CIFAR-10 Classification Using Deep Neural Networks (DNN/Multiple Layer Perceptron) Not_CNN**

- This case study covers data preprocessing, model design, training, evaluation, and challenges encountered while applying a DNN to CIFAR-10.

In [18]:
```
# Importing Library:
import os
import tensorflow as tf
import keras_tuner as kt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization
from tensorflow.keras.optimizers import Adam, RMSprop
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.datasets import cifar10
tf.__version__
```

Out[18]:
```
'2.19.0'
```

In [19]:
```
# Defining the data set:
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
```

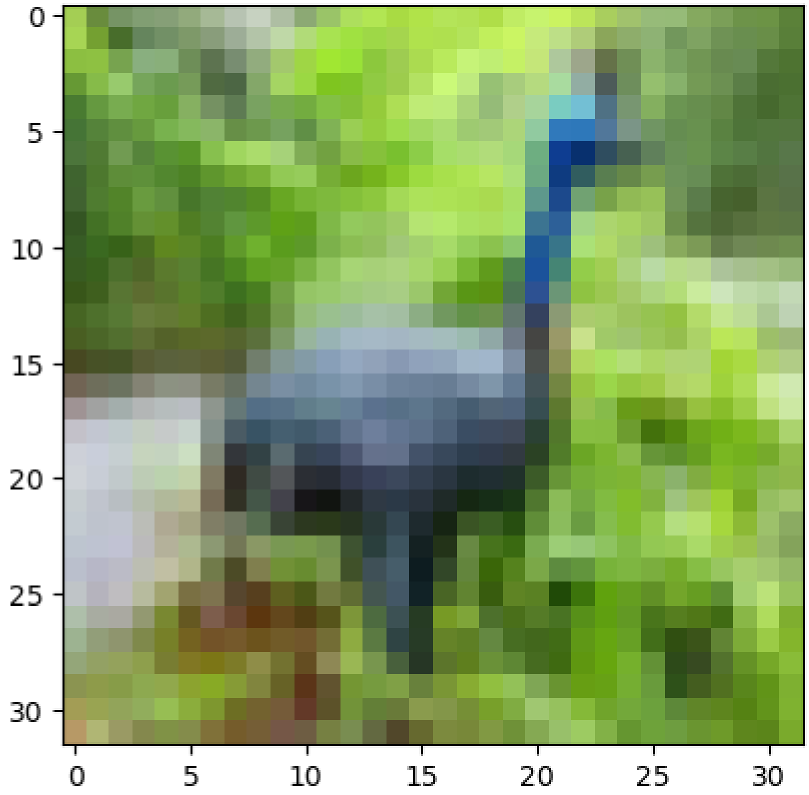
In [20]:
```
print("X_train shape:", x_train.shape)
print("Y_train shape:", y_train.shape)
print("X_test shape:", x_test.shape)
print("Y_test shape:", y_test.shape)
```

```
X_train shape: (50000, 32, 32, 3)
Y_train shape: (50000, 1)
X_test shape: (10000, 32, 32, 3)
Y_test shape: (10000, 1)
```

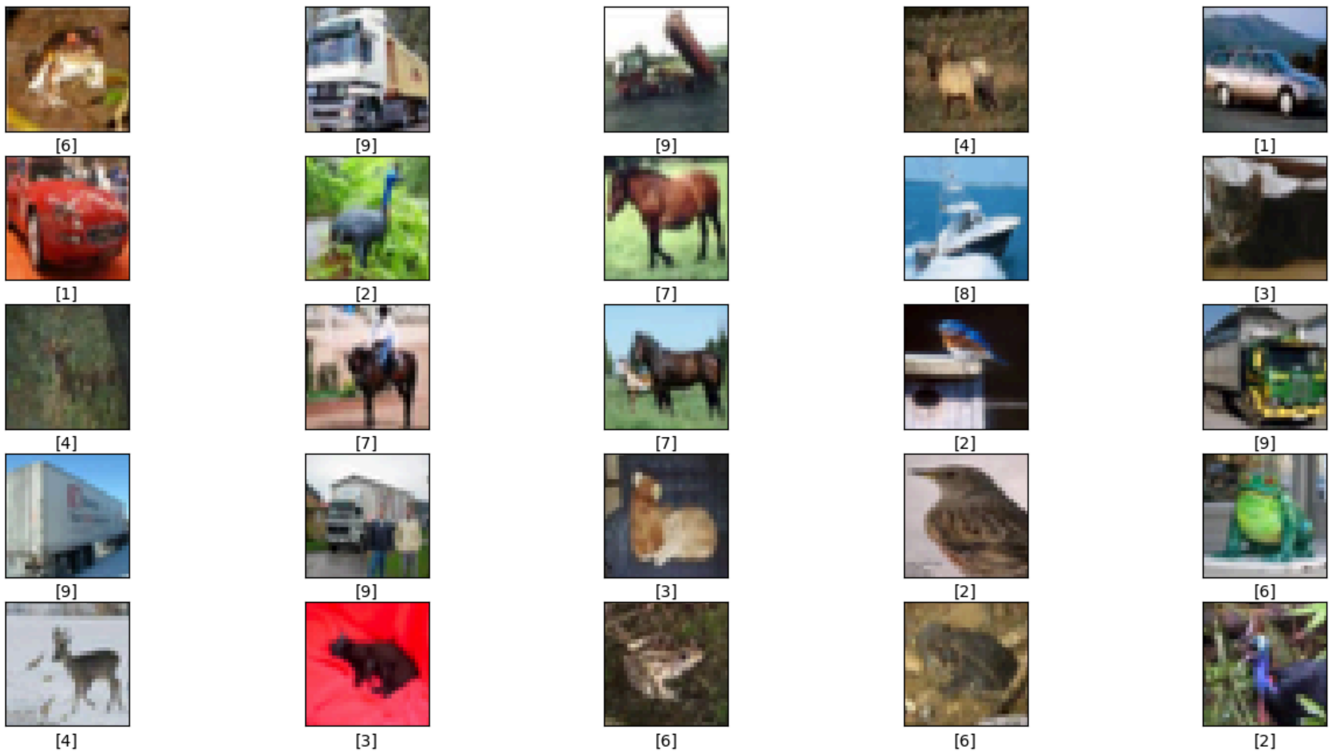
In [21]:
```
print(type(x_train))
print(type(x_test))
print(type(y_train))
print(type(y_test))
```

```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

In [22]:
```
# Check an image from data set:

import matplotlib.pyplot as plt
plt.imshow(x_train[6])
plt.show()
```




```
In [23]: import matplotlib.pyplot as plt

         plt.figure(figsize=(16, 8))

         for i in range(25):
             plt.subplot(5, 5, i + 1)
             plt.xticks([])
             plt.yticks([])
             plt.grid(False)
             plt.imshow(x_train[i])
             plt.xlabel(y_train[i])

         plt.show()
```




```
In [24]: # Feature Scalling:

         x_train = x_train/255.0
         x_test = x_test/255.0
```

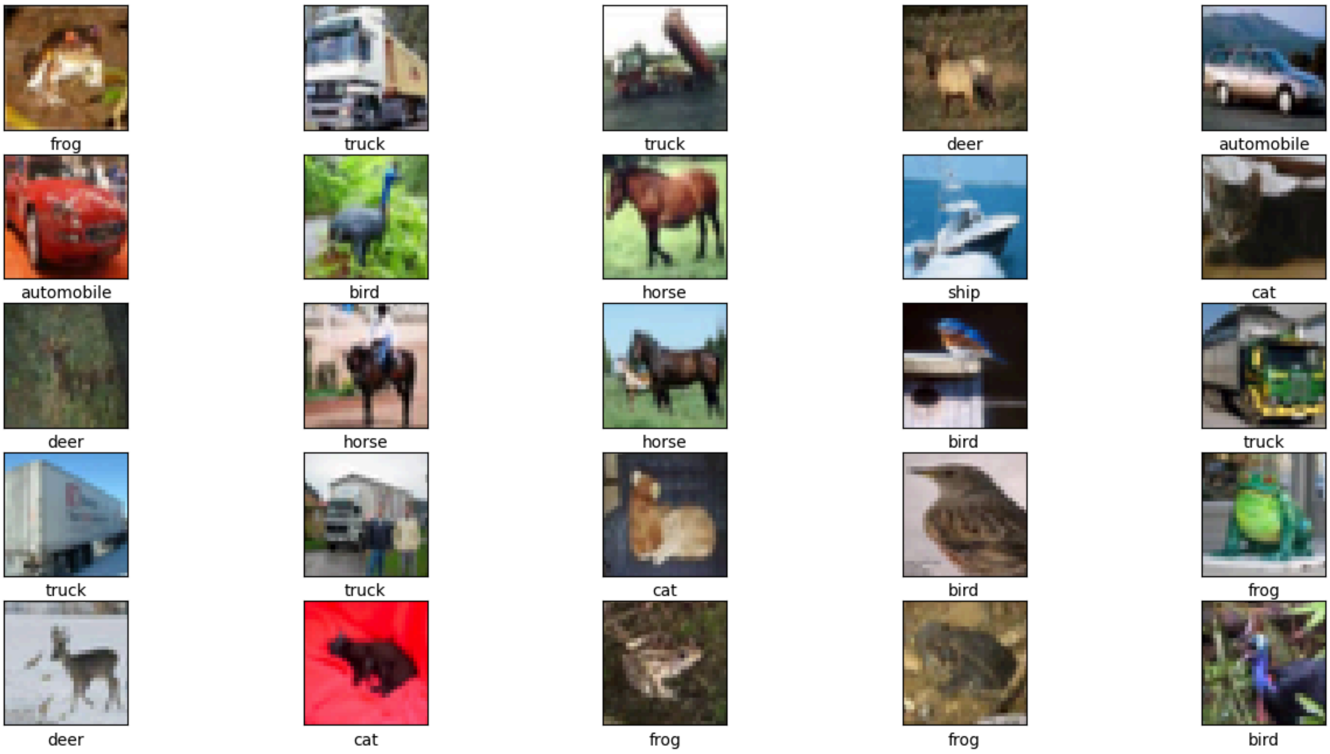
In [25]:
```python
x_train[0]
```

Out[25]:
```
array([[[0.23137255, 0.24313725, 0.24705882],
        [0.16862745, 0.18039216, 0.17647059],
        [0.19607843, 0.18823529, 0.16862745],
        ...,
        [0.61960784, 0.51764706, 0.42352941],
        [0.59607843, 0.49019608, 0.4       ],
        [0.58039216, 0.48627451, 0.40392157]],

       [[0.0627451 , 0.07843137, 0.07843137],
        [0.        , 0.        , 0.        ],
        [0.07058824, 0.03137255, 0.        ],
        ...,
        [0.48235294, 0.34509804, 0.21568627],
        [0.46666667, 0.3254902 , 0.19607843],
        [0.47843137, 0.34117647, 0.22352941]],

       [[0.09803922, 0.09411765, 0.08235294],
        [0.0627451 , 0.02745098, 0.        ],
        [0.19215686, 0.10588235, 0.03137255],
        ...,
        [0.4627451 , 0.32941176, 0.19607843],
        [0.47058824, 0.32941176, 0.19607843],
        [0.42745098, 0.28627451, 0.16470588]],

       ...,

       [[0.81568627, 0.66666667, 0.37647059],
        [0.78823529, 0.6       , 0.13333333],
        [0.77647059, 0.63137255, 0.10196078],
        ...,
        [0.62745098, 0.52156863, 0.2745098 ],
        [0.21960784, 0.12156863, 0.02745098],
        [0.20784314, 0.13333333, 0.07843137]],

       [[0.70588235, 0.54509804, 0.37647059],
        [0.67843137, 0.48235294, 0.16470588],
        [0.72941176, 0.56470588, 0.11764706],
        ...,
        [0.72156863, 0.58039216, 0.36862745],
        [0.38039216, 0.24313725, 0.13333333],
        [0.3254902 , 0.20784314, 0.13333333]],

       [[0.69411765, 0.56470588, 0.45490196],
        [0.65882353, 0.50588235, 0.36862745],
        [0.70196078, 0.55686275, 0.34117647],
        ...,
        [0.84705882, 0.72156863, 0.54901961],
        [0.59215686, 0.4627451 , 0.32941176],
        [0.48235294, 0.36078431, 0.28235294]]])
```

- In previous plot We are getting number instead of the actual class label because y_train[i] contains numerical labels (0–9) rather than their corresponding class names.
- In official CIFAR-10 label mapping IN KERAS website & The class names are indexed based on the label value so we will make it as class

In [26]:
```python
# Convert Labels to Class Names - X & Y train
class_names = ['airplane', 'automobile', 'bird', 'cat',
               'deer', 'dog', 'frog', 'horse', 'ship', 'truck']

plt.figure(figsize=(16, 8))
for i in range(25):
    plt.subplot(5, 5, i + 1)
```

```python
    plt.xticks([])
    plt.yticks([])
    plt.grid(True)
    plt.imshow(x_train[i])
    plt.xlabel(class_names[y_train[i][0]])
plt.show()
```



In [27]:

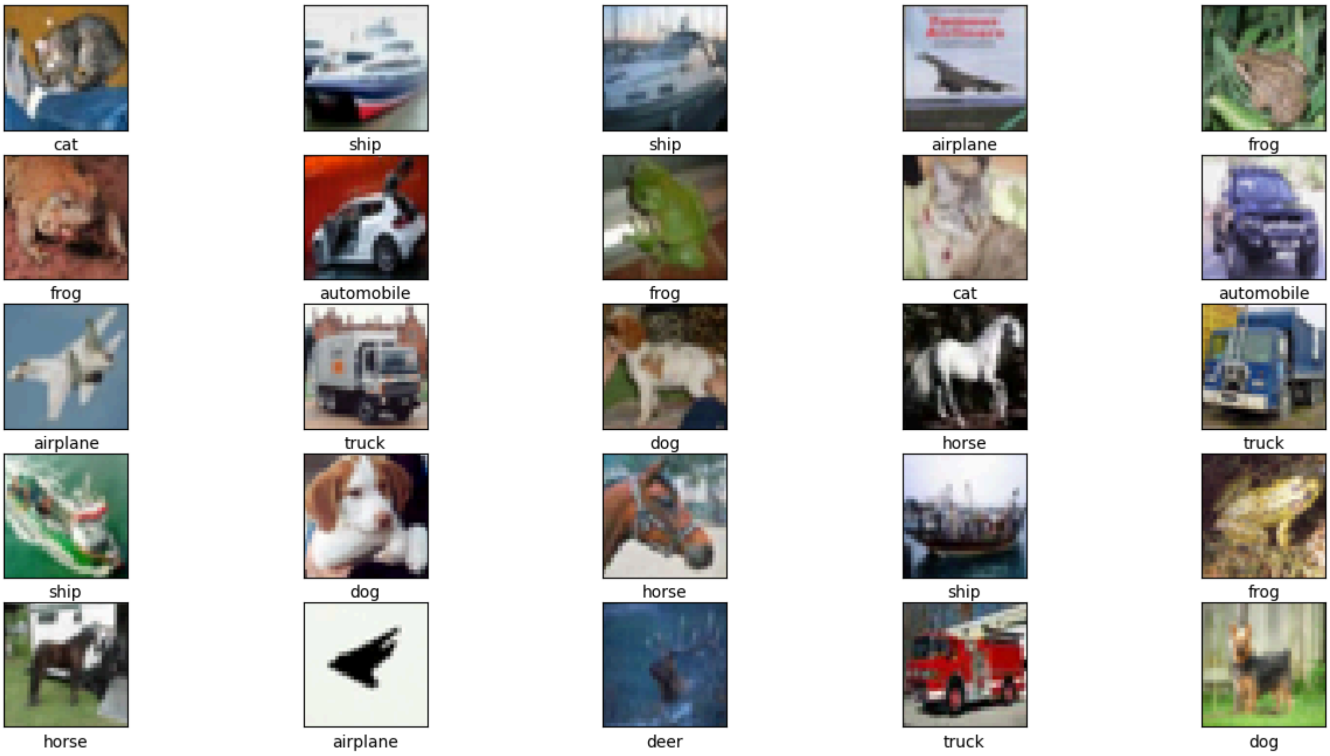
```python
# Check lebelling:
print(y_train[:25])
```

```
[[6]
 [9]
 [9]
 [4]
 [1]
 [1]
 [2]
 [7]
 [8]
 [3]
 [4]
 [7]
 [7]
 [2]
 [9]
 [9]
 [9]
 [3]
 [2]
 [6]
 [4]
 [3]
 [6]
 [6]
 [2]]
```

In [11]:

```python
# Convert Labels to Class Names - X & Y Test
class_names = ['airplane', 'automobile', 'bird', 'cat',
               'deer', 'dog', 'frog', 'horse', 'ship', 'truck']

plt.figure(figsize=(16, 8))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.xticks([])
```

```
    plt.yticks([])
    plt.grid(True)
    plt.imshow(x_test[i])
    plt.xlabel(class_names[y_test[i][0]])
plt.show()
```



In [12]:
```
print(y_test[:25])
```

```
[[3]
 [8]
 [8]
 [0]
 [6]
 [6]
 [1]
 [6]
 [3]
 [1]
 [0]
 [9]
 [5]
 [7]
 [9]
 [8]
 [5]
 [7]
 [8]
 [6]
 [7]
 [0]
 [4]
 [9]
 [5]]
```

In [28]:
```
# Convert Labels to One-Hot Encoding

from tensorflow.keras.utils import to_categorical

y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

In [29]:
```
print("Y_train shape after encoding:", y_train.shape)
print("Y_test shape after encoding:", y_test.shape)
```

```
Y_train shape after encoding: (50000, 10)
Y_test shape after encoding: (10000, 10)
```

In [30]:
```
print("x_train shape :", x_train.shape)
print("x_test shape :", x_test.shape)
print("Y_train shape :", y_train.shape)
print("Y_test shape:", y_test.shape)
```

```
x_train shape : (50000, 32, 32, 3)
x_test shape : (10000, 32, 32, 3)
Y_train shape : (50000, 10)
Y_test shape: (10000, 10)
```

dataset is now correctly preprocessed for training a deep learning model and ready for model training

Model Building: Building Multi Layer Perceptron Model:

In [16]:
```
! pip install keras-tuner --upgrade
```

```
Requirement already satisfied: keras-tuner in /opt/anaconda3/lib/python3.11/site-pack
ages (1.4.7)
Requirement already satisfied: keras in /opt/anaconda3/lib/python3.11/site-packages
(from keras-tuner) (3.9.0)
Requirement already satisfied: packaging in /opt/anaconda3/lib/python3.11/site-packag
es (from keras-tuner) (24.2)
Requirement already satisfied: requests in /opt/anaconda3/lib/python3.11/site-package
s (from keras-tuner) (2.32.3)
Requirement already satisfied: kt-legacy in /opt/anaconda3/lib/python3.11/site-packag
es (from keras-tuner) (1.0.5)
Requirement already satisfied: absl-py in /opt/anaconda3/lib/python3.11/site-packages
(from keras->keras-tuner) (2.1.0)
Requirement already satisfied: numpy in /opt/anaconda3/lib/python3.11/site-packages
(from keras->keras-tuner) (1.26.4)
Requirement already satisfied: rich in /opt/anaconda3/lib/python3.11/site-packages (f
rom keras->keras-tuner) (13.9.4)
Requirement already satisfied: namex in /opt/anaconda3/lib/python3.11/site-packages
(from keras->keras-tuner) (0.0.8)
Requirement already satisfied: h5py in /opt/anaconda3/lib/python3.11/site-packages (f
rom keras->keras-tuner) (3.12.1)
Requirement already satisfied: optree in /opt/anaconda3/lib/python3.11/site-packages
(from keras->keras-tuner) (0.14.1)
Requirement already satisfied: ml-dtypes in /opt/anaconda3/lib/python3.11/site-packag
es (from keras->keras-tuner) (0.4.0)
Requirement already satisfied: charset_normalizer<4,>=2 in /opt/anaconda3/lib/python
3.11/site-packages (from requests->keras-tuner) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /opt/anaconda3/lib/python3.11/site-pac
kages (from requests->keras-tuner) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /opt/anaconda3/lib/python3.11/si
te-packages (from requests->keras-tuner) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /opt/anaconda3/lib/python3.11/si
te-packages (from requests->keras-tuner) (2025.1.31)
Requirement already satisfied: typing-extensions>=4.5.0 in /opt/anaconda3/lib/python
3.11/site-packages (from optree->keras->keras-tuner) (4.12.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in /opt/anaconda3/lib/python3.1
1/site-packages (from rich->keras->keras-tuner) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /opt/anaconda3/lib/python3.
11/site-packages (from rich->keras->keras-tuner) (2.19.1)
Requirement already satisfied: mdurl~=0.1 in /opt/anaconda3/lib/python3.11/site-packa
ges (from markdown-it-py>=2.2.0->rich->keras->keras-tuner) (0.1.2)
```

Using Hyperparameter Tuning, we will dynamically build the model so that the machine can choose the optimal parameters, such as the number of hidden layers, the required number of neurons, the activation function, the dropout percentage, and the batch size. We will define a function and then use the Keras Tuner library to find the best configuration.

In [48]:
```
from tensorflow.keras.optimizers import Adam, RMSprop, SGD
from tensorflow.keras.regularizers import l2
import keras_tuner as kt
from kerastuner.tuners import *
import warnings
warnings.filterwarnings("ignore")
from tensorflow.keras.layers import LeakyReLU
```

In [50]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization, Leak
from tensorflow.keras.regularizers import l2
from tensorflow.keras.optimizers import Adam, RMSprop, SGD
import keras_tuner as kt

def build_model(hp):
    model = Sequential()
    model.add(Flatten(input_shape=(32, 32, 3)))  # Converts 3D image into 1D for MLP

    for i in range(hp.Int('num_layers', min_value=1, max_value=5)):
        units = hp.Int(f'num_neurons_{i}', min_value=32, max_value=512, step=32)
        activation = hp.Choice(f'activation_{i}', ['relu', 'sigmoid', 'tanh', 'leakyr

        # Adding Dense Layer
        if activation == 'leakyrelu':
            model.add(Dense(units, kernel_initializer=hp.Choice(f'kernel_initializer_
                                                                  ['he_uniform', 'gloro
                            kernel_regularizer=l2(0.001)))
            model.add(LeakyReLU(alpha=0.01))
        else:
            model.add(Dense(units, activation=activation,
                            kernel_initializer=hp.Choice(f'kernel_initializer_{i}',
                                                         ['he_uniform', 'glorot_unifo
                            kernel_regularizer=l2(0.001)))

        model.add(BatchNormalization())
        model.add(Dropout(hp.Choice(f'dropout_{i}', values=[0.1, 0.2, 0.3, 0.4, 0.5])

    model.add(Dense(10, activation='softmax'))  # Output layer for 10 classes

    # Optimizer Selection
    optimizer_choice = hp.Choice('optimizer', ['adam', 'rmsprop', 'sgd'])
    learning_rate = hp.Float('learning_rate', min_value=1e-4, max_value=1e-2, samplin
   #The learning rate is a floating-point number between 0.0001 and 0.01
    optimizers = {
        'adam': Adam(learning_rate=learning_rate),
        'rmsprop': RMSprop(learning_rate=learning_rate),
        'sgd': SGD(learning_rate=learning_rate, momentum=0.9)
    }

    model.compile(optimizer=optimizers[optimizer_choice],
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])

    return model
```

In [51]:
```
import keras_tuner as kt
from tensorflow.keras.callbacks import EarlyStopping

# Early stopping to prevent overfitting

early_stopping = EarlyStopping(
    monitor='val_loss',
    patience=5,
    min_delta=0.01,
```

```
    restore_best_weights=True,
    verbose=1
)
```

In [52]:
```
# Initialize Keras Tuner for 20 trails
tuner = kt.RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=20,
    executions_per_trial=1,
    directory='tuner_results',
    project_name='dnn_tuning_early_stop'
)
```

```
Reloading Tuner from tuner_results/dnn_tuning_early_stop/tuner0.json
```

In [53]:
```
# Start tuning
tuner.search(
    x_train, y_train,
    epochs=100,
    validation_data=(x_test, y_test),
    callbacks=[early_stopping]
)
```

```
Trial 20 Complete [00h 00m 33s]
val_accuracy: 0.2955000102519989

Best val_accuracy So Far: 0.5077999830245972
Total elapsed time: 01h 17m 45s
```

In [55]:
```
tuner.get_trial_dir
```

Out[55]:
```
<bound method BaseTuner.get_trial_dir of <keras_tuner.src.tuners.randomsearch.RandomS
earch object at 0x3059a8f90>>
```

In [58]:
```
best_hp_values = tuner.get_best_hyperparameters()[0].values
best_hp_values
```

Out[58]:
```
{'num_layers': 1,
 'num_neurons_0': 288,
 'activation_0': 'tanh',
 'kernel_initializer_0': 'glorot_uniform',
 'dropout_0': 0.3,
 'optimizer': 'sgd',
 'learning_rate': 0.00023934916758165718,
 'num_neurons_1': 160,
 'activation_1': 'tanh',
 'kernel_initializer_1': 'glorot_uniform',
 'dropout_1': 0.4,
 'num_neurons_2': 384,
 'activation_2': 'relu',
 'kernel_initializer_2': 'glorot_uniform',
 'dropout_2': 0.2,
 'num_neurons_3': 352,
 'activation_3': 'leakyrelu',
 'kernel_initializer_3': 'he_uniform',
 'dropout_3': 0.4}
```

In [59]:
```
best_model = tuner.get_best_models(num_models=1)[0]
best_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 3072)	0
dense (Dense)	(None, 288)	885,024
batch_normalization (BatchNormalization)	(None, 288)	1,152
dropout (Dropout)	(None, 288)	0
dense_1 (Dense)	(None, 10)	2,890

Total params: 889,066 (3.39 MB)

Trainable params: 888,490 (3.39 MB)

Non-trainable params: 576 (2.25 KB)

In [60]:
```
from tensorflow.keras.callbacks import *

reduce_lr = ReduceLROnPlateau( monitor='val_loss',
                              factor=0.5,
                              patience=5,
                              min_lr=1e-6)
```

In [61]:
```
early_stopping_history = EarlyStopping(
    monitor='val_loss',
    patience=10,
    min_delta=0.001, #change from 0.01 to 0.001
    restore_best_weights=True,
    verbose=1)
```

In [63]:
```
history = best_model.fit(
    x_train, y_train,
    batch_size=32,
    epochs=200,
    initial_epoch=100,
    validation_data=(x_test, y_test),
    callbacks=[early_stopping_history,reduce_lr])
```

```
Epoch 101/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5312 - loss: 1.5193 - val_ac
curacy: 0.5043 - val_loss: 1.5864 - learning_rate: 2.3935e-04
Epoch 102/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5312 - loss: 1.5266 - val_ac
curacy: 0.5161 - val_loss: 1.5738 - learning_rate: 2.3935e-04
Epoch 103/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5368 - loss: 1.5058 - val_ac
curacy: 0.5209 - val_loss: 1.5612 - learning_rate: 2.3935e-04
Epoch 104/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5380 - loss: 1.5017 - val_ac
curacy: 0.5112 - val_loss: 1.5759 - learning_rate: 2.3935e-04
Epoch 105/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5368 - loss: 1.5025 - val_ac
curacy: 0.4886 - val_loss: 1.6124 - learning_rate: 2.3935e-04
Epoch 106/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5340 - loss: 1.5090 - val_ac
curacy: 0.5184 - val_loss: 1.5524 - learning_rate: 2.3935e-04
Epoch 107/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.5440 - loss: 1.4937 - val_ac
curacy: 0.5183 - val_loss: 1.5518 - learning_rate: 2.3935e-04
Epoch 108/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5349 - loss: 1.5000 - val_ac
curacy: 0.5128 - val_loss: 1.5602 - learning_rate: 2.3935e-04
Epoch 109/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5326 - loss: 1.5166 - val_ac
curacy: 0.4977 - val_loss: 1.6089 - learning_rate: 2.3935e-04
Epoch 110/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5350 - loss: 1.4976 - val_ac
curacy: 0.5172 - val_loss: 1.5558 - learning_rate: 2.3935e-04
Epoch 111/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5351 - loss: 1.4964 - val_ac
curacy: 0.5047 - val_loss: 1.5845 - learning_rate: 2.3935e-04
Epoch 112/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5360 - loss: 1.4978 - val_ac
curacy: 0.4954 - val_loss: 1.5920 - learning_rate: 2.3935e-04
Epoch 113/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5457 - loss: 1.4716 - val_ac
curacy: 0.5181 - val_loss: 1.5369 - learning_rate: 1.1967e-04
Epoch 114/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5424 - loss: 1.4811 - val_ac
curacy: 0.5186 - val_loss: 1.5345 - learning_rate: 1.1967e-04
Epoch 115/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5432 - loss: 1.4808 - val_ac
curacy: 0.5088 - val_loss: 1.5580 - learning_rate: 1.1967e-04
Epoch 116/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5440 - loss: 1.4779 - val_ac
curacy: 0.5148 - val_loss: 1.5363 - learning_rate: 1.1967e-04
Epoch 117/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5417 - loss: 1.4712 - val_ac
curacy: 0.5209 - val_loss: 1.5345 - learning_rate: 1.1967e-04
Epoch 118/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5429 - loss: 1.4736 - val_ac
curacy: 0.5153 - val_loss: 1.5395 - learning_rate: 1.1967e-04
Epoch 119/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.5451 - loss: 1.4714 - val_ac
curacy: 0.5221 - val_loss: 1.5351 - learning_rate: 1.1967e-04
Epoch 120/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5453 - loss: 1.4608 - val_ac
curacy: 0.5222 - val_loss: 1.5338 - learning_rate: 5.9837e-05
Epoch 121/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5478 - loss: 1.4620 - val_ac
curacy: 0.5179 - val_loss: 1.5276 - learning_rate: 5.9837e-05
Epoch 122/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5474 - loss: 1.4614 - val_ac
curacy: 0.5192 - val_loss: 1.5325 - learning_rate: 5.9837e-05
Epoch 123/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5493 - loss: 1.4518 - val_ac
curacy: 0.5226 - val_loss: 1.5253 - learning_rate: 5.9837e-05
```

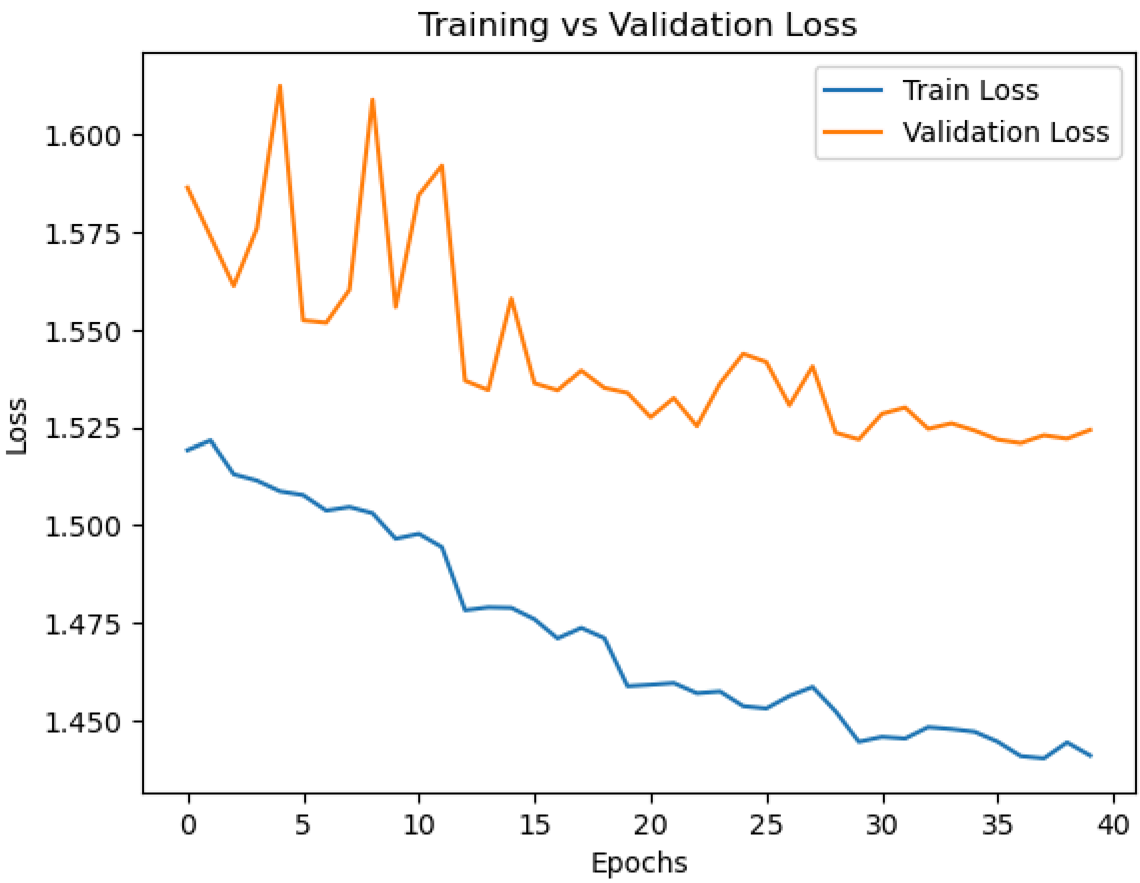
```
Epoch 124/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5486 - loss: 1.4510 - val_ac
curacy: 0.5124 - val_loss: 1.5362 - learning_rate: 5.9837e-05
Epoch 125/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5495 - loss: 1.4473 - val_ac
curacy: 0.5127 - val_loss: 1.5438 - learning_rate: 5.9837e-05
Epoch 126/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.5470 - loss: 1.4548 - val_ac
curacy: 0.5125 - val_loss: 1.5417 - learning_rate: 5.9837e-05
Epoch 127/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.5522 - loss: 1.4500 - val_ac
curacy: 0.5233 - val_loss: 1.5306 - learning_rate: 5.9837e-05
Epoch 128/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5480 - loss: 1.4507 - val_ac
curacy: 0.5140 - val_loss: 1.5406 - learning_rate: 5.9837e-05
Epoch 129/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5482 - loss: 1.4576 - val_ac
curacy: 0.5213 - val_loss: 1.5236 - learning_rate: 2.9919e-05
Epoch 130/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5488 - loss: 1.4493 - val_ac
curacy: 0.5217 - val_loss: 1.5219 - learning_rate: 2.9919e-05
Epoch 131/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5534 - loss: 1.4417 - val_ac
curacy: 0.5180 - val_loss: 1.5284 - learning_rate: 2.9919e-05
Epoch 132/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5479 - loss: 1.4531 - val_ac
curacy: 0.5187 - val_loss: 1.5300 - learning_rate: 2.9919e-05
Epoch 133/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.5523 - loss: 1.4411 - val_ac
curacy: 0.5242 - val_loss: 1.5246 - learning_rate: 2.9919e-05
Epoch 134/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5518 - loss: 1.4471 - val_ac
curacy: 0.5234 - val_loss: 1.5260 - learning_rate: 2.9919e-05
Epoch 135/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5532 - loss: 1.4387 - val_ac
curacy: 0.5257 - val_loss: 1.5242 - learning_rate: 2.9919e-05
Epoch 136/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5538 - loss: 1.4429 - val_ac
curacy: 0.5225 - val_loss: 1.5218 - learning_rate: 1.4959e-05
Epoch 137/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5579 - loss: 1.4358 - val_ac
curacy: 0.5236 - val_loss: 1.5210 - learning_rate: 1.4959e-05
Epoch 138/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5559 - loss: 1.4415 - val_ac
curacy: 0.5196 - val_loss: 1.5229 - learning_rate: 1.4959e-05
Epoch 139/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5577 - loss: 1.4461 - val_ac
curacy: 0.5199 - val_loss: 1.5221 - learning_rate: 1.4959e-05
Epoch 140/200
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.5531 - loss: 1.4395 - val_ac
curacy: 0.5221 - val_loss: 1.5243 - learning_rate: 1.4959e-05
Epoch 140: early stopping
Restoring model weights from the end of the best epoch: 130.
```

- The model started with an accuracy of 53.1% and gradually improved.
- Loss values decreased steadily, indicating better optimization over epochs.
- Validation accuracy fluctuated but showed an upward trend, reaching ~52.2% by epoch 130.
- Learning rate decayed gradually, helping to stabilize training.

- Model's validation accuracy is fluctuating around 50-52%, which suggests that it may not be learning complex patterns effectively.

- Hence Without convolutional layers, DNNs struggle to provide accuracy.

In [64]:
```python
import matplotlib.pyplot as plt

plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Training vs Validation Loss")
plt.show()
```



- Both losses are steadily decreasing , it means the model is learning patterns from the data correctly. and they are close to each other without a large gap, there is no overfitting.
- Model works fine but DNN not suitable for CIFAR 10 Image classifier should focous on CNN which will be a great model for this case.

In [67]:
```python
# evaluates the trained model on the test dataset

test_loss, test_acc = best_model.evaluate(x_test, y_test)
print(f"Test Loss: {test_loss:.4f}, Test Accuracy: {test_acc:.4%}")
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 868us/step - accuracy: 0.5237 - loss: 1.5084
Test Loss: 1.5219, Test Accuracy: 52.1700%
```

- Moderate accuracy (52%): The model is slightly better than random guessing (which would be 50% for a binary classification problem).
- High loss (1.52): The model's predictions are still quite uncertain.

In [72]:
```python
# Saving the model-

best_model.save("cifar10_model.keras")
```