Ensemble Classifier with Missing Data in Control Chart Patterns

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Abstract

The Control Chart Patterns Recognition (CCPR) is one of important tools in Statistical Process Control (SPC). The performance of CCPR depend on many factors, one of those the prediction algorithm. Furthermore, when data is substantially missing, the rate of false alarms and misclassification is high. This paper reported an investigation of five classifiers namely, Decision Tree, ANN, Linear Support Vector Machine, Gaussian Support Vector Machine, and KNN-5 with ensemble classifier. The results are compared with perfect sample pattern (without missing data) and sample patterns with missing data 5%, 10%, 15%, 20%, 30%, 40% and 50%. Two datasets having normal ± 3σ shifting range, and small shifting range less than ± 1.5σ was investigated. The results show that the ensemble classifier have higher recognition accuracy for sample patterns without missing data 99.55% and 98.64% for sample patterns with 20% missing data.

Keywords
Control chart pattern recognition, Ensemble Classifier, Missing data.

1. Introduction
The missing in a dataset occurs for many reasons, such as equipment malfunction, incomplete responses, operator errors, sensor errors, and data entry errors. For missing value data imputation, single and multiple data imputation have been developed. The missing data issues attracted many researchers to study this problem to find a robust approach to handle such data (Haghighati and Hassan 2019, Pauzi *et al.* 2021). The state of art research increased the accuracy of monitoring the process variations by using many helpful techniques for controlling process differences.
In control chart pattern recognition, facing some missing data or missing individual observation within a sample often happens for many reasons. Like human error, equipment malfunctioning, data transmission faulty, and all those effects of the sample do not get a good representation of data, whether the input data is raw data or features-based. For that reason, it is important to handle this missing data in CCPs to get the real presented data for each type of pattern. In literature, some researchers studied this issue and proposed many approaches. Some of them ignored the missing data, and in this case, it will get the data not complete to represent the process. Other researchers suggest techniques to handle this missing data like Mahmoud *et al.* (2014) argues that the effect of four imputation methods, namely stochastic regression, mean imputation, the expectation-maximization algorithm, and regression for estimating Phase I historical data set in control charts, and then estimated the unknown parameters in the Hotelling's T2 chart statistic. They showed that the stochastic regression approach outperformed all other competing methods in terms of overall performance. Haghighati and Hassan (2019) suggests that an imputation technique based on EWMA its best way to handle missing data.

Haghighati and Hassan (2018) evaluated the usefulness of exponential smoothing in recovering patterns in order to improve recognition accuracy in CCPR with incomplete data. The results showed that with extreme missingness, total recognition accuracy decreased from 99.57% without missing to 76.33 with 50% missing data. In the incomplete random and trend patterns, classification errors climbed to 38 and 44, respectively. An efficient imputation approach was exponential smoothing with a constant of 0.9 with 50% missingness, the imputed dataset's recognition accuracy improved by 99.2% and 19.4% in stable process and unstable process, respectively.

Reuter and Brambring (2016) implemented an imputation technique to the standard production control loop to mitigate the negative effects of missing, noisy, and data inconsistency in PPC systems. Gebremeskel *et al.* (2015) solved the missing values in univariate CCPs. They proposed incomplete and missing data based on the number of variables and data ordering to adopt treatment methods data that cannot be sought from other variables. Silva-Ramírez *et al.* (2015) used data imputation techniques to fill the gaps and a complete dataset to improve data quality. Numerous data imputation techniques were developed for multivariate classification problems. Mahmoud et al. (2014) used regression, stochastic regression, and expectation-maximization imputations in the SPC domain. They applied these techniques in multivariate classifications to predict the missing values.

Hassan (2008) suggest that the ensemble classifier has significant enhancement of the discrimination capability of the scheme and minimize the shortcoming of the individual classifier through ensemble classifiers or multiple recognitions. The combining of all-class-one network (ACON) with one-class-one network, (OCON) improved the recognition performance from 73.8% with ACON and 83.3% with OCON to with 87.1% (ACON+OCON). The results agreement with previous studies (Pham and Oztemel 1993, Pandya and Macy 1995, Simon 1999).

Another important thing must be to know how the data sample have gone the missing values, called the missingness mechanism. There are three major mechanisms introduced by Little and Rubin. Missing completely at random (MCAR) happens when the causes of missingness are independent of data. The missing at random (MAR) mechanism occurs with observed data yet is independent of the unobserved data. It is missing not at random (MNAR) because the pattern of missing data is non-random and depends on the missing variable. The literature can note that the best imputation approach is EWMA because it maintains the dynamic behavior and results in better estimations. EWMA gave a distinct prediction for every missing value that differed across incomplete data. It is better than the mean and median imputation.

This paper suggests a new approach with ensemble classifier to achieve the higher recognition accuracy with CCPR with different missing data percentages. This paper will fill these gaps by developing a robust classifier that detects the patterns with missing data in small variation dataset. The paper is organized as follows: Section 1 introduces the background of missing data in CCPR, Section 2 presents the methodology, Section 3 discusses the results, and finally Section 4, presents the conclusion.

2. Methodology

In this research, we will test out a model with five classifiers adding the ensemble classifier to see how is strong to get good detection of the type of pattern even if the data have missing data. We simulated the missing data depending on the MCAR mechanism because they already investigated it in previous work to compare our work with previous studies with this type of mechanism. Five common abnormal patterns namely Cycle, Increase Trend, Decrease Trend, upper Shift and downward Shift plus the normal pattern was investigated in this study which used in previous studies (Addeh 2016, Addeh and Maghsoudi 2016, Bayati 2017).Use the MATLAB R2017a program to generate missing data depending on the percentage. In this study, we select (5,10,15,30,40,50) % missing data and then use the EWMA to replace the missing data with estimated data depend on equation (1). The simulation for two datasets normal ± 3σ shifting range & small shifting range less than (± 1.5σ) to test for seven percent of missing data (5,10,15,20,30,40 and 50) % of data. The five classifiers employed with ensemble classifier after missing data imputation to find which level of missing data percentage can handling with imputation.

The features extraction from raw data was used as input. The six features were select depend on previous studies namely Mean, Std, Min, MSE, Slope and APSL depend on the Formulas in Table 1.

$$F_t = \alpha A_{(t-1)} + (1-\alpha)F_{(t-1)} \tag{1}$$

Where Ft and At represent predicted and real data at time t, respectively, and the smoothing factor, α which runs between Zero and one. In this study, α =0.4 was chosen for in-control patterns and α =0.7 for atypical CCPs, which included trend-up, shift-up, and cyclic patterns (Haghighati and Hassan 2019).

Table 1. Selected Formulas for Feature Extraction (Hassan *et al.* 2003, Zhang and Cheng 2015, Wong and Chua 2019, Zhang *et al.* 2020).

No.	Type of features	The formula
1	Mean (MEAN)	$mean = \frac{\sum_{i=1}^{n} x_i}{n}$
2	Standard deviation (Std)	$std = \sqrt{\frac{\sum_{i=1}^{n}(x_i - mean)^2}{n}}$
3	Slope (SLOPE)	$b_1 = \frac{(Y_i - b_o)}{x_i}$
4	Minimum point	$min(x_i)$
5	Mean-square error (MSE)	$x^{2\sim} = \frac{x_0^2 + x_1^2 + x_2^2 + \cdots + x_N^2}{N+1} = \frac{1}{N+1}\sum_{i=0}^{N} x_i^2$
6	APSL	$APSL = \sum_{i=1}^{m} \lvert x_i - \bar{x}_i \rvert$ $for\ \ i = 1,2,\dots,m \quad \bar{x}_i = \beta_1 t_i + \beta_0$

Random noise of 1/3σ will be added to all unstable patterns.

3. Results and Discussion

The result shows that when the percentage of missing data becomes high, the accuracy will deteriorate when compared with complete data. The recognition accuracy without missing data for five classifiers with ensemble classifier, can noted the ensemble classifier has higher recognition accuracy compare with other individual classifiers as shown in Table 2. When just 5% missing data (2 points from 30), the recognition accuracy for the ensemble is very good, 99.03% and 95.47 for (normal & small) shifting range for mean, respectively, as shown in Table 3. The recognition accuracy decreased to 99% and 94.78% with 10% missing data percentage (3 points from 30) for (normal & small) shifting respectively as shown in Table 4. With 15% missing data (5 points from 30), the recognition accuracy has 98.79% and 93.84% for (normal & small) shifting, respectively, as shown in Table 5. At 20% missing data (6 points from 30), the recognition accuracy equals 98.64% and 93.69% for (normal & small) shifting, respectively, as shown in Table 6. The recognition accuracy with 30% missing data (9 points from 30) was 97.22% and 91.28% for (normal & small) shifting, respectively, as shown in Table 7. The percentage was increased to 40% missing data (12 points from 30), and the result of recognition accuracy was equal to 95.80% and 89.38% for (normal & small) shifting, respectively, as shown in Table 8. Finally, the test of our classifiers with a 50% percentage of missing data (15 points from 30) and the recognition accuracy decreased to 94.20% and 86.73% for (normal & small) shifting, respectively, as shown in Table 9.

Table 2. The recognition accuracy without missing data.

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	99.51	61.16	99.44	44.50
ANN	99.07	81.5	98.74	84.166
Linear_SVM	99.02	95.16	98.28	92
gaussian SVM	99.05	97.5	98.35	93.83
KNN5	99.17	91.83	98.55	91.5
Ensemble	99.15	99.55	98.65	99.14

Table 3. The recognition accuracy with 5% missing data (2 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	99.74	98.83	98.51	94.12
ANN	99.57	99.26	95.93	95.52
Linear_SVM	99.49	99.35	95.33	95.19
gaussian SVM	99.53	99.36	95.50	95.25
KNN5	99.63	99.33	96.58	95.30
Ensemble	99.60	99.03	96.07	95.47

Table 4. The recognition accuracy with 10% missing data (3 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	99.65	98.31	98.34	93.36
ANN	99.35	99.07	95.34	94.89
Linear_SVM	99.21	98.98	94.73	94.72
gaussian SVM	99.28	99.05	94.88	94.78
KNN5	99.39	98.86	96.23	94.63
Ensemble	99.38	99	95.56	94.94

Table 5. The recognition accuracy with 15% missing data (5 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	99.38	97.49	97.85	91.63
ANN	98.78	98.58	94.24	93.78
Linear_SVM	98.66	98.53	93.49	93.28
gaussian SVM	98.73	98.57	93.60	93.31
KNN5	99.01	98.28	95.44	93.48
Ensemble	98.93	98.79	94.54	93.84

Table 6. The recognition accuracy with 20% missing data (6 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	99.40	97.33	97.65	91.59
ANN	98.61	98.37	93.59	93.57
Linear_SVM	98.47	98.59	92.76	93.02
gaussian SVM	98.55	98.54	92.95	93.35
KNN5	98.87	98.58	94.91	93.17
Ensemble	98.74	98.64	93.95	93.69

Table 7. The recognition accuracy with 30% missing data (9 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	98.93	96	97.08	89.42
ANN	97.54	97.01	91.78	91.15
Linear_SVM	97.34	97.05	90.97	90.68
gaussian SVM	97.54	97.15	91.29	90.75
KNN5	98.07	97.05	93.73	90.79
Ensemble	97.75	97.22	92.43	91.28

Table 8. The recognition accuracy with 40% missing data (12 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	98.42	93.52	96.47	89.23
ANN	95.82	95.53	89.72	88.99
Linear_SVM	95.46	95.44	88.72	88.74
gaussian SVM	95.75	95.67	89.10	88.96
KNN5	96.83	95.49	92.40	89.22
Ensemble	96.20	95.80	90.55	89.38

Table 9. The recognition accuracy with 50% missing data (15 points from 30).

Classifier	Normal Shifting (1.5-2.8) Sigma		Small Shifting less than (1.5) Sigma	
	Training Accuracy%	Testing Accuracy%	Training Accuracy%	Testing Accuracy%
decision Tree	97.78	91.64	95.85	83.67
ANN	94.52	93.89	87.20	86.30
Linear_SVM	93.77	93.94	85.90	85.51
gaussian SVM	94.14	94.12	86.17	85.93
KNN5	95.67	93.81	90.84	86.10
Ensemble	94.91	94.20	88.22	86.73

from these results, we can note the accuracy is still good with 50% missing data for a normal shift, but it decreases with a small shift dataset to 86.73%. The results show that the recognition accuracy with ensemble classifier decreased from 99.55% without missing data to 99.03% with just a 5% percentage of missing data, and to 99% with 10% missing data, while 98.79 with 15% missing data. But at 20% missing data can get recognition accuracy up to 98.64%. With 30% missing data can see the recognition accuracy it is 97.22%. The recognition accuracy achieves 95.80 with 40% missing data and finally, the recognition accuracy achieves to 94.20% with 50% missing data for the normal shifting dataset. For the small shifting, it's difficult to get higher accuracy because the small variation data range. The recognition accuracy for small variation with ensemble classifier is 99.14% without missing data and 95.47% with 5% missing data, It is 94.94% with 10% missing data. The recognition accuracy decreases with 15% missing data to 93.84% and 93.69% with 20% missing data. Until achieve just 86.73% with 50% missing data. This work was compared with previous studies. The accuracy still good until 20% missing data percentage it is 98.64%. That's mean the missing data in control chart effective about the accuracy recognition, The proposed model can handle the missing data and get good recognition accuracy. The recognition accuracy with ensemble classifier without missing data and with several missing data percentage can show in Figure 1.

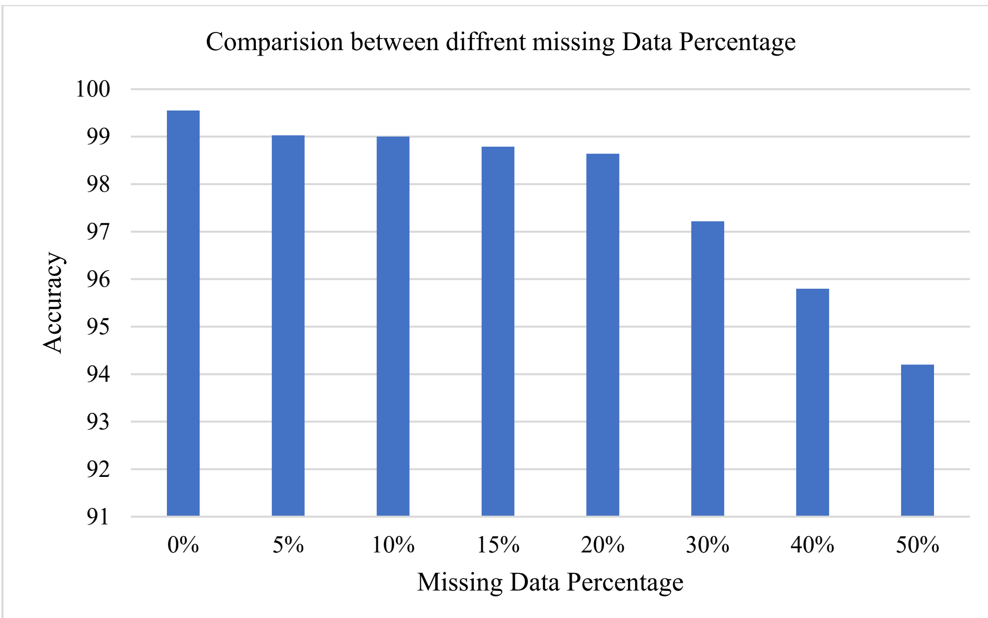

Figure 1. Comparison the recognition accuracy with several missing data percentage with ensemble classifier for Normal Shifting (1.5-2.8) Sigma range in mean.

In addition, the ensemble can get 99.14% with small shift range mean data without missing data. The recognition accuracy was decrease with increase the missing data percentage. It was detracted to 95.47% with just 5% missing data. At 10% missing data the recognition accuracy was reduce to 94.94%. At 15% missing data it is just 93.84%, when with 20% missing data the recognition accuracy is 93.69%. At 30% missing data the accuracy is 91.28%. with 40% missing data the recognition accuracy reduces to 89.38%. Finally, the recognition accuracy with 50% missing data is 86.73% as shown in Figure 2. and no one in the literature studied with small shifting. The experimental result shows that our model with five classifiers with ensemble classifier has significantly improved the correct recognition accuracy for CCPs with missing data in small shifts.

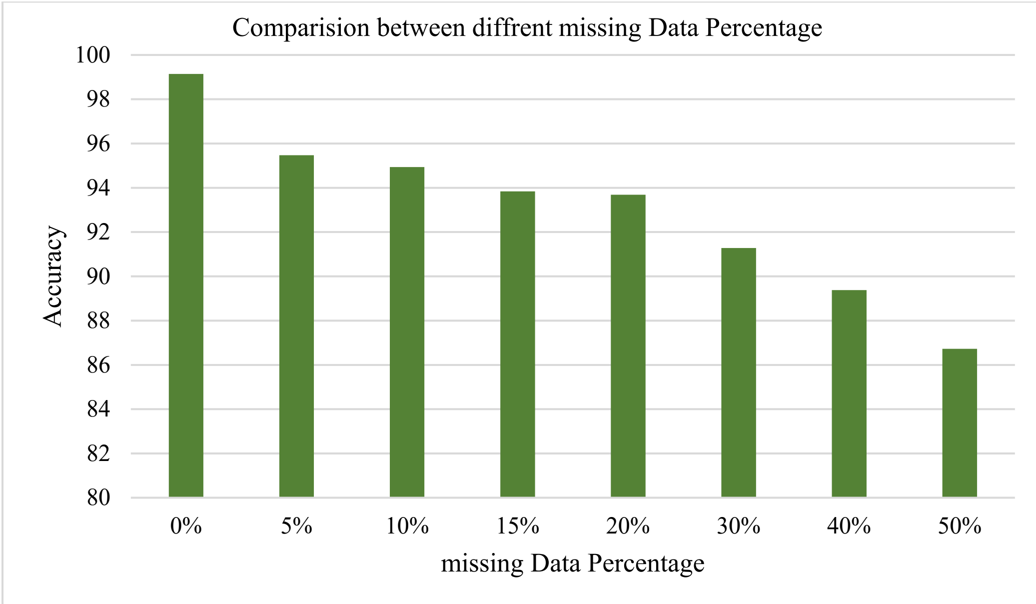

Figure 2. Comparison the recognition accuracy with several missing data percentage with ensemble classifier for Small Shifting less than (1.5) Sigma range in mean.

Haghighati and Hassan (2018) achieved the recognition accuracy of 96.67%, Askarian *et al.* (2016) got 79.8% with 20% missing data during (MACR) mechanism and our work got 98.64% in the normal shifting dataset, as shown in Figure 3.

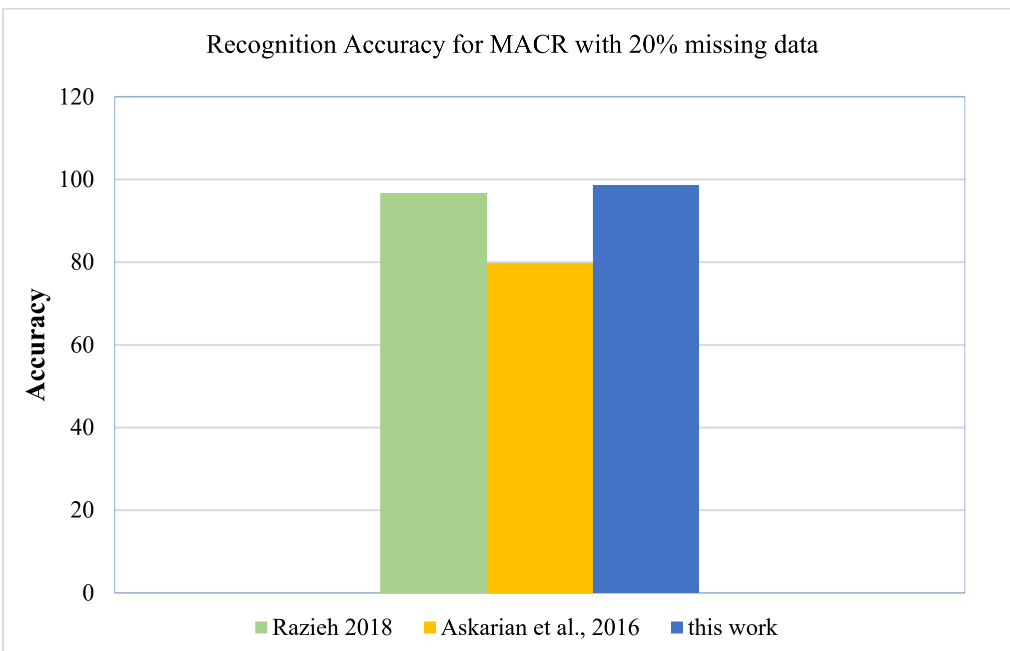

Figure 3. Compare the recognition accuracy of this work with previous work.

This study improved the recognition accuracy of missing data processes compared with previous research from 96.67% to 98.64% with 20% missing data. This study considers as improving the CCPR approach.

4. Conclusion

The ensemble classifier has the capability to get higher recognition accuracy compare with individual classifier. This paper investigated several missing data percentages for two dataset namely normal shifting range for mean (±3σ) and small shifting range for mean less than ((±1.5σ). The recognition accuracy without missing data 99.55% with ensemble classifier when it is 98.64% with 20% missing data for normal shifting range and 93.69 within small shift range in mean. The ensemble classifier can achieve higher recognition accuracy within missing data better than individual classifiers which used in previous studies. The EWMA computation to compensation the missing data it is better than another computation methods. The proposed method can handle the missing data with 50% missing data and the recognition accuracy still over 94%. For the future wark we suggest to investigate another classifier algorithms with ensemble classifier and investigate missing data in CCPR with data lees than 1.0 Sigma.

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