DEU FMD 27(81) (2025) 393-399

Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi
Dokuz Eylul University Faculty of Engineering Journal of Science and Engineering
Elektronik/Online ISSN: 2547-958X

RESEARCH ARTICLE

Impact of Feature Selection on the Performance of Classification Algorithms in Predicting Industrial Robot Failures

Endüstriyel Robot Arızalarının Tahmin Edilmesinde Özellik Seçiminin Sınıflandırma Algoritmalarının Performansına Etkisi

Fatma Günseli Yaşar Çıklaçandır *, Serfiraz Abdullah Mumcu, Berken Çam, Ikra Ceran

İzmir Katip Çelebi Üniversitesi Mühendislik ve Mimarlık Fakültesi Bilgisayar Mühendisliği Bölümü, İzmir, TÜRKİYE

Corresponding Author / Sorumlu Yazar *: fatmagunseli.yasar@ikcu.edu.tr

Abstract

Industrial robots enhance manufacturing efficiency, productivity, and precision. However, failures can disrupt production lines, leading to losses and significant system impact. In this study, robot failures are predicted using the UR3 CobotOps dataset and the impact of feature selection on the performance of various classification algorithms in predicting two targets (protective stops, and grip losses) is explored. Initially, the baseline performance of classifiers without feature selection has been evaluated. Then, two different feature selection methods (recursive feature elimination and chi-square) are applied to select the top 10 features and reassess the classifier's performance. High classification success rates are obtained with Decision Tree and Random Forest after feature selection in this study, which tests five different classifiers (Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and k-Nearest Neighbors) in the classification stage. This paper provides valuable insights into the different applications of classifiers, contributing to the field of machine learning by identifying different feature selection techniques and their impacts on classification accuracy. According to the experimental tests, an accuracy rate of about 99% has been obtained when Random Forest is used. This success has been also achieved when Chi-Square is used for feature selection. This paper shows that this prediction can be achieved in a shorter time using feature selection.

Keywords: *Predictive Maintenance, Operational Efficiency, Feature Selection, Machine Learning*

Öz

Endüstriyel robotlar üretim verimliliğini, üretkenliği ve hassasiyeti artırır. Ancak arızalar üretim hatlarını kesintiye uğratarak kayıplara ve önemli sistem etkilerine yol açabilir. Bu çalışmada, UR3 CobotOps veri seti kullanılarak robot arızaları tahmin edilmektedir. Özellik seçiminin, iki hedefi (protective stops, and grip losses) tahmin etmede çeşitli sınıflandırma algoritmalarının performansı üzerindeki etkisini araştırıyor. Başlangıçta öznitelik seçimi yapılmayan sınıflandırıcıların temel performansı değerlendirilmiştir. Daha sonra ilk 10 özniteliğin seçilmesi ve sınıflandırıcı performansının yeniden değerlendirilmesi için iki farklı öznitelik seçme yöntemi (özyinelemeli öznitelik eleme ve Ki-Kare) uygulanmıştır. Beş farklı sınıflandırıcının (lojistik regresyon, karar ağacı, rastgele orman, destek vektör makinesi, ve k-en yakın komşu) test edildiği bu çalışmada öznitelik seçimi sonrasında sınıflandırma aşamasında karar ağacı ve rastgele orman ile yüksek sınıflandırma başarıları elde edilmiştir. Bu makale, farklı öznitelik seçme tekniklerini ve bunların sınıflandırma doğruluğu üzerindeki etkilerini belirleyerek makine öğrenimi alanına katkıda bulunarak sınıflandırıcıların farklı uygulamalarına ilişkin değerli bilgiler sağlar. Yapılan deneyler, rastgele orman algoritmasının endüstriyel robot arızalarını 0,99'a varan bir doğrulukla tahmin edebildiğini göstermektedir. Feature selection için Ki-Kare kullanıldığında da bu başarıya erişilmiştir. Bu araştırma sayesinde feature selection kullanılarak daha kısa sürede bu tahminin gerçekleştirilebileceği görülür.

Anahtar Kelimeler: *Kestirimci Bakım, Operasyonel Verimlilik, Öznitelik Seçimi, Makine Öğrenmesi*

1. Introduction

Industrial robots are essential components of modern manufacturing, improving efficiency, productivity, and precision in a variety of applications [1]. Industrial robot failures can occur during real-world industrial operations, forcing production lines to stop and resulting in losses. Any failure of an industrial robot can have a significant impact on the overall operation of the system. Robot failures may be due to the following reasons: mechanical failures (wear and tear on components, improper maintenance, design flaws, corrosion and material fatigue), electrical issues (power supply disruptions, short circuits, overloading, faulty wiring and connections), human errors (incorrect programming, improper installation, lack of training, poor maintenance practices), software malfunctions (software bugs and glitches, incompatibility with hardware, outdated software versions, cybersecurity vulnerabilities), and environmental factors (temperature extremes, humidity and moisture, dust and debris, electromagnetic interference). As can be seen, robot failures can occur for a variety of reasons. These robots' frequent failures can have serious repercussions, including more downtime, lower production, and higher maintenance expenses [2]. Susto et al. categorize robot maintenance strategies into four groups based on their complexity and efficiency [3]. These are run-to-failure (RTF) maintenance, preventive maintenance, condition-based maintenance, and predictive maintenance. To reduce the

DOI: https://doi.org/10.21205/deufmd.2025278107

Geliş Tarihi / Received: 29.07.2024
Kabul Tarihi / Accepted: 26.11.2024

possibility of a production halt brought on by robot malfunctions, robot predictive maintenance should be effectively executed. This should be followed by suitable management during failure repairs. These procedures are often based on a study of the data gathered during the robot's operational period.

To overcome robot failures, the application of predictive maintenance strategies, especially through the use of machine learning algorithms, has received great attention in the industry. Predictive maintenance reduces maintenance costs while also preventing mechanical failures, which can lead to unscheduled production interruptions. The first phase of predictive maintenance methods involves estimating the parameters [4]. Forecasts for predictive maintenance are broadly classified into two types: cross-sectional forecasting and time series forecasting. Several studies have shown that predictive maintenance systems are useful in identifying probable issues before they occur. The systems developed by Strauß et al. and Ayvaz et al. [5-6] use real-time data from IoT sensors to detect early warning signals of probable failures, allowing operators to take preventative measures and reduce production downtime. A novel neural network-based method for predicting robot execution failures is presented in the study of Diryag et al. [7]. The neural network training has been made using real data, which includes robot forces and torques acquired after a system failure. In the study of Pinto and Carquitelli [8], the performances of Extremely Randomized Trees, k-nearest neighbors (KNN), and convolutional neural networks (CNN) in the classification stage have been investigated. The study also examines the effect of Principal component analysis (PCA) for feature selection. Morettini [9] provides a machine learning approach for conducting predictive maintenance with torque profiles. The methods used are evaluated on simulated data generated by wear and temperature models. A Random Forest (RF) based machine learning architecture for predictive maintenance is proposed by Paolanti et al. [10]. Predictions have been made with 95% accuracy on a dataset consisting of 15 different features (functional spindle rotor status, time for event recorded, running machine, spindle rotation speed, power absorbed by the spindle, spindle angular position, real-to-nominal position diff for all axis, speed for all axis, absorbed current for all axis) collected in real-time from the cutting machine. In the study of Susto et al. [11], where the performance comparison of KNN and support vector machine (SVM) are made, different maintenance techniques such as preventive maintenance and predictive maintenance are also examined.

This study aims to evaluate the baseline performance of multiple classification algorithms on a dataset of industrial robot operations, select the most relevant features for predicting protective stops and grip losses, and compare the performances of the classifiers before and after feature selection to determine the impact of this preprocessing step. Our research contributes to the field of machine learning in industrial applications by providing a comprehensive analysis of the role of feature selection in improving the accuracy and reliability of classification models. By identifying the optimal conditions for deploying algorithms like decision tree (DT) and RF, we offer practical insights for practitioners aiming to enhance predictive maintenance systems.

The remainder of the paper is organized as follows: Materials and Methods are given in Section 2. Experimental Results and discussions are given in Section 3. In Section 4, the paper's conclusion is provided.

2. Materials and Methods

2.1. The UR3 CobotOps Dataset

The UR3 CobotOps Dataset [12] has been used in this study. The experimental setup used to create this dataset is shown in Figure 1. It has 7409 instances and 20 features (Current_J0, Temperature_T0, Current_J1, Temperature_J1, Current_J2, Temperature_J2, Current_J3, Temperature_J3, Current_J4, Temperature_J4, Current_J5, Temperature_J5, Speed_J0, Speed_J1, Speed_J2, Speed_J3, Speed_J4, Speed_J5, Total_current, and Cycle). The features collected via MODBUS and real-time data exchange (RTDE) protocols and the targets are given in Table 1. Three features (speed, temperature and current) have been kept for each joint (J) of the production machine.

The UR3 CobotOps dataset provides insights into the operation of the UR3 robot, a flexible, lightweight 6-axis industrial robot equipped with 5 joints, designed for tasks requiring high precision in small workspaces. The UR3 robot, with a 3 kg payload and a 500 mm reach, is ideal for light assembly tasks and collaborative work, thanks to its built-in force/torque sensor and advanced safety features, allowing it to work efficiently alongside humans.

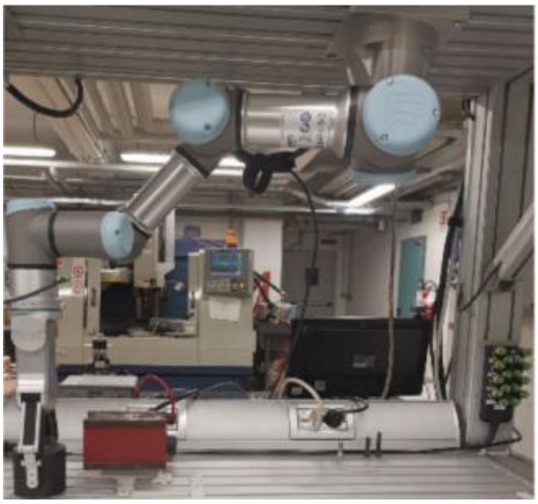

Figure 1. The experimental setup [13]

Additionally, the dataset records the gripper current and the operation cycle count, which together provide a comprehensive view of the robot's performance. These input parameters help us understand how the UR3 robot's operation leads to two key failure types—protective stops and grip losses. Protective stops occur when the UR3 robot halts its operations to prevent potential damage or ensure safety, often triggered by irregularities in joint movement or excessive force detected by the built-in sensors. Grip losses, on the other hand, indicate situations where the robot's gripper fails to maintain a firm hold on objects, which can result from improper gripper current or inaccuracies in joint movements, impacting the robot's ability to perform precise assembly tasks. The ranges of features and targets have been given in Table 2.

Table 1. Features and Targets

Features	
Electrical currents (J0-J5)	Current_J0, Current_J1, Current_J2, Current_J3, Current_J4, Current_J5
Temperatures (J0-J5)	Temperature_T0, Temperature_J1, Temperature_J2, Temperature_J3, Temperature_J4, Temperature_J5
Speeds across joints (J0-J5)	Speed_J0, Speed_J1, Speed_J2, Speed_J3, Speed_J4, Speed_J5
Gripper current	Tool_current
Operation cycle count	Cycle
Targets	
Protective stops	Robot_ProtectiveStop
Grip losses	grip_lost

Table 2. Ranges of the Features and Targets

Features	Min	Max
Current_J0	-6.2478	6.8069
Temperature_T0	27.8125	37.2500
Current_J1	-5.8087	1.0836
Temperature_J1	29.3125	40.5000
Current_J2	-4.1720	2.4649
Temperature_J2	29.3750	40.9375
Current_J3	-3.3331	2.2703
Temperature_J3	32.1250	43.4375
Current_J4	-4.7384	4.0894
Temperature_J4	32.2500	45.375
Current_J5	-0.4746	0.3925
Temperature_J5	32.0000	44.9375
Speed_J0	-0.6563	0.7919
Speed_J1	-0.3308	0.6155
Speed_J2	-2.7331	2.6798
Speed_J3	-1.2715	1.3631
Speed_J4	-0.2262	0.1939
Speed_J5	-1.6297	1.3780
Tool_current	0.0202	0.6021
Cycle	1	264
Targets	Min	Max
Robot_ProtectiveStop	0	1
grip_lost	TRUE	FALSE

2.2. Data Preprocessing Step

Data preprocessing involves standardizing the features using Standard Scaler to ensure all features contribute equally to the model performance [14]. This step is crucial as it helps mitigate the impact of varying scales of different features on the classification algorithms.

$$z = (x_i - \mu)\sigma^{-1} \tag{1}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N}(x_i) \tag{2}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{3}$$

The equation of the Standard Scaler is given in (1). μ is mean (2) and σ is standart deviation (3). Additionally, synthetic minority over-sampling technique (SMOTE) has been applied to prevent the unbalanced distribution in the dataset [15]. Thus, the performances of the algorithms are increased.

$$f_{new} = f_i + (f_i - f_j)c \tag{4}$$

To balance the distribution, synthetic samples are produced based on (4). f_i is the feature vector in the dataset. The difference between f_i and its nearest neighbor f_j is taken and this difference is multiplied by a random number c between 0-1.

2.3. Feature Selection Step

The relationship between the feature and the target is considered in feature selection techniques. The feature influence in classification problems is found by comparing the class distribution to a given class and calculating the difference.

Recursive feature elimination (RFE) and Chi-Square have been used as estimators to select the top 10 most relevant features for predicting the target variables. RFE iteratively removes the least significant features based on the model coefficients until the desired number of features is reached [16]. This method helps in identifying and retaining the most informative features while eliminating redundant or irrelevant ones. The Chi-Square is primarily a statistical test used to evaluate the association between two categorical variables [17]. It is not strictly a feature selection method, but it is commonly used in feature selection processes. Specifically, in classification problems, it can be employed to measure how strongly each feature is related to the target variable. Features with higher Chi-Square values are considered more relevant as they show a stronger relationship with the target variable.

2.4. Classification Step

Various algorithms can be employed for classification, each with its strengths and weaknesses. While classification algorithms may have advantages such as simplicity, efficiency, robustness, handling missing values, and flexibility; they may also have disadvantages such as high computational costs, low performance in small data sets, and susceptibility to overfitting. Therefore, the performances of five different classifiers have been examined in the classification phase: logistic regression (LR), DT, RF, SVM and KNN.

LR attempts to build a model between one or more independent variables and the outcome variable [18]. It is a popular option for many applications since it is specially designed to handle categorical outcomes, unlike linear regression, which is intended for continuous dependent variables.

DT is a frequently used classification algorithm [19]. Asking a series of questions about the data and utilizing the responses to go as quickly as possible to the outcome might be considered the fundamental idea behind creating a decision tree structure using training data. After compiling the responses, the decision tree generates decision rules.

RF produces decent results without hyperparameter estimation and may be used to solve regression and classification problems [20]. It can handle datasets with both continuous and categorical variables.

SVM has been developed for classification and regression analysis [21]. Typically, the dataset is separated into two subsets: the training set and the test set. The SVM method finds the optimal hyperplane dividing the classes using a labeled training set. To divide the two classes, more than one hyperplane could be employed. In this case, the hyperplane that maximizes the distance between each class's closest data points is considered the ideal one.

The k value in KNN is used in this method to indicate how many nearby data points should be taken into account for classification [22]. The similarity between the items in the dataset is measured using a variety of distance techniques, including Euclidean, Manhattan, and Minkowski. Next, by looking at the classes of the data point's closest neighbors, it guesses the class to which the data point belongs.

2.5. Evaluation Metrics

The performances of the classification models have been assessed using five different key metrics. The values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used to calculate these metrics [23].

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

$$F1Score = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{8}$$

- **Accuracy**: The proportion of cases that were correctly classified out of all the situations (5).
- **Precision**: The proportion of true positives to the sum of TP and FP (6).
- **Recall**: The proportion of true positives to the sum of TP and FN (7).
- **F1-Score**: The harmonic means of precision and recall (8).
- **Area Under the Curve (AUC)**: Estimating the area under the receiver operating characteristic (ROC) curve.

3. Experimental Results and Discussion

Flowchart of the system is given in Figure 2. In this study, where five different classification algorithms (LR, DT, RF, SVM and KNN) were compared in the experiments, the following steps were taken for each target variable:

• **Without Feature Selection:** Models have been trained and evaluated using the original, standardized dataset. This step shows the baseline performance of the algorithms.

• **With Feature Selection:** Models have been trained and evaluated using the dataset with the top 10 features selected.

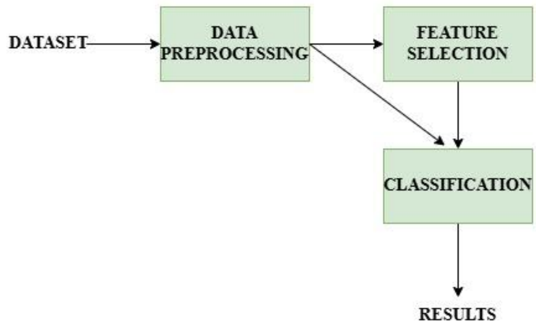

Figure 2. Flowchart of the system

The models' performances have been assessed prior to and following the implementation of feature selection. A potentially confusing point in the study is that the dataset has two targets. Supervised machine learning algorithms have been used in the study. Therefore, to measure the classification performance, the dataset must first be trained. In this study, the dataset is trained separately for each target and the classification results are recorded. The dataset has been split into training and testing sets with a 70:30 ratio.

Initially, the baseline performance of the classification models without applying feature selection has been evaluated (Table 3). The performance metrics for predicting 'Robot_ProtectiveStop' and 'grip_lost' using all available features indicated that the RF classifier exhibited the highest accuracy for both target variables (0.9848 for target 'Robot_ProtectiveStop' and 0.9898 for 'grip_lost' target), with DT and kNN also showing strong performance, particularly in terms of precision and recall. On the other hand, LR is the classifier with the lowest accuracy rate (0.7344 for target 'Robot_ProtectiveStop' and 0.7308 for 'grip_lost' target).

A correlation matrix is a statistical tool that demonstrates the strength and direction of a relationship between many variables. Figure 3 shows the correlation matrix for the features in the dataset considered in this study. When this matrix is examined, it is seen that there is a positive correlation between Temperature_J1 and Temperature_J2, while there is a negative correlation between Temperature_J1 and Current_J2.

After this stage, experiments focus on feature selection. Each feature selection method is applied to the dataset for each target. When feature selection methods are applied, the top 10 features with the highest priority for Robot_ProtectiveStop and grip_lost targets are given in Table 4.

Although the application of RFE slightly reduces the performance of the classifiers, the success of RF is particularly good (Table 5). While DT and RF are the classifiers least affected by RFE, other classifiers are more affected. While the accuracy rates of the DT classifier are 0.9767 for the 'Robot_ProtectiveStop' target and 0.9371 for the 'grip_lost' target, the accuracy rates of the RF are 0.9767 and 0.9596, respectively. Among the five classifiers, the classifier that is most affected by RFE and whose performance decreases the most is SVM.

The classification performances obtained after applying Chi-Square are given in Table 6. When the table is examined, it is seen that significantly different results are obtained compared to Table 5. While this difference is positive for all classifiers except SVM, it can be said that SVM should be avoided as a classifier if Chi-Square is to be used for feature selection. The highest performance is observed when classification is performed with

RF (0.9842 for the 'Robot_ProtectiveStop' target and 0.9885 for the 'grip_lost' target).

Figure 4 shows a comparison of the achieved accuracy rates. This figure can also be considered a summary of Table 3, Table 4, and Table 5. The accuracy rates of RF in all situations are quite remarkable.

By focusing on the most relevant features in this study, not only high accuracy rates are achieved, but also the computational complexity and training time are reduced, making the models more efficient for real-time applications.

Table 3. Experimental Results Before Feature Selection

Target	Model	Accuracy	Precision	Recall	F1-Score	AUC
Robot_ProtectiveStop	LR	0.7344	0.7004	0.8103	0.7513	0.7351
	DT	0.9710	0.9622	0.9800	0.9710	0.9711
	RF	0.9848	0.9729	0.9971	0.9849	0.9849
	SVM	0.9258	0.9043	0.9508	0.9270	0.9261
	KNN	0.9647	0.9369	0.9957	0.9654	0.9650
grip_lost	LR	0.7308	0.7316	0.7357	0.7337	0.7307
	DT	0.9592	0.9489	0.9714	0.9600	0.9591
	RF	0.9898	0.9862	0.9937	0.9900	0.9898
	SVM	0.8742	0.8611	0.8947	0.8776	0.8740
	KNN	0.9533	0.9232	0.9895	0.9552	0.9530

Table 4. Selected Features After RFE and Chi-Square

After RFE		After Chi-Square	
Robot_ProtectiveStop	grip_lost	Robot_ProtectiveStop	grip_lost
Temperature_T0	Current_J0	Temperature_T0	Temperature_J5
Temperature_J1	Temperature_T0	Temperature_J1	Temperature_J3
Current_J2	Temperature_J1	Temperature_J2	Temperature_J4
Temperature_J2	Current_J2	Tool_current	Temperature_J2
Temperature_J3	Current_J3	Temperature_J5	Temperature_J1
Temperature_J5'	Temperature_J3	Temperature_J3	Temperature_T0
Speed_J0	Temperature_J4	Temperature_J4	Tool_current
Speed_J3	Current_J5	Current_J1	Current_J1
Speed_J5	Speed_J3	Current_J2	Current_J2
Tool_current	Tool_current	Current_J3	Current_J5

Table 5. Experimental Results After Feature Selection (RFE)

Target	Model	Accuracy	Precision	Recall	F1	AUC
Robot_ProtectiveStop	LR	0.6552	0.6341	0.7183	0.6736	0.6558
	DT	0.9562	0.9438	0.9693	0.9564	0.9563
	RF	0.9767	0.9626	0.9914	0.9768	0.9768
	SVM	0.8569	0.8161	0.9180	0.8640	0.8575
	KNN	0.9110	0.8773	0.9536	0.9139	0.9114
grip_lost	LR	0.6823	0.7250	0.5955	0.6539	0.6830
	DT	0.9371	0.9272	0.9498	0.9383	0.9370
	RF	0.9596	0.9489	0.9721	0.9604	0.9595
	SVM	0.7634	0.7885	0.7252	0.7555	0.7638
	KNN	0.9019	0.8695	0.9477	0.9069	0.9016

Table 6. Experimental Results After Feature Selection (Chi-Square)

Target	Model	Accuracy	Precision	Recall	F1	AUC
Robot_ProtectiveStop	LR	0.7156	0.7109	0.7322	0.7214	0.7496
	DT	0.9647	0.9559	0.9747	0.9652	0.9646
	RF	0.9842	0.9726	0.9967	0.9845	0.9988
	SVM	0.6115	0.5911	0.7378	0.6564	0.6979
	KNN	0.9567	0.9221	0.9981	0.9586	0.9834
grip_lost	LR	0.7165	0.7182	0.7081	0.7131	0.7988
	DT	0.9595	0.9489	0.9708	0.9597	0.9595
	RF	0.9885	0.9855	0.9915	0.9885	0.9994
	SVM	0.5928	0.6590	0.3766	0.4793	0.6736
	KNN	0.9524	0.9171	0.9944	0.9541	0.9838

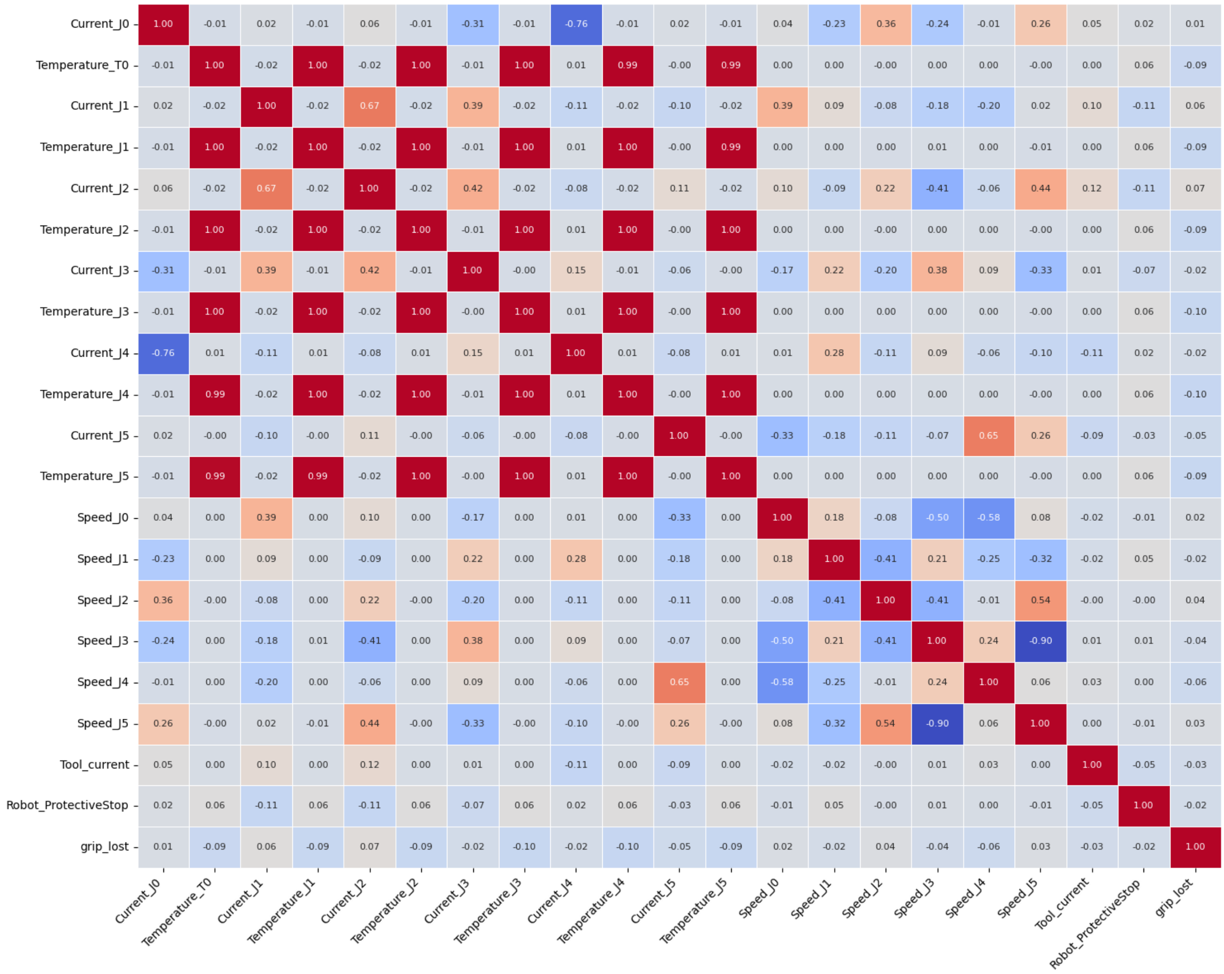

Figure 3. Correlation Matrix

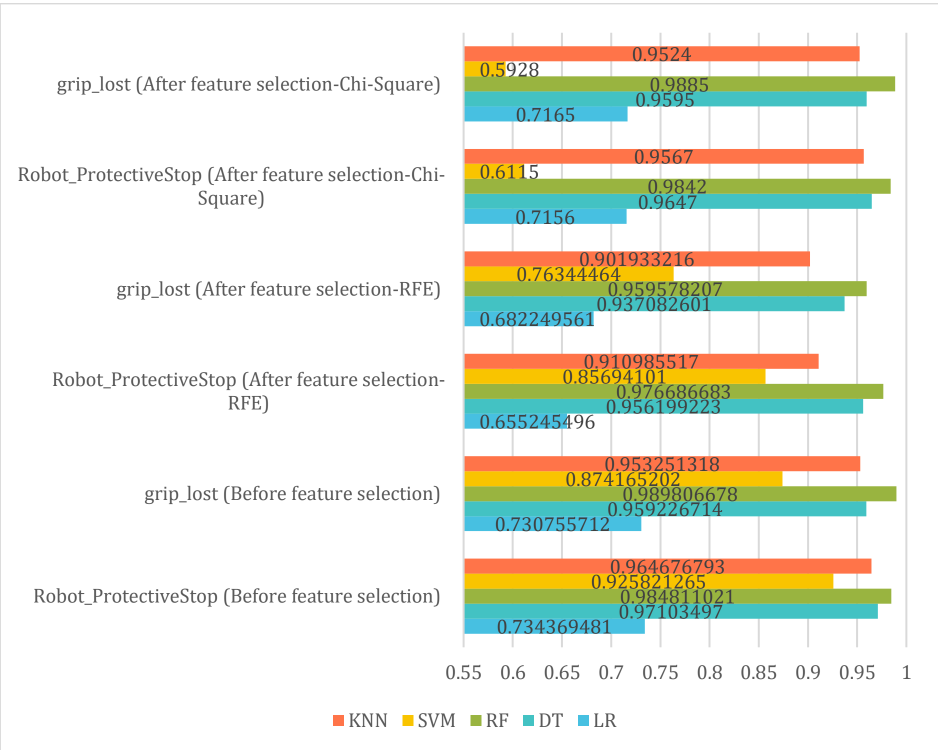

Figure 4. Comparison of the classifiers

4. Conclusions

Recurrent operational failures in manufacturing systems require careful consideration. Both the temporary interventions and the prolonged malfunctioning states incur excessive time and financial cost. In this study, a machine learning based model for system failure prediction is built by using the values of electrical currents, temperatures, speeds across joints, gripper current, and operation cycle count of the robot system. Predictive maintenance of the machinery is effectively managed by the proposed study.

Our study demonstrated the significant impact of feature selection on the performance of classification models used for predictive maintenance in industrial applications. Although there are decreases in the accuracy, precision, recall, F1 score and AUC values of the classifiers after applying RFE, the least decrease is in the RF classifier. On the other hand, the results obtained after the application of Chi-Square are different from the results obtained after the application of RFE. When Chi-Square is used, the classifiers of DT and RF are as successful as the results before feature selection. In this study, the Chi-Square test has been used as a tool to assess the importance of features and select those with the most significant impact on the target variable. It has proven effective in identifying key features that enhance model performance, demonstrating the utility of the Chi-Square test in feature selection.

As shown in experiments, the structure of DT and RF made it inherently more robust, thus benefiting more from feature selection techniques. Our findings highlight feature selection as a crucial preprocessing step that reduces computational complexity and training time, making the models more suitable for real-time applications.

Since the dataset used is a newly shared and not yet discovered dataset, the results obtained in the study are important in terms of comparison with future studies. Additionally, our study underscores the need for careful feature selection in industrial applications of machine learning. In the future studies, the performances of other feature selection methods, such as principal component analysis, could be explored and the experiments could be extended using other types of industrial data and failure modes. Additionally, integrating domain knowledge into the feature selection process could further enhance model performance and reliability.

References

[1] Alobaidy, M.A.A., Abdul-Jabbar, J.M., Al-khayyt, S.Z. 2020. Faults diagnosis in robot systems: A review. Al-Rafidain Engineering Journal (AREJ), Vol.25(2), pp.164–175.

[2] Koca, O., Kaymakci, O.T., Mercimek, M. 2020. Advanced predictive maintenance with machine learning failure estimation in industrial packaging robots. In: 2020 International Conference on Development and Application Systems (DAS), pp.1–6.

[3] Susto, G.A., Beghi, A., De Luca, C. 2012. A predictive maintenance system for epitaxy processes based on filtering and prediction techniques. Transactions on Semiconductor Manufacturing, Vol.25(4), pp.638–649.

[4] Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E., Loncarski, J. 2018. Machine learning approach for predictive maintenance in industry 4.0. In: 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), pp.1–6.

[5] Strauß, P., Schmitz, M., Wöstmann, R., Deuse, J. 2018. Enabling of predictive maintenance in the brownfield through low-cost sensors, an IIoT-architecture and machine learning. In: 2018 IEEE International Conference on Big Data (Big Data), pp.1474–1483.

[6] Ayvaz, S., Alpay, K. 2021. Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications, Vol.173, p.114598.

[7] Diryag, A., Mitić, M., Miljković, Z. 2014. Neural networks for prediction of robot failures. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, Vol.228(8), pp.1444–1458.

[8] Pinto, R., Cerquitelli, T. 2019. Robot fault detection and remaining life estimation for predictive maintenance. Procedia Computer Science, Vol.151, pp.709–716.

[9] Morettini, S. 2021. Machine learning in predictive maintenance of industrial robots. Master's Thesis, KTH Royal Institute of Technology, School of Electrical Engineering and Computer Science.

[10] Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E., Loncarski, J. 2018. Machine learning approach for predictive maintenance in industry 4.0. 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), pp.1–6.

[11] Susto, G.A., Schirru, A., Pampuri, S., McLoone, S., Beghi, A. 2014. Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, Vol.11(3), pp.812–820.

[12] Tyrovolas, M., Aliev, K., Antonelli, D., Stylios, C. 2024. UR3 CobotOps, UCI Machine Learning Repository. DOI: 10.24432/C5J891.

[13] Tyrovolas, M., Stylios, C., Aliev, K., Antonelli, D. 2024. Leveraging information flow-based fuzzy cognitive maps for interpretable fault diagnosis in industrial robotics. In: Doctoral Conference on Computing, Electrical and Industrial Systems, pp.98–110. Cham: Springer Nature Switzerland.

[14] Zamri, N., Pairan, M.A., Azman, W.N.A.W., Abas, S.S., Abdullah, L., Naim, S., Gao, M. 2022. A comparison of unsupervised and supervised machine learning algorithms to predict water pollutions. Procedia Computer Science, Vol.204, pp.172–179.

[15] Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P. 2002. SMOTE: synthetic minority over-sampling technique. Journal of Artificial Intelligence Research, Vol.16, pp.321–357.

[16] Yan, K., Zhang, D. 2015. Feature selection and analysis on correlated gas sensor data with recursive feature elimination. Sensors and Actuators B: Chemical, Vol.212, pp.353–363.

[17] McHugh, M.L. 2013. The chi-square test of independence. Biochemia Medica, Vol.23(2), pp.143–149.

[18] Cox, D.R. 1958. The regression analysis of binary sequences. Journal of the Royal Statistical Society Series B: Statistical Methodology, Vol.20(2), pp.215–232.

[19] Morgan, J.N., Sonquist, J.A. 1963. Problems in the analysis of survey data, and a proposal. Journal of the American Statistical Association, Vol.58(302), pp.415–434.

[20] Breiman, L. 2001. Random forests. Machine Learning, Vol.45, pp.5–32.

[21] Cortes, C., Vapnik, V. 1995. Support-vector networks. Machine Learning, Vol.20, pp.273–297.

[22] Cover, T., Hart, P. 1967. Nearest neighbor pattern classification. IEEE Transactions on Information Theory, Vol.13(1), pp.21–27.

[23] Zhang, Z. 2016. Introduction to machine learning: k-nearest neighbors. Annals of Translational Medicine, Vol.4(11).