Statistical Learning Lab : Assignment 9

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Importing all the necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import Accuracy
```

Reading and splitting the data

The data is read into a dataframe from the Excel file. Then it is divided into the training, testing and validation sets. The precentages are 70% training, 15% testing and 15% validation. The column "Car ID" is dropped because logically, Car ID should not affect the Purhase.

In [2]:
```
# Load the dataset
df = pd.read_csv("Practice_car_Data.csv")

# Drop the 'Car ID' column (assuming it's not useful for prediction)
df = df.drop(columns=["Car ID"])

# Separate features (X) and target variable (y)
X = df.drop(columns=["Purchased"])
y = df["Purchased"]

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# First, split into Train and Test (85%-15%)
X_train, X_test, y_train, y_test = train_test_split( X_scaled, y, test_si
```

```
# Then, split Train into Train and Validation (Total 85% = 15% + 75%)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_

# Print dataset sizes
print(f"Train size: {X_train.shape[0]}, Validation size: {X_val.shape[0]}
```

```
Train size: 279, Validation size: 61, Test size: 60
```

Creating the Artificial Neural Network Model

A model with two hidden layers, having 16 and 8 units respectively, and finally an output layer was created. The two hidden layers had ReLU activation while the output layer had sigmoid activation.

In [3]:
```
# Define the ANN model
#model = Sequential([
#    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),  # Fi
#    Dropout(0.1),  # Dropout to prevent overfitting
#    Dense(32, activation='relu'),  # Second hidden layer
#    Dense(16, activation='relu'),  # Third hidden layer
#    Dense(1, activation='sigmoid')  # Output layer for binary classifica
#])

model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.2),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Show the ANN layers
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               512

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 32)                2080

 dense_3 (Dense)             (None, 16)                528

 dense_4 (Dense)             (None, 1)                 17

=================================================================
Total params: 11393 (44.50 KB)
Trainable params: 11393 (44.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Training the ANN Model

Optimiser used: Adam (with a learning rate of 0.001) Loss: Binary Crossentropy Loss (since, the output is binary and categorical) Performance Metric: Accuracy

In [4]:
```
# Compile the model
model.compile(optimizer='adam',
              loss="binary_crossentropy",
              metrics=["accuracy"])

# Train the model
history = model.fit(X_train, y_train,
                    validation_data=(X_val, y_val),
                    epochs=50, batch_size=8, verbose=1)
```

```
Epoch 1/50
35/35 [==============================] - 3s 17ms/step - loss: 0.6523 - acc
uracy: 0.7276 - val_loss: 0.5847 - val_accuracy: 0.8197
Epoch 2/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5786 - accu
racy: 0.7742 - val_loss: 0.5302 - val_accuracy: 0.8197
Epoch 3/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5469 - accu
racy: 0.7814 - val_loss: 0.5154 - val_accuracy: 0.8197
Epoch 4/50
35/35 [==============================] - 0s 6ms/step - loss: 0.5402 - accu
racy: 0.7814 - val_loss: 0.5001 - val_accuracy: 0.8197
Epoch 5/50
35/35 [==============================] - 0s 6ms/step - loss: 0.5289 - accu
racy: 0.7814 - val_loss: 0.5073 - val_accuracy: 0.8033
```

```
Epoch 6/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5194 - accu
racy: 0.7921 - val_loss: 0.4900 - val_accuracy: 0.8197
Epoch 7/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5228 - accu
racy: 0.7885 - val_loss: 0.4876 - val_accuracy: 0.8197
Epoch 8/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5159 - accu
racy: 0.7885 - val_loss: 0.4732 - val_accuracy: 0.8197
Epoch 9/50
35/35 [==============================] - 0s 5ms/step - loss: 0.5128 - accu
racy: 0.7849 - val_loss: 0.4726 - val_accuracy: 0.8361
Epoch 10/50
35/35 [==============================] - 0s 4ms/step - loss: 0.5051 - accu
racy: 0.7849 - val_loss: 0.4963 - val_accuracy: 0.8197
Epoch 11/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4987 - accu
racy: 0.7885 - val_loss: 0.4773 - val_accuracy: 0.8197
Epoch 12/50
35/35 [==============================] - 0s 4ms/step - loss: 0.4794 - accu
racy: 0.8065 - val_loss: 0.4868 - val_accuracy: 0.8197
Epoch 13/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4864 - accu
racy: 0.7814 - val_loss: 0.4793 - val_accuracy: 0.7869
Epoch 14/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4802 - accu
racy: 0.8029 - val_loss: 0.4934 - val_accuracy: 0.8197
Epoch 15/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4898 - accu
racy: 0.7921 - val_loss: 0.4766 - val_accuracy: 0.8033
Epoch 16/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4863 - accu
racy: 0.7885 - val_loss: 0.4881 - val_accuracy: 0.8033
Epoch 17/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4812 - accu
racy: 0.7921 - val_loss: 0.4927 - val_accuracy: 0.8197
Epoch 18/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4697 - accu
racy: 0.7921 - val_loss: 0.4815 - val_accuracy: 0.7705
Epoch 19/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4761 - accu
racy: 0.8029 - val_loss: 0.4779 - val_accuracy: 0.7705
Epoch 20/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4634 - accu
racy: 0.8029 - val_loss: 0.5057 - val_accuracy: 0.8033
Epoch 21/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4581 - accu
racy: 0.8029 - val_loss: 0.4991 - val_accuracy: 0.8033
Epoch 22/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4597 - accu
racy: 0.7957 - val_loss: 0.5378 - val_accuracy: 0.8033
Epoch 23/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4557 - accu
```

```
racy: 0.7921 - val_loss: 0.4866 - val_accuracy: 0.7869
Epoch 24/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4481 - accu
racy: 0.8029 - val_loss: 0.5350 - val_accuracy: 0.7705
Epoch 25/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4377 - accu
racy: 0.8100 - val_loss: 0.5230 - val_accuracy: 0.7705
Epoch 26/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4482 - accu
racy: 0.7993 - val_loss: 0.5259 - val_accuracy: 0.7705
Epoch 27/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4393 - accu
racy: 0.8136 - val_loss: 0.5158 - val_accuracy: 0.7541
Epoch 28/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4420 - accu
racy: 0.7885 - val_loss: 0.5085 - val_accuracy: 0.7869
Epoch 29/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4441 - accu
racy: 0.8029 - val_loss: 0.4991 - val_accuracy: 0.7705
Epoch 30/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4410 - accu
racy: 0.8065 - val_loss: 0.5018 - val_accuracy: 0.7705
Epoch 31/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4532 - accu
racy: 0.7921 - val_loss: 0.4831 - val_accuracy: 0.8033
Epoch 32/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4327 - accu
racy: 0.7957 - val_loss: 0.5006 - val_accuracy: 0.7705
Epoch 33/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4425 - accu
racy: 0.8029 - val_loss: 0.5378 - val_accuracy: 0.7541
Epoch 34/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4382 - accu
racy: 0.8172 - val_loss: 0.5288 - val_accuracy: 0.7213
Epoch 35/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4233 - accu
racy: 0.8351 - val_loss: 0.5509 - val_accuracy: 0.8033
Epoch 36/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4427 - accu
racy: 0.7885 - val_loss: 0.5202 - val_accuracy: 0.7541
Epoch 37/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4278 - accu
racy: 0.8029 - val_loss: 0.5445 - val_accuracy: 0.7705
Epoch 38/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4285 - accu
racy: 0.7885 - val_loss: 0.5408 - val_accuracy: 0.7541
Epoch 39/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4253 - accu
racy: 0.8172 - val_loss: 0.5510 - val_accuracy: 0.7705
Epoch 40/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4279 - accu
racy: 0.8065 - val_loss: 0.5485 - val_accuracy: 0.7541
Epoch 41/50
```

```
35/35 [==============================] - 0s 6ms/step - loss: 0.4185 - accu
racy: 0.8029 - val_loss: 0.5373 - val_accuracy: 0.7705
Epoch 42/50
35/35 [==============================] - 0s 7ms/step - loss: 0.4250 - accu
racy: 0.8172 - val_loss: 0.5494 - val_accuracy: 0.7541
Epoch 43/50
35/35 [==============================] - 0s 6ms/step - loss: 0.4290 - accu
racy: 0.7993 - val_loss: 0.5489 - val_accuracy: 0.7541
Epoch 44/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4101 - accu
racy: 0.8172 - val_loss: 0.5602 - val_accuracy: 0.7705
Epoch 45/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4210 - accu
racy: 0.7921 - val_loss: 0.5744 - val_accuracy: 0.7541
Epoch 46/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4234 - accu
racy: 0.8172 - val_loss: 0.5501 - val_accuracy: 0.7705
Epoch 47/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4110 - accu
racy: 0.8100 - val_loss: 0.5626 - val_accuracy: 0.7705
Epoch 48/50
35/35 [==============================] - 0s 5ms/step - loss: 0.4144 - accu
racy: 0.8172 - val_loss: 0.5547 - val_accuracy: 0.7541
Epoch 49/50
35/35 [==============================] - 0s 6ms/step - loss: 0.3996 - accu
racy: 0.8423 - val_loss: 0.5357 - val_accuracy: 0.7705
Epoch 50/50
35/35 [==============================] - 0s 6ms/step - loss: 0.3973 - accu
racy: 0.8100 - val_loss: 0.5528 - val_accuracy: 0.7377
```

In [5]:
```
from sklearn.metrics import accuracy_score

y_train_pred_prob = model.predict(X_train)

y_train_pred = (y_train_pred_prob > 0.5).astype(int)

# Manually calculate accuracy
manual_accuracy = accuracy_score(y_train, y_train_pred)

print(f"Manual Accuracy: {manual_accuracy:.4f}")
```

```
9/9 [==============================] - 0s 2ms/step
Manual Accuracy: 0.8244
```

In [6]:
```
test_loss, test_accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"Test Accuracy: {test_accuracy:.4f}")
```

```
Test Accuracy: 0.7000
```

Analysis of Results

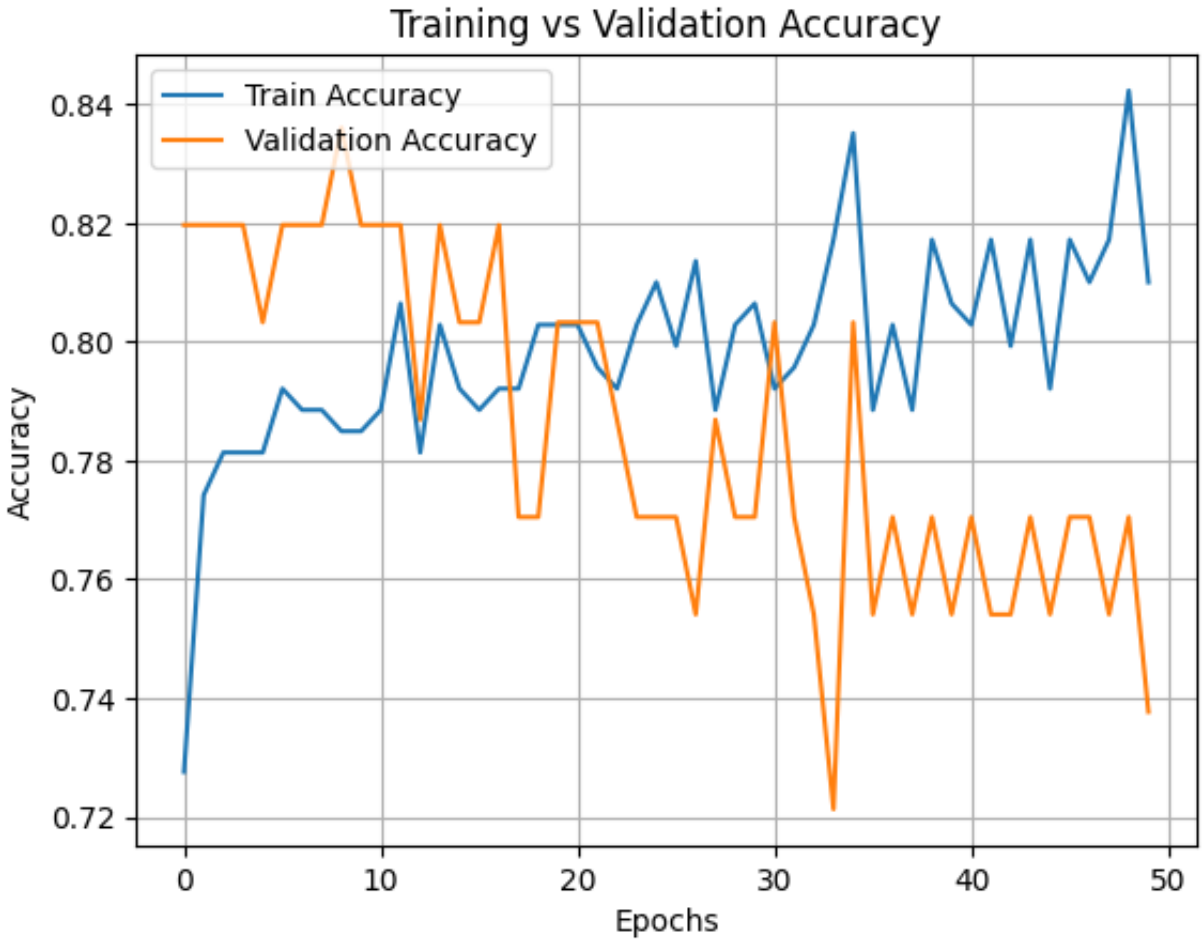
Plot of the Train set and Validation set Accuracy over Epochs

In [7]:
```
import matplotlib.pyplot as plt

# Plot training & validation accuracy values
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

# Labels and Title
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy')
plt.legend()
plt.grid(True)

# Show the plot
plt.show()
```



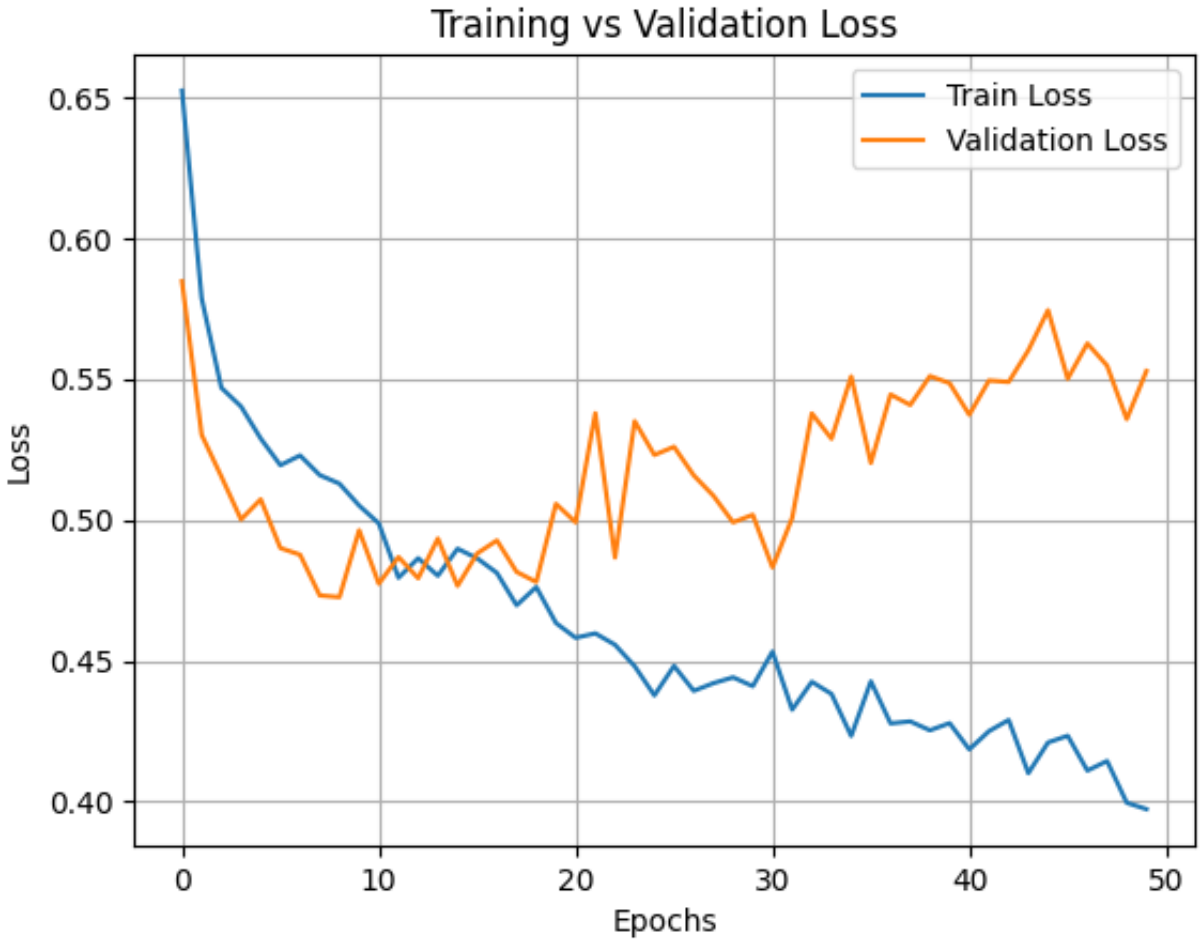
Plot of the Train set and Validation set Loss over Epochs

In [8]:
```
# Plot training & validation loss values
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')

# Labels and Title
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```
plt.title('Training vs Validation Loss')
plt.legend()
plt.grid(True)

# Show the plot
plt.show()
```



Evaluating the Model on the Test set

In [9]:
```
test_loss, test_accuracy = model.evaluate(X_test, y_test, verbose=2)

print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

```
2/2 - 0s - loss: 0.7058 - accuracy: 0.7000 - 53ms/epoch - 26ms/step
Test Loss: 0.7058
Test Accuracy: 0.7000
```

Classification Report and Confusion Matrix

In [10]:
```
from sklearn.metrics import classification_report, confusion_matrix

# Predict class labels for the test set
y_pred_prob = model.predict(X_test)
```

```
y_pred = (y_pred_prob > 0.5).astype(int)  # Convert probabilities to bina

# Print classification report
print("Classification Report:\n", classification_report(y_test, y_pred))

# Compute and display confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", conf_matrix)
```

```
2/2 [==============================] - 0s 4ms/step
Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.85      0.79        39
           1       0.60      0.43      0.50        21

    accuracy                           0.70        60
   macro avg       0.67      0.64      0.64        60
weighted avg       0.69      0.70      0.69        60

Confusion Matrix:
 [[33  6]
 [12  9]]
```