Automobile Engine Fault Diagnosis Using Machine Learning Method

School of Mechanical & Control Engineering

Handong Global Univ.

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Industrial AI & Automation
Project 1
Prof. Young-Keun Kim

21900416 An Gyeonheal

21900727 Jin Garam

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1. Proposal Review

1. Proposal Review

- Objective -

By **Developing a Model** that Outperforms those Implemented in **Existing Journals**,
Accurately **Identify** types of **Engine faults**, Providing Greater Speed and Precision in Engine Repairs.

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RESEARCH ARTICLE

EngineFaultDB: A Novel Dataset for Automotive Engine Fault Classification and Baseline Results

MARY VERGARA[1], LEO RAMOS[2,3], (Student Member, IEEE), NÉSTOR DIEGO RIVERA-CAMPOVERDE[4], (Member, IEEE), AND FRANCKLIN RIVAS-ECHEVERRÍA[3,5], (Senior Member, IEEE)
[1]Higher School of Engineering, Science and Technology, Valencian International University, 46002 Valencia, Spain
[2]Computer Vision Center, Universitat Autònoma de Barcelona, Bellaterra, 08193 Barcelona, Spain
[3]Kauel Inc., Houston, TX 77027, USA
[4]Grupo de Investigación en Ingeniería del Transporte (GIIT), Universidad Politécnica Salesiana, Cuenca 010105, Ecuador
[5]Escuela de Ingeniería, Pontificia Universidad Católica del Ecuador Sede Ibarra, Ibarra 100112, Ecuador

Corresponding authors: Mary Vergara (maryjosefina.vergara@professoruniversidadviu.com) and Leo Ramos (leo.ramos@kauel.com)

This work was supported by the Grupo de Investigación en Ingeniería del Transporte (GIIT) at the Universidad Politécnica Salesiana, Ecuador.

- Goal -

A machine learning model that diagnoses 4 types of defects
using 14 input variables.
Over the Journal F-1 Score (≥ 75.1%)

- Expected Effective -

By building a model capable of early **diagnosis** of **automotive defects**, expect positive effects on **time**, **cost**, and **safety**.

By Applying **Machine Learning**, Classification to Identify **Types of Engine Faults**.

Quickly Diagnose and resolve Engine Faults, Enabling Fast, and Efficient Repairs.

[1] Vergara, M., Ramos, L., Rivera-Campoverde, N. D., & Rivas-Echeverría, F. (2023). Enginefaultdb: a novel dataset for automotive engine fault classification and baseline results. *IEEE Access*, *11*, 126155-126171.

1. Proposal Review

- Data Sets Name-

EngineFaultDB (Supervised Learning)

<Engine Data Collection / Gas Analyzer Device>

- Acquisition -

DAQ, Gas Analyzer

- Input -

MAP, TPS, Force, Power, RPM,

Consumption(L/H),

Consumption(L/100), Speed, CO,

HC, CO2, O2, Lambda, AFR

- Output -

Fault type 0: Normal (16,000 entries)

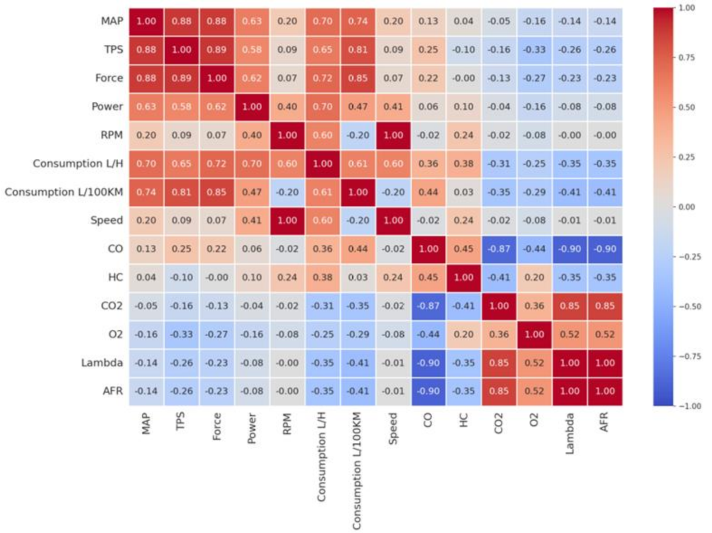
Fault type 1: Rich mixture - High Pressure, Incorrect Sensor, etc. (10,988 entries)

Fault type 2: Lean mixture – Low Pressure, Incorrect Sensor, etc. (15,000 entries)

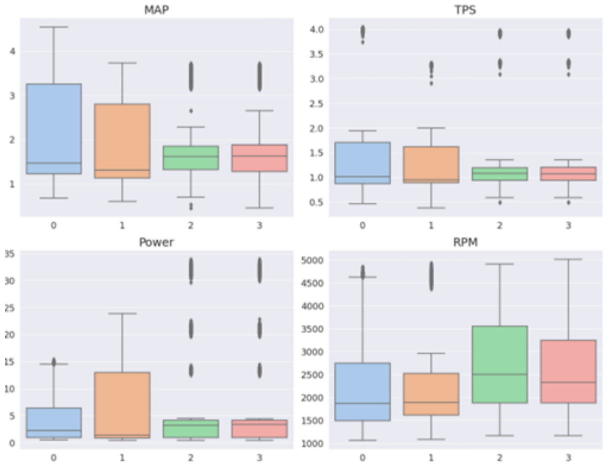
Fault type 3: Low Voltage – Worn Spark, Defective Coil, etc. (14,001 entries)

1. Proposal Review

- How Baseline Journal did-



1. Correlation Analyze



2. Tendency & Outlier

< Journal Performance >

Classifier	Accuracy	Precision	Recall	F1-score
LR	0.576	0.574	0.576	0.574
DT	0.750	0.750	0.750	0.750
RF	0.748	0.748	0.748	0.748
SVC	0.747	**0.768**	0.747	0.715
KNN	**0.751**	0.751	**0.751**	**0.751**
NB	0.394	0.370	0.394	0.353
Neural Net.	0.749	0.748	0.749	0.748

Best Model Performance of Baseline

→ 75.1%

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

3. Min-Max Scaling

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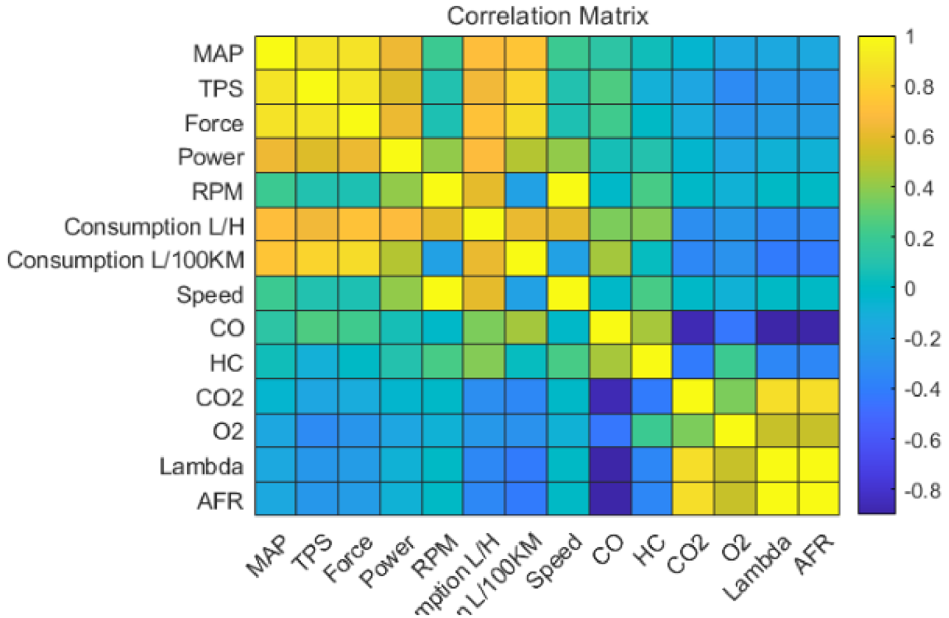
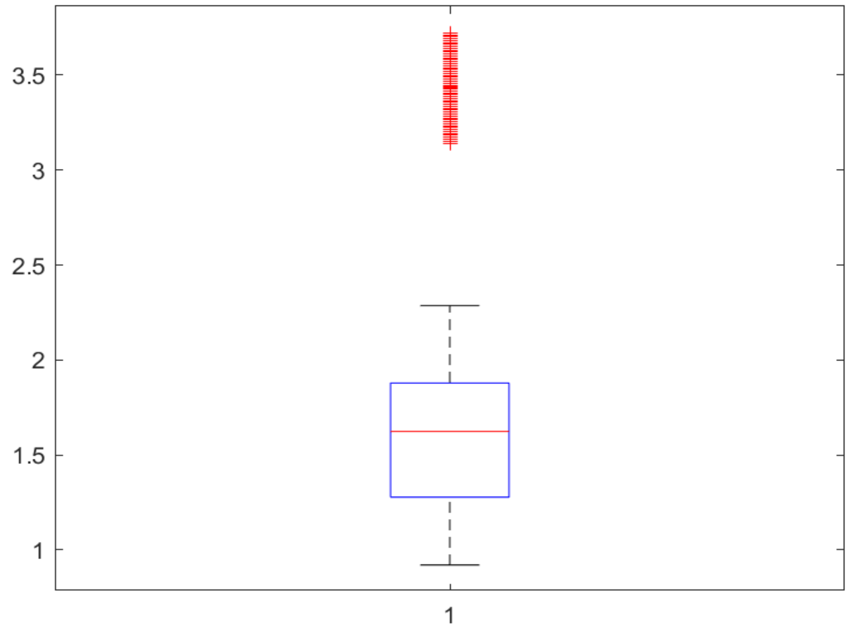
2. Baseline Journal Implementation

2. Baseline Journal Implementation

Following Journal’s Method in MATLAB



< Correlation Analysis >



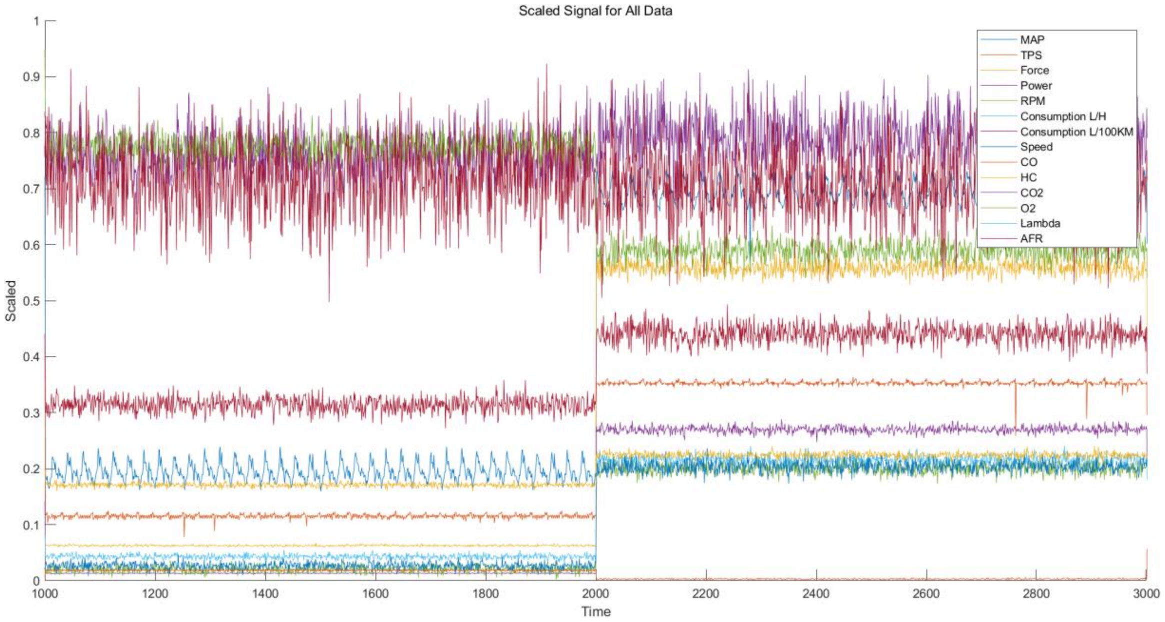
< Box Plot Analysis>

Identified trends using a **correlation table**.

A box plot examines the distribution of **outliers**.

2. Baseline Journal Implementation

Following Journal’s Method in MATLAB



< Min-Max Scaling >

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Accuracy	0.59	0.74	0.75	0.48
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F1 Score	0.57	0.75	0.76	0.48

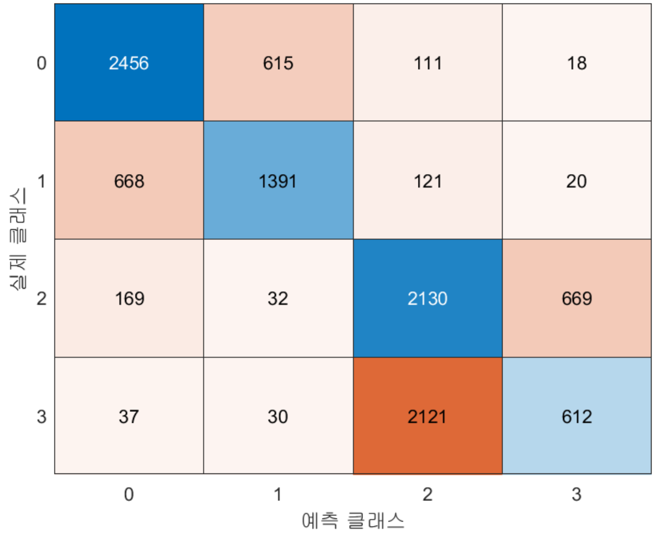
< Performance >

Applied **min-max scaling** to ensure effective training.

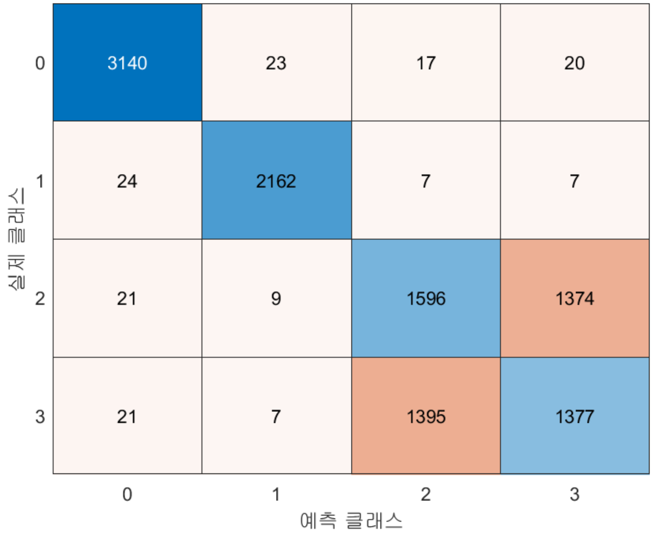
Achieved **similar outcomes** to those reported in the paper.

2. Baseline Journal Implementation

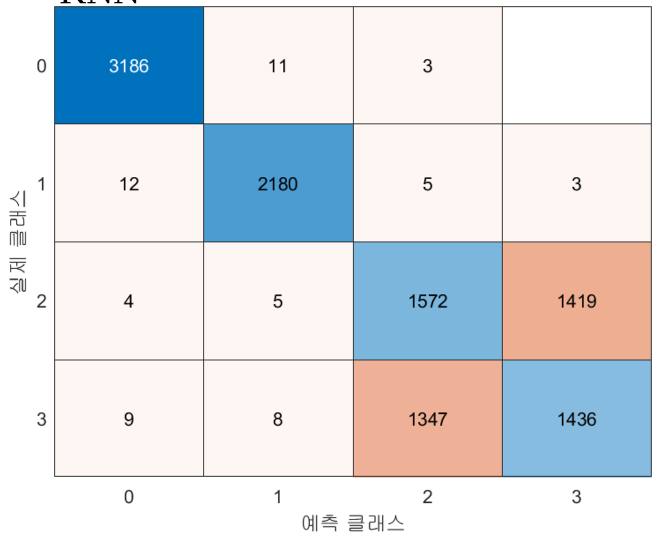
SVM



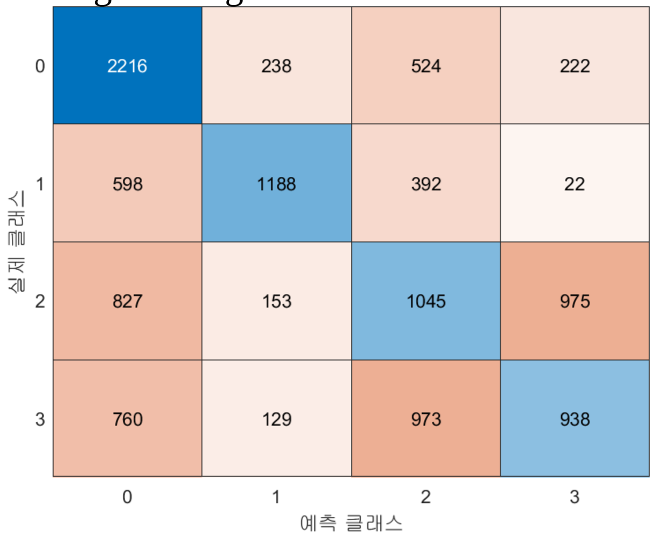
TREE



KNN



Logistic Regression



< Follow Journal Performance >

< Journal Performance >

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Almost Same!!

< Following Journal Performance >

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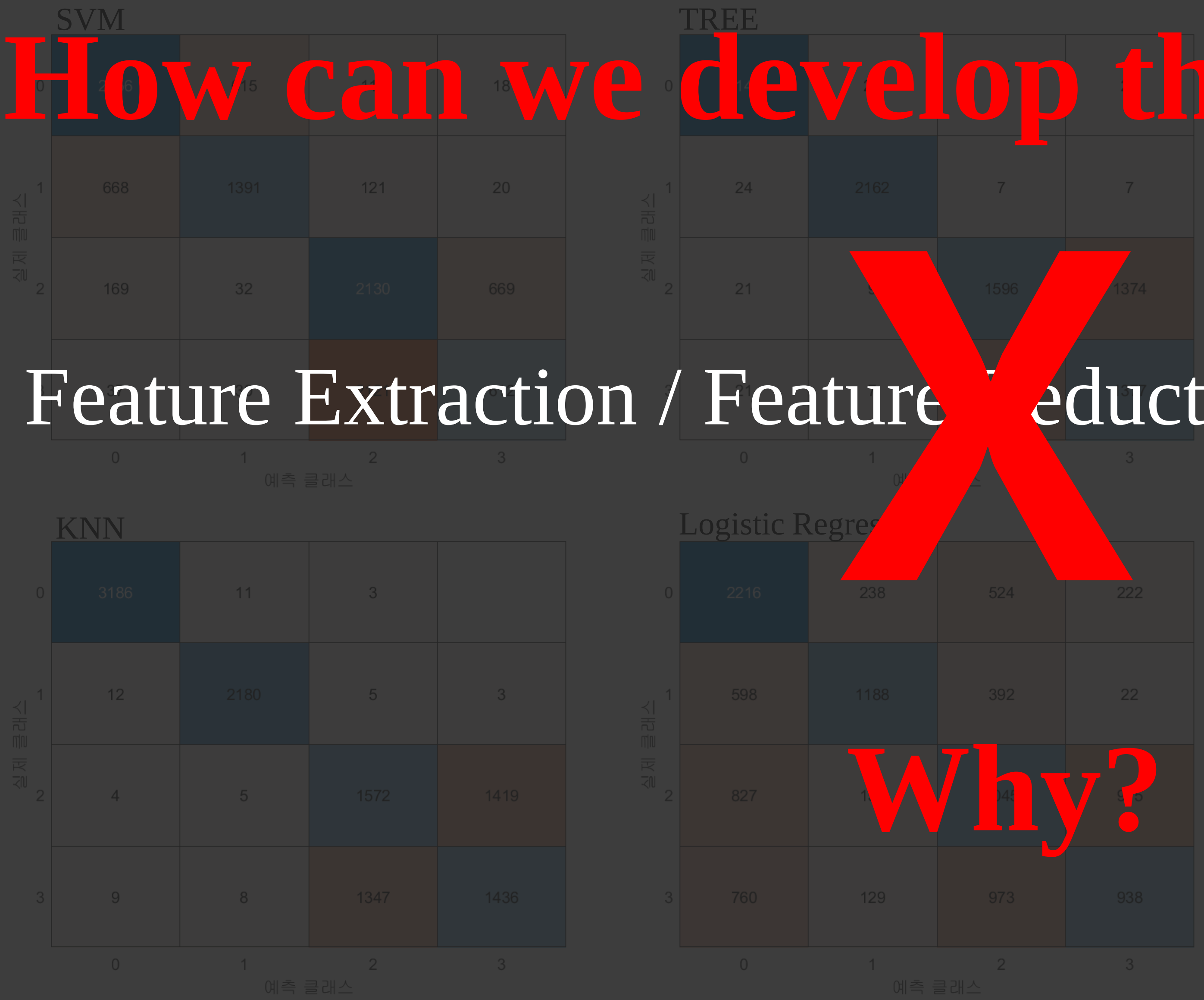
2. Baseline Journal Implementation

How can we develop the performance?



Classifier	Accuracy	Precision	Recall	F1-score
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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< Performance >

Feature Extraction / Feature Reduction / Selecting Features

X

	SVM	TREE	KNN	LR
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Why?

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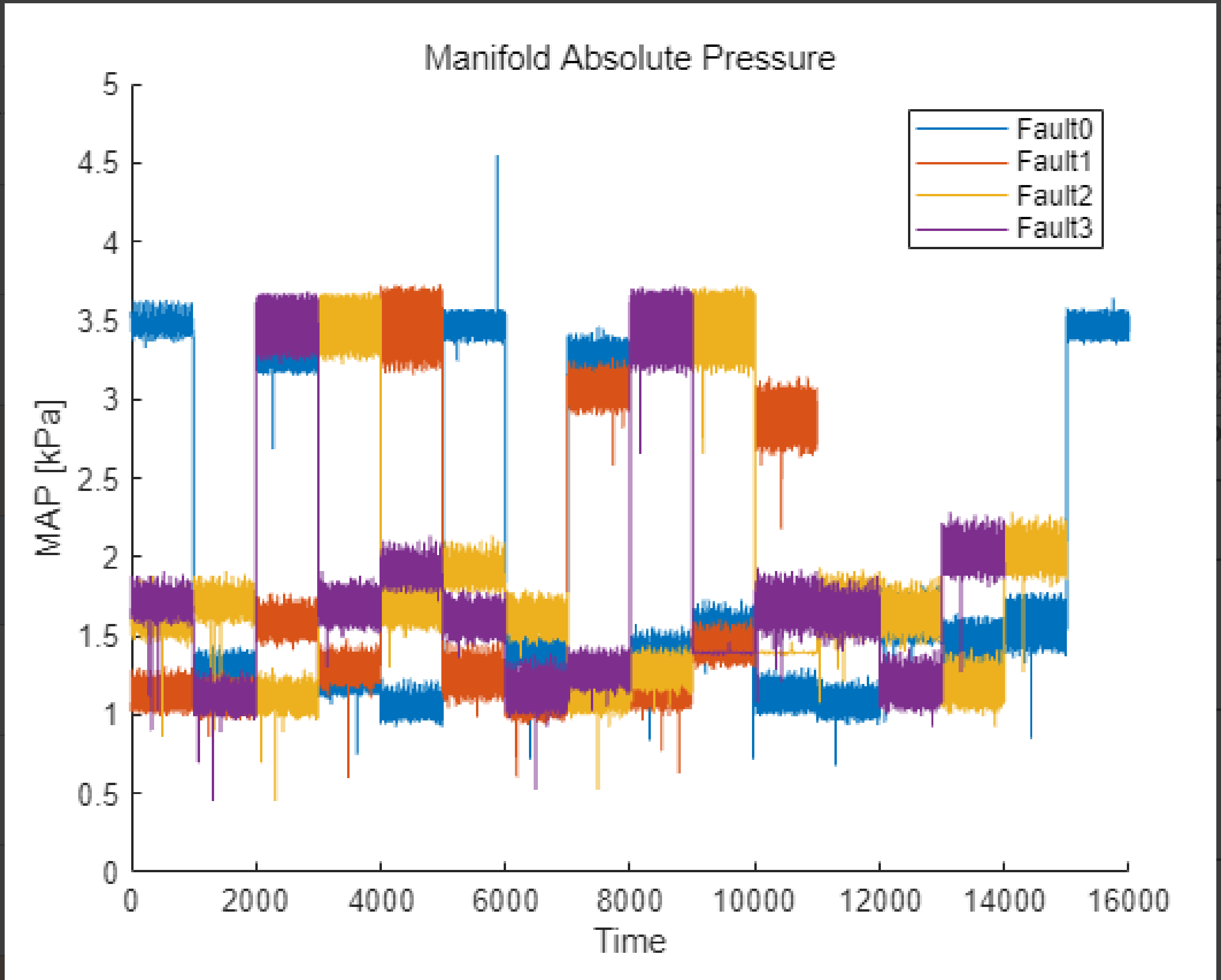
2. Baseline Journa



It’s Important to Focus on Data Distribution

→ Data Preprocessing is Necessary

3. Data Preprocessing

3. Data Preprocessing

Proposal Objective	New Objective
Preprocessing	Preprocessing (Scaling, Train & Test Data)
Feature Extraction Feature Reduction Selecting Features	?
Classification (SVM, Tree, KNN etc)	Classification (SVM, Tree, KNN etc)
Evaluation	Evaluation

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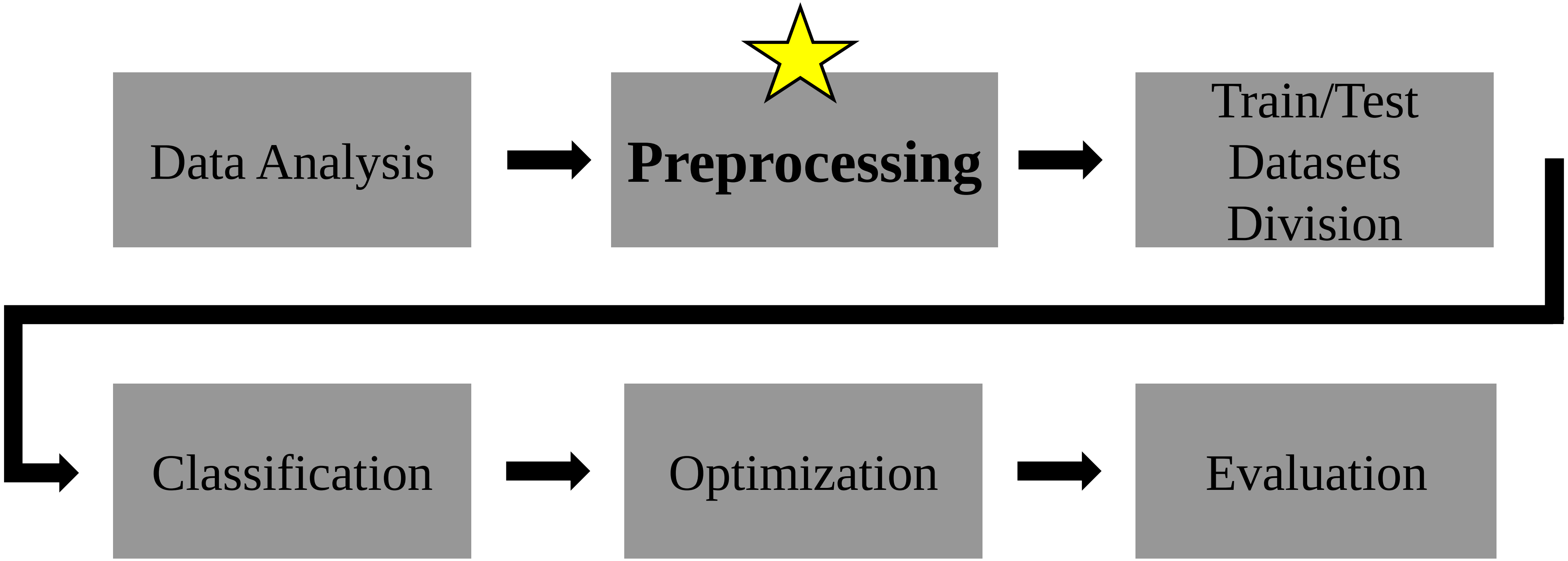
3. Data Preprocessing



3. Data Preprocessing

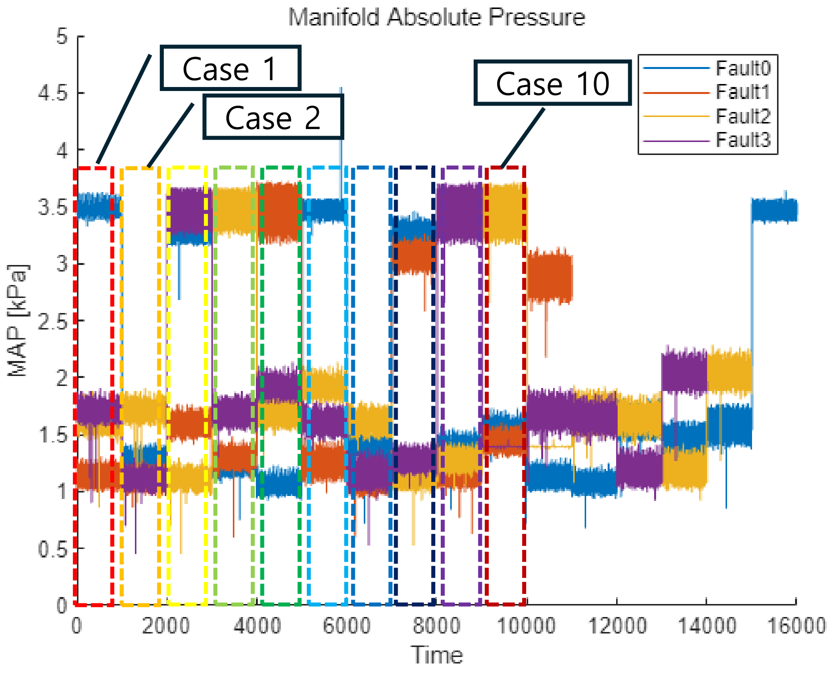
1. Selection

Fault type 0: Normal (16,000 entries) → (10,000 entries)

Fault type 1: Rich mixture - High Pressure, Incorrect Sensor, etc. (10,988 entries) → (10,000 entries)

Fault type 2: Lean mixture – Low Pressure, Incorrect Sensor, etc. (15,000 entries) → (10,000 entries)

Fault type 3: Low Voltage – Worn Spark, Defective Coil, etc. (14,001 entries) → (10,000 entries)



✓ **Equalize the number of normal and defective data**

✓ **10,000 = 1,000 × 10 Cases**

✓ **All the Preprocessing Method Should Apply to each Cases**

- Outlier Replacement
- Min-Max Scaling
- Filtering

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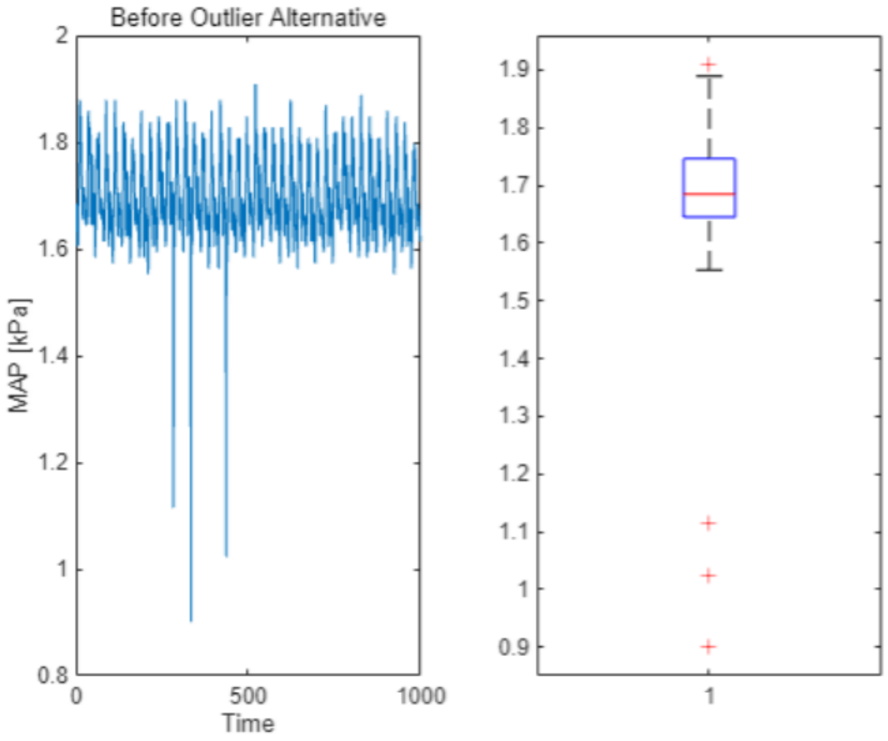
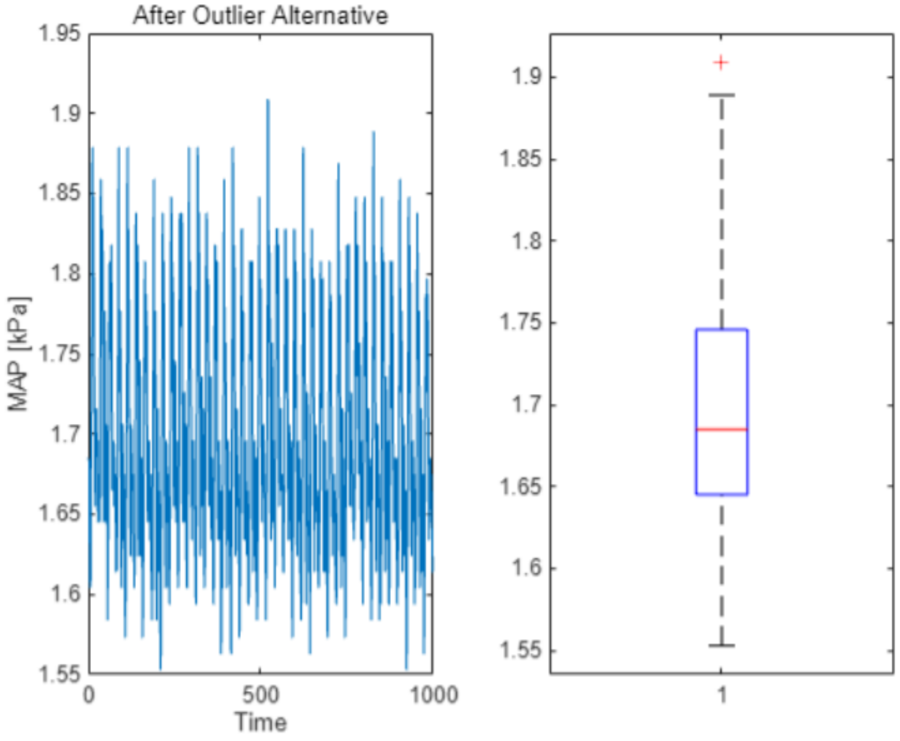
3. Data Preprocessing

2. Replacement Outlier

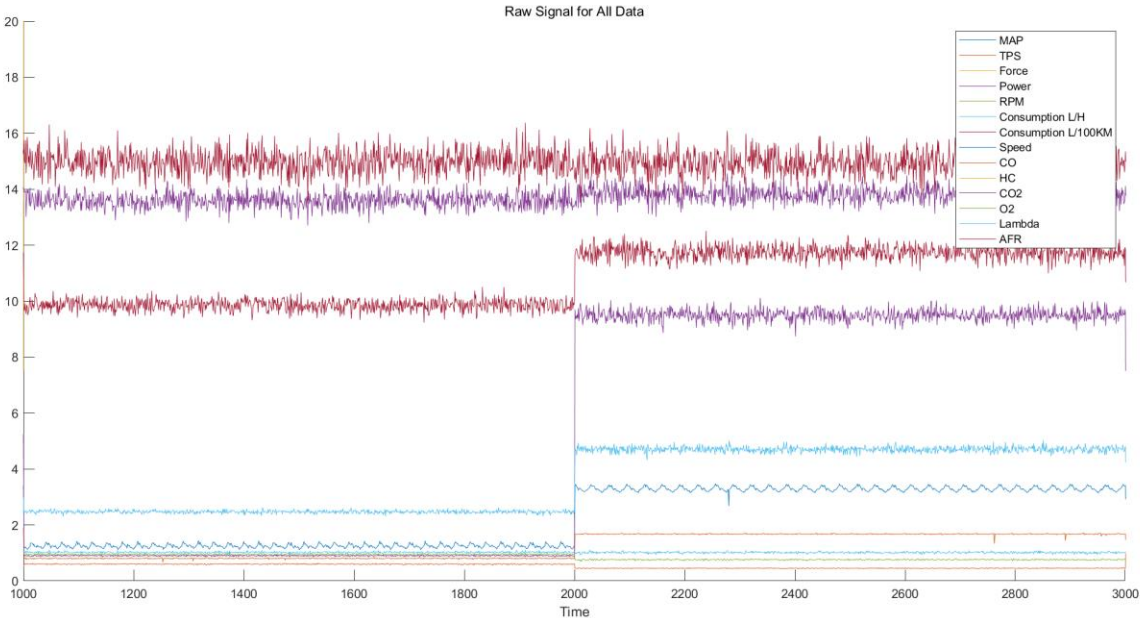


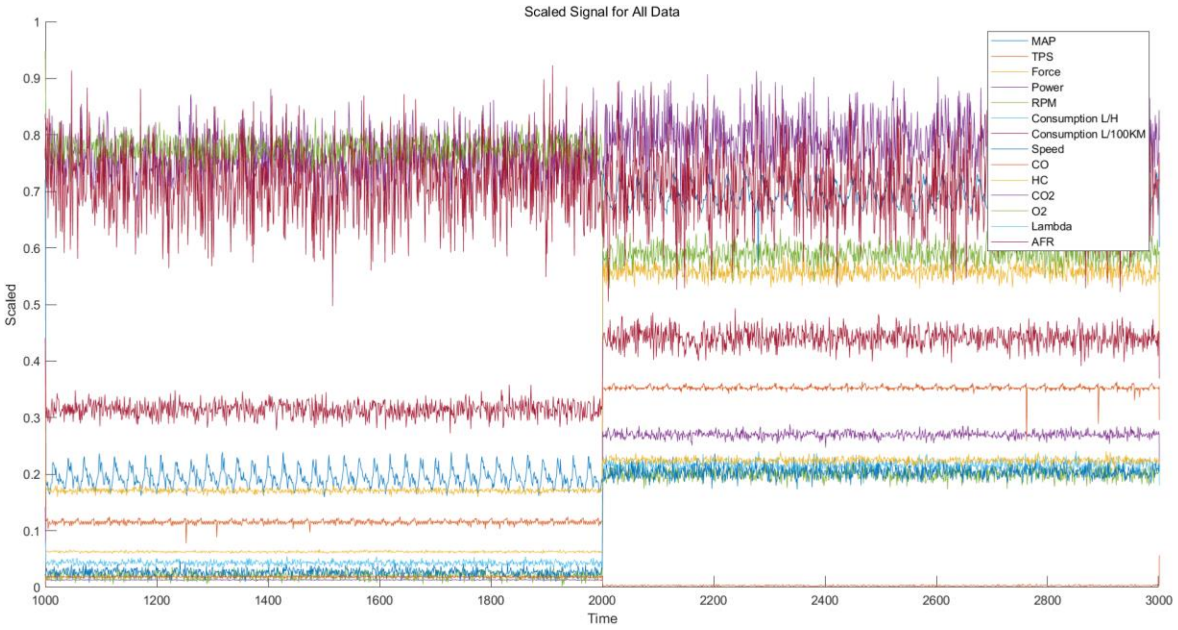


Replace the Outliers: Used **Linear Interpolation**

3. Data Preprocessing

3. Min-Max scaling





14 Variables have **different magnitude ranges** (ex. %, rpm, Pa etc.).

→ Min-Max Scaling [0, 1].

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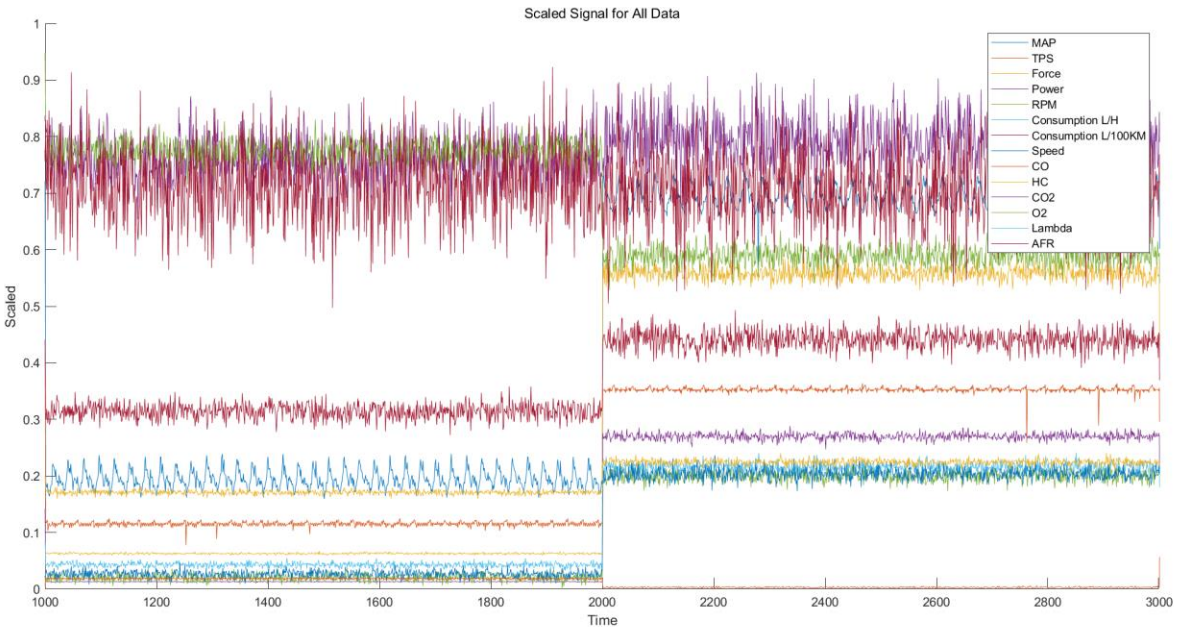
3. Data Preprocessing

4. Butterworth Low Pass Filter



Don’t Focus on Changes Over Time
Focus on the **Distribution** of Variables

Noise → Distributed with a **Large Standard Deviation**

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4. Classification Model Improvement

3. Data Preprocessing

Test / Train Datasets Split

StratifiedKFold: The Kfold is designed for label datasets with **imbalanced distributions**.

Fault type 0: Normal (10,000 entries)

Fault type 1: Rich mixture - High Pressure, Incorrect Sensor, etc. (10,000 entries)

Fault type 2: Lean mixture – Low Pressure, Incorrect Sensor, etc. (10,000 entries)

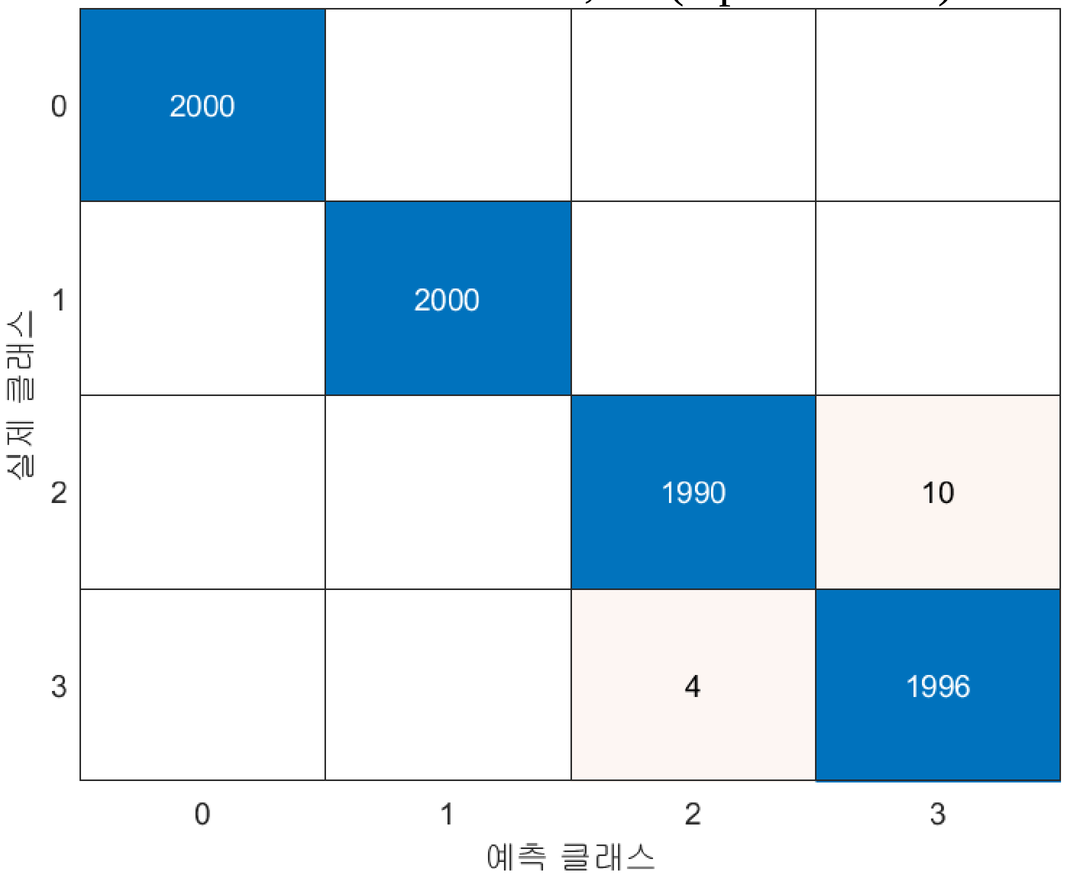
Fault type 3: Low Voltage – Worn Spark, Defective Coil, etc. (10,000 entries)

Choose: (Train: 32,000, Test: 8,000)

The Same Number of Train & Test → **Fairness Train**

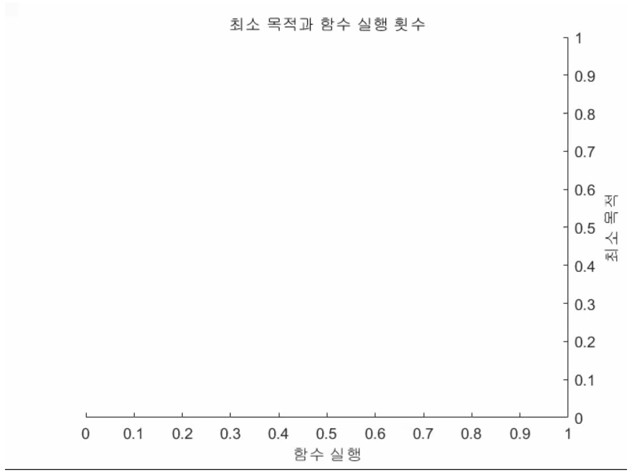
4. Classification Model Improvement

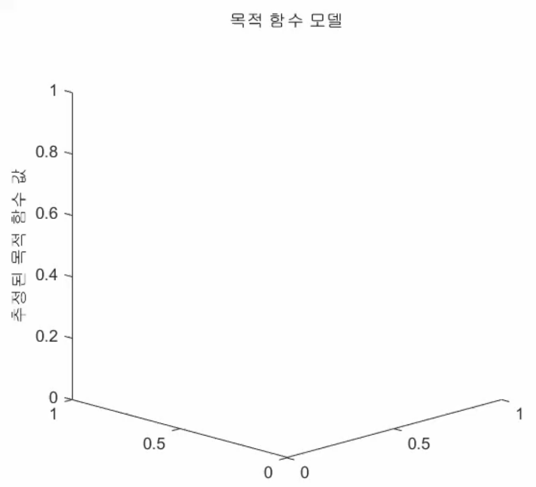
KNN-Number of data: 40,000(Optimization)



Accuracy: 0.99
Recall: 0.99
Precision: 0.99
F1-Score: 0.99

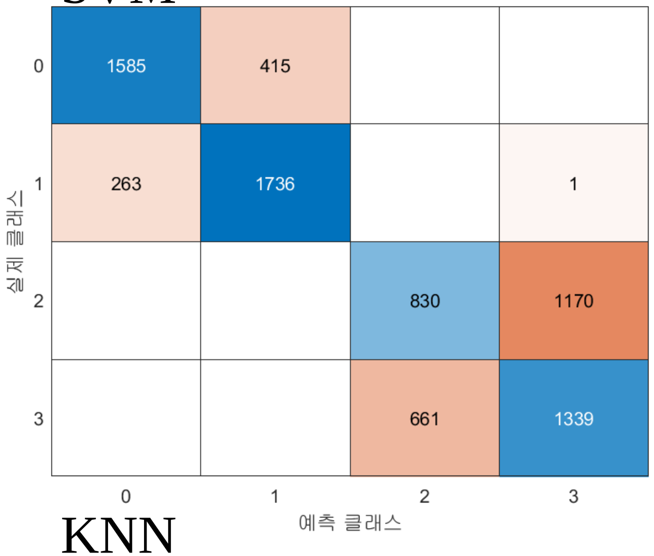
Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	NumNeighbors	Distance
1	Best	0.16416	3.4096	0.16416	0.16416	103	seuclidean
2	Best	0.064031	2.2297	0.064031	0.068012	16	cityblock
3	Accept	0.75	11.597	0.064031	0.080004	4717	hamming
4	Accept	0.62934	41.8	0.064031	0.087232	11982	cityblock
5	Accept	0.082187	3.5239	0.064031	0.064168	22	cityblock
6	Best	0.004625	3.1968	0.004625	0.0046084	1	cityblock
7	Accept	0.70094	60.35	0.004625	0.004651	15779	seuclidean
8	Accept	0.013875	4.6199	0.004625	0.0046277	1	seuclidean
9	Accept	0.01825	3.9159	0.004625	0.0046241	1	chebychev
10	Accept	0.19809	6.1951	0.004625	0.0046263	338	chebychev
11	Best	0.0036562	3.1542	0.0036562	0.0036813	1	correlation
12	Accept	0.18462	4.8023	0.0036562	0.0036877	240	correlation
13	Accept	0.0037187	2.8983	0.0036562	0.0036849	1	cosine
14	Accept	0.18262	4.9677	0.0036562	0.0036849	224	cosine



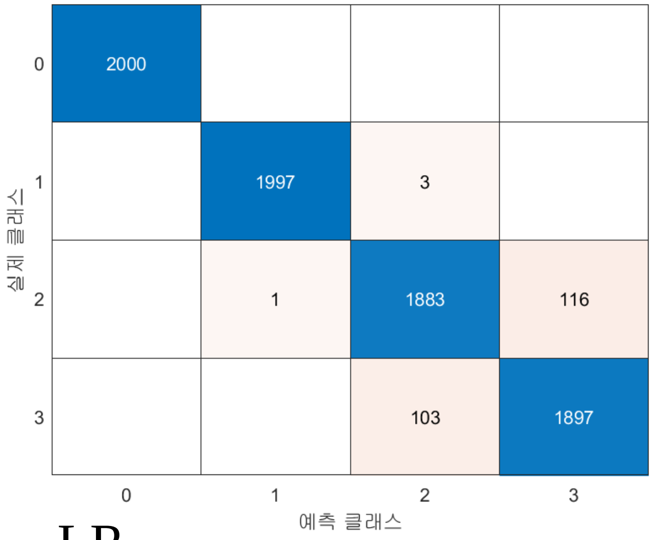


5. Result & Discussion

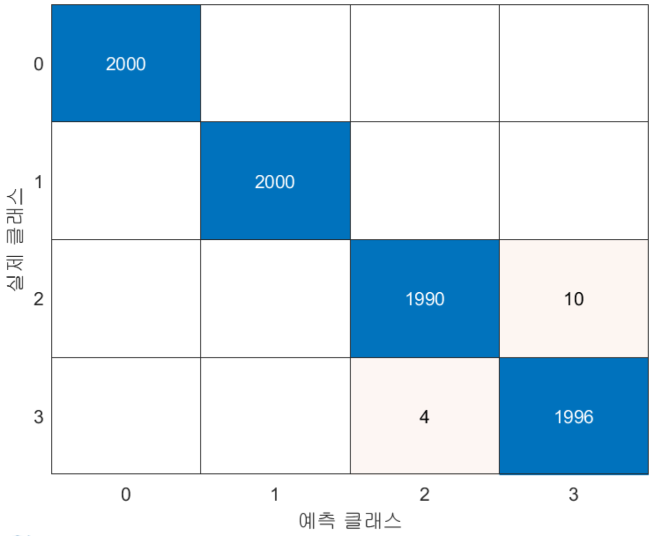
SVM



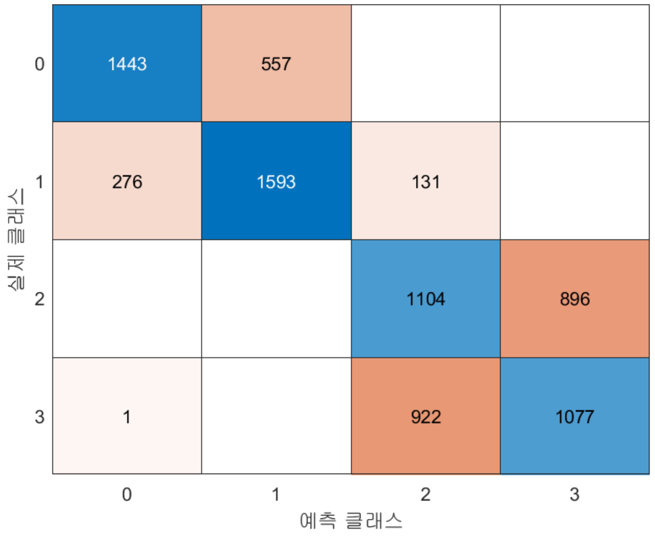
TREE



KNN



LR



< Final Performance Each Model>

	SVM	TREE	KNN	LR
Accuracy	0.69	0.97	0.99	0.65
Precision	0.69	0.97	0.99	0.65
Recall	0.69	0.97	0.99	0.66
F1 Score	0.68	0.97	0.99	0.65

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5. Result & Discussion

5. Result & Discussion

< Following Journal Performance >

	SVM	TREE	KNN	LR
Accuracy	0.59	0.74	0.75	0.48
Precision	0.58	0.75	0.76	0.48
Recall	0.59	0.75	0.76	0.50
F1 Score	0.57	0.75	0.76	0.48

→

< Final Performance Each Model>

	SVM	TREE	KNN	LR
Accuracy	0.69	0.97	0.99	0.65
Precision	0.69	0.97	0.99	0.65
Recall	0.69	0.97	0.99	0.66
F1 Score	0.68	0.97	0.99	0.65

✓ **76% → 99% (+23%)**

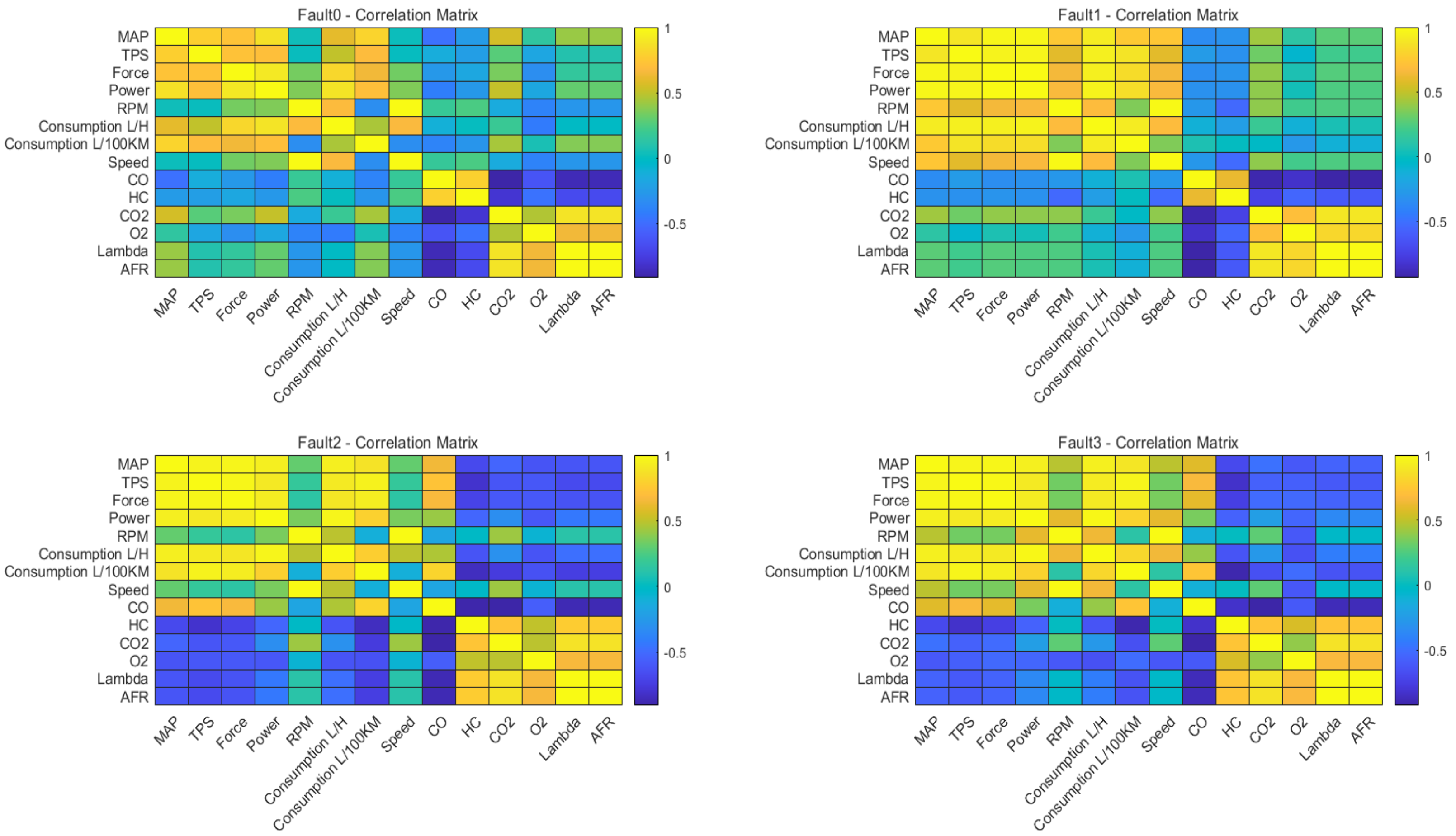
Why KNN & Tree Model has Better Performance than others?

✓ KNN has benefited from having variables with **similar patterns**

✓ Decision Tree(clear classification rules) has advantage in **multiple input**

❖ KNN & Tree is vulnerable to **noise → Butterworth Lowpass Filter**

5. Result & Discussion



- ✓ **Fault2 & Fault3** Show **Similar Tendency.**→ **Difficult to Classification**
- ✓ **AFR, CO, CO2, O2** Correlation: **Exhaust, Combustion Process**.(Fault3)
- ✓ **MAP, TPS, Power, Force** Correlation: **Engine Intake System**. (Fault3)

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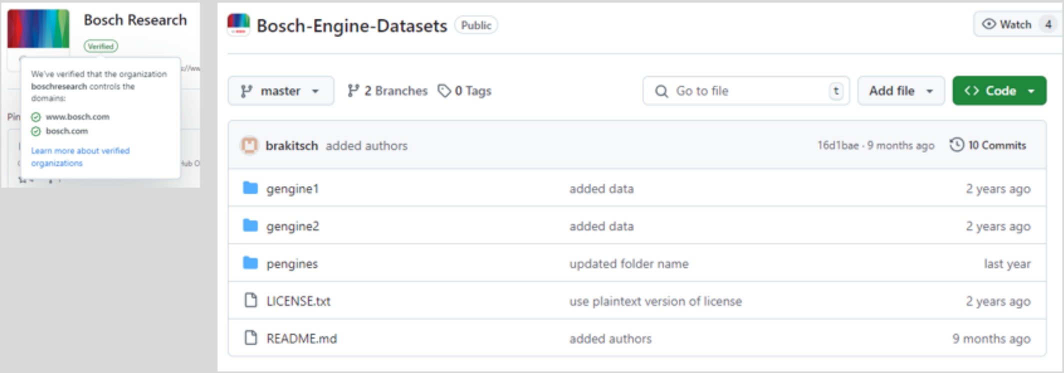
6. Additional Research
- BOSCH Datasets

5. Additional Research

Further Study

Apply the Model to the Open BOSCH Engine Dataset Available on BOSCH's Official GitHub.

Datasets Information



*Unlabeled about Engine Fault

Datasets #

#1. gengine 1
- Speed, Load, Lambda, Ignition Angle, Fuel cutoff, CO, CO2, HC, NOx, O2, Temperature(Manifold), Temperature (Catalyst)

#2. gengine 2
- Speed, Load, Lambda, Ignition Angle, HC, NOx, O2, Temperature(Manifold), Temperature (Catalyst)

#3. pengines
- engine speed, engine load, intake valve opening, air fuel ratio, specific fuel consumption, temperature exhaust manifold, temperature (Catalyst), cylinder pressure, HC, NOx

[5] Bosch Research. (n.d.). Bosch Engine Datasets. GitHub. https://github.com/boschresearch/Bosch-Engine-Datasets

Strategy:

① Using **regression techniques**, **output variables** can be predicted from **input variables**.

② In other words, **physical data that is easily obtainable**, such as engine speed, load, fuel cutoff, etc., **can be used to predict** CO, CO2, HC, etc., as well as temperatures within the engine manifold — data that typically requires a gas analyzer.

③ This allows for **identifying types of engine faults** using only easily accessible data and the predicted output variables.

5. Additional Research

Fuel Cutoff Data Preprocessing

Box Plot & Outlier Replacement

Noise Reduction (Butterworth Low pass filter)

Min-Max Scaling

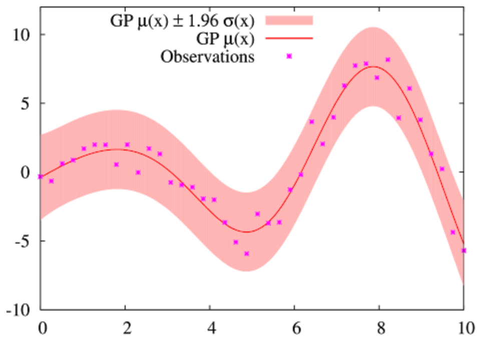
Add Fuel Cutoff Data

Down Sampling

Train/Test Data Split

GPR | Linear Regression | Random Forest | SVR | MOGP

*Python



*** <Gaussian Process Regression>**

Non-parametric, probabilistic regression method that learns the **distribution** of functions.

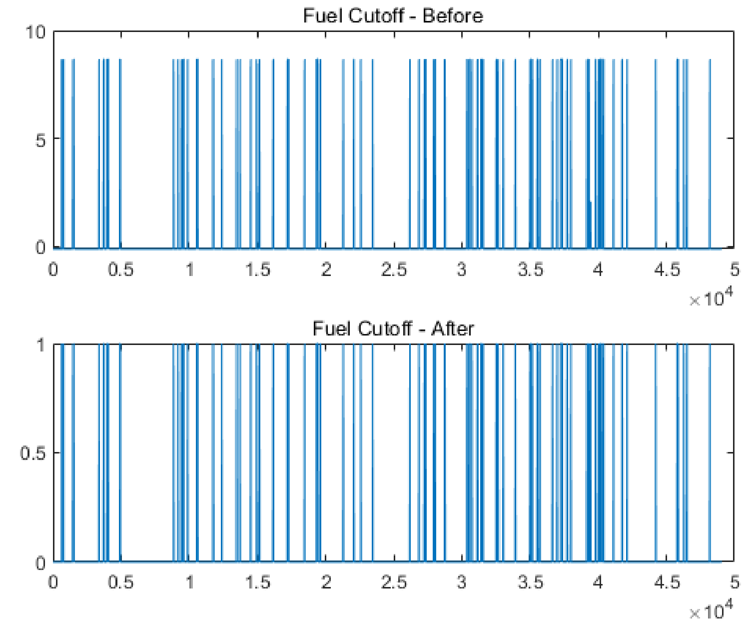
Measures the **correlation** (similarity) between data points.

Data points that are **closer** to each other have **higher similarity**.

Provides **uncertainty estimates** for the data, allowing evaluation of predictions along with **confidence intervals**.

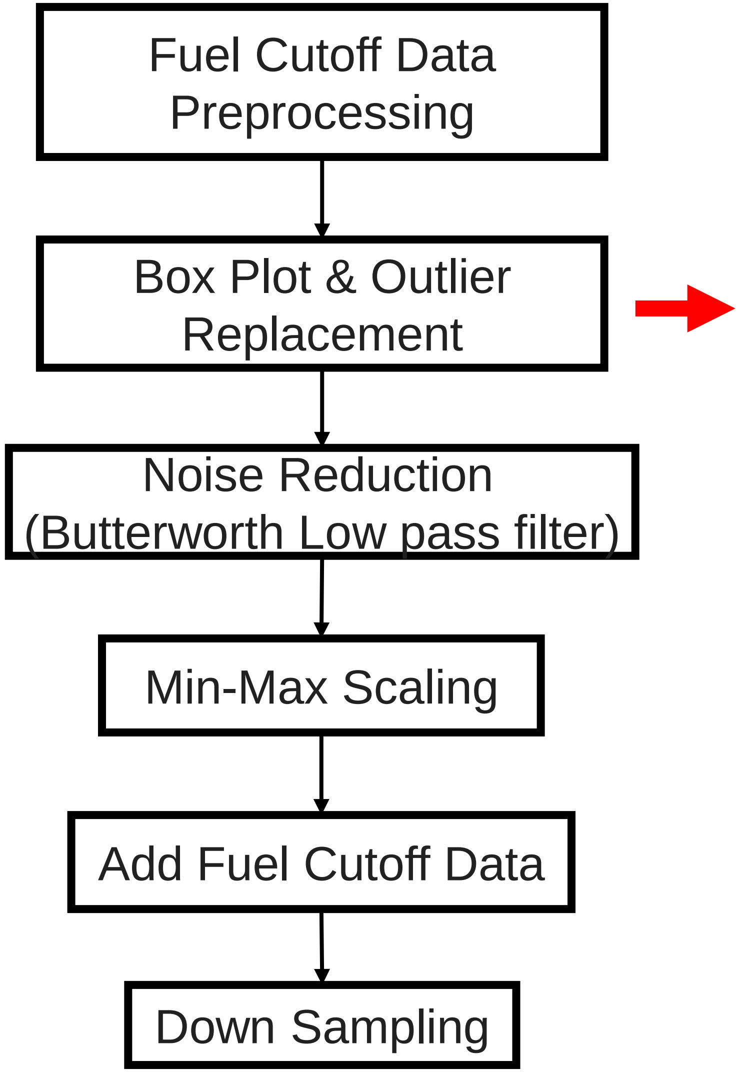
5. Additional Research

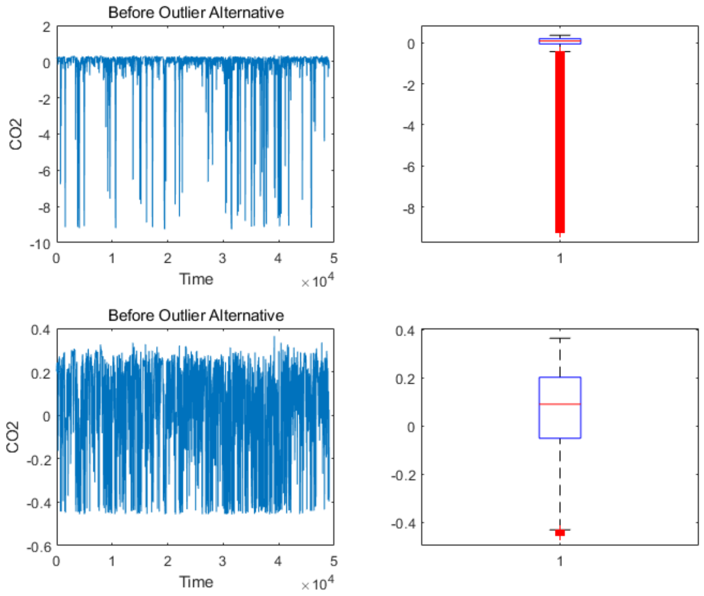
Fuel Cutoff Data Preprocessing
↓
Box Plot & Outlier Replacement
↓
Noise Reduction (Butterworth Low pass filter)
↓
Min-Max Scaling
↓
Add Fuel Cutoff Data
↓
Down Sampling



- ✓ *Fuel Cutoff* data represents the state or timing when the fuel supply to the engine is cut off.
- ✓ *Fuel Cutoff* data is binary, with values of 0 or 1
- ✓ Excluded from preprocessing
- ✓ $\begin{cases} Fuel\ Cutoff < 0 : Fuel\ Cutoff = 0 \\ Fuel\ Cutoff \geq 0 : Fuel\ Cutoff = 1 \end{cases}$

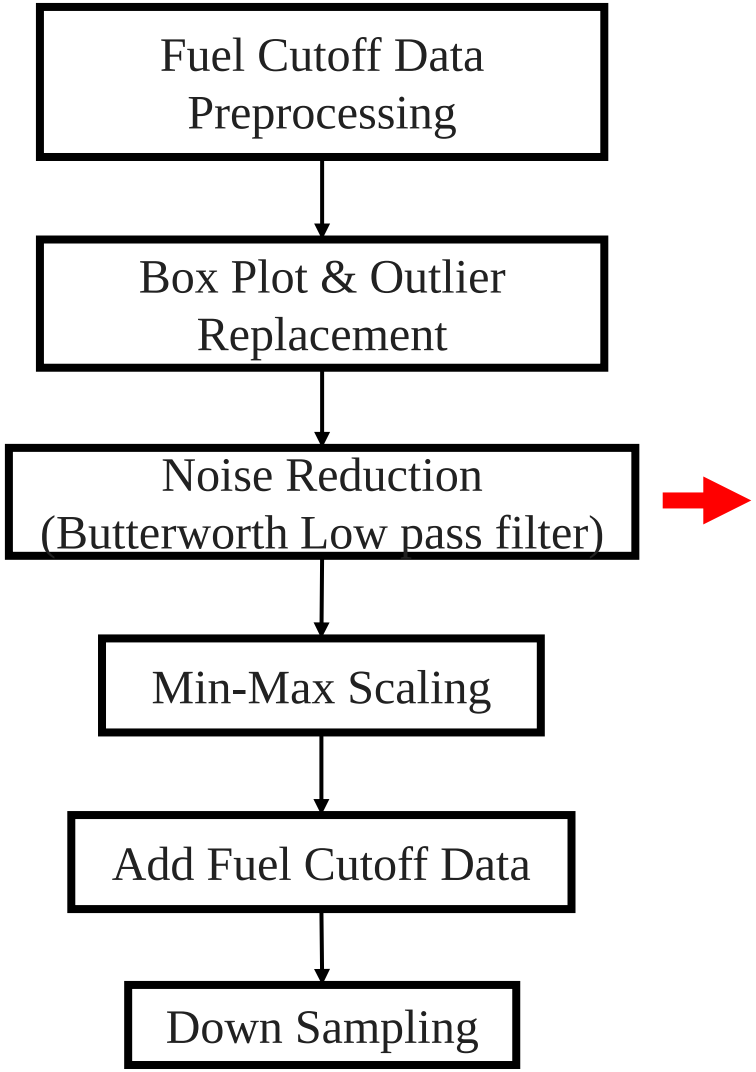
5. Additional Research

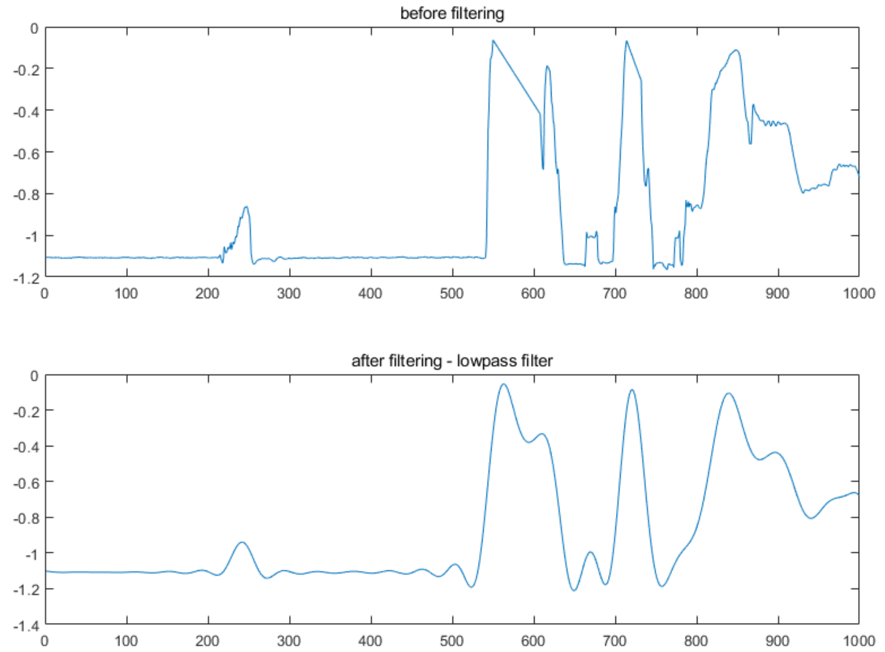




- ✓ Linear interpolation was used to replace outliers.
- ✓ A box plot was utilized to assess the improvement in outlier reduction.

5. Additional Research

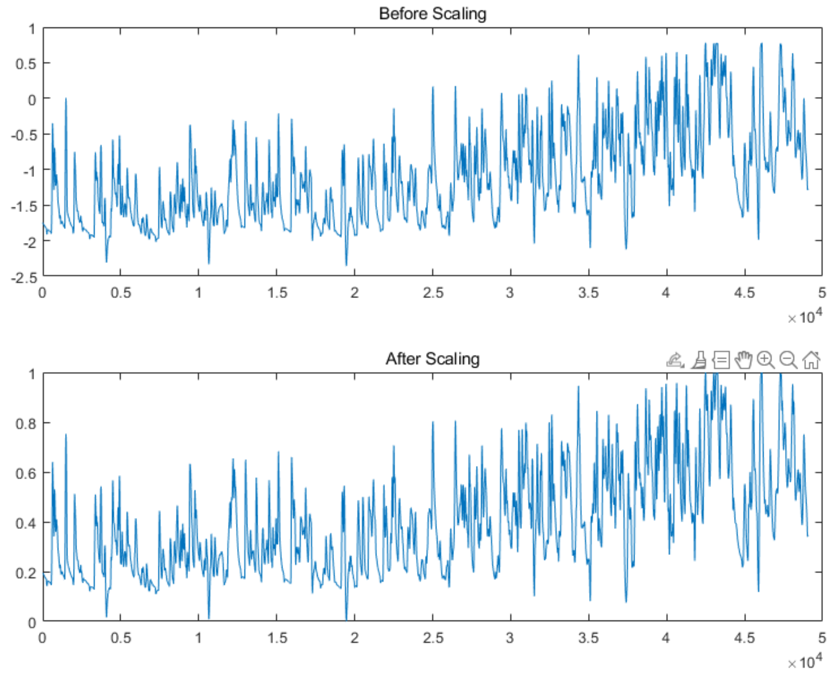




- ✓ A Butterworth low-pass filter was used to manage noise introduced during data acquisition.

5. Additional Research

1. Fuel Cutoff Data Preprocessing
2. Box Plot & Outlier Replacement
3. Noise Reduction (Butterworth Low pass filter)
4. Min-Max Scaling
5. Add Fuel Cutoff Data
6. Down Sampling



- ✓ Scaling was applied due to the differing ranges across variables.
- ✓ Min-Max Scaling was used to normalize the data within a [0, 1] range.

$$X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

5. Additional Research

Fuel Cutoff Data Preprocessing

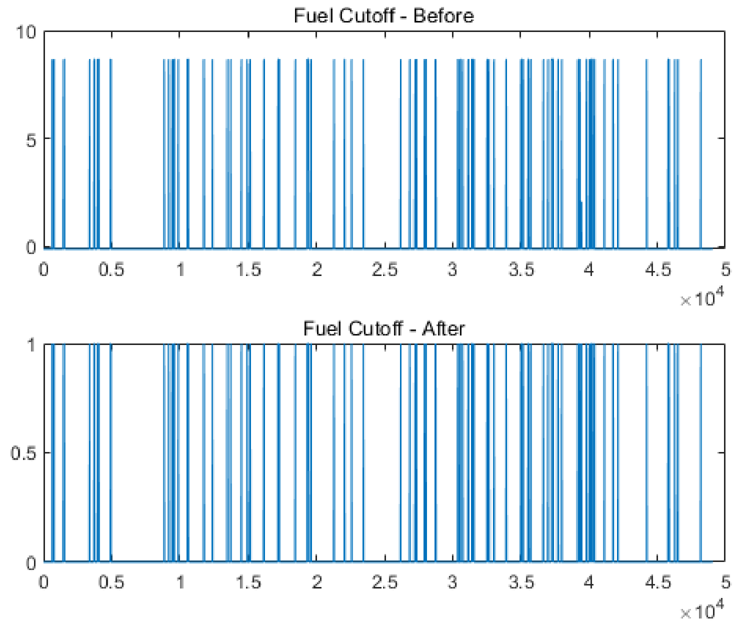
Box Plot & Outlier Replacement

Noise Reduction (Butterworth Low pass filter)

Min-Max Scaling

Add Fuel Cutoff Data

Down Sampling



- ✓ Re-importing Preprocessed Cutoff Data from Step 1
- ✓ The binary data for Fuel Cutoff was not subjected to additional preprocessing.

5. Additional Research

Fuel Cutoff Data Preprocessing

↓

Box Plot & Outlier Replacement

↓

Noise Reduction (Butterworth Low pass filter)

↓

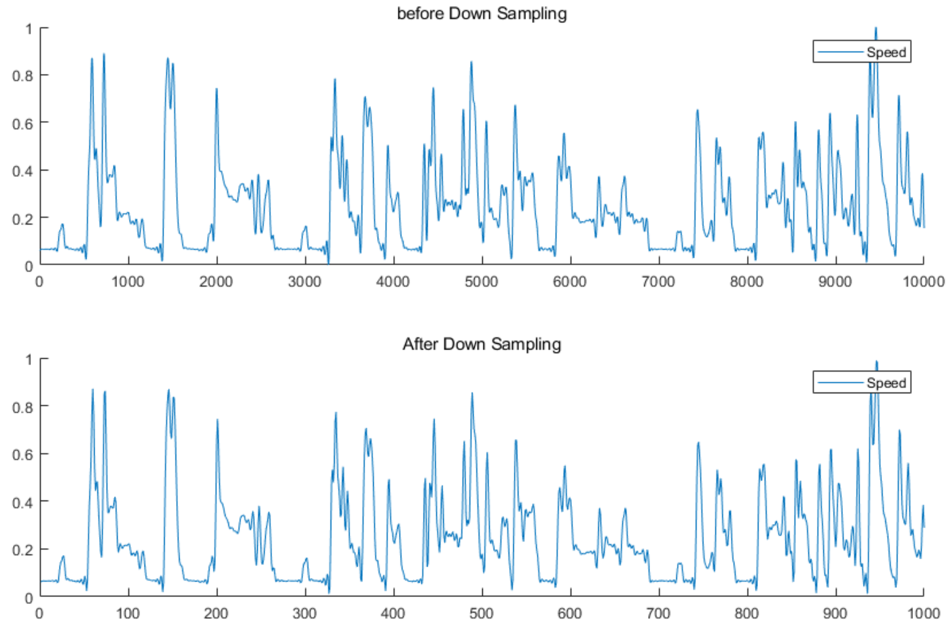
Min-Max Scaling

↓

Add Fuel Cutoff Data

↓

Down Sampling →



- ✓ The computational load of Gaussian Process Regression increases exponentially with the number of input data points.
- ✓ Down-sampling was applied to reduce the data size while preserving trends.
- ✓ Data Entries: 49007 → 4907

5. Additional Research

Train/Test Data Split

GPR

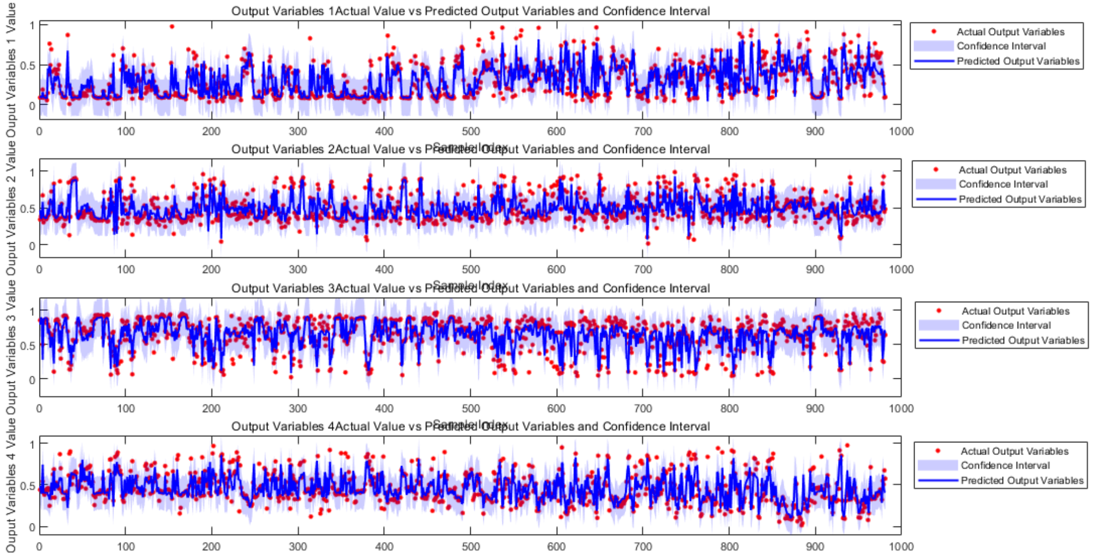
Linear Regression

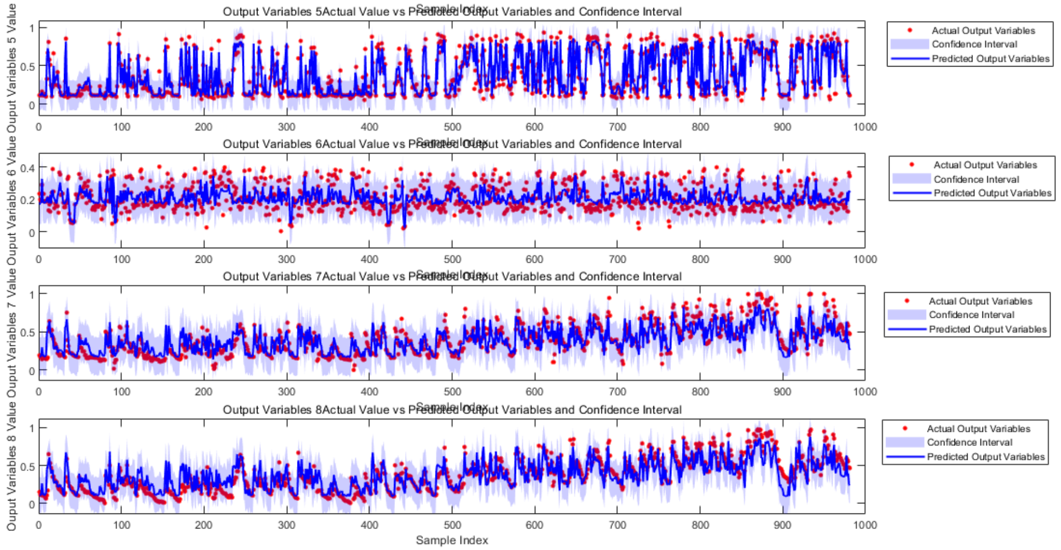
Random Forest

SVR

MOGP

*Python

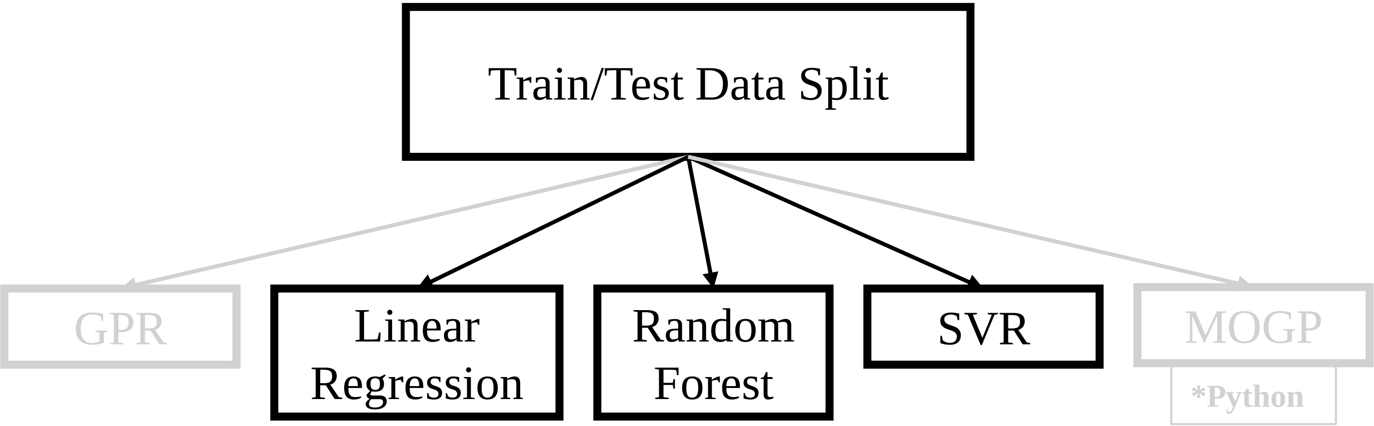




- ✓ Since MATLAB lacks Multi-Output Gaussian Process functions, separate GPR models were trained for each output variable.
- ✓ Confidence intervals and predicted values can be compared to actual values.

✓ GPR Average RMSE = 0.1174

5. Additional Research




```
LinearRegression Model - Output Variables 1 - RMSE: 0.1373
LinearRegression Model - Output Variables 2 - RMSE: 0.1526
LinearRegression Model - Output Variables 3 - RMSE: 0.1944
LinearRegression Model - Output Variables 4 - RMSE: 0.1411
LinearRegression Model - Output Variables 5 - RMSE: 0.1296
LinearRegression Model - Output Variables 6 - RMSE: 0.0781
LinearRegression Model - Output Variables 7 - RMSE: 0.1513
LinearRegression Model - Output Variables 8 - RMSE: 0.1438
```

```
RandomForest Model - Output Variables 1 - RMSE: 0.1180
RandomForest Model - Output Variables 2 - RMSE: 0.1269
RandomForest Model - Output Variables 3 - RMSE: 0.1529
RandomForest Model - Output Variables 4 - RMSE: 0.1149
RandomForest Model - Output Variables 5 - RMSE: 0.1023
RandomForest Model - Output Variables 6 - RMSE: 0.0656
RandomForest Model - Output Variables 7 - RMSE: 0.1272
RandomForest Model - Output Variables 8 - RMSE: 0.1195
```

```
SVM Model - Output Variables 1 - RMSE: 0.1378
SVM Model - Output Variables 2 - RMSE: 0.1564
SVM Model - Output Variables 3 - RMSE: 0.2031
SVM Model - Output Variables 4 - RMSE: 0.1456
SVM Model - Output Variables 5 - RMSE: 0.1312
SVM Model - Output Variables 6 - RMSE: 0.0810
SVM Model - Output Variables 7 - RMSE: 0.1530
SVM Model - Output Variables 8 - RMSE: 0.1444
```

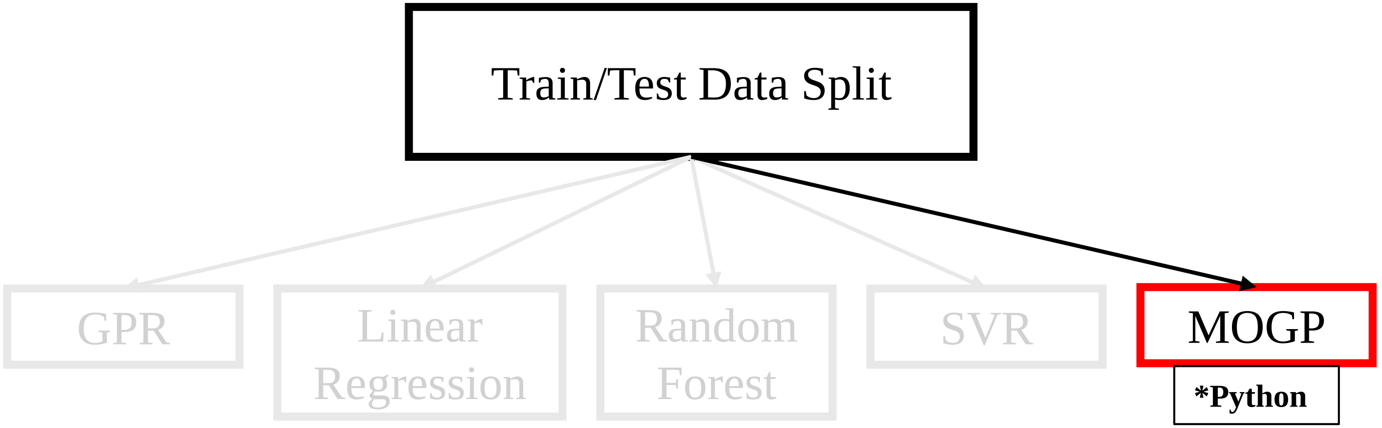
- ✓ Three additional regression models were trained to compare performance with Gaussian Process Regression (GPR).

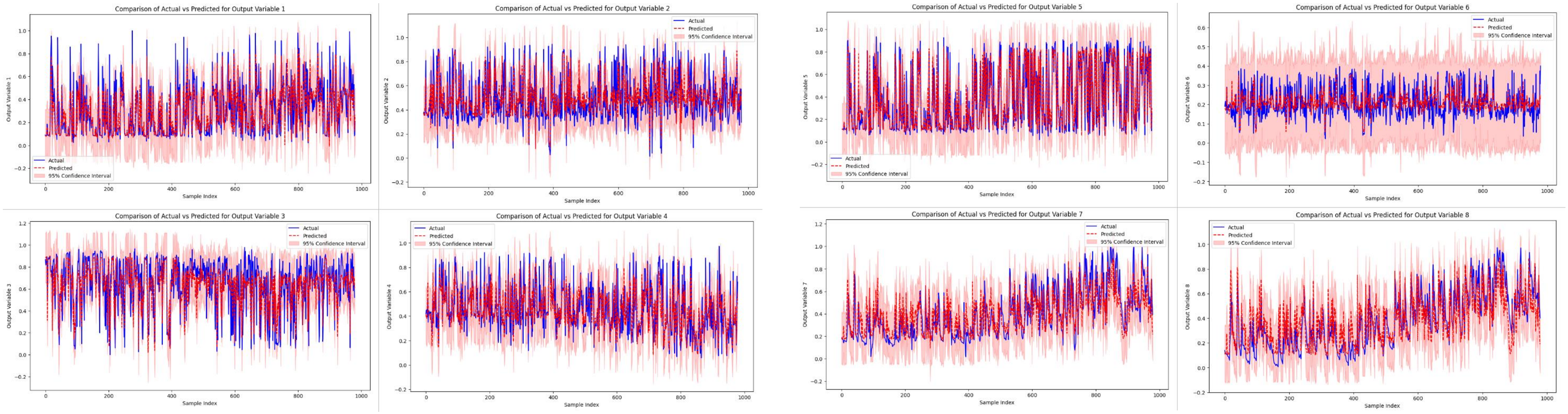
✓ Linear Regression Average RMSE = 0.1410

✓ Random Forest Regression Average RMSE = 0.1159

✓ SVR Average RMSE = 0.1441

5. Additional Research





- ✓ MATLAB does not support Multi-Output Gaussian Process (MOGP), but Python does through the GPy module.
- ✓ MOGP Average RMSE = 0.1188

5. Additional Research – Result & Discussion

	GPR	Linear Regression	Random Forest	SVR	MOGP
RMSE	0.1174	0.1405	0.1180	0.1424	0.1188

✓ **Advantages of GPR/MOGP Over Other Regression Models**

① **Interdependency Modeling:** MOGP captures relationships between multiple output variables, improving accuracy.
② **Uncertainty Estimation:** Provides confidence intervals, enhancing reliability in applications like fault detection.
③ **Non-Linear Capability:** GPR's kernel-based approach effectively models complex, non-linear relationships.

✓ **Computational Considerations of GPR/MOGP**

① **High Cost:** GPR/MOGP is computationally intensive due to the large kernel matrix.
② **Benefit of Large Data:** More data improves accuracy and reliability but increases computational load.

✓ **Conclusion**

GPR/MOGP's advantages in accuracy and uncertainty estimation make it highly **suitable** for **complex, interdependent datasets** like BOSCH Engine Datasets.

✓ **Adaption**

Output Variables must be measured with **expensive equipment** such as a Gas Analyzer, but if Output Variables can be accurately **estimated with Input Variables**, the status or defect of the **engine can be identified using the data**.

Reference

[1] Vergara, M., Ramos, L., Rivera-Campoverde, N. D., & Rivas-Echeverría, F. (2023). Enginefaultdb: a novel dataset for automotive engine fault classification and baseline results. *IEEE Access*, *11*, 126155-126171.

[2] Li, C. Y., Rakitsch, B., & Zimmer, C. (2022, May). Safe active learning for multi-output gaussian processes. In International Conference on Artificial Intelligence and Statistics (pp. 4512-4551). PMLR.