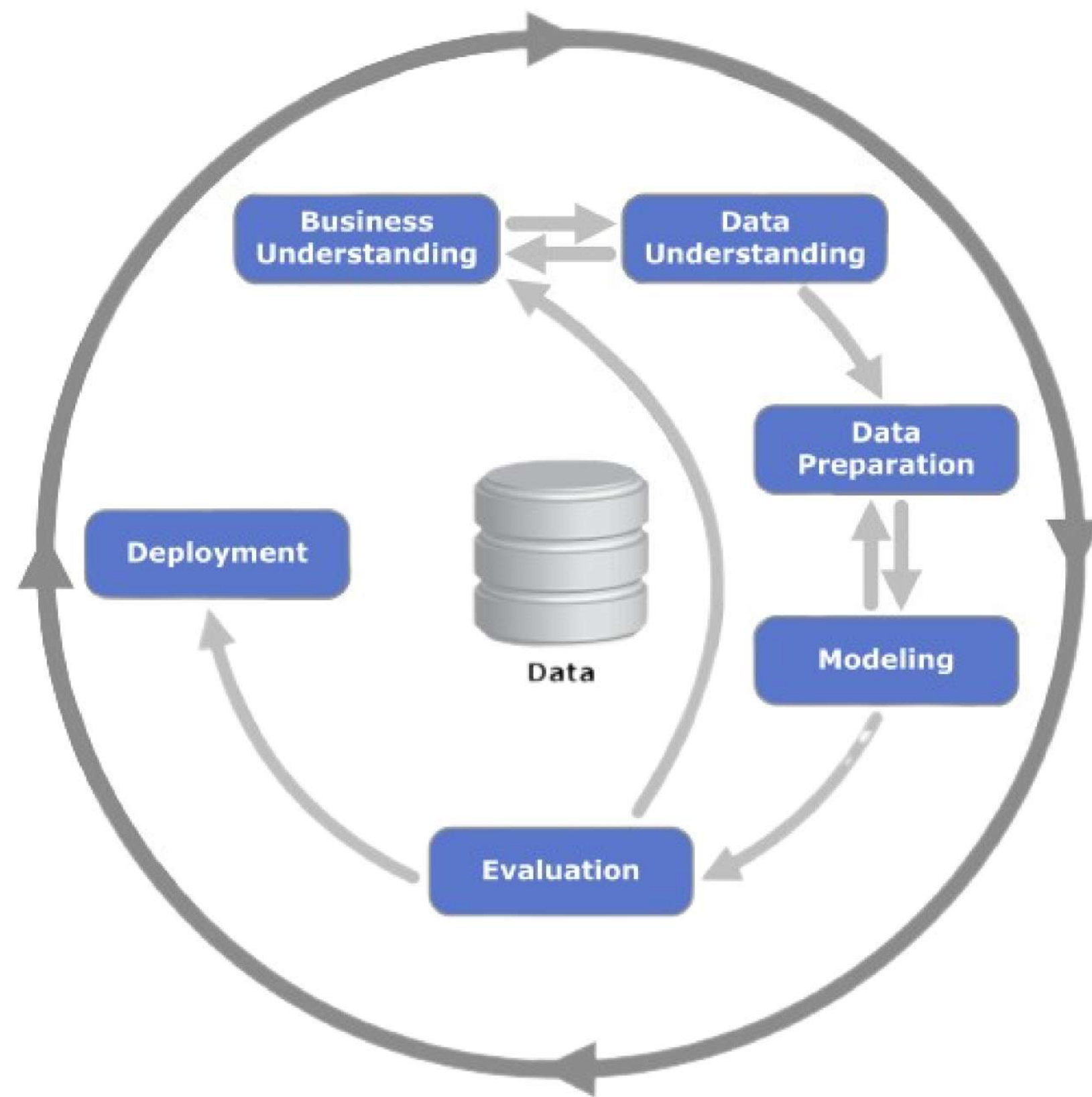


CRISP-DM

a process model that serves as the base for a data science process.



Business Understanding

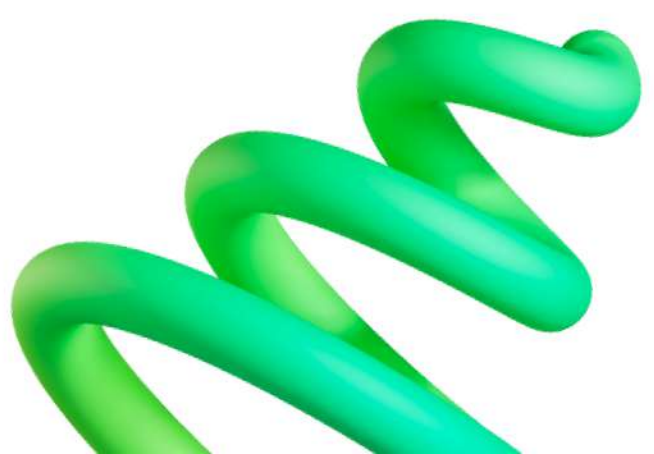


Problem

Sebuah perusahaan X sering terjadi kerusakan mesin (machine failure) tak terduga pada saat berjalannya produksi.

Effect

Muncul biaya - biaya tambahan perbaikan, sehingga perusahaan dinilai belum layak untuk melakukan penambahan kapasitas produksi dan melakukan ekspansi bisnis ke pasar mancanegara.



DATA UNDERSTANDING

Dataset in General



The Champions

10.000
data

14
feature

5
independent
failures

UID

product ID

type

air
temperature
[K]

process
temperature
[K]

Machine
failure

rotational
speed [rpm]

torque [Nm]

tool wear
[min]

Power Label

Label Power Set

Multilabel to Multiclass

TWF
(tool wear
failure)

HDF
(heat dissipation
failure)

PWF
(power failure)

Another
Failure

OSF
(overstrain
failure)

RNF
(random
failures)



DATA UNDERSTANDING

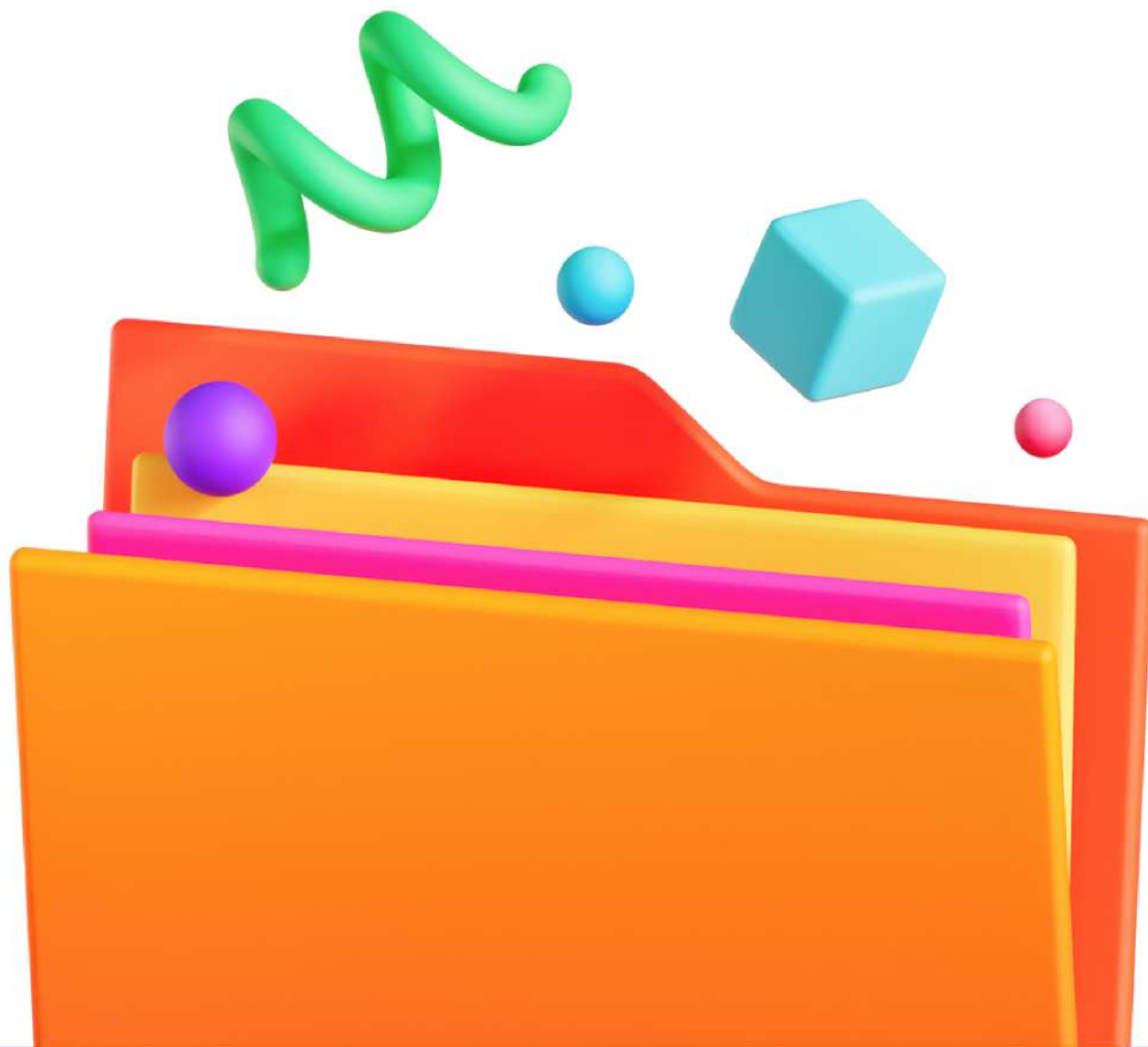
EDA



- No missing value.
- No duplicate data.
- Many outlier values (but in machine failure category 1). Therefore, this outlier value can be left for analysis purposes, being transformed, or separated into new columns.
- There are several machine failures that have more than 1 independent failure category
- There are 9 data that fall into the category of machine damage based on "Machine Failure", but do not fall into the five independent damage categories.
- There is an imbalanced class.



DATA PREPARATION



1

Dummy Variable

2

New Class

3

Problem Transformation

4

Feature Selection

5

Data Transformation

6

Handling Imbalanced Dataset

7

Hyperparameter Tuning



MODELING

The selected model is the model with the highest Recall value

Model	MLPClassifier	RandomForestClassifier	LGBMClassifier	DecisionTreeClassifier	XGBClassifier	LogisticRegression	SVC	GaussianNB	RidgeClassifier	AdaBoostClassifier
Accuracy	0.960333	0.977	0.979667	0.948333	0.976667	0.380667	0.641667	0.030333	0.078	0.002
Recall	0.362839	0.328871	0.28157	0.267313	0.257733	0.189284	0.170234	0.12939	0.090134	0.001237
Precision	0.389869	0.255542	0.2557	0.26318	0.25517	0.356303	0.364393	0.126899	0.195592	0.164167
F1-Score	0.354589	0.280579	0.267215	0.235179	0.255874	0.184003	0.189412	0.047569	0.034081	0.002359



Evaluation

Train vs Test



	Before Hyperparameter Tuning	After Hyperparameter Tuning
Train	0.998477	0.999840
Test	0.958000	0.970400

Evaluation

Classification Report



Before Hyperparameter Tuning

Class	Precision	Recall	F1-Score	Support
0	0.99	0.97	0.98	2422
1	0	0	0	2
2	0	0	0	6
3	0.68	1	0.81	15
4	0.67	0.82	0.74	17
5	1	0.25	0.4	4
6	0.47	0.8	0.59	20
8	0	0	0	2
9	0.12	0.45	0.19	11
11	0	0	0	1
12	0	0	0	0
Accuracy			0.96	2500
Macro Average	0.36	0.39	0.34	2500

After Hyperparameter Tuning

Class	Precision	Recall	F1-Score	Support
0	0.99	0.98	0.98	2422
1	0	0	0	2
2	0	0	0	6
3	0.67	0.8	0.73	15
4	0.58	0.65	0.61	17
5	0.75	0.75	0.75	4
6	0.54	0.7	0.61	20
8	0	0	0	2
9	0.21	0.27	0.24	11
11	0	0	0	1
Accuracy			0.97	2500
Macro Average	0.37	0.42	0.39	2500

Evaluation

Value



Class	Data Test	Before Hyperparameter Tuning	After Hyperparameter Tuning
0	2422	2362	2410
1	2	8	4
2	6	7	5
3	15	22	18
4	17	21	19
5	4	1	4
6	20	34	26
7	0	0	0
8	2	1	0
9	11	41	14
10	0	0	0
11	1	1	0
12	0	0	0

Conclusion

From the value of hyperparameter tuning and metrics evaluation, the results given by the model between before HT and after HT did not have major differences, but when viewed the values in each model class, model with HT were less affected by the majority class. So, we will use the model from Hyperparameter Tuning and this model gives the best recall too.

Evaluation

AUC Best Model




Class	0	1	2	3	4	5	6	7	8	9	10	11	12
AUC	0.81887	0.4992	0.499	0.89879	0.82192	0.8748	0.84758	0	0.5	0.63415	0	0.5	0
Support	2422	2	6	15	17	4	20	0	2	11	0	1	0

Judging from the AUC value of each class, it can be said that the model can classify well (there are 5 classes with AUC values above 80%). However, for some classes due to certain conditions, such as a small number of class members, the AUC value in the class is also low, in this case the model can be said to still work well because it can still classify even in conditions with a small amount of data.

Feature Importance

We can't say specifically which feature gives the most effect because neural network is more like a black box model. In this case we only show feature importance based on specific row.



Feature	Feature Value	Importance
Tool Wear	-0.32	0.01
Torque	-1.24	0.17
Process Temperature	-1.72	0.1
Rotational Speed	0.81	0.14
Air Temperature	1.82	0.02
Type_L	-5.2	0.19
Type_H	5.2	0.03

Row 450



Prediction Results

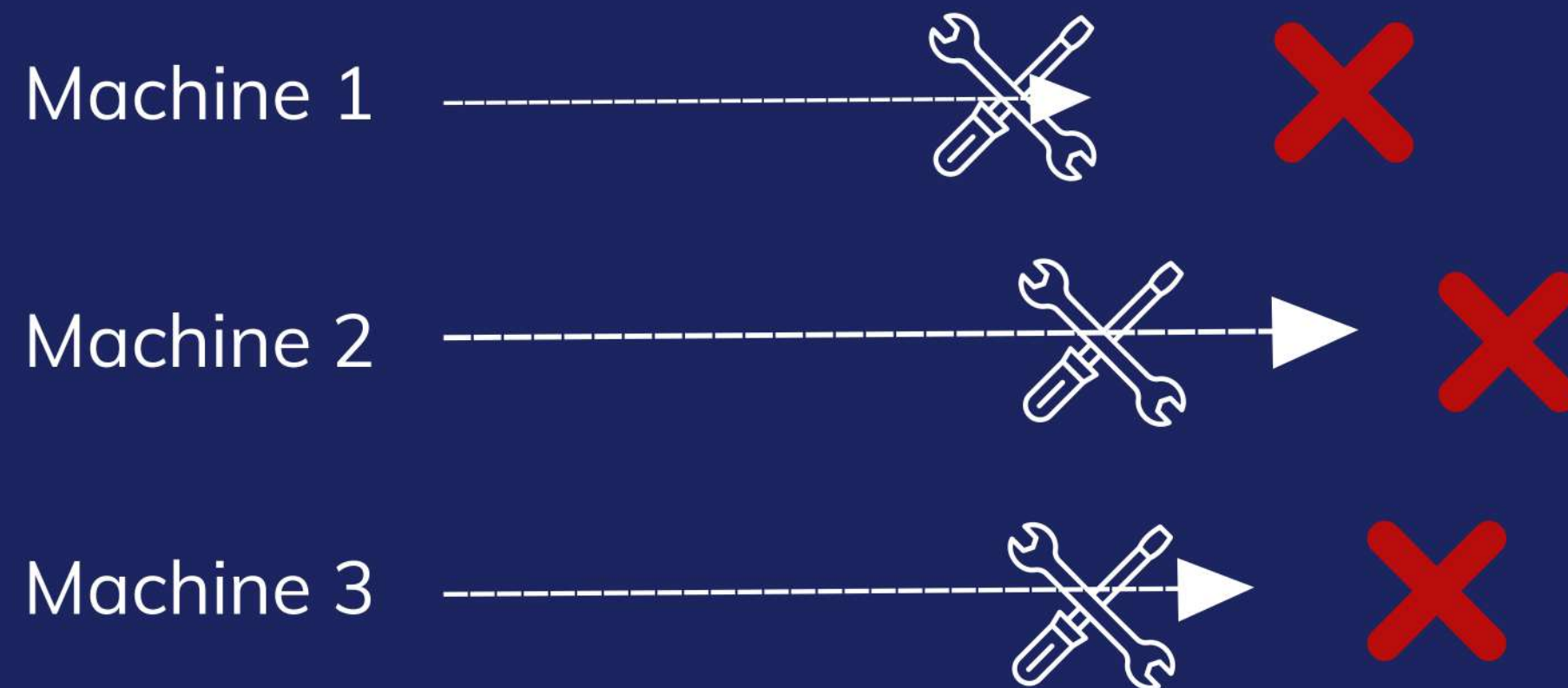


Maintenance Strategy



Predictive Maintenance

Fixes issues before they occur



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Maintenance Strategy

Predictive maintenance for fixes issues before they occur.



Advantages

- Lowering the operating risk
- Control cost of maintenance
- Find trends related to various maintenance issues.

Open New Business Strategies

- By providing Predictive Maintenance services for its products, a company can proposes extra value for its consumers.

Common Ways To Reach Predictive Maintenance

- Internet of Things
- Cloud Computing
- Artificial intelligence (AI)

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THANK YOU