```
# Load CIFAR-10 dataset and preprocess
import numpy as np
from tensorflow.keras.datasets import cifar10
# Load the dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
# Flatten label arrays
y_train = y_train.flatten()
y_test = y_test.flatten()
# Normalize pixel values (0-255 to 0-1)
X_train = X_train / 255.0
X_{\text{test}} = X_{\text{test}} / 255.0
# Flatten images for Random Forest (from 32x32x3 to 3072 features)
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)
# Print shapes to confirm
print("Training data shape:", X_train_flat.shape)
print("Training labels shape:", y_train.shape)
print("Test data shape:", X_test_flat.shape)
print("Test labels shape:", y_test.shape)
→ Downloading data from <a href="https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz">https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz</a>
     170498071/170498071 -
                                                - 4s 0us/step
     Training data shape: (50000, 3072)
     Training labels shape: (50000,)
     Test data shape: (10000, 3072)
     Test labels shape: (10000,)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
# Use a smaller training sample for faster tuning
X_train_small = X_train_flat[:5000]
y_train_small = y_train[:5000]
# Smaller parameter grid
param_grid = {
    'n_estimators': [50],
    'max_depth': [10, None],
    'min_samples_split': [2],
    'min_samples_leaf': [1]
}
# Initialize model
```

```
rf = RandomForestClassifier(random state=42, n jobs=-1)
# Grid Search with 3-fold cross-validation
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=3, verbose=2,
# Fit the model
grid_search.fit(X_train_small, y_train_small)
# Best parameters
print("Best parameters found:", grid_search.best_params_)
# Best estimator
best_rf = grid_search.best_estimator_
→ Fitting 3 folds for each of 2 candidates, totalling 6 fits
     Best parameters found: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, classification_
import seaborn as sns
import matplotlib.pyplot as plt
# Predict on the test data
y_pred = best_rf.predict(X_test_flat)
# Accuracy
accuracy = accuracy_score(y_test, y_pred)
# Precision, Recall, F1-Score
precision, recall, f1, _ = precision_recall_fscore_support(y_test, y_pred, average='weighted
# Print scores
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred))
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Plot confusion matrix
plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
```

plt.show()

→ Accuracy: 0.3767 Precision: 0.3759 Recall: 0.3767 F1 Score: 0.3728

Classification Report:

precision	recall	f1-score	support
0.43	0.52	0.47	1000
0.43	0.37	0.40	1000
0.24	0.26	0.25	1000
0.24	0.18	0.21	1000
0.32	0.39	0.35	1000
0.36	0.31	0.33	1000
0.38	0.45	0.41	1000
0.44	0.29	0.35	1000
0.48	0.54	0.51	1000
0.44	0.45	0.45	1000
		0.38	10000
0.38	0.38	0.37	10000
0.38	0.38	0.37	10000
	0.43 0.43 0.24 0.24 0.32 0.36 0.38 0.44 0.48	0.43	0.43 0.52 0.47 0.43 0.37 0.40 0.24 0.26 0.25 0.24 0.18 0.21 0.32 0.39 0.35 0.36 0.31 0.33 0.38 0.45 0.41 0.44 0.29 0.35 0.48 0.54 0.51 0.44 0.45 0.45

Confusion Matrix

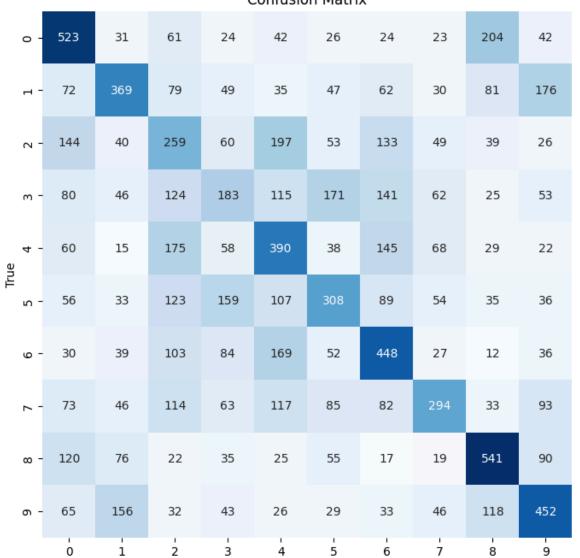
- 500

- 400

- 300

- 200

- 100



```
# Feature Importance Visualization
importances = best_rf.feature_importances_
# Get top 20 important features (pixels)
top_indices = importances.argsort()[-20:]
# Plot
plt.figure(figsize=(12,6))
plt.barh(range(20), importances[top_indices], color='skyblue')
plt.yticks(range(20), top_indices)
plt.xlabel('Feature Importance')
plt.title('Top 20 Important Features (Pixels)')
plt.show()
₹
                                         Top 20 Important Features (Pixels)
        86
        89
       164
       173
        80
       818
         5
       221
        53
       212
       620
       464
       305
      1109
       197
      2192
        20
      2437
       314
      1685
                                0.0004
                                                                    0.0010
                                                                                0.0012
        0.0000
                    0.0002
                                            0.0006
                                                        0.0008
                                                                                            0.0014
import cv2
# Preprocessing function for new image
def preprocess_image(img_path):
    Load and preprocess image for prediction
    img = cv2.imread(img_path)
    if img is None:
        raise ValueError("Image not found or can't be opened.")
    img_resized = cv2.resize(img, (32, 32))
```

img_norm = img_resized / 255.0

```
img_flat = img_norm.flatten().reshape(1, -1)
    return img_flat
# Prediction function
def predict_new_image(img_path, model=best_rf):
    img_processed = preprocess_image(img_path)
    prediction = model.predict(img_processed)
    return prediction[0]
img_path = 'converted_image.jpg' # your uploaded image filename
predicted_class = predict_new_image(img_path)
# CIFAR-10 class labels
cifar10 labels = {
    0: 'airplane',
    1: 'automobile',
    2: 'bird',
    3: 'cat',
   4: 'deer',
    5: 'dog',
   6: 'frog',
   7: 'horse',
   8: 'ship',
   9: 'truck'
}
print(f"Predicted class: {predicted_class}")
print(f"Predicted label: {cifar10_labels[predicted_class]}")
→ Predicted class: 3
     Predicted label: cat
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import time
# Use smaller sample for faster training like before
X_train_small = X_train_flat[:5000]
y_train_small = y_train[:5000]
# Initialize SVM with default parameters (you can tune later)
svm = SVC(kernel='rbf', random_state=42)
# Measure training time
start_time = time.time()
svm.fit(X_train_small, y_train_small)
end_time = time.time()
print(f"SVM training time: {end_time - start_time:.2f} seconds")
```

```
# Predict on test set
y_pred_svm = svm.predict(X_test_flat)
# Evaluate
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"SVM Accuracy: {accuracy_svm:.4f}")
print("\nClassification Report (SVM):")
print(classification_report(y_test, y_pred_svm))
# Optional: Confusion matrix plot
import seaborn as sns
import matplotlib.pyplot as plt
cm_svm = confusion_matrix(y_test, y_pred_svm)
plt.figure(figsize=(10,8))
sns.heatmap(cm_svm, annot=True, fmt='d', cmap='Greens')
plt.title("SVM Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```



SVM training time: 62.01 seconds

SVM Accuracy: 0.4435

Classification Report (SVM):

	precision	recall	f1-score	support
0	0.51	0.52	0.52	1000
1	0.55	0.48	0.51	1000
2	0.33	0.34	0.33	1000
3	0.34	0.24	0.28	1000
4	0.36	0.40	0.38	1000
5	0.38	0.36	0.37	1000
6	0.43	0.52	0.47	1000
7	0.52	0.41	0.46	1000
8	0.53	0.65	0.58	1000
9	0.47	0.53	0.50	1000
accuracy			0.44	10000
macro avg	0.44	0.44	0.44	10000
weighted avg	0.44	0.44	0.44	10000

SVM Confusion Matrix





Introduction This project focuses on classifying images from the CIFAR-10 dataset, which contains 60,000 color images in 10 classes. We implemented two machine learning models: Random Forest and Support Vector Machine (SVM), to compare their performance on this multi-class image classification task.

93 237 90 205 133 64 36 65

Methodology Data Preprocessing: Loaded CIFAR-10 images, normalized pixel values (scaled to [0,1]), and flattened 32x32x3 images into 3072-length feature vectors suitable for traditional ML models.