```python
import numpy as np
import tensorflow as tf

from sklearn.metrics import accuracy_score, classification_report
from sklearn.naive_bayes import  MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
import pandas as pd
from time import time
import gc



from tensorflow.keras.applications import VGG19
from tensorflow.keras.models import Model



# Load and preprocess reduced dataset
print("Loading and preprocessing data : \n")

n_samples = 10000

(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

# Reduce dataset size
x_train = x_train[:n_samples]
y_train = y_train[:n_samples]

# Using 1/4 of n_samples for test set
x_test = x_test[:n_samples//4]
y_test = y_test[:n_samples//4]

print(f"Training samples: {x_train.shape[0]}")
print(f"Testing samples: {x_test.shape[0]}")
```

```
Loading and preprocessing data :

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 4s 0us/step
Training samples: 10000
Testing samples: 2500
```

```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelBinarizer

# Normalize pixel values
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# Convert labels to one-hot encoding
lb = LabelBinarizer()
y_train = lb.fit_transform(y_train)
y_test = lb.transform(y_test)


def create_feature_extractors():

    ## Create feature extractors from different VGG19 layers
    base_model = VGG19(weights='imagenet', include_top=False, input_shape=(32, 32, 3))

    layers_to_extract = [
        'block3_conv2',
        'block4_conv3',
        'block5_conv4'
    ]


    feature_extractors = {
        layer: Model(inputs=base_model.input, outputs=base_model.get_layer(layer).output)
        for layer in layers_to_extract
    }

    return feature_extractors, layers_to_extract
```

```
#Extract the features in batches to manage the memory efficiently

def extract_features_in_batches(model, data, batch_size=32):

    num_samples = data.shape[0]
    features_list = []

    # Processing the  data in batches
    for i in range(0, num_samples, batch_size):
        batch_data = data[i:min(i + batch_size, num_samples)]

        # Extracting the features for the batch
        batch_features = model.predict(batch_data, verbose=0)

        # Reshaping features to 2D array
        batch_features_reshaped = batch_features.reshape(batch_features.shape[0], -1)
        features_list.append(batch_features_reshaped)

        # Clear memory
        del batch_data, batch_features
        gc.collect()

    # Combine all batches
    return np.concatenate(features_list, axis=0)


# Evaluation function

def evaluate_model(clf, X_train, X_test, y_train, y_test):

    # Training  the model
    start_time = time()
    clf.fit(X_train, y_train)
    train_time = time() - start_time

    # Make predictions
    start_time = time()
    y_pred = clf.predict(X_test)
    predict_time = time() - start_time

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
```

```python
    report = classification_report(y_test, y_pred, output_dict=True)

    metrics = {
        'accuracy': accuracy,
        'precision': report['weighted avg']['precision'],
        'recall': report['weighted avg']['recall'],
        'f1': report['weighted avg']['f1-score'],
        'train_time': train_time,
        'predict_time': predict_time
    }

    print(f"{clf.__class__.__name__} Metrics:")
    for key, value in metrics.items():
        print(f"{key}: {value:.4f}")
    print("-" * 40)

    return metrics



# Create feature extractors
print("Creating feature extractors : \n")
feature_extractors, layer_names = create_feature_extractors()

# Extract features for each layer
print("Extracting features for each layer : ")
features_train = {}
features_test = {}

for layer in layer_names:
    print(f"\nProcessing layer: {layer}")

    # Extract features for training data
    print("Extracting training features : ")

    features_train[layer] = extract_features_in_batches(
        feature_extractors[layer],
        x_train,
        batch_size=32
    )

    # Extract features for test data
```

```python
    print("Extracting test features...")
    features_test[layer] = extract_features_in_batches(
        feature_extractors[layer],
        x_test,
        batch_size=32
    )

    # Print feature shapes
    print(f"Features from {layer}:")
    print(f"Train shape: {features_train[layer].shape}")
    print(f"Test shape: {features_test[layer].shape}")
```

```
Creating feature extractors :

Extracting features for each layer :

Processing layer: block3_conv2
Extracting training features :
Extracting test features...
Features from block3_conv2:
Train shape: (10000, 16384)
Test shape: (2500, 16384)

Processing layer: block4_conv3
Extracting training features :
Extracting test features...
Features from block4_conv3:
Train shape: (10000, 8192)
Test shape: (2500, 8192)

Processing layer: block5_conv4
Extracting training features :
Extracting test features...
Features from block5_conv4:
Train shape: (10000, 2048)
Test shape: (2500, 2048)
```

```python
# Define different classifiers used for classification
classifiers = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'KNN': KNeighborsClassifier(),
```

```
    'Random Forest': RandomForestClassifier(),
    'Decision Tree': DecisionTreeClassifier()
}




# Storing the results after each evaluation here
results = []

# For each layer and classifier combination
for layer in layer_names:
    print(f"\nLAYER USED : {layer}")

    # Scale features
    scaler = StandardScaler()
    x_train_scaled = scaler.fit_transform(features_train[layer])
    x_test_scaled = scaler.transform(features_test[layer])

    # Evaluate each classifier one by one
    for clf_name, clf in classifiers.items():
        print(f"Evaluating {clf_name} :")

        metrics = evaluate_model(
            clf,
            x_train_scaled,
            x_test_scaled,
            y_train.argmax(axis=1),
            y_test.argmax(axis=1)
        )

        print()

        results.append({
            'Layer': layer,
            'Classifier': clf_name,
            **metrics
        })
```

```
LAYER USED : block3_conv2
Evaluating Logistic Regression :
LogisticRegression Metrics:
accuracy: 0.7112
precision: 0.7080
recall: 0.7112
f1: 0.7091
train_time: 53.4955
predict_time: 0.1994
----------------------------------------

Evaluating KNN :
KNeighborsClassifier Metrics:
accuracy: 0.5236
precision: 0.6108
recall: 0.5236
f1: 0.5214
train_time: 0.0938
predict_time: 26.8649
----------------------------------------

Evaluating Random Forest :
RandomForestClassifier Metrics:
accuracy: 0.5968
precision: 0.5919
recall: 0.5968
f1: 0.5925
train_time: 119.4140
predict_time: 0.1401
----------------------------------------

Evaluating Decision Tree :
DecisionTreeClassifier Metrics:
accuracy: 0.3304
precision: 0.3316
recall: 0.3304
f1: 0.3305
train_time: 222.0527
predict_time: 0.0172
----------------------------------------


LAYER USED : block4_conv3
Evaluating Logistic Regression :
```

```
LogisticRegression Metrics:
accuracy: 0.7088
precision: 0.7076
recall: 0.7088
f1: 0.7077
train_time: 35.4347
predict_time: 0.1297
----------------------------------------

Evaluating KNN :
KNeighborsClassifier Metrics:
accuracy: 0.5488
precision: 0.5743
```

```
# Convert results to DataFrame
results_df = pd.DataFrame(results)

# Find best combination
best_idx = results_df['accuracy'].idxmax()
best_combination = results_df.iloc[best_idx]

# Print results
print("\nResults Summary:")
print(results_df.round(4))
```

```
Results Summary:
          Layer           Classifier  accuracy  precision  recall      f1  \
0   block3_conv2  Logistic Regression    0.7112     0.7080  0.7112  0.7091
1   block3_conv2                  KNN    0.5236     0.6108  0.5236  0.5214
2   block3_conv2        Random Forest    0.5968     0.5919  0.5968  0.5925
3   block3_conv2        Decision Tree    0.3304     0.3316  0.3304  0.3305
4   block4_conv3  Logistic Regression    0.7088     0.7076  0.7088  0.7077
5   block4_conv3                  KNN    0.5488     0.5743  0.5488  0.5435
6   block4_conv3        Random Forest    0.6112     0.6082  0.6112  0.6079
7   block4_conv3        Decision Tree    0.3524     0.3520  0.3524  0.3514
8   block5_conv4  Logistic Regression    0.4772     0.4759  0.4772  0.4763
9   block5_conv4                  KNN    0.4156     0.4264  0.4156  0.4162
10  block5_conv4        Random Forest    0.4920     0.4910  0.4920  0.4895
11  block5_conv4        Decision Tree    0.2984     0.3014  0.2984  0.2993

    train_time  predict_time
0      53.4955        0.1994
```

```
1        0.0938       26.8649
2      119.4140        0.1401
3      222.0527        0.0172
4       35.4347        0.1297
5        0.0476       12.9837
6       62.4682        0.1736
7       82.7409        0.0090
8       62.2427        0.0500
9        0.0269        4.4697
10      17.2083        0.0960
11      10.5556        0.0040
```

```python
print("\nBest Combination : \n")
print(f"Layer: {best_combination['Layer']}")
print(f"  Classifier: {best_combination['Classifier']}")
print(f"  Accuracy: {best_combination['accuracy']:.4f}")
print(f"  F1 Score: {best_combination['f1']:.4f}")
print(f"  Precision: {best_combination['precision']:.4f}")
print(f"  Recall: {best_combination['recall']:.4f}")
```

```
Best Combination :

Layer: block3_conv2
  Classifier: Logistic Regression
  Accuracy: 0.7112
  F1 Score: 0.7091
  Precision: 0.7080
  Recall: 0.7112
```

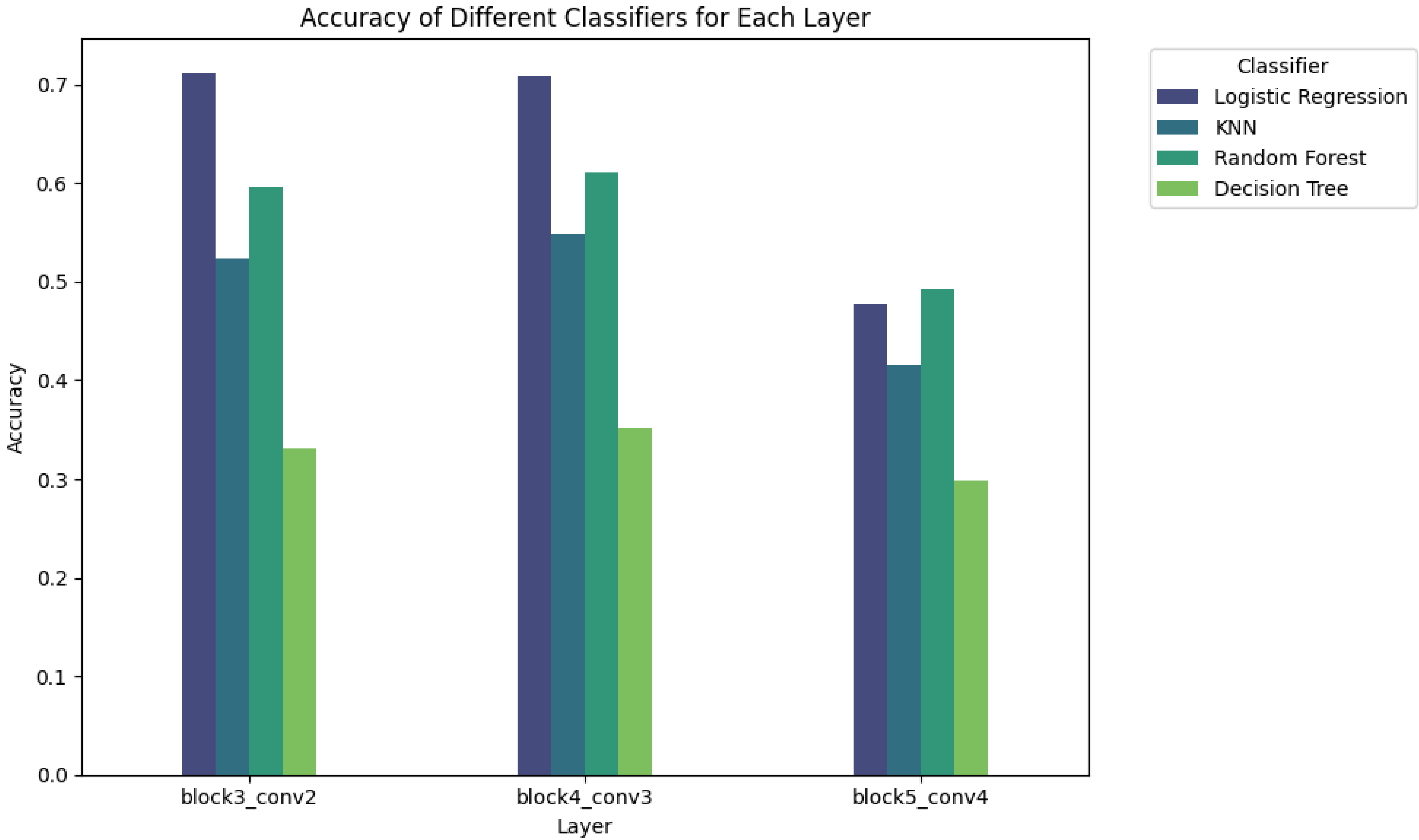
```python
results_df
```

	Layer	Classifier	accuracy	precision	recall	f1	train_time	predict_time
0	block3_conv2	Logistic Regression	0.7112	0.707951	0.7112	0.709083	53.495470	0.199412
1	block3_conv2	KNN	0.5236	0.610789	0.5236	0.521419	0.093800	26.864911
2	block3_conv2	Random Forest	0.5968	0.591878	0.5968	0.592525	119.414001	0.140121
3	block3_conv2	Decision Tree	0.3304	0.331609	0.3304	0.330535	222.052744	0.017242
4	block4_conv3	Logistic Regression	0.7088	0.707557	0.7088	0.707692	35.434690	0.129703
5	block4_conv3	KNN	0.5488	0.574333	0.5488	0.543543	0.047579	12.983659
6	block4_conv3	Random Forest	0.6112	0.608237	0.6112	0.607908	62.468225	0.173598
7	block4_conv3	Decision Tree	0.3524	0.351986	0.3524	0.351439	82.740882	0.008976
8	block5_conv4	Logistic Regression	0.4772	0.475899	0.4772	0.476336	62.242664	0.050000
9	block5_conv4	KNN	0.4156	0.426365	0.4156	0.416185	0.026869	4.469676
10	block5_conv4	Random Forest	0.4920	0.491046	0.4920	0.489524	17.208297	0.096048
11	block5_conv4	Decision Tree	0.2984	0.301377	0.2984	0.299273	10.555551	0.004042

Next steps: Generate code with results_df | View recommended plots | New interactive sheet

```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'results_df' is your DataFrame from the previous code
# Create the bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='Layer', y='accuracy', hue='Classifier', data=results_df, palette="viridis", width=0.4)  # Using a different c
plt.title('Accuracy of Different Classifiers for Each Layer')
plt.xlabel('Layer')
plt.ylabel('Accuracy')
plt.xticks(rotation=0)
plt.legend(title='Classifier', bbox_to_anchor=(1.05, 1), loc='upper left') #Move the legend outside the plot
plt.tight_layout()
plt.show()
```


Accuracy of Different Classifiers for Each Layer
Accuracy
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
block3_conv2
block4_conv3
block5_conv4
Layer
Classifier
Logistic Regression
KNN
Random Forest
Decision Tree