Integrating Artificial Intelligence Process Reliability Operations

By Matthew Harper

Moore’s Law

- Every year or two, the capacities of computers have approximately doubled inexpensively. This remarkable trend often is called Moore’s Law, named for the person who identified it in the 1960s, Gordon Moore, co-founder of Intel—one of the leading manufacturers of the processors in today’s computers and embedded systems.
- Computer processing is increasing exponentially and becoming less expensive to manufacture.
- Positive slope on logarithmic graph is illustrates exponential growth.

Quantum Computing

- The “quantum computers” now under development theoretically could operate at 18,000,000,000,000,000,000 (18 “exa”) times the speed of today’s “conventional computers”!

- This number is so extraordinary that in one second, a quantum computer theoretically could do staggeringly more calculations than the total number of calculations performed by all computers since the world’s first computer appeared.

[3] Deitel, P.J., & Deitel, H.M. (2022). *Intro to Python for Computer Science and Data Science*: Learning with AI, Big Data, and the Cloud.

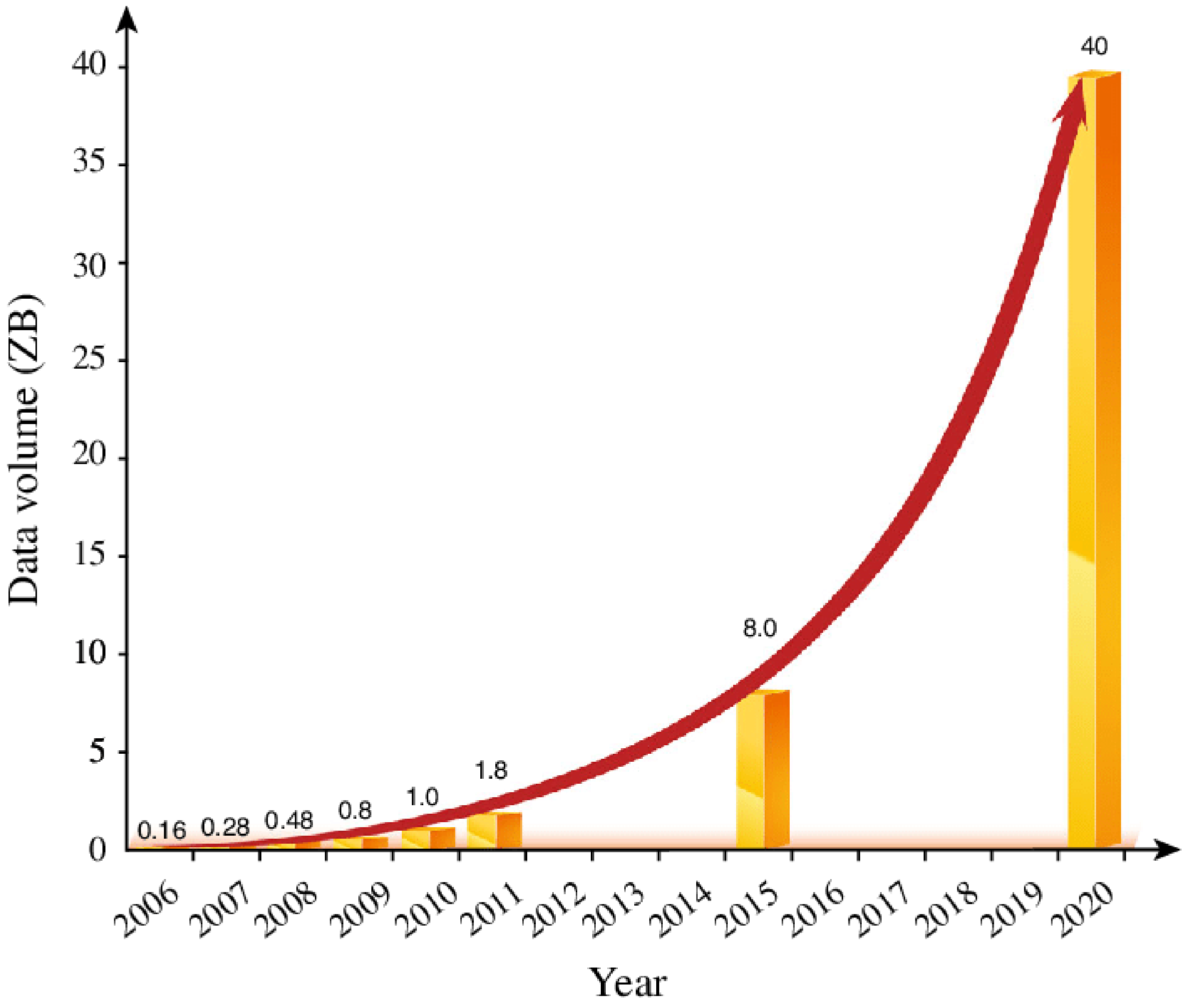
Big Data & Information

- Data & information will be so rapid in the near future that industry and society will not only need AI it will require AI to process all of the available data.

- According to IBM, approximately 2.5 quintillion bytes (2.5 exabytes) of data are created daily.

- 90% of the world’s data was created in the last two years!

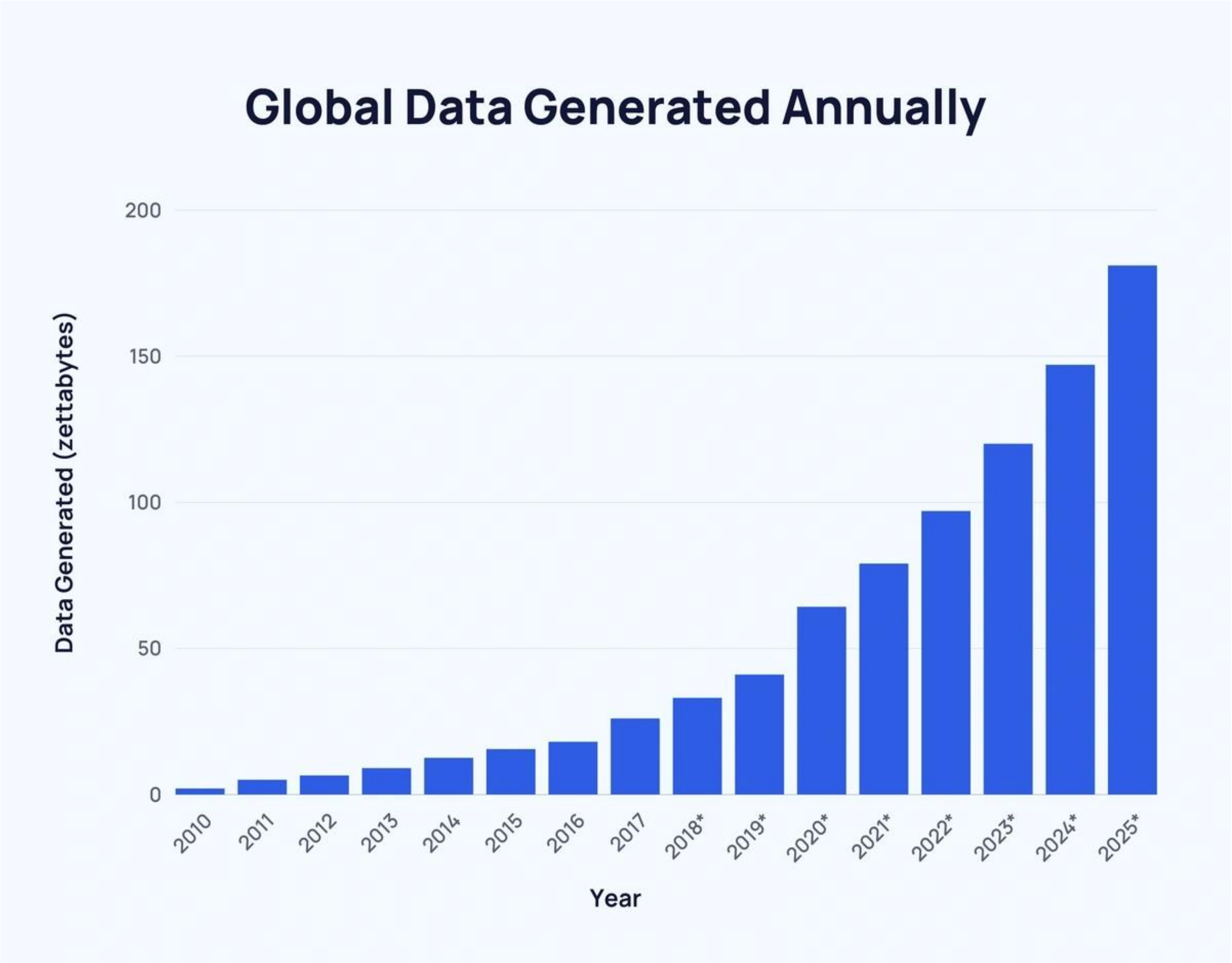
- According to IDC, the global data supply will reach 175 zettabytes (equal to 175 trillion gigabytes or 175 billion terabytes) annually by 2025.



[4] Dahdouh, Karim & Dakkak, Ahmed & Oughdir, Lahcen. (2017). Integrating Big Data technologies in a dynamic environment EIAH dedicated to e-learning systems based on cloud infrastructure. 1-7. 10.1145/3167486.3167506.

Modern Process Control in the Chemical Industry

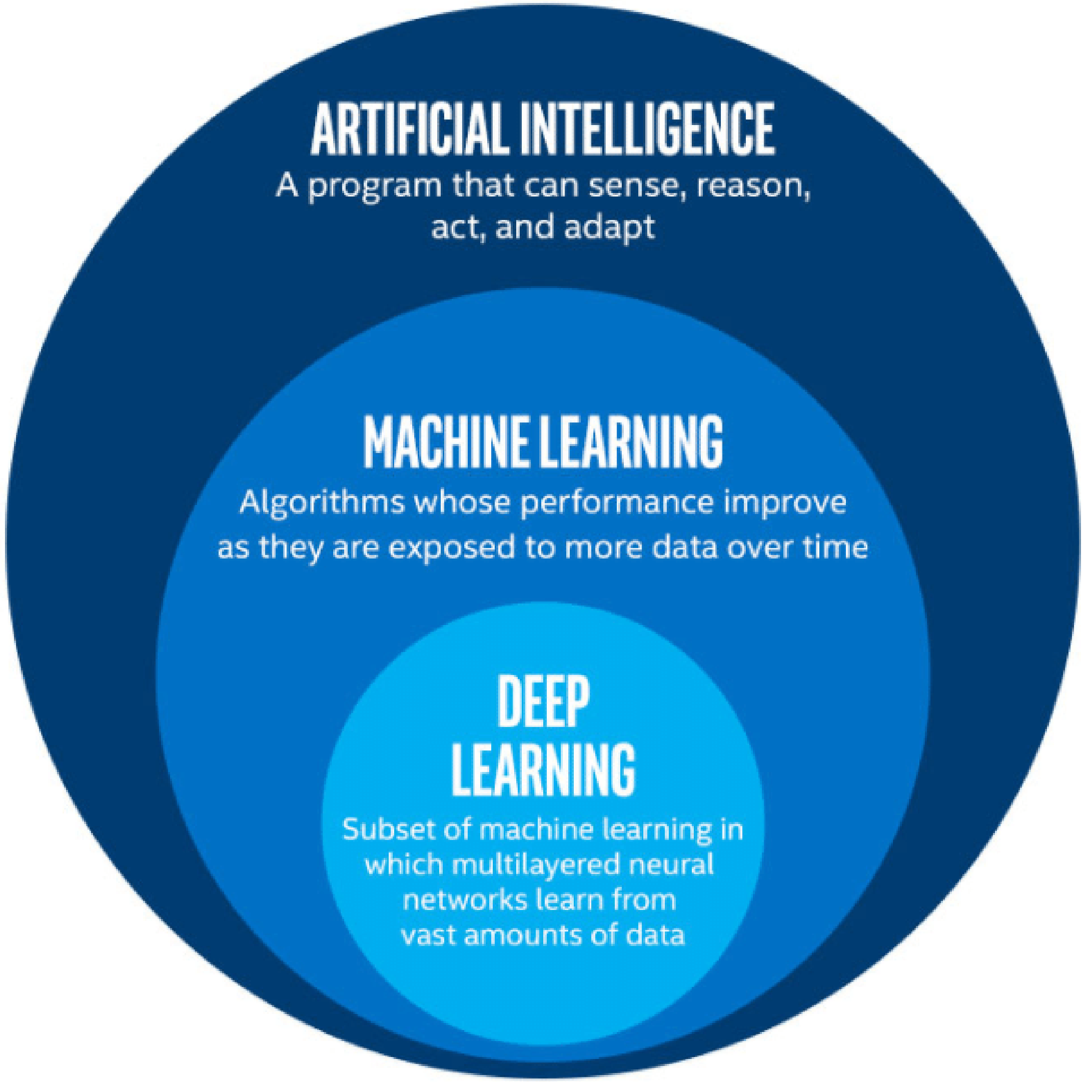
- When we think about how data has increased in modern times this is no surprise to operations involving process control, process safety, and reliability in a chemical processing plant.
- We now utilize many smart devices such as instruments, valve positioners, programmable controllers, rotating equipment monitoring devices, electrical motor and switchgear monitoring systems, safety alarms and safety systems, and much more.
- All of these devices continually produce a stream of data much of which is never even seen by the human eye.
- According to current estimates, only a very small percentage of new data generated in the "big data" era is actually seen by humans.
- Approximately less than 0.5% of all data is analyzed and used, meaning the vast majority of data is unseen by human eyes.
- Artificial intelligence and machine learning can assist reliability and plant operations by processing large amounts of copious or abundant data.



What is Artificial Intelligence or Machine Learning?

- Artificial Intelligence (AI) is a broader concept that refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. This includes tasks like learning, reasoning, problem-solving, perception, and language understanding.

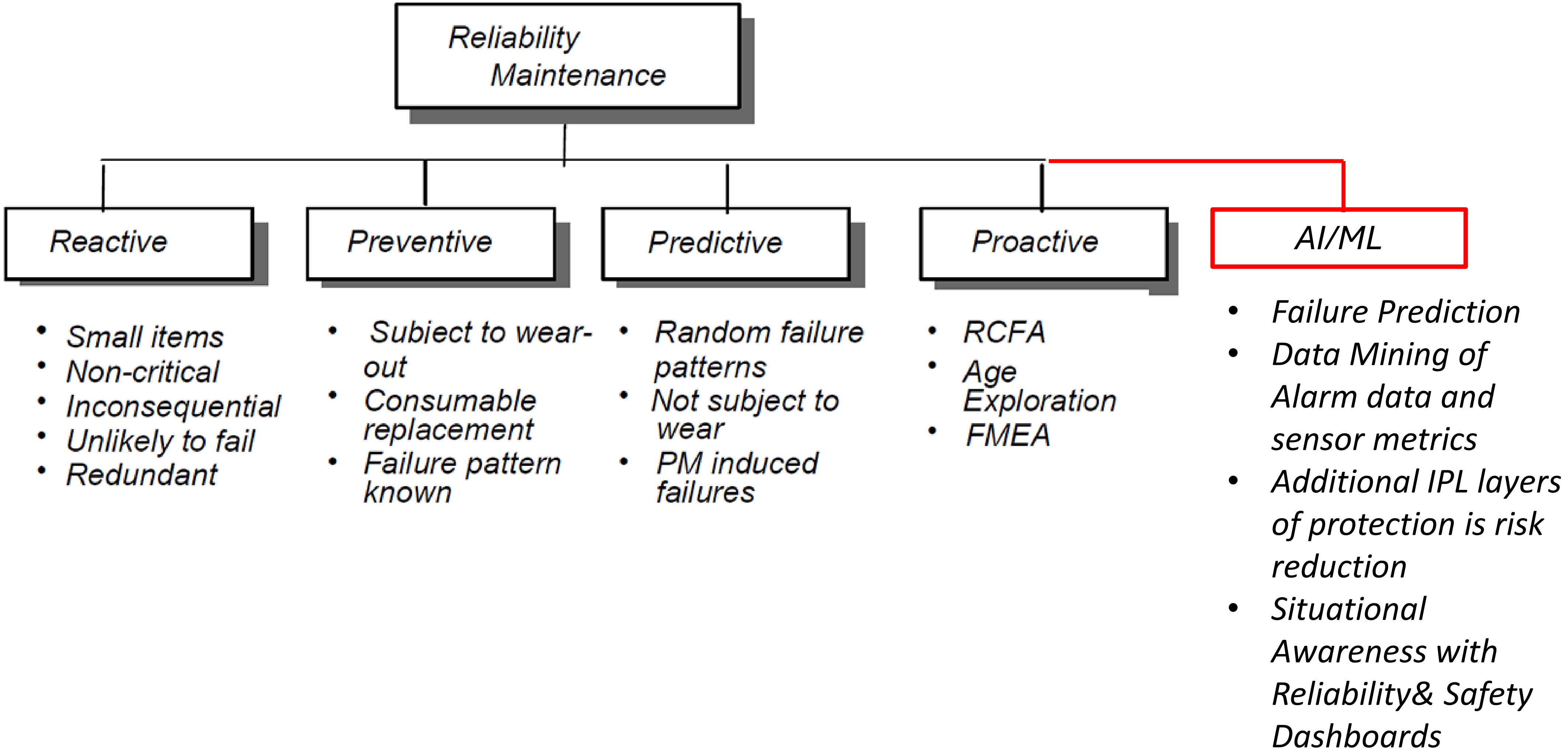
- Machine Learning (ML) is a subset of AI that focuses on the idea that machines can learn from data without being explicitly programmed. It involves algorithms that allow computers to identify patterns in data, make predictions, and improve their performance over time.



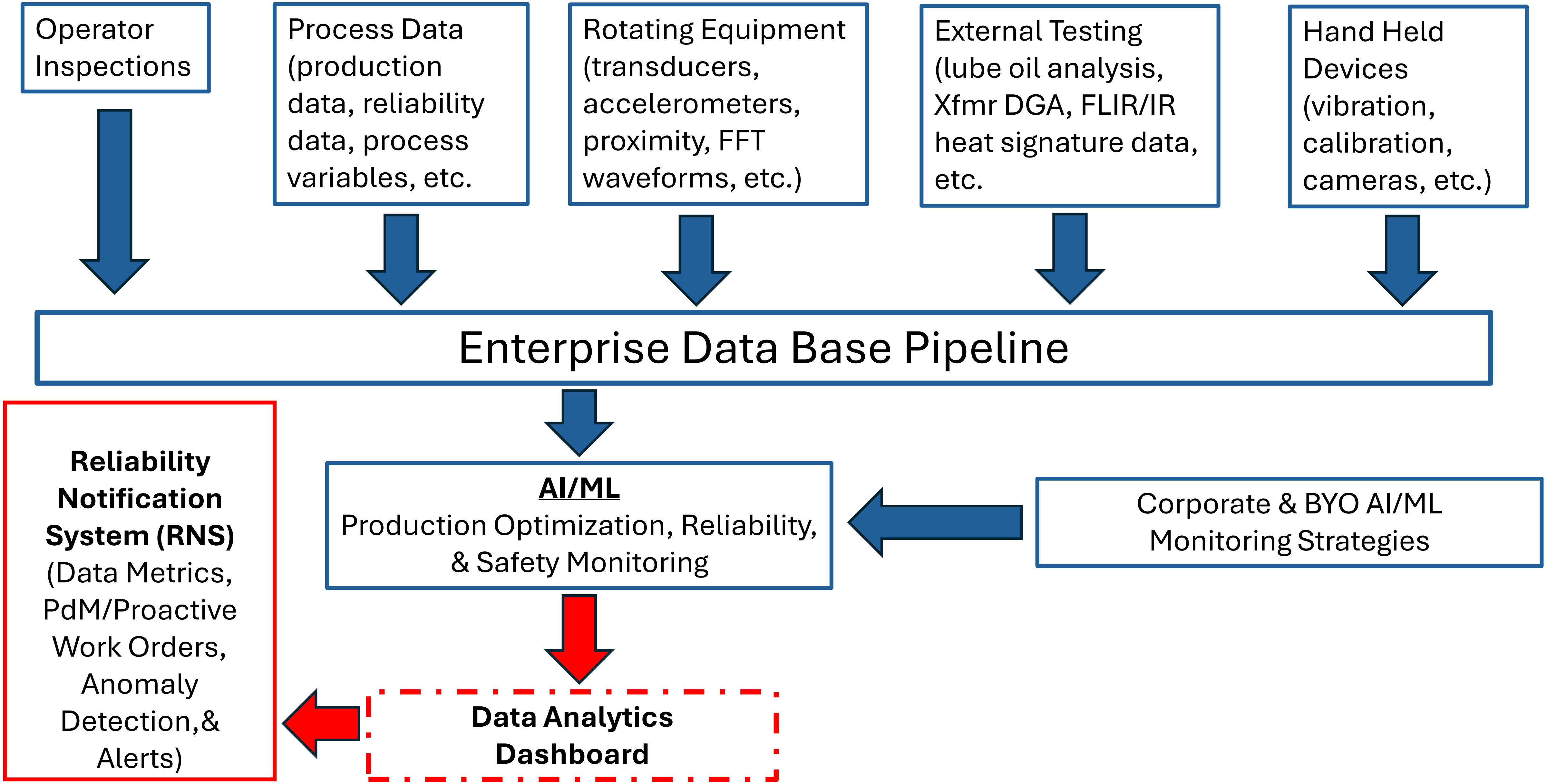
Integrating AI/ML Models into the Reliability Centered Maintenance Process

- Reliability Centered Maintenance
- Reliability-Centered Maintenance (RCM) is a structured approach to maintenance that focuses on maintaining the functions of a system or asset.
- RCM seeks to mitigate risk through the following strategies:
  - Predictive maintenance tasks
  - Preventive Restoration or Preventive Replacement maintenance tasks
  - Detective maintenance tasks
  - Run-to-Failure

AI/ML Integrated into RCM Work Process



AI/ML Data Pipeline and Work Process



How can Predictive AI/ML and Data Analytics monitor asset performance and Increase Reliability?

Key Concept: By leveraging the power of AI and ML, predictive analytics enables organizations to proactively and predictively manage their assets, optimize maintenance strategies, and achieve significant improvements in overall asset performance, safety, and reliability.

Convergence of Analytics and AI

In recent years, we have seen a convergence of analytics and artificial intelligence [1].
Major differences between analytics and AI:

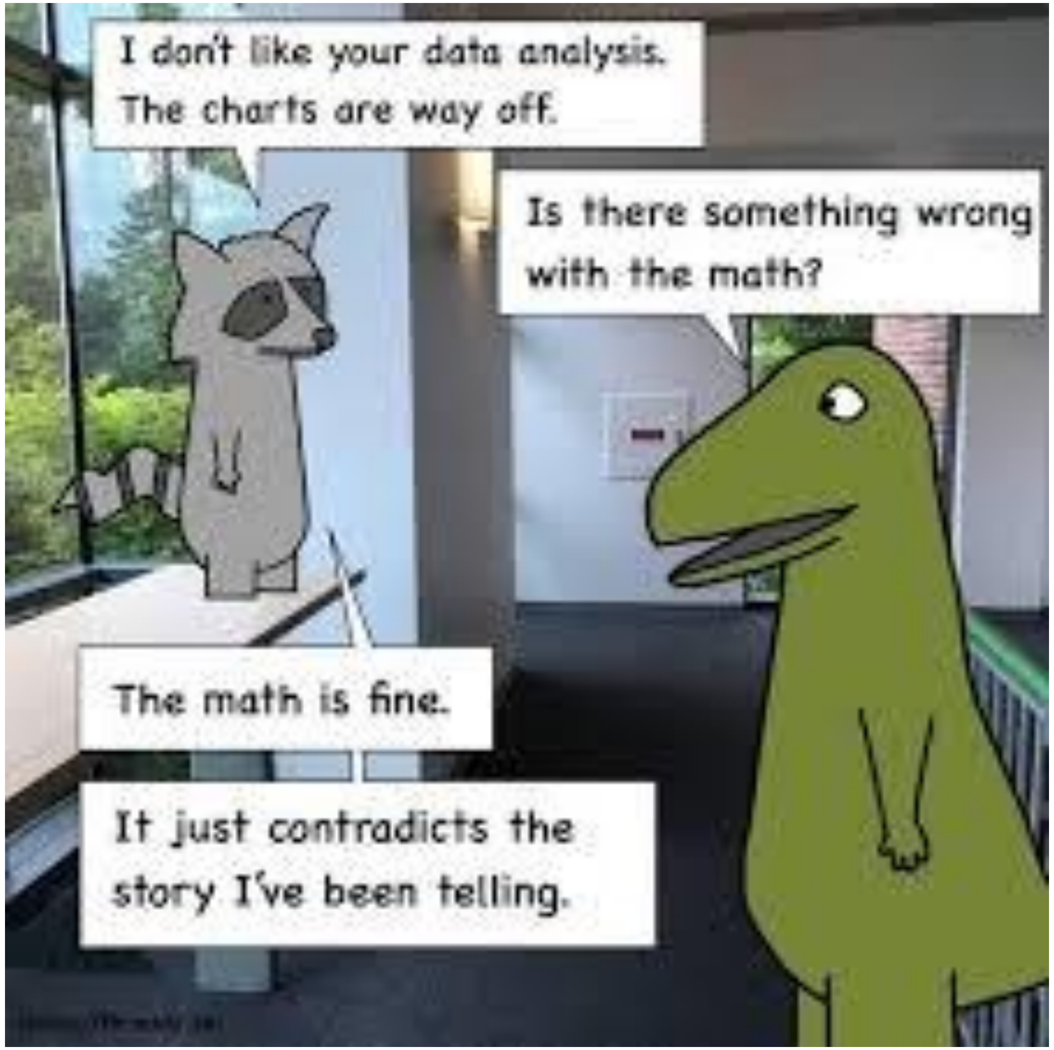
Analytics process using historical data to develop insights.
Artificial intelligence on the other hand is defined as behavior of a machine deemed intelligent (i.e. if performed by a human being would be deemed intelligent).

Many reasons to combine the two :

Results of analytics may not be insightful enough.
Problems may become complex requiring more robust techniques such as deep learning.
Data may and is often incomplete making many statistical approaches less ideal.
Unsupervised and Supervised models can learn data sets in Artificial Intelligence.

- *Data analytics* or simply "analytics" is the process of developing actionable decisions for actions based on insights generated from historical data [2].
- Three (3) levels of analytics:
  - Descriptive – What happened?
  - Predictive – What will happen?
  - Prescriptive – What should happen?

- *Predictive Analytics* aims to determine what is likely to occur in the future [1].
- Based on statistical and data mining techniques.
- Data mining is a business process for exploring large amounts of data to discover meaningful patterns, insights, and rules [2].
- *Predictive analytics* is widely held to be the most actionable form of business intelligence [1].
- According to IBM, "If business can be considered a numbers game, predictive analytics is the way the game is best played and won".
- Using the term analytics synonymously with data analytics and predictive analytics as in this presentation; importance to understand the differences.



Predicitve Analytics Process

1. **Data Collection and Integration:**

- **Sensor Data:** Collects data from various sensors attached to assets, such as temperature, vibration, pressure, and energy consumption.
- **Operational Data:** Gathers information from operational systems like SCADA, DCS, PLC.
- **Historical Data:** Utilizes historical maintenance records and asset performance data.

2. **Data Preprocessing and Feature Engineering:**

- **Data Cleaning:** Removes noise, inconsistencies, and outliers from the collected data.
- **Feature Extraction:** Identifies relevant features or variables that significantly impact asset health and performance.
- **Data Transformation:** Converts data into suitable formats for analysis, such as normalization and scaling.

Predictive Analytics & Data Modeling

3. Predictive Modeling:

- **Machine Learning Algorithms:** Employs various ML algorithms like time series analysis, regression, and classification to build predictive models.
- **Anomaly Detection:** Identifies unusual patterns or deviations from normal behavior that may indicate potential failures.
- **Remaining Useful Life (RUL) Prediction:** Estimates the remaining lifespan of assets based on historical data and current performance.

4. Predictive Insights and Actionable Recommendations:

- **Failure Prediction:** Predicts potential failures before they occur, allowing for timely maintenance interventions.
- **Optimized Maintenance Scheduling:** Determines optimal maintenance schedules based on predicted failure probabilities and asset criticality.
- **Prescriptive Maintenance:** Provides specific recommendations for maintenance actions, such as part replacement or adjustments.

Real-Time Monitoring & Benefits

5. Real-time Monitoring and Alerting:

- **Continuous Monitoring:** Tracks asset performance in real-time using sensor data and model predictions.
- **Automated Alerts:** Sends timely alerts to maintenance teams when anomalies or potential failures are detected.

Benefits of Predictive Analytics for Asset Performance:

- **Reduced Downtime:** Proactive maintenance minimizes unplanned outages.
- **Increased Asset Lifespan:** Optimized maintenance practices extend the life of assets.
- **Improved Operational Efficiency:** Efficient resource allocation and streamlined maintenance processes.
- **Cost Savings:** Reduced maintenance costs and increased productivity.
- **Enhanced Safety:** Proactive identification of potential hazards.
- **Data-Driven Decision Making:** Informed decision-making based on accurate predictions and insights.

Case Example - Artificial Neural Network Model Utilized for Instrument Failure Prediction

- Instrument sensor data set containing 124, 495 devices with 12 features for monitoring.
- Classification Machine Learning Model using Multi-Layer Perceptron ANN model.
- Two (2) class categories of Failure and No Failure predicted.

1	date	device	metric1	metric2	metric3	metric4	metric5	metric6	metric7	metric8	metric9	failure
124487	11/2/2015	Z1F0GB8A	92823192	0	0	0	9	357127	0	0	0	0
124488	11/2/2015	Z1F0GE1M	2.23E+08	0	0	0	10	349826	0	0	0	0
124489	11/2/2015	Z1F0KJDS	79883648	0	0	0	11	358121	0	0	0	0
124490	11/2/2015	Z1F0KKN4	2.19E+08	0	0	0	9	353525	0	0	0	0
124491	11/2/2015	Z1F0MA1S	18310224	0	0	0	10	353705	8	8	0	0
124492	11/2/2015	Z1F0Q8RT	1.73E+08	96	107	4	11	332792	0	0	13	0
124493	11/2/2015	Z1F0QK05	19029120	4832	0	0	11	350410	0	0	0	0
124494	11/2/2015	Z1F0QL3N	2.27E+08	0	0	0	12	358980	0	0	0	0
124495	11/2/2015	Z1F0QLC1	17572840	0	0	0	10	351431	0	0	70000	0
124496												
124497												

Case Example MLP Classification Model

Neural Network Instrument Failure Prediction Model

Dataset consist of 124,495 instrument devices and 12 features for model analysis.

Developed by Matthew Harper as a Proof of Concept for BYO LT

Case Example of Using Neural Networks in the Detection and Predictrion of Instrument Failures in a Plant environment.

In [2]:

```
from sklearn.neural_network import MLPClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
import pandas as pd

#Upload or load CSV file containing maintenance dataset 124,495 rows x 12 columns
path = "C:\\Users\\harpe\\my_desktop_stuff\\_Resume\\LyondellBassel\\AI_ML Example\\predictive_maintenance_dataset.csv
data=pd.read_csv(path)
df=pd.DataFrame(data)
#print(df)

#Select the features for training and classification
X = df.iloc[:,[1,2,3,4,5,6,7,8,9,10]].values
y = df.iloc[:,[11]].values

# Generate a synthetic dataset
X, y = make_classification(n_samples=1000, random_state=1)

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)

# Create an MLP classifier
clf = MLPClassifier(hidden_layer_sizes=(100,), max_iter=1000, random_state=1)

# Fit the model to the training data
clf.fit(X_train, y_train)

# Predict the labels for the testing data
y_pred = clf.predict(X_test)

# Calculate the accuracy of the model
accuracy = clf.score(X_test, y_test)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.836
```

MLP Classification with Scikit Learn

- Read the CSV file into the pandas DataFrame
- Select the feature attributes into the X and y model variables with the iloc method.
- Generate a synthetic dataset for data diversity.
- Split data into train and test sets.
- Create the MLP classifier instance.
- Fit the model.
- Predict with the model.
- Analyze results and accuracy.

Model Results without Fine-Tuning

```
# Lets visualize the accuracy report
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

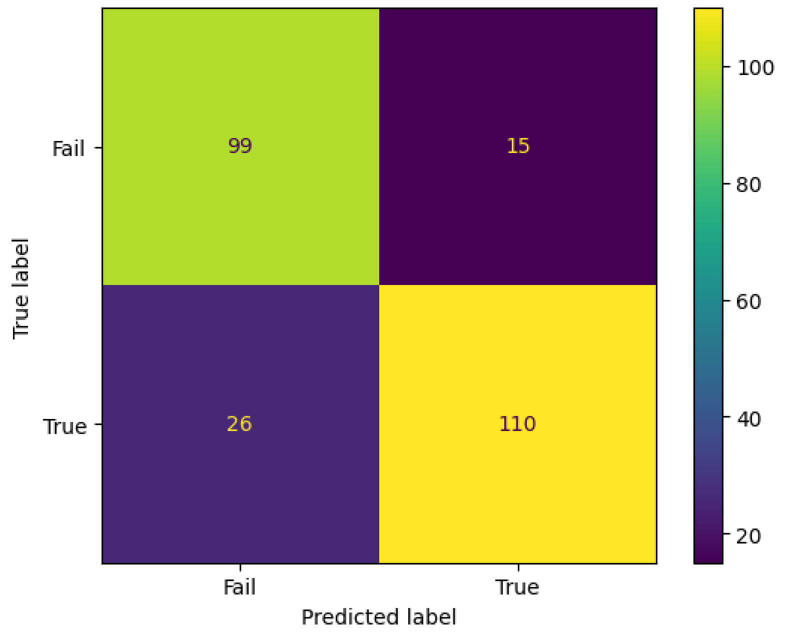
```
              precision    recall  f1-score   support

           0       0.79      0.87      0.83       114
           1       0.88      0.81      0.84       136

    accuracy                           0.84       250
   macro avg       0.84      0.84      0.84       250
weighted avg       0.84      0.84      0.84       250
```

Accuracy displays 84% for the initial model without fine-tuning the model parameters.
Challenges to MLP and Neural Networks
- Vanishing Gradients
- Over/Under Fitting
- Sensitivity
- Local Maxima/Minima

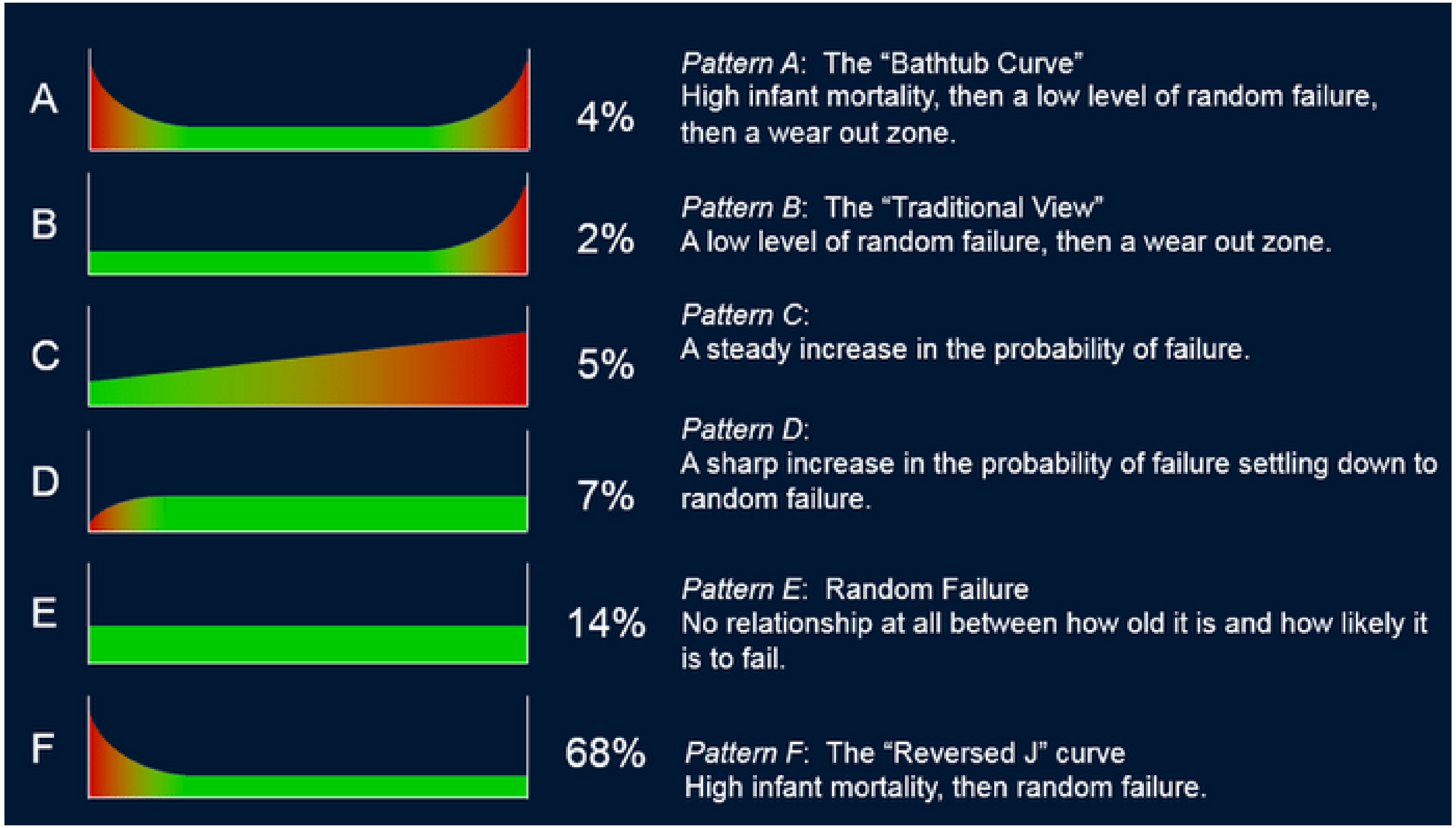
Confusion Matrix



By observing the confusion matrix we have the following results:

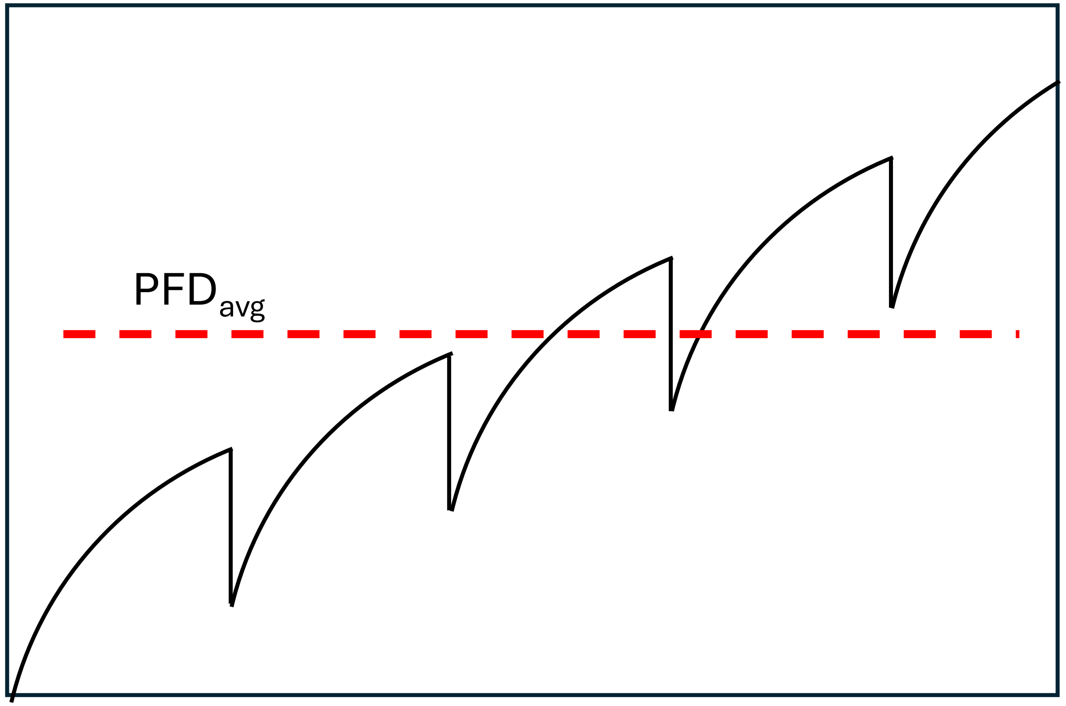
True Negative (TN) = 99, False Negative (FN) = 15
True Positive (TP) = 110, False Positive (FP) = 26

AI/ML for Equipment Failure Pattern Detection



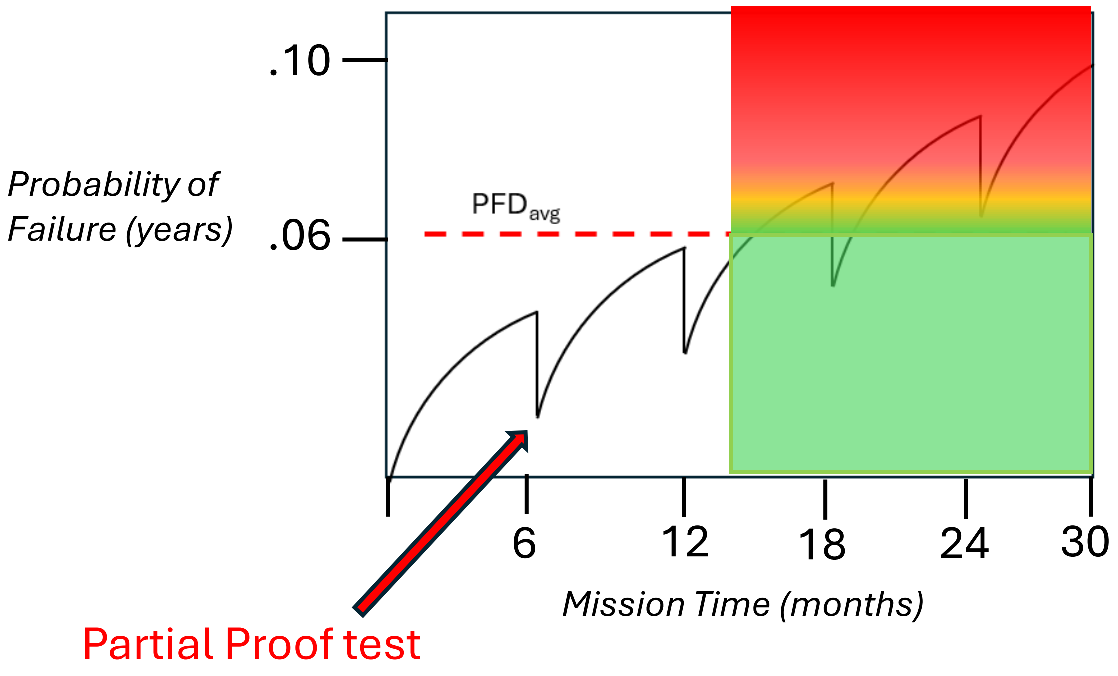
Additional Use Cases for AI/ML in Process Reliability

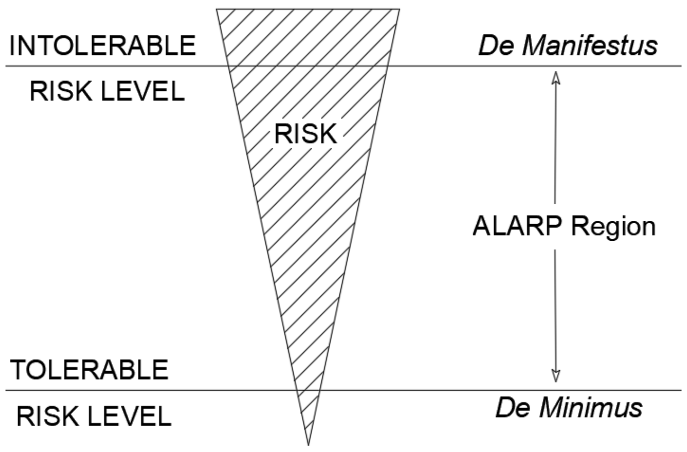
- Safety functions typically utilize the probability of failure on demand.



AI/ML as an Independent Protection Layer (IPL) and for monitoring safety integrity levels in real-time.

- Safety functions typically utilize the average of probability of failure on demand.
- This sometimes leave process operations vulnerable to failure and increases risk.





Questions AI/ML can help with?
1. What time of year or season is it? (Winter)
2. Has the Safety valve moved if so re-calculate the PFD in real-time.
3. What is the AI predicted failure and how does this compare to the PFD?

Thank You for Your Time