INTRODUCTION

RAIN PREDECTION

Predicting rainfall is one of the challenging and unpredictable jobs that has a big influence on human society. Proactively reducing human and financial loss can be achieved by timely and accurate forecasting. This article provides a series of experiments that employ popular machine learning techniques to build models that can forecast the likelihood of rain or not in major Australian cities based on the weather data for that particular day.

The dataset intrigued me since I've always been curious in the factors meteorologists consider before issuing a weather forecast. From an expert's perspective, however, this dataset is not too complicated.

IMPORTING LIBRARIES

```
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import seaborn as sns
from keras.layers import Dense, BatchNormalization, Dropout, LSTM
from keras.models import Sequential
from keras.utils import to_categorical
from keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classification_report, accuracy_score, f1_score
from keras import callbacks
!pip install plotly
import plotly.express as px
np.random.seed(0)
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (5.15.0)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly) (8.4.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from plotly) (24.1)
```

```
#to hide any warnings
import warnings
warnings.filterwarnings('ignore')
```

LOADING DATA

The dataset is about four years' worth of daily weather measurements from various places in Australia are included in this collection.The dataset for this I got it form Kaggle.

```
data = pd.read_csv("/content/Dataset1.csv")
data.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDi
0	01/01/2014	Albury	12.0	27.4	0.0	NaN	NaN	WNV
1	02/01/2014	Albury	16.7	27.7	0.0	NaN	NaN	V
2	03/01/2014	Albury	18.9	30.6	0.2	NaN	NaN	WSV
3	04/01/2014	Albury	13.1	25.6	0.0	NaN	NaN	V
4	05/01/2014	Albury	8.4	29.4	0.0	NaN	NaN	WNV

5 rows × 23 columns

PROBLEM STATEMENT

This project's main goal is to forecast whether or not it will rain in Australia. The likelihood of rain is dependent on several variables, including temperature, humidity, wind direction, and speed.

Our goal is to create a model that, with the least amount of error and highest accuracy, can forecast whether or not it will rain.

Exploratory Data Analysis

The dataset represent:

Date: The date of observation.

Location: The location of the weather station.

MinTemp: Minimum temperature (°C) for the day.

MaxTemp: Maximum temperature (°C) for the day.

Rainfall: Amount of rainfall (mm).

Evaporation: Evaporation (mm).

Sunshine: Sunshine (hours).

WindGustDir: Direction of the strongest wind gust.

WindGustSpeed: Speed of the strongest wind gust (km/h).

WindDir9am: Wind direction at 9 AM.

WindDir3pm: Wind direction at 3 PM.

WindSpeed9am: Wind speed at 9 AM (km/h).

WindSpeed3pm: Wind speed at 3 PM (km/h).

Humidity9am: Humidity at 9 AM (%).

Humidity3pm: Humidity at 3 PM (%).

Pressure9am: Atmospheric pressure at 9 AM (hPa).

Pressure3pm: Atmospheric pressure at 3 PM (hPa).

Cloud9am: Cloud cover at 9 AM (oktas).

Cloud3pm: Cloud cover at 3 PM (oktas).

Temp9am: Temperature at 9 AM (°C).

Temp3pm: Temperature at 3 PM (°C).

RainToday: Whether it rained today ("Yes" or "No").

RainTomorrow: Whether it will rain tomorrow ("Yes" or "No").

The dataset contains various meteorological variables that can be used for weather analysis, prediction models, or clustering to find patterns in weather data.

```
#checking the information of the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62327 entries, 0 to 62326
Data columns (total 30 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           62327 non-null  datetime64[ns]
 1   Location       62327 non-null  object
 2   MinTemp        61460 non-null  float64
 3   MaxTemp        61522 non-null  float64
 4   Rainfall       60610 non-null  float64
 5   Evaporation    29796 non-null  float64
 6   Sunshine       25343 non-null  float64
 7   WindGustDir    58475 non-null  object
 8   WindGustSpeed  58498 non-null  float64
 9   WindDir9am     58031 non-null  object
 10  WindDir3pm     59987 non-null  object
 11  WindSpeed9am   61680 non-null  float64
 12  WindSpeed3pm   60395 non-null  float64
 13  Humidity9am    61116 non-null  float64
 14  Humidity3pm    59158 non-null  float64
 15  Pressure9am    55048 non-null  float64
 16  Pressure3pm    55062 non-null  float64
 17  Cloud9am       36395 non-null  float64
 18  Cloud3pm       33878 non-null  float64
 19  Temp9am        61555 non-null  float64
 20  Temp3pm        59604 non-null  float64
 21  RainToday      60610 non-null  object
 22  RainTomorrow   60605 non-null  object
```

```
 23  year           62327 non-null  int32
 24  month          62327 non-null  int32
 25  month_sin      62327 non-null  float64
 26  month_cos      62327 non-null  float64
 27  day            62327 non-null  int32
 28  day_sin        62327 non-null  float64
 29  day_cos        62327 non-null  float64
dtypes: datetime64[ns](1), float64(20), int32(3), object(6)
memory usage: 13.6+ MB
```

```
#checking the shape of the data
data.shape
```

```
(62327, 30)
```

```
data.describe()
```

	Date	MinTemp	MaxTemp	Rainfall	Evaporation	S
count	62327	61460.000000	61522.000000	60610.000000	29796.000000	25343
mean	2015-09-28 11:45:19.046320128	12.584344	23.778825	2.213910	6.004893	7
min	2014-01-01 00:00:00	-8.200000	-4.800000	0.000000	0.000000	C
25%	2014-11-14 12:00:00	8.000000	18.300000	0.000000	3.000000	4
50%	2015-09-28 00:00:00	12.500000	23.300000	0.000000	5.200000	E
75%	2016-08-11 00:00:00	17.300000	29.000000	0.600000	8.000000	1C
max	2017-06-25 00:00:00	31.900000	47.300000	247.200000	145.000000	14
std	NaN	6.464053	7.311552	8.002869	4.793020	3

8 rows × 24 columns

```
#checking the datatypes of the column
data.dtypes
```

```
Date            datetime64[ns]
Location                 int64
MinTemp                float64
MaxTemp                float64
Rainfall               float64
Evaporation            float64
Sunshine               float64
WindGustDir              int64
WindGustSpeed          float64
WindDir9am               int64
WindDir3pm               int64
WindSpeed9am           float64
WindSpeed3pm           float64
Humidity9am            float64
Humidity3pm            float64
Pressure9am            float64
Pressure3pm            float64
Cloud9am               float64
Cloud3pm               float64
Temp9am                float64
Temp3pm                float64
RainToday                int64
RainTomorrow             int64
year                     int32
month                    int32
month_sin              float64
month_cos              float64
day                      int32
day_sin                float64
day_cos                float64
Cluster                  int32
PCA1                   float64
PCA2                   float64
dtype: object
```

```
#checking for the missing values
data.isnull().sum()
```

```
Date              0
Location          0
```

```
MinTemp            867
MaxTemp            805
Rainfall          1717
Evaporation      32531
Sunshine         36984
WindGustDir       3852
WindGustSpeed     3829
WindDir9am        4296
WindDir3pm        2340
WindSpeed9am       647
WindSpeed3pm      1932
Humidity9am       1211
Humidity3pm       3169
Pressure9am       7279
Pressure3pm       7265
Cloud9am         25932
Cloud3pm         28449
Temp9am            772
Temp3pm           2723
RainToday         1717
RainTomorrow      1722
year                 0
month                0
month_sin            0
month_cos            0
day                  0
day_sin              0
day_cos              0
dtype: int64
```

Data cleaning

```
#Altering dates for ANN
data['Date'] = pd.to_datetime(data['Date'], format='%d/%m/%Y')
data['year'] = data.Date.dt.year

def encode(data, col, max_val):
    data[col + '_sin'] = np.sin(2 * np.pi * data[col]/max_val)
    data[col + '_cos'] = np.cos(2 * np.pi * data[col]/max_val)
    return data

data['month'] = data.Date.dt.month
data = encode(data, 'month', 12)

data['day'] = data.Date.dt.day
data = encode(data, 'day', 31)

data.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wi
0	2014-01-01	Albury	12.0	27.4	0.0	NaN	NaN	WNW	
1	2014-01-02	Albury	16.7	27.7	0.0	NaN	NaN	W	
2	2014-01-03	Albury	18.9	30.6	0.2	NaN	NaN	WSW	
3	2014-01-04	Albury	13.1	25.6	0.0	NaN	NaN	W	
4	2014-01-05	Albury	8.4	29.4	0.0	NaN	NaN	WNW	

5 rows × 30 columns

Categorical and Numerical variables changes

```
#Filling missing values with mode of the column value
s = (data.dtypes == "object")
object_cols = list(s[s].index)

print("Categorical variables:")
print(object_cols)
```

```
Categorical variables:
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday', 'RainTomorrow']
```

```
# Missing values in categorical variables

for i in object_cols:
    print(i, data[i].isnull().sum())
```

```
Location 0
WindGustDir 3852
WindDir9am 4296
WindDir3pm 2340
RainToday 1717
RainTomorrow 1722
```

```
# Filling missing values with mode of the column in value

for i in object_cols:
    data[i].fillna(data[i].mode()[0], inplace=True)
```

```
#Filling missing values with median of the column value
t = (data.dtypes == "float64")
num_cols = list(t[t].index)

print("Neumeric variables:")
print(num_cols)
```

```
Neumeric variables:
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humic
```

```
for i in num_cols:
    print(i, data[i].isnull().sum())
```

```
MinTemp 867
MaxTemp 805
Rainfall 1717
Evaporation 32531
Sunshine 36984
WindGustSpeed 3829
WindSpeed9am 647
WindSpeed3pm 1932
Humidity9am 1211
Humidity3pm 3169
Pressure9am 7279
Pressure3pm 7265
Cloud9am 25932
Cloud3pm 28449
Temp9am 772
Temp3pm 2723
month_sin 0
month_cos 0
day_sin 0
day_cos 0
```

```
# Filling missing values with median of the column in value

for i in num_cols:
    data[i].fillna(data[i].median(), inplace=True)

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62327 entries, 0 to 62326
Data columns (total 30 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           62327 non-null  datetime64[ns]
 1   Location       62327 non-null  object
 2   MinTemp        62327 non-null  float64
 3   MaxTemp        62327 non-null  float64
 4   Rainfall       62327 non-null  float64
 5   Evaporation    62327 non-null  float64
 6   Sunshine       62327 non-null  float64
 7   WindGustDir    62327 non-null  object
 8   WindGustSpeed  62327 non-null  float64
 9   WindDir9am     62327 non-null  object
 10  WindDir3pm     62327 non-null  object
 11  WindSpeed9am   62327 non-null  float64
 12  WindSpeed3pm   62327 non-null  float64
 13  Humidity9am    62327 non-null  float64
 14  Humidity3pm    62327 non-null  float64
 15  Pressure9am    62327 non-null  float64
 16  Pressure3pm    62327 non-null  float64
 17  Cloud9am       62327 non-null  float64
```

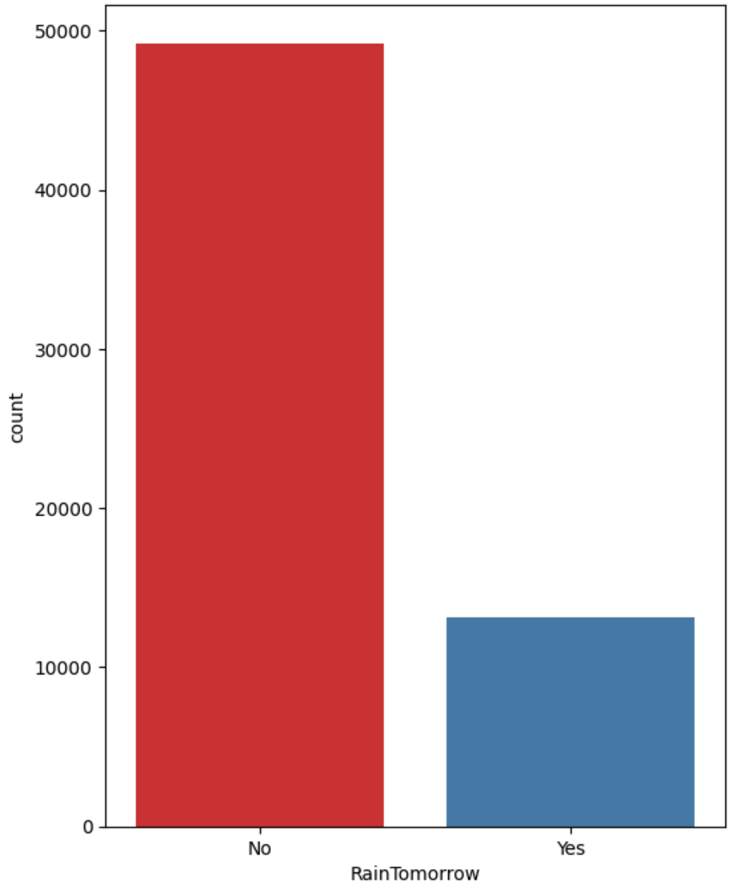
```
 18  Cloud3pm       62327 non-null  float64
 19  Temp9am        62327 non-null  float64
 20  Temp3pm        62327 non-null  float64
 21  RainToday      62327 non-null  object
 22  RainTomorrow   62327 non-null  object
 23  year           62327 non-null  int32
 24  month          62327 non-null  int32
 25  month_sin      62327 non-null  float64
 26  month_cos      62327 non-null  float64
 27  day            62327 non-null  int32
 28  day_sin        62327 non-null  float64
 29  day_cos        62327 non-null  float64
dtypes: datetime64[ns](1), float64(20), int32(3), object(6)
memory usage: 13.6+ MB
```

DATA VISUALIZATION

COUNT PLOT

```
f, ax = plt.subplots(figsize=(6, 8))
ax = sns.countplot(x="RainTomorrow", data=data, palette="Set1")
plt.show()
```

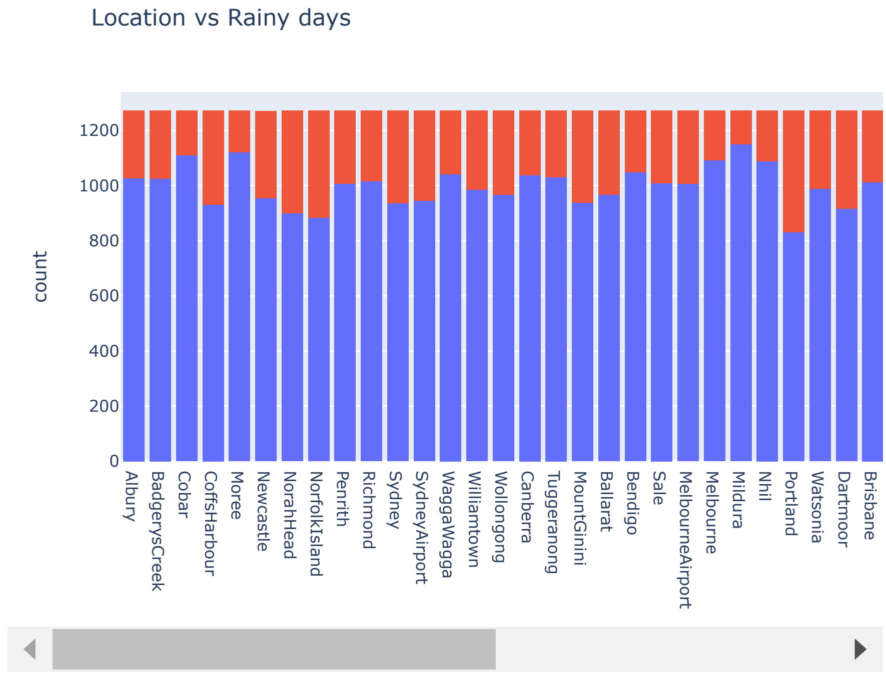
```
<ipython-input-19-5f55b69ff7a4>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  ax = sns.countplot(x="RainTomorrow", data=data, palette="Set1")
```



The graph displays a comparison of two categories, ‘No’ and ‘Yes’, under the label ‘RainTomorrow’. The ‘No’ bar is significantly taller, indicating a higher count of days without rain, while the ‘Yes’ bar is shorter, showing fewer days with rain. This suggests that the data represents the frequency of rainy days versus non-rainy days, with non-rainy days being more common.

HISTOGRAM

```
px.histogram(data, x='Location', color=data['RainToday'], title="Location vs Rainy days")
```

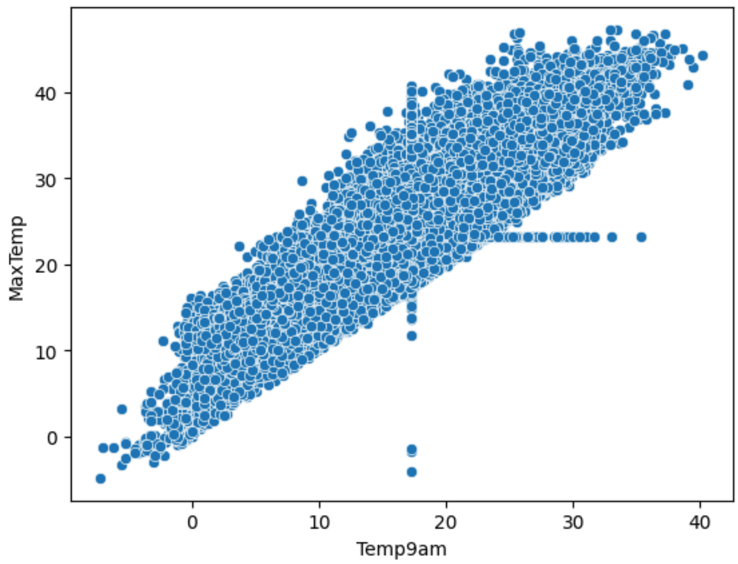


The bar graph with two sets of bars, one blue and one red, represents counts of a binary categorical data set across various categories, likely locations. The blue bars labeled “No” and the red bars labeled “Yes” could indicate the presence or absence of a condition, such as rain, for each location.

scatter plot

```
sns.scatterplot(data ,x='Temp9am',y='MaxTemp')
```

```
<Axes: xlabel='Temp9am', ylabel='MaxTemp'>
```



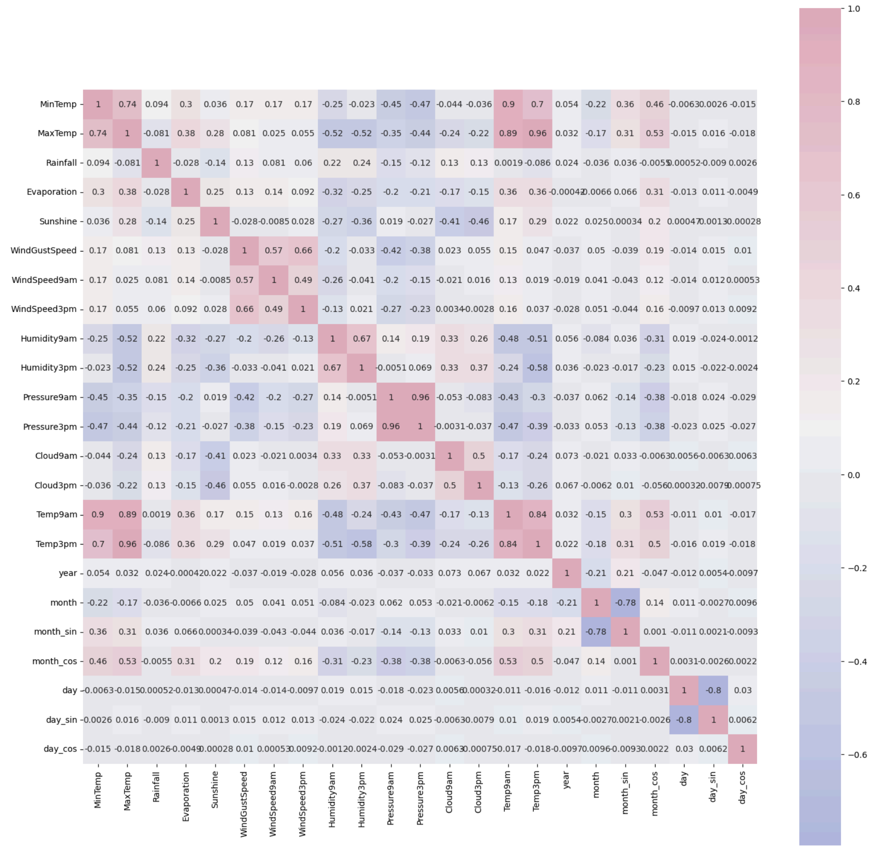
The scatter plot graph displays a positive correlation between ‘Temp9am’ and ‘MaxTemp’, indicating that higher temperatures at 9 am are generally associated with higher maximum temperatures for the day.

In most of the cases, when it rain today, the temp difference between MinTemp and MaxTemp is not much.

Correlation Heatmap

```
# Correlation amongst numeric attributes
corrmat = data.select_dtypes(include=['float', 'int']).corr() # Select only numeric columns
cmap = sns.diverging_palette(260,-10,s=50, l=75, n=6, as_cmap=True)
plt.subplots(figsize=(18,18))
sns.heatmap(corrmat,cmap= cmap,annot=True, square=True)
```

<Axes: >

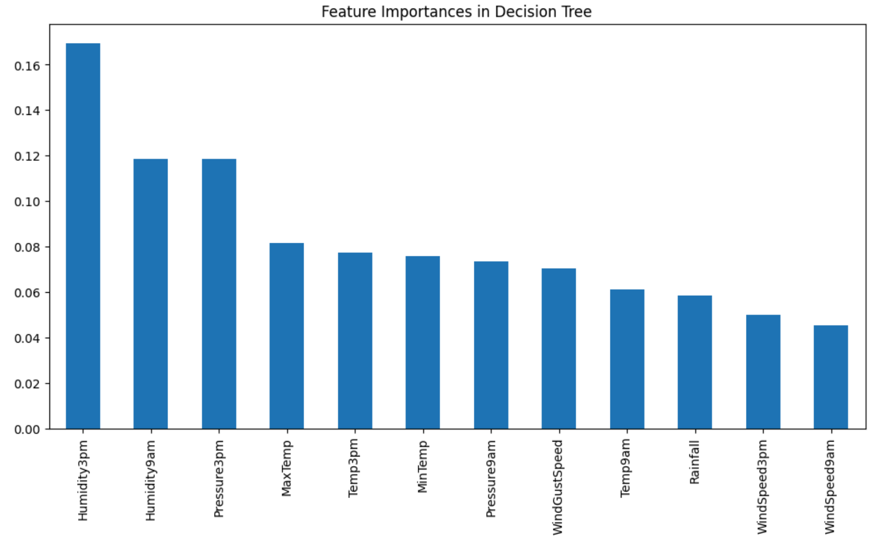


The image shows a correlation matrix heatmap, which is used to display the correlation coefficients between variables. The colors indicate the strength and direction of the correlation, with blue for negative, red for positive, and white for no correlation. The scale from -1 to 1 reflects the range of the Pearson correlation coefficient.

Decision Tree

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
import seaborn as sns


# Selecting relevant numeric features and the target variable (assuming 'RainTomorrow' is the target)
# Converting 'RainTomorrow' to numeric for classification (Yes = 1, No = 0)
data['RainTomorrow'] = data['RainTomorrow'].map({'Yes': 1, 'No': 0})

features = data[['MinTemp', 'MaxTemp', 'Rainfall', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm',
                 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Temp9am', 'Temp3pm']]
target = data['RainTomorrow']

# Ensure all data is numeric and handle missing values by dropping rows with missing values
data_cleaned = features.dropna()
target_cleaned = target[data_cleaned.index]

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data_cleaned, target_cleaned, test_size=0.2, random_state=0)

# Applying Decision Tree model
params_dt = {'max_depth': 20,
             'max_features': "sqrt",
             'splitter':'best',
             'max_leaf_nodes':None}

model_dt = DecisionTreeClassifier(**params_dt)
model_dt.fit(X_train, y_train)

# Predicting on test data
y_pred = model_dt.predict(X_test)

# Evaluating the model
accuracy_dt = accuracy_score(y_test, y_pred)
report_dt = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy_dt}")
print("Classification Report:")
print(report_dt)

# Plotting feature importances
plt.figure(figsize=(12, 6))
feature_importances = pd.Series(model_dt.feature_importances_, index=features.columns)
feature_importances.sort_values(ascending=False).plot(kind='bar')
plt.title('Feature Importances in Decision Tree')
plt.show()
```

```
Accuracy: 0.7984918979624579
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.88      0.87      9841
           1       0.52      0.48      0.50      2625

    accuracy                           0.80     12466
   macro avg       0.69      0.68      0.69     12466
weighted avg       0.79      0.80      0.80     12466
```

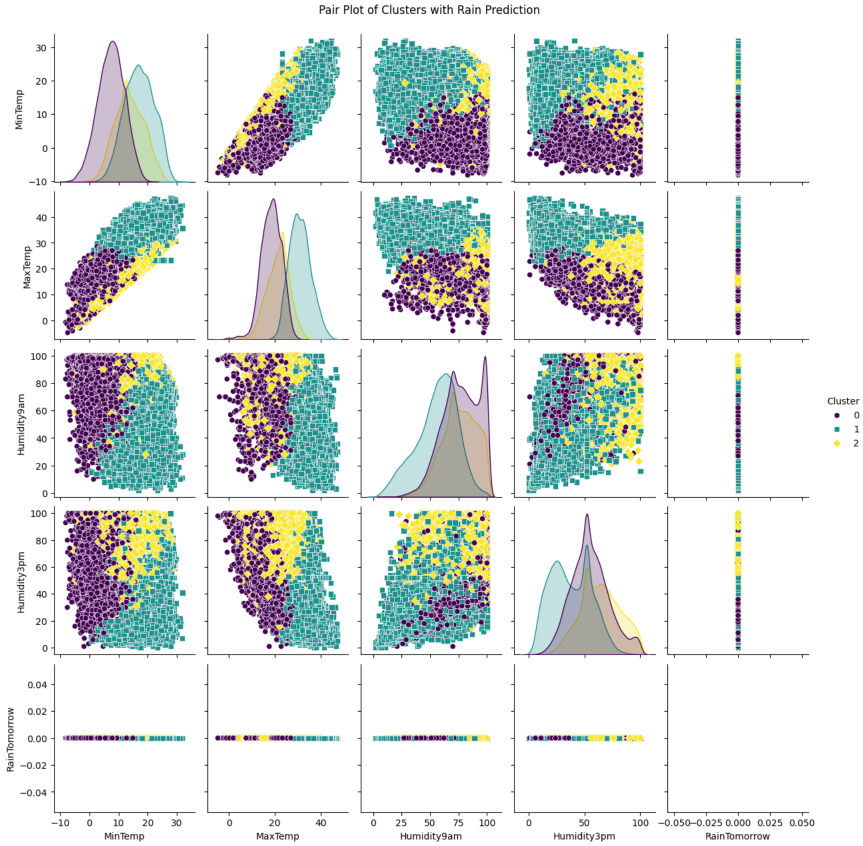


This output shoes a classification report, which includes metrics like accuracy, precision, recall, f1-score, and support for two classes. It also shows an ROC AUC score. On the right is a bar chart titled "**Feature Importances in Decision Tree**," displaying various features with their importance scores. This visualization help us to understand the performance of a classification model and the significance of different features in making predictions.

K-Mean Cluster

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# Define the features and the target
features = ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
            'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
            'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm',
            'Temp9am', 'Temp3pm', 'month_sin', 'month_cos', 'day_sin', 'day_cos']
target = 'RainTomorrow'

# Preprocess data
# Convert 'RainTomorrow' to numeric if it's not already
data[target] = data[target].apply(lambda x: 1 if x == 'Yes' else 0)

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(data[features])

# Apply K-means clustering
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Add cluster labels to the dataframe
data['Cluster'] = clusters


# Pair plot of selected features
selected_features = ['MinTemp', 'MaxTemp', 'Humidity9am', 'Humidity3pm', 'RainTomorrow', 'Cluster']
pair_plot_df = data[selected_features]
sns.pairplot(pair_plot_df, hue='Cluster', palette='viridis', diag_kind='kde', markers=['o', 's', 'D'])
plt.suptitle('Pair Plot of Clusters with Rain Prediction', y=1.02)
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning
  warnings.warn(
```



The pair plot offers a thorough graphic representation of the relationship between meteorological characteristics and clustering and rain forecasts. It displays unique patterns among several clusters, denoted by diamonds, squares, and circles, which stand for various meteorological circumstances. All things considered, this visualisation makes it easier to comprehend how various weather conditions match up with rain forecasts, emphasising the potential of clustering approaches to classify and analyse meteorological data for improved weather pattern interpretation and predictive modelling.

Artificial neural network (ANN)

```
# Apply label encoder to each column with categorical data
label_encoder = LabelEncoder()
for i in object_cols:
    data[i] = label_encoder.fit_transform(data[i])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62327 entries, 0 to 62326
Data columns (total 30 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           62327 non-null  datetime64[ns]
 1   Location       62327 non-null  int64
 2   MinTemp        62327 non-null  float64
 3   MaxTemp        62327 non-null  float64
 4   Rainfall       62327 non-null  float64
 5   Evaporation    62327 non-null  float64
 6   Sunshine       62327 non-null  float64
 7   WindGustDir    62327 non-null  int64
 8   WindGustSpeed  62327 non-null  float64
 9   WindDir9am     62327 non-null  int64
 10  WindDir3pm     62327 non-null  int64
 11  WindSpeed9am   62327 non-null  float64
 12  WindSpeed3pm   62327 non-null  float64
 13  Humidity9am    62327 non-null  float64
 14  Humidity3pm    62327 non-null  float64
 15  Pressure9am    62327 non-null  float64
 16  Pressure3pm    62327 non-null  float64
 17  Cloud9am       62327 non-null  float64
 18  Cloud3pm       62327 non-null  float64
 19  Temp9am        62327 non-null  float64
 20  Temp3pm        62327 non-null  float64
 21  RainToday      62327 non-null  int64
 22  RainTomorrow   62327 non-null  int64
 23  year           62327 non-null  int32
 24  month          62327 non-null  int32
 25  month_sin      62327 non-null  float64
 26  month_cos      62327 non-null  float64
 27  day            62327 non-null  int32
 28  day_sin        62327 non-null  float64
 29  day_cos        62327 non-null  float64
dtypes: datetime64[ns](1), float64(20), int32(3), int64(6)
memory usage: 13.6 MB
```

```
# Prepairing attributes of scale data

features = data.drop(['RainTomorrow', 'Date','day', 'month'], axis=1) # dropping target and extra columns

target = data['RainTomorrow']

#Set up a standard scaler for the features
col_names = list(features.columns)
s_scaler = preprocessing.StandardScaler()
features = s_scaler.fit_transform(features)
features = pd.DataFrame(features, columns=col_names)

features.describe().T
```

	count	mean	std	min	25%	50%	75%
Location	62327.0	-7.296153e-18	1.000008	-1.697043	-0.848521	0.000000	0.848521
MinTemp	62327.0	-1.459231e-17	1.000008	-3.237813	-0.714013	-0.012957	0.719256
MaxTemp	62327.0	-4.377692e-16	1.000008	-3.933283	-0.739593	-0.065063	0.705827
Rainfall	62327.0	3.100865e-17	1.000008	-0.272518	-0.272518	-0.272518	-0.196569
Evaporation	62327.0	-2.334769e-16	1.000008	-1.672980	-0.115267	-0.115267	-0.115267
Sunshine	62327.0	-3.100865e-16	1.000008	-3.354302	0.146620	0.146620	0.146620
WindGustDir	62327.0	6.566538e-17	1.000008	-1.703943	-0.852663	0.211437	0.849897
WindGustSpeed	62327.0	1.527632e-16	1.000008	-2.502667	-0.655153	-0.193275	0.499543
WindDir9am	62327.0	8.025769e-17	1.000008	-1.548805	-0.883192	0.004293	0.891778
WindDir3pm	62327.0	-3.648077e-17	1.000008	-1.725583	-0.838957	0.047669	0.934296
WindSpeed9am	62327.0	1.358909e-16	1.000008	-1.590830	-0.787202	-0.098377	0.590447
WindSpeed3pm	62327.0	8.755384e-17	1.000008	-2.152366	-0.630340	-0.162025	0.657527
Humidity9am	62327.0	2.918461e-16	1.000008	-3.503896	-0.623257	0.057621	0.738500
Humidity3pm	62327.0	-1.313308e-16	1.000008	-2.499553	-0.692816	0.039645	0.674444
Pressure9am	62327.0	-2.672581e-14	1.000008	-5.371616	-0.603716	-0.005860	0.591996
Pressure3pm	62327.0	1.247642e-14	1.000008	-5.767370	-0.614461	-0.013539	0.602406

```
#full data for
features["RainTomorrow"] = target

#Dropping with outlier

features = features[(features["MinTemp"]<2.3)&(features["MinTemp"]>-2.3)]
features = features[(features["MaxTemp"]<2.3)&(features["MaxTemp"]>-2)]
features = features[(features["Rainfall"]<4.5)]
features = features[(features["Evaporation"]<2.8)]
features = features[(features["Sunshine"]<2.1)]
features = features[(features["WindGustSpeed"]<4)&(features["WindGustSpeed"]>-4)]
features = features[(features["WindSpeed9am"]<4)]
features = features[(features["WindSpeed3pm"]<2.5)]
features = features[(features["Humidity9am"]>-3)]
features = features[(features["Humidity3pm"]>-2.2)]
features = features[(features["Pressure9am"]< 2)&(features["Pressure9am"]>-2.7)]
features = features[(features["Pressure3pm"]< 2)&(features["Pressure3pm"]>-2.7)]
features = features[(features["Cloud9am"]<1.8)]
features = features[(features["Cloud3pm"]<2)]
features = features[(features["Temp9am"]<2.3)&(features["Temp9am"]>-2)]
features = features[(features["Temp3pm"]<2.3)&(features["Temp3pm"]>-2)]


features.shape
```

```
(54546, 27)
```

BUILDING ANN

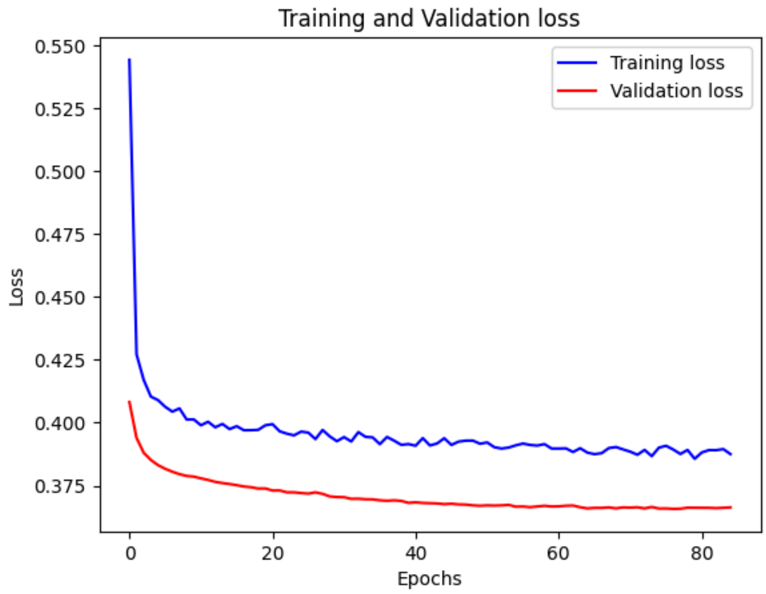
```
X = features.drop(["RainTomorrow"], axis=1)
y = features["RainTomorrow"]

# Splitting test and training sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)

X.shape
```

```
(54546, 26)
```

```
#Early stopping
early_stopping = callbacks.EarlyStopping(
    min_delta=0.001, # minimium amount of change to count as an improvement
    patience=20, # how many epochs to wait before stopping
    restore_best_weights=True,
)

# Initialising the NN
model = Sequential()

# layers

model.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu', input_dim = 26))
model.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(units = 16, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dropout(0.25))
model.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dropout(0.5))
model.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))

# Compiling the ANN
opt = Adam(learning_rate=0.00009)
model.compile(optimizer = opt, loss = 'binary_crossentropy', metrics = ['accuracy'])

# Train the ANN
history = model.fit(X_train, y_train, batch_size = 32, epochs = 150, callbacks=[early_stopping], validation_split=0.2)
```

```
Epoch 1/150
1091/1091 [==============================] - 4s 3ms/step - loss: 0.5442 - accuracy: 0.7931 - val_loss: 0.4082 - val_accuracy: 0
Epoch 2/150
1091/1091 [==============================] - 3s 2ms/step - loss: 0.4271 - accuracy: 0.7933 - val_loss: 0.3940 - val_accuracy: 0
Epoch 3/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.4170 - accuracy: 0.7933 - val_loss: 0.3881 - val_accuracy: 0
Epoch 4/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.4104 - accuracy: 0.7933 - val_loss: 0.3852 - val_accuracy: 0
Epoch 5/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.4090 - accuracy: 0.7933 - val_loss: 0.3832 - val_accuracy: 0
Epoch 6/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.4063 - accuracy: 0.7933 - val_loss: 0.3817 - val_accuracy: 0
Epoch 7/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.4044 - accuracy: 0.7933 - val_loss: 0.3805 - val_accuracy: 0
Epoch 8/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.4057 - accuracy: 0.7933 - val_loss: 0.3796 - val_accuracy: 0
Epoch 9/150
1091/1091 [==============================] - 3s 2ms/step - loss: 0.4013 - accuracy: 0.7933 - val_loss: 0.3789 - val_accuracy: 0
Epoch 10/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.4013 - accuracy: 0.7933 - val_loss: 0.3786 - val_accuracy: 0
Epoch 11/150
1091/1091 [==============================] - 3s 2ms/step - loss: 0.3990 - accuracy: 0.7933 - val_loss: 0.3779 - val_accuracy: 0
Epoch 12/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.4004 - accuracy: 0.7933 - val_loss: 0.3773 - val_accuracy: 0
Epoch 13/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.3982 - accuracy: 0.7933 - val_loss: 0.3765 - val_accuracy: 0
Epoch 14/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3995 - accuracy: 0.7933 - val_loss: 0.3760 - val_accuracy: 0
Epoch 15/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3975 - accuracy: 0.7933 - val_loss: 0.3756 - val_accuracy: 0
Epoch 16/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3986 - accuracy: 0.7933 - val_loss: 0.3752 - val_accuracy: 0
Epoch 17/150
1091/1091 [==============================] - 4s 4ms/step - loss: 0.3970 - accuracy: 0.7933 - val_loss: 0.3747 - val_accuracy: 0
Epoch 18/150
1091/1091 [==============================] - 3s 2ms/step - loss: 0.3970 - accuracy: 0.7933 - val_loss: 0.3744 - val_accuracy: 0
Epoch 19/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.3972 - accuracy: 0.7933 - val_loss: 0.3739 - val_accuracy: 0
Epoch 20/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3990 - accuracy: 0.7933 - val_loss: 0.3739 - val_accuracy: 0
Epoch 21/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3994 - accuracy: 0.7933 - val_loss: 0.3731 - val_accuracy: 0
Epoch 22/150
1091/1091 [==============================] - 3s 3ms/step - loss: 0.3966 - accuracy: 0.7933 - val_loss: 0.3731 - val_accuracy: 0
Epoch 23/150
1091/1091 [==============================] - 3s 2ms/step - loss: 0.3957 - accuracy: 0.7933 - val_loss: 0.3724 - val_accuracy: 0
Epoch 24/150
1091/1091 [==============================] - 2s 2ms/step - loss: 0.3950 - accuracy: 0.7933 - val_loss: 0.3723 - val_accuracy: 0
Epoch 25/150
```

```
history_df = pd.DataFrame(history.history)

plt.plot(history_df.loc[:, ['loss']], "blue", label='Training loss')
plt.plot(history_df.loc[:, ['val_loss']],"red", label='Validation loss')
plt.title('Training and Validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(loc="best")

plt.show()
```



The machine learning model's training and validation loss over epochs is represented as a graph. This is a thorough explanation:

Loss Representation Lines: The training loss is shown by the blue line, which gets smaller as the number of epochs rises.

Red Line: Depicts the validity loss and indicates a gradual decline over time.

Axes: X-axis: Known as "Epochs," this axis shows the total number of passes through the training dataset and is labelled from 0 to just over 80. Y-axis: Known as "Loss," this axis represents the prediction inaccuracy of the model and runs from roughly 0.45 to little over 0.55.

Training Process: As seen by the declining loss values, the downward trend of both lines implies that the model is successfully learning from the data.

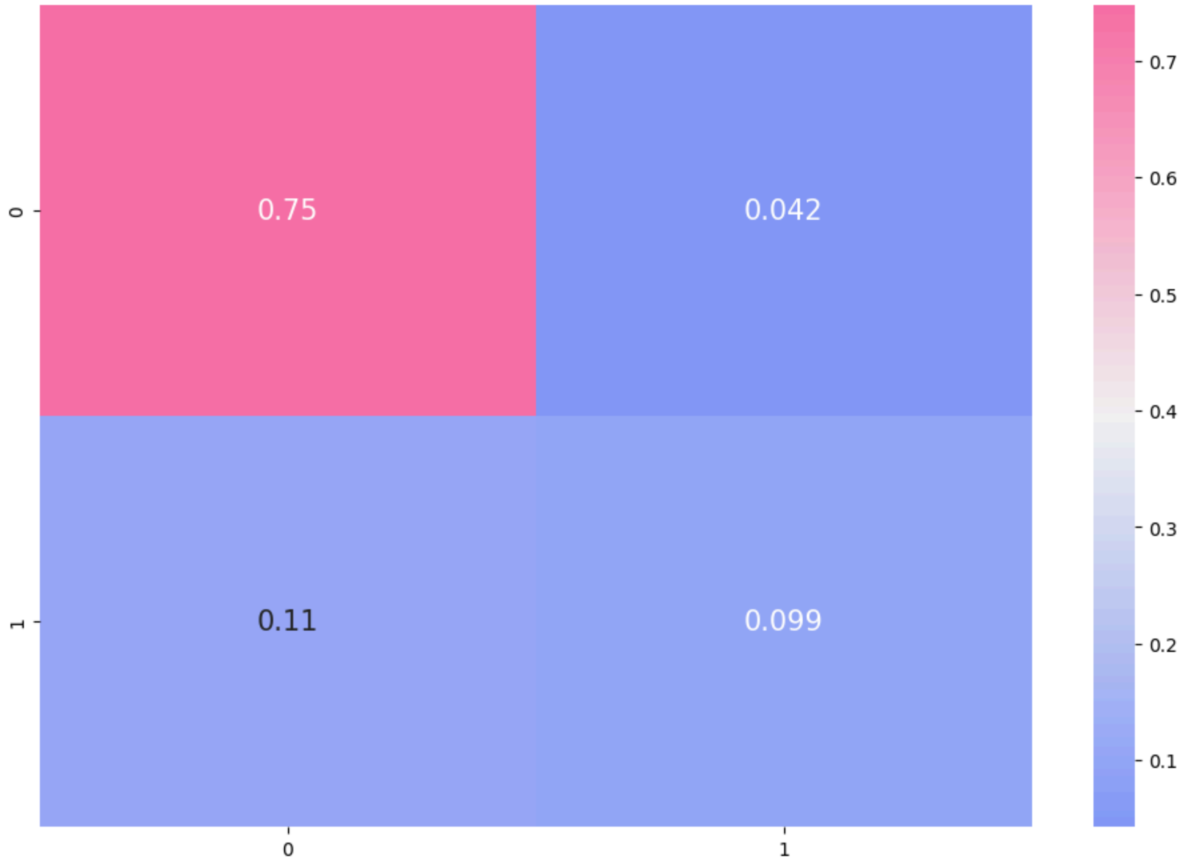
Code Snippet: The code snippet behind the graph indicates that the model will be used to predict results on a test set (X_test) following the training phase.

```
# Predicting the test set results
y_pred = model.predict(X_test)
y_pred = (y_pred > 0.5)
```

```
341/341 [==============================] - 1s 2ms/step
```

```
# confusion matrix
cmap1 = sns.diverging_palette(260,-10,s=90, l=65, n=5, as_cmap=True)
plt.subplots(figsize=(12,8))
cf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(cf_matrix/np.sum(cf_matrix), cmap = cmap1, annot = True, annot_kws = {'size':15})
```

<Axes: >



The matrix or heatmap including four quadrants. A numerical value is associated with each quadrant, and the colour intensity represents the size of that number. This is an explanation:

Upper Left Quadrant: With a value of 0.75, this region is the darkest tinted. Top Right Quadrant: It correlates to a value of 0.042 and has a lighter tint.

Bottom Left Quadrant: A value of 0.11 is shown by this medium shade. Bottom Right Quadrant: Its shade corresponds to a value of 0.099, much as the top right. The matrix's axes have increments of 0.1 and span from -1 to 1.

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.95      0.91      8620
           1       0.70      0.47      0.56      2290

    accuracy                           0.85     10910
   macro avg       0.79      0.71      0.74     10910
weighted avg       0.84      0.85      0.84     10910
```

The metrics table for machine learning classification models evaluation. This is an overview:

Precision and Recall: Precision gauges how well positive predictions are made, whereas recall evaluates how well all positive examples can be located. F1-Score: The F1-score offers a balance between recall and precision by taking the harmonic mean of both.

Support: The number of real instances of each class in the dataset is shown in this column. Regarding class "0":

Precision: 0.87 F1-Score: 0.91; Recall: 0.95 Assistance: 8620 Regarding class "1":

Accuracy: 0.70 F1-Score: 0.56 Recall: 0.47 Assistance: 2290 The model's overall accuracy, based on 10910 examples examined, is 0.85. The higher scores for class '0' indicate that the model is more accurate at class '0' identification than class '1'.

Conclusion

Using a variety of machine learning approaches, this research sought to forecast rainfall in Australian cities. Key elements affecting rain forecasts were found by examining and preprocessing the data. Numerous models were used, such as Artificial Neural Networks (ANN), Decision Trees, and K-Means clustering. Using insights into feature relevance, the Decision Tree model produced a notably accurate result. Separate meteorological patterns associated with rain forecasts were identified by K-Means clustering. Based on training and validation loss graphs, the ANN showed promise for predictive modelling. Overall, these methods demonstrate how machine learning may be used to better analyse meteorological data and forecast weather.