Predictive Maintenance

June Kwon

Image Source: Google

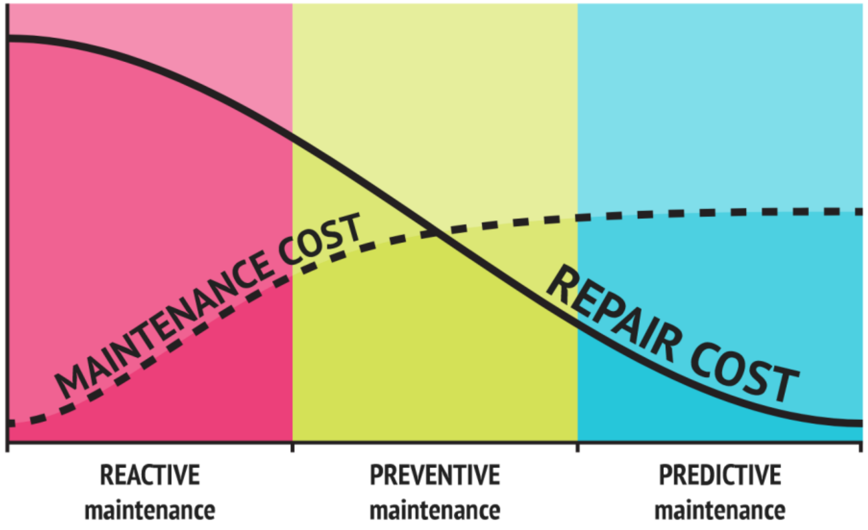
Introduction

- **Sooner or later, all machines run to failure, but with a wide range of consequences…**
- **An unexpected malfunction in a power plant has the potential to leave thousands of people in total darkness for hours and cause a multimillion-dollar loss.**
- **The average cost of unplanned downtime in energy, manufacturing, transportation, and other industries runs at $250,000 per hour or $2 million per working day. [1]**
- **To prevent expensive outages from happening and alleviate the damage caused by breakdowns, companies need an efficient maintenance policy.**
- **Among many available strategies and resources, one of the most advanced approaches is – "Predictive Maintenance".**

Image Source: Altexsoft [1]

Introduction

- As shown right, in the past, people used to perform the reactive maintenance, meaning that the actions were taken when the equipment was already down.
    - While the reactive maintenance requires no initial maintenance costs, it turns out to be very expensive in terms of the repair cost.



- Then people looked at the preventive maintenance, where people performed regular equipment inspections to mitigate the degradations and reduce the likelihood of failures.
    - However, it still came with a medium range maintenance & repair cost, causing the companies to take the risk of performing too much maintenance or not enough.

Image Source: Google

Introduction

- **Predictive Maintenance solves these issues.**
- **Predictive Maintenance is a type of condition-based maintenance where maintenance is only scheduled when specific conditions are met and before the equipment breaks down.**
    - **Driven by automation, machine learning, and real-time data, we can monitor the trends of the machine performance, and once unhealthy trends are identified, we will estimate when the maintenance should be performed to replace/repair the damaged parts to avoid more costly failures.**
- **It promises more cost savings over routine or time-based preventive maintenance.**

Data Preparation

- Let's take a look at the data I obtained.
- AI4I 2020 Predictive Maintenance Dataset – UCI Machine Learning Repository

UCI Machine Learning Repository

Features *Targets*

UDI	Product ID	Type	Air temperature [K]	Process Temperature [K]	Rotational Speed [rpm]	Torque [Nm]	Tool Wear Time [min]	Machine Failure	Tool Wear Failure (TWF)	Heat Dissipation Failure (HDF)	Power Failure (PWF)	Overstrain Failure (OSF)
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2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0
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2380	H31793	M	299.1	308.2	1450	46.1	112	0	0	0	0	0
4872	L52051	L	303.7	312.4	1513	40.1	135	0	0	0	0	0

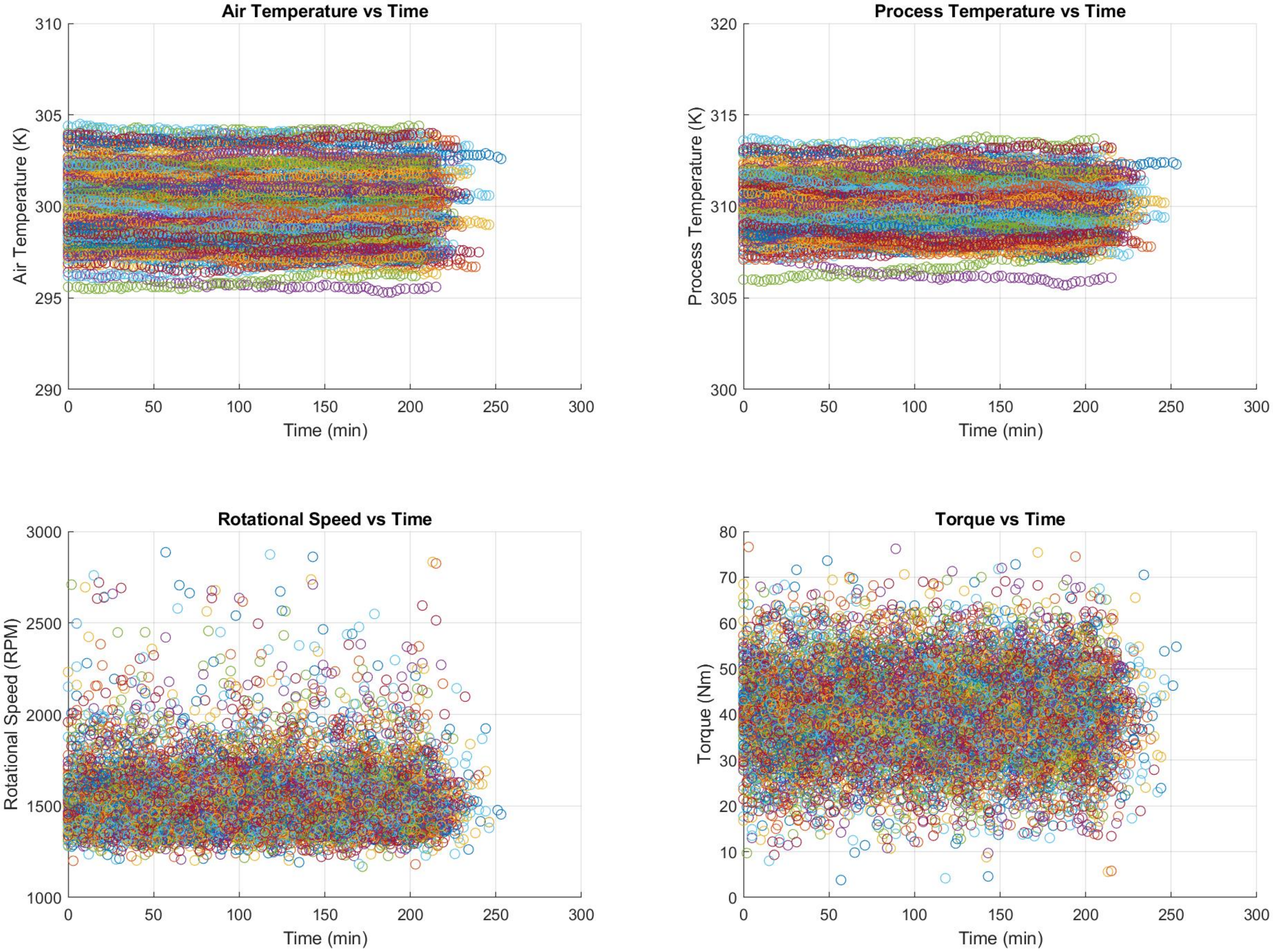
If at least one of these four failure modes is set to true, the process fails, and the "Machine Failure" label is set to true.

- 120 Units – each unit containing 75-85 observations.
- Thus, in total, this dataset contains 10,000 observations.

Data Analysis

- **In order to have deeper understanding of the data, the distribution of each data point was visualized as shown in the picture right.**
- **Air Temperature and Process Temperature show quite consistent data distribution over the wear time. Most of the data in Air Temperature and Process Temperature reside at the temperature of 300 Kelvin and 310 Kelvin, respectively.**
- **For Rotational Speed and Torque data, it can be noted that the most of data reside at the speed of 1500 RPM and at the Torque value of 40 Nm.**
- **By visualizing the data, I can understand the data more deeply. For example, it can be expected that any values deviated from the accumulated region may be classified as "Abnormal".**

[Data Description] Plot of Feature over Time



Data Analysis

- **Moreover, the PCA has been performed for deeper understanding of the data as shown in the picture right. It represents the data plotted over the 1st principal component as x-axis and 2nd principal component as y-axis.**
- **From the figure, it can be noted that most of the data reside at from 1400 to 1600 on the 1st principal component (x-axis), and from 0 to 200 on the 2nd principal component (y-axis)**
- **It can then be expected that values deviated from this accumulated region can be classified as "Abnormal".**

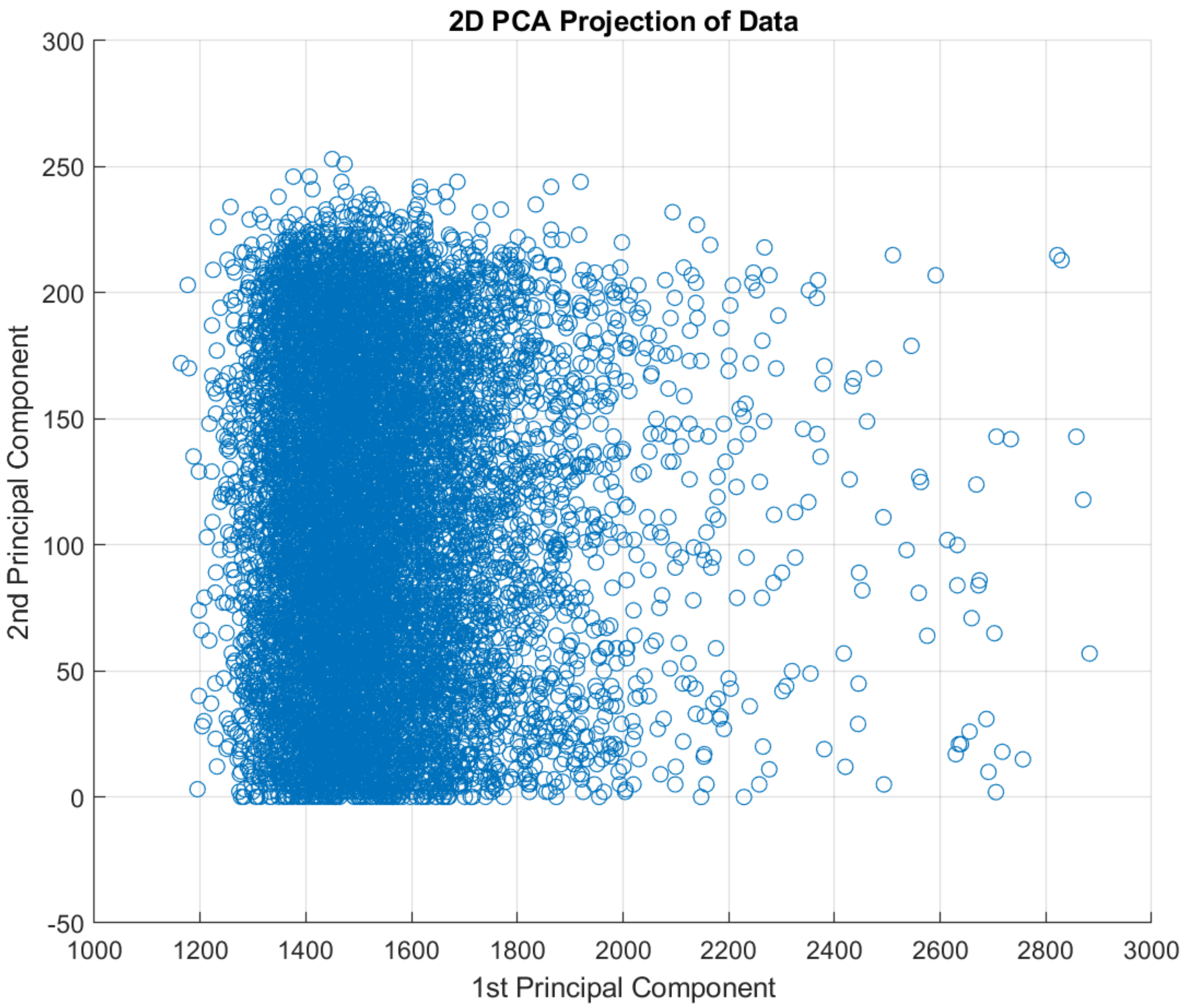


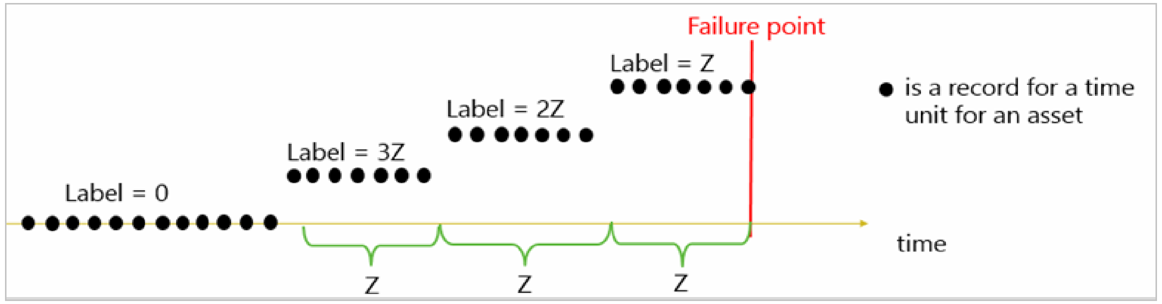
Image Source: Microsoft [2]

Approach

- **Now we've looked at data and its distribution, let's talk about the types of approaches to implement the predictive maintenance.**
- **There are two types of analysis we can perform as shown below.**

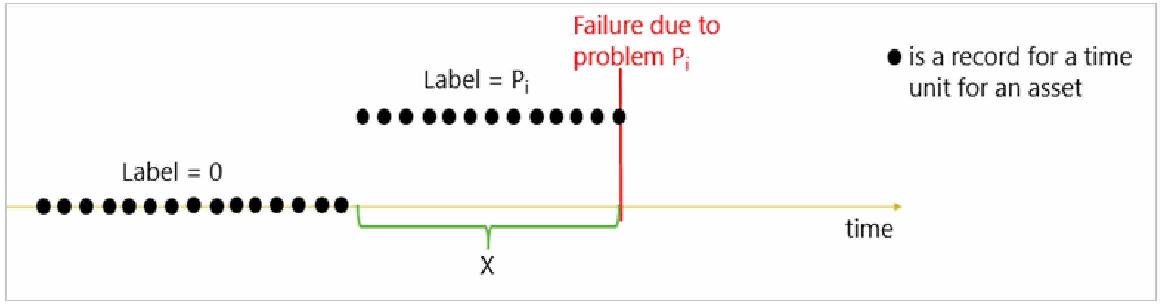
1. Predict the remaining useful life of an equipment (RUL Analysis)

- **Enables monitoring for health diagnostic, and plan maintenance schedules.**



2. Predict the possible root cause of the failure.

- **Recommends the right set of maintenance actions to fix a failure**

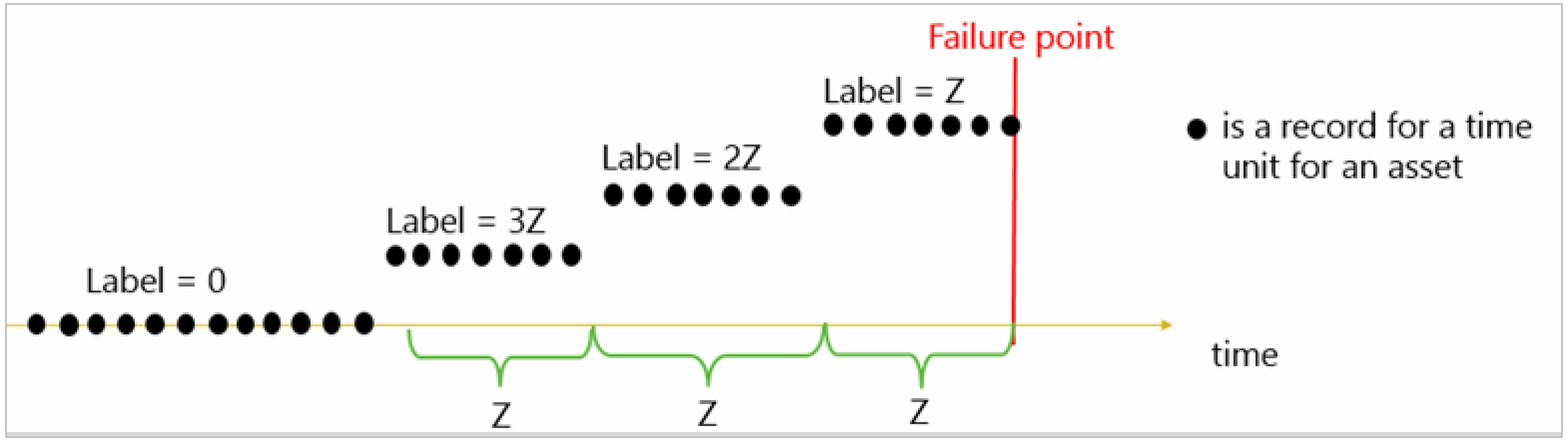


"Let's look at each type of analysis."

Image Source: Microsoft [2]

Approach : Remaining Useful Life Analysis

- **For RUL analysis, the amount of time that an equipment can be operational before the failure is to be estimated.**
- **To do this, we predict two future outcomes**
  1. **The first outcome is a range of time to failure for the equipment (Z – Range). The equipment is then assigned to one of the multiple possible periods of time.**
  2. **The second outcome is the likelihood of failure in a future period due to one of the multiple root causes. This prediction enables the maintenance crew to watch for symptoms and plan maintenance schedules.**



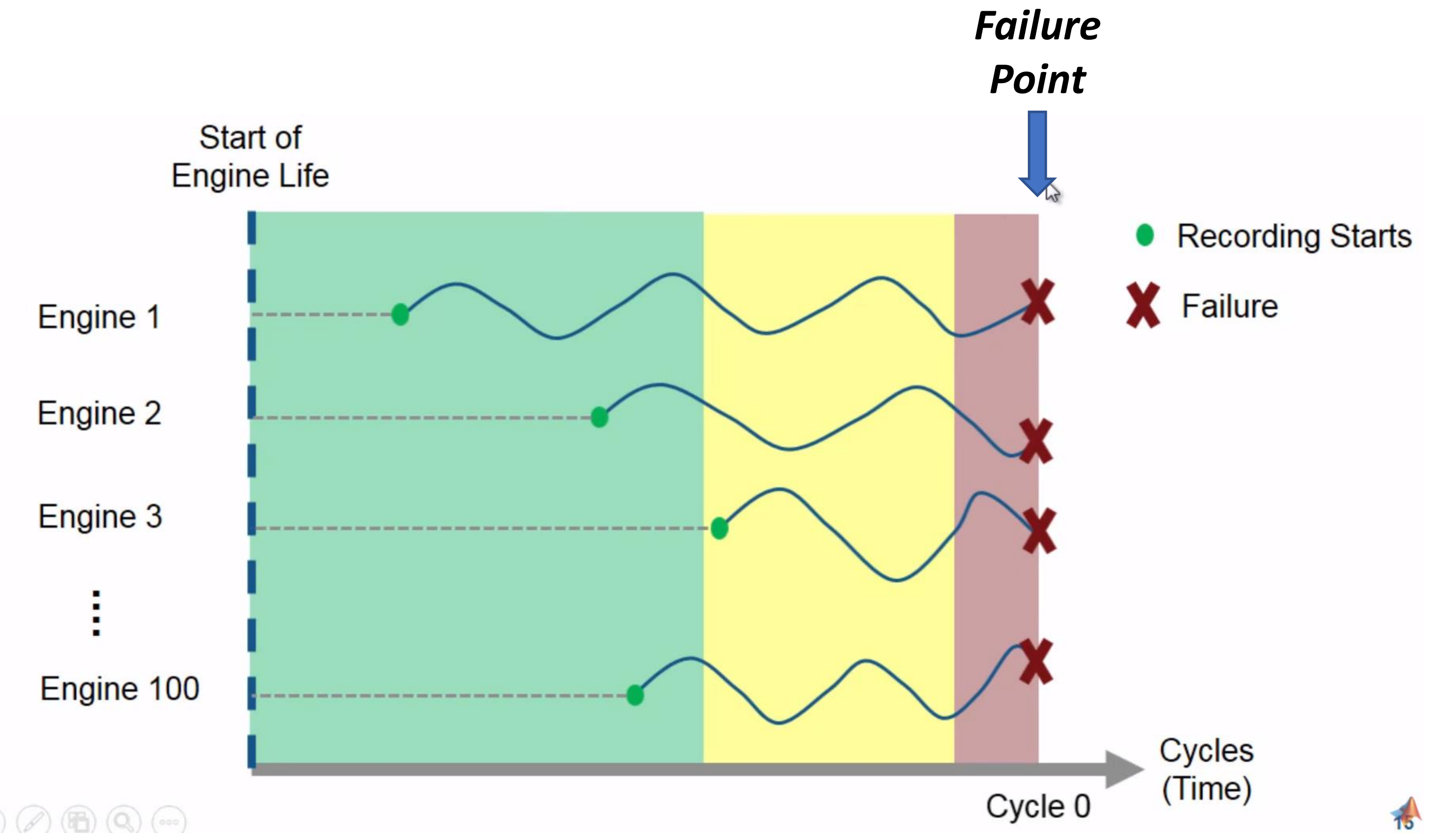
Labeling for multi-class classification for failure time prediction

"What is the probability that an equipment will fail in the next nZ units of time (where n is the number of periods) ?"

Approach : Remaining Useful Life Analysis

Image Source: MathWorks [4]

- **Let's take a look at the example.**
- **Looking at the entire timeline of the engine life, we align the failure point on same timeline, and from there, the specific user-defined range of time that is closest to the failure point will be assigned a class "Urgent".**
- **Then, next closest range of time will be assigned a class "Medium", and the most distant range of time from failure point will be assigned a class "Long" which means it still has long remaining useful life. (it does not require maintenance as of now.)**
- **Using this modeling techniques, it is possible to properly construct the specific classes on the data.**

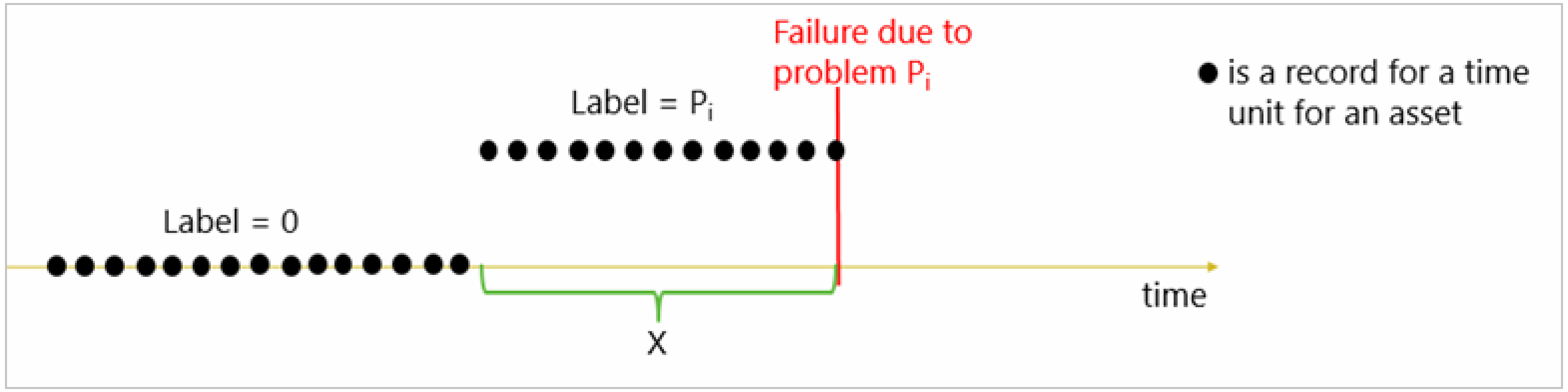


Modeling Techniques
(Specific Label Construction Method)

Image Source: Microsoft [2]

Approach : Possible Root Cause Analysis

- **For Possible Root Cause Analysis, the most likely root cause of a given failure is to be estimated.**
  - **This outcome recommends the right set of maintenance actions to fix a failure. A list of root causes can be ranked to recommend repairs which can help technicians prioritize their repair actions after a failure.**



Labeling for multi-class classification for root cause prediction

"What is the probability that an equipment will fail in the next X units of time due to root cause/problem P_i?" (where i is the number of possible root causes).

Image Source: Google

Result

- **Finally, let's apply various machine learning techniques to the given dataset to train the model.**
- **I will consider below four classifiers to train my models…**
  1. **Logistic Regression (with Cross Validation)**
  2. **Naïve Bayes**
  3. **Decision Tree**
  4. **K-Nearest Neighbors**

  (All as a multiclassification problem…)
- **Then the performance of each classifier will be evaluated to choose the best classifier for the given dataset…**
  - **Consider/compare their accuracies, precisions, recalls, f-measures, confusion matrix, etc.**
- **Then I would like to use above two types of predictive maintenance scenarios to predict the time to failure and the possible root cause of the failure.**

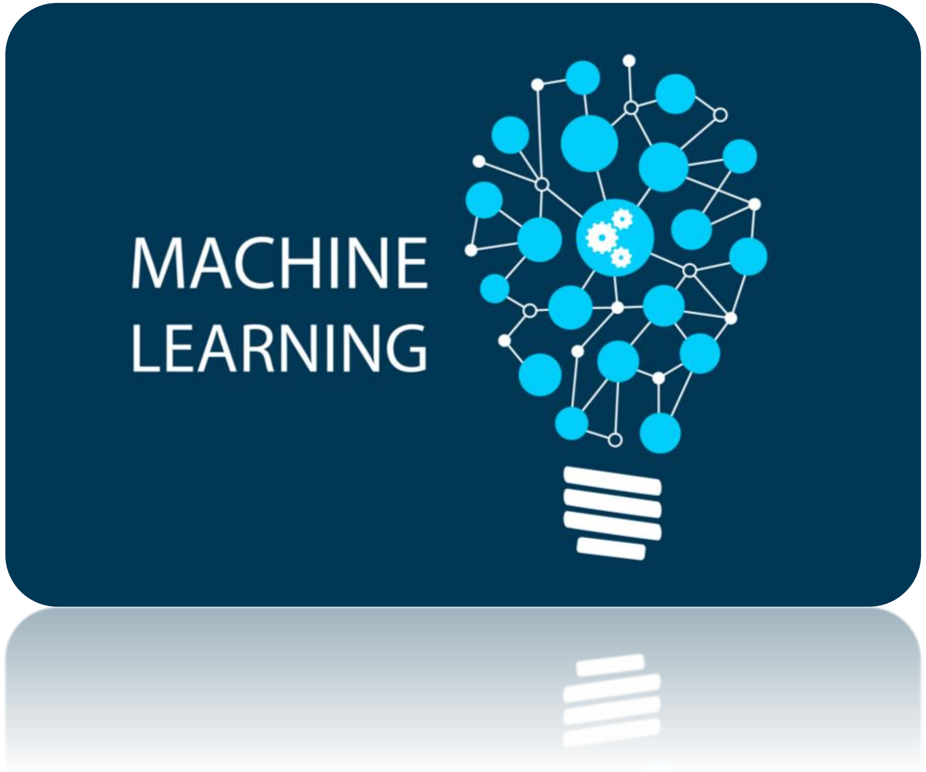
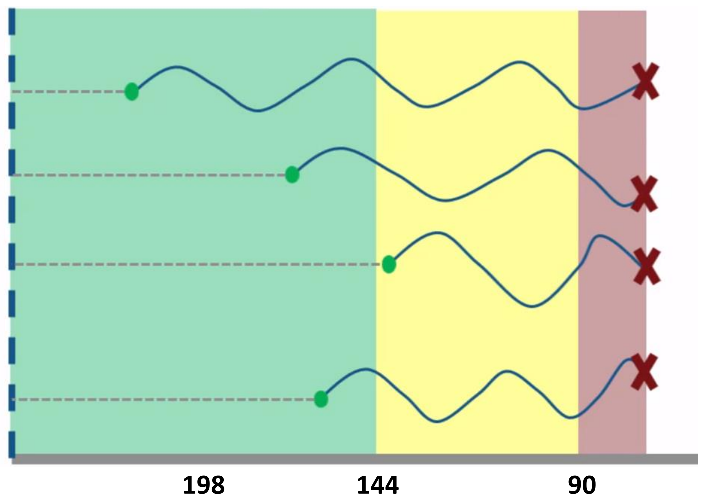


Image Source: MathWorks [4]

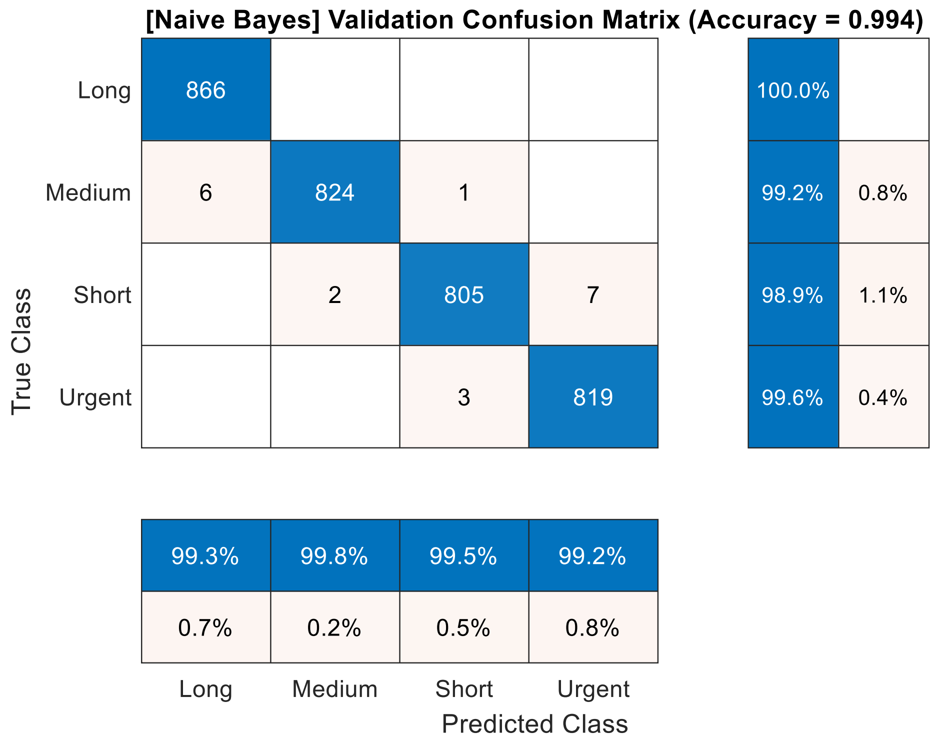


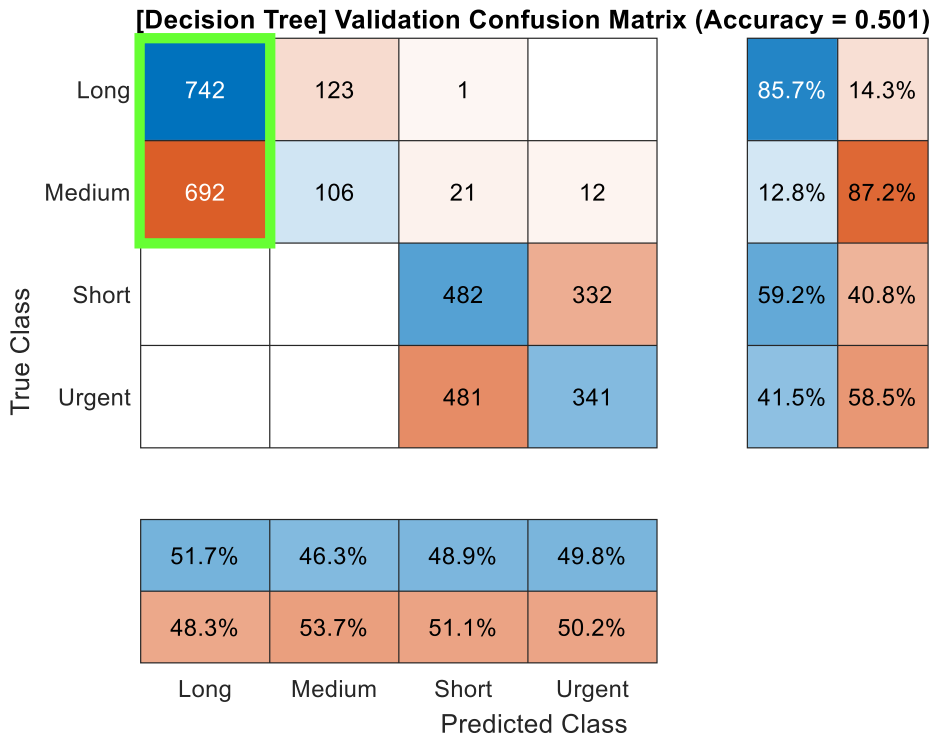
Results : 1. Remaining Useful Life

- **Remaining Useful Life Analysis has been performed by modelling the failure time into multiple time ranges as follows:**
  - **Assign Class Y = 4 (Urgent) for 90 min before failure**
  - **Assign Class Y = 3 (Short) for 144 min before failure**
  - **Assign Class Y = 2 (Medium) for 198 min before failure**
  - **Assign Class Y = 1 (Long) for greater than 198 min before failure.**

		1st Feature	2nd Feature	3rd Feature	4th Feature	5th Feature	Y = nZ	6th Feature		**Features and Targets were selected as shown here for RUL analysis.**		
UDI	Product ID	Type	Air temperature [K]	Process Temperature [K]	Rotational Speed [rpm]	Torque [Nm]	Tool Wear Time [min]	Machine Failure	Tool Wear Failure (TWF)	Heat Dissipation Failure (HDF)	Power Failure (PWF)	Overstrain Failure (OSF)
1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0
2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0
443	L47622	L	297.4	308.5	1399	61.5	61	1	0	0	1	0
1997	M16856	L	298.4	308	1416	38.2	198	1	1	0	0	0
2126	L49305	L	299.3	308.9	1258	69.4	119	1	0	0	1	0
2380	H31793	M	299.1	308.2	1450	46.1	112	0	0	0	0	0
4872	L52051	L	303.7	312.4	1513	40.1	135	0	0	0	0	0

Results : 1. Remaining Useful Life



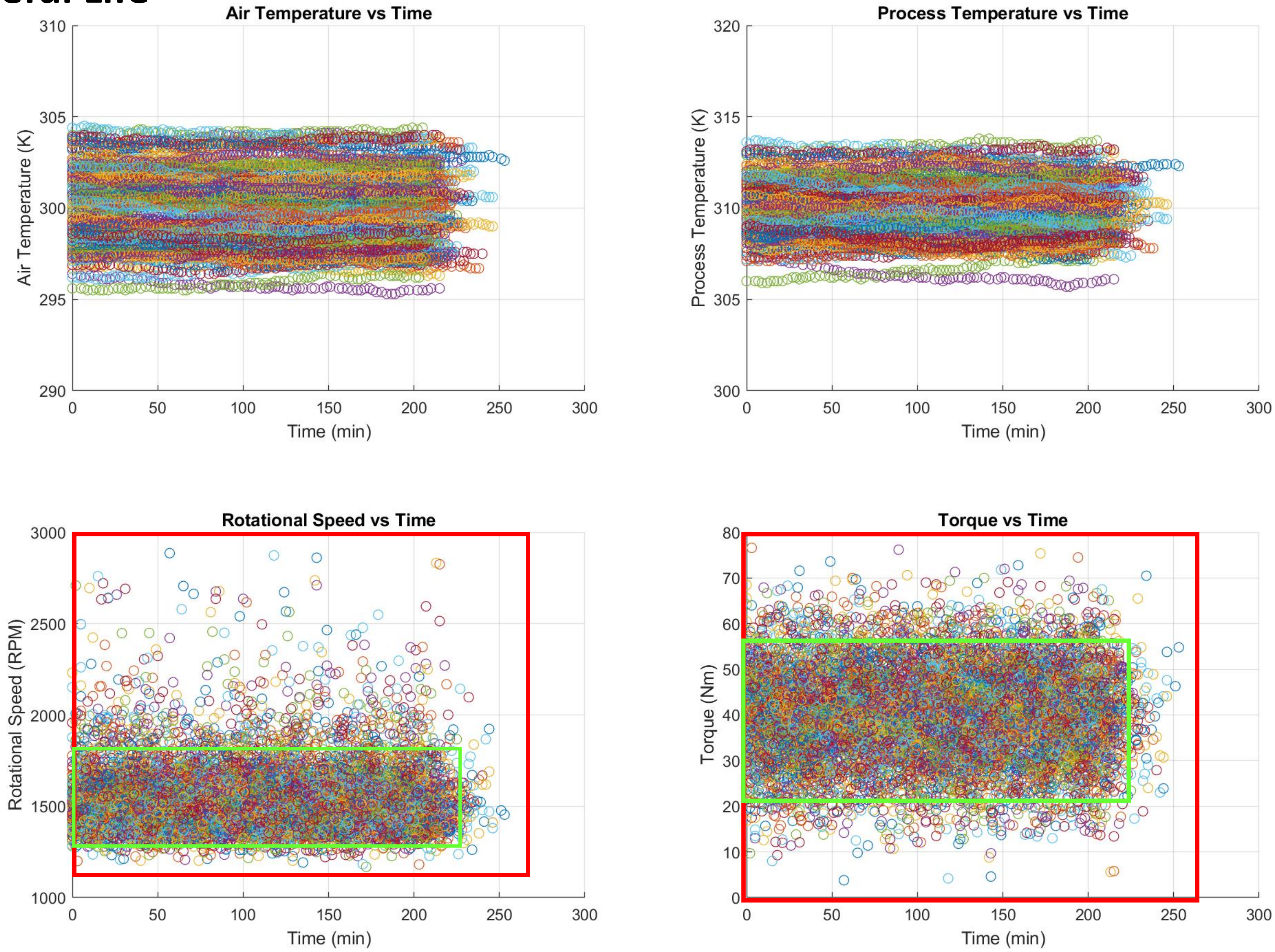


- **First, Naïve Bayes & Decision Tree Classifiers were used to train the model, and above two pictures show the resulting confusion matrix.**
  - **For Naive Bayes Model, an accuracy of 0.994 was achieved.**
  - **For Decision Tree Model, an accuracy of 0.501 was achieved.**
- **It is evident that the decision tree model did not perform as good as the naive bayes model. It also can be noted that the decision tree model is unable to distinguish the difference between "Long (Y = 1)" and "Medium (Y = 2)“ classes (green box). It seems that the decision tree model mis-classified the medium class to be the long class.**

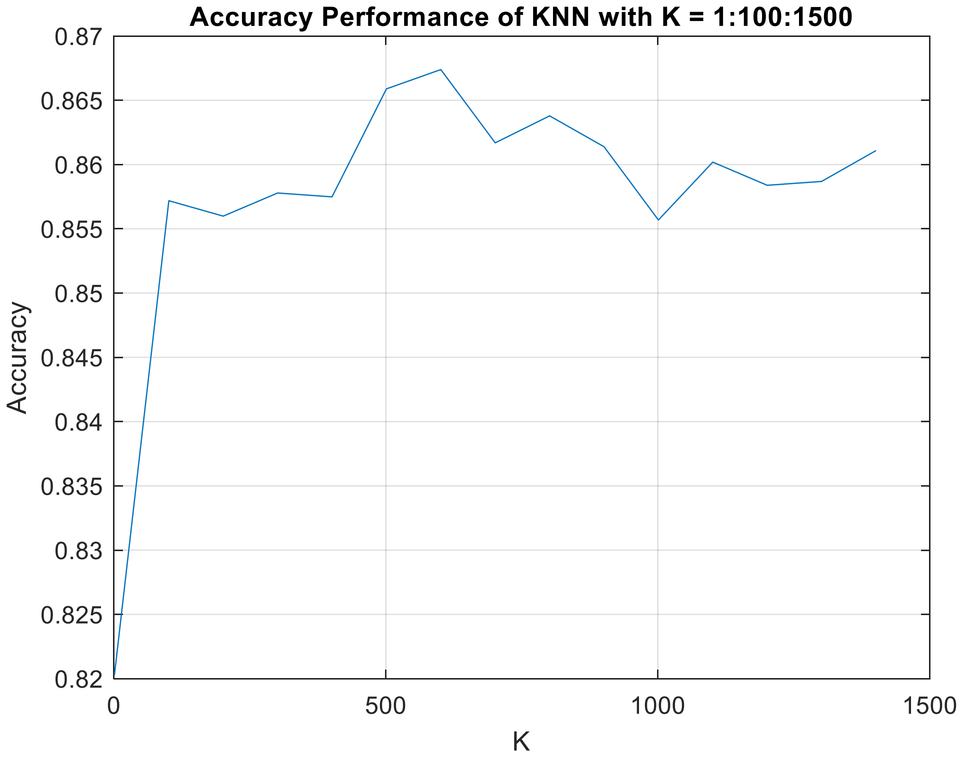
Results : 1. Remaining Useful Life

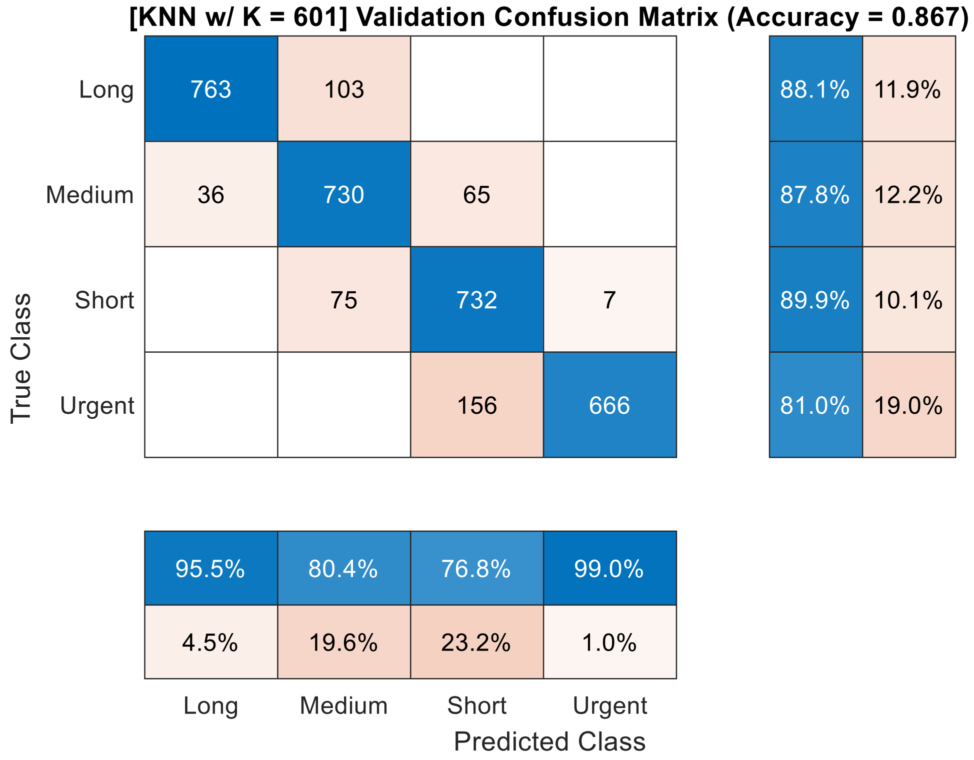
- I suspect that the possible source of this error is due the highly biased distribution in the data.
- As the unit approaches the failure point, deviation of malfunctioning units (such as Urgent and Short classes) are clearly identifiable from the accumulated region in the dataset.
- However, for the normal operation such as Long and Medium classes, it can become highly unpredictable for the model to distinguish the difference between the two normal operation classes because both Long and Medium classes reside in accumulated regions (green box).
- Thus, this is the possible reason why decision tree did not work well for the given dataset. Thus, the possible solution is to install more sensors that can induce/identify the difference between the Long and the Medium class.

[Data Description] Plot of Feature over Time



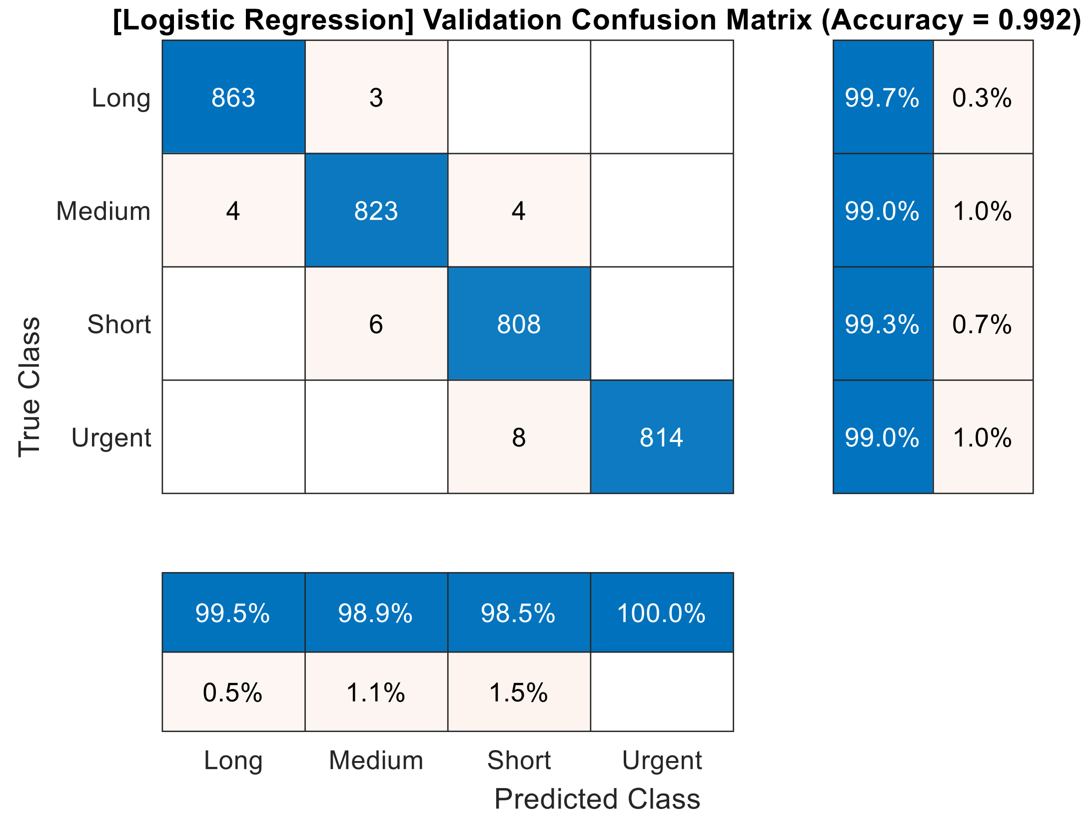
Results : 1. Remaining Useful Life





- **For K-Nearest Neighbor classifier, the algorithm was run with varying K from 1 to 1500 in the increment of 100.**
  - **At K = 601, the highest accuracy of 0.867 was achieved.**
- **The model is achieving around 86% to 88% which is good, but not as high as the Naïve Bayes classifier.**

Results : 1. Remaining Useful Life



Algorithm	Accuracy
Naïve Bayes	0.994
Decision Tree	0.501
K-Nearest Neighbor	0.867
Logistic Regression	0.992

Prediction Performance on Remaining Useful Life Analysis

- **For Logistic Regression classifier, the algorithm was run with varying learning rate.**
  - **At the learning rate of 0.1, the highest accuracy of 0.992 was achieved.**
- **Therefore, considering all four algorithms, it has been determined that Naïve Bayes Classifier performed the best for Remaining Useful Life Analysis.**

Results : 2. Possible Root Cause

- **Possible Root Cause Analysis has been performed by modelling each failure mode as follows:**
  - **Assign Class Y = 1 for No Failure (Normal)**
  - **Assign Class Y = 2 for Tool Wear Failure (TWF)**
  - **Assign Class Y = 3 for Heat Dissipation Failure (HDF)**
  - **Assign Class Y = 4 for Power Failure (PWF)**
  - **Assign Class Y = 5 for Overstrain Failure (OSF)**

- **However, there was highly biased distribution in data.**
- **Out of 10,000 observations,**
  - **Nearly 9670 observations are Class Y = 1**
  - **Nearly 40 observations are Class Y = 2**
  - **Nearly 110 observations are Class Y = 3**
  - **Nearly 80 observations are Class Y = 4**
  - **Nearly 100 observations are Class Y = 5**

		1st Feature	2nd Feature	3rd Feature	4th Feature	5th Feature	6th Feature		Y = 2	Y = 3	Y = 4	Y = 5
UDI	Product ID	Type	Air temperature [K]	Process Temperature [K]	Rotational Speed [rpm]	Torque [Nm]	Tool Wear Time [min]	Machine Failure	Tool Wear Failure (TWF)	Heat Dissipation Failure (HDF)	Power Failure (PWF)	Overstrain Failure (OSF)
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4872	L52051	L	303.7	312.4	1513	40.1	135	0	0	0	0	0

Results : 2. Possible Root Cause

- To mitigate the highly biased distribution, I reduced the dataset.
- From Full Dataset...
- Out of 10,000 observations,
    - Nearly 9670 observations are Class Y = 1
    - Nearly 40 observations are Class Y = 2
    - Nearly 110 observations are Class Y = 3
    - Nearly 80 observations are Class Y = 4
    - Nearly 100 observations are Class Y = 5

- Reduce to create Balanced Dataset
- Down to 440 observations,
    - Nearly 110 observations are Class Y = 1
    - Nearly 40 observations are Class Y = 2
    - Nearly 110 observations are Class Y = 3
    - Nearly 80 observations are Class Y = 4
    - Nearly 100 observations are Class Y = 5

Selected Features and Targets for PRC analysis.		1st Feature	2nd Feature	3rd Feature	4th Feature	5th Feature	6th Feature		Y = 2	Y = 3	Y = 4	Y = 5
UDI	Product ID	Type	Air temperature [K]	Process Temperature [K]	Rotational Speed [rpm]	Torque [Nm]	Tool Wear Time [min]	Machine Failure	Tool Wear Failure (TWF)	Heat Dissipation Failure (HDF)	Power Failure (PWF)	Overstrain Failure (OSF)
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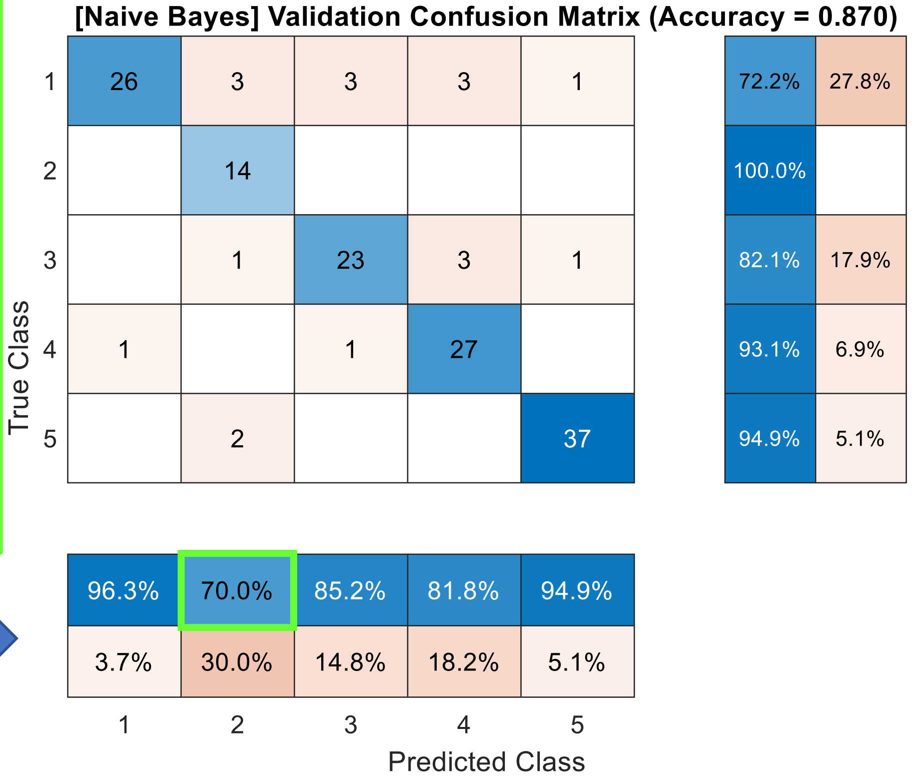
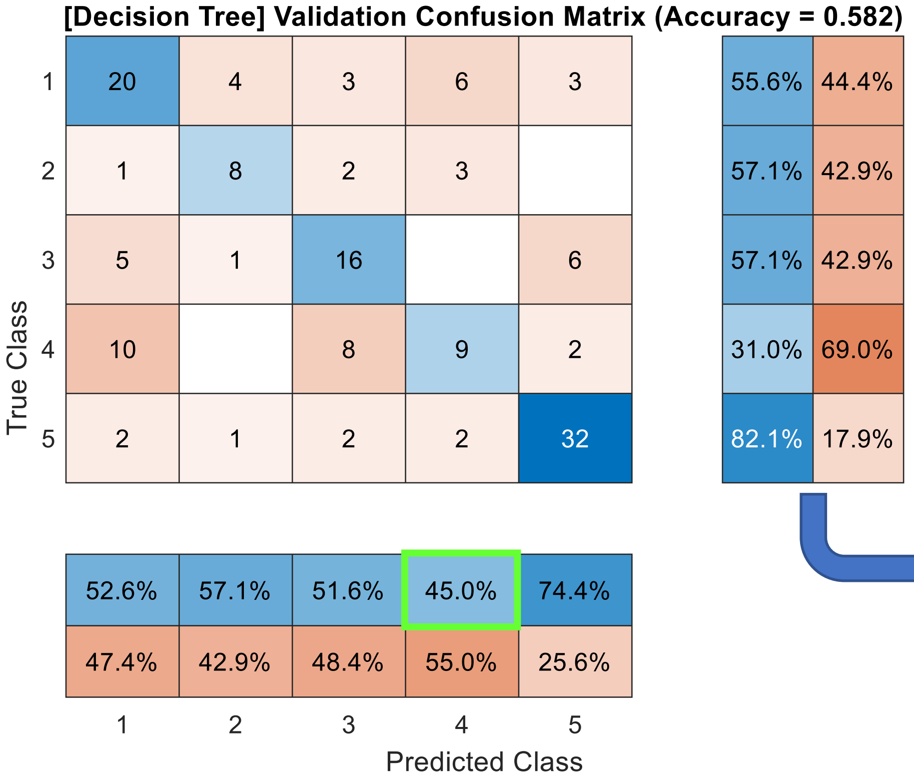
4872	L52051	L	303.7	312.4	1513	40.1	135	0	0	0	0	0

Results : 2. Possible Root Cause

Bottom Box tells the accuracy of the predicted class. In other words, it indicates the "Performance of the Trained Model" – how well the model predicted the class correctly. (From the model's point of view)

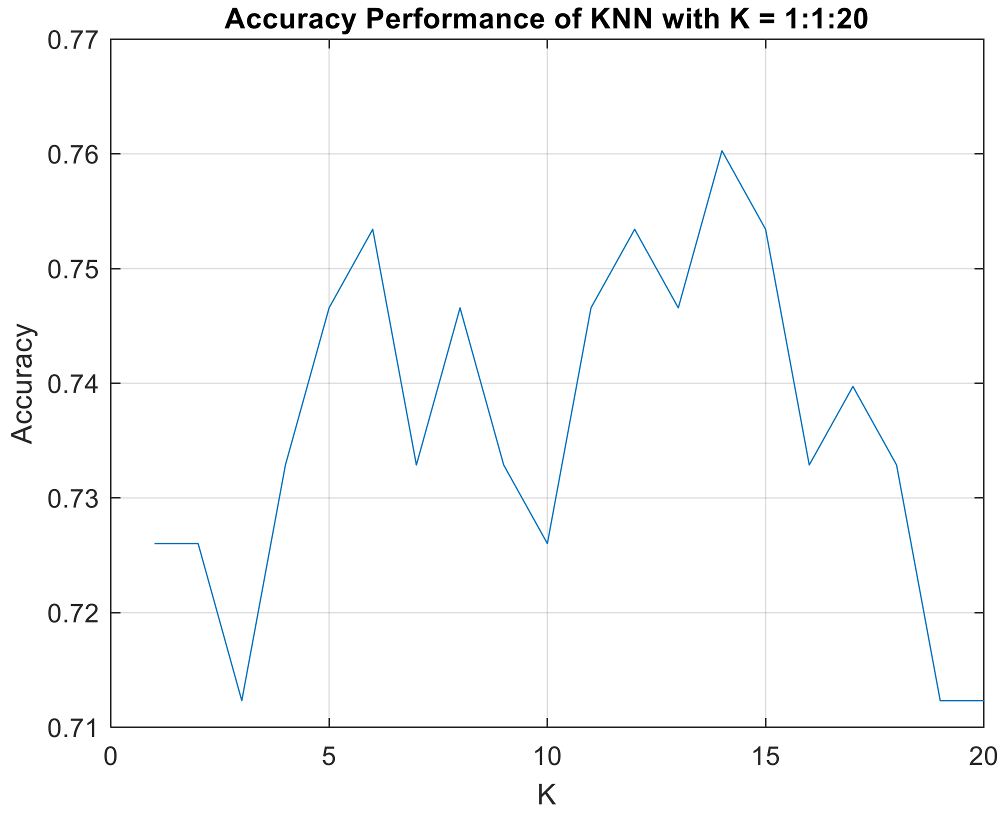


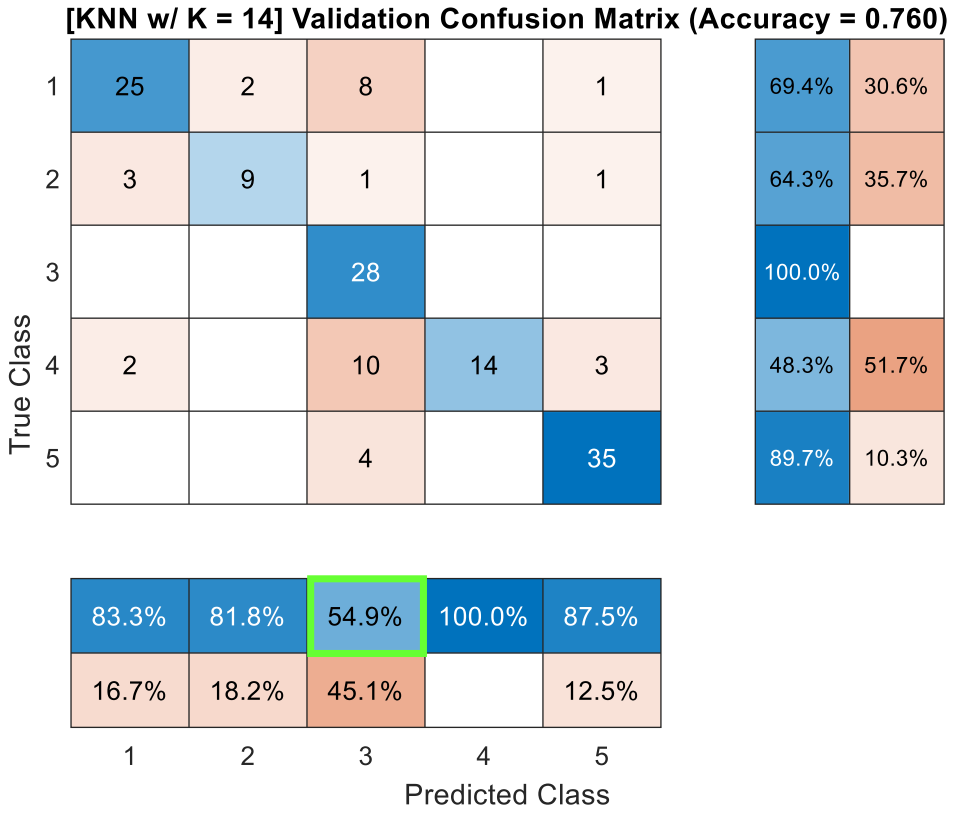


Right Box tells the accuracy of the true class. In other words, it indicates the "Statistical result of Trained Model" – how the predicted classes performed in the dataset. (From the data's point of view)

- **Naïve Bayes & Decision Tree Classifiers were used to train the model, and above two pictures show the resulting confusion matrix.**
  - **For Naive Bayes Model, an accuracy of 0.870 was achieved.**
  - **For Decision Tree Model, an accuracy of 0.582 was achieved.**
- **Looking at the confusion matrix for both Naïve Bayes and Decision Tree models, it can be noted that both models predicted Class 5 (OSF: Overstrain Failure) well.**
  - **However, in Naïve Bayes model (thus, from model's point of view), it can be noted that Class 2 (TWF: Tool Wear Failure) yields relatively low accuracy with 70%.**
  - **In Decision Tree model, it can be noted that Class 4 (PWF: Power Failure) also yields relatively low accuracy with 45%. (Why?)**

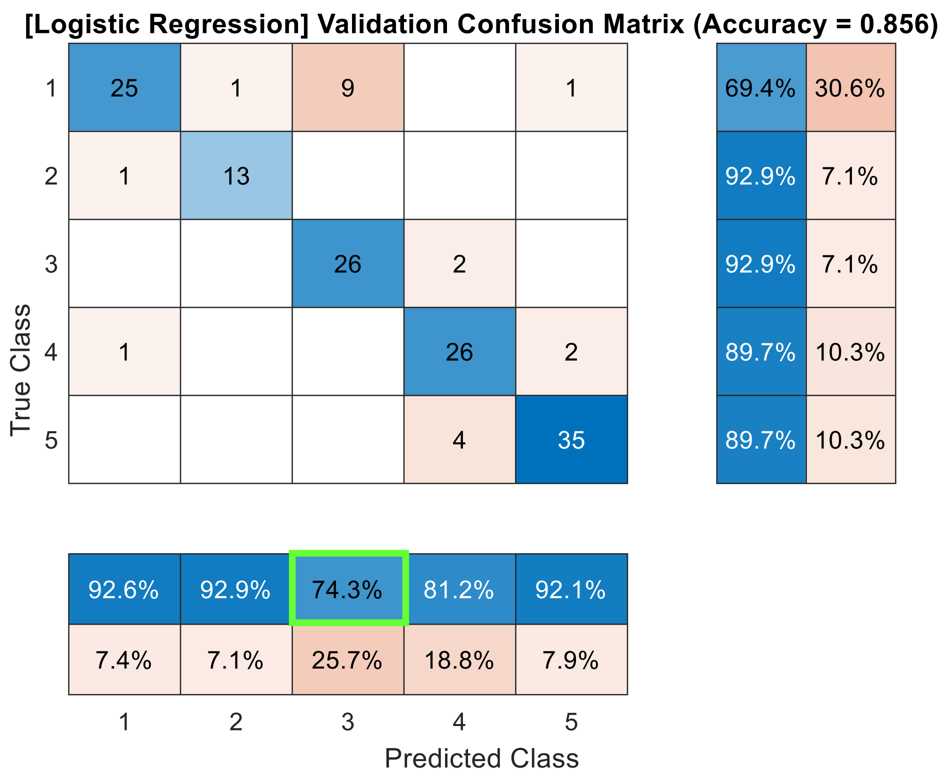
Results : 2. Possible Root Cause





- **For K-Nearest Neighbor classifier, the algorithm was run with varying K from 1 to 20 in the increment of 1.**
  - **At K = 14, the highest accuracy of 0.760 was achieved.**
- **It can be noted that the KNN model predicts Class 5 (OSF: Overstrain Failure) well, but Class 3 (HDF: Heat Dissipation Failure) yields relatively low accuracy with 54.9% in confusion matrix.**

Results : 2. Possible Root Cause



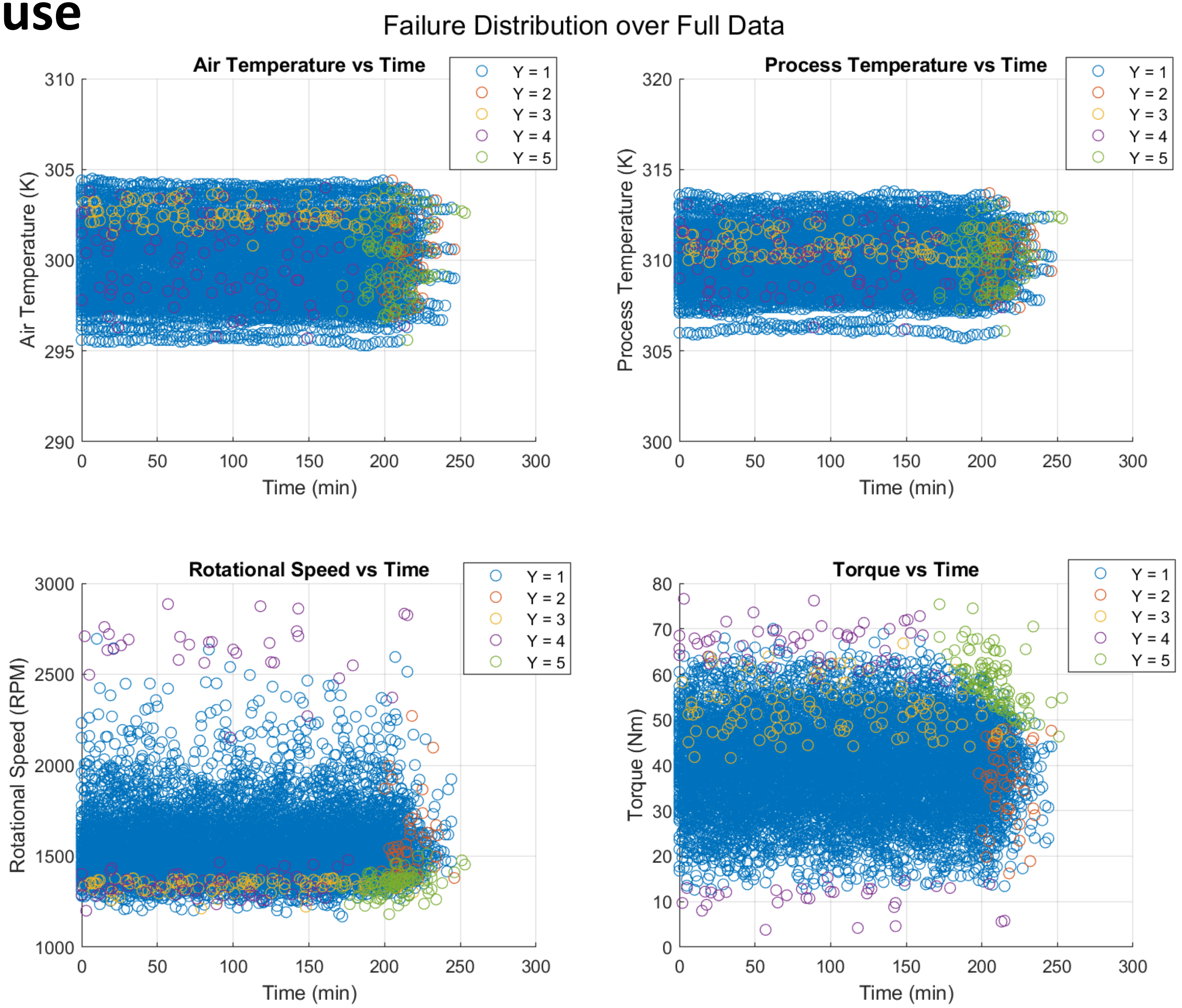
Algorithm	Accuracy
Naïve Bayes	**0.870**
Decision Tree	**0.582**
K-Nearest Neighbor	**0.760**
Logistic Regression	**0.856**

Prediction Performance on Possible Root Cause Analysis

- **For Logistic Regression Classifier, the algorithm was run with varying learning rate.**
  - **At the learning rate of 0.1, the highest accuracy of 0.856 was achieved.**
- **It can be noted that the LR Classifier predicts Class 5 (OSF: Overstrain Failure) well, but it yields relatively low accuracy in Class 3 (HDF: Heat Dissipation Failure) with 74.3% in confusion matrix.**
- **Therefore, considering all four algorithms, it has been determined that Naïve Bayes Classifier performed the best for Possible Root Cause Analysis.**

Results : 2. Possible Root Cause

- Thus, plotting all the possible root cause of the failure modes over the full dataset, as was expected in the beginning, the malfunctioning units reside in the "edges" of the accumulated regions (or in the "deviated regions") as shown in the plots right.
- Interestingly, it was communicated that Class 2, 3, and 4 were hard to predict by the machine learning models. (having a relatively low accuracy.)
- The possible sources of error of why Class 2, 3, and 4 were hard to predict are as follows:
- For Class 3 and 4, as shown in Air Temperature and Process Temperature plots, it can be noted that **Class 3 and 4 (Yellow and Purple) deeply reside in the accumulated regions (Class 1), making it harder for the models to distinguish the difference of Class 3 & 4 from Class 1.**
- For Class 2, as shown in Air Temperature, Process Temperature, and Rotational Speed plots, it can be noted that **Class 2 reside in the location that is too close to Class 1 and Class 5, making it harder for the models to distinguish the difference of Class 2 from Class 1 & 5.**



Conclusion

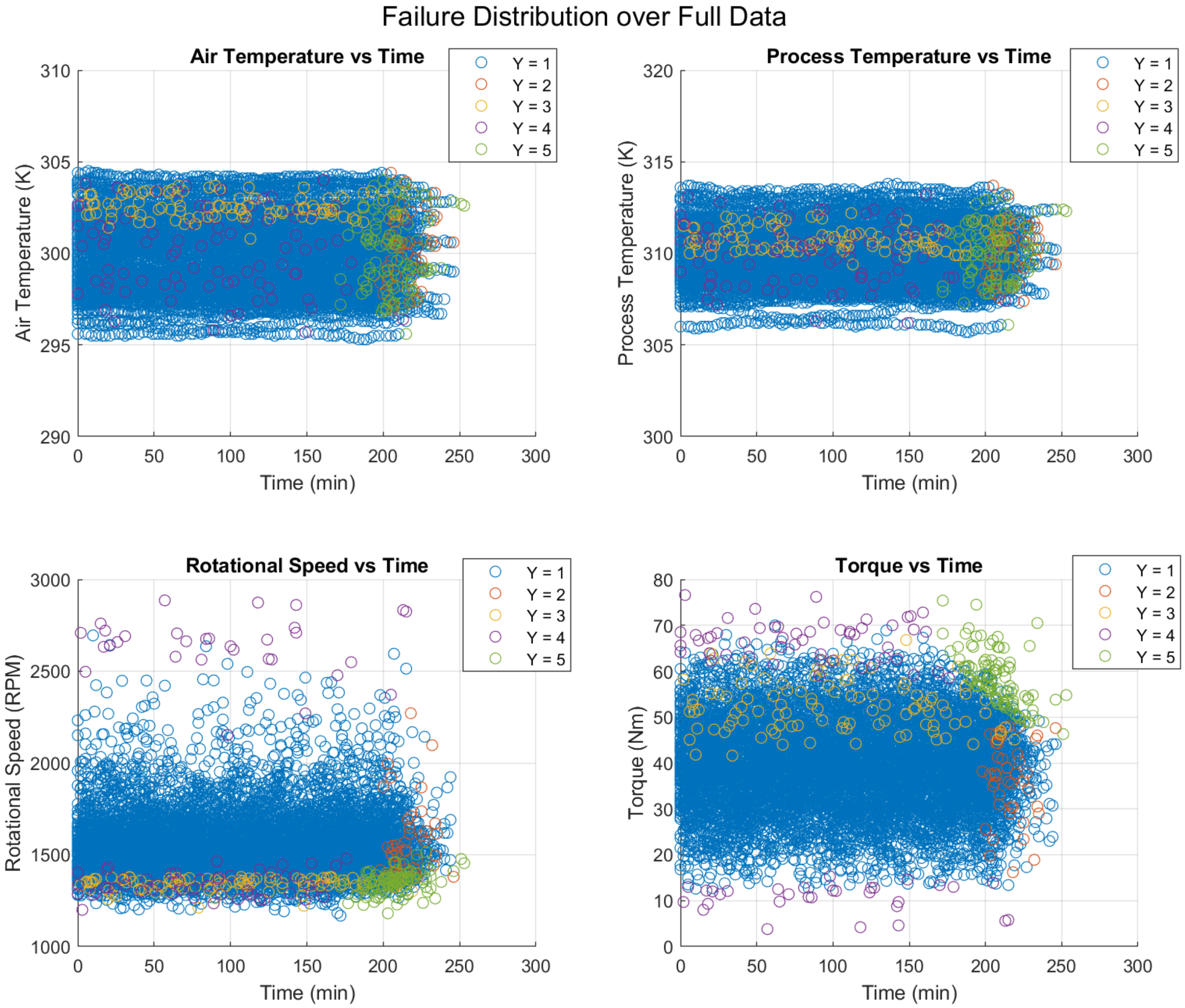
Algorithm	Accuracy (Remaining Useful Life)	Accuracy (Possible Root Cause)
Naïve Bayes	0.994	0.870
Decision Tree	0.501	0.582
K-Nearest Neighbor	0.867	0.760
Logistic Regression	0.992	0.856

- **Therefore, out of four algorithms to train the model for predicitve maintenance, it has been identified that Naive Bayes Classifier works the best for the current given dataset with an accuracy of 0.994 for Remaining Useful Life Analysis, and 0.870 for Possible Root Cause Analysis.**
- **The second algorithm that yields the best accuracy after Naive Bayes classifier is Logistic Regression Classifier – with proper time settings (learning rate), the performance of the LR could increase further.**
- **With the trained model on Reaming Useful Life Analysis, the equipment health can be monitored and determined to see if the maintenance should be performed or not.**
- **With the trained model on Possible Root Cause Analysis, when the failure occurs, this model will help the technicians on the site to choose the right set of maintenance actions to fix a failure.**

Conclusion

$$P(y|x) = \frac{P(y)\, P(x|y)}{P(x)} \approx \frac{P(y)\, \prod_{j=1}^{D} P(x_j|y)}{P(x)}$$

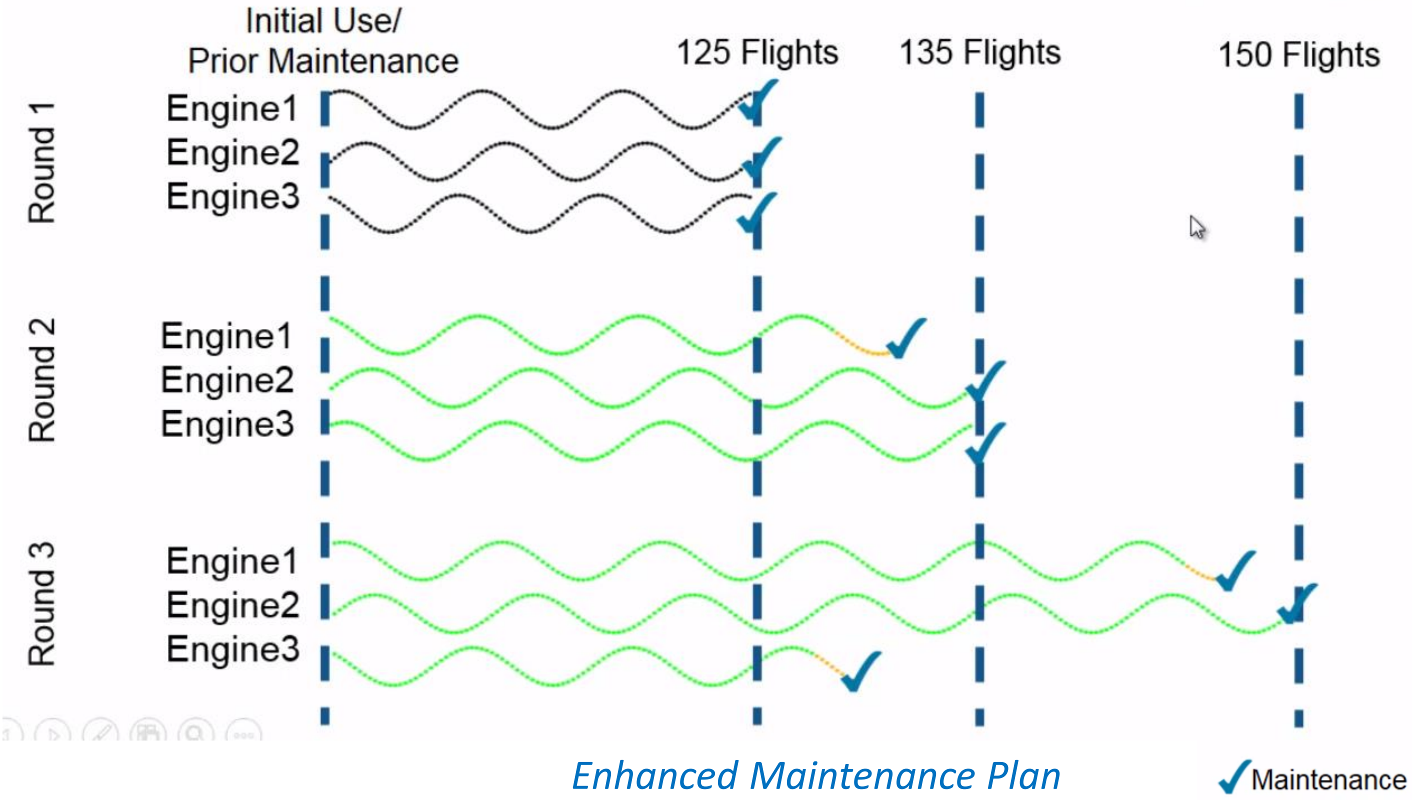
- **I believe Naïve Bayes Classifier worked the best for the given dataset because of its unique assumption driven from "Bayes' Theorem".**
- **Looking at the distribution of the data as shown right and considering the nature of the data sources – a mechanical component, it can be clear that the features (Air Temp, Process Temp, etc.) in the given data are highly correlated to one another, making it harder for the models to distinguish the difference between the classes as we have talked about earlier in the slides.**
- **Thus, we need a classifier that trains the model without considering the correlation between the features in the data.**
- **Naïve Bayes Classifier exactly does this by using Bayes' Theorem which assumes that the value of a particular feature is independent of the value of any other feature. (It is a strong (thus, naïve) independence assumption between the features.)**
- **And thus, when training the model with Naïve Bayes Classifier for this specific dataset, the performance of such model will generally be better than the other machine learning classifiers.**



Conclusion

Image Source: MathWorks [4]

- **Now, with the trained model, the predictive maintenance system can be implemented.**
- **As shown in the picture right, Round 1 represents the maintenance plan without implementing the predictive maintenance system. As shown, it is required to perform the maintenance every 125 flights. However, this could be still costly for the airline company. Thus, it is desired to implement the predictive maintenance to reduce (optimize) the cost of the maintenance.**
- **Round 2 represents the maintenance plan after implementing the predictive maintenance, the performance/condition of the engine will be monitored, and if it is in "long" condition (green), indicating that the engine still has long remaining useful life until failure, the regular maintenance schedule can then be postponed and extended to every 135 flights, saving the cost of maintenance. If one of the engines shows the "medium" condition (yellow), indicating that the engine's remaining useful life has been reduced, then the maintenance should be performed regardless of the engine's current number of flights.**
- **This way, as shown in Round 3, maintenance can be performed only when it is necessary and when the specific conditions are met, helping us to reduce (optimize) the cost of the maintenance, and increase the productivity of the equipment.**



Enhanced Maintenance Plan

Image Source: Google

Conclusion

- Like this, the benefits that predictive maintenance brings to the business are huge. It leads to…
  - Major Cost Savings (EX: Lower costs on maintenance operations)
  - Increased Availability of Systems
  - Prolonged Equipment Life
  - Reduced Downtime
  - Increased Production Capacity
  - Enhanced Safety

- Predicative Maintenance promises…[1]
  - 20 – 50% Reduction in time required to plan the maintenance.
  - 10 – 20% Increase in equipment uptime and availability.
  - 5 – 10% Reduction in overall maintenance cost.

Image Source: Google

Future Work

- It is highly recommended to explore the data refining technique. Most of time, the refinement of data increases the performance of any algorithm.
- For the given dataset, there was high imbalance in the distribution. Therefore, obtaining more data for other missing classes to balance the dataset would highly increase the model performance.
- Moreover, a self-tuning machine learning technique is also highly recommended to implement the model on the embedded system.
- Training & comparing with other various machine learning techniques would also widen the perspective and help the model selection.
- **Lastly, for Remaining Useful Life Analysis, if the performance is low for the urgent classes, a cost matrix can be implemented to put more emphasis on the urgent class.**

Thank you

Citations / Resources

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