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04/10/2024
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CS 634 104 Data Mining

Final term Project Report

Implementation and Code Usage

Supervised Machine Learning (Classification)

Abstract:
In this project, I delve into the various machine learning algorithms for classifying the different dry bean. The algorithms are evaluated using F1-Score metric.

Introduction:
Supervised machine learning learns the patterns in the dataset and tries to best-fit the dataset so that it can accurately differentiate between items.

In this implementation, I've applied Random Forest, SVM, KNN and Conv1D algorithm to a dry bean dataset. Key steps in this process included:

- Loading the dataset from CSV files.
- Data analysis.
- Data pre-processing
- Model training

Core Concepts and Principles:

Supervised Machine Learning:
Supervised Machine learning is a part of Machine learning where the algorithm has access to the data points as well as label associated with that data point.

Neuron:
Neuron in neural network is machine representation of the biological neuron. The neuron accepts inputs, performs computation that is dot product of the input and weights, outputs activated computation.

Neural Network:
Neural network is an interconnection of the neurons.

F1-Score:
It is calculated based on model's precision and recall. The precision and recall are calculated on TP, FP, TN and TP.

K-Fold Cross Validation:
This is a technique to divide the training dataset into train and validation dataset. This way we can train the model as well as check how well it is performing on the unseen data without exposing it to the test data.

Project Workflow:

Our project follows a structured workflow involving various stages and the application of the various machine learning algorithm**s.**

Data Loading
We begin by loading csv dry bean dataset. Each item contains of 16 attributes and a label.

Data Analysis
We analyse data for any missing values, observe the attribute distribution, label distribution and correlations between different attributes.

Data Pre-processing:
To ensure clean and compatible data, we pre-process the dataset by converting string to numerical representation, normalizing dataset for SVM and Neural Networks.

Machine Learning Algorithms
- **Random Forest**
- **SVM**
- **KNN**
- **Conv1D Deep Learning**

Results and Evaluation:
The machine learning's accuracy and efficiency are evaluated based on performance measures such as F1-score, precision, recall and confusion metrics.

Conclusion:

In conclusion, this project demonstrates the application and evaluation of supervised data mining (Machine Learning) concepts and methods on dry bean classification dataset.

Directory Structure:

-------- dataset/ => This contains all the data files needed to run the code
-------- models/ => This is the saved neural net model.
-------- docs/ => This contains images for documentation
-------- .gitignore => Ignore files / folders to include in git history
-------- main.ipynb => This is the main Jupyter notebook that contains the code to run brute force and library's algorithm
-------- Finalterm-Project-Report.pdf => Obviously, project report
-------- README.md => This contains all the instructions to setup the project locally
-------- requirements.txt => This contains all the packages to run the code

---

Steps to run the program:

1. Make sure that you've python installed on your machine. To download and install Python, go to https://www.python.org/. To check if you've python installed, run `python3 --version`.
   NOTE - I have used python version 3.11.7 to run the program

2. Create a virtual environment using command `python3 -m venv .venv`.
3. Activate the virtual environment using command `source .venv/bin/activate`.
4. Install all the packages in **requirements.txt** using `pip install -r requirements.txt`.
5. Select existing `.venv` python environment as the kernel for the `main.ipynb` Jupyter notebook.
6. Run cells in `main.ipynb` Jupyter notebook.

Screenshots:

Pre-requisite steps

Step – 1

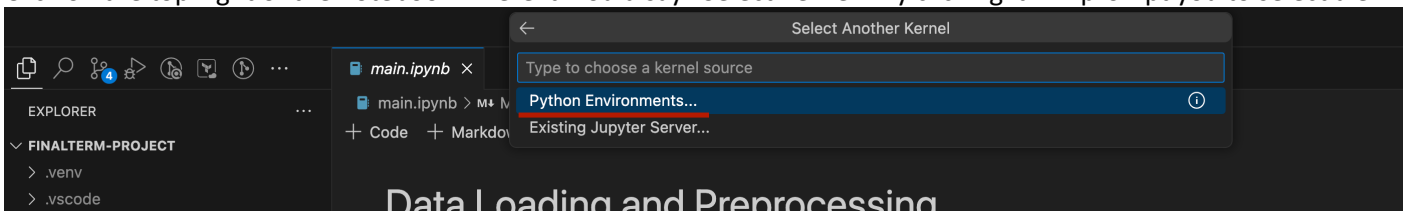
Step – 2

Step – 3

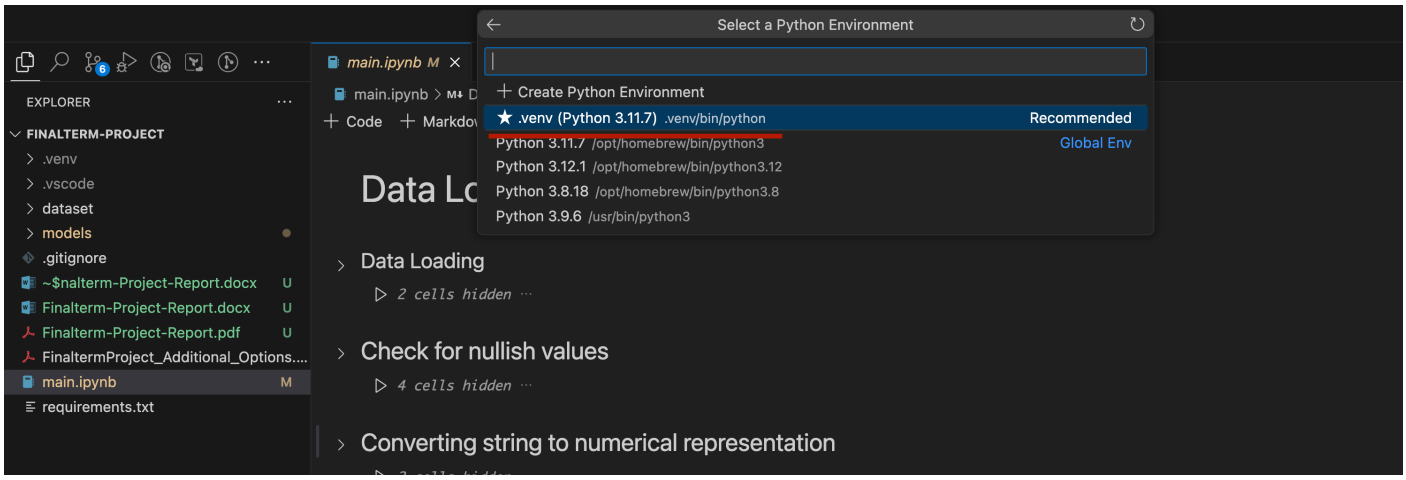
Step – 4

Step – 5

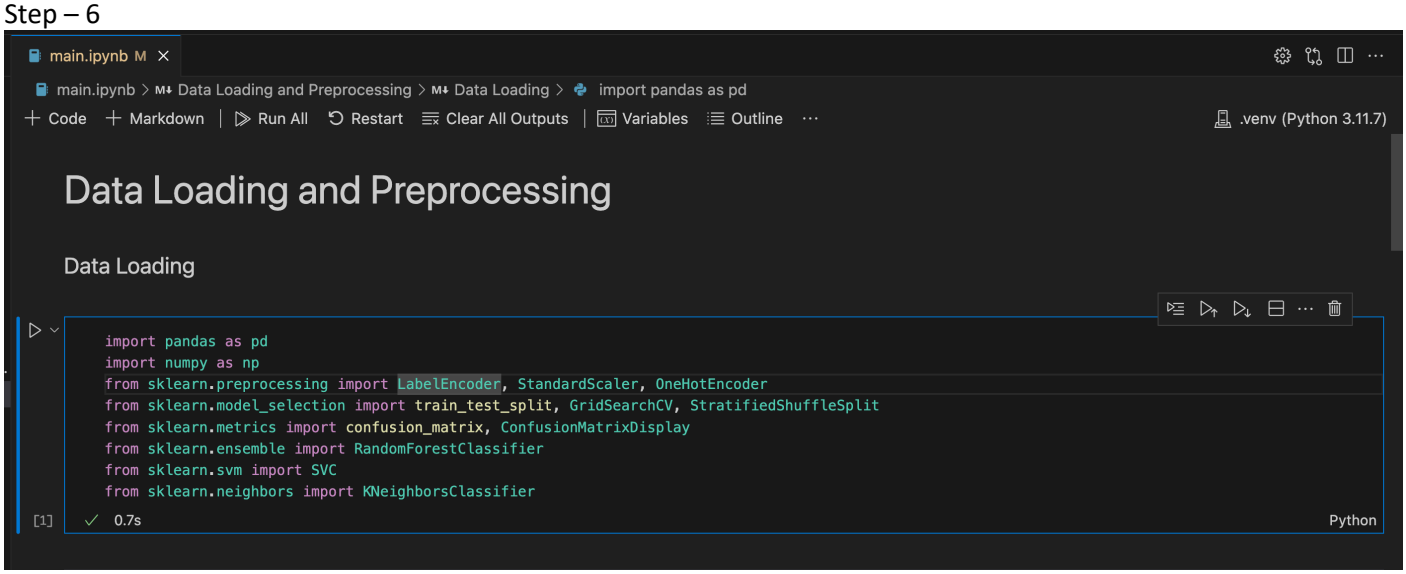
Click on the top-right of the notebook where it would say “Select Kernel”. By clicking it will prompt you to select a env.



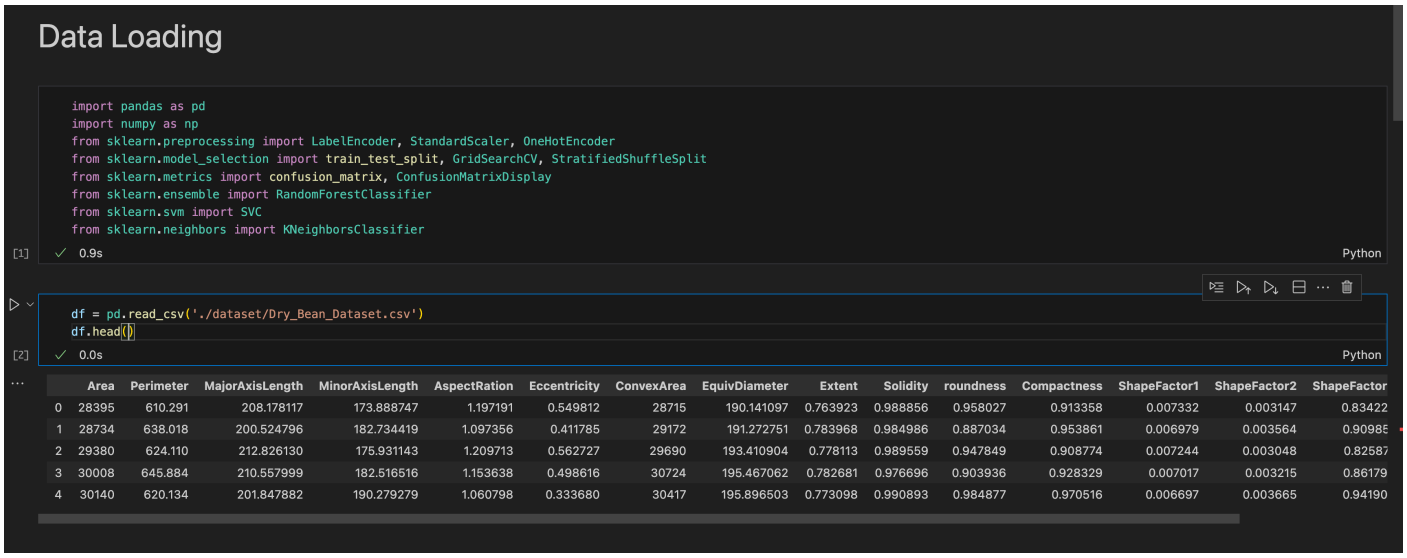
Now select the virtual we created in step – 2 as the environment. After that, it would show you the selected kernel in top-right section.


Select a Python Environment
Create Python Environment
.venv (Python 3.11.7) .venv/bin/python
Recommended
Python 3.11.7 /opt/homebrew/bin/python3
Global Env
Python 3.12.1 /opt/homebrew/bin/python3.12
Python 3.8.18 /opt/homebrew/bin/python3.8
Python 3.9.6 /usr/bin/python3
main.ipynb M
EXPLORER
FINALTERM-PROJECT
.venv
.vscode
dataset
models
.gitignore
~$nalterm-Project-Report.docx
Finalterm-Project-Report.docx
Finalterm-Project-Report.pdf
FinaltermProject_Additional_Options....
main.ipynb
requirements.txt
Code
Data Loading
2 cells hidden
Check for nullish values
4 cells hidden
Converting string to numerical representation

Step – 6


main.ipynb M
main.ipynb > Data Loading and Preprocessing > Data Loading > import pandas as pd
Code
Markdown
Run All
Restart
Clear All Outputs
Variables
Outline
.venv (Python 3.11.7)
Data Loading and Preprocessing
Data Loading
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedShuffleSplit
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
[1]
0.7s
Python

Below are screenshots of the running code from Jupyter notebook:
Data loading



Data Loading

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedShuffleSplit
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
```

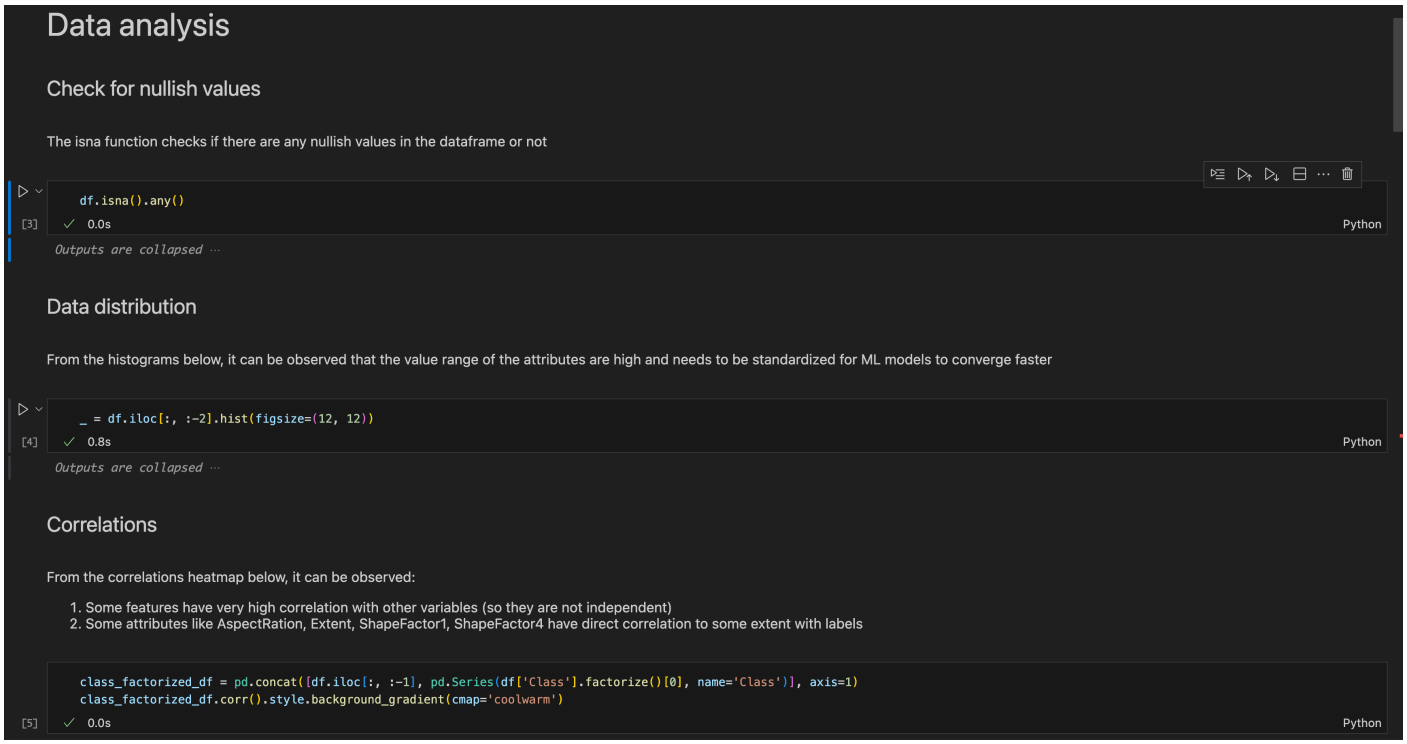
[1] ✓ 0.9s Python

```
df = pd.read_csv('./dataset/Dry_Bean_Dataset.csv')
df.head()
```

[2] ✓ 0.0s Python

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	190.141097	0.763923	0.988856	0.958027	0.913358	0.007332	0.003147	0.83422
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	191.272751	0.783968	0.984986	0.887034	0.953861	0.006979	0.003564	0.90985
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	193.410904	0.778113	0.989559	0.947849	0.908774	0.007244	0.003048	0.82587
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	195.467062	0.782681	0.976696	0.903936	0.928329	0.007017	0.003215	0.86179
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	195.896503	0.773098	0.990893	0.984877	0.970516	0.006697	0.003665	0.94190

Data analysis



Data analysis

Check for nullish values

The isna function checks if there are any nullish values in the dataframe or not

```
df.isna().any()
```

[3] ✓ 0.0s Python

Outputs are collapsed ···

Data distribution

From the histograms below, it can be observed that the value range of the attributes are high and needs to be standardized for ML models to converge faster

```
_ = df.iloc[:, :-2].hist(figsize=(12, 12))
```

[4] ✓ 0.8s Python

Outputs are collapsed ···

Correlations

From the correlations heatmap below, it can be observed:

1. Some features have very high correlation with other variables (so they are not independent)
2. Some attributes like AspectRation, Extent, ShapeFactor1, ShapeFactor4 have direct correlation to some extent with labels

```
class_factorized_df = pd.concat([df.iloc[:, :-1], pd.Series(df['Class'].factorize()[0], name='Class')], axis=1)
class_factorized_df.corr().style.background_gradient(cmap='coolwarm')
```

[5] ✓ 0.0s Python

Correlations

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1. Some features have very high correlation with other variables (so they are not independent)
2. Some attributes like AspectRation, Extent, ShapeFactor1, ShapeFactor4 have direct correlation to some extent with labels

```
class_factorized_df = pd.concat([df.iloc[:, :-1], pd.Series(df['Class'].factorize()[0], name='Class')], axis=1)
class_factorized_df.corr().style.background_gradient(cmap='coolwarm')
```

[5] ✓ 0.0s Python

Outputs are collapsed ···

Label distribution

From the below bar graph, we can infer following points:

1. There aren't any out-of-place/nullish class values
2. We need to convert the string values of class to numerical representation
3. The class distribution is unbalanced, so the training data needs to be split with stratification.

+ Code + Markdown

```
df['Class'].value_counts().plot(kind='bar')
```

[6] ✓ 0.0s Python

Outputs are collapsed ···

Data pre-processing

Data Preprocessing

Converting string to numerical representation

```
encoder = LabelEncoder()
df['Class_numerical'] = encoder.fit_transform(df['Class'])
```

[7] ✓ 0.0s Python

```
encoder.inverse_transform([0, 1, 2, 3, 4, 6, 5])
```

[8] ✓ 0.0s Python

```
··· array(['BARBUNYA', 'BOMBAY', 'CALI', 'DERMASON', 'HOROZ', 'SIRA', 'SEKER'],
      dtype=object)
```

Normalizing dataset

+ Code + Markdown

```
X_train, X_test, y_train, y_test = train_test_split(
    df.iloc[:, :-2],
    df["Class_numerical"],
    test_size=0.2,
    random_state=42,
    shuffle=True,
    stratify=df["Class_numerical"],
)
```

[9] ✓ 0.0s Python

Normalizing dataset

```
X_train, X_test, y_train, y_test = train_test_split(
    df.iloc[:, :-2],
    df["Class_numerical"],
    test_size=0.2,
    random_state=42,
    shuffle=True,
    stratify=df["Class_numerical"],
)
```

[9] ✓ 0.0s Python

```
scaler = StandardScaler()
scaled_features = scaler.fit_transform(X_train)
X_train = pd.DataFrame(scaled_features, columns=df.columns[:-2])
X_test = pd.DataFrame(scaler.transform(X_test), columns=df.columns[:-2])
X_train.head()
```

[10] ✓ 0.0s Python

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFa
0	-0.371362	-0.531131	-0.695370	0.086657	-1.293800	-1.515964	-0.380039	-0.361098	0.857421	1.256100	1.516864	1.446832	-0.339818	1.118082	1.4
1	0.028952	0.498818	0.783518	-0.540352	2.401812	1.493455	0.035323	0.150320	-2.941719	-0.843829	-2.378161	-1.999948	0.551406	-1.321497	-1.8
2	0.727078	0.795005	0.824382	0.924849	0.076902	0.330836	0.717120	0.923243	1.203117	0.618792	0.254498	-0.201104	-1.160932	-0.787674	-0.2
3	0.732131	0.883592	1.020897	0.725643	0.614895	0.721194	0.735383	0.928419	0.870459	-0.479395	-0.253981	-0.715959	-0.969786	-1.032437	-0.7
4	-0.133509	-0.257497	-0.481242	0.494139	-1.381023	-1.713495	-0.144039	-0.049766	0.713863	1.247235	1.531060	1.569816	-0.786632	0.919368	1.6

+ Code + Markdown

As you can see in below histograms, the range of features are normalized

```
_ = X_train.iloc[:, :-1].hist(figsize=(12, 12))
```

[11] ✓ 0.5s Python

Outputs are collapsed ···

Model Training

Random Forest

Model Training

Random Forest

```
params = {
    # "n_estimators": [100, 200, 300],
    # "max_depth": [10, 12],
    "n_estimators": [200],
    "max_depth": [12],
}
stratified_split = StratifiedShuffleSplit(n_splits=10, test_size=0.1, random_state=42)
gridsearch_rf = GridSearchCV(
    RandomForestClassifier(n_jobs=-1),
    params,
    cv=stratified_split,
    n_jobs=-1,
    verbose=1,
)
gridsearch_rf.fit(X_train, y_train)

# Scores
gridsearch_rf.score(X_train, y_train), gridsearch_rf.score(X_test, y_test)
```

[12] ✓ 5.8s Python

```
Fitting 10 folds for each of 1 candidates, totalling 10 fits
```

```
(0.9839272593681117, 0.9214102093279471)
```

```
# If you uncomment the commented parameters and comment out the current parameters,
# you will get the following output

# gridsearch_rf.best_params_
# Output - {'max_depth': 12, 'n_estimators': 200}
```

[13] ✓ 0.0s Python

```
y_pred = gridsearch_rf.predict(X_test)
matrix = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay.from_predictions(
    y_test,
    y_pred,
    display_labels=encoder.inverse_transform([0, 1, 2, 3, 4, 5, 6]),
    xticks_rotation="vertical",
)
```

[14] ✓ 0.1s Python

Outputs are collapsed ···

```
def f1_score_weighted(y_true, y_pred):
    matrix = confusion_matrix(y_true, y_pred)
    precision = np.diag(matrix) / matrix.sum(axis=0)
    recall = np.diag(matrix) / matrix.sum(axis=1)
    f1 = 2 * precision * recall / (precision + recall)
    weighted_f1 = np.sum(f1 * matrix.sum(axis=1) / matrix.sum())
    return weighted_f1
```

[15] ✓ 0.0s Python

```
f1_score_weighted(y_test, y_pred)
```

[16] ✓ 0.0s Python

··· 0.9214155306246664

```
# If you uncomment below code, you will get the following output
# The output is the same as the formula calculation above

# from sklearn.metrics import f1_score

# f1_score(y_test, y_pred, average="weighted")

# Output: 0.922548837254795
```

[17] ✓ 0.0s Python

SVM

Additional Algorithm - SVM

```
params = {
    # "C": [10, 100, 1000],
    # "kernel": ["linear", "rbf", "sigmoid", "poly"],
    # 'degree': [2, 4, 6]
    "C": [100],
    "kernel": ["rbf"],
    'degree': [2]

}
stratified_split = StratifiedShuffleSplit(n_splits=10, test_size=0.1, random_state=42)
gridsearch_svc = GridSearchCV(
    SVC(random_state=42),
    params,
    cv=stratified_split,
    n_jobs=-1,
    verbose=1,
)
gridsearch_svc.fit(X_train, y_train)

# Scores
gridsearch_svc.score(X_train, y_train), gridsearch_svc.score(X_test, y_test)
```

[18] ✓ 2.3s Python

··· Fitting 10 folds for each of 1 candidates, totalling 10 fits

··· (0.9457200587803086, 0.9250826294528094)

```
# If you uncomment the commented parameters and comment out the current parameters,
# you will get the following output

# gridsearch_svc.best_params_
# Output - {'C': 100, 'degree': 2, 'kernel': 'rbf'}
```

[19] ✓ 0.0s Python

```python
y_pred = gridsearch_svc.predict(X_test)
matrix = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay.from_predictions(
    y_test,
    y_pred,
    display_labels=encoder.inverse_transform([0, 1, 2, 3, 4, 5, 6]),
    xticks_rotation="vertical",
)
```

[20] ✓ 0.2s Python

Outputs are collapsed ···

```python
f1_score_weighted(y_test, y_pred)
```

[21] ✓ 0.0s Python

```
0.9249781563467131
```

```python
# If you uncomment below code, you will get the following output
# The output is the same as the formula calculation above

# from sklearn.metrics import f1_score

# f1_score(y_test, y_pred, average="weighted")

# Output: 0.924978156346713
```

[22] ✓ 0.0s Python

KNN

Additional Algorithm - KNN

```python
params = {
    # "n_neighbors": [3, 5, 7],
    # "weights": ["uniform", "distance"],
    # "algorithm": ["ball_tree", "kd_tree", "brute"],
    # "leaf_size": [10, 30, 50],
    # "p": [1, 2, 3],
    "n_neighbors": [7],
    "weights": ["uniform"],
    "algorithm": ["ball_tree"],
    "leaf_size": [10],
    "p": [2],
}
stratified_split = StratifiedShuffleSplit(n_splits=6, test_size=0.1, random_state=42)
gridsearch_svc = GridSearchCV(
    KNeighborsClassifier(n_jobs=-1),
    params,
    cv=stratified_split,
    n_jobs=-1,
    verbose=1,
)
gridsearch_svc.fit(X_train, y_train)

# Scores
gridsearch_svc.score(X_train, y_train), gridsearch_svc.score(X_test, y_test)
```

[23] ✓ 0.6s Python

```
Fitting 6 folds for each of 1 candidates, totalling 6 fits
```

```
(0.9391991182953711, 0.9136981270657363)
```

```
# If you uncomment the commented parameters and comment out the current parameters,
# you will get the following output

# gridsearch_svc.best_params_
# Output - {'algorithm': 'ball_tree',
#  'leaf_size': 10,
#  'n_neighbors': 7,
#  'p': 2,
#  'weights': 'uniform'}
```

[24] ✓ 0.0s Python

```
y_pred = gridsearch_svc.predict(X_test)
matrix = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay.from_predictions(
    y_test,
    y_pred,
    display_labels=encoder.inverse_transform([0, 1, 2, 3, 4, 5, 6]),
    xticks_rotation="vertical",
)
```

[25] ✓ 0.1s Python

Outputs are collapsed ···

```
f1_score_weighted(y_test, y_pred)
```

[26] ✓ 0.0s Python

```
0.9138644968689182
```

```
# If you uncomment below code, you will get the following output
# The output is the same as the formula calculation above

# from sklearn.metrics import f1_score

# f1_score(y_test, y_pred, average='weighted')

# Output: 0.9142227933487637
```

[27] ✓ 0.0s Python

Conv1D

Additional Deep Learning Algorithm - Conv1D

```
import torch
from torch import nn
from torch.utils.data import DataLoader, TensorDataset
from torchinfo import summary

device = (
    "cuda"
    if torch.cuda.is_available()
    else "mps" if torch.backends.mps.is_available() else "cpu"
)
print(f"Using {device} device for torch models")
```

[28] ✓ 0.5s Python

```
Using mps device for torch models
```

```
class Conv1DNNModel(nn.Module):
    def __init__(self, *args, **kwargs) -> None:
        super().__init__(*args, **kwargs)
        self.conv1d_relu_stack = nn.Sequential(
            nn.Conv1d(in_channels=1, out_channels=128, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(128),
            nn.Conv1d(in_channels=128, out_channels=64, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(64),
            nn.Conv1d(in_channels=64, out_channels=32, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(32),
            nn.Flatten(),
            nn.Linear(32 * 10, 32),
            nn.ReLU(),
            nn.BatchNorm1d(32),
            nn.Linear(32, 7),
        )

    def forward(self, x):
```

```python
class Conv1DNNModel(nn.Module):
    def __init__(self, *args, **kwargs) -> None:
        super().__init__(*args, **kwargs)
        self.conv1d_relu_stack = nn.Sequential(
            nn.Conv1d(in_channels=1, out_channels=128, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(128),
            nn.Conv1d(in_channels=128, out_channels=64, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(64),
            nn.Conv1d(in_channels=64, out_channels=32, kernel_size=3),
            nn.ReLU(),
            nn.BatchNorm1d(32),
            nn.Flatten(),
            nn.Linear(32 * 10, 64),
            nn.ReLU(),
            nn.BatchNorm1d(64),
            nn.Linear(64, 7),
        )

    def forward(self, x):
        return self.conv1d_relu_stack(x)
```

[29] ✓ 0.0s Python

+ Code + Markdown

```python
learning_rate = 1e-1
batch_size = 64
epochs = 50

conv1d_model = Conv1DNNModel().to(device)
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adamax(conv1d_model.parameters(), lr=learning_rate)
lr_scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.45)
summary(conv1d_model, input_size=(batch_size, 1, 16))
```

[30] ✓ 0.4s Python

Outputs are collapsed ···

```python
def training_loop(
    train_loader,
    model: nn.Module,
    loss_fn: nn.CrossEntropyLoss,
    optimizer: torch.optim.Optimizer,
):
    model.train()
    for X_batch, y_batch in train_loader:
        pred = model(X_batch)
        loss = loss_fn(pred, y_batch)

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()

    model.eval()
    with torch.no_grad():
        pred = model(train_loader.dataset.tensors[0])
        y_train = train_loader.dataset.tensors[1]
        print(
            f"Training metrics\nLoss: {loss.item()}\nF1 Score: {f1_score_weighted(y_train.argmax(dim=1), pred.argmax(dim=1))}"
        )


def test_nn_model(
    test_dataset: TensorDataset, model: nn.Module, loss_fn: nn.CrossEntropyLoss
):
    model.eval()
    with torch.no_grad():
        X_test, y_test = test_dataset.tensors
        pred = model(X_test)
        loss = loss_fn(pred, y_test)

        print(
            f"Test metrics\nLoss: {loss.item()}\nF1 Score: {f1_score_weighted(y_test.argmax(dim=1), pred.argmax(dim=1))}"
        )
        return f1_score_weighted(y_test.argmax(dim=1), pred.argmax(dim=1))
```

[31] ✓ 0.0s Python

```
one_hot_encoder = OneHotEncoder(
    sparse_output=False,
    max_categories=df["Class_numerical"].value_counts().shape[0],
)
_ = one_hot_encoder.fit(df["Class_numerical"].values.reshape(-1, 1))
y_train_one_hot = one_hot_encoder.transform(y_train.values.reshape(-1, 1))
y_test_one_hot = one_hot_encoder.transform(y_test.values.reshape(-1, 1))
```

[32] ✓ 0.0s Python

```
train_dataset = TensorDataset(
    torch.tensor(X_train.values.reshape((-1, 1, 16)), dtype=torch.float32),
    torch.tensor(y_train_one_hot, dtype=torch.float32),
)
test_dataset = TensorDataset(
    torch.tensor(X_test.values.reshape((-1, 1, 16)), dtype=torch.float32),
    torch.tensor(y_test_one_hot, dtype=torch.float32),
)
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
```

[33] ✓ 0.0s Python

```
best_f1_score = 0
for epoch in range(epochs):
    print(f"Epoch {epoch + 1}\n-------------------------------")
    training_loop(train_loader, conv1d_model, loss_fn, optimizer)
    lr_scheduler.step()
    print()

    test_f1_score = test_nn_model(test_dataset, conv1d_model, loss_fn)
    if (test_f1_score > best_f1_score):
        print("\nFound better model, saving it...")
        best_f1_score = test_f1_score
        torch.save(conv1d_model, "models/best_model.pth")

    print()
```

[34] ✓ 2m 3.1s Python

Outputs are collapsed ···

Link to Git Repository: https://github.com/amishfaldu-njit/cs-634104-final-term-project