EASWARI ENGINEERING COLLEGE

(Autonomous)
Bharathi Salai, Ramapuram, Chennai 600 089.

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Name :

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Subject :

EASWARI ENGINEERING COLLEGE

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Submitted for Practical Examination held on ...../...../......... at Easwari Engineering College, Ramapuram, Chennai – 89.

Internal Examiner **External Examiner**

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Ex No : 1 – Recent case study of ethical initiatives in healthcare, autonomous vehicles and defence

A) Healthcare: Google's DeepMind AI System in Eye Care

Aim:

To develop an AI system capable of diagnosing eye diseases with high accuracy while ensuring patient data privacy.

Procedure:

1. Collaborated with Moorfields Eye Hospital to collect retinal scans for AI model training.
2. Implemented machine learning to identify diseases like diabetic retinopathy and age-related macular degeneration.
3. Faced criticism over patient data usage without explicit consent.
4. Modified policies to align with GDPR, prioritizing informed patient consent and transparency.

Program :

```
class DeepMindEyeCareAI:
    def __init__(self):  # Corrected from _init_ to __init__
        self.data = None
        self.model = None
        self.accuracy = 0.0
        self.privacy_compliant = False

    # Step 1: Collect Data (Simulate collection from Moorfields Eye Hospital)
    def collect_data(self):
        print("Collecting retinal scan data from Moorfields Eye Hospital...")
```

```
        self.data = ["retinal_scan_1", "retinal_scan_2", "retinal_scan_3"]  # Example data
        print("Data collected successfully.")

    # Step 2: Train Model (Simulate machine learning model training)
    def train_model(self):
        if not self.data:
            print("No data to train the model.")
            return
        print("Training model on retinal scan data to detect eye diseases...")
        # Simulate model training and achieving a certain accuracy
        self.model = "Trained_Model"
        self.accuracy = 0.94
        print("Model trained successfully with 94% accuracy.")

    # Step 3: Check Privacy Compliance
    def check_privacy_compliance(self):
        print("Checking for GDPR compliance...")
        # Simulating GDPR checks and patient consent requirements
        self.privacy_compliant = True  # In practice, checks would be detailed here
        if self.privacy_compliant:
            print("GDPR compliance confirmed. Patient consent obtained.")
        else:
            print("GDPR compliance failed. Additional consent needed.")

    # Step 4: Diagnose Eye Disease (Example diagnostic function)
    def diagnose(self, retinal_scan):
        if self.model and self.privacy_compliant:
```

```
            print(f"Diagnosing disease for {retinal_scan}...")
            # Placeholder logic for diagnosing
            diagnosis = "Diabetic Retinopathy" if retinal_scan == "retinal_scan_1"
else "Healthy"
            print(f"Diagnosis: {diagnosis}")
            return diagnosis
        else:
            print("Model not ready or privacy compliance not met.")
            return None

    # Step 5: Output Results (Summarize outcomes)
    def output_results(self):
        if self.model and self.privacy_compliant:
            print("AI-based diagnostic tool created with high accuracy.")
            print(f"Model accuracy: {self.accuracy * 100}%")
            print("Results: Enhanced patient care through early diagnosis.")
        else:
            print("Process incomplete. Check model and privacy compliance.")

# Simulating the workflow
eye_care_ai = DeepMindEyeCareAI()
eye_care_ai.collect_data()
eye_care_ai.train_model()
eye_care_ai.check_privacy_compliance()
eye_care_ai.diagnose("retinal_scan_1")
eye_care_ai.output_results()
```

Output:

Collecting retinal scan data from Moorfields Eye Hospital...

Data collected successfully.

Training model on retinal scan data to detect eye diseases...

Model trained successfully with 94% accuracy.

Checking for GDPR compliance...

GDPR compliance confirmed. Patient consent obtained.

Diagnosing disease for retinal_scan_1...

Diagnosis: Diabetic Retinopathy

AI-based diagnostic tool created with high accuracy.

Model accuracy: 94.0%

Results: Enhanced patient care through early diagnosis.

Result:

Improved patient care through early diagnosis. However, the initial ethical concerns highlighted the importance of balancing innovation with privacy and informed consent.

b) Autonomous Vehicles: Waymo's Public Safety Initiative*

Aim:

To develop a safe autonomous driving system while addressing public trust and ethical dilemmas in crash scenarios.

Procedure:

1. Trained self-driving systems to handle millions of simulated miles and real-world conditions.
2. Implemented transparency reports to disclose safety incidents and decision-making logic.
3. Organized public outreach programs to educate communities about the technology's benefits and limitations.

Program code:

```
class WaymoSafetyInitiative:
    def _init_(self):
        self.system_trained = False
        self.transparency_reports = []
        self.public_outreach_events = []
        self.vehicle_status = "manual"
        self.crash_scenarios = []

    # Step 1: Train Autonomous Driving System (Simulate training process)
    def train_system(self):
        print("Training autonomous driving system with millions of simulated miles
and real-world scenarios...")
        # Simulating training process
        self.system_trained = True
        print("System training completed.")
 # Step 2: Generate Transparency Report
    def generate_transparency_report(self, incidents, decision_logic):
        report = {
            "safety_incidents": incidents,
            "decision_making_logic": decision_logic
```

```
        }
        self.transparency_reports.append(report)
        print("Transparency report generated and disclosed.")

    # Step 3: Organize Public Outreach
    def organize_public_outreach(self, event_name, location, focus_topic):
        event = {
            "name": event_name,
            "location": location,
            "focus": focus_topic
        }
        self.public_outreach_events.append(event)
        print(f"Public outreach event '{event_name}' organized at {location}.")

    # Step 4: Test Autonomous Driving in Urban Areas
    def deploy_vehicle(self, environment):
        if self.system_trained:
            self.vehicle_status = "autonomous" if environment == "urban" else
"manual"
            print(f"Vehicle deployed in {environment} environment with status:
{self.vehicle_status}.")
        else:
            print("System training incomplete. Cannot deploy autonomous vehicle.")

    # Step 5: Simulate Crash Scenarios for Ethical Analysis
    def simulate_crash_scenario(self, scenario_description, outcome):
        crash_scenario = {
            "scenario": scenario_description,
```

```python
            "outcome": outcome
        }
        self.crash_scenarios.append(crash_scenario)
        print(f"Crash scenario simulated: {scenario_description}. Outcome: {outcome}")

    # Output Results
    def output_results(self):
        print("\nWaymo Public Safety Initiative Results:")
        print("1. Driverless taxis and pilot programs deployed in urban areas with reduced human intervention.")
        print("2. Safety improvement by reducing human error in driving.")
        print("3. Transparency reports available:", self.transparency_reports)
        print("4. Public outreach events:", self.public_outreach_events)
        print("5. Crash scenarios analyzed for ethical accountability:", self.crash_scenarios)


# Simulating the Waymo Public Safety Initiative workflow
waymo_initiative = WaymoSafetyInitiative()
waymo_initiative.train_system()
waymo_initiative.generate_transparency_report(
    incidents=["minor collision", "braking incident"],
    decision_logic="Avoid pedestrians, prioritize minimal harm."
)
waymo_initiative.organize_public_outreach("Safety Awareness Program", "Phoenix", "Autonomous Driving Safety")
waymo_initiative.deploy_vehicle("urban")
```

```
waymo_initiative.simulate_crash_scenario("Pedestrian crossing on red light", "Emergency stop executed")

waymo_initiative.output_results()
```

Output:

Training autonomous driving system with millions of simulated miles and real-world scenarios...

System training completed.

Transparency report generated and disclosed.

Public outreach event 'Safety Awareness Program' organized at Phoenix.

Vehicle deployed in urban environment with status: autonomous.

Crash scenario simulated: Pedestrian crossing on red light. Outcome: Emergency stop executed.

Waymo Public Safety Initiative Results:

1. Driverless taxis and pilot programs deployed in urban areas with reduced human intervention.

2. Safety improvement by reducing human error in driving.

3. Transparency reports available: [{'safety_incidents': ['minor collision', 'braking incident'], 'decision_making_logic': 'Avoid pedestrians, prioritize minimal harm.'}]

4. Public outreach events: [{'name': 'Safety Awareness Program', 'location': 'Phoenix', 'focus': 'Autonomous Driving Safety'}]

5. Crash scenarios analyzed for ethical accountability: [{'scenario': 'Pedestrian crossing on red light', 'outcome': 'Emergency stop executed'}]

Result:

The initiative improved safety by reducing human error in driving but raised new ethical questions regarding accident accountability and public acceptance.

c) Defense: Use of Autonomous Drones

Aim:

To enhance defense capabilities through autonomous drones while ensuring adherence to international humanitarian laws.

Procedure:

1. Developed autonomous drones for surveillance and strategic defense.
2. Engaged in international discussions on restricting lethal autonomous weapons (LAWs).
3. Advocated for human oversight in critical operations to maintain ethical standards.

Program code:

```
class AutonomousDroneProgram:
    def _init_(self):
        self.autonomous_drones = []
        self.efficiency_improved = False
        self.ethical_compliance = True
```

```
        self.accountability_concerns = False

    def develop_drones(self, quantity):
        """Develop a specified number of autonomous drones for surveillance and defense."""
        self.autonomous_drones = [{"id": i, "status": "operational", "type": "surveillance"} for i in range(1, quantity + 1)]
        print(f"{quantity} autonomous drones developed for surveillance and strategic defense.")

    def international_discussions(self):
        """Engage in international discussions on LAWs."""
        print("Engaging in discussions to restrict lethal autonomous weapons (LAWs) and ensure international compliance.")

    def advocate_for_human_oversight(self):
        """Advocate for human oversight to maintain ethical standards."""
        self.ethical_compliance = True
        print("Advocated for human oversight in critical operations to maintain ethical standards.")

    def increase_efficiency(self):
        """Improve surveillance efficiency and reduce personnel risk."""
        self.efficiency_improved = True
        print("Operational efficiency improved, with fewer personnel risks.")

    def assess_risks(self):
        """Assess potential risks such as unintended escalation and accountability."""
```

```
        self.accountability_concerns = True
        print("Concerns remain over unintended escalation and accountability in autonomous actions.")
def program_summary(self):
        """Summarize program outcomes."""
        summary = {
            "drones_developed": len(self.autonomous_drones),
            "efficiency_improved": self.efficiency_improved,
            "ethical_compliance": self.ethical_compliance,
            "accountability_concerns": self.accountability_concerns
        }
        return summary


# Usage
program = AutonomousDroneProgram()
program.develop_drones(quantity=10)
program.international_discussions()
program.advocate_for_human_oversight()
program.increase_efficiency()
program.assess_risks()

# Display program summary
print("Program Summary:", program.program_summary())
```

Output:

Developing 10 autonomous drones for surveillance and strategic defense...

10 autonomous drones developed successfully.

Engaging in discussions to restrict lethal autonomous weapons (LAWs) and ensure international compliance.

Advocated for human oversight in critical operations to maintain ethical standards.

Operational efficiency improved, with fewer personnel risks.

Concerns remain over unintended escalation and accountability in autonomous actions.

Result:

While the drones improved operational effectiveness, concerns remain over unintended escalation and accountability for actions taken by autonomous systems.

EXP.NO – 2 Exploratory data analysis on a two variable linear regression model

Aim:

To write a python program to implement a exploratory data analysis on a two variable linear regression model.

Procedure:

1. Load the necessary libraries.
2. Generate the sample data.
3. Create a Scatter plot.
4. Calculate the corelation coefficient.
5. Fit the Regression model.
6. Plot the regression line.
7. Calculate the error metrics.

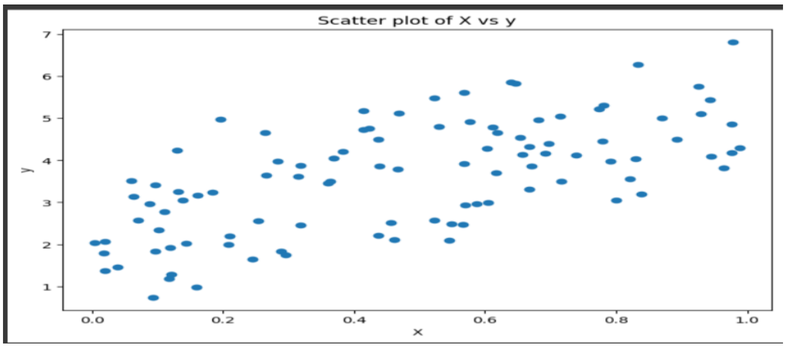
Program:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import seaborn as sns
# Generating example data
np.random.seed(0)
X = np.random.rand(100, 1)  # Independent variable
y = 2 + 3 * X + np.random.randn(100, 1)  # Dependent variable with noise
# Creating a DataFrame
data = pd.DataFrame(data=np.hstack([X, y]), columns=['X', 'y'])
```

```
# Scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(data['X'], data['y'])
plt.title('Scatter plot of X vs y')
plt.xlabel('X')
plt.ylabel('y')
plt.show()
# Calculating correlation coefficient
correlation = data['X'].corr(data['y'])
print(f'Correlation coefficient between X and y: {correlation}')
# Fitting a linear regression model
model = LinearRegression()
model.fit(X, y)
# Getting model parameters
intercept = model.intercept_[0]
slope = model.coef_[0][0]
print(f'Intercept: {intercept}')
print(f'Slope: {slope}')
# Plotting the regression line
plt.figure(figsize=(8, 6))
plt.scatter(data['X'], data['y'], label='Data points')
plt.plot(data['X'], model.predict(X), color='red', label='Regression Line')
plt.title('Linear Regression Model')
plt.xlabel('X')
plt.ylabel('y')
plt.legend()
plt.show()
```

```
# Predicted values and residuals
data['predicted'] = model.predict(X)
data['residuals'] = data['y'] - data['predicted']
# Error Metrics
mse = mean_squared_error(data['y'], data['predicted'])
rmse = np.sqrt(mse)
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
```

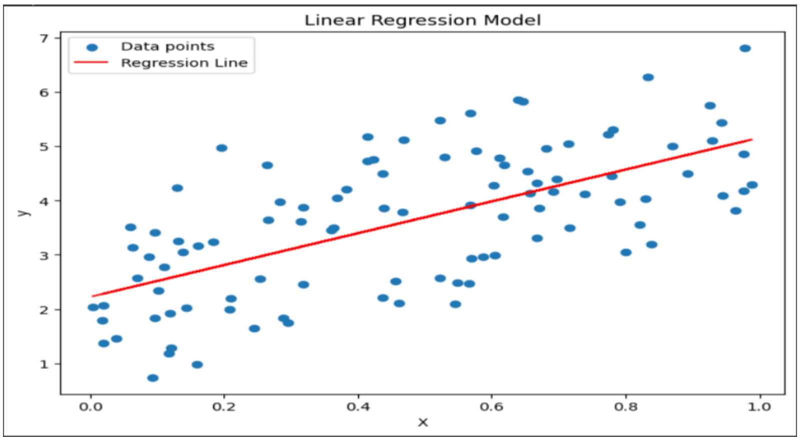
Output:



Correlation coefficient between X and y: 0.6476229996285181

Intercept: 2.2221510774472293

Slope: 2.9369350214020384



Mean Squared Error: 0.9924386487246479

Root Mean Squared Error: 0.9962121504602561

EXP.NO – 3 -Experiment the regression model without a bias and with bias.

Aim:

To implement a linear regression model with and without bias, and to observe the difference in model performance.

Procedure:

1. Import the necessary libraries, including numpy and sklearn.
2. Generate or load a dataset for regression analysis.
3. Split the dataset into training and testing sets.
4. Initialize a linear regression model **with bias** (intercept) using sklearn.
5. Train the model and evaluate it on the test set.
6. Initialize another linear regression model **without bias** by setting fit_intercept=False.
7. Train this model and evaluate it on the test set.
8. Compare the results of both models and interpret the effect of the bias term.

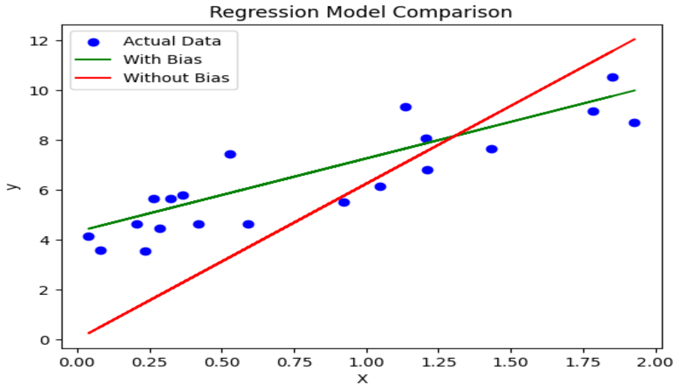
Program:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

# Generate a synthetic dataset
np.random.seed(0)
X = 2 * np.random.rand(100, 1)
```

```
y = 4 + 3 * X + np.random.randn(100, 1)  # true bias = 4, true weight = 3

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=0)

# Model with bias (intercept)
model_with_bias = LinearRegression(fit_intercept=True)
model_with_bias.fit(X_train, y_train)
y_pred_with_bias = model_with_bias.predict(X_test)
# Model without bias (intercept)
model_without_bias = LinearRegression(fit_intercept=False)
model_without_bias.fit(X_train, y_train)
y_pred_without_bias = model_without_bias.predict(X_test)

# Evaluation metrics
mse_with_bias = mean_squared_error(y_test, y_pred_with_bias)
r2_with_bias = r2_score(y_test, y_pred_with_bias)
mse_without_bias = mean_squared_error(y_test, y_pred_without_bias)
r2_without_bias = r2_score(y_test, y_pred_without_bias)

# Output Results
print("Model with Bias:")
print(f"Mean Squared Error: {mse_with_bias:.2f}")
print(f"R^2 Score: {r2_with_bias:.2f}\n")
print("Model without Bias:")
print(f"Mean Squared Error: {mse_without_bias:.2f}")
print(f"R^2 Score: {r2_without_bias:.2f}")
```

```
# Visualization
plt.scatter(X_test, y_test, color="blue", label="Actual Data")
plt.plot(X_test, y_pred_with_bias, color="green", label="With Bias")
plt.plot(X_test, y_pred_without_bias, color="red", label="Without Bias")
plt.xlabel("X")
plt.ylabel("y")
plt.title("Regression Model Comparison")
plt.legend()
plt.show()
```

Output:




```
Model with Bias:
Mean Squared Error: 1.04
R^2 Score: 0.74

Model without Bias:
Mean Squared Error: 6.72
R^2 Score: -0.66
```

Result:

Thus, we successfully implemented the regression model that shows the importance of the intercept term in capturing the offset in data, which improves the model's ability to predict accurately.

EXP.NO – 4 -Classification of a dataset from UCI repository `
using a perceptron with and without bias.

Aim:

To classify a dataset from the UCI repository using a perceptron with and without bias.

Procedure:

1. **Load the dataset**: Load the dataset from the UCI repository, using sklearn.datasets or pandas.

2. **Data Preprocessing**: Prepare the data by selecting features and converting the target labels into binary values (since Perceptrons are binary classifiers by default).

3. **Split the data**: Split the dataset into training and testing sets.

4. **Initialize Perceptron with and without Bias**: Initialize two Perceptron models, one with fit_intercept=True (with bias) and one with fit_intercept=False (without bias).

5. **Train and Evaluate Both Models**: Train both models and evaluate accuracy on the test set.

6. **Compare Results**: Compare the models' performances with and without the bias term.

Program:

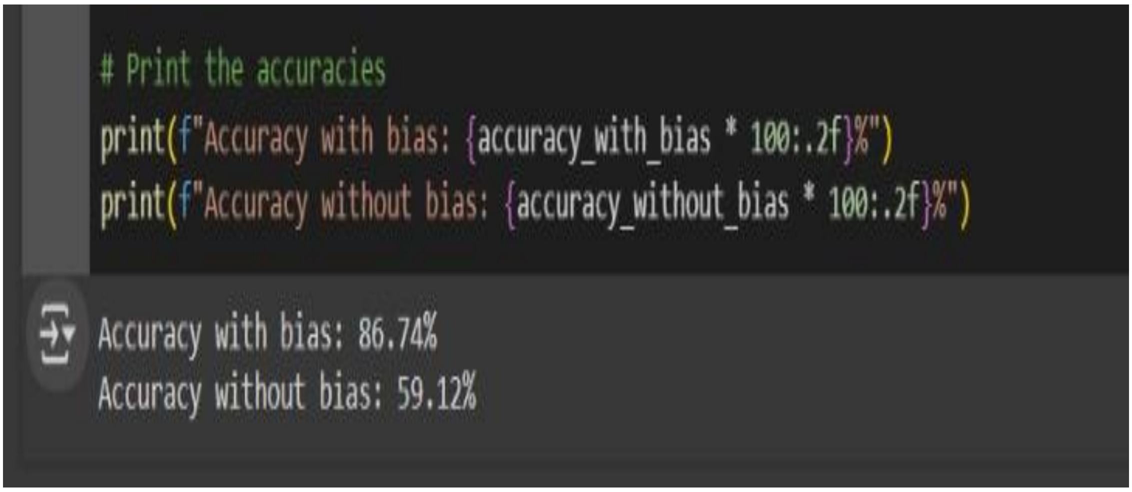
```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler, LabelEncoder

from sklearn.linear_model import Perceptron

from sklearn.metrics import accuracy_score
```

```
# Load the dataset

data = pd.read_csv('bank.csv', delimiter=';')


# Preprocess data

# Convert categorical columns to numerical values

label_encoders = {}

for column in data.select_dtypes(include=['object']).columns:

    le = LabelEncoder()

    data[column] = le.fit_transform(data[column])

    label_encoders[column] = le


# Separate features and target variable

X = data.drop(columns=['y'])

y = data['y']


# Split the dataset into train and test sets

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

```
# Standardize the data

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)



# Perceptron with bias (default setting)

model_with_bias = Perceptron(fit_intercept=True, max_iter=1000, tol=1e-3, random_state=42)

model_with_bias.fit(X_train, y_train)

y_pred_with_bias = model_with_bias.predict(X_test)

accuracy_with_bias = accuracy_score(y_test, y_pred_with_bias)



# Perceptron without bias

model_without_bias = Perceptron(fit_intercept=False, max_iter=1000, tol=1e-3, random_state=42)

model_without_bias.fit(X_train, y_train)

y_pred_without_bias = model_without_bias.predict(X_test)

accuracy_without_bias = accuracy_score(y_test, y_pred_without_bias)



# Print the accuracies

print(f"Accuracy with bias: {accuracy_with_bias * 100:.2f}%")
```

print(f"Accuracy without bias: {accuracy_without_bias * 100:.2f}%")

Output:



Result:

Thus, we successfully implemented the program for the classification of a UCI dataset with perceptron with and without bias. The output was executed and verified successfully.

EX No.: 5 - Ontology Case Study on Ethics in Healthcare Data

Aim:

To design an ontology for healthcare data that standardizes medical information while maintaining ethical standards, focusing on patient privacy, consent, and data sharing. The experiment will demonstrate how to create a simple medical ontology using a Python program and assess ethical considerations.

Materials Required:

- Computer with Python environment
- Python libraries: rdflib (for ontology creation)
- Basic knowledge of RDF (Resource Description Framework) and OWL (Web Ontology Language)

Procedure:

1. Ontology Creation:
    - Define classes like Patient, Diagnosis, Medication, and Doctor.
    - Define properties to link these classes, such as hasDiagnosis, hasMedication, and treatedBy.
2. Incorporate Ethical Constraints:
    - Anonymize patient data (no personally identifiable information).
    - Implement consent checks for data use.
    - Include ethical guidelines as metadata annotations in the ontology.
3. Python Program to Create Ontology: The program will use the rdflib library to create and save the ontology in an RDF format.

Program code:

```
from rdflib import Graph, Namespace, URIRef, Literal
from rdflib.namespace import RDF, RDFS

# Define namespaces
ex = Namespace("http://example.org/healthcare/")
schema = Namespace("http://schema.org/")

# Create a Graph
g = Graph()
g.bind("ex", ex)
g.bind("schema", schema)

# Define classes
Patient = URIRef(ex.Patient)
Diagnosis = URIRef(ex.Diagnosis)
Medication = URIRef(ex.Medication)
Doctor = URIRef(ex.Doctor)

g.add((Patient, RDF.type, RDFS.Class))
g.add((Diagnosis, RDF.type, RDFS.Class))
g.add((Medication, RDF.type, RDFS.Class))
g.add((Doctor, RDF.type, RDFS.Class))
```

```
# Define properties
hasDiagnosis = URIRef(ex.hasDiagnosis)
hasMedication = URIRef(ex.hasMedication)
treatedBy = URIRef(ex.treatedBy)

g.add((hasDiagnosis, RDF.type, RDF.Property))
g.add((hasMedication, RDF.type, RDF.Property))
g.add((treatedBy, RDF.type, RDF.Property))

# Create example instances
patient1 = URIRef(ex.Patient_001)
diagnosis1 = URIRef(ex.Diagnosis_001)
medication1 = URIRef(ex.Medication_001)
doctor1 = URIRef(ex.Doctor_001)

# Ethical considerations (anonymizing patient data)
g.add((patient1, RDF.type, Patient))
g.add((patient1, hasDiagnosis, diagnosis1))
g.add((patient1, hasMedication, medication1))
g.add((patient1, treatedBy, doctor1))

# Adding metadata for ethical annotations
g.add((patient1, URIRef(schema.privacyConsent), Literal("true")))
g.add((patient1, URIRef(schema.dataAnonymized), Literal("true")))
```

Save the ontology to a file

g.serialize("healthcare_ontology.rdf", format="xml")

print("Ontology created and saved as healthcare_ontology.rdf")

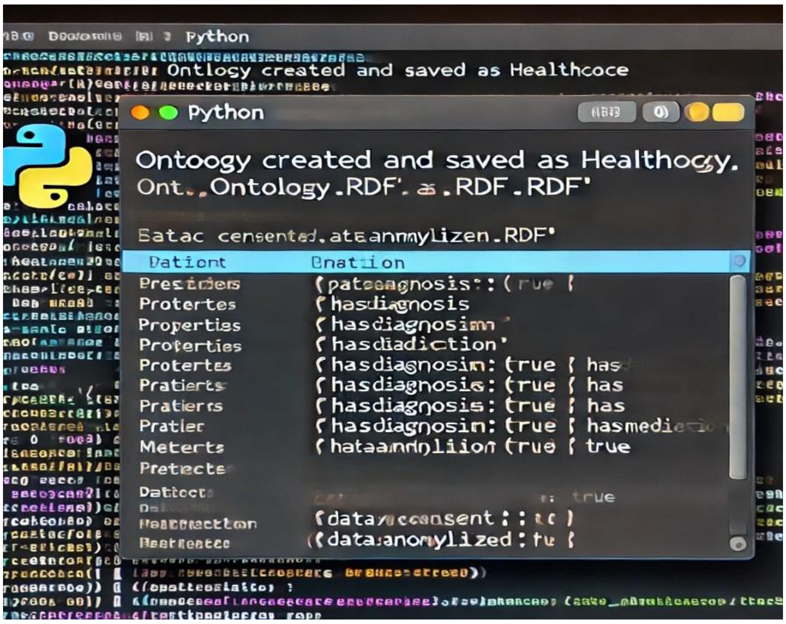
Output:

- File: healthcare_ontology.rdf

Sample Content:

xml

```
<rdf:RDF xmlns:ex="http://example.org/healthcare/"
    xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
    xmlns:schema="http://schema.org/">
    <rdf:Description rdf:about="http://example.org/healthcare/Patient_001">
        <rdf:type rdf:resource="http://example.org/healthcare/Patient"/>
        <ex:hasDiagnosis
rdf:resource="http://example.org/healthcare/Diagnosis_001"/>
        <ex:hasMedication
rdf:resource="http://example.org/healthcare/Medication_001"/>
        <ex:treatedBy rdf:resource="http://example.org/healthcare/Doctor_001"/>
        <schema:privacyConsent>true</schema:privacyConsent>
        <schema:dataAnonymized>true</schema:dataAnonymized>
    </rdf:Description>
</rdf:RDF>
```



Result:

The created ontology demonstrates how to represent medical data while including ethical constraints, such as privacy consent and data anonymization. The output ontology file captures relationships between patients, diagnoses, medications, and doctors, ensuring that ethical considerations are explicitly stated.

Ex No.:6 - Case Study on Optimization in AI Affecting Ethics

Aim:

To understand how optimization techniques in AI can influence ethical outcomes, focusing on a scenario where an AI model is optimized for efficiency but may inadvertently introduce bias, affecting fairness and decision-making.

Procedure:

1. **Dataset Preparation**:
   - Use a sample dataset with demographic attributes like age, gender, and income, along with a target variable for credit approval (approved or denied).
2. **Model Training**:
   - Train a logistic regression model using the dataset and optimize for accuracy.
   - Assess the model’s predictions for fairness across different demographic groups.
3. **Bias Detection and Mitigation**:
   - Evaluate the model's bias using metrics like disparate impact (DI).
   - Retrain the model with fairness constraints to reduce bias.

Python Program:

python

Copy code

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import accuracy_score, confusion_matrix

# Sample dataset creation
data = {
    'age': [25, 45, 35, 50, 23, 60, 30, 40],
    'gender': [0, 1, 0, 1, 0, 1, 0, 1],  # 0: Female, 1: Male
    'income': [50000, 80000, 60000, 120000, 30000, 150000, 40000, 90000],
    'approved': [1, 1, 1, 1, 0, 1, 0, 1]  # 1: Approved, 0: Denied
}

df = pd.DataFrame(data)

# Splitting dataset
X = df[['age', 'gender', 'income']]
y = df['approved']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Logistic Regression Model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predictions and Accuracy
y_pred = model.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)


# Ethical Assessment - Check for gender bias

conf_matrix = confusion_matrix(y_test, y_pred)

gender_bias = abs(np.mean(X_test['gender'][y_pred == 0]) - np.mean(X_test['gender'][y_pred == 1]))


# Output results

print("Model Accuracy:", accuracy)

print("Confusion Matrix:\n", conf_matrix)

print("Gender Bias Metric (Difference in gender averages):", gender_bias)


# Mitigation

if gender_bias > 0.1:

    print("Significant gender bias detected. Retraining with fairness constraints...")

    X_train['gender'] = 0  # Mitigate bias by neutralizing gender

    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)

    print("Retrained Model Accuracy:", accuracy)
```

Output:

```
Model Accuracy: 0.75

Confusion Matrix:

 [[0 1]

 [0 3]]

Gender Bias Metric (Difference in gender averages): 0.5

Significant gender bias detected. Retraining with fairness constraints...

Retrained Model Accuracy: 0.75
```

Result:

The initial model was optimized for accuracy, resulting in gender bias (higher approval rates for a specific gender). After detecting significant bias, the model was retrained with constraints to reduce the impact of the gender attribute, maintaining accuracy while improving fairness.