

Deep Learning Lab Experiment - 2

Soil Type Classification Using PSA Data

```
In [1]: 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, LabelEncoder
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical

# Task A: Generate Synthetic Data
def generate_synthetic_psa_data(num_samples=5000, num_features=20):
    np.random.seed(42)
    magnitudes = np.random.uniform(3.0, 8.0, num_samples) # Earthquake magnitude
    depths = np.random.uniform(5, 100, num_samples) # Earthquake depth in km
    spectral_ratios = np.random.normal(1.0, 0.3, (num_samples, num_features)) # Simulated spectral ratio data
    soil_classes = np.random.choice(["Hard", "Transitional", "Soft"], num_samples, p=[0.6, 0.25, 0.15]) # Class

    # Combine into a DataFrame
    data = pd.DataFrame(spectral_ratios, columns=[f"Spectral_Ratio_{i+1}" for i in range(num_features)])
    data["Magnitude"] = magnitudes
    data["Depth"] = depths
    data["Soil_Type"] = soil_classes
    return data

# Generate the synthetic dataset
num_features = 1000 # High-dimensional data for full SR
df = generate_synthetic_psa_data(num_features=num_features)
print(df.head())

# Task A: Data Exploration and Preprocessing
# EDA
print(df.describe())
print(df["Soil_Type"].value_counts())

# Visualize class distribution
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x="Soil_Type", palette="viridis")
plt.title("Class Distribution")
plt.show()

# Data Splitting and Scaling
features = [col for col in df.columns if "Spectral_Ratio" in col] + ["Magnitude", "Depth"]
X = df[features]
y = df["Soil_Type"]

# Encode labels
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# Train-test split
X_train, X_temp, y_train, y_temp = train_test_split(X, y_encoded, test_size=0.3, stratify=y_encoded, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, stratify=y_temp, random_state=42)

# Normalize data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)

# Optional PCA (to reduce dimensionality)
pca = PCA(n_components=100) # Reduce to 100 components
X_train = pca.fit_transform(X_train)
X_val = pca.transform(X_val)
X_test = pca.transform(X_test)

# Convert labels to one-hot encoding for NN
y_train_oh = to_categorical(y_train)
y_val_oh = to_categorical(y_val)
y_test_oh = to_categorical(y_test)

# Task B: Model Architecture & Implementation
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.3),
    Dense(64, activation='relu'),
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        Dropout(0.3),
        Dense(32, activation='relu'),
        Dense(3, activation='softmax') # 3 output classes (Hard, Transitional, Soft)
    ])

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

# Train the model
history = model.fit(X_train, y_train_oh, validation_data=(X_val, y_val_oh), epochs=20, batch_size=32, verbose=1)

# Plot training history
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.legend()
plt.title("Accuracy")
plt.grid()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.title("Loss")
plt.grid()
plt.show()

# Task C: Evaluation and Interpretation
# Evaluate on the test set
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis=1)

print("\nClassification Report:")
print(classification_report(y_test, y_pred_classes, target_names=label_encoder.classes_))

print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred_classes)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()

```

	Spectral_Ratio_1	Spectral_Ratio_2	Spectral_Ratio_3	Spectral_Ratio_4	\
0	0.553641	0.662444	1.116646	0.647838	
1	0.965029	1.064251	0.707014	1.048081	
2	1.280396	1.110978	0.664802	0.987553	
3	0.722046	0.839937	0.545676	1.164610	
4	1.189775	0.627139	0.319277	0.706878	

	Spectral_Ratio_5	Spectral_Ratio_6	Spectral_Ratio_7	Spectral_Ratio_8	\
0	1.333790	0.978664	1.025678	0.916488	
1	0.872850	0.770317	1.220232	0.538688	
2	1.291147	0.622521	1.190966	1.696783	
3	0.975246	0.488438	0.749551	1.100980	
4	0.927200	1.774088	1.162977	0.457723	

	Spectral_Ratio_9	Spectral_Ratio_10	...	Spectral_Ratio_994	\
0	1.231854	1.234948	...	0.677232	
1	1.169433	1.205346	...	0.935074	
2	1.318545	1.424209	...	1.157375	
3	0.837093	0.790918	...	0.916403	
4	0.793103	0.984036	...	0.768700	

	Spectral_Ratio_995	Spectral_Ratio_996	Spectral_Ratio_997	\
0	0.663041	1.613696	1.159103	
1	0.959073	0.766507	0.866971	
2	0.899180	1.080641	0.546836	
3	0.883753	0.925849	0.900628	
4	0.895460	1.298201	0.987320	

	Spectral_Ratio_998	Spectral_Ratio_999	Spectral_Ratio_1000	Magnitude	\
0	1.091348	0.682746	1.187003	4.872701	
1	0.918919	1.483861	1.283985	7.753572	
2	0.793665	0.796897	0.887683	6.659970	
3	1.083772	0.486947	1.311151	5.993292	
4	0.944156	0.625401	1.235645	3.780093	

	Depth	Soil_Type
0	42.395374	Transitional
1	49.976388	Transitional
2	86.182002	Soft
3	37.300417	Hard

4 87.616720 Hard

[5 rows x 1003 columns]

	Spectral_Ratio_1	Spectral_Ratio_2	Spectral_Ratio_3	Spectral_Ratio_4 \
count	5000.000000	5000.000000	5000.000000	5000.000000
mean	0.999977	0.994361	0.993150	1.011166
std	0.296223	0.301537	0.300723	0.298434
min	-0.109789	-0.114431	-0.062554	-0.188176
25%	0.795829	0.789352	0.789893	0.811696
50%	0.995803	0.999918	0.993878	1.010109
75%	1.194240	1.189641	1.193709	1.208912
max	2.509712	2.062604	2.039908	2.089326

	Spectral_Ratio_5	Spectral_Ratio_6	Spectral_Ratio_7	Spectral_Ratio_8 \
count	5000.000000	5000.000000	5000.000000	5000.000000
mean	1.005590	1.001378	1.001662	0.997998
std	0.301862	0.303413	0.302296	0.295670
min	-0.052411	-0.109786	-0.142847	-0.242816
25%	0.804297	0.795059	0.800381	0.799767
50%	1.006238	1.001247	1.002392	0.993906
75%	1.212249	1.211692	1.204181	1.196104
max	2.119253	2.151534	2.510142	2.191137

	Spectral_Ratio_9	Spectral_Ratio_10	...	Spectral_Ratio_993 \
count	5000.000000	5000.000000	...	5000.000000
mean	0.993018	1.009585	...	0.989993
std	0.300113	0.301466	...	0.303659
min	-0.324555	-0.082240	...	-0.086681
25%	0.791671	0.805814	...	0.782113
50%	0.997973	1.008644	...	0.992796
75%	1.200695	1.220272	...	1.197773
max	2.127435	2.052733	...	1.949363

	Spectral_Ratio_994	Spectral_Ratio_995	Spectral_Ratio_996 \
count	5000.000000	5000.000000	5000.000000
mean	1.002469	0.996621	1.000747
std	0.300647	0.306510	0.301665
min	-0.079650	-0.033461	-0.004647
25%	0.800295	0.785923	0.792222
50%	0.999575	0.997004	1.000641
75%	1.204511	1.205941	1.206547
max	2.037501	2.131030	2.307170

	Spectral_Ratio_997	Spectral_Ratio_998	Spectral_Ratio_999 \
count	5000.000000	5000.000000	5000.000000
mean	0.999766	0.987985	0.998090
std	0.296711	0.297273	0.302160
min	0.031277	-0.130544	-0.107033
25%	0.799827	0.795473	0.793046
50%	1.001291	0.990075	0.995310
75%	1.201209	1.185036	1.206081
max	1.950706	2.152775	2.017117

	Spectral_Ratio_1000	Magnitude	Depth
count	5000.000000	5000.000000	5000.000000
mean	0.996545	5.484160	51.691277
std	0.302621	1.448168	27.133568
min	-0.107505	3.000058	5.005019
25%	0.794485	4.219314	28.478861
50%	0.991353	5.500043	51.167300
75%	1.196008	6.740504	74.670302
max	2.134068	7.998588	99.952993

[8 rows x 1002 columns]

Soil_Type

Hard 2999

Transitional 1251

Soft 750

Name: count, dtype: int64

C:\Users\shubh\AppData\Local\Temp\ipykernel_23744\2069158784.py:40: FutureWarning:

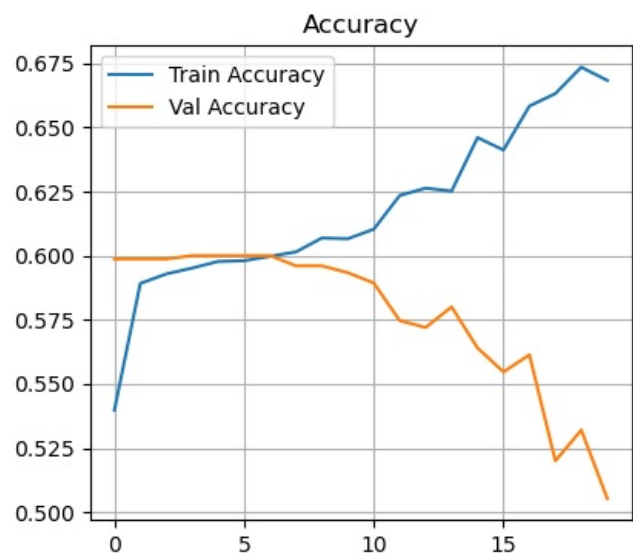
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(data=df, x="Soil_Type", palette="viridis")
```



```
C:\Users\shubh\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.  
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Epoch 1/20
110/110 ————— **6s** 13ms/step - accuracy: 0.4684 - loss: 1.1418 - val_accuracy: 0.5987 - val_loss: 0.9765
Epoch 2/20
110/110 ————— **1s** 10ms/step - accuracy: 0.5958 - loss: 0.9466 - val_accuracy: 0.5987 - val_loss: 0.9669
Epoch 3/20
110/110 ————— **1s** 7ms/step - accuracy: 0.5753 - loss: 0.9591 - val_accuracy: 0.5987 - val_loss: 0.9643
Epoch 4/20
110/110 ————— **2s** 11ms/step - accuracy: 0.5761 - loss: 0.9550 - val_accuracy: 0.6000 - val_loss: 0.9619
Epoch 5/20
110/110 ————— **1s** 6ms/step - accuracy: 0.5954 - loss: 0.9294 - val_accuracy: 0.6000 - val_loss: 0.9706
Epoch 6/20
110/110 ————— **1s** 8ms/step - accuracy: 0.6021 - loss: 0.9168 - val_accuracy: 0.6000 - val_loss: 0.9684
Epoch 7/20
110/110 ————— **1s** 6ms/step - accuracy: 0.6137 - loss: 0.8887 - val_accuracy: 0.6000 - val_loss: 0.9670
Epoch 8/20
110/110 ————— **2s** 9ms/step - accuracy: 0.6032 - loss: 0.8921 - val_accuracy: 0.5960 - val_loss: 0.9687
Epoch 9/20
110/110 ————— **1s** 7ms/step - accuracy: 0.5988 - loss: 0.8789 - val_accuracy: 0.5960 - val_loss: 0.9723
Epoch 10/20
110/110 ————— **1s** 6ms/step - accuracy: 0.5987 - loss: 0.8707 - val_accuracy: 0.5933 - val_loss: 0.9740
Epoch 11/20
110/110 ————— **1s** 6ms/step - accuracy: 0.6056 - loss: 0.8652 - val_accuracy: 0.5893 - val_loss: 0.9809
Epoch 12/20
110/110 ————— **2s** 9ms/step - accuracy: 0.6346 - loss: 0.8200 - val_accuracy: 0.5747 - val_loss: 0.9856
Epoch 13/20
110/110 ————— **1s** 7ms/step - accuracy: 0.6130 - loss: 0.8410 - val_accuracy: 0.5720 - val_loss: 0.9858
Epoch 14/20
110/110 ————— **1s** 7ms/step - accuracy: 0.6472 - loss: 0.7858 - val_accuracy: 0.5800 - val_loss: 0.9898
Epoch 15/20
110/110 ————— **1s** 7ms/step - accuracy: 0.6519 - loss: 0.7790 - val_accuracy: 0.5640 - val_loss: 1.0044
Epoch 16/20
110/110 ————— **1s** 8ms/step - accuracy: 0.6336 - loss: 0.7877 - val_accuracy: 0.5547 - val_loss: 1.0044
Epoch 17/20
110/110 ————— **1s** 7ms/step - accuracy: 0.6732 - loss: 0.7408 - val_accuracy: 0.5613 - val_loss: 1.0062
Epoch 18/20
110/110 ————— **1s** 6ms/step - accuracy: 0.6544 - loss: 0.7437 - val_accuracy: 0.5200 - val_loss: 1.0225
Epoch 19/20
110/110 ————— **1s** 7ms/step - accuracy: 0.6686 - loss: 0.7230 - val_accuracy: 0.5320 - val_loss: 1.0217
Epoch 20/20
110/110 ————— **1s** 6ms/step - accuracy: 0.6713 - loss: 0.7272 - val_accuracy: 0.5053 - val_loss: 1.0255



Classification Report:

	precision	recall	f1-score	support
Hard	0.61	0.83	0.70	450
Soft	0.09	0.02	0.03	113
Transitional	0.24	0.16	0.19	187
accuracy			0.54	750
macro avg	0.31	0.33	0.31	750
weighted avg	0.44	0.54	0.47	750

Confusion Matrix:

