

Applied Machine learning

Lab File

A

Lab File

Submitted for Applied Machine Learning

Lab Evaluation

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Experiment – 1

Setting The Environment

Google Colab is a cloud-based Jupyter notebook environment that allows users to write and execute Python code in the cloud without installing anything on their local machine. It is widely used for machine learning (ML), data science, and deep learning projects.

The process of setting up the environment in Google Colab, including logging in, creating a new notebook, changing the runtime type, setting up a virtual environment, installing Python libraries, and saving the environment to Google Drive.

Step 1: Logging into Google Collab

- **Steps to Log in to Google Collab:**

1. Open your web browser.
2. Go to **Google Collaboratory**.
3. Click "**Sign in**" in the top right corner if you are not already logged into your Google account.
4. Once logged in, you will see the **Google Colab welcome page** with several options for opening a notebook.

Step 2: Creating a New Notebook

A **notebook** in Google Colab is, where you can write and execute Python code in separate cells.

2.1 Steps to Create a New Notebook:

1. After logging into Google Colab, click on "**File**" then "**New Notebook**."
2. A new notebook will open, containing:
 - A **code cell** for Python code and to execute it.
 - A **text cell** to write Markdown-formatted documentation.

3. Rename the notebook by clicking on "**"Untitled.ipynb"** at the top and entering a new name

Step 3: Changing the Runtime Type

By default, Google Colab runs on a CPU. If your project requires more computational power, you can **enable GPU or TPU acceleration**.

Click "**Save.**"

Step 4: Installing and Importing Python Libraries and Packages

Google Colab comes pre-installed with many Python libraries, but some specialized packages may need to be installed manually.

4.1 Installing Libraries

- Install a package using pip:

Example : pip install scikit-learn

- To install multiple packages at once:

4.2 Importing Libraries

After installing, you can **import the libraries** in Python:

Example :

```
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt
```

4.3 Checking Installed Libraries

Check if a package is installed

Step 5: Saving Your Environment to Google Drive

Google Colab allows you to **save your work and datasets** in Google Drive for future use.

5.1 Mount Google Drive

To access Google Drive from Colab, run:

```
from google.colab import drive  
drive.mount('/content/drive')
```

- After running the command, a **link** will appear.
- Click the link, **authorize Google Drive access**, and copy the authentication code back into Colab.
- Your Google Drive is now accessible at:

5.2 Saving Your Notebook to Google Drive

- Click "File" then "**Save a copy in Drive.**"
- A copy will be stored in **Google Drive** then **Colab Notebooks**.

5.3 Loading a Dataset from Google Drive

```
import pandas as pd  
df = pd.read_csv('/content/drive/My Drive/dataset.csv')
```

Libraries In Python:

- **NumPy (Numerical Python)**

It is a fundamental library for numerical computing in Python, providing support for multi-dimensional arrays and matrices, along with a collection of mathematical functions to perform efficient computations. It is widely used in scientific computing, data analysis, and machine learning due to its ability to handle large datasets and perform vectorized operations efficiently. NumPy also supports functions for linear algebra, Fourier transforms, and random number generation, making it essential for high-performance computing.

- **Pandas**

It is a powerful data manipulation and analysis library built on top of NumPy. It provides two main data structures: Series (1D) and DataFrame (2D), which allow users to efficiently organize, clean, transform, and analyze data. Pandas supports operations such as reading and writing files (CSV, Excel, SQL, JSON),

handling missing values, filtering data, and performing group-based operations. It is widely used in data preprocessing for machine learning models and business analytics, as it simplifies working with structured data.

- **Matplotlib**

It is a widely used data visualization library that enables the creation of line plots, bar charts, scatter plots, histograms, and more. It provides extensive customization options for labels, titles, colors, legends, and grid lines, making it an essential tool for exploratory data analysis (EDA). Matplotlib allows users to visualize trends, distributions, and relationships between variables, helping to gain insights from data before applying machine learning models.

- **Scikit-learn**

It is a comprehensive machine learning library built on NumPy and Pandas. It offers a variety of tools for classification, regression, clustering, dimensionality reduction, and model evaluation. Additionally, it includes functionalities for data preprocessing, feature selection, hyperparameter tuning, and cross-validation, making it an essential tool for building and optimizing machine learning models. Scikit-learn is widely used for tasks such as spam detection, sentiment analysis, fraud detection, and recommendation systems.

- **SciPy (Scientific Python)**

It extends NumPy's capabilities by providing additional tools for scientific and technical computing. It includes modules for optimization, integration, signal processing, image processing, and statistical analysis. SciPy is particularly useful in scientific research, engineering, and medical image processing, where complex mathematical computations are required. It is also widely used for hypothesis testing, probability distributions, and solving differential equations, making it a valuable tool for advanced analytics and computational applications.

- **Seaborn**

Seaborn is a high-level data visualization library built on top of Matplotlib. It provides an easy way to create attractive and informative statistical graphics, making it particularly useful for exploratory data analysis (EDA). Seaborn simplifies the process of creating complex plots like heatmaps, violin plots, box plots, and pair plots, which help understand data distributions and correlations. Unlike Matplotlib, Seaborn has built-in support for data frames, allowing users to directly visualize Pandas datasets without additional data manipulation.

Experiment: 2 -3

Data Preprocessing

- Housing Dataset

```
▶ import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
#Ishita garg 500122821

[ ] url = "https://raw.githubusercontent.com/ageron/handson-ml2/master/datasets/housing/housing.csv"
df = pd.read_csv(url)
#Ishita garg 500122821
```

```
▶ print("Dataset Preview:")
display(df.head())
print("\nDataset Information:")
df.info()
#Ishita garg 500122821
```

```
Dataset Preview:
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  population  households  median_income  median_house_value  ocean_proximity
0     -122.23      37.88             41.0       880.0          129.0      322.0        126.0        8.3252      452600.0        NEAR BAY
1     -122.22      37.86             21.0      7099.0         1106.0      2401.0       1138.0        8.3014      358500.0        NEAR BAY
2     -122.24      37.85             52.0       1467.0          190.0       496.0        177.0        7.2574      352100.0        NEAR BAY
3     -122.25      37.85             52.0       1274.0          235.0       558.0        219.0        5.6431      341300.0        NEAR BAY
4     -122.25      37.85             52.0       1627.0          280.0       565.0        259.0        3.8462      342200.0        NEAR BAY

Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   longitude        20640 non-null   float64
 1   latitude         20640 non-null   float64
 2   housing_median_age 20640 non-null   float64
 3   total_rooms      20640 non-null   float64
 4   total_bedrooms   20433 non-null   float64
 5   population       20640 non-null   float64
 6   households       20640 non-null   float64
 7   median_income    20640 non-null   float64
 8   median_house_value 20640 non-null   float64
 9   ocean_proximity  20640 non-null   object  
dtypes: float64(9), object(1)
memory usage: 1.6+ MB

[ ] df['rooms_per_household'] = df['total_rooms'] / df['households']
df['bedrooms_ratio'] = df['total_bedrooms'] / df['total_rooms']
df['population_per_household'] = df['population'] / df['households']
df['income_per_capita'] = df['median_income'] / (df['population'] / df['households'])

df['bedrooms_per_household'] = df['total_bedrooms'] / df['households']
df['population_per_room'] = df['population'] / df['total_rooms']
df['income_per_household'] = df['median_income'] * df['households'] / df['population']
df['rooms_per_person'] = df['total_rooms'] / df['population']
df['bedrooms_per_person'] = df['total_bedrooms'] / df['population']

[ ] print("\nMissing values before handling:")
print(df.isnull().sum())
#Ishita garg 500122821
```

```

Missing values before handling:
longitude          0
latitude           0
housing_median_age 0
total_rooms        0
total_bedrooms     207
population         0
households         0
median_income      0
median_house_value 0
ocean_proximity    0
rooms_per_household 0
bedrooms_ratio     207
population_per_household 0
income_per_capita  0
bedrooms_per_household 207
population_per_room 0
income_per_household 0
rooms_per_person   0
bedrooms_per_person 207
dtype: int64

numeric_columns = df.select_dtypes(include=['number']).columns
df[numeric_columns] = df[numeric_columns].fillna(df[numeric_columns].median)

print("\nMissing values after handling:")
print(df.isnull().sum())

#Ishita garg 500122821

Missing values after handling:
longitude          0
latitude           0
housing_median_age 0
total_rooms        0
total_bedrooms     0
population         0
households         0
median_income      0
median_house_value 0
ocean_proximity    0
rooms_per_household 0
bedrooms_ratio     0
population_per_household 0
income_per_capita  0
bedrooms_per_household 0
population_per_room 0
income_per_household 0
rooms_per_person   0
bedrooms_per_person 0
dtype: int64

```

```
[ ] df_processed = pd.get_dummies(df, columns=['ocean_proximity'], drop_first=True)
# Feature Selection
X = df_processed.drop("median_house_value", axis=1)
y = df_processed["median_house_value"]

#Ishita garg 500122821

[ ] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
#Ishita garg 500122821

[ ] scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

#Ishita garg 500122821

[ ] model = LinearRegression()
model.fit(X_train_scaled, y_train)

#Ishita garg 500122821
→ LinearRegression ⓘ ? LinearRegression()

[ ] y_pred = model.predict(X_test_scaled)
#Ishita garg 500122821

[ ] mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print("\nModel Evaluation Metrics:")
print(f"Mean Absolute Error: {mae:.2f}")
print(f"Mean Squared Error: {mse:.2f}")
print(f"Root Mean Squared Error: {rmse:.2f}")
print(f"R2 Score: {r2:.4f}")

#Ishita garg 500122821
```

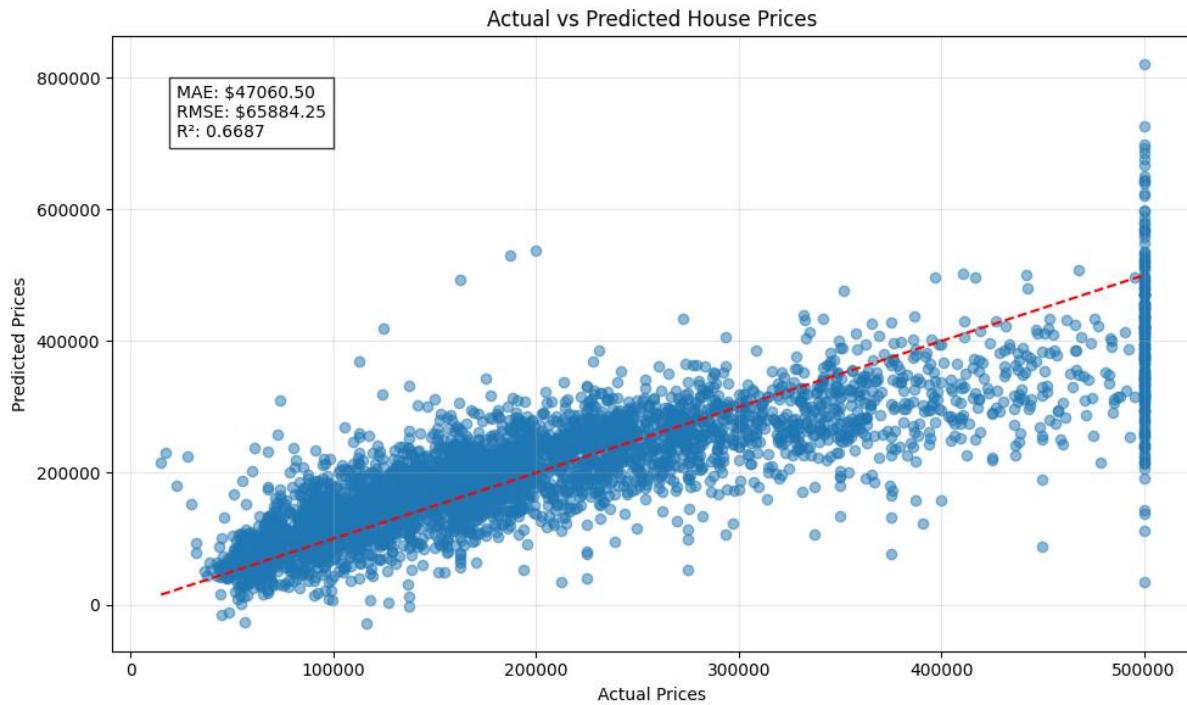
```
[ ] Model Evaluation Metrics:
→ Mean Absolute Error: 47060.50
Mean Squared Error: 4340734574.69
Root Mean Squared Error: 65884.25
R2 Score: 0.6687

▶ plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted House Prices")
plt.grid(True, alpha=0.3)

# Add text for evaluation metrics
plt.figtext(0.15, 0.8, f"MAE: {mae:.2f}\nRMSE: {rmse:.2f}\nR2: {r2:.4f}",
bbox=dict(facecolor='white', alpha=0.8))

plt.tight_layout()
plt.show()

#Ishita garg 500122821
```



- *Employee Dataset*

```
[ ] import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
#Ishita Garg 500122821

[ ] url = "https://raw.githubusercontent.com/mwaskom/seaborn-data/master/exercise.csv"
df = pd.read_csv(url)
#Ishita Garg 500122821

❶ print("Dataset shape:", df.shape)
print("\nColumns:", df.columns.tolist())
print("\nFirst few rows:")
print(df.head())
print("\nData types:")
print(df.dtypes)
print("\nMissing values:")
print(df.isnull().sum())

#Ishita Garg 500122821

```

Dataset shape: (90, 6)

Columns: ['Unnamed: 0', 'id', 'diet', 'pulse', 'time', 'kind']

First few rows:

	Unnamed: 0	id	diet	pulse	time	kind
0	0	1	low fat	85	1 min	rest
1	1	1	low fat	85	15 min	rest
2	2	1	low fat	88	30 min	rest
3	3	2	low fat	90	1 min	rest
4	4	2	low fat	92	15 min	rest

Data types:

	Unnamed: 0	id	diet	pulse	time	kind
dtype:	int64	int64	object	int64	object	object

```

[ ] Missing values:
[ ]   Unnamed: 0      0
[ ]   diet         0
[ ]   pulse        0
[ ]   time         0
[ ]   kind         0
[ ]   dtype: int64

[ ] for column in df.columns:
[ ]     if df[column].dtype == 'object':
[ ]         df[column].fillna(df[column].mode()[0], inplace=True)
[ ]     else:
[ ]         df[column].fillna(df[column].median(), inplace=True)

#Ishita Garg 500122821

[ ] <ipython-input-5-e7e0c6e0e099>:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

[ ] df[column].fillna(df[column].median(), inplace=True)
[ ] <ipython-input-5-e7e0c6e0e099>:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

[ ] df[column].fillna(df[column].mode()[0], inplace=True)

[ ] if 'monthly_income' in df.columns:
[ ]     target_column = 'monthly_income'
[ ]     feature_columns = [col for col in df.columns if col != target_column]
[ ]     df_selected = df[feature_columns + [target_column]]
[ ] else:
[ ]     target_column = 'pulse'
[ ]     feature_columns = [col for col in df.columns if col != target_column]
[ ]     df_selected = df[feature_columns + [target_column]]

#Ishita Garg 500122821

[ ] categorical_columns = df_selected.select_dtypes(include=['object']).columns
[ ] if len(categorical_columns) > 0:
[ ]     df_encoded = pd.get_dummies(df_selected, columns=categorical_columns, drop_first=True)
[ ] else:
[ ]     df_encoded = df_selected.copy()

#Ishita Garg 500122821

[ ] X = df_encoded.drop(target_column, axis=1)
[ ] y = df_encoded[target_column]

#Ishita Garg 500122821

[ ] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#Ishita Garg 500122821

[ ] scaler = StandardScaler()
[ ] numerical_cols = X_train.select_dtypes(include=['float64', 'int64']).columns
[ ] X_train_scaled = X_train.copy()
[ ] X_test_scaled = X_test.copy()
[ ] X_train_scaled[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
[ ] X_test_scaled[numerical_cols] = scaler.transform(X_test[numerical_cols])

#Ishita Garg 500122821

[ ] model = RandomForestRegressor(n_estimators=100, random_state=42)
[ ] model.fit(X_train_scaled, y_train)

#Ishita Garg 500122821

[ ] y_pred = model.predict(X_test_scaled)

#Ishita Garg 500122821

[ ] print("\nModel Evaluation:")
[ ] print(f"MAE: {mean_absolute_error(y_test, y_pred)}")
[ ] print(f"MSE: {mean_squared_error(y_test, y_pred)}")
[ ] print(f"RMSE: {np.sqrt(mean_squared_error(y_test, y_pred))}")
[ ] print(f"R2 Score: {r2_score(y_test, y_pred)}")

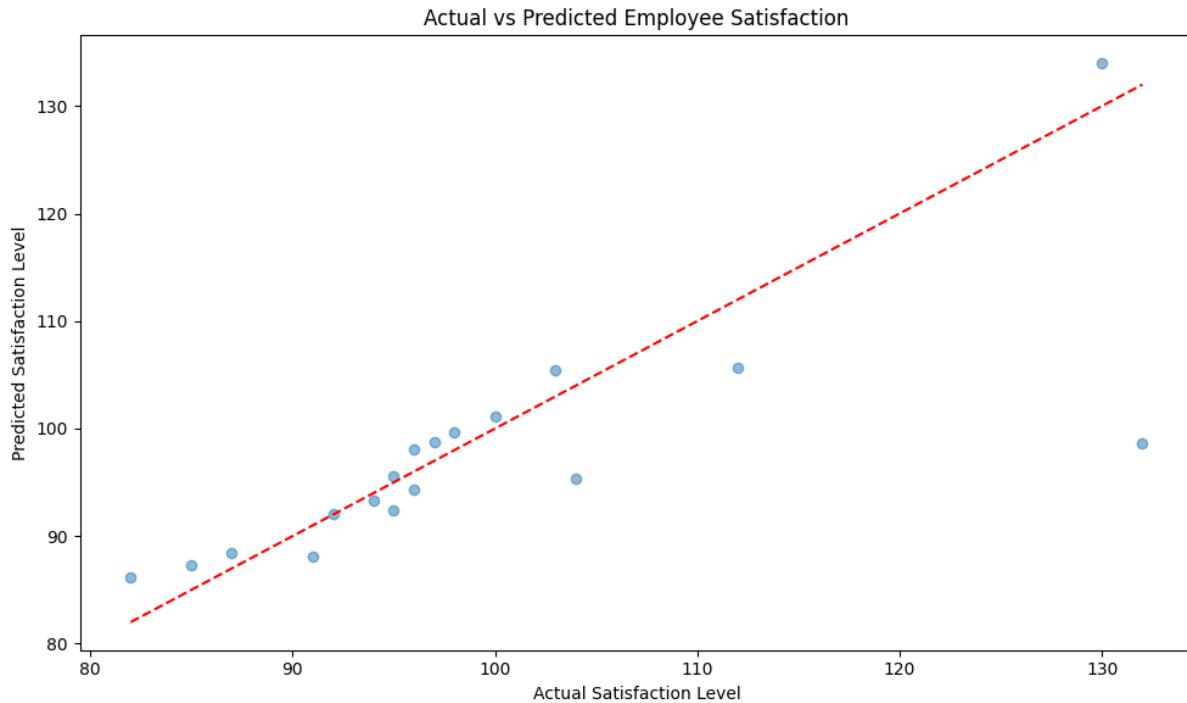
#Ishita Garg 500122821

[ ] Model Evaluation:
MAE: 4.327222222222222
MSE: 72.39056111111113
RMSE: 8.508264283102113
R2 Score: 0.5769764306970872

```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual Satisfaction Level")
plt.ylabel("Predicted Satisfaction Level")
plt.title("Actual vs Predicted Employee Satisfaction")
plt.tight_layout()
plt.show()

#Ishita Garg 500122821
```



- Government Dataset

```

❶ import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold, GridSearchCV
from sklearn.preprocessing import RobustScaler
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import warnings
warnings.filterwarnings('ignore')

#Ishita Garg 500122821

[2] df = pd.read_csv('/content/Cities1.csv')
df.drop(columns=['S. No.'], errors='ignore', inplace=True)
#Ishita Garg 500122821

[3] df.fillna(df.median(numeric_only=True), inplace=True)
for col in df.select_dtypes(include=['object']):
    df[col].fillna(df[col].mode()[0], inplace=True)
#Ishita Garg 500122821

[4] df = pd.get_dummies(df, drop_first=True)
#Ishita Garg 500122821

[5] X = df.drop(["AirQuality"], axis=1)
y = df["AirQuality"]
#Ishita Garg 500122821

[6] rf_params = {'n_estimators': [50, 100], 'max_depth': [None, 10]}
rf = GridSearchCV(RandomForestRegressor(random_state=42, n_jobs=-1), rf_params, cv=2, n_jobs=-1)
#Ishita Garg 500122821

[7] kf = KFold(n_splits=2, shuffle=True, random_state=42)
scores, preds, actuals = [], [], []
#Ishita Garg 500122821

```



```

print("\nTraining Random Forest for AirQuality:")

pipeline = Pipeline([("scaler", RobustScaler()), ("rf", rf)])

for train_idx, test_idx in kf.split(X):
    X_train, X_test = X.iloc[train_idx], X.iloc[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]

    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    scores.append(r2_score(y_test, y_pred))
    preds.extend(y_pred)
    actuals.extend(y_test)

#Ishita Garg 500122821

Training Random Forest for AirQuality:

avg_r2 = np.mean(scores)
print(f" Avg R2: {avg_r2:.4f}")

#Ishita Garg 500122821

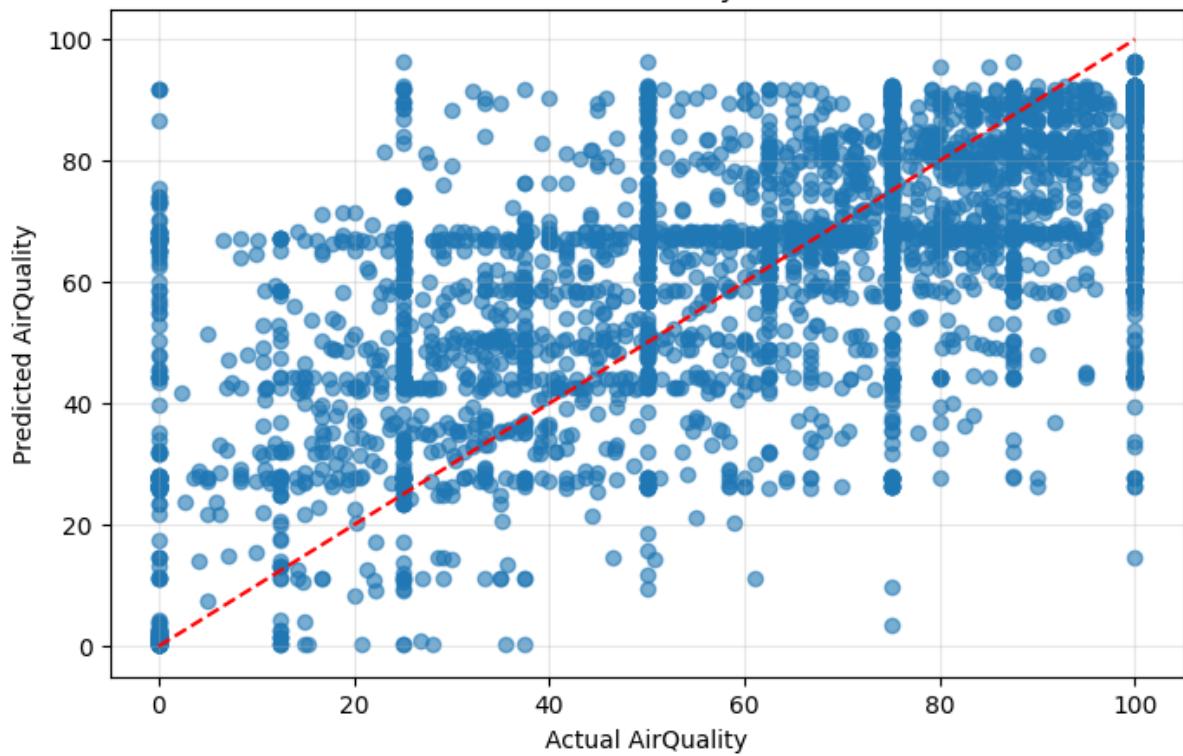
Avg R2: 0.4754

plt.figure(figsize=(8, 5))
plt.scatter(actuals, preds, alpha=0.6)
plt.plot([min(actuals), max(actuals)], [min(actuals), max(actuals)], 'r--')
plt.xlabel("Actual AirQuality")
plt.ylabel("Predicted AirQuality")
plt.title("Actual vs Predicted AirQuality (Random Forest)")
plt.grid(alpha=0.3)
plt.show()

#Ishita Garg 500122821

```

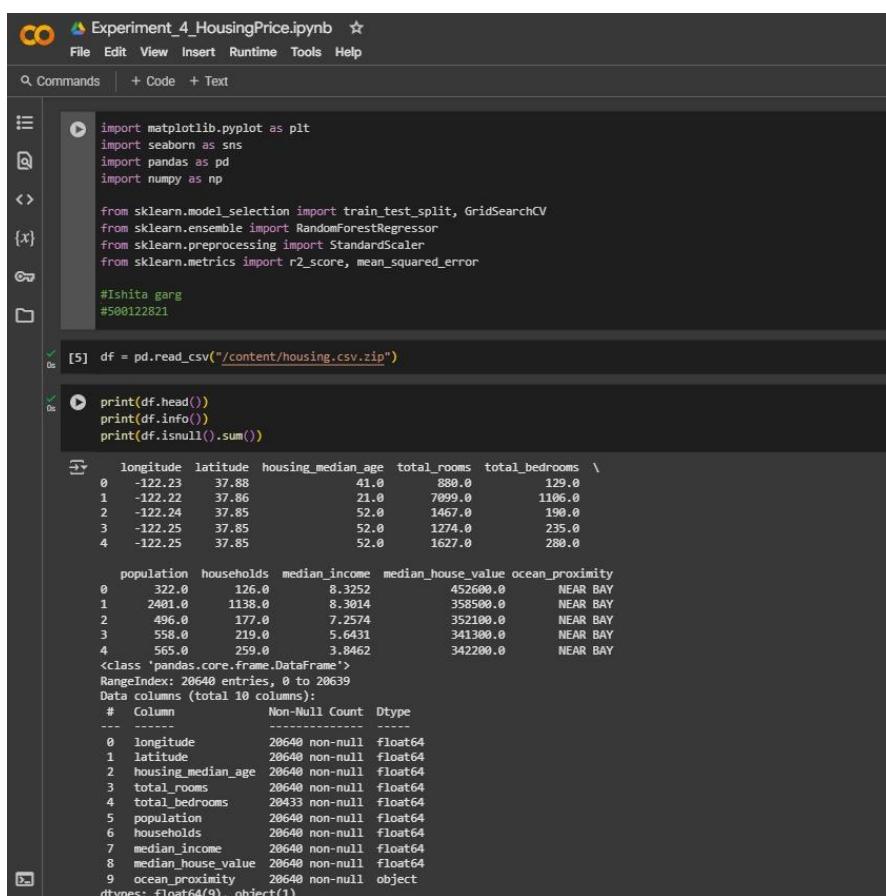
Actual vs Predicted AirQuality (Random Forest)



Experiment: 4-5

Model Development & Hyper Parameter Tuning for Regression Problems

- Housing Dataset



The screenshot shows a Jupyter Notebook interface with the following code and output:

```
File Edit View Insert Runtime Tools Help
Commands + Code + Text

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error

#Ishita garg
#500122821

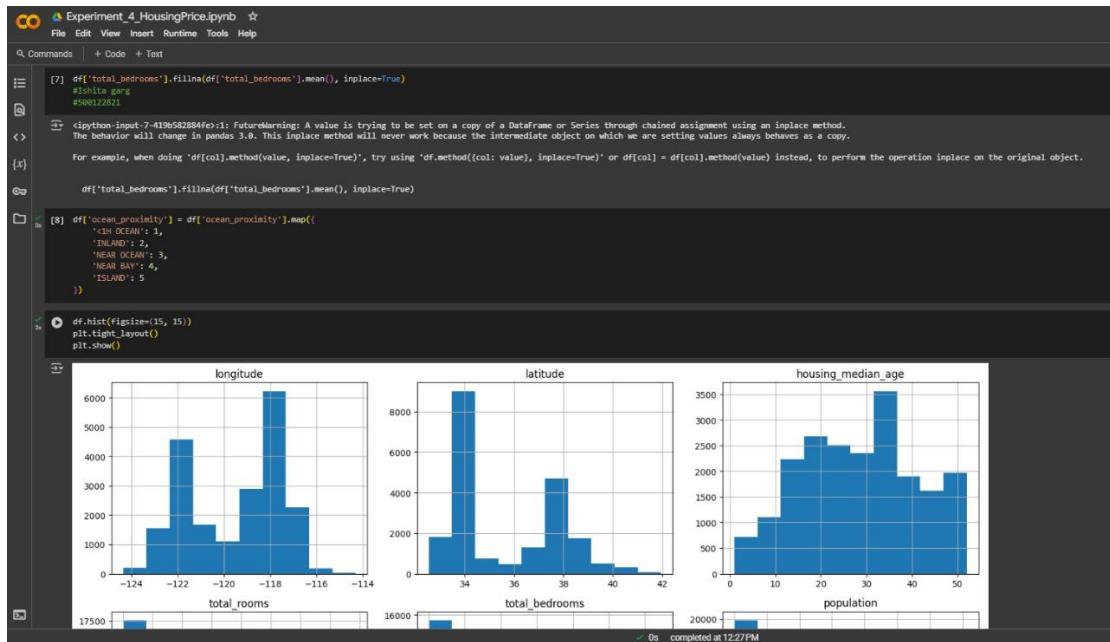
[5] df = pd.read_csv("/content/housing.csv.zip")

[6] print(df.head())
print(df.info())
print(df.isnull().sum())

    longitude  latitude housing_median_age total_rooms total_bedrooms \
0     -122.23      37.88            41.0       886.0          129.0
1     -122.22      37.86            21.0       7099.0         1106.0
2     -122.24      37.85            52.0       1467.0          190.0
3     -122.25      37.85            52.0       1274.0          235.0
4     -122.25      37.85            52.0       1627.0          280.0

population  households  median_income  median_house_value ocean_proximity
0        322.0        126.0        8.3252        452600.0    NEAR BAY
1       2401.0       1138.0        8.3014        358500.0    NEAR BAY
2        496.0        177.0        7.2574        352100.0    NEAR BAY
3        558.0        219.0        5.6431        341300.0    NEAR BAY
4        565.0        259.0        3.8462        342200.0    NEAR BAY

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   longitude        20640 non-null   float64
 1   latitude         20640 non-null   float64
 2   housing_median_age 20640 non-null   float64
 3   total_rooms      20640 non-null   float64
 4   total_bedrooms   20640 non-null   float64
 5   population       20640 non-null   float64
 6   households       20640 non-null   float64
 7   median_income    20640 non-null   float64
 8   median_house_value 20640 non-null   float64
 9   ocean_proximity  20640 non-null   object 
dtypes: float64(9), object(1)
```



The screenshot shows a Jupyter Notebook interface with the following content:

```
X = df.drop('median_house_value', axis=1)
y = df['median_house_value']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
#Ishita garg
#500122821

[X]

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

[Y]

model = RandomForestRegressor(random_state=42)

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
}

[Z]

grid_search = GridSearchCV(
    estimator=model,
    param_grid=param_grid,
    cv=5,
    scoring='r2',
    n_jobs=-1,
    verbose=1
)

grid_search.fit(X_train_scaled, y_train)
```

A tooltip for the `GridSearchCV` object is shown, displaying its structure:

```
GridSearchCV
  best_estimator_:
    RandomForestRegressor
      RandomForestRegressor
```

Text at the bottom indicates the process is fitting 5 folds for each of 24 candidates, totalling 120 fits.

```

best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test_scaled)

print("Best Parameters:", grid_search.best_params_)
print("R2 Score:", r2_score(y_test, y_pred))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
#Ishita garg
#500122821

Best Parameters: {'max_depth': 20, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 200}
R2 Score: 0.818389925477026
RMSE: 48807.40434097664

```

- Employee Dataset

The screenshot shows the Jupyter Notebook interface with the file 'Experiment_4_Employee.ipynb' open. The code cell contains the following:

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

#Ishita garg
#500122821

df = pd.read_csv('/content/employee_attrition_dataset.csv')

```

Below the code, the output shows the first few rows of the dataset:

#	Column	Non-Null Count	Dtype
0	Employee_ID	1000	int64
1	Age	1000	float64
2	Gender	1000	non-null object
3	Marital_Status	1000	non-null object
4	Department	1000	non-null object
5	Job	1000	non-null object
6	Job_Level	1000	non-null int64
7	Monthly_Income	1000	non-null int64
8	Hourly_Income	1000	non-null int64
9	Years_at_Company	1000	non-null int64
10	Years_in_Current_Role	1000	non-null int64
11	Years_Since_Last_Promotion	1000	non-null int64
12	Work_Life_Balance	1000	non-null int64
13	Job_Satisfaction	1000	non-null int64
14	Performance_Rating	1000	non-null int64
15	Training_Hours_Last_Year	1000	non-null int64
16	Overtime	1000	non-null object
17	OverTime_Count	1000	non-null int64
18	Average_Hours_Worked_Per_Week	1000	non-null int64
19	Absenteeism	1000	non-null int64
20	Work_Environment_Satisfaction	1000	non-null int64
21	Relationship_with_Manager	1000	non-null int64
22	Job_Involvement	1000	non-null int64
23	Distance_From_Home	1000	non-null int64
24	Number_of_Companies_Worked	1000	non-null int64
25	Attrition	1000	non-null object

0s completed at 12:38PM

The screenshot shows the Jupyter Notebook interface with the file 'Experiment_4_Employee.ipynb' open. The code cell contains the following:

```

for col in df.select_dtypes(include='object').columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
#Ishita garg
#500122821

X = df.drop('Attrition', axis=1)
y = df['Attrition']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

model = RandomForestClassifier(random_state=42)

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
}

grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy', n_jobs=-1, verbose=1)
grid_search.fit(X_train_scaled, y_train)

```

The output shows the results of the GridSearchCV search:

```

Fitting 5 folds for each of 24 candidates, totalling 120 fits
- GridSearchCV
  - best_estimator_:
    - RandomForestClassifier
      - RandomForestClassifier

```

```

File Edit View Insert Runtime Tools Help
Saving...
Commands + Code Test
Files Connecting to a runtime to enable file browsing
{x}
Go
[1]: best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test_scaled)

print("Best Parameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

Best Parameters: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Accuracy: 0.81

Classification Report:
precision recall f1-score support
0 0.81 1.00 0.90 162
1 0.80 0.80 0.80 38

accuracy 0.81 0.80 0.81 200
macro avg 0.81 0.80 0.80 200
weighted avg 0.81 0.80 0.81 200

Confusion Matrix:
[[162  0]
 [ 0  38]]

```

- Government Dataset

```

File Edit View Insert Runtime Tools Help
Saving...
Commands + Code Test
Files Analyze your files with code written by Gemini
Upload
{x}
sample_data
India Tourism Statistics 2021-Ta...
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import mean_squared_error, r2_score

#Initialising
#\$NB0122821

[2]: df = pd.read_csv('/content/India-Tourism-Statistics-2021-Table-5-2.3.csv')

[3]: df.columns = df.columns.str.strip()

[4]: print(df.shape)
print(df.info())
print(df.isnull().sum())

[5]: Circle Name of the Monument Domestic-2019-20 Foreign-2019-20 % Growth 2021-21/2019-20-Domestic
0 Agra Taj Mahal 4429738 665415 -71.56
1 Agra Agra Fort 1627154 306522 -50.33
2 Agra Fatehpur Sikri 4585 10000 -50.36
3 Agra Akbar Tomb Sikandra 229770 19625 -56.68
4 Agra Marjan tomb Sikandra 22517 414 -56.63

% Growth 2021-21/2019-20-Foreign
0 138340 9834 -71.56
1 311340 200000 -50.33
2 574 76.27
3 321 56.68
4 31 56.63

% Growth 2021-21/2019-20-Domestic
0 138340 9834 -71.56
1 311340 200000 -50.33
2 574 76.27
3 321 56.68
4 31 56.63

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype  
--- 
 0   Circle               178 non-null    object 
 1   Name of the Monument 178 non-null    object 

```

Experiment_4_Government.ipynb

File Edit View Insert Runtime Tools Help

Commands + Code + Text

Files

Analyze your files with code written by Gemini Upload

{x} .. sample_data India-Tourism-Statistics-2021-Ta...

```
[5] for col in ['Circle', 'Name of the Monument']:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])

#Ishita garg
#500122821

[6] df.fillna(df.mean(numeric_only=True), inplace=True)

[7] X = df.drop('Foreign-2019-20', axis=1)
y = df['Foreign-2019-20']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

[8] scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

[9] model = RandomForestRegressor(random_state=42)

param_grid = [
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
]

grid_search = GridSearchCV(model, param_grid, cv=5, scoring='r2', n_jobs=-1, verbose=1)
grid_search.fit(X_train_scaled, y_train)
```

Fitting 5 folds for each of 24 candidates, totalling 120 fits

GridSearchCV best_estimator_ RandomForestRegressor RandomForestRegressor

```
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test_scaled)

print("Best Parameters:", grid_search.best_params_)
print("R^2 Score:", r2_score(y_test, y_pred))
```

Disk 70.76 GB available

Experiment_4_Government.ipynb

File Edit View Insert Runtime Tools Help

Commands + Code + Text

Files

Analyze your files with code written by Gemini Upload

{x} .. sample_data India-Tourism-Statistics-2021-Ta...

```
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test_scaled)

print("Best Parameters:", grid_search.best_params_)
print("R^2 Score:", r2_score(y_test, y_pred))

rmse = mean_squared_error(y_test, y_pred) ** 0.5
print("RMSE:", rmse)
Ishita garg
#500122821

Best Parameters: {'max_depth': 20, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 100}
R^2 Score: 0.8579152130594683
RMSE: 46872.2135962094
```

Experiment: 6-7

Classification Problem

- Iris Flower Classification

MI_Lab_28_01_2025.ipynb

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
#Ishita Garg
#Sap Id = 500122821

data = pd.read_csv('/content/IRIS.csv')
#Ishita Garg
#Sap Id = 500122821

data.head()
#Ishita Garg
#Sap Id = 500122821

sepal_length sepal_width petal_length petal_width species
0 5.1 3.5 1.4 0.2 Iris-setosa
1 4.9 3.0 1.4 0.2 Iris-setosa
2 4.7 3.2 1.3 0.2 Iris-setosa
3 4.6 3.1 1.5 0.2 Iris-setosa
4 5.0 3.6 1.4 0.2 Iris-setosa

x = data[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]
y = data['species']
#Ishita Garg
#Sap Id = 500122821

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2)
#Ishita Garg
#Sap Id = 500122821

model = DecisionTreeClassifier()
model.fit(x_train, y_train)
#Ishita Garg
#Sap Id = 500122821
```

DecisionTreeClassifier

```
y_pred = model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred) #random state is used to do hit & trial approach and it influences the accuracy
#Ishita Garg
#Sap Id = 500122821

print("Model Accuracy:", accuracy*100 ,"%")
#Ishita Garg
#Sap Id = 500122821

Model Accuracy: 96.66666666666667 %
```

[] Start coding or generate with AI.

- Breast Cancer Diagnosis

```

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

#Ishita garg
#500122821

[3] df = pd.read_csv("/content/breast-cancer.csv")

[4] df.drop(columns=['id'], inplace=True)

[5] df['diagnosis'] = df['diagnosis'].map({'M': 1, 'B': 0})

[6] X = df.drop('diagnosis', axis=1)
y = df['diagnosis']

[7] scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

[8] X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)

[9] clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)

RandomForestClassifier(random_state=42)

```

```

[10] y_pred = clf.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))

Accuracy: 0.9736842105263158

Classification Report:
precision    recall  f1-score   support

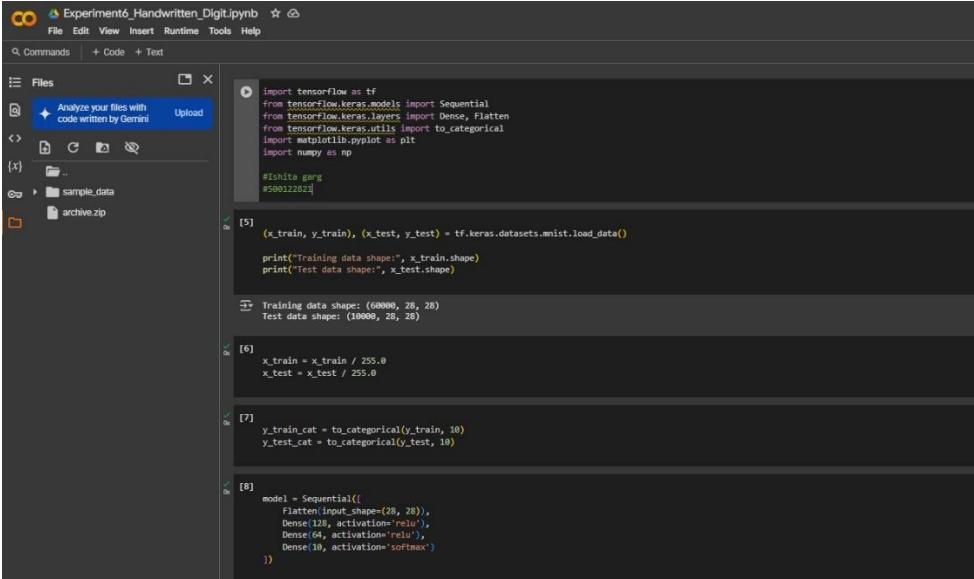
          0       0.96      1.00      0.98      72
          1       1.00      0.93      0.96      42

   accuracy                           0.97      114
  macro avg       0.98      0.96      0.97      114
weighted avg       0.97      0.97      0.97      114

Confusion Matrix:
[[72  0]
 [ 3 39]]
```

[] Start coding or generate with AI.

- *Handwritten Digit Recognition – MNIST*



Experiment6_Handwritten_Digit.ipynb

```

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
import numpy as np

#shlita gerg
#50012202

[5]
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

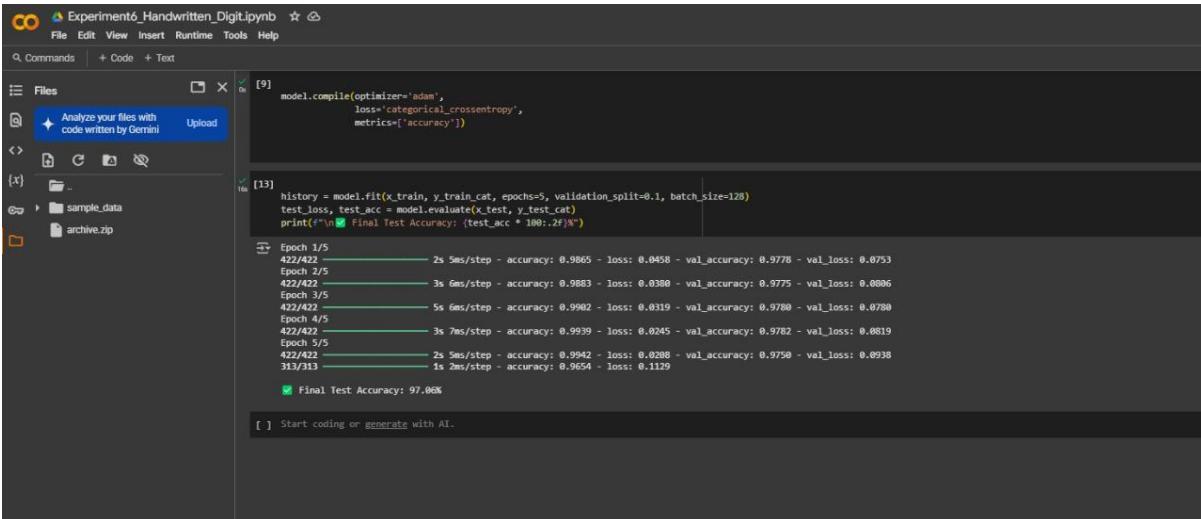
print("Training data shape:", x_train.shape)
print("Test data shape:", x_test.shape)

[6]
x_train = x_train / 255.0
x_test = x_test / 255.0

[7]
y_train_cat = to_categorical(y_train, 10)
y_test_cat = to_categorical(y_test, 10)

[8]
model = Sequential([
    Flatten(input_shape=(28, 28)),
    Dense(128, activation='relu'),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])

```



Experiment6_Handwritten_Digit.ipynb

```

[9]
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

[13]
history = model.fit(x_train, y_train_cat, epochs=5, validation_split=0.1, batch_size=128)
test_loss, test_acc = model.evaluate(x_test, y_test_cat)
print(f"\n{checkmark} Final Test Accuracy: {test_acc * 100:.2f}%")

```

Epoch 1/5
422/422 - 2s 5ms/step - accuracy: 0.9865 - loss: 0.0458 - val_accuracy: 0.9778 - val_loss: 0.0753
Epoch 2/5
422/422 - 3s 6ms/step - accuracy: 0.9883 - loss: 0.0380 - val_accuracy: 0.9775 - val_loss: 0.0806
Epoch 3/5
422/422 - 5s 6ms/step - accuracy: 0.9902 - loss: 0.0319 - val_accuracy: 0.9780 - val_loss: 0.0788
Epoch 4/5
422/422 - 3s 7ms/step - accuracy: 0.9939 - loss: 0.0245 - val_accuracy: 0.9782 - val_loss: 0.0819
Epoch 5/5
422/422 - 2s 5ms/step - accuracy: 0.9942 - loss: 0.0288 - val_accuracy: 0.9750 - val_loss: 0.0938
313/313 - 1s 2ms/step - accuracy: 0.9654 - loss: 0.1129

Final Test Accuracy: 97.06%

[] Start coding or generate with AI.

- Bank Churn Dataset

```

File Edit View Insert Runtime Tools Help
Commands + Code + Text
Files
Analyze your files with code written by Gemini Upload
[x] .. sample_data Churn_Modelling.csv
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, classification_report

#Ishita garg
#500122821

[3] df = pd.read_csv("./content/Churn_Modelling.csv")

[4] df = df.drop(["RowNumber", "CustomerId", "Surname"], axis=1)

[5] le_geo = LabelEncoder()
le_gender = LabelEncoder()
df['Geography'] = le_geo.fit_transform(df['Geography'])
df['Gender'] = le_gender.fit_transform(df['Gender'])

[6] df = df.fillna(df.median(numeric_only=True))

[7] X = df.drop("Exited", axis=1)
y = df["Exited"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

[8] clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)

```

```

y_pred = clf.predict(X_test)

print(" Accuracy:", accuracy_score(y_test, y_pred))
print("\n Classification Report:\n", classification_report(y_test, y_pred))

#Ishita garg
#500122821

Accuracy: 0.8685657171414293

Classification Report:
precision    recall    f1-score   support
          0       0.88      0.96      0.92     1599
          1       0.76      0.50      0.61      402

   accuracy                           0.87     2001
    macro avg       0.82      0.73      0.76     2001
 weighted avg       0.86      0.87      0.86     2001

```

[] Start coding or generate with AI.

Experiment: 8-9

Clustering Problems

- Disease Diagnosis from Medical Images

The screenshot shows a Jupyter Notebook interface with the following details:

- Title:** Experiment_8_DiseaseDetection.ipynb
- Toolbar:** File, Edit, View, Insert, Runtime, Tools, Help
- Cells:** There are four cells visible:
 - Cell 8:** Contains code for extracting a zip file and defining variables for image paths and size.
 - Cell 9:** Contains a function definition for loading images from a folder, including image loading, flattening, and appending to lists.
 - Cell 10:** Contains code for creating arrays X and true_labels by concatenating yes_images and no_images, and yes_labels and no_labels respectively, and normalizing X.
- Code Content:**

```
import os
import zipfile
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.manifold import TSNE
from tensorflow.keras.preprocessing.image import load_img, img_to_array
#Ishita garg
#500122821

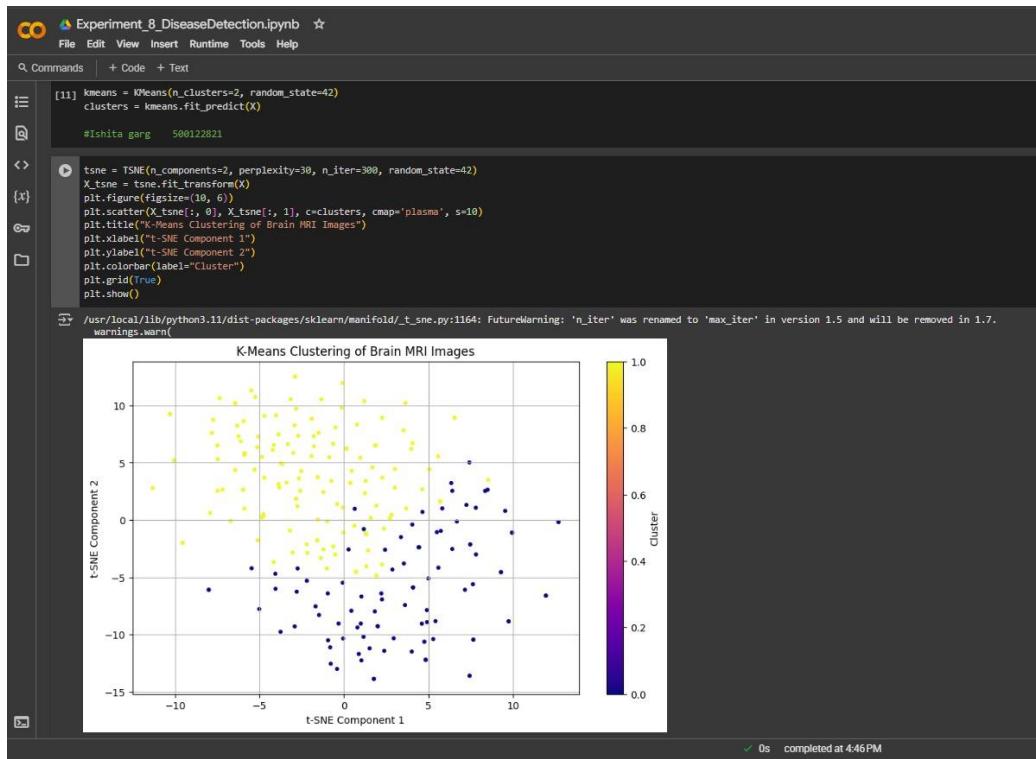
[8]
with zipfile.ZipFile("/content/archive (1).zip") as zip_ref:
    zip_ref.extractall("/content/brain_tumor_dataset")

yes_path = "/content/brain_tumor_dataset/yes"
no_path = "/content/brain_tumor_dataset/no"
img_size = (64, 64)

[9]
def load_images_from_folder(folder, label):
    images, labels = [], []
    for filename in os.listdir(folder):
        if filename.lower().endswith((".jpg", ".png")):
            img = load_img(os.path.join(folder, filename), target_size=img_size, color_mode='grayscale')
            img_array = img_to_array(img).flatten()
            images.append(img_array)
            labels.append(label)
    return images, labels

yes_images, yes_labels = load_images_from_folder(yes_path, 1)
no_images, no_labels = load_images_from_folder(no_path, 0)

[10]
X = np.array(yes_images + no_images) / 255.0
true_labels = np.array(yes_labels + no_labels)
```



- *DBSCAN*

