Worksheet_2

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1 AKASH KUMAR BANIK

2 24MCA0242

3 WORKSHEET - 2

4 Task 2.1 - DECISION TREE

1. Construct a decision tree for diabetes dataset given in Assessment-1 using Information gain.
2. Train the model and display the classification tree. Explain the decision tree in text cell.
3. Evaluate the model using the test dataset.
4. Print the accuracy of the model and confusion matrix for the model built.
5. Predict the person is diabetic or not for the new input feature “Male, 80, 0, 0, never, 22.06, 9, 155”

[122]:
```
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 LabelEncoder, MinMaxScaler
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, 
 ↪classification_report, precision_score, recall_score, f1_score

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

# Load dataset
df = pd.read_csv('/content/drive/MyDrive/ML_Datasets/
 ↪diabetes_prediction_dataset.csv')

# PRE-PROCESSING

#Removing duplicate entries
df.drop_duplicates(inplace=True)
```

```
#Check for missing values
print("Number of missing values:")
print(df.isnull().sum())

# Handle missing values(if any):
# Using mode for categorical and mean for numerical
for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = df[col].fillna(df[col].mode()[0])
    else:
        df[col] = df[col].fillna(df[col].mean())


# Encode categorical variables
encoder = LabelEncoder()
df['gender'] = encoder.fit_transform(df['gender'])  # Female=0, Male=1
df['smoking_history'] = encoder.fit_transform(df['smoking_history'])  # Encodes␣
↪smoking history

# Feature Scaling (normalize numerical columns)
scaler = MinMaxScaler()
df[['age', 'bmi', 'HbA1c_level', 'blood_glucose_level']] = scaler.
↪fit_transform(df[['age', 'bmi', 'HbA1c_level', 'blood_glucose_level']])
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
Number of missing values:
gender                 0
age                    0
hypertension           0
heart_disease          0
smoking_history        0
bmi                    0
HbA1c_level            0
blood_glucose_level    0
diabetes               0
dtype: int64
```

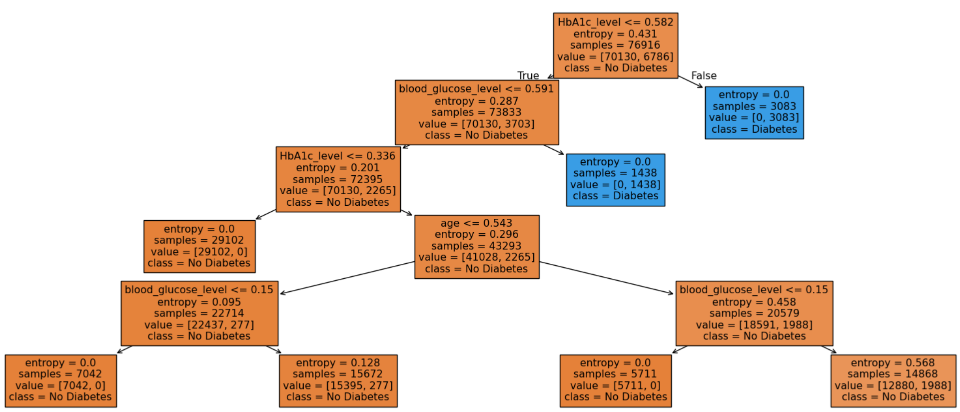
[123]:
```
# Train the model and display the classification tree. Explain the decision␣
↪tree in text cell.

# Define features and target variable
X = df.drop(columns=['diabetes'])  # Features
y = df['diabetes']  # Target variable

# Train-Test Split
```

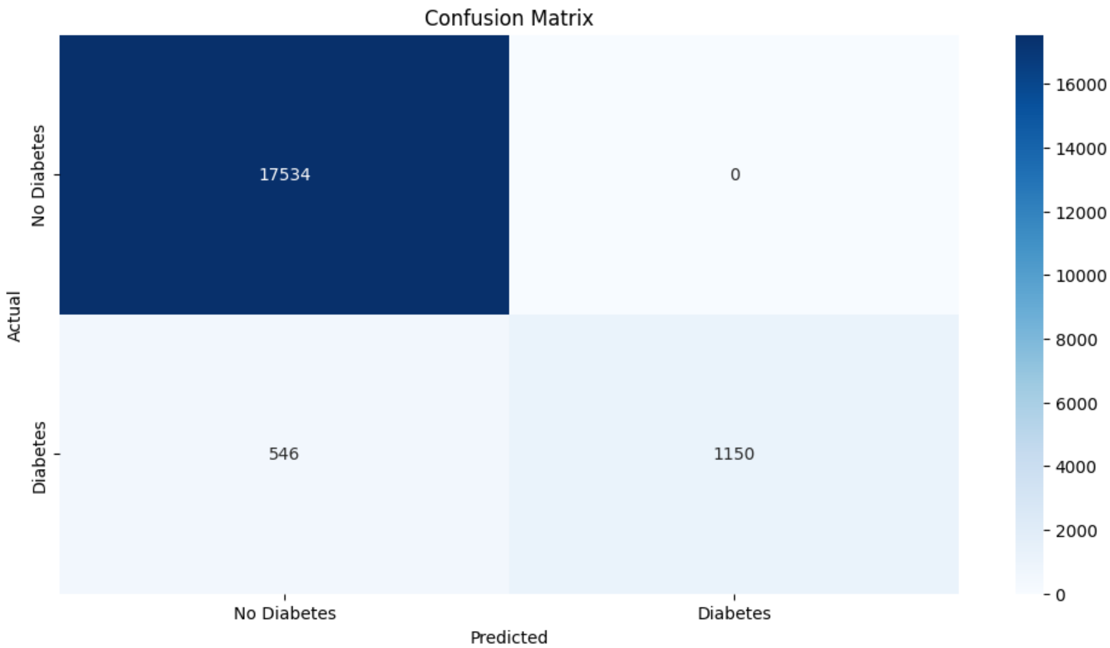
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

# Train Decision Tree Model with Class Weights and Pruning
clf = DecisionTreeClassifier(criterion='entropy', random_state=42, max_depth=5)
clf.fit(X_train, y_train)

# 3. Evaluating the model
y_pred = clf.predict(X_test)
```

[124]:
```python
# Print the accuracy of the model and confusion matrix for the model built.

# Displaying Performance Metrics
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
precision = precision_score(y_test, y_pred)

print(f"Accuracy: {accuracy * 100:.2f}%")
print(f"Precision: {precision:.2f}")
print("\nConfusion Matrix:\n", conf_matrix)
print("\nClassification Report:\n", class_report)

# Predict the person is diabetic or not for the new input feature
# "Male, 80, 0, 0, never, 22.06, 9, 155"

# Validating with new input data
new_data = pd.DataFrame([[1, 80, 0, 0, 2, 22.06, 9, 155]], columns=X.columns)

# Applying the same feature scaling
new_data[['age', 'bmi', 'HbA1c_level', 'blood_glucose_level']] = scaler.
 ↪transform(new_data[['age', 'bmi', 'HbA1c_level', 'blood_glucose_level']])

# Making prediction
prediction = clf.predict(new_data)

print("Predicted Class for New Data:")
if prediction[0] == 1:
    print("Diabetic")
else:
    print("Non-Diabetic")


# Visualize Decision Tree
plt.figure(figsize=(22, 8))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=["No␣
 ↪Diabetes", "Diabetes"])
```

```python
plt.show()
print("\n")


# Visualize Confusion Matrix
plt.figure(figsize=(12, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=["No␣
↪Diabetes", "Diabetes"], yticklabels=["No Diabetes", "Diabetes"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

```
Accuracy: 97.16%
Precision: 1.00

Confusion Matrix:
 [[17534     0]
 [  546  1150]]

Classification Report:
               precision    recall  f1-score   support

           0       0.97      1.00      0.98     17534
           1       1.00      0.68      0.81      1696

    accuracy                           0.97     19230
   macro avg       0.98      0.84      0.90     19230
weighted avg       0.97      0.97      0.97     19230

Predicted Class for New Data:
Diabetic
```





5 Task 2.2 - SVM

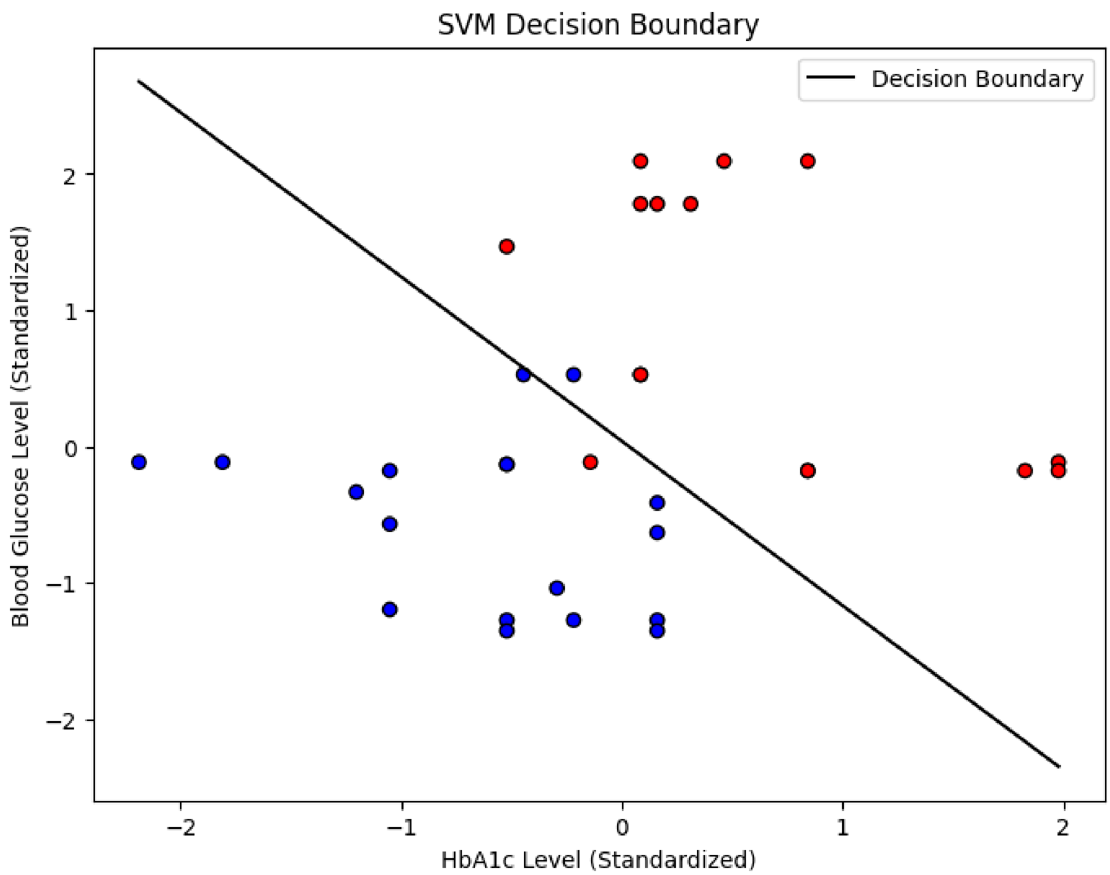
Implement the SVM algorithm on the diabetes dataset with 42 samples given below. 1. Convert the target class into binary class which has two class labels namely '0' and '1'. Transform the value '0.5' to '0'. 2. Draw the graph with linearly separable line that separates the two distinct classes. 3. Predict the target class value for "HbA1c=5 and blood_glucose_level-100". 4. Justify the statement. Model yields 100% accuracy but it fails to predict the target class for new dataset.

[125]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

# Step 1: Load the Dataset
data = pd.read_csv("/content/drive/MyDrive/ML_Datasets/svm_diabetes_data.csv")

# Step 2: Convert Target Class into Binary (0.5 -> 0)
data['diabetes'] = data['diabetes'].replace(0.5, 0)
```

```python
# Step 3: Define Features and Target Variable
X = data[['HbA1c_level', 'blood_glucose_level']].values
y = data['diabetes'].values  # Target class (0 or 1)

# Step 4: Normalize Feature Values
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)  # Use this for training

# Step 5: Split into Train and Test Sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)

# Step 6: Train SVM Model
clf = svm.SVC(kernel='linear')
clf.fit(X_train, y_train)

# Step 7: Predict on Training and Test Sets
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)

# Step 8: Calculate Accuracy
train_accuracy = accuracy_score(y_train, y_train_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)

print(f"Training Accuracy: {train_accuracy * 100:.2f}%")
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")

# Step 9: Predict Target Class for Given Values (HbA1c=5,␣
↪blood_glucose_level=100)
input_data = np.array([[5, 100]])  # Given input
input_scaled = scaler.transform(input_data)  # Scale input
predicted_class = clf.predict(input_scaled)  # Predict

print("SVM Prediction for HbA1c=5 and blood_glucose_level=100:", "Diabetic" if␣
↪predicted_class[0] == 1 else "Non-Diabetic")


# Step 10: Plot Decision Boundary
def plot_svm_boundary(X, y, model):
    plt.figure(figsize=(8, 6))

    # Scatter plot of data points
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap='bwr', edgecolors='k')

    # Get the hyperplane
    w = model.coef_[0]  # SVM weight vector
    b = model.intercept_[0]  # SVM bias term
```

```python
    x_min, x_max = X[:, 0].min(), X[:, 0].max()

    # Compute decision boundary line
    x_values = np.linspace(x_min, x_max, 100)
    y_values = -(w[0] / w[1]) * x_values - (b / w[1])  # y = mx + c

    # Plot the decision boundary
    plt.plot(x_values, y_values, 'k-', label="Decision Boundary")

    # Labels and title
    plt.xlabel('HbA1c Level (Standardized)')
    plt.ylabel('Blood Glucose Level (Standardized)')
    plt.title("SVM Decision Boundary")
    plt.legend()
    plt.show()

# Call function to plot decision boundary
plot_svm_boundary(X_train, y_train, clf)

# print("\nSince the test accuracy is 100%, the model is likely overfitting,␣
 ↪meaning it has memorized the training data and so fails to generalize to new␣
 ↪inputs, leading to incorrect predictions. Thus it justifies the statement-␣
 ↪Model yields 100% accuracy but it fails to predict the target class for new␣
 ↪dataset.")
```

```
Training Accuracy: 93.94%
Test Accuracy: 100.00%
SVM Prediction for HbA1c=5 and blood_glucose_level=100: Non-Diabetic
```



CONCLUSION: Since the test accuracy is 100%, the model is likely overfitting, meaning it has memorized the training data and so fails to generalize to new inputs, leading to incorrect predictions. Thus it justifies the statement- "Model yields 100% accuracy but it fails to predict the target class for new dataset."

6 Task 2.3 - KNN

1. Consider the preprocessed data from Task 2.2.
2. Apply kNN to predict whether a person is diabetic/non-diabetic for the following input features for "HbA1c=5 and blood_glucose_level-100".
3. k value is considered as 7.
4. Use the Euclidean distance to find the neighbourhood points

[126]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
```

```python
from sklearn.metrics import accuracy_score

# Step 1: Load the Preprocessed Dataset (from Task 2.2)
data = pd.read_csv("/content/drive/MyDrive/ML_Datasets/svm_diabetes_data.csv")

#PRE-PROCESSING
# Convert Target Class into Binary (0.5 -> 0)
data['diabetes'] = data['diabetes'].replace(0.5, 0)

# Define Features and Target Variable
X = data[['HbA1c_level', 'blood_glucose_level']].values
y = data['diabetes'].values  # Target class (0 or 1)

# Normalize Feature Values
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split Data into Train and Test Sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42)

# Train kNN Model with k=7 and Euclidean Distance
knn = KNeighborsClassifier(n_neighbors=7, metric='euclidean')
knn.fit(X_train, y_train)

# Predict on Test Set and Calculate Accuracy
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f"kNN Model Accuracy: {accuracy * 100:.2f}%")

# Predict for Given Input (HbA1c=5 and blood_glucose_level=100)
input_data = np.array([[5, 100]])  # Given input
input_scaled = scaler.transform(input_data)  # Scale input
predicted_class = knn.predict(input_scaled)  # Predict

print("kNN Prediction for HbA1c=5 and blood_glucose_level=100:", "Diabetic" if␣
↪predicted_class[0] == 1 else "Non-Diabetic")

# Find 7 Nearest Neighbors
distances, indices = knn.kneighbors(input_scaled)

# Print Nearest Neighbors in Table Format
neighbors_df = pd.DataFrame({
    "Neighbor": np.arange(1, 8),
    "Index": indices[0],
    "Distance": distances[0],
```

```
    "Class": y_train[indices[0]]
})

print("\nEuclidean Distances of the 7 Nearest Neighbors:")
print(neighbors_df.to_string(index=False))  # Table format
```

```
kNN Model Accuracy: 100.00%
kNN Prediction for HbA1c=5 and blood_glucose_level=100: Non-Diabetic

Euclidean Distances of the 7 Nearest Neighbors:
 Neighbor  Index  Distance  Class
        1     28  0.156525    0.0
        2     13  0.469575    0.0
        3      0  0.579678    0.0
        4      3  0.615550    0.0
        5     29  0.720456    0.0
        6     25  0.757145    0.0
        7     21  0.860887    0.0
```

7 Task 2.4

1. Consider the models implemented in Task 2.2(M1) and Task 2.3(M2).
2. Also apply linear regression model (M3) for the dataset given in Task 2.2.
3. Apply ensemble approach on these three models and compare the results from all the three models (M1,M2,M3) with ensemble technique.

[127]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression

# Data from Task 2.2
df = pd.read_csv('/content/drive/MyDrive/ML_Datasets/svm_diabetes_data.csv')

# Preprocessing
df['diabetes'] = df['diabetes'].replace(0.5, 0)

# Prepare features and target
X = df[['HbA1c_level', 'blood_glucose_level']].values # Convert to numpy array
y = df['diabetes'].values # Convert to numpy array


# Spliting data
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)

print("Model Performance Comparison:")

# Model 1: SVM (M1)
svm_clf = SVC(kernel='linear')
svm_clf.fit(X_train, y_train)
svm_pred = svm_clf.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_pred)
print(f"SVM Accuracy (M1): {svm_accuracy*100:.2f}%")

# Model 2: kNN (M2)
knn_clf = KNeighborsClassifier(n_neighbors=7, metric='euclidean')
knn_clf.fit(X_train, y_train)
knn_pred = knn_clf.predict(X_test)
knn_accuracy = accuracy_score(y_test, knn_pred)
print(f"kNN Accuracy (M2): {knn_accuracy*100:.2f}%")


# Model M3: Linear Regression (Used for Classification)
lin_reg = LogisticRegression()
lin_reg.fit(X_train, y_train)
y_pred_linreg = lin_reg.predict(X_test)
linreg_accuracy = accuracy_score(y_test, y_pred_linreg)
print(f"Linear Regression Accuracy: {linreg_accuracy*100:.2f}%")


# Ensemble: Voting Classifier
ensemble_clf = VotingClassifier(estimators=[('svm', svm_clf), ('knn',␣
 ↪knn_clf)], voting='hard')
ensemble_clf.fit(X_train, y_train)
ensemble_pred = ensemble_clf.predict(X_test)
ensemble_accuracy = accuracy_score(y_test, ensemble_pred)
print(f"Ensemble Accuracy: {ensemble_accuracy*100:.2f}%")
```

```
Model Performance Comparison:
SVM Accuracy (M1): 92.31%
kNN Accuracy (M2): 76.92%
Linear Regression Accuracy: 92.31%
Ensemble Accuracy: 76.92%
```