

Ensemble Learning-based Fault Detection in Nuclear Power Plant Screen Cleaners

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Abstract: This paper presents a fault detection approach based on feature selection and ensemble machine learning technique for nuclear power plant (NPP) screen cleaner condition monitoring. Firstly, comprehensive set of statistical features are extracted from *in-field* raw accelerometer data. Then, a separability based feature selection metric is utilized to select relevant features in order to enhance accuracy of fault detection algorithm. Afterwards, Extreme Gradient Boosting (XGBoost), which is a decision-tree-based ensemble Machine Learning algorithm, is trained using the selected features for fault detection. The comparative analysis on fault detection is also conducted in this study using different classifiers next to XGBoost. The approach is validated on different fault types of screen cleaners. The results show that the ensemble learning outperforms other classifiers in terms of accuracy and can be effectively used for NPP screen cleaners condition monitoring.

Keywords: Feature selection, Separability, Ensemble learning, XGBoost, Fault classification, Nuclear power plant screen cleaners.

1. INTRODUCTION

To maintain the reliability, availability and safety of components have been one of the challenging tasks in Nuclear Industry. The Nuclear Power Plants (NPP) can be considered as one of the biggest sustainable energy resources in order to provide the energy needs of tomorrow (J. B. Coble and Upadhyaya (2015)). Hence, it is important to develop condition monitoring solutions for component health-state assessment to ensure safety, reliability and availability in NPP.

In literature, there are many scientific papers that have proposed different approaches on performance management of NPP (Agarwal et al. (2015)). For example, in (Al-Atat et al. (2011)) the authors proposed nuclear reactor perturbation analysis framework based on deep-learning by utilizing Convolution Neural Net-works (3D-CNN) and Recurrent Neural Network (RNN) algorithms. The classifiers were trained using time-based and frequency-based features for perturbation analysis. Another deep-learning approach based on a combination of CNN, auto encoder and k-means clustering was proposed in (Caliva et al. (2018)) for fault detection in nuclear reactor. A hybrid fault detection in NPP reactor coolant was developed using simulated signals in (Peng et al. (2018b)). A fault diagnostics methodology using deep belief network was presented in (Peng et al. (2018a)) for NPP monitoring using simulated data. Whereas in (Mandal et al. (2017)), an Enhanced Singular Value Decomposition(ESVD) and generalized likelihood ratio test (GLRT) algorithms were utilized for fault detection in NPP components. The fea-

tures were reconstructed with ESVD, and detection was performed with GLRT. The overall accuracy of any fault detection algorithms depend on the feature quality. Hence, feature evaluation can be assumed as a key step before model selection in condition monitoring.

There are different feature selection metrics which were developed for fault diagnostics and prognostics, in literature. Generally, the feature selection metrics are classified as inherent – *filters the least related feature from the given population based on some ranking criteria (e.g. e.g. separability (Camci et al. (2013)), monotonicity (Liao (2013)) etc.)*, consistent – *filters the least relevant feature from population by utilizing between-similarity metrics*, and hybrid (Atamuradov et al. (2018b)) – *which is the combination of the first two selection metrics*. There are plenty of works developed feature evaluation approaches for condition monitoring of different applications such as, gearbox (Bechhoefer et al. (2012)), (Al-Atat et al. (2011)), batteries (Atamuradov and Camci (2017)), point machines (Eker et al. (2012)). Therefore, development of robust feature selection methodologies play an important role in fault detection.

The fault detection problem, on the other hand, can be defined as the detection of any anomalies or abnormal behaviors of the component being monitored. The authors in (Atamuradov et al. (2018a)) proposed unsupervised incipient fault detection approach for railway point machines next to feature selection and fault severity extraction steps. In literature, proposed fault detection approaches in NPP components generally was developed for specific

machine fault types. However, as the system/assets can have more than one fault types, condition monitoring system should be capable of detecting multi-fault types as well, which is in the main scope of our research. In contrary to the above-mentioned papers, this current work studies multi-fault classification problem in NPP, rather than concentrating only on a specific fault type.

The proposed fault detection approach consists of feature extraction, unsupervised feature selection, and ensemble-learning based fault detection steps. First, comprehensive set of statistical features are extracted from *in-field* raw accelerometer data for each fault type. Then, unsupervised feature selection and ranking method is conducted based on within-feature evaluation technique, which is called separability metric. After the feature ranking process, the best features are selected according to the overall separability parameter. The selected features are then used in training fault detection algorithm. The proposed approach is then validated on the NPP water screen cleaners data. The water screens supply the secondary cooling circuit and the primary raw water circuit pumps, and a failure of these systems can cause very catastrophic results if not properly monitored and maintained. Hence, it is essential to develop smart condition monitoring systems to trace and monitor the activity of the screens and thus anticipate maintenance operations. Moreover, to the best of our knowledge, it is one of the initial work in its domain, which studies fault detection in NPP screen cleaners. The main contributions of this paper can be summarized as follows:

- Development of multi-fault feature selection method based on within-feature evaluation techniques.
- Ensemble-learning based multi-fault detection.
- Comparative analysis of different Machine Learning algorithms on multi-fault detection problem.
- Application to NPP screen cleaners.

The paper is structured as follows: Section 2 explains the proposed ensemble-learning based fault detection approach. Section 3 describes the system, data collection and discusses the results of the proposed approach. Section 4 concludes the paper.

2. PROPOSED FAULT DETECTION APPROACH

The proposed ensemble-learning based fault detection approach consists of feature extraction and selection and ranking, and fault detection steps. The general scheme of the proposed approach is shown in Fig.1.

2.1 Feature Extraction & Selection

The Python package so called Time Series FeatuRe Extraction on basis of Scalable Hypothesis tests (*tsfresh*) has been utilized in this study to extract comprehensive set of time-based features. The *tsfresh* (Christ et al. (2018)) package generates 794 different time-based features (categorical and continuous) by using 63 characteristics statistical methods. The resulting time series features are then used for training supervised Machine Learning algorithms after feature selection steps. Note that only numerical(continuous) time series features are used in this study. The extracted features are then ranked by using

separability metrics. The significance of the extracted features play an important role in classification problems, because training a Machine Learning classifier with too many irrelevant features can result in overfitting. Hence, in this study the authors have utilized the separability metrics in feature selection and ranking.

The separability technique was first developed to evaluate better prognostics features in (Camci et al. (2013)). The extracted features from bearing data were divided into equal segments, then the separability value within the segment distributions of features were calculated to select best prognostics feature. Apart from the previous study, the separability feature selection is first proposed in this study for fault diagnostics rather than prognostics. The separability value of each fault type is calculated by using equation (1). A feature having a higher total separability value considered as a best feature for fault diagnostics.

$$S = \frac{\sum_{t=1}^T s_t}{T} \quad (1)$$

Where S is the average separability value, s_t (2) is the separability value at health state t and T is the number of health states. The data point distribution of each health state is used to measure the separability at a given state. The illustration of separability measure is shown in Fig.2.

$$s_t = \frac{a}{L} - \frac{x}{N_t} \quad (2)$$

$$X = \begin{cases} 0, & \text{if } \frac{a}{L} \neq 1 \\ a, & \text{if } \frac{a}{L} = 1 \end{cases} \quad (3)$$

where L is the representation of the distance between 25^{th} and 75^{th} percentiles of data distribution, s_T is a separability value, a is a length of non-overlapping portion. After all, the feature set is sorted starting from the highest relevant feature to the lowest relevant feature. Once the feature ranking step is completed, the classifiers are trained accordingly.

2.2 Fault Detection

Fault detection problem can be described as a study of the change in component health state magnitudes by measuring the statistics of a fault propagation to characterize them as normal or faulty. The fault detection problem has been extensively studied in literature in different applications using Machine Learning, signal processing and statistical algorithms. In this study, supervised Machine Learning algorithms have been utilized to study fault detection in NPP screen cleaners based on ensemble XG-Boost learning, Support Vector Machines (SVM) and K-Nearest Neighbor (KNN). All mentioned Machine Learning algorithms are briefly introduced in below subsections.

Support Vector Machines (SVM) : which was introduced by Vapnik (Müller et al. (1997)), is a very popular machine-learning classification tool and it has a good accuracy and capability of performing linear and nonlinear data classification. The initial principle of SVM is to separate given data into distinct two classes by using a linear hyperplane. The linear separation of two classes can be achieved by finding an optimum decision hyperplane that maximizes the margin between two imaginary parallel

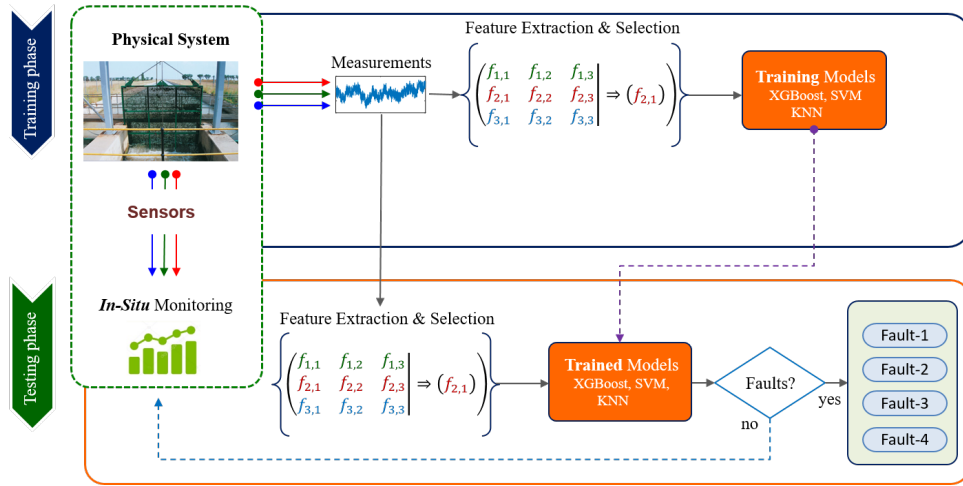


Fig. 1. Supervised Fault Detection Scheme.

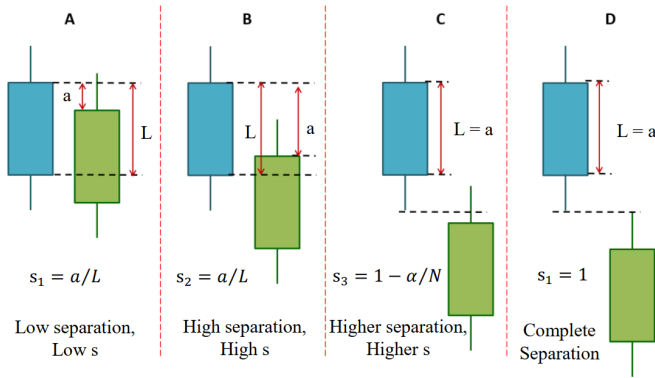


Fig. 2. Separability metrics calculation.

planes. In SVM, the kernel function describes the similarity measure of given data points. There are several kernel functions used in SVM-based classifications. In this study, linear kernel is used in fault type classification.

K-Nearest Neighbor (KNN) : is known as non-parametric supervised machine learning algorithm (Miljković (2011)). The non-parametric means there is no assumption for underlying data distribution, which means the model structure determined from the dataset. In KNN, K is the number of nearest neighbors, which is the core deciding factor. For finding closest similar points, the distance between points are calculated using distance measures such as Euclidean distance, Hamming distance, Manhattan distance and Minkowski distance are used.

Extreme Gradient Boosting (XGBoost) : is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework (Chen and Guestrin (2016)). The ensemble learning strategy offers a systematic solution by combining the predictive power of multiple learners producing the aggregated output. The predictive models here is the decision trees. XGBoost builds number of trees in an ensemble manner and tries to average out their prediction results. Firstly, a decision tree is build and the labels of the input data are predicted. The second tree will focus on correcting the misclassified data points using the first tree results. Correction is maintained by assigning more weights to wrongly predicted results to lay more

importance on a correct prediction in the next decision tree. The iterative process continues until the user pre-defined tree number is reached. There is one important parameter that needs to be tuned while building XGBoost learning trees which is the tree depth. The XGBoost ensemble learning has better training performance compared to other classifiers but gets computationally expensive as tree numbers increase. The interested readers are kindly referred to (Chen and Guestrin (2016)) for more details.

3. APPLICATION & RESULTS

3.1 Nuclear Power Plant Screen Cleaners

In this research, we studied multi-fault detection problem in NPP screen cleaners, which is operated by the French Electricity Company (EDF) located in a village called Flamanville, northwestern of France (Fig.3).



Fig. 3. EDF Nuclear Power Plant, Flamanville.

The water screen cleaners (see Fig.4) clean grids in pumping stations where seawater is collected for reactor cooling. As being a mechanical system, the screen cleaners can fail either due to the amount of load (e.g. garbage in sea-water) on the component(s) as the run-time increases or due to the component degradation. The three axial accelerometers was installed on the screen cleaners for

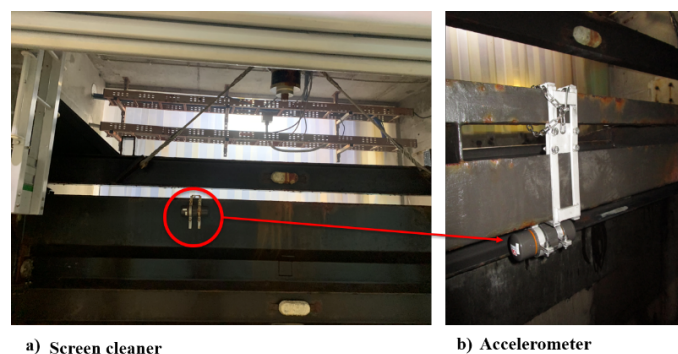


Fig. 4. NPP screen cleaner and installed sensor.

the purpose of online monitoring and data collection. The cleaning basket moves in vertical and horizontal positions, while cleaning. The basket dives into the sea in a vertical position and changes its position to a horizontal position before the cleaning process takes place. The movement of the basket is illustrated in Fig.5 on healthy cycle data. Each day the screen cleaner completes 14 cleaning cycles on average. The installed accelerometer records the acceleration of the water screen in three axes such as x-y-z (Fig.7). The movement of the basket occurs only in y and z-axis, therefore, x-axis data points were excluded in this study. There are four types of faults detected in the screen cleaners (Fig.6).

- Type-1: is an abnormality in the cleaning process where the basket changes its position from horizontal to vertical for a short period of time.
- Type-2: is the change of basket position to vertical inside the water, which can be referred to as incomplete cleaning.
- Type-3: is an unstable oscillation of basket while cleaning.
- Type-4: is the similar fault type as type-1 but with the vibration pattern.

In total there are 5227 number of cycles, which includes 796 healthy cycles, 61 cycles for type-1, 1141 cycles for type-2, 1738 cycles for type-3 and 1491 cycles for type-4.

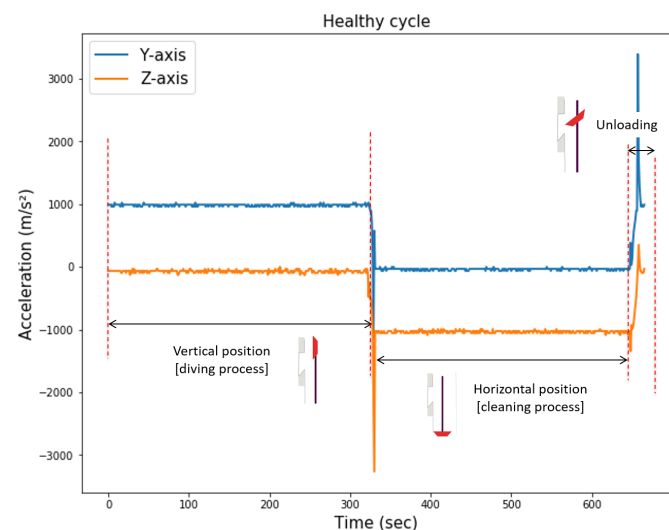


Fig. 5. Healthy cycle and basket movements in cleaning.

3.2 Results & Discussions

Initially, the y and z-axis data sets were normalized and combined to form a single signal before feature extraction. Then, combined raw data were fed into tsfresh python package for feature extraction. 711 different time-based features were extracted by using tsfresh package and were fed to separability function for ranking. As there are comprehensive set of extracted features, only the best and the worst feature samples are illustrated after separability metrics in Fig.8. As can be seen from Fig.8 the separability can select the most significant features for the component health state assessment. Hence, we can derive from this analysis that a feature which has a higher separability parameter for each fault types, can be accepted as the best feature for component health state assessment.

The fault detection in NPP was demonstrated by using two different scenarios. In scenario-1, all classifiers were trained by unranked feature set, which means in each training random number of features were selected to train classifiers. In scenario-2, the classifiers were trained on ranked features after selection. The main objective of this demonstration is to analyze and see the effect of feature selection technique on each algorithm performance. First, the learning parameters of each classifier were optimized by using cross-validated grid-search technique in python scikit package. The decision tree *depth* for XGBoost had been identified as 30, the *K* parameter for KNN was 5, and the *C* parameter of SVM with linear kernel was identified as 100. The fault detection accuracy for KNN, SVM and XGBoost algorithms are shown in Fig.9. Fig.9(a) shows the fault detection accuracy plot after feature selection, where as Fig.9(b) for fault detection using randomly chosen features from given set. As can be seen from the given plots, the XGBoost and SVM have better prediction performances in both scenarios. However, the classifiers learns faster with the selected features (scenario-2) and converges to the optimum prediction accuracy by using least number of training set compared to random feature selection. In contrast to XGBoost and SVM, the prediction accuracy of KNN decreases as the quantity of bad features increases, which means that KNN is very noise sensitive algorithm. Note that, in this study no noise filtration technique was conducted to filter the noise effect. The fault detection accuracy of three classifiers are shown in Table1.

As a conclusion, one can conclude that XGBoost and

Table 1. Fault detection results.

| Id | Classifiers | Scen-1 Acc(%) | Scen-2 Acc(%) |
|-----------|--------------------|----------------------|----------------------|
| 1 | XGBoost | 0.98 | 0.98 |
| 2 | SVM | 0.96 | 0.97 |
| 3 | KNN | 0.89 | 0.95 |

SVM have higher prediction accuracy in both scenarios, but converges to maximum accuracy by using ranked features more faster. Whereas for KNN the best prediction accuracy was reached based on scenario-1, which is by using ranked features.

4. CONCLUSION

In this paper, ensemble learning-based fault detection approach was proposed for NPP screen cleaners. Compre-

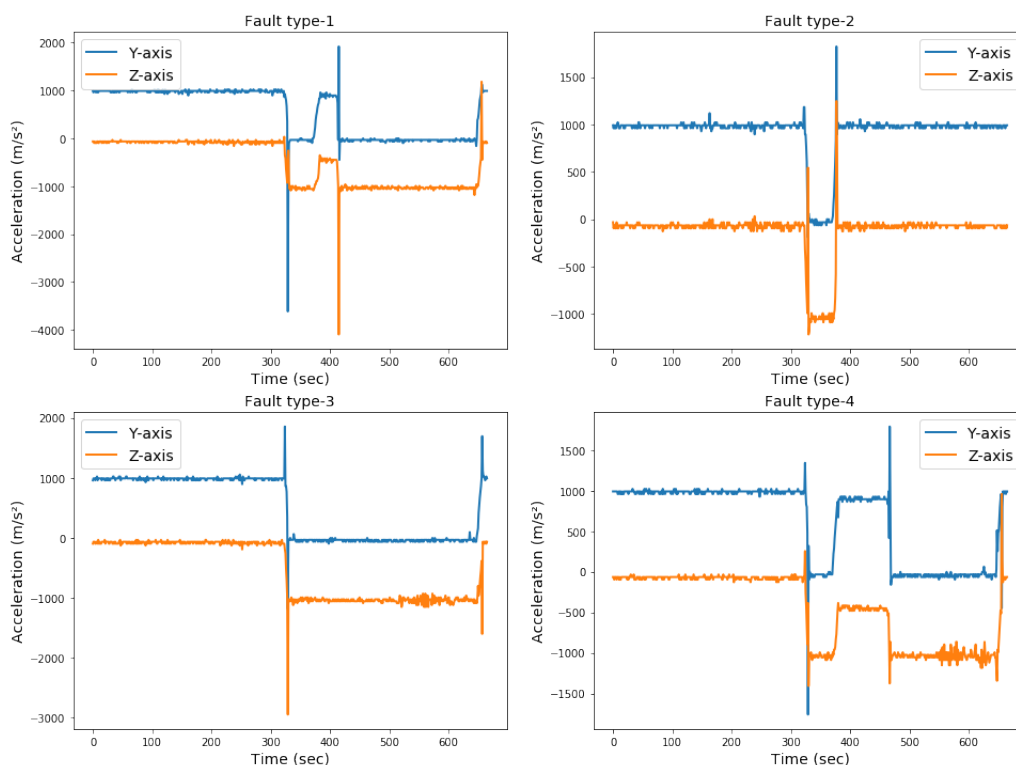


Fig. 6. Screen cleaner fault types.

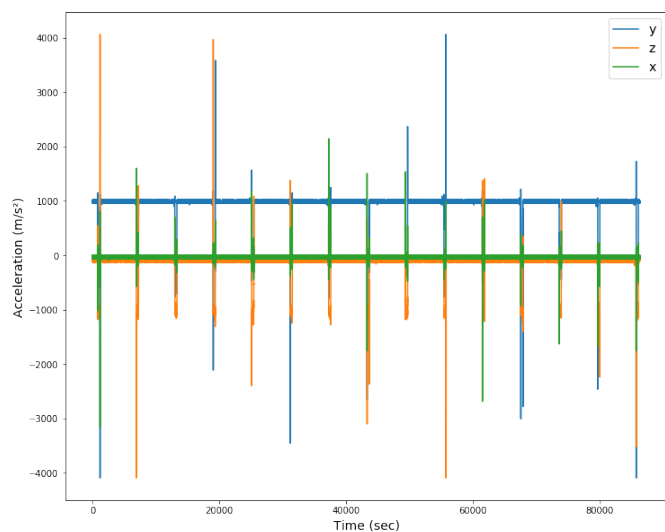


Fig. 7. Raw accelerometer data.

hensive time-based statistical features were extracted from accelerometer data using python tsfresh package. Comparison between Machine Learning algorithms was presented and their advantages and disadvantages were discussed in fault detection problem. Comparative analysis showed that the XGBoost algorithm had a better detection performance compared to SVM and KNN classifiers in both scenarios and the KNN performance had been improved by using ranked features. Separability feature selection technique was presented and its significance in fault detection had been discussed. Disadvantage of ensemble learning-based fault detection approach is that it need more time in learning, which is computationally expensive.

As a future work, it is planned to study different ensemble Machine Learning algorithms next to feature reduction techniques on fault detection in NPP condition monitoring.

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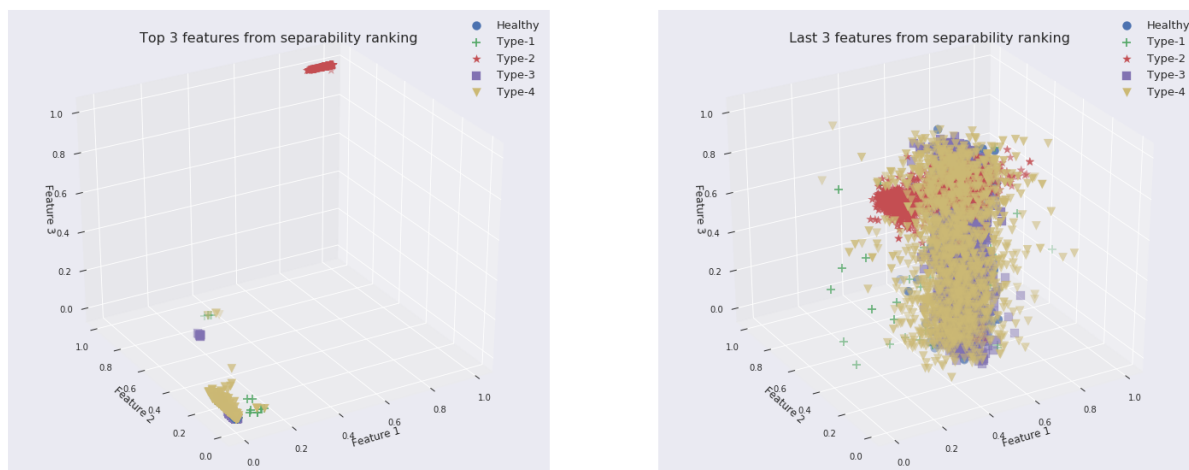


Fig. 8. Top and Last 3 features from separability ranking.

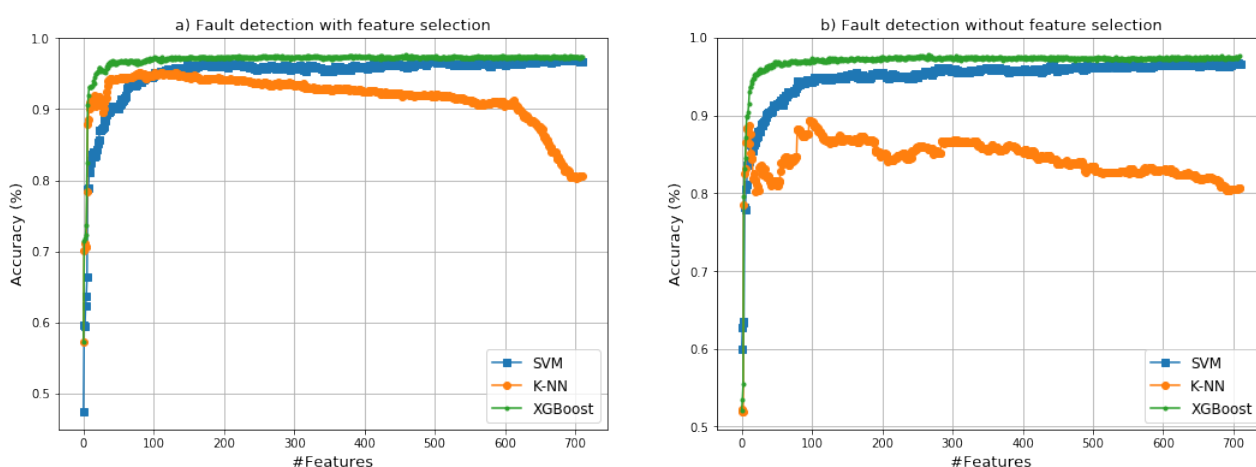


Fig. 9. Fault detection accuracy plots.

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