使用 MEMS 感測器實現以 IoT 為基礎的預測性維護

D0748284 楊孟軒

1 Introduction

1.1 Motivation

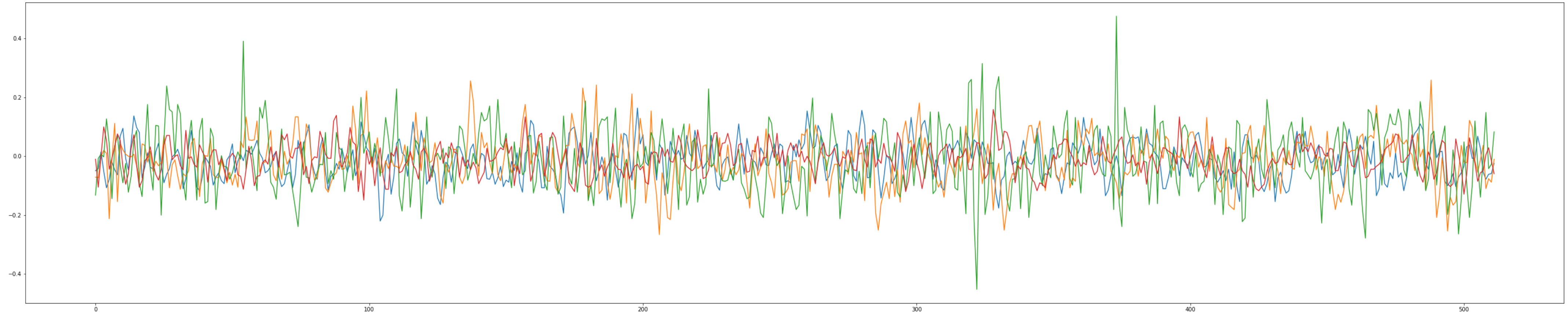
隨著工業機械能夠完成越來越複雜化、自動化的任務，這樣的發展意味著機械各部件得承受更為複雜的運作模式，也就是說，在該作業環境可能易遭受高溫高壓和高運轉量的困擾。因此，故障是不可避免的問題。由於機械設備故障容易導致經濟及能源消耗的損失，故機械狀態監控的需求變得日趨重要。
簡單來說：~~大專生計劃錢都拿了現在逃不掉了 嗚嗚~~

1.2 Task Definition

1. 利用遷入式設備搜集工具機運作數據
2. 輕量化模型並直接在遷入式設備部署
3. 考慮到多個axis交互關係分析軸承運作狀態

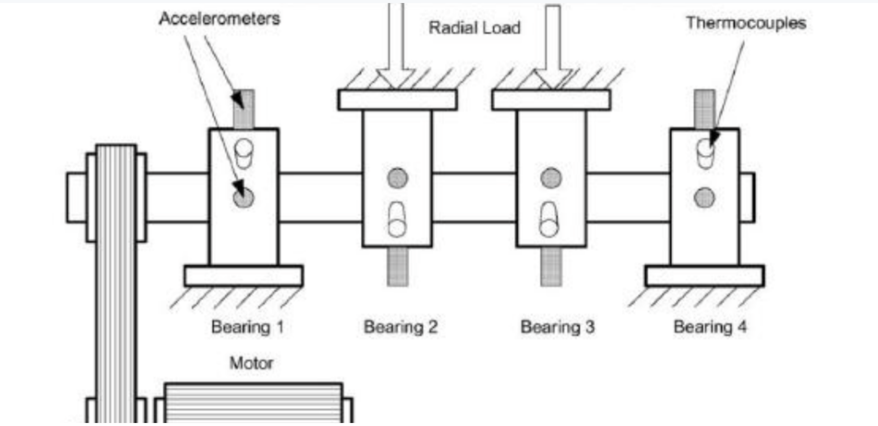
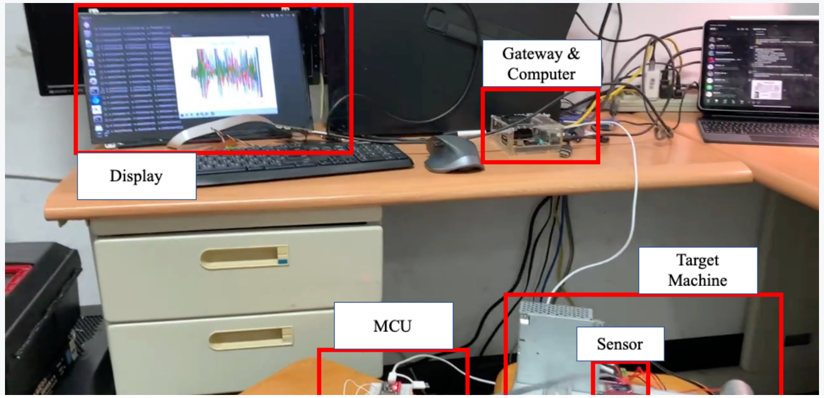
2 Dataset description

1. IMS dataset(aka NASA Bearing Dataset)
2. 實際設備搜集資料



- fig2-1 震動感應器原始數據

2.1 Dataset description

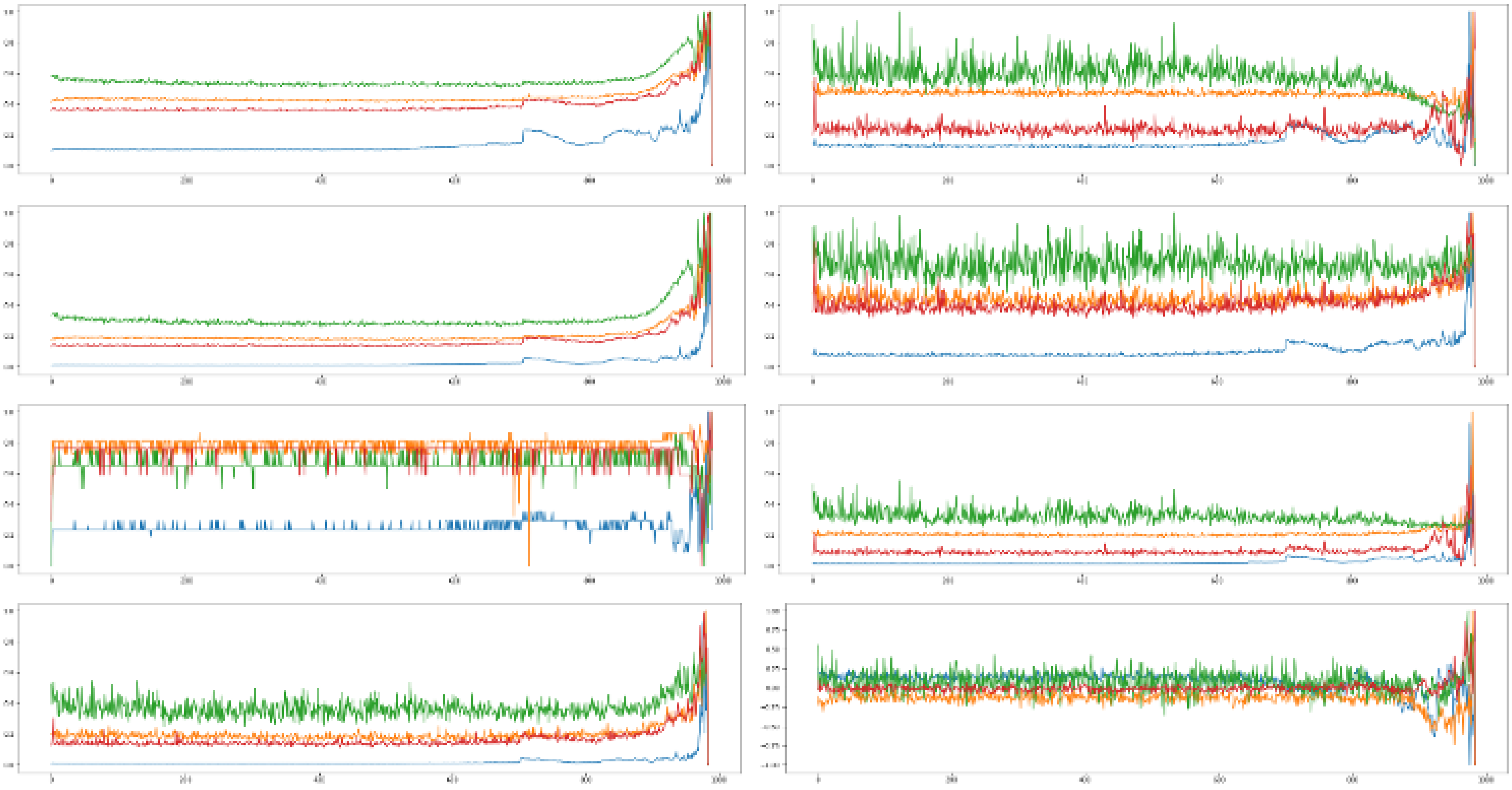
	IMS	實際設備搜集資料
Channels	4	3
Number of files	$\approx 20M$	$\geq 20k$
Window size(frequence)	10240	4096
setup		

3 Learning techniques

3.1 feature extraction

將震動數據依照$window\ size$ 分開
並分別計算個別的時域特徵($time domain features$)

- $\mathrm{RMS} = \sqrt{(\frac{1}{N})\sum_{i=1}^{N}(x)^2}$
- $\mathrm{VAR} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2$
- $\mathrm{KUR} = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\overline{x})^4}{\sigma^4}$
- $\mathrm{PeakValue} = \max\mathrm{value} - \min\mathrm{value}$
- $\mathrm{SKW} = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i-\overline{x})^3}{\sigma^3}$
- $\mathrm{MED} = (\frac{N+1}{2})^{th}$



- Normalized features used as training data

3.2 Classifiers model

分別用以下幾種演算法對資料進行訓練，比較輸出結果並考量實際效率以進行部署

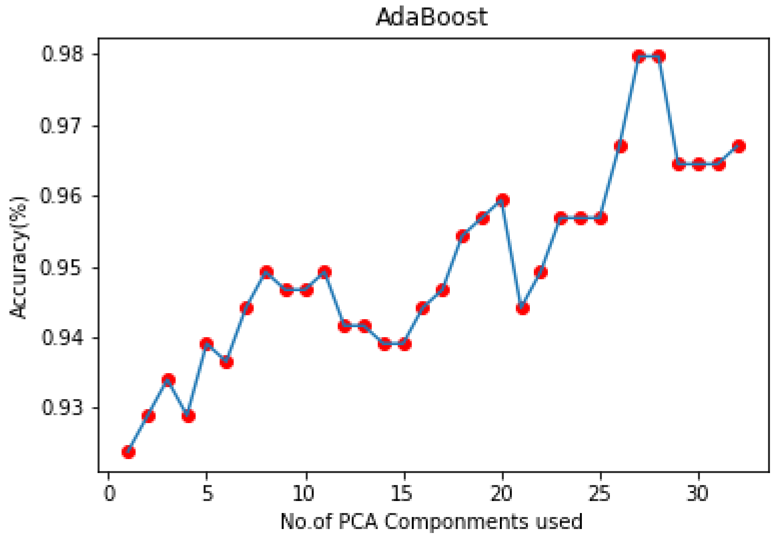
1. Nearest Neighbors
2. Linear SVM
3. RBF SVM
4. Decision Tree
5. Random Forest
6. AdaBoost
7. Naive Bayes

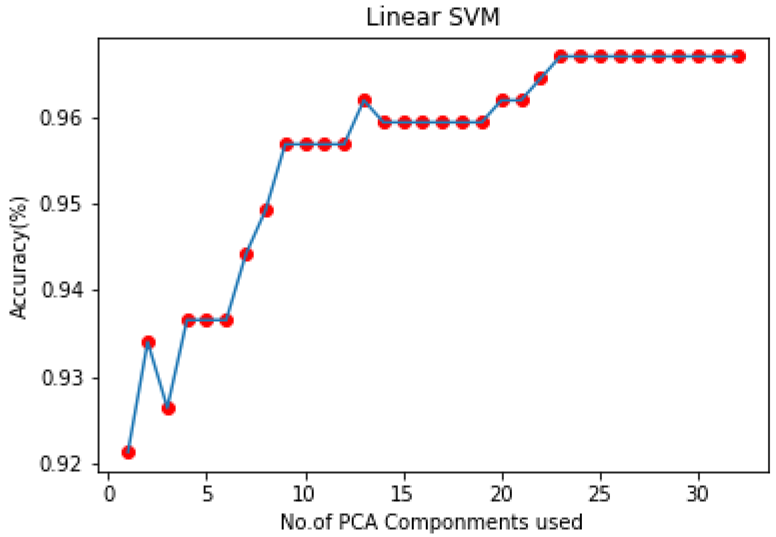
4 Result and disscussion

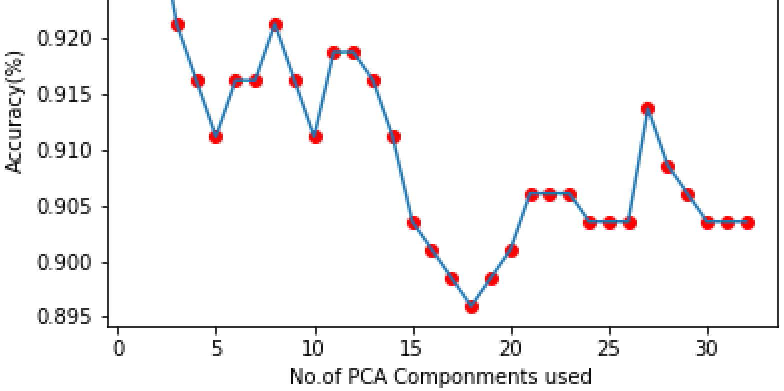
4.1 Classification Results Obtained Without PCA

model	Accuracy(%)	Parameter
Nearest Neighbors	93.4	N=3
Linear SVM	83.2	kernel="linear", C=0.025
RBF SVM	93.4	gamma=2, C=1
Decision Tree	97.9	max_depth=5
Random Forest	94.7	max_depth=5
AdaBoost	98.4	
Naive Bayes	87.5	

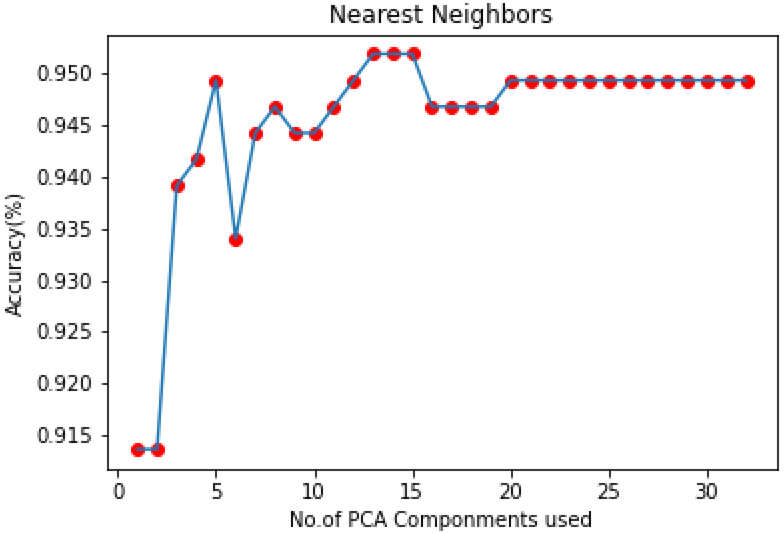
4.2 Classification Results Obtained using PCA



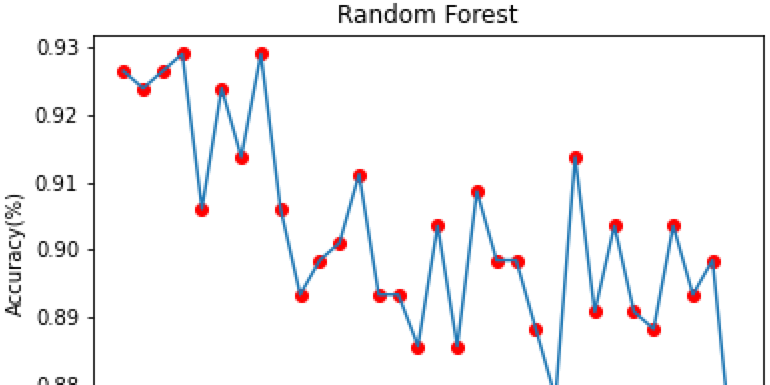




0.920
0.915
0.910
0.905
0.900
0.895
Accuracy(%)
0
5
10
15
20
25
30
No.of PCA Componments used



Nearest Neighbors
0.950
0.945
0.940
0.935
0.930
0.925
0.920
0.915
Accuracy(%)
0
5
10
15
20
25
30
No.of PCA Componments used



Random Forest
0.93
0.92
0.91
0.90
0.89
Accuracy(%)

4.3 Time it

Nearest Neighbors

100 loops, best of 5: 15.5 ms per loop

Linear SVM

100 loops, best of 5: 3.57 ms per loop

Decision Tree

1000 loops, best of 5: 570 µs per loop

Random Forest

100 loops, best of 5: 2.24 ms per loop

AdaBoost

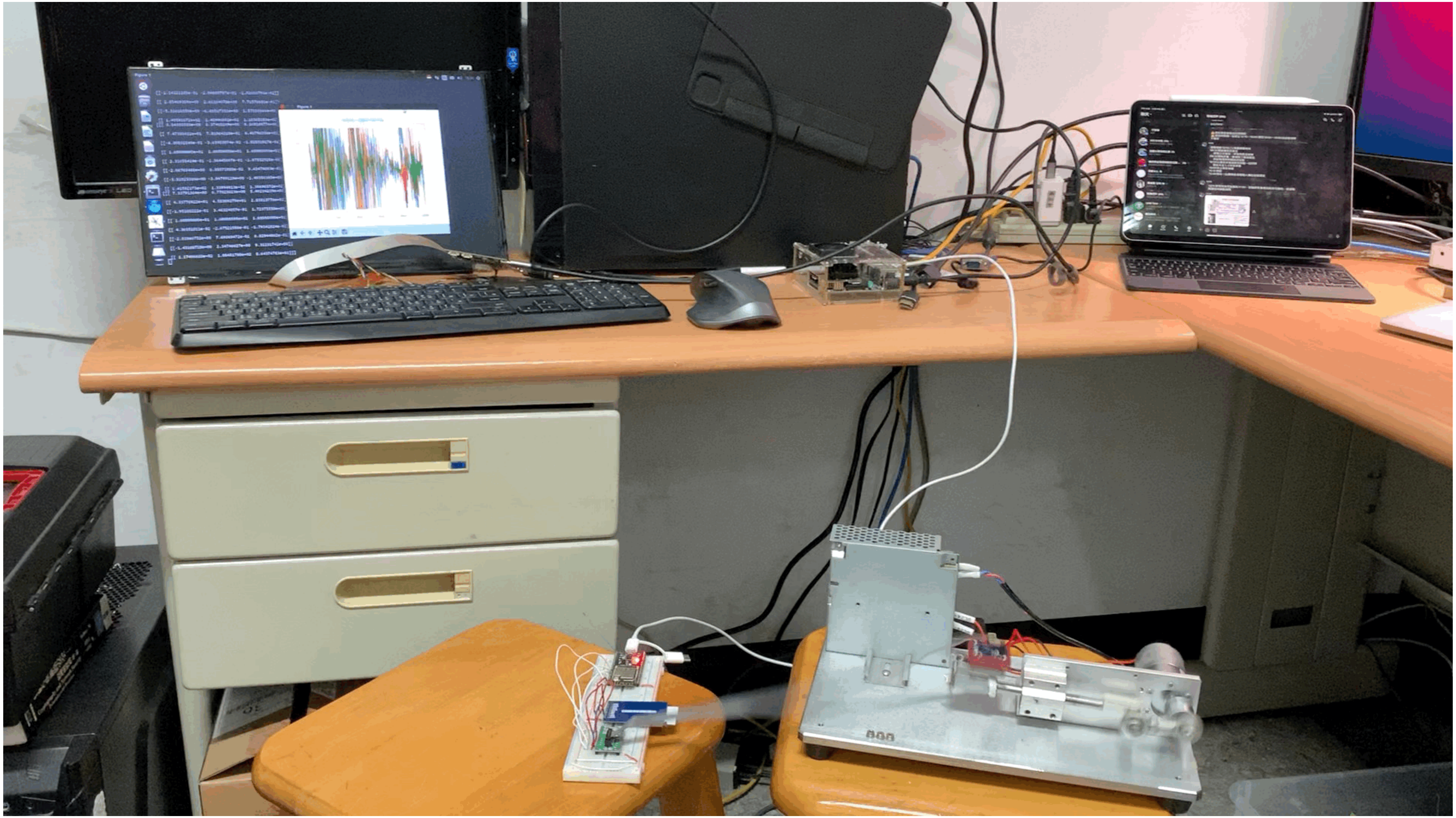
100 loops, best of 5: 10.5 ms per loop

Naive Bayes

1000 loops, best of 5: 666 µs per loop

`Intel(R) Xeon(R) CPU @ 2.20GHz`

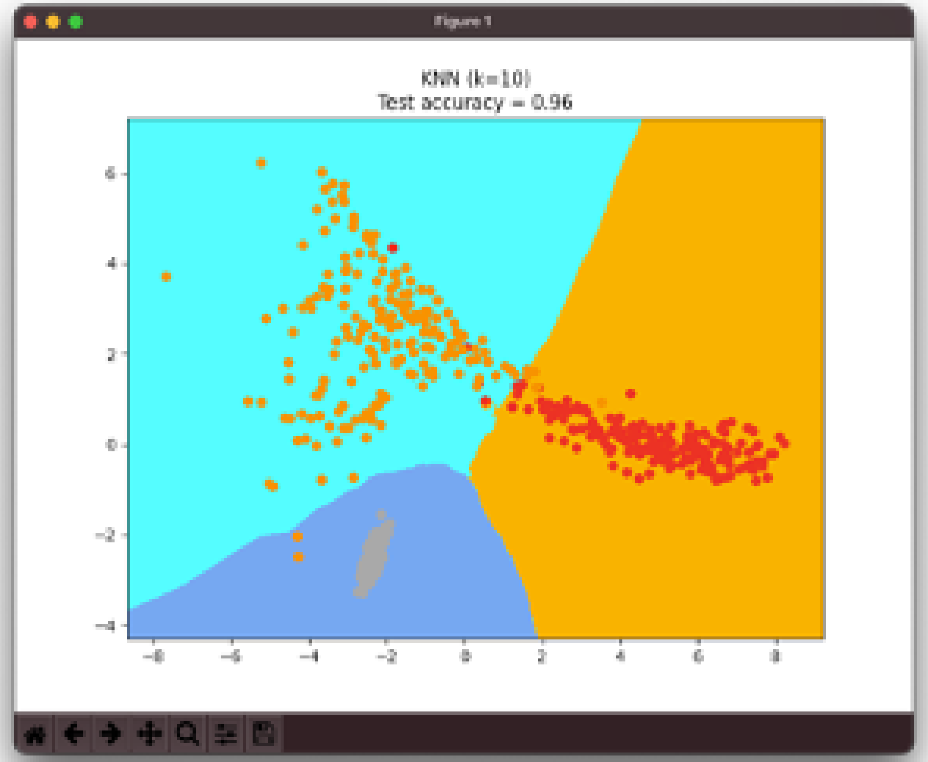
4.4 Deploy model in MCUs



5 Conclusion

5.1 Conclusion

要把模型用到MCU會需要比較多的步驟，因此這次在實際部署在MCU上目前只有使用PCA+KNN測試，同時我們也嘗試定義其他工具機的狀態標籤，但因為感應器的限制，當工具機高功率運作加速度會大於最大採樣值，因此本次以三個狀態作為標記。



5.2 未來展望

這次研究在實際部署中，遇到最大的問題是要在兼顧模型正確性的同時顧慮到MCU的計算量，因此希望未來可以用兩段式的架構，先藉由前端MCU搜集數據後傳送道伺服器分析，以使用更複雜的模型進行處理

6 References

- [1]Analysis of NASA Bearing Dataset of the University of Cincinnati by Means of Hjorth's Parameters
- [2]Analysis of the Rolling Element Bearing data set of the Center for Intelligent Maintenance Systems of the University of Cincinnat
- [3] A. Widodo, E. Y. Kim, J. D. Son, B. S. Yang, A. C. Tan, D. S. Gu, … and J. Mathew, “Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine,” Expert systems with applications, vol. 36 no. 3, pp. 7252-7261, 2009.