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FORECASTING REPAIR AND MAINTENANCE SERVICES OF MEDICAL DEVICES USING SUPPORT VECTOR MACHINE

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ABSTRACT

Accurate prediction of product failures and the need for repair services become critical for various reasons, including understanding the warranty performance of manufacturers, defining cost-efficient repair strategies, and compliance with safety standards. The purpose of this study is to use machine learning tools to analyze several parameters crucial for achieving a robust repair service system, including the number of repairs, the time of the next repair ticket or product failure, and the time to repair. A large dataset of over 530,000 repairs and maintenance of medical devices has been investigated by employing the Support Vector Machine (SVM) tool. SVM with four kernel functions is used to forecast the timing of the next failure or repair request in the system for two different products and two different failure types, namely random failure and physical damage. A frequency analysis is also conducted to explore the product quality level based on product failure and the time to repair it. Besides, the best probability distributions are fitted for the number of failures, the time between failures, and the time to repair. The results reveal the value of data analytics and machine learning tools in analyzing post-market product performance and the cost of repair and maintenance operations.

Keywords: Machine Learning, Support Vector Machine, Repair, Maintenance, Forecasting

NOMENCLATURE

AIC	Akaike information criterion
BIC	Bayesian information criterion
n	Number of the probability distribution parameters
$\hat{h}$	The maximum value of the likelihood function
s	The number of samples
$\hat{y}$	Target data
x	Input vector
w	Weight of support vector machine
$\phi(x)$	Nonlinear function
b	Bias
R	Structural risk function
c^*	Penalty parameter
$L_\epsilon(\hat{y})$	Vapnik's ϵ -insensitive loss function
ϵ	Error tolerance
ξ, ξ^*	Slack variables
a, a^*	Lagrange multipliers
$K(x, x_k)$	Kernel function
x_k	Support vector
r	Scaling factor
d	Degree term
RMSE	Root mean square error
MAE	Mean absolute error
CC	Correlation coefficient

1. INTRODUCTION

Most products experience some sort of failure during their lifespan. Several reasons for product failures include insufficient reliability, poor quality, wrong design, uncertain usage, and production conditions [1]. Product failure can cause adverse effects such as financial cost, consumer dissatisfaction, and ruining manufacturers' market image [2]. Product repair is often part of the product lifecycle events. For example, once the product reaches the end-of-use or the end-of-life, customers may decide to upgrade their product due to technological advances or repair, refurbish, or remanufacturer to extend the product lifespan [3].

The concept of end-of-use product recovery and extending the product lifecycle is nothing new in the literature. Previous studies have already discussed product recovery challenges that are facing different industries such as building material stocks [4], automobile [5], and household electric and electronic equipment [6]. Mathematical models have been developed to overcome some of those challenges (e.g., uncertain quality and quantity of waste stream) and help remanufacturers decide what to do with used devices [7],[8].

Among the six common recovery strategies (e.g., reuse, repair, recondition/refurbishment, remanufacturing, cannibalization, and material recovery), repair has received less attention in the literature. However, predicting product failure has always been of interest to both academia and industry. Several studies have discussed the forecasting of product failure. To name a few, Yoon and Sohn (2007) built several random-effects regression models to forecast the mean time between failure (MTBF) [9]. Al-Garni et al. (2007) used the Weibull family to build a relationship with aircraft air-conditioning failure [10]. Wang and Yuan (2017) completed the failure rate prediction based on the AR model [11]. Wang and Yin (2019) adopted Weibull distribution to failure rate prediction [12]. Sexton et al. (2018) used different rules such as single-tag and rules-based to extract keywords to estimate median time to failure [13]. Brundage et al. (2021) also studied technical language processing by considering human-in-the-loop, natural language processing tools and text analysis to analyze documents that contain the equipment maintenance data [14]. While the previous studies have discussed product failure and maintenance, the number of studies that have worked with real industry datasets is very limited. The practical insights derived from analyzing big industry datasets help us define proper repair and maintenance strategies for corporations towards cost reduction and sustainability goals.

This study aims to show how machine learning tools can help businesses analyze the overwhelming dataset of product post-market performance and identify the depth and significance of the demand for repair and maintenance services. The SVM regression model simulates the product failure scenario and predicts the timing of the next repair service. The forecasting accuracy of SVM in regression is already confirmed by several studies [15]–[17]. In this

study, the dataset is collected from 2004 to 2018 under different management policies. Although some bias and dataset noise influence the decision to repair, the SVM model can still forecast failure time.

Besides, this study runs a frequency analysis to analyze the product quality based on the probability distributions of failure count, time between failure (TBF), and time to repair (TTR). The frequency analysis provides information about each product maintenance condition.

This study provides an overview of products maintenance condition by frequency analysis and offers a way to forecast product failure and the timing of the subsequent repair service request. Figure 1 shows the overall structure of this study.

2. OVERVIEW OF DATASET

2.1 Elements of the dataset

In the current study, we investigate 536,597 records of repair and maintenance of medical devices, 90,278 individual products, and 9,351 product types from 2004 to 2018. The management policies may affect the collection and documentation of the repair dataset and might have imposed some biases in how the data is reported. The data come from one of the largest health care providers in the United States. The dataset includes 9,351 different products with different functions and purposes such as infusion pumps, pulse detection, and oximeters. The average number of repair orders is 35,773 per year or 98 repair orders per day. Therefore, the need for a maintenance plan is significant for the health care provider.

TABLE 1: THE DESCRIPTION OF DATASET FIELDS.

Data Attribute	Description
1. WO Number	The work order of repair
2. Type Code	Product type
3. First Asset Number	Property unique number
4. First Asset Description	Function of product
5. First Asset Manufacturer Name	Manufacturer
6. First Asset Model Number	Product name
7. First Asset Serial Number	Unique serial number
8. Date Created	Repair start time
9. Completed Date	Repair completion time
10. Repair Attribute	The reason for repair

Table 1 shows an overview of the available fields of data for each repair and maintenance record. First Asset Number is the unique code to identify an individual product. First Asset Description is the information of product function, and First Asset Model Number is the name of each type of product. Date Created and Completed Date fields are the start time and the completion time on the repair. Based on the Date Created and Completed Date, we can identify TBF and TTR. The TBF is the time between an individual product's failures, and the TTR is the repair start time to repair completion time. TBF and TTR are good indicators of product reliability and cost of repair. The long TBF and short

TTR means that a product has high reliability and may be easier to be maintained.

Figure 2 shows the distribution of 35 repair reasons among the top 10 product categories. We have only relabeled the equipment names, including CA type 1, CA type 2, M8 type 1, PA type 1, PC type 1, MF type 1, CSE type 1, VE type 1, R type 1, and M8 type 2. We have not relabeled the repair codes such as failure reasons and

product type to train the models. As shown in Figure 2, 35 repair reasons are listed for the relabeled products. The repair attributes field in the dataset provides specific details on why an individual product needs repair. For example, Random Failure (RF) is a physical failure with excessive stress of the device and can happen at any time [18], [19].

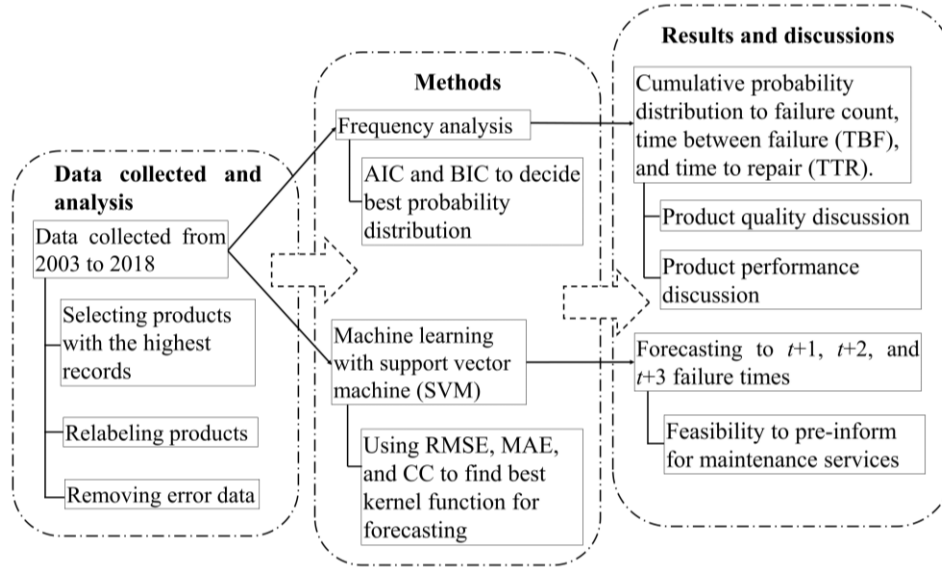


FIGURE 1: THE GENERAL DATA COLLECTION AND ANALYSIS PROCEDURE OF THIS STUDY.

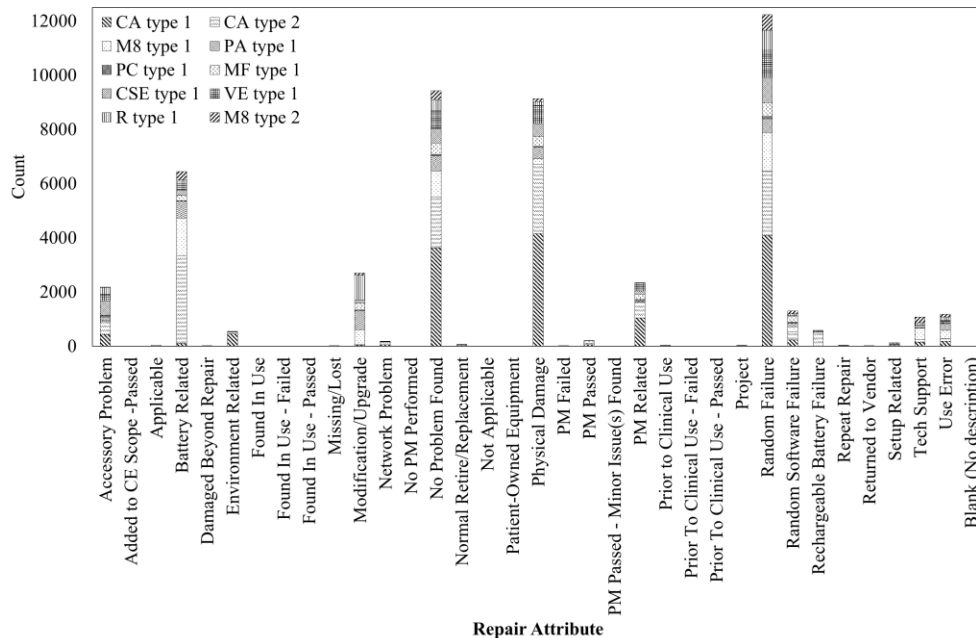


FIGURE 2: SUMMARY OF ALL REPAIR TYPES FOR ALL PRODUCTS AND SHOWING THE COUNT OF TOP 10 PRODUCTS (AMONG THE REPAIR REASONS, MOST REPAIR RECORDS ARE A RANDOM FAILURE.).

Figures 3 and 4 show the number of random failures and physical damage for the top 10 categories of products, respectively. The top 10 categories of products have the highest records of data among all 9,351 product types. Among the top 10 categories, the CA type 1 and CA type 2 are selected for the forecasting part of the study due to enough sample size. The number of RF and Physical Damage (PD) is the highest among other failure reasons.

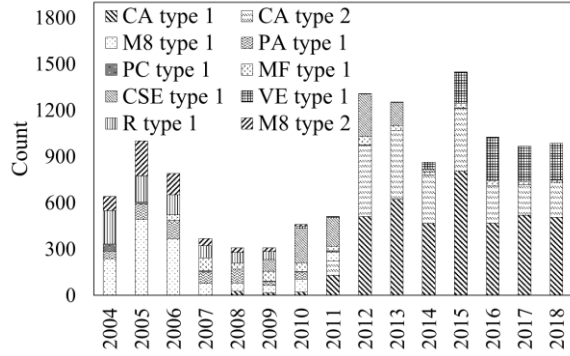


FIGURE 3: THE NUMBER OF RANDOM FAILURES FOR THE TOP 10 PRODUCT TYPES OVER TIME.

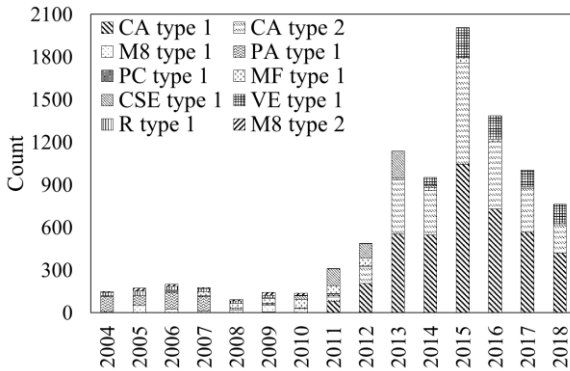


FIGURE 4: THE NUMBER OF PHYSICAL DAMAGES FOR THE TOP 10 PRODUCT TYPES OVER TIME.

TABLE 2: THE SUMMARY OF FUNCTION FOR THE TOP 10 PRODUCT CATEGORIES.

Product	First Asset Description
CA type 1	Infusion Pumps, Multitherapy
CA type 2	Controllers, Infusion Pump Systems, Programmable
M8 type 1	Infusion Pumps, Multitherapy
PA type 1	Infusion Pumps, Multitherapy
PC type 1	Hospital Communication Systems, Nurse Call
MF type 1	Infusion Pumps, Multitherapy, Syringe
CSE type 1	Circulatory Assist Units, Peripheral Compression, Sequential
VE type 1	Circulatory Assist Units, Peripheral Compression, Sequential
R type 1	Oximeters, Pulse
M8 type 2	Infusion Pumps, Multitherapy

According to Table 2, some product categories serve the same functions. For example, there are many products with infusion pumps and multitherapy functions. Four product categories, including CA type 1, M8 type 1, PA type 1, and M8 type 2 have the same function.

2.2 Data frequency analysis

This section describes the frequency analysis of the number of failures, TBF, and TTR. To analyze the reliability based on the above indices, we need to fit the best probability distribution for each product type. In the previous studies, Patil applied Normal, Lognormal, and Weibull distributions to reliability and maintainability analysis on hardware and software failures [20]. Lampreia et al. used the Weibull probability density function to analyze Mean Time Between Failure (MTBF) on the reliability analysis [21]. Sukhwani et al. applied Gamma distribution to analyze the reliability of NASA space flight software [22]. Tronskar et al. analyzed corrosion damage for pipelines and pressure vessels by using Gumbel distribution [23]. Four probability distributions, including Gumbel, Gamma, Normal, and Weibull distributions, have been applied to this study. The frequency analysis is also conducted for five categories of products: CA type 1, CA type 2, M8 type 1, PA type 1, and M8 type 2.

The best-fitted probability distributions for the number of failures, TBF, and TTR are determined by the Akaike information criterion (AIC) and Bayesian information criterion (BIC). The AIC test that measures the discrepancy among the true model and simulated model is proposed by Akaike (1973) [24], and the BIC test is based on the Bayesian framework [25]. Several studies had applied the AIC or BIC to compute the best-fitted probability distributions and showed the AIC and BIC are good indices for this purpose [26]–[29]. The probability distribution with the minimum AIC and BIC, among other distributions, is the best-fitted distribution. The AIC is constituted by the principle of maximum entropy and is expressed as:

$$AIC = 2n - 2\ln(\hat{h}) \quad (1)$$

where $\hat{h}$ indicates the maximum value of the likelihood function, and n is the number of probability distribution parameters. The BIC is constructed by the Bayesian framework and is given as:

$$BIC = \ln(s)n - 2\ln(\hat{h}) \quad (2)$$

Where s expresses the number of samples.

Table 3 shows the best-fitted probability distributions of RF and PD. As seen, the best-fitted probability distributions are either Weibull or Gamma. It is reasonable as the histograms of failure count, TBF, and TTR are similar to exponential shape. The example shown in Figures 5 and 6 illustrates the probability density function (PDF) and the cumulative distribution function (CDF) of failure count for RF in CA type 2.

TABLE 3: THE BEST-FITTED PROBABILITY DISTRIBUTION OF RF AND PD (WEI: WEIBULL, GAM: GAMMA).

Product	Failure Count	TBF (Year)	TTR (10 days)
CA type 1	Wei, Wei	Gam, Gam	Wei, Wei
	AIC:	AIC:	AIC:
	4922, 737	926, 585	3653, 5411
	BIC:	BIC:	BIC:
CA type 2	Wei, Wei	Wei, Gam	Wei, Wei
	AIC:	AIC:	AIC:
	1819, 583	604, 606	6981, 4670
	BIC:	BIC:	BIC:
M8 type 1	Wei, Wei	Wei, Gam	Wei, Wei
	AIC:	AIC:	AIC: 36948,
	2109, 373	570, 342	485
	BIC:	BIC:	BIC: 36975,
PA type 1	Wei, Wei	Gam, Gam	Wei, Wei
	AIC:	AIC:	AIC:
	398, 410	542, 461	664, 999
	BIC:	BIC:	BIC:
M8 type 2	Wei, Wei	Gam, Gam	Wei, Wei
	AIC:	AIC:	AIC:
	1388, 530	491, 445	5208, 13214
	BIC:	BIC:	BIC:
	1401, 540	508, 446	5225, 1325

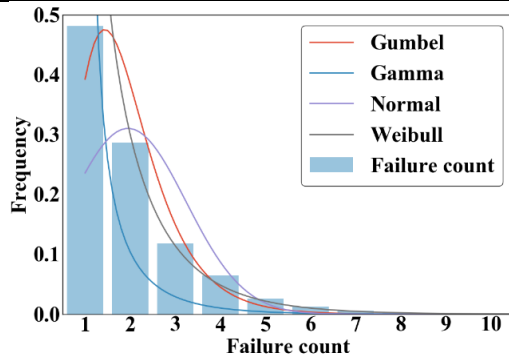


FIGURE 5: FOUR FITTED PDF OF FAILURE COUNT FOR RF OF CA TYPE 2.

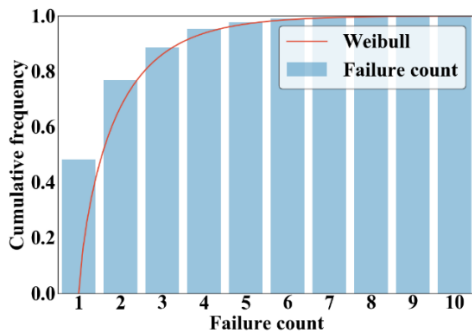


FIGURE 6: BEST-FITTED CDF OF FAILURE COUNT FOR RF OF CA TYPE 2.

TABLE 4: THE PROBABILITY (0~100%) OF RF AND PD CONSIDERING THE BEST-FITTED PDF: $P(X \geq 1)$ TO $P(X \geq 5)$.

Product	Random Failure, Physical Damage				
	$P(X \geq 1)$	$P(X \geq 2)$	$P(X \geq 3)$	$P(X \geq 4)$	$P(X \geq 5)$
Failure count					
CA type 1	100, 100	40, 32	32, 13	28, 5	25, 2
CA type 2	100, 100	33, 30	14, 12	6, 5	3, 2
M8 type 1	100, 100	43, 14	26, 9	17, 6	12, 5
PA type 1	99, 100	29, 22	26, 7	24, 2	23, 1
M8 type 2	94, 100	77, 07	55, 2	37, 0	24, 0
TBF (Year)					
CA type 1	51, 53	29, 27	16, 13	9, 6	5, 3
CA type 2	44, 55	23, 27	12, 13	7, 6	4, 3
M8 type 1	39, 58	19, 36	10, 22	5, 14	3, 9
PA type 1	50, 45	28, 24	16, 13	9, 7	6, 4
M8 type 2	38, 68	17, 42	8, 23	3, 12	2, 6
TTR (10 days)					
CA type 1	40, 31	33, 22	29, 17	26, 14	24, 12
CA type 2	25, 22	19, 15	15, 11	12, 09	11, 7
M8 type 1	31, 46	19, 27	13, 17	9, 11	7, 7
PA type 1	20, 2	10, 0.3	6, 0	4, 0	3, 0
M8 type 2	39, 66	30, 50	26, 39	23, 31	21, 26

Table 4 represents the frequency analysis results for RF and PD with the best-fitted PDF. The $P(X \geq 1)$ for failure count means the probability that at least one failure happens. For TBF, it means the probability that an individual product has a normal operation of at least 1 year before it is broken. For TTR, it means the probability that an individual product needs at least 10 days to be repaired.

Comparing RF and PD, the overall probability of RF is larger than PD. For example, the $P(X \geq 1)$ to $P(X \geq 5)$ of CA type 1 is from 1.00 to 0.25 on RF but is from 1.00 to 0.02 on PD. It reveals that random failure is the most repair reason for these products. The $P(X \geq 1)$ and $P(X \geq 2)$ of CA type 1 to CA type 2 on RF are almost similar, but the $P(X \geq 3)$ to $P(X \geq 5)$ of CA type 2 is smaller than of CA type 1. It means that CA type 2 is more stable than CA type 1. Also, comparing CA type 1, M8 type 1, PA type 1, and M8 type 2 under the same functional purposes (Infusion Pumps, Multitherapy) on RF, the PA type 1 is more reliable among these products. Although $P(X \geq 4)$ and $P(X \geq 5)$ of PA type 1 are slightly higher than of M8 type 1, the overall $P(X \geq 2)$ to $P(X \geq 3)$ are smaller among the same functional products. M8 type 2 is not reliable among products with the same function since it has a high-value $P(X \geq 2)$. Almost 77% of M8 type 2 products fail at least twice.

The overall $P(X \geq 1)$ to $P(X \geq 5)$ for TBF among RF and PD are very similar. The TBF reveals that products can normally operate at least 1 year to 3 years before they fail. CA type 1 and PA type 1 have higher $P(X \geq 1)$ on RF among all products. It means that CA type 1 and PA type 1 have higher probabilities of operating more than 1 year, among others. M8 type 2 can endure more PD because it has a higher probability of $P(X \geq 1)$ to $P(X \geq 3)$ than others with the same functional purpose.

The TTR results reveal that CA type 1 and M8 type 2 are not easy to repair among all products. These two products have higher $P(X \geq 1)$ to $P(X \geq 5)$ than others, especially in $P(X \geq 5)$. Once a random failure occurs, it takes up to 50 days to repair the device. Also, CA type 1, M8 type 2, and M8 type 1 take a longer time to repair in the case of physical damage. Therefore, the cost of repair is likely higher for CA type 1 and M8 type 2. In contrast, PA type 1 is easier to be repaired among other products. Therefore, after analyzing Table 4, the PA type 1 category is more cost-effective for Infusion Pumps and Multitherapy functions.

3. METHOD: SUPPORT VECTOR MACHINE

Vapnik proposed support vector networks in 1995 to solve the classification problem and later developed it for regression analysis [30]. SVM has confirmed its forecasting accuracy through previous work [15]–[17]. It has been applied to different fields for various predictions, such as dewpoint temperature prediction [31], stock prediction [32], and flood forecasting [16], [33]. Further details on SVM can be found in [34].

According to [16], given the training set of $[(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)]$ with the input vector x and the target data y . The regression function can be expressed as:

$$\hat{y} = f(x) = \mathbf{w}^T \phi(x) + b \quad (3)$$

where $\hat{y}$ is the output, $\mathbf{w}$ is weight, $\phi(x)$ is a nonlinear function, and b is the bias. According to the structural risk minimization (SRM) principle, the $\mathbf{w}$ and b can be derived by minimizing the structural risk function as follow:

$$\text{Min } R(\mathbf{w}, b, \xi, \xi^*) = \frac{1}{2} \|\mathbf{w}\|^2 + c^* \sum_{i=1}^n L_\varepsilon(\xi + \xi^*) \quad (6)$$

$$\text{Subject to } \begin{cases} y_i - \hat{y}_i = \hat{y}_i - (\mathbf{w}^T \phi(x) + b) \leq \varepsilon + \xi_i \\ y_i - \hat{y}_i = (\mathbf{w}^T \phi(x) + b) - \hat{y}_i \leq \varepsilon + \xi'_i \\ \xi_i \geq 0 \\ \xi'_i \geq 0 \\ i = 1, 2, \dots, n \end{cases} \quad (7)$$

where c^* is a penalty parameter for making a tradeoff between model complexity, and ε is error tolerance as a range between target data y and output data $\hat{y}$. ξ and ξ^* are slack variables. The Lagrange multipliers with a and a^* can be used to solve the above-mentioned optimization problem:

$$f(x) = \sum_{i=1}^s (a_i - a_i^*) K(x_k, x) + b \quad (8)$$

Where s is the number of support vector, x_k is the support vector, and $K(x_k, x)$ is a kernel function. SVM has four kernel functions as follow:

Linear function:

$$K(x_i, x_j) = x_i^T \cdot x_j \quad (9)$$

Polynomial function:

$$K(x_i, x_j) = (r \cdot x_i^T \cdot x_j + c)^d \quad (10)$$

Radial basis function:

$$K(x_i, x_j) = \exp(-r \|x_i - x_j\|^2) \quad (11)$$

Sigmoid function:

$$K(x_i, x_j) = \tanh(r \cdot x_i^T \cdot x_j + c) \quad (12)$$

Where r is a scaling factor, c is the bias term, d is the degree term. This study uses the grid search method [35] to find parameters (r , c^* , d , and ε). Figure 7 shows an overview of the SVM structure.

4. FORECASTING THE TIME OF NEXT RANDOM FAILURE OR REPAIR SERVICE TICKET

4.1 The input of SVM

Four different kernel functions, including Linear (LN), Polynomial (PL), Radial basis (RBF), and Sigmoid (SIG) function, are selected to see which one has better forecasting performance. The input variable to the SVM model is the cumulative seconds, as illustrated in Table 5. The definition of cumulative seconds is the difference between the current failure time and the subsequent failure time. We should note that the current and upcoming failure may not be for the same individual product. The output of SVM is the forecasted time of the next failure. When the failure time is $t+1$, $t+2$, or $t+3$, the SVM model will forecast the next first, second, and third failure times in advance. The relationship of the failure time to the input factor is shown in Table 6. The $T(t)$, $T(t-1)$, and $T(t-2)$ denote current, previous, and the second-to-last product failure time as an input factor, respectively. This study selects $T(t-6)$, $T(t-5)$, $T(t-4)$, $T(t-3)$, $T(t-2)$, $T(t-1)$, $T(t)$ as input factor to forecast the time of the next failure since these input factors have a high correlation coefficient with output data. Also, when the time of failure increases, the number of input factors is reduced. The reason for reducing the input factor is to maintain the high correlation coefficient between input and output data.

We have selected two products, including CA type 1 and CA type 2, for prediction since these two products have enough sample sizes and are commonly used in medical applications. Table 6 shows the basic information for CA type 1 and CA type 2.

The proportion of training and test sample sizes is 7 and 3. The available data on the start time and the end time for CA type 1 and CA type 2 are from 2008-7-23 11:00:00 to 2018-12-31 8:14:23 and from 2011-6-25 14:00:00 to 2018-12-27 16:16:40, respectively. The length of the dataset is at least 7.5 years for both products. The forecasting results will be discussed in the next section.

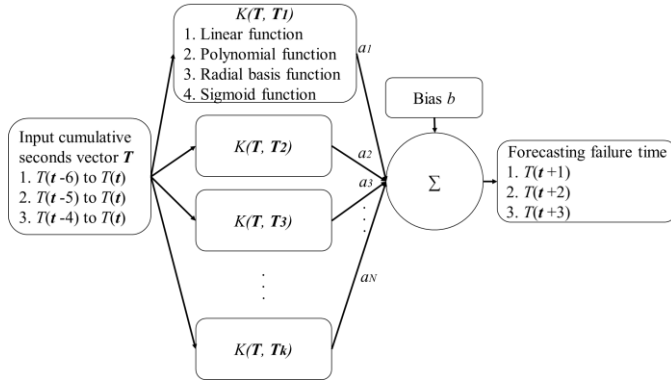


FIGURE 7: THE STRUCTURE OF THE SUPPORT VECTOR MACHINE.

TABLE 5: EXAMPLE OF CALCULATING CUMULATIVE SECONDS (E.G., TIME OF THE FIRST FAILURE, THE SECOND FAILURE).

Order	Failure time	Cumulative seconds
1	2008-07-23 11:00:00	0 s (Time 1 – Time1)
2	2008-07-24 08:00:00	75600 s (Time 2 - Time 1)
3	2008-07-28 09:00:00	424800 s (Time 3 - Time 1)
4	2008-08-08 09:00:00	1375200 s (Time 4 – Time 1)
5	2008-08-08 09:00:00	1375200 s (Time 5-Time 1)
6	2008-09-04 09:00:00	3708000 s (Time 6-Time 1)

TABLE 6: BASIC INFORMATION ABOUT CA TYPE 1 AND CA TYPE 2.

Information	CA type 1	CA type 2
Training RF dataset	5141	3256
Testing RF dataset	2203	1395
Data start time	2008-7-23 11:00:00	2011-6-25 14:00:00
Data end time	2018-12-31 8:14:23	2018-12-27 16:16:40
Dataset length (years)	10.5	7.51
Failure Time (order)	Input factor	
$t+1$	$T(t-6), T(t-5), T(t-4), T(t-3), T(t-2), T(t-1), T(t)$	
$t+2$	$T(t-5), T(t-4), T(t-3), T(t-2), T(t-1), T(t)$	
$t+3$	$T(t-4), T(t-3), T(t-2), T(t-1), T(t)$	

4.2 The forecasting results for random failure

The training and testing results for SVM-LN, SVM-PL, SVM-RBF, and SVM-SIG are shown in Tables 7 and 8. According to the tables, the SVM-PL has better performance on training and testing, among other kernel functions. When the time is $t+1$, $t+2$, and $t+3$, both SVM-LN and SVM-PL can forecast the time of the next random failure for CA type 1 and CA type 2 shown in Figures 8 to 11. The codes SVM-LN, SVM-PL, SVM-RBF, and SVM-

SIG means the kernel of SVM including linear, polynomial, radial basis, and sigmoid function, respectively. As time increases, it is obvious that the forecasting performance is decreased. Figures 9 and 11 provide specific details on the above-mentioned discussion. Based on Tables 7 to 8 and Figures 8 to 11, the performance of SVM models with different kernel functions can forecast the next random failure without overfitting. For the indices such as RMSE, MAE, and CC, the test results have a good forecasting performance as shown in each Figure. Each SVM model based on different kernel functions catches the trend of observation. Also, when the time is increasing, the SVM-PL will give overestimated values for both products. Although the SVM-PL will overestimate values as time increases, the model does not lose its forecasting performance with higher failure time. In Figure 9 on order 5,184 to 5,189 and Figure 11 on order 3,277 to 3,283, the SVM-PL with time $t+3$ provides forecasting value near to the observation. The actual failure time and the forecasted failure time for these orders are shown in Table 9.

Since the observed trend is close to linear or polynomial function, SVM-LN and SVM-PL have a better performance than the other two models. SVM-PL is more suitable than SVM-LN since the trend of observation is like a polynomial function.

All models have a value of 1.0 for CC. They perform with similar trends, as shown in Figures 8 to 11. Although all models have a similar trend, they do not guarantee small residual errors based on RMSE and MAE listed in Tables 7 to 8.

TABLE 7: THE TRAINING AND TESTING RESULTS FOR RANDOM FAILURE IN CA TYPE 1.

Failure time (Order)	Train, Test		
	RMSE (sec.)	MAE (sec.)	CC
SVM-LN			
$t+1$	400871, 49757	116881, 40583	1.0, 1.0
$t+2$	518767, 61001	137235, 46601	1.0, 1.0
$t+3$	674727, 80082	156101, 55303	1.0, 1.0
SVM-PL			
$t+1$	316582, 41586	104599, 25892	1.0, 1.0
$t+2$	479382, 59246	126297, 43609	1.0, 1.0
$t+3$	587345, 72843	149849, 54131	1.0, 1.0
SVM-RBF			
$t+1$	657926, 180843	148978, 145477	1.0, 1.0
$t+2$	767078, 186720	166230, 153202	1.0, 1.0
$t+3$	869516, 210683	190072, 174058	1.0, 1.0
SVM-SIG			
$t+1$	561663, 68182	132766, 47432	1.0, 1.0
$t+2$	728044, 81871	160764, 57391	1.0, 1.0
$t+3$	820536, 89412	192585, 63175	1.0, 1.0

Figures 12 and 13 show the error between forecasting $t+1$ and observation for CA type 1 and CA type 2. SVM-PL has a better performance than others. In addition, the trend of error has a cycle period in both Figures. Figure 12 shows the models overestimate the

actual day, but sometimes the models can catch the actual failure time. Figure 13 also shows a similar trend, such as error with the cycle period. Based on the current observation, the future work suggests training an error model that can forecast the next error between forecasting and actual failure time to reduce the error between forecasting and observation.

TABLE 8: THE TRAINING AND TESTING RESULTS FOR RANDOM FAILURE IN CA TYPE 2.

Failure time (Order)	Train, Test		
	RMSE (sec.)	MAE (sec.)	CC
SVM-LN			
t+1	107236, 98583	78451, 67329	1.0, 1.0
t+2	156948, 132817	126061, 105525	1.0, 1.0
t+3	181359, 162836	134489, 120174	1.0, 1.0
SVM-PL			
t+1	95388, 87427	71958, 56968	1.0, 1.0
t+2	133387, 124724	91799, 84560	1.0, 1.0
t+3	168557, 149977	132054, 119583	1.0, 1.0
SVM-RBF			
t+1	175961, 146894	118780, 113243	1.0, 1.0
t+2	201158, 167534	135506, 128570	1.0, 1.0
t+3	221640, 182546	150537, 143188	1.0, 1.0
SVM-SIG			
t+1	128303, 129916	88436, 88981	1.0, 1.0
t+2	171729, 146100	126134, 116760	1.0, 1.0
t+3	200389, 179164	142448, 132439	1.0, 1.0

The outcomes provide helpful insights into enhancing the sustainability of medical devices. For example, the forecasting results provide information on product maintenance needs and the degree of reparability. Also, predicting time between failures gives repair service providers and technicians sufficient advance notice for predicting the resources needed for repair and proper resource management for repair services. Moreover, the prediction outcomes can be used for forecasting the amount of waste generated if the malfunctioning medical devices

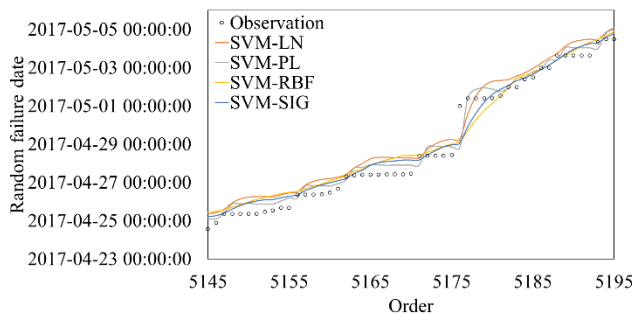


FIGURE 8: TESTING RESULTS OF FORECASTING $T+1$ AMONG ALL KERNEL FUNCTIONS FOR CA TYPE 1.

would not be repaired. Forecasting waste provides further information on how to define strategies for the reduction of GHG emissions.

TABLE 9: THE ACTUAL FAILURE TIME AND FORECASTING FAILURE TIME WITH SVM-PL FOR ORDER 5,184 TO 5,189 OF CA TYPE 1 AND ORDER 3,277 TO 3,283 OF CA TYPE 2.

Actual failure time	Forecasting failure time		
	$t+1$	$t+2$	$t+3$
CA type 1			
2017-05-02	2017-05-02	2017-05-02	2017-05-02
09:20:16	11:29:20	14:07:12	06:36:32
2017-05-02	2017-05-02	2017-05-02	2017-05-02
12:07:12	19:00:00	17:07:28	20:07:44
2017-05-02	2017-05-02	2017-05-03	2017-05-02
23:59:44	22:45:04	02:53:04	21:14:56
2017-05-02	2017-05-03	2017-05-03	2017-05-03
23:59:44	09:38:24	04:22:40	05:08:00
2017-05-03	2017-05-03	2017-05-03	2017-05-03
15:22:56	10:00:48	17:30:56	09:15:28
2017-05-03	2017-05-04	2017-05-03	2017-05-03
15:24:00	01:01:36	19:46:24	20:53:36
CA type 2			
2016-09-01	2016-09-01	2016-09-01	2016-09-01
10:28:00	22:02:40	06:14:08	14:28:16
2016-09-02	2016-09-02	2016-09-02	2016-09-02
08:08:16	02:16:32	06:30:08	05:23:28
2016-09-02	2016-09-02	2016-09-02	2016-09-03
15:09:52	21:25:20	08:03:44	06:19:44
2016-09-02	2016-09-03	2016-09-03	2016-09-03
15:10:40	06:33:04	06:19:44	08:06:24
2016-09-03	2016-09-03	2016-09-03	2016-09-04
21:29:52	08:06:24	13:40:32	07:02:24
2016-09-04	2016-09-04	2016-09-03	2016-09-04
13:56:16	09:29:20	13:27:12	13:29:52
2016-09-04	2016-09-05	2016-09-04	2016-09-04
14:02:24	03:31:28	19:30:40	12:36:16

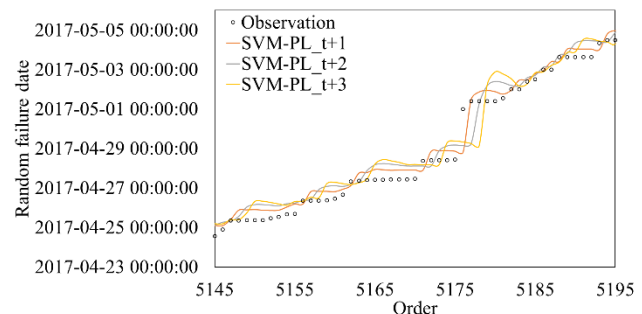


FIGURE 9: TESTING RESULTS OF FORECASTING $T+1$ TO $T+3$ WITH POLYNOMIAL KERNEL FUNCTION FOR CA TYPE 1.

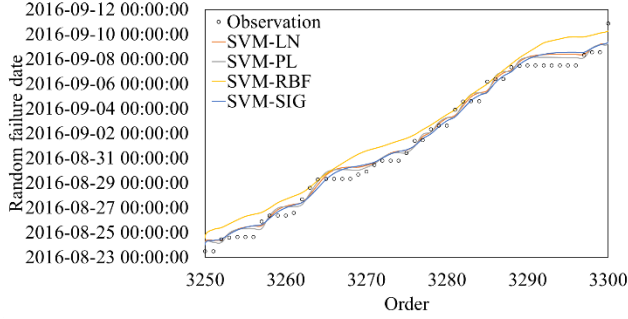


FIGURE 10: TESTING RESULTS OF FORECASTING $T+1$ AMONG ALL KERNEL FUNCTIONS FOR CA TYPE 2.

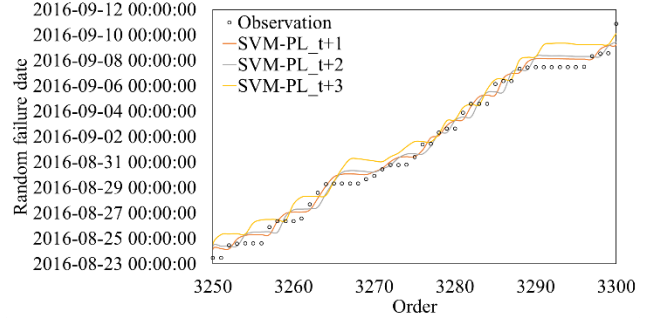


FIGURE 11: TESTING RESULTS OF FORECASTING $T+1$ TO $T+3$ WITH POLYNOMIAL KERNEL FUNCTION FOR CA TYPE 2.

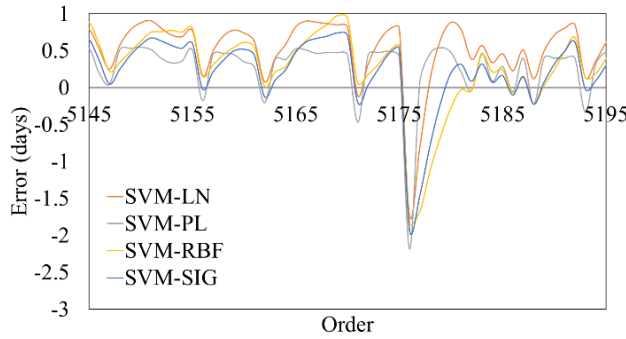


FIGURE 12: FORECAST ERROR OF $T+1$ IN CA TYPE 1.

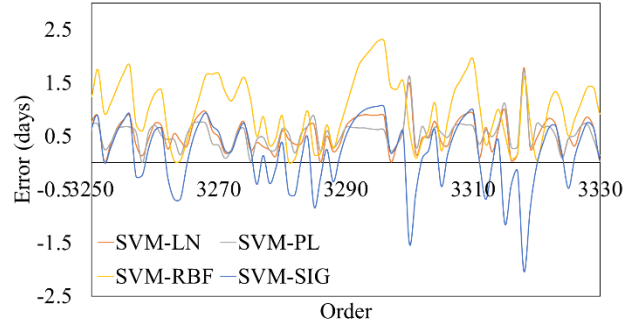


FIGURE 13: FORECAST ERROR OF $T+1$ IN CA TYPE 2.

5. CONCLUSION

This study aims to forecast the arrival time of the next repair order or the failure time by applying the SVM model into a medical device dataset with over 530,000 records of repair and maintenance activities. Four SVM kernel functions, including SVM-LN, SVM-PL, SVM-RBF, and SVM-SIG, have been compared for forecasting the next failure time of two categories of products labeled as CA type 1 and CA type 2. The results reveal that the SVM-LN and SVM-PL perform well in forecasting the time of the next repair request or failure time. Among all functions, SVM-PL has the best forecasting performance based on the RMSE and MAE values for testing.

In addition, frequency analysis has been run to analyze the data further, and identify the best-fitted distributions to the failure count, the time between failure, and the time to repair. Four probability distributions, including Gumbel, Gamma, Normal, and Weibull distribution, have been analyzed. Analyzing the failure count reveals that PA type 1 is more reliable among products with the same function. CA type 1 and PA type 1 have higher $P(X \geq 1)$ among all products in terms of random failure. M8 type 2 has higher TBF in terms of physical damage among other products with the same function. Finally, analyzing TTR reveals that CA type 1 and M8 type 2 are not easy to repair among all products.

The study shows the importance of machine learning tools such as SVM models in predicting the time of repair orders. Forecasting the time to failure and time to repair provides guidelines to designers for improving product reparability. The SVM model can further be used in forecasting the waste generation rate.

The study can be extended in several ways. First, other categories of products and types of failures can be compared together to identify the most vulnerable products and the type of repairs needed in each category. Second, the study outcome, which includes after-market repair and maintenance requests, can be linked to the product design features to identify design improvement directions. Third, the data analytics results can be fed to cost modeling techniques to quantify the business outcomes of repair services and identify the best repair strategies companies need to adopt. Decisions such as whether to handle repair services by in-house teams or outsource them to original equipment manufacturers or third-party repair service providers, depending on the demand and repair cost, can be informed by the current data analyses. Fourth, the study outcomes can be fed to resource allocation and scheduling models to help enterprises manage workforce requirements for repair services. Fifth, other machine learning tools can be employed to facilitate data analytics efforts. Finally, training an error model that can forecast the following error between forecasting and actual failure time will be further analyzed.

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