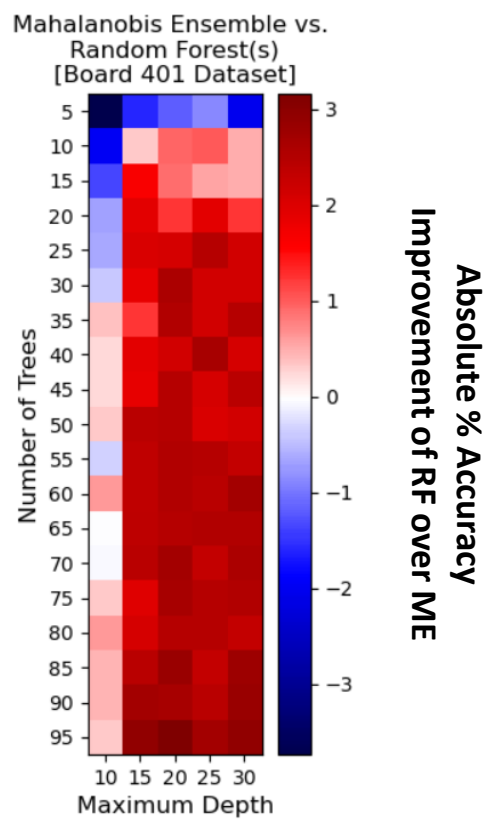
Philadelphia Dataset(s)



Dataset(s):

philadelphia_9_10_19
philadelphia_9_11_19_Act_1
philadelphia_9_11_19_Act_2
philadelphia_9_11_19_Act_5
philadelphia_9_11_19_Act_6

Board_401 Dataset

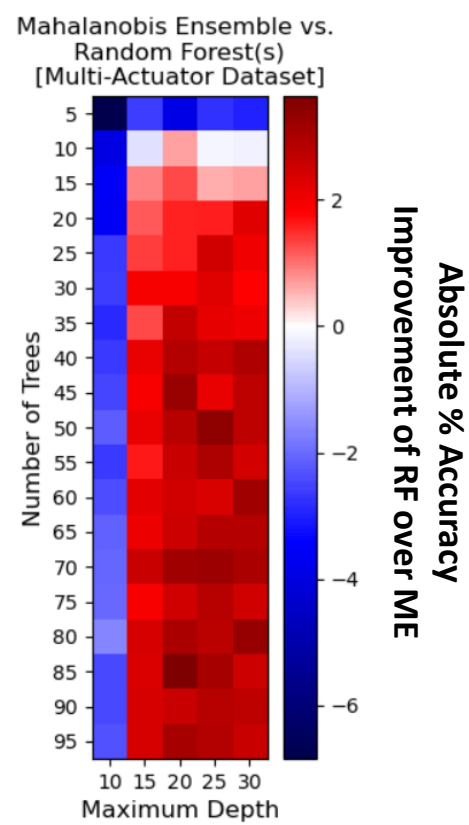


Dataset(s):

ali (Board_401)

RF **worse** than ME
RF **better** than ME

Multi-Actuator Dataset(s)



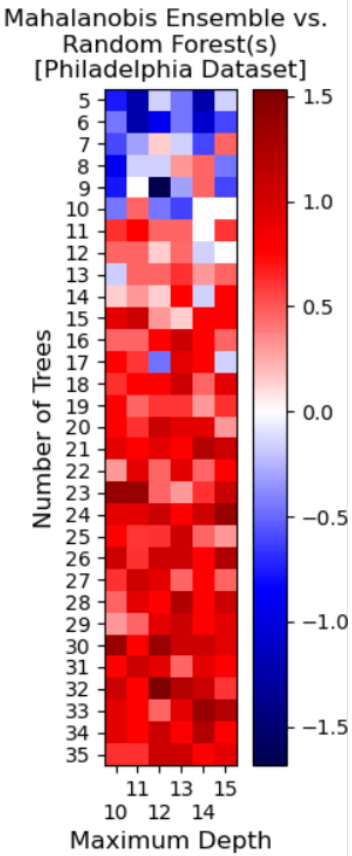
Dataset(s):

25K_Cycles
51.4K_Cycles
101K_Cycles

Performance Maps for each Dataset [Using Ali's Features] [Detail]

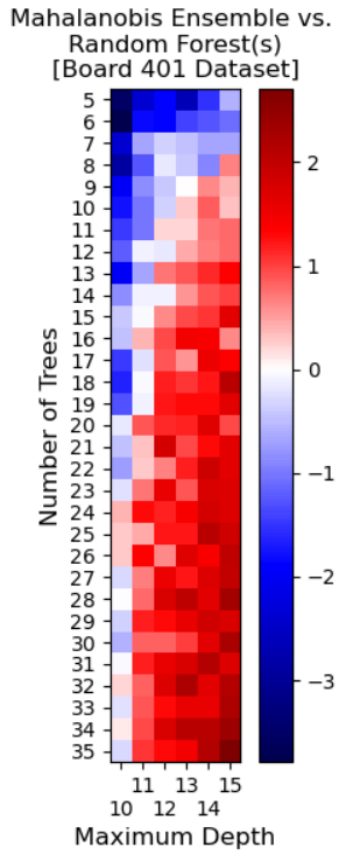
[Mahalanobis Ensemble v. Random Forest] **% Improvement of RF over ME shown by color.**

Philadelphia Dataset(s)



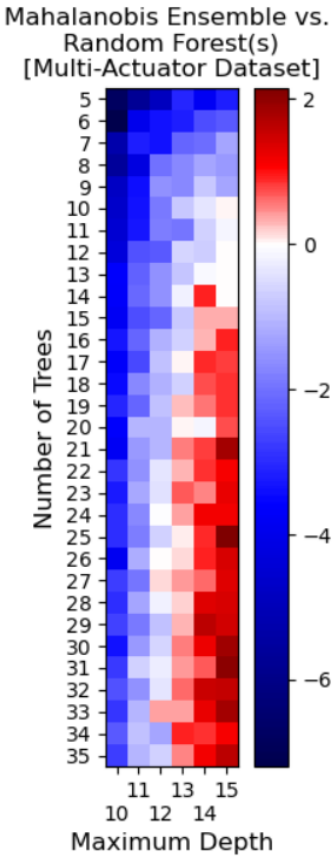
~650 Samples

Board_401 Dataset



~2,000 Samples

Multi-Cycle Dataset(s)



~3,000 Samples

The accuracy crossing point seems to be around **10 trees with a depth of 12**. Having either fewer trees or less deep trees for the same amount of depth or number of trees results in worse performance than the Mahalanobis Ensemble. However, for the multi-cycle dataset, it seems slightly more trees/greater depth are required for the RF to perform as well as the ME (14+ trees, depth of 13-14+, [>106,496 numbers]).

(10 * 2^12) = 40,960 numbers, if the trees are all densely populated (using 10 trees with a max depth of 12)
(21 * 13^13) = 46,137 numbers, when using 21 classes and 13 features.

Time & Space Complexity

Mahalanobis Ensemble

For C classes and F-dimensional feature vectors:

Mahalanobis Ensemble scales with the **number of features**.

Time complexity: O(C * (F^3)) C [FxF] matrix multiplications.
Space complexity: O(C * (F^2)) C [FxF] matrices.

Random Forest

For T trees with maximum depth D:

Random Forest scales **with number of trees** and **max depth of trees**.

Time complexity: O(T * D) T traversals of D-deep trees.
Space complexity: O(T * 2^D) T D-deep trees.

If the random forest is checking multiple variables (say m) at each node of its trees, then the time & space complexities just change linearly: O(m * T * D) for time, O(m * T * 2^D) for space.