Tugas Prapraktikum

Tugas Prapraktikum dikerjakan dengan *dataset* Rain in Australia. Tanpa meninjau waktu (`date`), prediksi status hujan pada keesokan harinya (`RainTomorrow`). Berikan nilai `1` jika diprediksi hujan pada keesokan harinya, `0` jika tidak.

Oleh :

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0. Persiapan Data and Pustaka

```
# Letakkan pustaka di sini.
import numpy as np
import pandas as pd
import scipy.stats as zscore
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split, cross_val_score,
GridSearchCV
import matplotlib.pyplot as plt
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from sklearn.exceptions import ConvergenceWarning
import warnings
warnings.filterwarnings("ignore", category=ConvergenceWarning)

# Baca data di sini.

data = pd.read_csv("weatherAUS.csv")
df = pd.DataFrame(data)
df.head()
```

```
         Date Location  MinTemp  MaxTemp  Rainfall  Evaporation
Sunshine  \
0  2008-12-01   Albury     13.4     22.9       0.6          NaN
NaN
1  2008-12-02   Albury      7.4     25.1       0.0          NaN
NaN
2  2008-12-03   Albury     12.9     25.7       0.0          NaN
NaN
3  2008-12-04   Albury      9.2     28.0       0.0          NaN
NaN
4  2008-12-05   Albury     17.5     32.3       1.0          NaN
NaN
```

```
  WindGustDir  WindGustSpeed WindDir9am  ... Humidity9am  Humidity3pm  
\
0           W           44.0          W  ...        71.0         22.0   

1         WNW           44.0        NNW  ...        44.0         25.0   

2         WSW           46.0          W  ...        38.0         30.0   

3          NE           24.0         SE  ...        45.0         16.0   

4           W           41.0        ENE  ...        82.0         33.0   


   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  
RainToday  \
0       1007.7       1007.1       8.0       NaN     16.9     21.8        
No
1       1010.6       1007.8       NaN       NaN     17.2     24.3        
No
2       1007.6       1008.7       NaN       2.0     21.0     23.2        
No
3       1017.6       1012.8       NaN       NaN     18.1     26.5        
No
4       1010.8       1006.0       7.0       8.0     17.8     29.7        
No

   RainTomorrow  
0            No  
1            No  
2            No  
3            No  
4            No  

[5 rows x 23 columns]
```

I. Pemahaman Data

Tujuan dari bagian ini adalah peserta dapat memahami kualitas dari data yang diberikan. Hal yang diliputi adalah sebagai berikut:

1. Ukuran data
2. Statistik dari tiap fitur
3. Pencilan (*outlier*)
4. Korelasi
5. Distribusi

I.1

Carilah:

1. Ukuran dari data (instansi dan fitur)
2. Tipe dari setiap fitur
3. Banyak nilai unik dari fitur yang bertipe kategorikal
4. Nilai minimum, maksimum, rata-rata, median, dan standar deviasi dari fitur nonkategorikal

I.1.1

Ukuran Data

```
df.shape
```

```
(145460, 23)
```

Terdapat **23 fitur** dan **145460 instansi**

I.1.2

Tipe dari setiap fitur

```
df.dtypes
```

```
Date              object
Location          object
MinTemp          float64
MaxTemp          float64
Rainfall         float64
Evaporation      float64
Sunshine         float64
WindGustDir       object
WindGustSpeed    float64
WindDir9am        object
WindDir3pm        object
WindSpeed9am     float64
WindSpeed3pm     float64
Humidity9am      float64
Humidity3pm      float64
Pressure9am      float64
Pressure3pm      float64
Cloud9am         float64
Cloud3pm         float64
Temp9am          float64
Temp3pm          float64
RainToday         object
RainTomorrow      object
dtype: object
```

I.1.3

Banyak nilai unik dari fitur yang bertipe kategorikal

```
# Fitur-fitur kategorikal
categorical_features = [col for col in df.columns if df[col].dtype ==
"object"]
categorical_features
```

```
['Date',
 'Location',
 'WindGustDir',
 'WindDir9am',
 'WindDir3pm',
 'RainToday',
 'RainTomorrow']
```

```
print("Jumlah nilai unik:")
for feature in categorical_features:
    print(f" - {feature:<13}: {df[feature].nunique():>4}")
```

```
Jumlah nilai unik:
 - Date         : 3436
 - Location     :   49
 - WindGustDir  :   16
 - WindDir9am   :   16
 - WindDir3pm   :   16
 - RainToday    :    2
 - RainTomorrow :    2
```

I.1.4

Nilai minimum, maksimum, rata-rata, median, dan standar deviasi dari fitur nonkategorikal

```
# Fitur non kategorikal
noncategorical_features = [col for col in df.columns if df[col].dtype
!= "object"]
noncategorical_features
```

```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Pressure3pm',
 'Cloud9am',
```

```
 'Cloud3pm',
 'Temp9am',
 'Temp3pm']

(
    df[noncategorical_features]
        .describe()
        .loc[["min", "max", "mean", "50%", "std"]]
        .rename(index={'50%': 'median'})
)
```

```
          MinTemp    MaxTemp    Rainfall  Evaporation   Sunshine  \
min     -8.500000  -4.800000    0.000000     0.000000   0.000000   
max     33.900000  48.100000  371.000000   145.000000  14.500000   
mean    12.194034  23.221348    2.360918     5.468232   7.611178   
median  12.000000  22.600000    0.000000     4.800000   8.400000   
std      6.398495   7.119049    8.478060     4.193704   3.785483   

        WindGustSpeed  WindSpeed9am  WindSpeed3pm  Humidity9am  
Humidity3pm  \
min          6.000000      0.000000      0.000000     0.000000   
0.000000   
max        135.000000    130.000000     87.000000   100.000000   
100.000000   
mean        40.035230     14.043426     18.662657    68.880831   
51.539116   
median      39.000000     13.000000     19.000000    70.000000   
52.000000   
std         13.607062      8.915375      8.809800    19.029164   
20.795902   

        Pressure9am  Pressure3pm  Cloud9am  Cloud3pm    Temp9am   
Temp3pm  
min       980.50000   977.100000  0.000000  0.000000  -7.200000  -
5.40000  
max      1041.00000  1039.600000  9.000000  9.000000  40.200000   
46.70000  
mean     1017.64994  1015.255889  4.447461  4.509930  16.990631   
21.68339  
median   1017.60000  1015.200000  5.000000  5.000000  16.700000   
21.10000  
std         7.10653     7.037414  2.887159  2.720357   6.488753   
6.93665  
```

I.2

Carilah:

1. Nilai hilang (*missing*) dari setiap fitur
2. Nilai pencilan (*outlier*) dari setiap fitur

```python
# I.2.1 Nilai hilang (missing) dari setiap fitur

missing_value = df.isnull().sum()
missing_value = missing_value.to_frame()
missing_value.columns = ['jumlah missing value']
missing_value
```

```
               jumlah missing value
Date                              0
Location                          0
MinTemp                        1485
MaxTemp                        1261
Rainfall                       3261
Evaporation                   62790
Sunshine                      69835
WindGustDir                   10326
WindGustSpeed                 10263
WindDir9am                    10566
WindDir3pm                     4228
WindSpeed9am                   1767
WindSpeed3pm                   3062
Humidity9am                    2654
Humidity3pm                    4507
Pressure9am                   15065
Pressure3pm                   15028
Cloud9am                      55888
Cloud3pm                      59358
Temp9am                        1767
Temp3pm                        3609
RainToday                      3261
RainTomorrow                   3267
```

```python
'''
I.2.2 Nilai pencilan (outlier) dari setiap fitur

Proses pencarian nilai pencilan dari setiap fitur menggunakan metode
IQR untuk fitur
yang memiliki tipe data numerical dan menggunakan metode frequency
distribution untuk
fitur yang memiliki tipe data kategorikal.
Data yang dianggap pencilan untuk fitur yang memiliki tipe numerical
adalah data yang
berada di luar rentang Q1 - 1.5*IQR dan Q3 + 1.5*IQR dengan IQR = Q3 -
Q1.
Data yang dianggap pencilan untuk fitur yang memiliki tipe kategorikal
adalah data yang
frekuensi z-scorenya lebih dari 2.5.

'''
```

```
def IQR_outlier(data, col):

    # Nilai Q1 dan Q3
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    # Nilai IQR
    IQR = Q3 - Q1
    # Lower bound dan upper bound
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # Nilai outlier
    outlier = data[(data[col] < lower_bound) | (data[col] >
upper_bound)]
    return outlier, lower_bound, upper_bound

# Nilai pencilan dari setiap fitur
outliers_data = pd.DataFrame(columns = ['Fitur', 'Jumlah nilai
pencilan', 'Upper bound', 'Lower bound', 'Nilai pencilan'])

for col in df.columns:
    if df[col].dtype == 'float64' or df[col].dtype == 'int64':
        outliers, lower_bound, upper_bound = IQR_outlier(df, col)
        if len(outliers) > 0:
            res = pd.DataFrame({'Fitur':[col], 'Jumlah nilai
pencilan':[len(outliers)], 'Upper bound':[upper_bound], 'Lower bound':
[lower_bound], 'Nilai pencilan':None})
            outliers_data = pd.concat([outliers_data, res])
        else:
            res = pd.DataFrame({'Fitur':[col], 'Jumlah nilai
pencilan':[len(outliers)], 'Upper bound':[upper_bound], 'Lower bound':
[lower_bound], 'Nilai pencilan':None})
            outliers_data = pd.concat([outliers_data, res])
    else:
        # Nilai frekuensi dari setiap nilai kategorikal
        freq = df[col].value_counts()
        # Nilai z-score dari setiap nilai kategorikal
        z = zscore.zscore(freq)
        # Nilai pencilan
        outliers = freq[z > 2.5]
        if len(outliers) > 0:
            res = pd.DataFrame({'Fitur':[col], 'Jumlah nilai
pencilan':[len(outliers)], 'Upper bound':None, 'Lower bound':[2.5],
'Nilai pencilan':outliers.index.tolist()}, index = [0])
            outliers_data = pd.concat([outliers_data, res])
        else:
            res = pd.DataFrame({'Fitur':[col], 'Jumlah nilai
pencilan':[len(outliers)], 'Upper bound':None, 'Lower bound':[2.5],
'Nilai pencilan':None}, index = [0])
            outliers_data = pd.concat([outliers_data, res])
outliers_data = outliers_data.reset_index(drop = True)
```

```python
outliers_data

# Untuk fitur dengan tipe data numerical, value dari nilai pencilan tidak ditambahkan di data frame, karena nilai tersebut
# terlalu banyak sehingga tidak dapat ditampilkan. Untuk fitur dengan tipe data kategorikal, value dari nilai pencilan terdapat pada kolom
# nilai pencilan.
```

	Fitur	Jumlah nilai pencilan	Upper bound	Lower bound	Nilai pencilan
0	Date	0	None	2.5	None
1	Location	0	None	2.5	None
2	MinTemp	54	30.85	-6.35	None
3	MaxTemp	489	43.65	2.45	None
4	Rainfall	25578	2.0	-1.2	None
5	Evaporation	1995	14.6	-4.6	None
6	Sunshine	0	19.3	-3.9	None
7	WindGustDir	0	None	2.5	None
8	WindGustSpeed	3092	73.5	5.5	None
9	WindDir9am	1	None	2.5	N
10	WindDir3pm	0	None	2.5	None
11	WindSpeed9am	1817	37.0	-11.0	None
12	WindSpeed3pm	2523	40.5	-3.5	None
13	Humidity9am	1425	122.0	18.0	None
14	Humidity3pm	0	109.5	-6.5	None
15	Pressure9am	1191	1036.65	998.65	None
16	Pressure3pm	919	1034.4	996.0	None
17	Cloud9am	0	16.0	-8.0	None
18	Cloud3pm	0	14.5	-5.5	None
19	Temp9am	262	35.55	-1.65	None

```
20         Temp3pm                      764         41.1          1.9
None
21       RainToday                        0         None          2.5
None
22    RainTomorrow                        0         None          2.5
None
```

I.3

Lakukan:

1. Pencarian korelasi antarfitur
2. Visualisasi distribusi setiap fitur (kategorikal dan kontinu)
3. Visualisasi distribusi setiap fitur per target (`RainTomorrow`)

I.3.1

Pencarian korelasi antarfitur

```
# I.3 Kode di sini.
df[noncategorical_features].corr()
```

```
                MinTemp   MaxTemp  Rainfall  Evaporation  Sunshine  \
MinTemp        1.000000  0.736555  0.103938     0.466993  0.072586
MaxTemp        0.736555  1.000000 -0.074992     0.587932  0.470156
Rainfall       0.103938 -0.074992  1.000000    -0.064351 -0.227549
Evaporation    0.466993  0.587932 -0.064351     1.000000  0.365602
Sunshine       0.072586  0.470156 -0.227549     0.365602  1.000000
WindGustSpeed  0.177415  0.067615  0.133659     0.203021 -0.034750
WindSpeed9am   0.175064  0.014450  0.087338     0.193084  0.005499
WindSpeed3pm   0.175173  0.050300  0.057887     0.129400  0.053834
Humidity9am   -0.232899 -0.504110  0.224405    -0.504092 -0.490819
Humidity3pm    0.006089 -0.508855  0.255755    -0.390243 -0.629130
Pressure9am   -0.450970 -0.332061 -0.168154    -0.270362  0.041970
Pressure3pm   -0.461292 -0.427167 -0.126534    -0.293581 -0.019719
Cloud9am       0.078754 -0.289370  0.198528    -0.183793 -0.675323
Cloud3pm       0.021605 -0.277921  0.172403    -0.182618 -0.703930
Temp9am        0.901821  0.887210  0.011192     0.545115  0.291188
Temp3pm        0.708906  0.984503 -0.079657     0.572893  0.490501

               WindGustSpeed  WindSpeed9am  WindSpeed3pm  Humidity9am
\
MinTemp             0.177415      0.175064      0.175173    -0.232899

MaxTemp             0.067615      0.014450      0.050300    -0.504110

Rainfall            0.133659      0.087338      0.057887     0.224405

Evaporation         0.203021      0.193084      0.129400    -0.504092
```

Sunshine	-0.034750	0.005499	0.053834	-0.490819
WindGustSpeed	1.000000	0.605303	0.686307	-0.215070
WindSpeed9am	0.605303	1.000000	0.519547	-0.270858
WindSpeed3pm	0.686307	0.519547	1.000000	-0.145525
Humidity9am	-0.215070	-0.270858	-0.145525	1.000000
Humidity3pm	-0.026327	-0.031614	0.016432	0.666949
Pressure9am	-0.458744	-0.228743	-0.296351	0.139442
Pressure3pm	-0.413749	-0.175817	-0.255439	0.186858
Cloud9am	0.071736	0.025112	0.053337	0.452297
Cloud3pm	0.109168	0.054639	0.025396	0.357326
Temp9am	0.150150	0.128545	0.163030	-0.471354
Temp3pm	0.032748	0.004569	0.027778	-0.498399

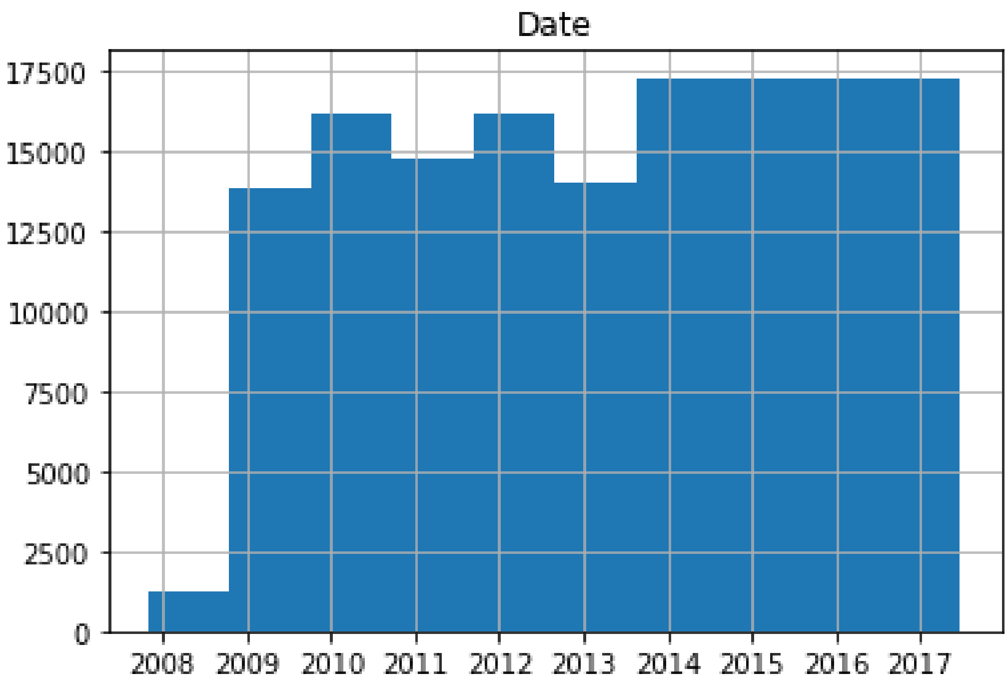
	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm \
MinTemp	0.006089	-0.450970	-0.461292	0.078754	0.021605
MaxTemp	-0.508855	-0.332061	-0.427167	-0.289370	-0.277921
Rainfall	0.255755	-0.168154	-0.126534	0.198528	0.172403
Evaporation	-0.390243	-0.270362	-0.293581	-0.183793	-0.182618
Sunshine	-0.629130	0.041970	-0.019719	-0.675323	-0.703930
WindGustSpeed	-0.026327	-0.458744	-0.413749	0.071736	0.109168
WindSpeed9am	-0.031614	-0.228743	-0.175817	0.025112	0.054639
WindSpeed3pm	0.016432	-0.296351	-0.255439	0.053337	0.025396
Humidity9am	0.666949	0.139442	0.186858	0.452297	0.357326
Humidity3pm	1.000000	-0.027544	0.051997	0.517120	0.523120
Pressure9am	-0.027544	1.000000	0.961326	-0.129796	-0.147861

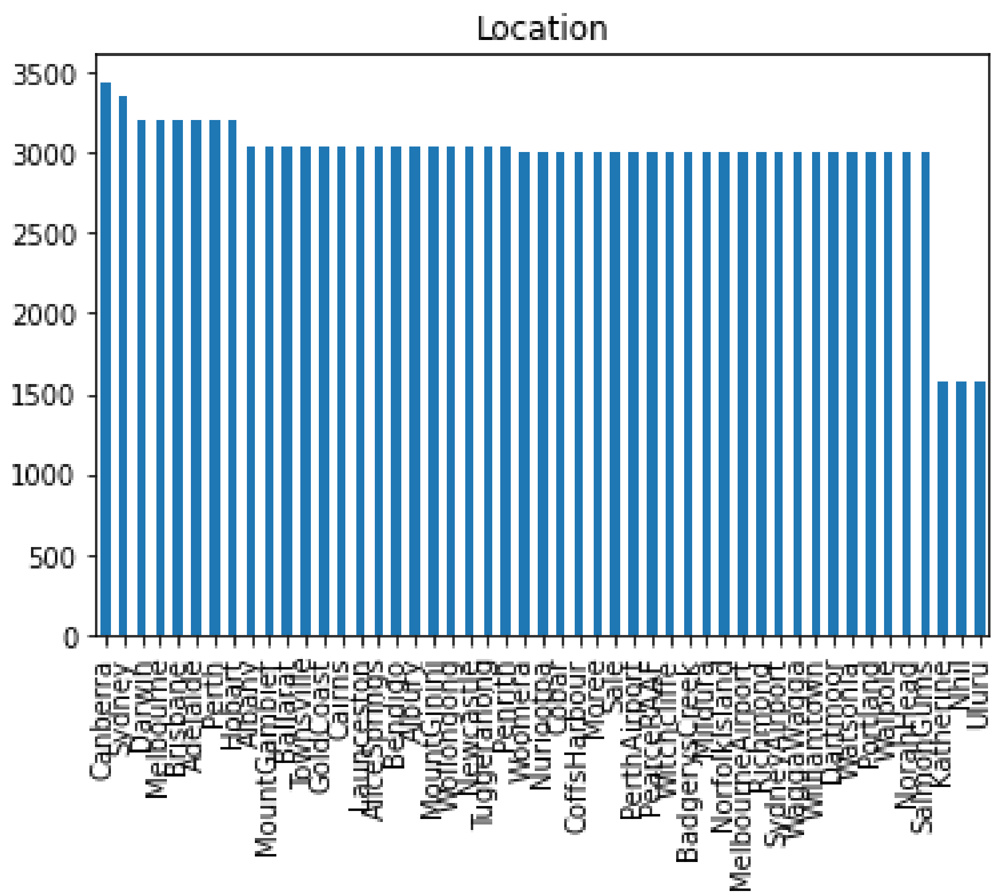
```
Pressure3pm       0.051997     0.961326     1.000000 -0.060772 -
0.084778
Cloud9am          0.517120    -0.129796    -0.060772  1.000000
0.603564
Cloud3pm          0.523120    -0.147861    -0.084778  0.603564
1.000000
Temp9am          -0.221019    -0.422556    -0.470187 -0.136959 -
0.126659
Temp3pm          -0.557841    -0.286770    -0.389548 -0.302060 -
0.317420

                Temp9am   Temp3pm
MinTemp        0.901821  0.708906
MaxTemp        0.887210  0.984503
Rainfall       0.011192 -0.079657
Evaporation    0.545115  0.572893
Sunshine       0.291188  0.490501
WindGustSpeed  0.150150  0.032748
WindSpeed9am   0.128545  0.004569
WindSpeed3pm   0.163030  0.027778
Humidity9am   -0.471354 -0.498399
Humidity3pm   -0.221019 -0.557841
Pressure9am   -0.422556 -0.286770
Pressure3pm   -0.470187 -0.389548
Cloud9am      -0.136959 -0.302060
Cloud3pm      -0.126659 -0.317420
Temp9am        1.000000  0.860591
Temp3pm        0.860591  1.000000
```

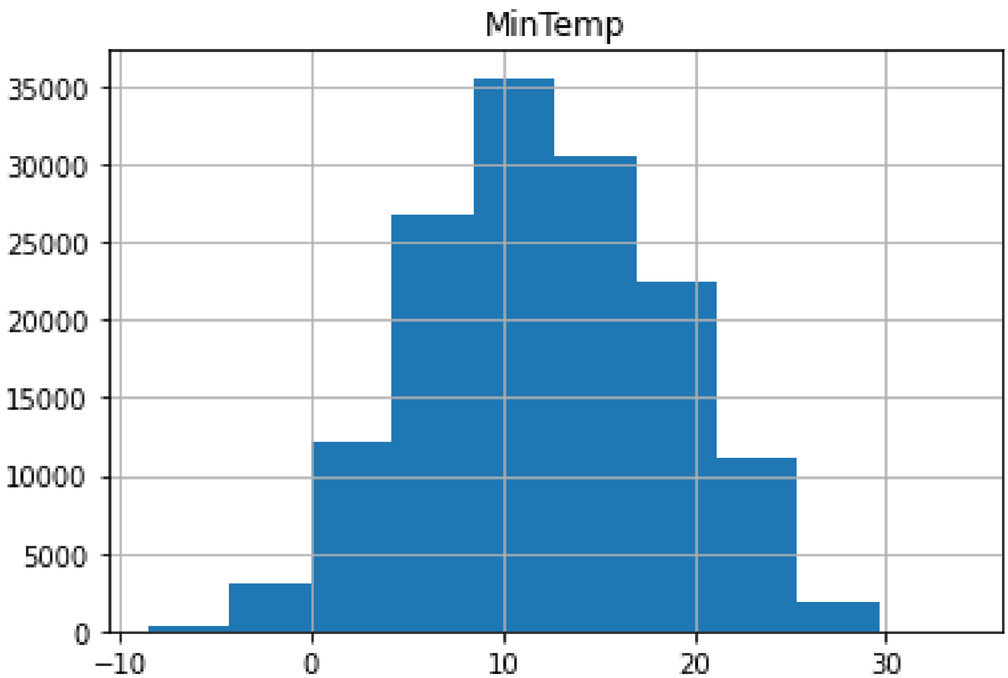
I.3.2

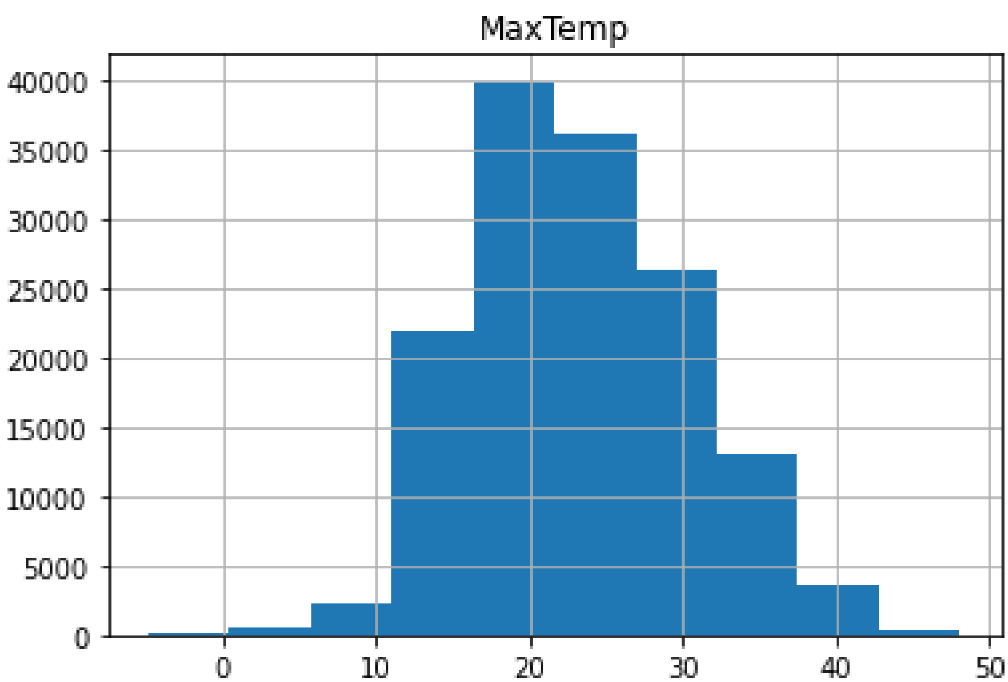
Visualisasi distribusi setiap fitur (kategorikal dan kontinu)

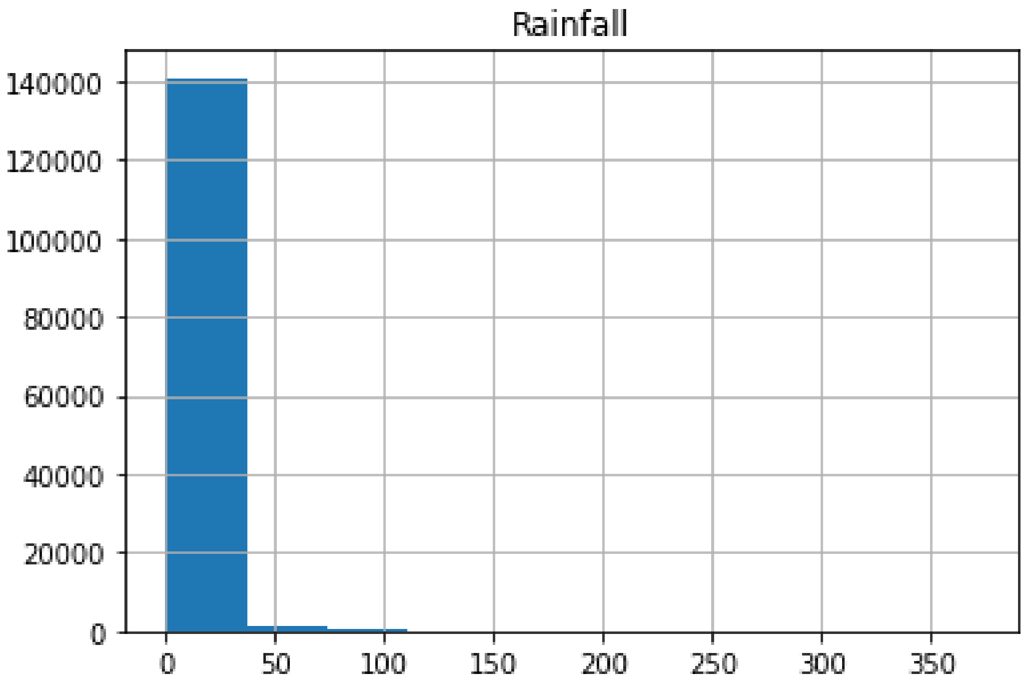
```python
# Ubah kolom tanggal dari string ke Datetime
df_clean_date = df.copy(deep=True)
df_clean_date['Date'] = pd.to_datetime(df_clean_date['Date'])

for col in df_clean_date.columns:
    if df_clean_date[col].dtype == 'object':
        df_clean_date[col].value_counts().plot(kind='bar')
    else:
        df_clean_date[col].hist()
    plt.title(col)
    plt.show()
```

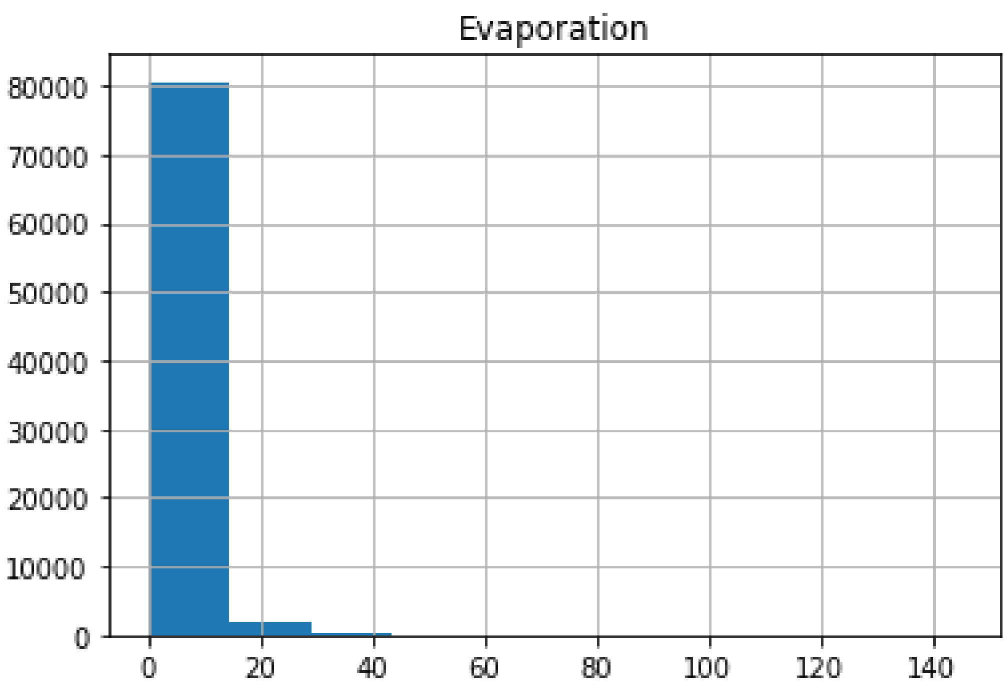

Date
0
2500
5000
7500
10000
12500
15000
17500
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

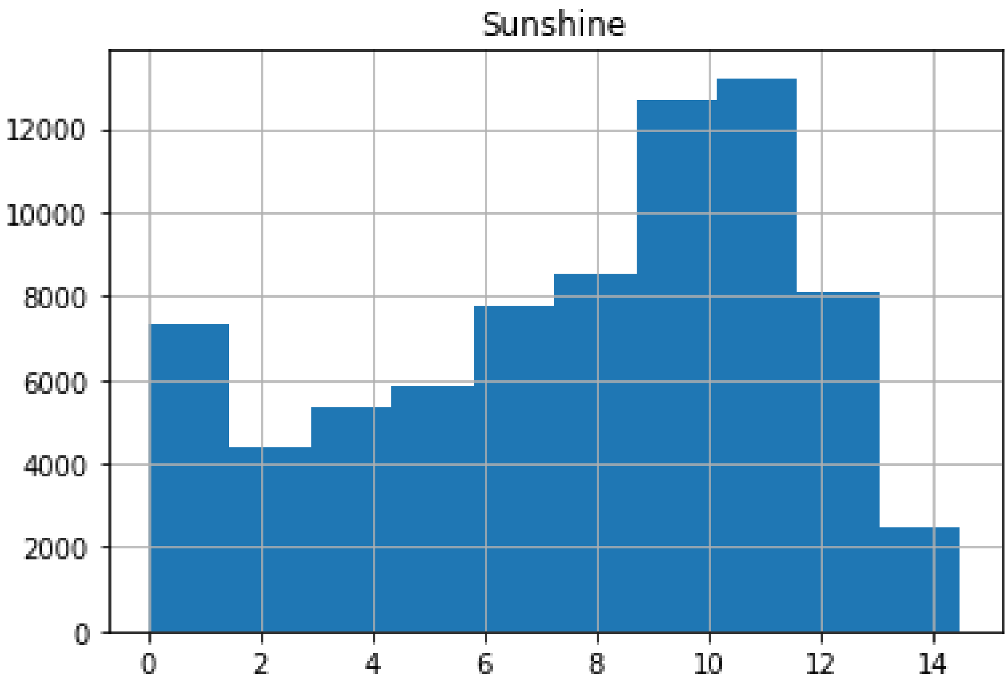

Location
0
500
1000
1500
2000
2500
3000
3500
Canberra
Sydney
Darwin
Melbourne
Brisbane
Adelaide
Perth
Hobart
Albany
MountGambier
Ballarat
Townsville
GoldCoast
Cairns
Launceston
AliceSprings
Bendigo
Albury
MountGinini
Wollongong
Newcastle
Tuggeranong
Penrith
Woomera
Nuriootpa
Cobar
CoffsHarbour
Moree
Sale
PerthAirport
PearceRAAF
Witchcliffe
BadgerysCreek
Mildura
NorfolkIsland
MelbourneAirport
Richmond
SydneyAirport
WaggaWagga
Williamtown
Dartmoor
Watsonia
Portland
Walpole
NorahHead
SalmonGums
Katherine
Nhil
Uluru

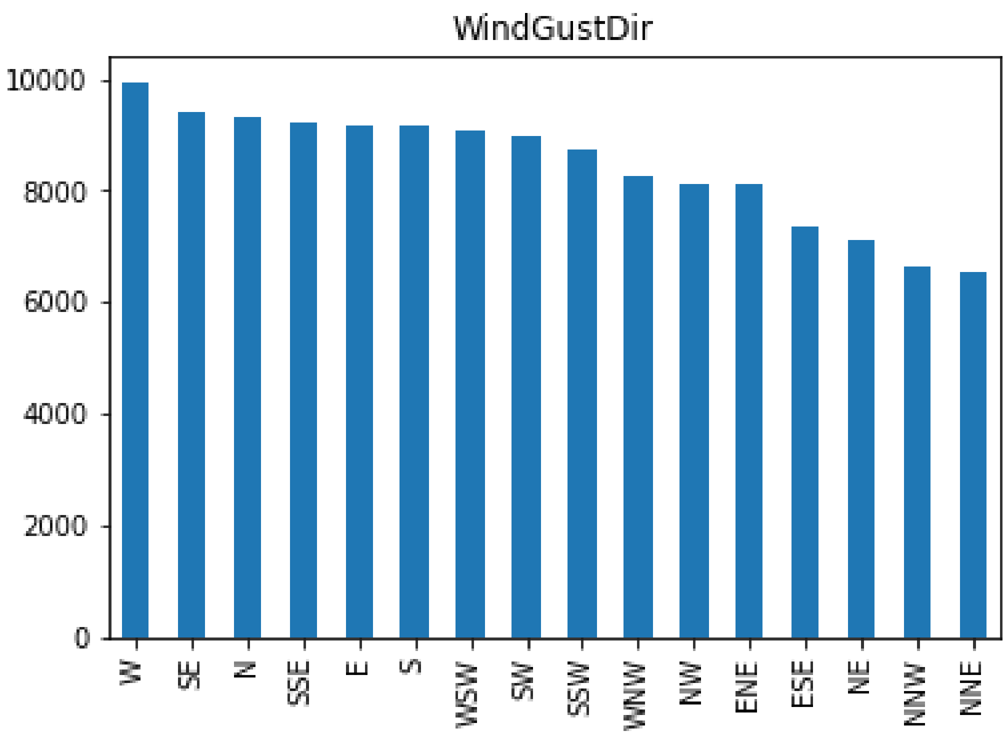

MinTemp
35000
30000
25000
20000
15000
10000
5000
0
−10
0
10
20
30

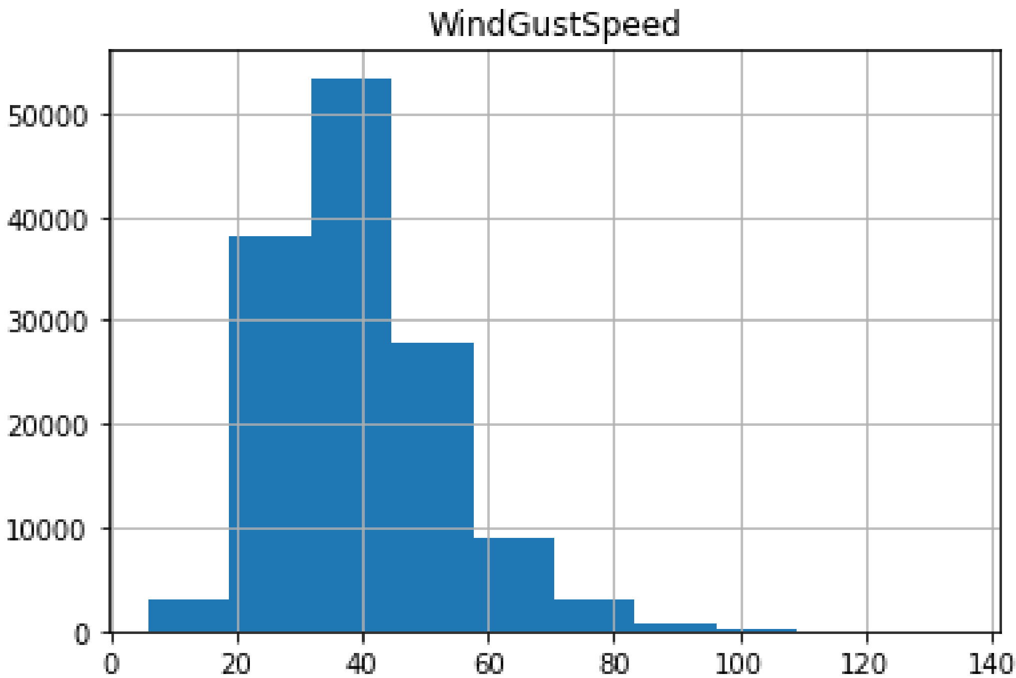

MaxTemp
40000
35000
30000
25000
20000
15000
10000
5000
0
0
10
20
30
40
50

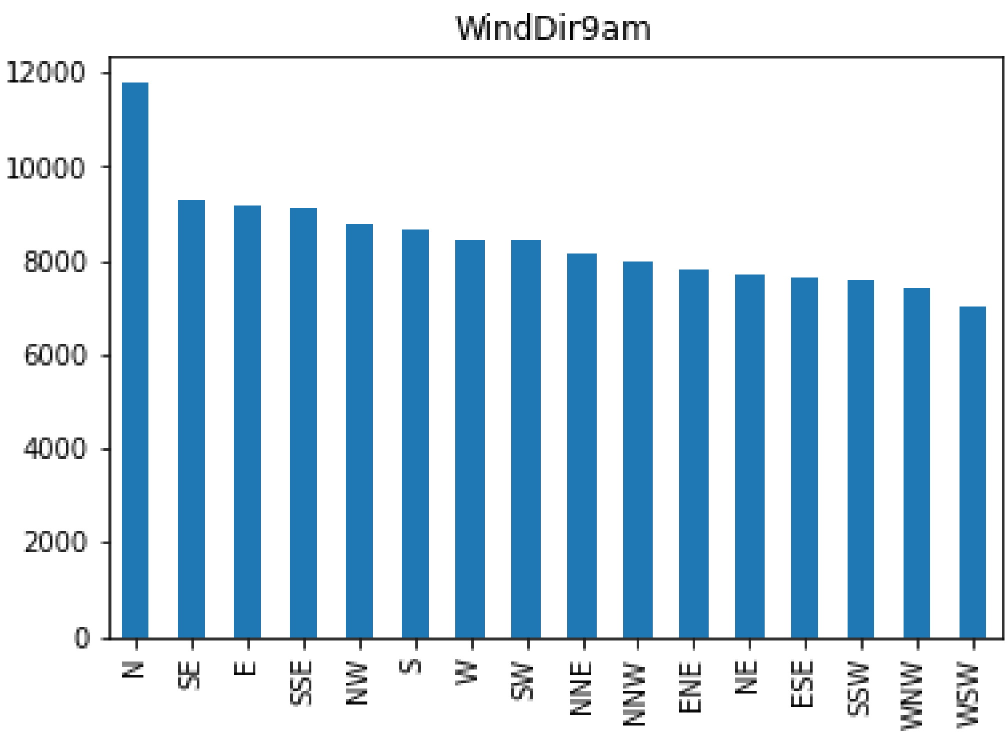

Rainfall
140000
120000
100000
80000
60000
40000
20000
0
0
50
100
150
200
250
300
350

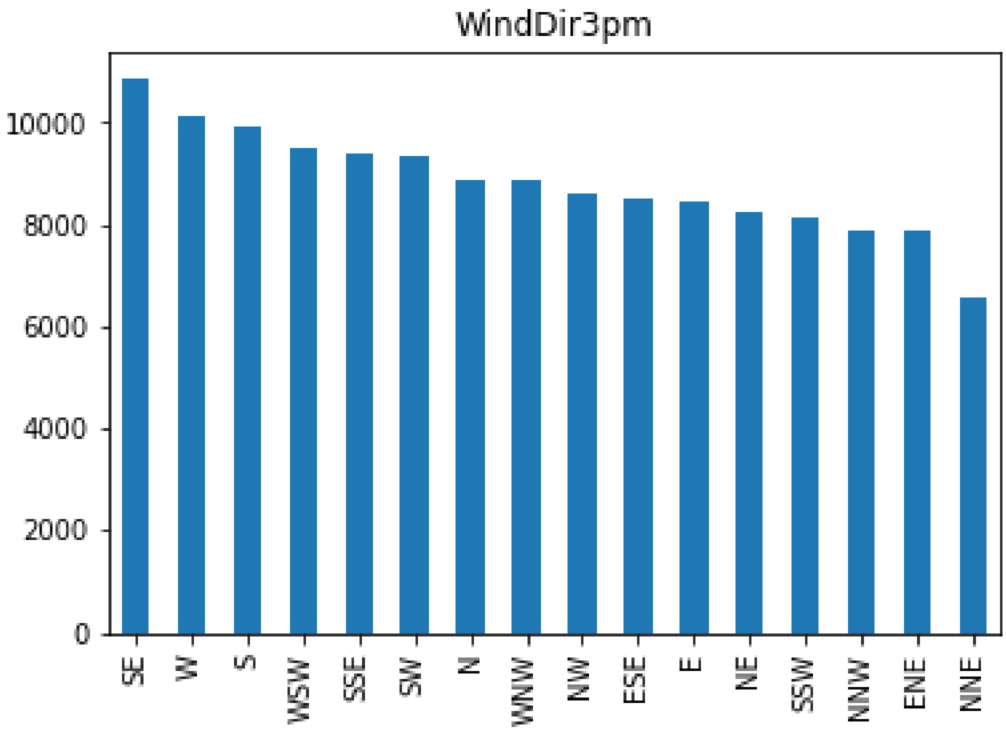

Evaporation
80000
70000
60000
50000
40000
30000
20000
10000
0
0
20
40
60
80
100
120
140

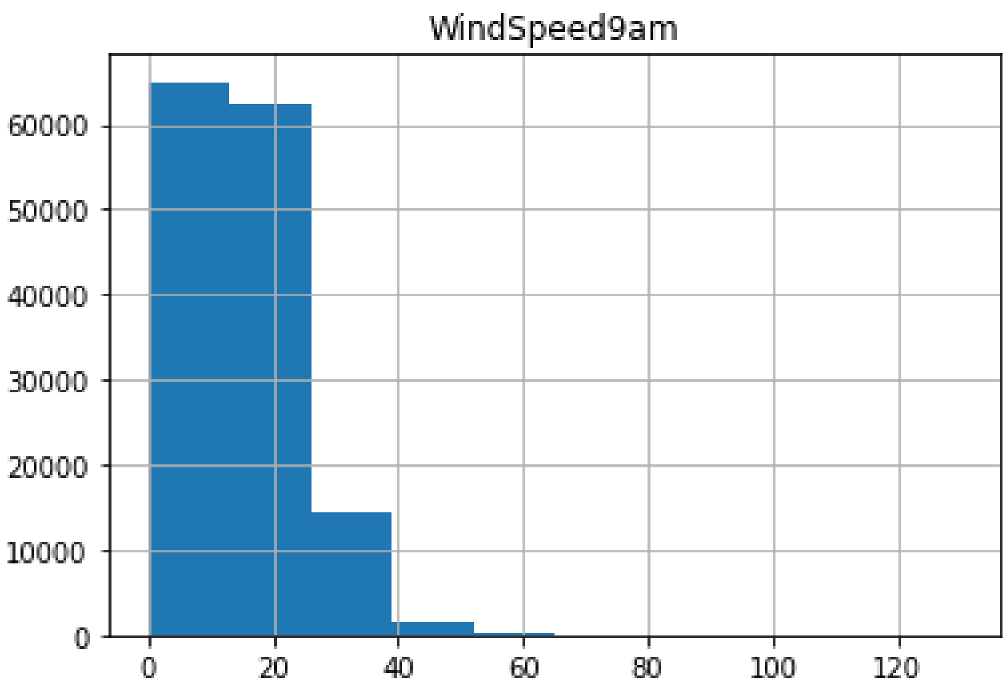

Sunshine
12000
10000
8000
6000
4000
2000
0
0
2
4
6
8
10
12
14

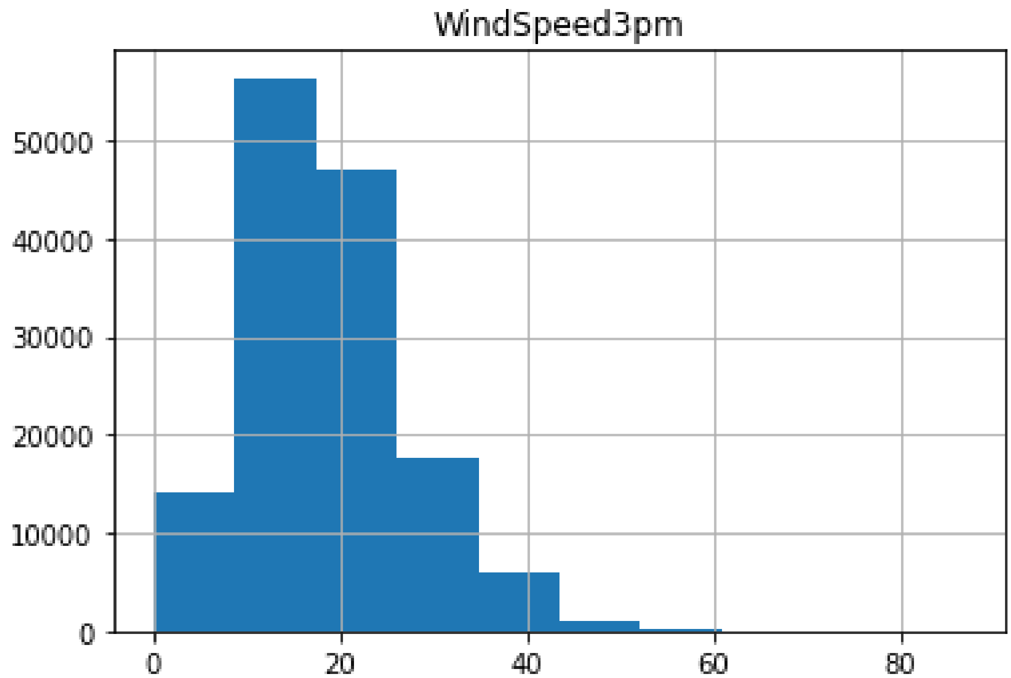

WindGustDir
10000
8000
6000
4000
2000
0
W
SE
N
SSE
E
S
WSW
SW
SSW
WNW
NW
ENE
ESE
NE
NNW
NNE

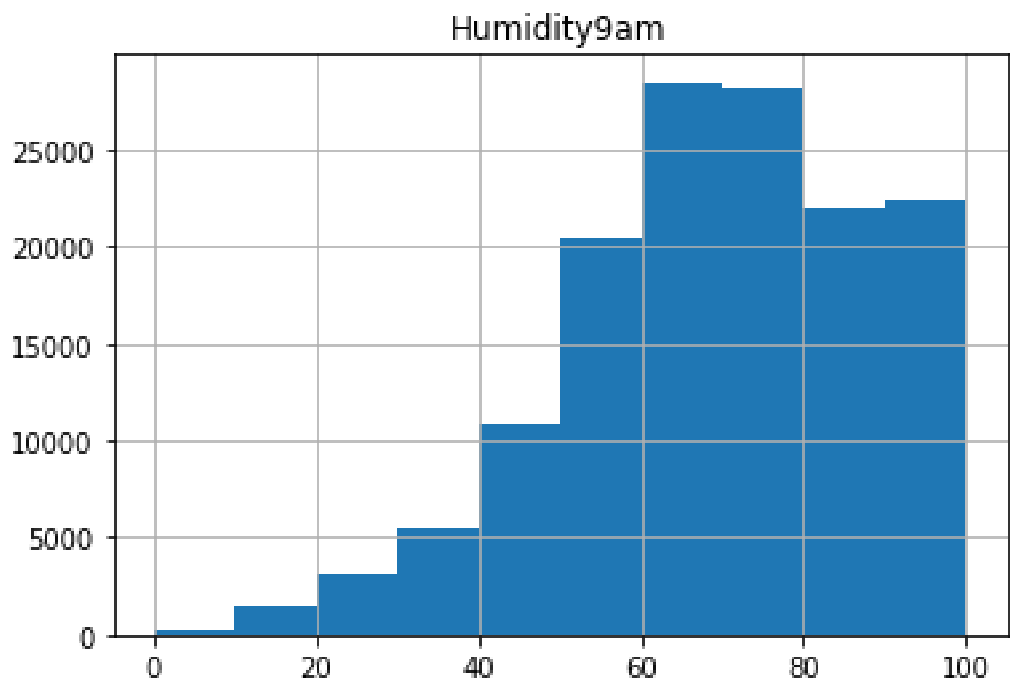

WindGustSpeed
0
10000
20000
30000
40000
50000
0
20
40
60
80
100
120
140

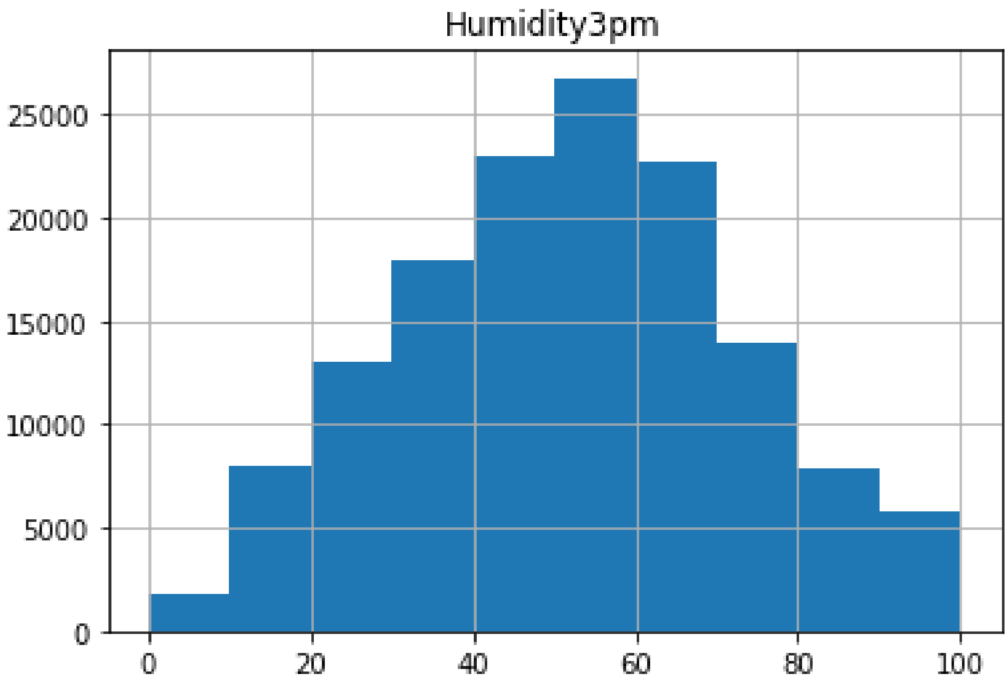

WindDir9am
0
2000
4000
6000
8000
10000
12000
N
SE
E
SSE
NW
S
W
SW
NNE
NNW
ENE
NE
ESE
SSW
WNW
WSW

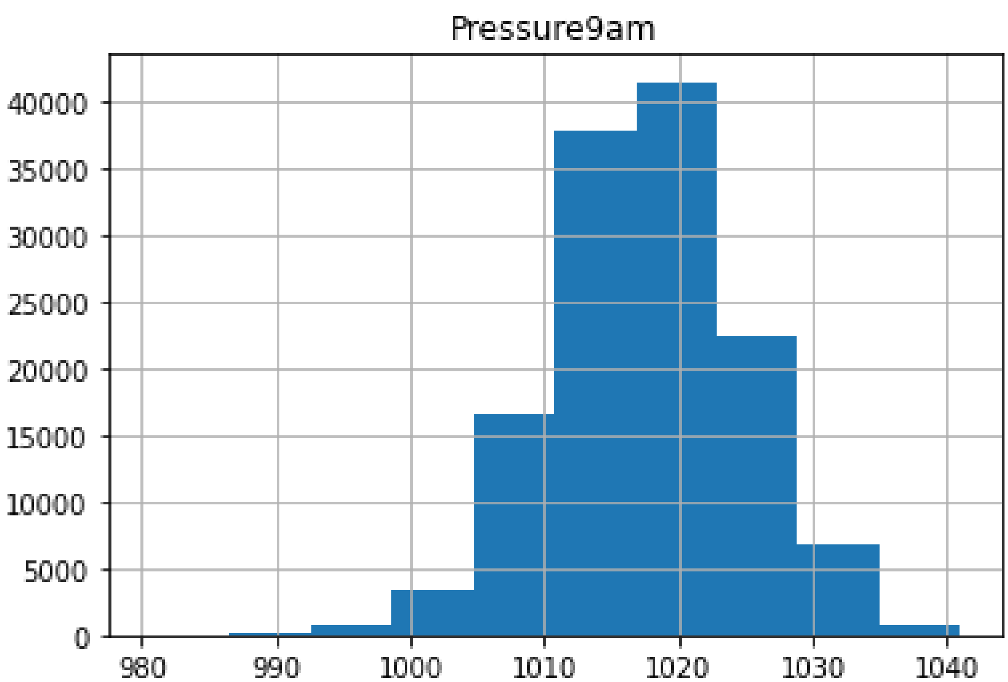

WindDir3pm
10000
8000
6000
4000
2000
0
SE
W
S
WSW
SSE
SW
N
WNW
NW
ESE
E
NE
SSW
NNW
ENE
NNE

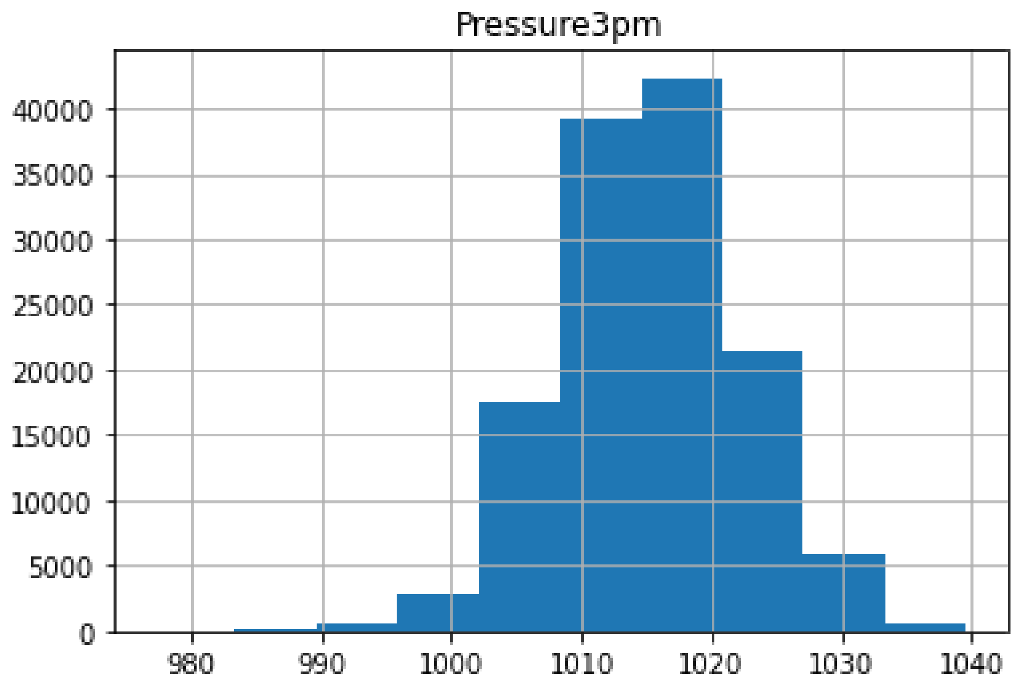

WindSpeed9am
60000
50000
40000
30000
20000
10000
0
0
20
40
60
80
100
120

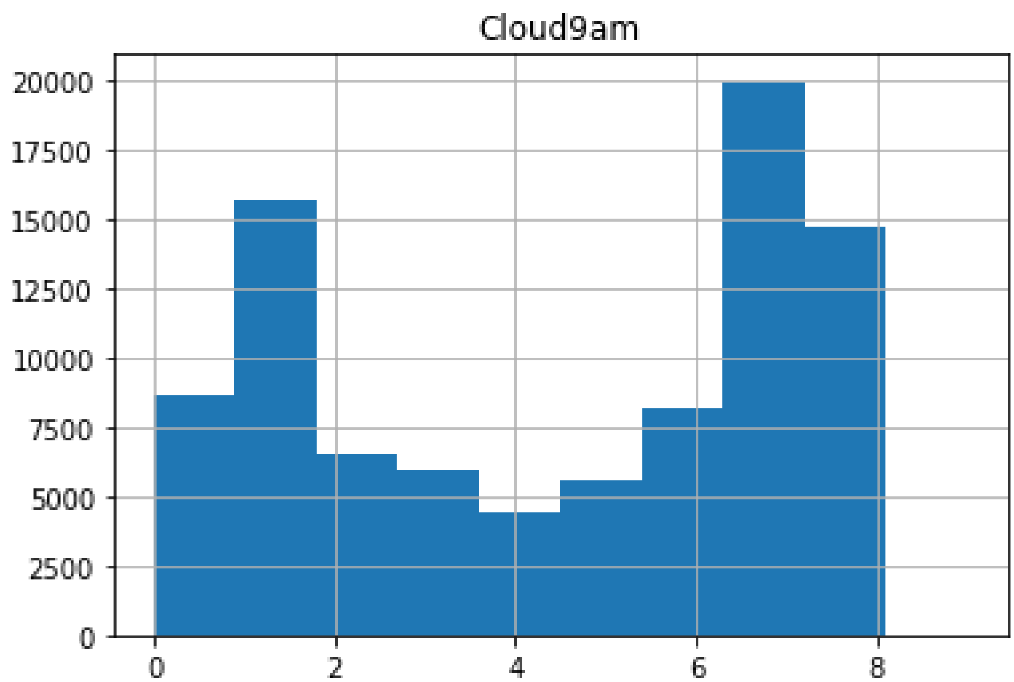

WindSpeed3pm
50000
40000
30000
20000
10000
0
0
20
40
60
80

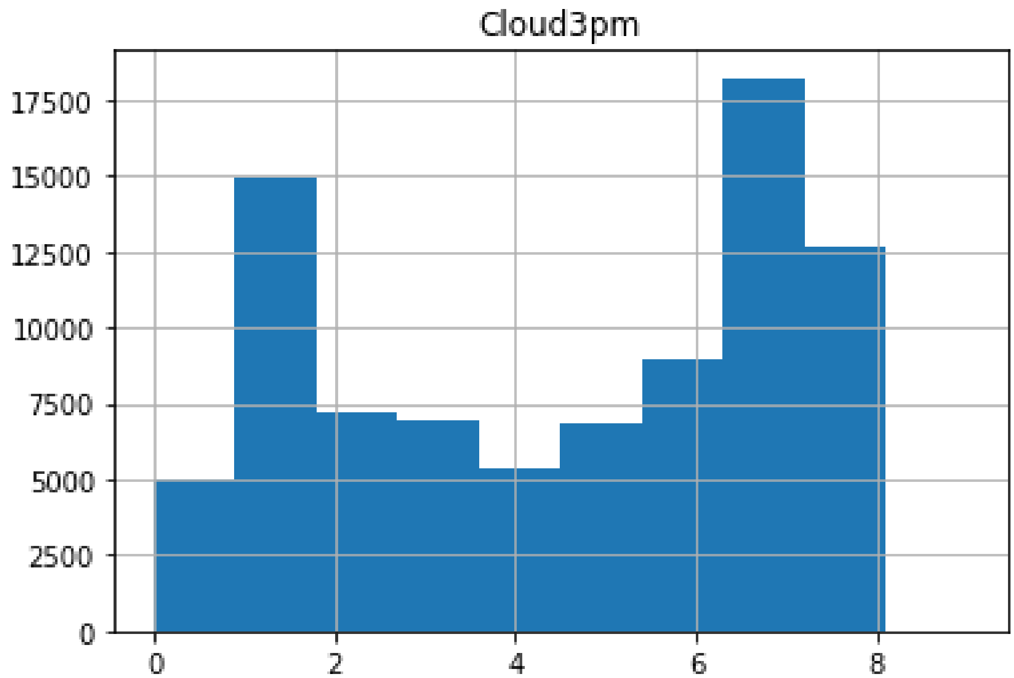

Humidity9am
25000
20000
15000
10000
5000
0
0
20
40
60
80
100


Humidity3pm
25000
20000
15000
10000
5000
0
0
20
40
60
80
100

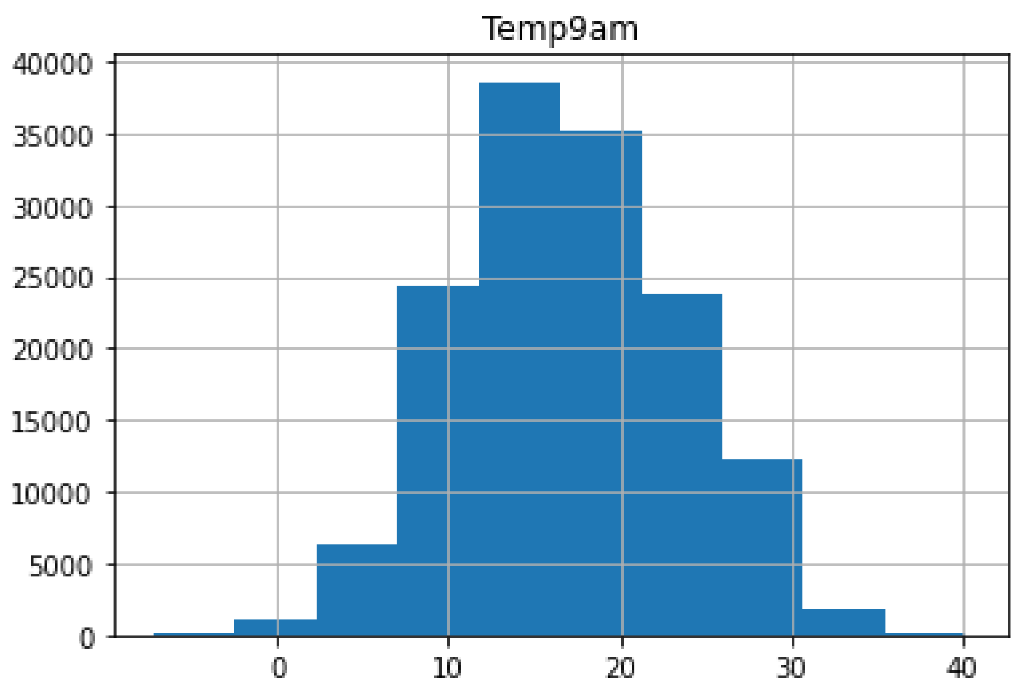

Pressure9am
40000
35000
30000
25000
20000
15000
10000
5000
0
980
990
1000
1010
1020
1030
1040


Pressure3pm
40000
35000
30000
25000
20000
15000
10000
5000
0
980
990
1000
1010
1020
1030
1040

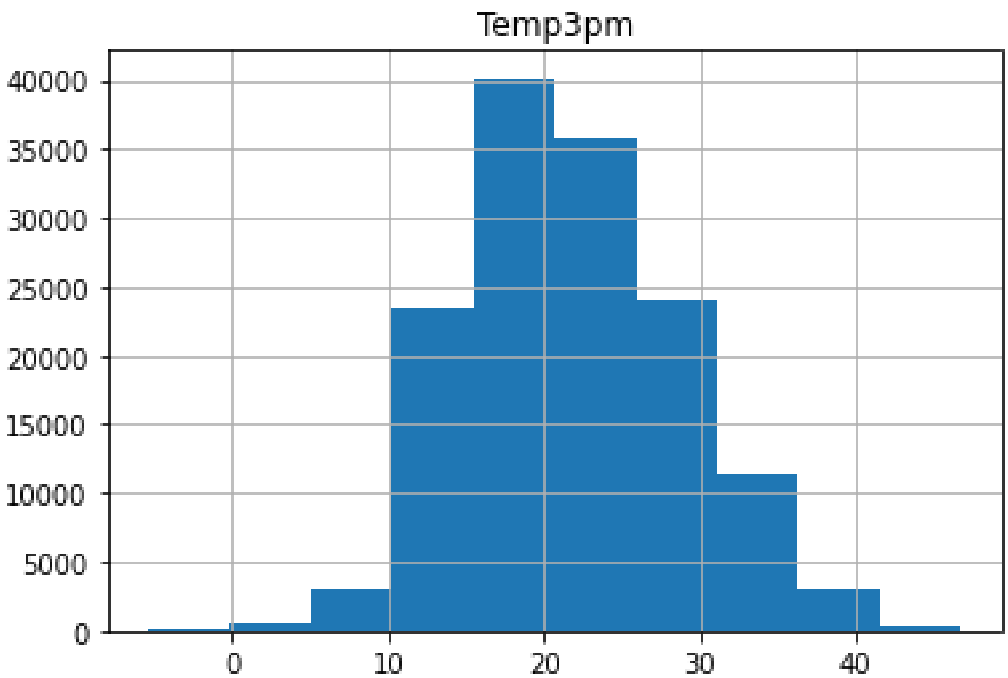

Cloud9am
20000
17500
15000
12500
10000
7500
5000
2500
0
0
2
4
6
8



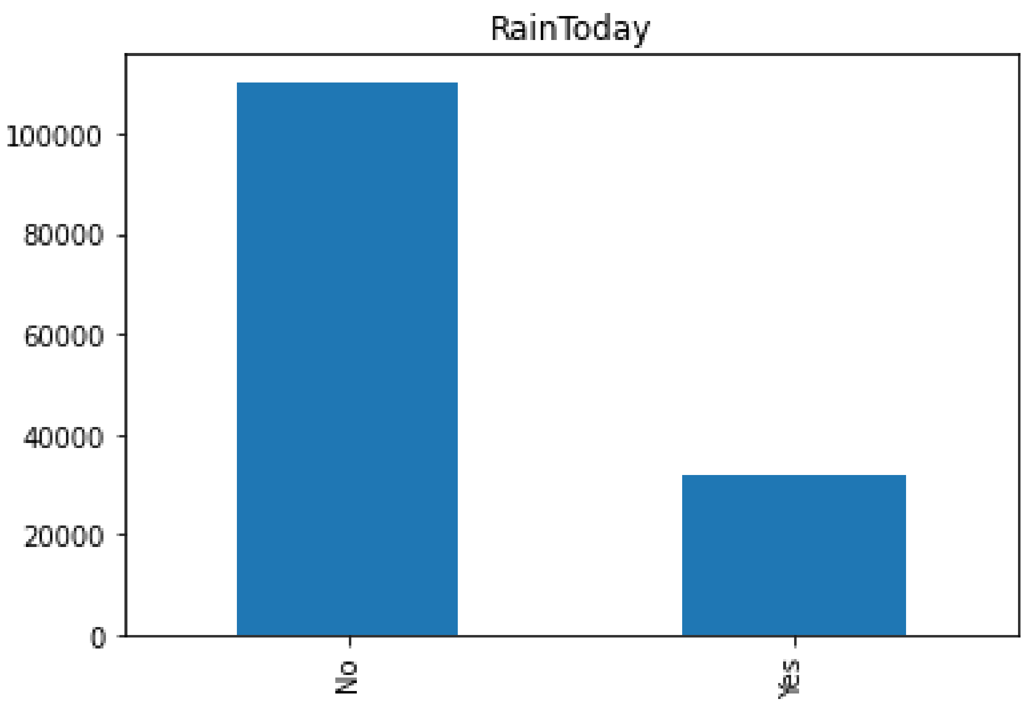
Cloud3pm
17500
15000
12500
10000
7500
5000
2500
0
0
2
4
6
8



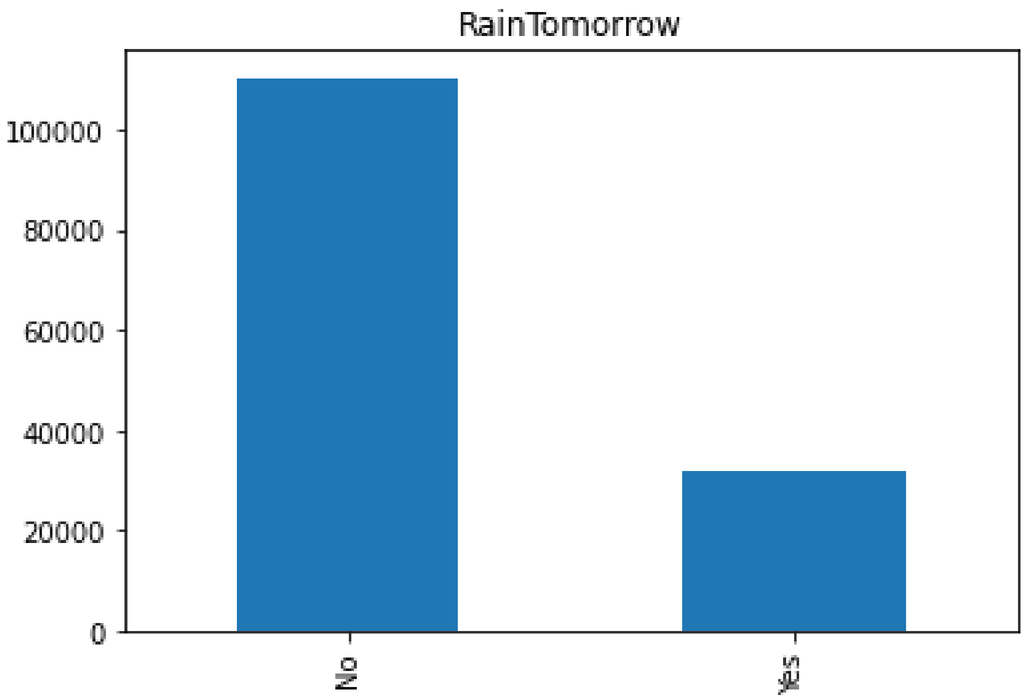
Temp9am
40000
35000
30000
25000
20000
15000
10000
5000
0
0
10
20
30
40



Temp3pm
40000
35000
30000
25000
20000
15000
10000
5000
0
0
10
20
30
40



RainToday
100000
80000
60000
40000
20000
0
No
Yes

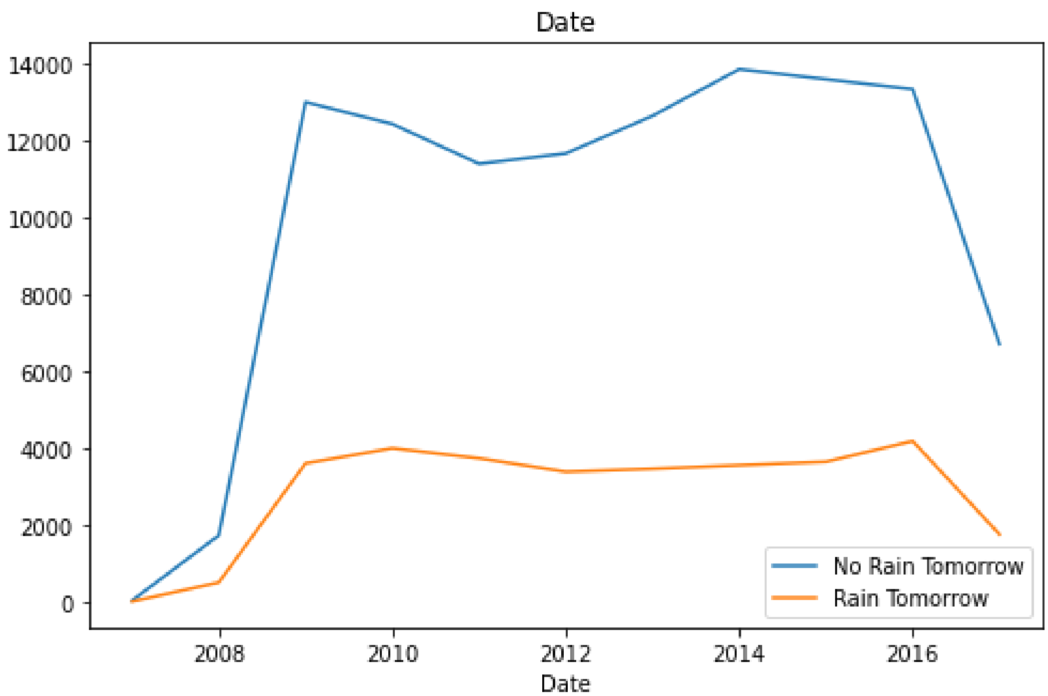


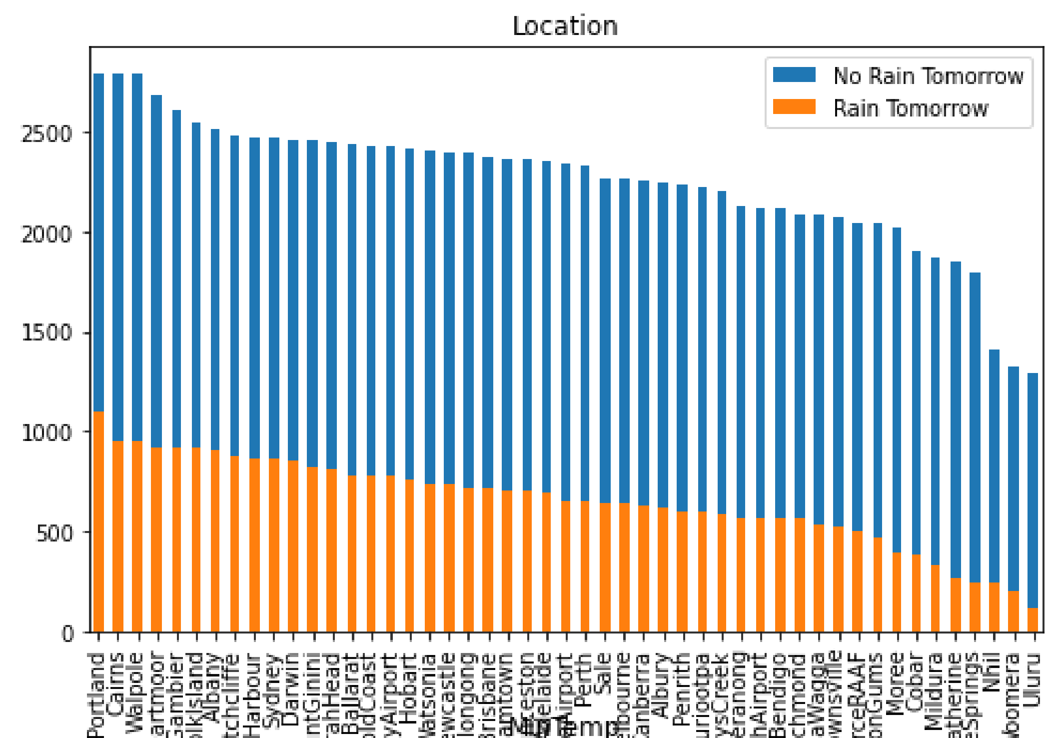
I.3.3

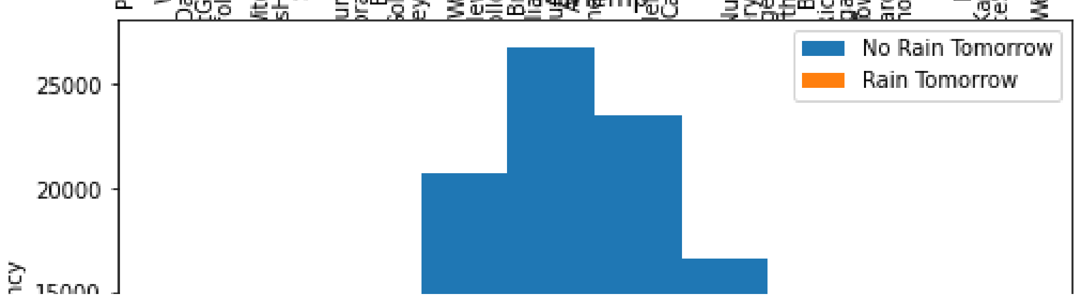
Visualisasi distribusi setiap fitur per target (`RainTomorrow`)

```
# create subplots
fig, axes = plt.subplots(nrows=len(df_clean_date.columns) - 1,
ncols=1, figsize=(8, (len(df_clean_date.columns) - 1) * 6))
# loop over the columns
for i, col in enumerate(df_clean_date.columns):
    if col == 'RainTomorrow':
        continue
    elif df_clean_date[col].dtype == 'object':
        # categorical column - use bar chart
        df_clean_date[df_clean_date['RainTomorrow'] == 'No']
[col].value_counts().plot.bar(ax=axes[i], label='No Rain Tomorrow',
color='tab:blue')
        df_clean_date[df_clean_date['RainTomorrow'] == 'Yes']
[col].value_counts().plot.bar(ax=axes[i], label='Rain Tomorrow',
color='tab:orange')
        axes[i].set_title(col)
        axes[i].legend()
    elif df_clean_date[col].dtype == 'datetime64[ns]':
        no_date = df_clean_date[df_clean_date['RainTomorrow'] == 'No']
[['Date', 'RainTomorrow']]
        no_date.groupby(no_date["Date"].dt.year).count()
['RainTomorrow'].plot(kind='line', label='No Rain Tomorrow',
ax=axes[i], legend=True, color='tab:blue')
        yes_date = df_clean_date[df_clean_date['RainTomorrow'] ==
'Yes'][['Date', 'RainTomorrow']]
```

```
        yes_date.groupby(yes_date["Date"].dt.year).count()
['RainTomorrow'].plot(kind='line', label='Rain Tomorrow', ax=axes[i],
legend=True, color='tab:orange')
        axes[i].set_title(col)
    else:
        # non-categorical column - use histogram
        df_clean_date[df_clean_date['RainTomorrow'] == 'No']
[col].plot.hist(ax=axes[i], label='No Rain Tomorrow',
color='tab:blue')
        df_clean_date[df_clean_date['RainTomorrow'] == 'Yes']
[col].plot.hist(ax=axes[i], label='Rain Tomorrow', color='tab:orange')
        axes[i].set_title(col)
        axes[i].legend()

# show the plot
plt.show()
```


Date
14000
12000
10000
8000
6000
4000
2000
0
2008
2010
2012
2014
2016
Date
No Rain Tomorrow
Rain Tomorrow


Location
2500
2000
1500
1000
500
0
No Rain Tomorrow
Rain Tomorrow
Portland
Cairns
Walpole
Albany
Sydney
Darwin
Ballarat
Hobart
Watsonia
Brisbane
Adelaide
Perth
Sale
Canberra
Albury
Penrith
Bendigo
Moree
Cobar
Mildura
Katherine
Nhil
Woomera
Uluru


25000
20000
No Rain Tomorrow
Rain Tomorrow

I.4

Lakukanlah analisis lebih lanjut jika diperlukan, kemudian lakukan hal berikut:

1. Penambahan fitur jika memungkinkan
2. Pembuangan fitur yang menurut kalian tidak dibutuhkan
3. Penanganan nilai hilang
4. Transformasi data kategorikal menjadi numerikal (*encoding*)
5. *Scaling* dengan `MinMaxScaler`

I.4.1 Penambahan fitur jika memungkinkan

Dari hasil analisis data, tidak diperlukan penambahan fitur baru. Data yang ada sudah cukup untuk melakukan prediksi status hujan pada keesokan harinya.

```
'''
I.4.2 Pembuangan fitur yang tidak diperlukan

Dari hasil analisis data, fitur yang tidak diperlukan adalah fitur
'Date' dan 'Location'.
'''

# Pembuangan fitur yang tidak diperlukan
df.drop(['Date', 'Location'], axis = 1, inplace = True)
df.head()
```

```
   MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine WindGustDir  \
0     13.4     22.9       0.6          NaN       NaN           W
1      7.4     25.1       0.0          NaN       NaN         WNW
2     12.9     25.7       0.0          NaN       NaN         WSW
3      9.2     28.0       0.0          NaN       NaN          NE
4     17.5     32.3       1.0          NaN       NaN           W

   WindGustSpeed WindDir9am WindDir3pm  WindSpeed9am  ...  Humidity9am
\
0           44.0          W        WNW          20.0  ...         71.0

1           44.0        NNW        WSW           4.0  ...         44.0

2           46.0          W        WSW          19.0  ...         38.0

3           24.0         SE          E          11.0  ...         45.0

4           41.0        ENE         NW           7.0  ...         82.0


   Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am
\
0         22.0       1007.7       1007.1       8.0       NaN     16.9
```

```
1          25.0       1010.6       1007.8       NaN       NaN     17.2

2          30.0       1007.6       1008.7       NaN       2.0     21.0

3          16.0       1017.6       1012.8       NaN       NaN     18.1

4          33.0       1010.8       1006.0       7.0       8.0     17.8


   Temp3pm  RainToday RainTomorrow
0     21.8         No           No
1     24.3         No           No
2     23.2         No           No
3     26.5         No           No
4     29.7         No           No

[5 rows x 21 columns]
```

```python
'''
I.4.3 Penanganan nilai hilang (missing)

Dari hasil analisis data penangan terhadap nilai hilang dibagi menjadi
2 bagian, yaitu
penanganan nilai hilang pada fitur yang memiliki tipe data numerical
dan penanganan
nilai hilang pada fitur yang memiliki tipe data kategorikal. Untuk
penanganan nilai
hilang pada fitur yang memiliki tipe data numerical, nilai hilang
diisi dengan nilai
rata rata dari fitur tersebut. Untuk penanganan nilai hilang pada
fitur yang memiliki tipe
data kategorikal, nilai hilang diisi dengan nilai modus dari fitur
tersebut.
'''

# Penanganan nilai hilang pada fitur yang memiliki tipe data numerical
for col in df.columns:
    if df[col].dtype == 'float64' or df[col].dtype == 'int64':
        df[col].fillna(df[col].mean(), inplace = True)
    else:
        df[col].fillna(df[col].mode()[0], inplace = True)

# I.4.4 Transformasi data kategorikal menjadi numerikal (encoding)

encoder = LabelEncoder()
for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = encoder.fit_transform(df[col])
df.head()
```

```
   MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustDir  \
0     13.4     22.9       0.6     5.468232  7.611178           13
1      7.4     25.1       0.0     5.468232  7.611178           14
2     12.9     25.7       0.0     5.468232  7.611178           15
3      9.2     28.0       0.0     5.468232  7.611178            4
4     17.5     32.3       1.0     5.468232  7.611178           13

   WindGustSpeed  WindDir9am  WindDir3pm  WindSpeed9am  ...
Humidity9am  \
0           44.0          13          14          20.0  ...
71.0
1           44.0           6          15           4.0  ...
44.0
2           46.0          13          15          19.0  ...
38.0
3           24.0           9           0          11.0  ...
45.0
4           41.0           1           7           7.0  ...
82.0

   Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am
\
0         22.0       1007.7       1007.1  8.000000   4.50993     16.9

1         25.0       1010.6       1007.8  4.447461   4.50993     17.2

2         30.0       1007.6       1008.7  4.447461   2.00000     21.0

3         16.0       1017.6       1012.8  4.447461   4.50993     18.1

4         33.0       1010.8       1006.0  7.000000   8.00000     17.8


   Temp3pm  RainToday  RainTomorrow
0     21.8          0             0
1     24.3          0             0
2     23.2          0             0
3     26.5          0             0
4     29.7          0             0

[5 rows x 21 columns]
```

```
# I.4.5 Scaling dengan metode MinMaxScaler

scaler = MinMaxScaler()
scaled_df = scaler.fit_transform(df)
scaled_df = pd.DataFrame(scaled_df, columns = df.columns)
scaled_df.head()
```

```
    MinTemp   MaxTemp  Rainfall  Evaporation  Sunshine  WindGustDir  \
0  0.516509  0.523629  0.001617     0.037712  0.524909     0.866667
1  0.375000  0.565217  0.000000     0.037712  0.524909     0.933333
2  0.504717  0.576560  0.000000     0.037712  0.524909     1.000000
3  0.417453  0.620038  0.000000     0.037712  0.524909     0.266667
4  0.613208  0.701323  0.002695     0.037712  0.524909     0.866667

   WindGustSpeed  WindDir9am  WindDir3pm  WindSpeed9am  ...
Humidity9am  \
0       0.294574    0.866667    0.933333      0.153846  ...
0.71
1       0.294574    0.400000    1.000000      0.030769  ...
0.44
2       0.310078    0.866667    1.000000      0.146154  ...
0.38
3       0.139535    0.600000    0.000000      0.084615  ...
0.45
4       0.271318    0.066667    0.466667      0.053846  ...
0.82

   Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm   Temp9am
\
0         0.22     0.449587       0.4800  0.888889  0.501103  0.508439

1         0.25     0.497521       0.4912  0.494162  0.501103  0.514768

2         0.30     0.447934       0.5056  0.494162  0.222222  0.594937

3         0.16     0.613223       0.5712  0.494162  0.501103  0.533755

4         0.33     0.500826       0.4624  0.777778  0.888889  0.527426


    Temp3pm  RainToday  RainTomorrow
0  0.522073        0.0           0.0
1  0.570058        0.0           0.0
2  0.548944        0.0           0.0
3  0.612284        0.0           0.0
4  0.673704        0.0           0.0

[5 rows x 21 columns]
```

II. Desain Eksperimen

Tujuan dari bagian ini adalah peserta dapat memahami cara melakukan eksperimen mencari metode terbaik dengan benar. Hal yang diliputi adalah sebagai berikut:

1. Pembuatan model

2. Proses validasi
3. *Hyperparameter tuning*

II.1

Tentukanlah metrik yang akan digunakan pada eksperimen kali ini. Metrik yang dapat lebih dari satu jenis.

1. Accuracy
2. Recall
3. F1 Score
4. Precisision

II.2

Bagi data dengan perbandingan 0,8 untuk data latih dan 0,2 untuk data validasi.

```
# II.2 Kode di sini

x = df[['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm',
'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
'Temp3pm', 'RainToday']]
y = df['RainTomorrow']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =
0.2,  train_size=0.8, random_state = 42)
```

II.3

Lakukan hal berikut:

1. Prediksi dengan menggunakan model *logistic regression* sebagai *baseline*.
2. Tampilkan evaluasi dari model yang dibangun dari metrik yang ditentukan pada II.1
3. Tampilkan *confusion matrix*.

```
# II.3.1  Prediksi dengan menggunakan model logistic regression
sebagai baseline

lr = LogisticRegression()
lr.fit(x_train, y_train)
y_pred = lr.predict(x_test)

# II.3.2  Evaluasi dari model logistic regression

print("Evaluasi dari model logistic regression dengan metrics yang
sudah ditentukan sebelumnya: ")
print(classification_report(y_test, y_pred))
print('Accuracy: ', accuracy_score(y_test, y_pred))
```

```
print('Precision: ', precision_score(y_test, y_pred))
print('Recall: ', recall_score(y_test, y_pred))
print('F1 Score: ', f1_score(y_test, y_pred))
```

```
Evaluasi dari model logistic regression dengan metrics yang sudah
ditentukan sebelumnya:
              precision    recall  f1-score   support

           0       0.86      0.95      0.90     22672
           1       0.71      0.45      0.55      6420

    accuracy                           0.84     29092
   macro avg       0.79      0.70      0.73     29092
weighted avg       0.83      0.84      0.82     29092

Accuracy:  0.8387872954764196
Precision:  0.7128444881889764
Recall:  0.4512461059190031
F1 Score:  0.552651659671881
```

```
# II.3.3  Confusion matrix dari model logistic regression

print("Confusion matrix dari model logistic regression: ")
print(pd.DataFrame(confusion_matrix(y_test, y_pred), columns =
['Predicted No', 'Predicted Yes'], index = ['Actual No', 'Actual
Yes']))
```

```
Confusion matrix dari model logistic regression:
            Predicted No  Predicted Yes
Actual No          21505           1167
Actual Yes          3523           2897
```

II.4

Lakukanlah:

1. Pembelajaran dengan model lain
2. *Hyperparameter tuning* untuk model yang dipakai dengan menggunakan *grid search* (perhatikan *random factor* pada beberapa algoritma model)
3. Validasi dengan *cross validation*

```
# Target yang kosong
df['RainTomorrow'].isna().sum()
```

```
0
```

```
# II.4 Kode di sini.
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer
import pandas as pd

# Ada yang kosong di Target, jadi di Drop aja
df_dropped = df.dropna(subset=['RainTomorrow'])
X = df_dropped.drop(['RainTomorrow'], axis=1)
y = df_dropped['RainTomorrow']

# Tanganin yang kosong dengan masukin mode
# Terus di onehot encode
categorical_features = [col for col in X.columns if X[col].dtype ==
"object"]
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Tanganin yang kosong dengan masukin mean
numeric_features = [col for col in X.columns if X[col].dtype !=
"object"]
numeric_transformer = SimpleImputer(strategy='mean')

preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features),
        ('num', numeric_transformer, numeric_features)
    ]
)

# Create an instance of the DecisionTreeClassifier class with the
preprocessor
dt = DecisionTreeClassifier(random_state=42)

dt_params = {
    'max_depth': [5, 10, 15, 20],
    'criterion': ['gini', 'entropy', 'log_loss']
}

# Fit the preprocessor on the training data and transform the training
and testing data
X_preprocessed = preprocessor.fit_transform(X)

scorers = ['accuracy', 'precision', 'recall', 'f1']

for scorer in scorers:
```

```
  grid_search = GridSearchCV(dt, param_grid=dt_params, cv=5, 
scoring=scorer, n_jobs=-1)
  grid_search.fit(X_preprocessed, y)
  print(f"Grid Search for metric {scorer}")
  print("Best hyperparameters:", grid_search.best_params_)
  print("Best score:", grid_search.best_score_)
```

```
Grid Search for metric accuracy
Best hyperparameters: {'criterion': 'entropy', 'max_depth': 5}
Best score: 0.8353430496356387
Grid Search for metric precision
Best hyperparameters: {'criterion': 'gini', 'max_depth': 5}
Best score: 0.725360780509838
Grid Search for metric recall
Best hyperparameters: {'criterion': 'gini', 'max_depth': 20}
Best score: 0.5037810957758261
Grid Search for metric f1
Best hyperparameters: {'criterion': 'entropy', 'max_depth': 10}
Best score: 0.5470329876467206
```

III. Improvement

Pada bagian ini, kalian diharapkan dapat:

1. melakukan pelatihan dengan data hasil *oversampling* / *undersampling*, disertai dengan validasi yang benar; serta
2. menerapkan beberapa metode untuk menggabungkan beberapa model.

Kedua hal ini adalah contoh metode untuk meningkatkan kinerja dari model.

III.1

Lakukanlah:

1. *Oversampling* pada kelas minoritas pada data latih
2. *Undersampling* pada kelas mayoritas pada data latih

Pada setiap tahap, latih dengan model *baseline* (II.3), dan validasi dengan data validasi. Data latih dan validasi adalah data yang disusun pada bagian II.2.

```
# III.1.1 Oversampling pada kelas minoritas pada data latih

over_sampler = RandomOverSampler(sampling_strategy="not majority", 
random_state = 42)
over_x_train, over_y_train = over_sampler.fit_resample(x_train, 
y_train)

lr.fit(over_x_train, over_y_train)
over_y_pred = lr.predict(x_test)
```

```python
print("Evaluasi dari baseline model dengan oversampling: ")
print(classification_report(y_test, over_y_pred))
print('Accuracy: ', accuracy_score(y_test, over_y_pred))
print('Precision: ', precision_score(y_test, over_y_pred))
print('Recall: ', recall_score(y_test, over_y_pred))
print('F1 Score: ', f1_score(y_test, over_y_pred))

crossval_score = cross_val_score(lr, x_train, y_train.values.ravel(),
cv=5)
print("Cross validation score: ", crossval_score)
```

```
Evaluasi dari baseline model dengan oversampling:
              precision    recall  f1-score   support

           0       0.92      0.79      0.85     22672
           1       0.51      0.75      0.60      6420

    accuracy                           0.78     29092
   macro avg       0.71      0.77      0.73     29092
weighted avg       0.83      0.78      0.80     29092

Accuracy:  0.7826206517255603
Precision:  0.5050135784416127
Recall:  0.7531152647975078
F1 Score:  0.6046017256471177
Cross validation score:  [0.84368824 0.83651285 0.83857523 0.83929876
0.83916985]
```

```python
# III.1.2 Undersampling pada kelas mayoritas pada data latih

under_sampler = RandomUnderSampler(sampling_strategy=1, random_state =
42)
under_x_train, under_y_train = under_sampler.fit_resample(x_train,
y_train)

lr.fit(under_x_train, under_y_train)
under_y_pred = lr.predict(x_test)

print("Evaluasi dari baseline model dengan undersampling: ")
print(classification_report(y_test, under_y_pred))
print('Accuracy: ', accuracy_score(y_test, under_y_pred))
print('Precision: ', precision_score(y_test, under_y_pred))
print('Recall: ', recall_score(y_test, under_y_pred))
print('F1 Score: ', f1_score(y_test, under_y_pred))

crossval_score = cross_val_score(lr, x_train, y_train.values.ravel(),
cv=5)
print("Cross validation score: ", crossval_score)
```

```
Evaluasi dari baseline model dengan undersampling:
              precision    recall  f1-score   support

           0       0.92      0.79      0.85     22672
           1       0.50      0.76      0.60      6420

    accuracy                           0.78     29092
   macro avg       0.71      0.77      0.72     29092
weighted avg       0.83      0.78      0.79     29092

Accuracy:  0.7792520280489482
Precision:  0.4998969497114592
Recall:  0.755607476635514
F1 Score:  0.601711734061027
Cross validation score:  [0.84368824 0.83651285 0.83857523 0.83929876
0.83916985]
```

III.2

Lakukanlah:

1. Eksplorasi *soft voting*, *hard voting*, dan *stacking*.
2. Buatlah model *logistic regression* dan SVM.
3. Lakukanlah *soft voting* dari model-model yang dibangun pada poin 2.
4. Lakukan *hard voting* dari model-model yang dibangun pada poin 2.
5. Lakukanlah *stacking* dengan *final classifier* adalah *logistic regression* dari model-model yang dibangun pada poin 2.
6. Lakukan validasi dengan metrics yang telah ditentukan untuk poin 3, 4, dan 5.

(Tuliskan hasil eksplorasi III.2 poin 1 di sini.)

```python
# III.2 Kode di sini.
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import VotingClassifier, StackingClassifier

lr = LogisticRegression(random_state=42)
# SVC kelamaan, jadinya max_iter dikurangi
svm = SVC(random_state=42, max_iter=100, probability=True)

soft_vote_clf = VotingClassifier(estimators=[('lr', lr), ('svm',
svm)], voting='soft')
soft_vote_clf.fit(x_train, y_train)
softvote_prediction = soft_vote_clf.predict(x_test)

print("Hasil Soft Voting")
print(classification_report(y_test, softvote_prediction))
print(f"Precision: {precision_score(y_test, softvote_prediction)}")
print(f"Recall   : {recall_score(y_test, softvote_prediction)}")
```

```python
print(f"F1-score : {f1_score(y_test, softvote_prediction)}")
print(f"Accuracy : {accuracy_score(y_test, softvote_prediction)}")

crossval_score = cross_val_score(soft_vote_clf, x_train,
y_train.values.ravel(), cv=5)
print(f"Cross validation score: {crossval_score}")

hard_vote_clf = VotingClassifier(estimators=[('lr', lr), ('svm',
svm)], voting='hard')
hard_vote_clf.fit(x_train, y_train)
hardvote_prediction = soft_vote_clf.predict(x_test)

print("Hasil Hard Voting")
print(classification_report(y_test, hardvote_prediction))
print(f"Precision: {precision_score(y_test, hardvote_prediction)}")
print(f"Recall   : {recall_score(y_test, hardvote_prediction)}")
print(f"F1-score : {f1_score(y_test, hardvote_prediction)}")
print(f"Accuracy : {accuracy_score(y_test, hardvote_prediction)}")

crossval_score = cross_val_score(hard_vote_clf, x_train,
y_train.values.ravel(), cv=5)
print(f"Cross validation score: {crossval_score}")

stacking_clf = StackingClassifier(estimators=[('lr', lr), ('svm',
svm)], final_estimator=LogisticRegression())
stacking_clf.fit(x_train, y_train)
stacking_prediction = stacking_clf.predict(x_test)

print("Hasil Stacking")
print(classification_report(y_test, stacking_prediction))
print(f"Precision: {precision_score(y_test, stacking_prediction)}")
print(f"Recall   : {recall_score(y_test, stacking_prediction)}")
print(f"F1-score : {f1_score(y_test, stacking_prediction)}")
print(f"Accuracy : {accuracy_score(y_test, stacking_prediction)}")

crossval_score = cross_val_score(stacking_clf, x_train,
y_train.values.ravel(), cv=5)
print(f"Cross validation score: {crossval_score}")
```

```
Hasil Soft Voting
              precision    recall  f1-score   support

           0       0.82      0.99      0.89     22672
           1       0.85      0.21      0.34      6420

    accuracy                           0.82     29092
   macro avg       0.83      0.60      0.62     29092
weighted avg       0.82      0.82      0.77     29092
```

```
Precision: 0.85375
Recall   : 0.21277258566978194
F1-score : 0.34064837905236905
Accuracy : 0.8182318163068885
Cross validation score: [0.83543869 0.82443929 0.82413852 0.82297082
0.83809565]
Hasil Hard Voting
              precision    recall  f1-score   support

           0       0.82      0.99      0.89     22672
           1       0.85      0.21      0.34      6420

    accuracy                           0.82     29092
   macro avg       0.83      0.60      0.62     29092
weighted avg       0.82      0.82      0.77     29092

Precision: 0.85375
Recall   : 0.21277258566978194
F1-score : 0.34064837905236905
Accuracy : 0.8182318163068885
Cross validation score: [0.8436023  0.83646988 0.8386182  0.83929876
0.83899798]
Hasil Stacking
              precision    recall  f1-score   support

           0       0.86      0.95      0.90     22672
           1       0.71      0.45      0.55      6420

    accuracy                           0.84     29092
   macro avg       0.79      0.70      0.73     29092
weighted avg       0.83      0.84      0.82     29092

Precision: 0.7146766169154228
Recall   : 0.44750778816199377
F1-score : 0.5503831417624521
Accuracy : 0.8386498006324763
Cross validation score: [0.8434734  0.83586835 0.83883303 0.83990031
0.83916985]
```

IV. Analisis

Bandingkan hasil dari hal-hal berikut:

1. Model *baseline* (II.3)
2. Model lain (II.4)
3. Hasil *undersampling*
4. Hasil *oversampling*
5. Hasil *soft voting*

6. Hasil *hard voting*
7. Hasil *stacking*

Model Baseline vs Model lain

- Model baseline
  - Precision Score : 0.7128444881889764
  - Recall Score : 0.4512461059190031
  - F1 Score : 0.552651659671881
  - Accuracy Score : 0.8387872954764196
- Model lain
  - Decision Tree Learning
    - Precision Score : 0.725360780509838
    - Recall Score : 0.5037810957758261
    - F1 Score : 0.5470329876467206
    - Accuracy Score : 0.8353430496356387

Pembelajaran dataset dengan menggunakan model Decision Tree Learning yang sudah di-tune hyperparameternya menghasilkan nilai precision dan recall yang lebih baik, tetapi untuk nilai f1 dan accuracy model logistic regression memberikan nilai yang lebih tinggi daripada model Decistion Tree Learning. Oleh karena itu, model Decision Tree Learning yang sudah di-tune hyperparameternya lebih baik jika dibandingkan dengan logistic regression.

Oversampling vs Undersampling

- Oversampling
  - Precision Score : 0.5050135784416127
  - Recall Score : 0.7531152647975078
  - F1 Score : 0.6046017256471177
  - Accuracy Score : 0.7826206517255603
- Undersampling
  - Precision Score : 0.4998969497114592
  - Recall Score : 0.755607476635514
  - F1 Score : 0.601711734061027
  - Accuracy Score : 0.7792520280489482

Pembelajaran dataset dengan menggunakan strategi improvement Oversampling menghasilkan nilai precision dan f1 yang lebih tinggi, tetapi untuk nilai recall dan accuracy strategi improvement Undersampling menghasilkan nilai yang lebih tinggi. Namun, secara keseluruhan baik strategi Oversampling dan Undersampling menghasilkan nilai yang kurang lebih sama.

Soft Voting vs Hard Voting vs Stacking

- Soft Voting
  - Precision Score : 0.85375

- Recall Score : 0.21277258566978194
  - F1 Score : 0.34064837905236905
  - Accuracy Score : 0.8182318163068885
- Hard Voting
  - Precision Score : 0.8540100250626567
  - Recall Score : 0.21230529595015576
  - F1 Score : 0.34006986027944114
  - Accuracy Score : 0.8181630688849169
- Stacking
  - Precision Score : 0.7144638403990025
  - Recall Score : 0.4462616822429907
  - F1 Score : 0.5493767976989454
  - Accuracy Score : 0.8384435583665613

Voting dan Stacking adalah beberapa tipe dari Ensemble Learning, dimana dilakukan training pada beberapa model dan harapannya dengan menggabungkan hasil banyak model dapat didapatkan hasil yang lebih bagus. Pada kasus ini, skor dari Soft Voting dan Hard Voting sangatlah mirip. Namun, skor kedua tipe Voting lebih rendah daripada skor untuk Stacking. Oleh karena itu, pada kasus ini, dapat disimpulkan bahwa Stacking merupakan ensemble method yang lebih baik.