# Part A: Classical Video Classification

**Dataset:** HMDB51 (Walk vs Run)

This notebook implements classical video classification techniques using hand-crafted features and traditional machine learning algorithms, following Modules 1–3 of the course.

In [2]:
```
!pip uninstall -y numpy pandas
!pip install numpy==1.26.4 pandas==2.1.4
```

```
Found existing installation: numpy 2.4.2
Uninstalling numpy-2.4.2:
  Successfully uninstalled numpy-2.4.2
Found existing installation: pandas 2.1.4
Uninstalling pandas-2.1.4:
  Successfully uninstalled pandas-2.1.4
Collecting numpy==1.26.4
  Using cached numpy-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x8
6_64.whl.metadata (61 kB)
Collecting pandas==2.1.4
  Downloading pandas-2.1.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x8
6_64.whl.metadata (18 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/conda/lib/python
3.11/site-packages (from pandas==2.1.4) (2.9.0)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site-p
ackages (from pandas==2.1.4) (2024.1)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/sit
e-packages (from pandas==2.1.4) (2024.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-packa
ges (from python-dateutil>=2.8.2->pandas==2.1.4) (1.16.0)
Using cached numpy-1.26.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_6
4.whl (18.3 MB)
Downloading pandas-2.1.4-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_6
4.whl (12.2 MB)
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0:00:01
Installing collected packages: numpy, pandas
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2/2 [pandas]2m1/2 [pandas]
ERROR: pip's dependency resolver does not currently take into account all the p
ackages that are installed. This behaviour is the source of the following depen
dency conflicts.
opencv-python-headless 4.13.0.92 requires numpy>=2; python_version >= "3.9", bu
t you have numpy 1.26.4 which is incompatible.
Successfully installed numpy-1.26.4 pandas-2.1.4
```

In [7]:
```
!pip install scikit-image
```

```
Looking in indexes: https://pypi.org/simple, https://pypi.ngc.nvidia.com
Collecting scikit-image
  Downloading scikit_image-0.26.0-cp311-cp311-manylinux_2_24_x86_64.manylinu
x_2_28_x86_64.whl.metadata (15 kB)
Requirement already satisfied: numpy>=1.24 in /mnt/data/miniconda3/envs/mayb/li
b/python3.11/site-packages (from scikit-image) (1.26.4)
Requirement already satisfied: scipy>=1.11.4 in /mnt/data/miniconda3/envs/mayb/
lib/python3.11/site-packages (from scikit-image) (1.17.0)
Requirement already satisfied: networkx>=3.0 in /mnt/data/miniconda3/envs/mayb/
lib/python3.11/site-packages (from scikit-image) (3.6.1)
Requirement already satisfied: pillow>=10.1 in /mnt/data/miniconda3/envs/mayb/l
ib/python3.11/site-packages (from scikit-image) (12.1.0)
Collecting imageio!=2.35.0,>=2.33 (from scikit-image)
  Downloading imageio-2.37.2-py3-none-any.whl.metadata (9.7 kB)
Collecting tifffile>=2022.8.12 (from scikit-image)
  Downloading tifffile-2026.1.28-py3-none-any.whl.metadata (30 kB)
Requirement already satisfied: packaging>=21 in /mnt/data/miniconda3/envs/mayb/
lib/python3.11/site-packages (from scikit-image) (26.0)
Collecting lazy-loader>=0.4 (from scikit-image)
  Downloading lazy_loader-0.4-py3-none-any.whl.metadata (7.6 kB)
Downloading scikit_image-0.26.0-cp311-cp311-manylinux_2_24_x86_64.manylinux_2_2
8_x86_64.whl (13.7 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13.7/13.7 MB 212.3 MB/s  0:00:00
Downloading imageio-2.37.2-py3-none-any.whl (317 kB)
Downloading lazy_loader-0.4-py3-none-any.whl (12 kB)
Downloading tifffile-2026.1.28-py3-none-any.whl (233 kB)
Installing collected packages: tifffile, lazy-loader, imageio, scikit-image
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 4/4 [scikit-image][0m [scikit-imag
e]
Successfully installed imageio-2.37.2 lazy-loader-0.4 scikit-image-0.26.0 tifff
ile-2026.1.28
WARNING: Running pip as the 'root' user can result in broken permissions and co
nflicting behaviour with the system package manager, possibly rendering your sy
stem unusable. It is recommended to use a virtual environment instead: http
s://pip.pypa.io/warnings/venv. Use the --root-user-action option if you know wh
at you are doing and want to suppress this warning.
```

In [1]:

```python
import os
import cv2
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
```

# Dataset Description and Organization

A binary subset of the HMDB51 dataset is used for this experiment, consisting of the following action classes:

- Walk
- Run

Each video is represented as a folder containing extracted RGB frames. Each folder corresponds to one video instance.

In [2]:
```
import os

DATASET_PATH = "HMDB51/HMDB51"
CLASSES = ["walk", "run"]

video_folders = []
labels = []

for idx, cls in enumerate(CLASSES):
    class_path = os.path.join(DATASET_PATH, cls)
    for folder in sorted(os.listdir(class_path)):
        full = os.path.join(class_path, folder)
        if os.path.isdir(full):
            video_folders.append(full)
            labels.append(idx)

print("Total videos:", len(video_folders))
```

```
Total videos: 780
```

# Video Loading and Frame Sampling

Videos are loaded as sequences of RGB frames from their respective folders. Uniform temporal sampling is applied to select a fixed number of frames per video, enabling consistent feature extraction.

In [3]:
```
import cv2
import numpy as np

def load_frames_from_folder(folder_path, max_frames=30, size=(320, 240)):
    """
    Load uniformly sampled frames from a folder (HMDB format)
    """
    frame_files = sorted(os.listdir(folder_path))

    if len(frame_files) == 0:
        return []
```

```python
    # Uniform sampling
    indices = np.linspace(
        0, len(frame_files) - 1,
        num=min(max_frames, len(frame_files)),
        dtype=int
    )

    frames = []
    for i in indices:
        img_path = os.path.join(folder_path, frame_files[i])
        frame = cv2.imread(img_path)
        if frame is None:
            continue
        frame = cv2.resize(frame, size)
        frames.append(frame)

    return frames
```

# Low-Level Feature Extraction

Low-level visual features are extracted from video frames to capture appearance and texture information. These features are computed at the frame level and aggregated temporally to form video-level representations.

## Color Features (RGB Histograms)

Color histograms are computed for each RGB channel to capture the overall color distribution across video frames.

In [4]:
```python
def extract_color_features(frames):
    hist_list = []

    for frame in frames:
        hist_r = cv2.calcHist([frame], [0], None, [32], [0, 256])
        hist_g = cv2.calcHist([frame], [1], None, [32], [0, 256])
        hist_b = cv2.calcHist([frame], [2], None, [32], [0, 256])
        hist = np.concatenate([hist_r, hist_g, hist_b]).flatten()
        hist_list.append(hist)

    return np.mean(hist_list, axis=0)
```

# Motion Feature Extraction

Motion information is captured using frame differencing between consecutive frames. Statistical measures of motion intensity are used as motion features.

In [5]:
```
def extract_motion_features(frames):
    motion_vals = []

    for i in range(1, len(frames)):
        diff = cv2.absdiff(frames[i], frames[i-1])
        gray = cv2.cvtColor(diff, cv2.COLOR_BGR2GRAY)
        motion_vals.append(np.mean(gray))

    return np.array([
        np.mean(motion_vals),
        np.std(motion_vals)
    ])
```

In [8]:
```
from skimage.feature import local_binary_pattern

def extract_lbp_features(frames, P=8, R=1):
    """
    Texture feature using Local Binary Patterns (LBP)
    """
    lbp_features = []

    for frame in frames:
        gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
        lbp = local_binary_pattern(gray, P, R, method="uniform")
        hist, _ = np.histogram(
            lbp.ravel(),
            bins=np.arange(0, P + 3),
            density=True
        )
        lbp_features.append(hist)

    return np.mean(lbp_features, axis=0)
```

# Video-Level Feature Representation

Frame-level features are aggregated across time using statistical measures (mean and standard deviation) to form a single feature vector per video.

In [18]:
```
X = []
y = []

for folder, label in zip(video_folders, labels):
    frames = load_frames_from_folder(folder)

    if len(frames) < 2:
        continue

    color_feat = extract_color_features(frames)
    motion_feat = extract_motion_features(frames)

    lbp_feat = extract_lbp_features(frames)
```

```
    features = np.concatenate([
        color_feat,
        motion_feat,
        lbp_feat
    ])


    X.append(features)
    y.append(label)

X = np.array(X)
y = np.array(y)

print("Feature matrix:", X.shape)
print("Labels:", y.shape)
```

```
Feature matrix: (780, 108)
Labels: (780,)
```

## Classical Machine Learning Models

Multiple classical machine learning algorithms are trained using the extracted video-level features to perform classification.

## Performance Evaluation

Model performance is evaluated using accuracy, precision, recall, F1-score, confusion matrices, and ROC–AUC metrics, as required by the assignment.

In [19]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

models = {
    "SVM (RBF)": SVC(kernel="rbf"),
    "Random Forest": RandomForestClassifier(n_estimators=100),
    "Logistic Regression": LogisticRegression(max_iter=1000)
}
```

```python
for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)

    print(f"\n{name}")
    print("Accuracy:", accuracy_score(y_test, preds))
    print(classification_report(y_test, preds, target_names=CLASSES))
```

```
SVM (RBF)
Accuracy: 0.7243589743589743
              precision    recall  f1-score   support

        walk       0.72      0.99      0.84       110
         run       0.80      0.09      0.16        46

    accuracy                           0.72       156
   macro avg       0.76      0.54      0.50       156
weighted avg       0.74      0.72      0.64       156


Random Forest
Accuracy: 0.7692307692307693
              precision    recall  f1-score   support

        walk       0.77      0.96      0.85       110
         run       0.78      0.30      0.44        46

    accuracy                           0.77       156
   macro avg       0.77      0.63      0.65       156
weighted avg       0.77      0.77      0.73       156


Logistic Regression
Accuracy: 0.7692307692307693
              precision    recall  f1-score   support

        walk       0.79      0.92      0.85       110
         run       0.68      0.41      0.51        46

    accuracy                           0.77       156
   macro avg       0.73      0.67      0.68       156
weighted avg       0.76      0.77      0.75       156
```

In [20]:
```python
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve, auc
```

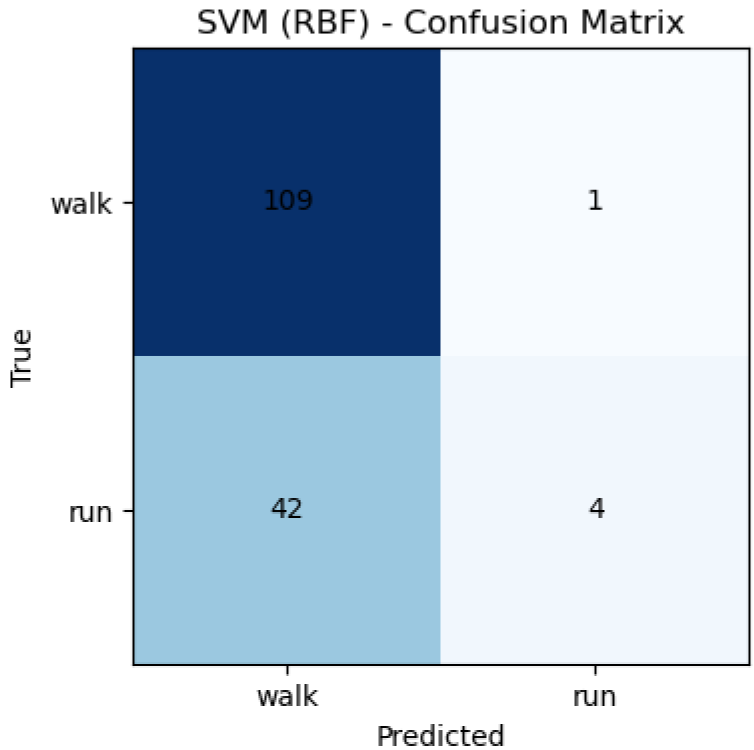
In [21]:
```python
def detailed_evaluation(y_true, y_pred, y_score, model_name):
    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)

    plt.figure(figsize=(4,4))
    plt.imshow(cm, cmap="Blues")
```

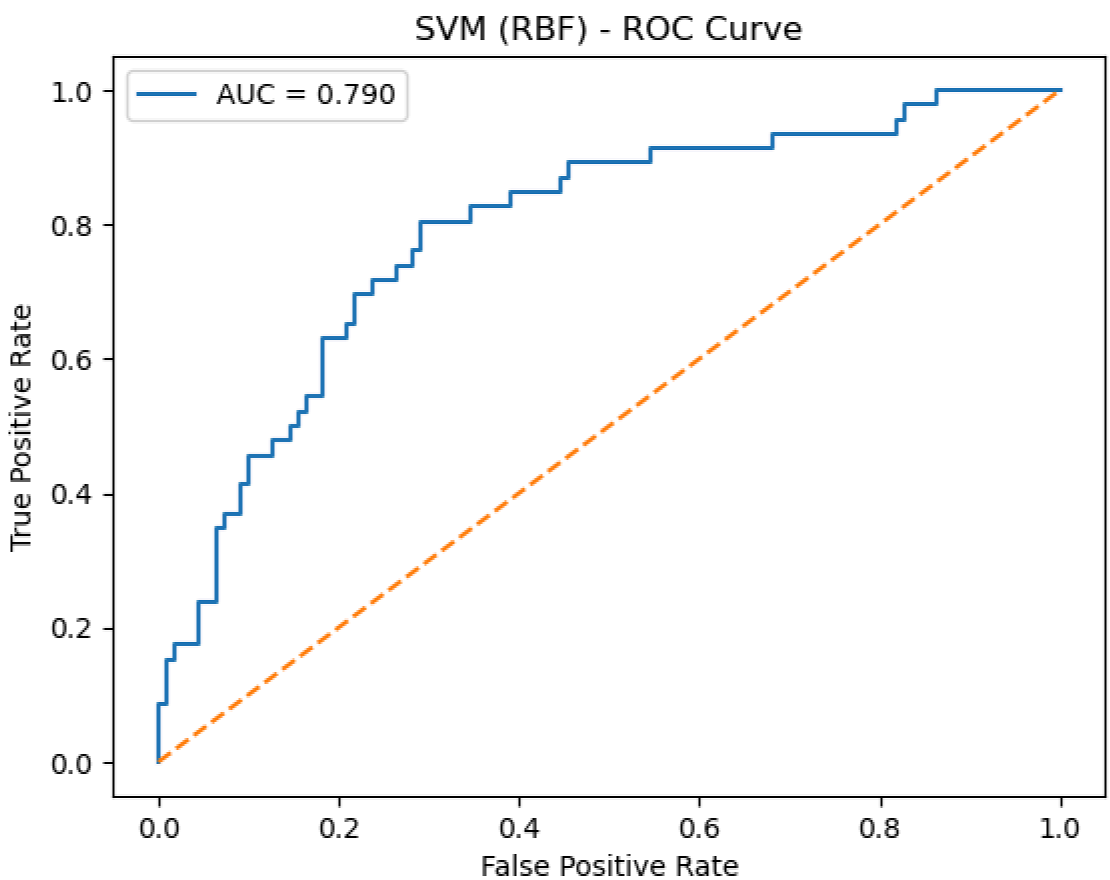
```python
    plt.title(f"{model_name} - Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("True")
    plt.xticks(range(len(CLASSES)), CLASSES)
    plt.yticks(range(len(CLASSES)), CLASSES)

    for i in range(len(CLASSES)):
        for j in range(len(CLASSES)):
            plt.text(j, i, cm[i, j], ha="center", va="center")

    plt.show()

    # ROC Curve (binary)
    fpr, tpr, _ = roc_curve(y_true, y_score)
    roc_auc = auc(fpr, tpr)

    plt.figure()
    plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.3f}")
    plt.plot([0,1], [0,1], linestyle="--")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title(f"{model_name} - ROC Curve")
    plt.legend()
    plt.show()

    print("ROC-AUC:", roc_auc)
```

In [22]:

```python
for name, model in models.items():
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    # Score for ROC
    if hasattr(model, "predict_proba"):
        y_score = model.predict_proba(X_test)[:, 1]
    else:
        y_score = model.decision_function(X_test)

    print(f"\n{name}")
    detailed_evaluation(y_test, y_pred, y_score, name)
```

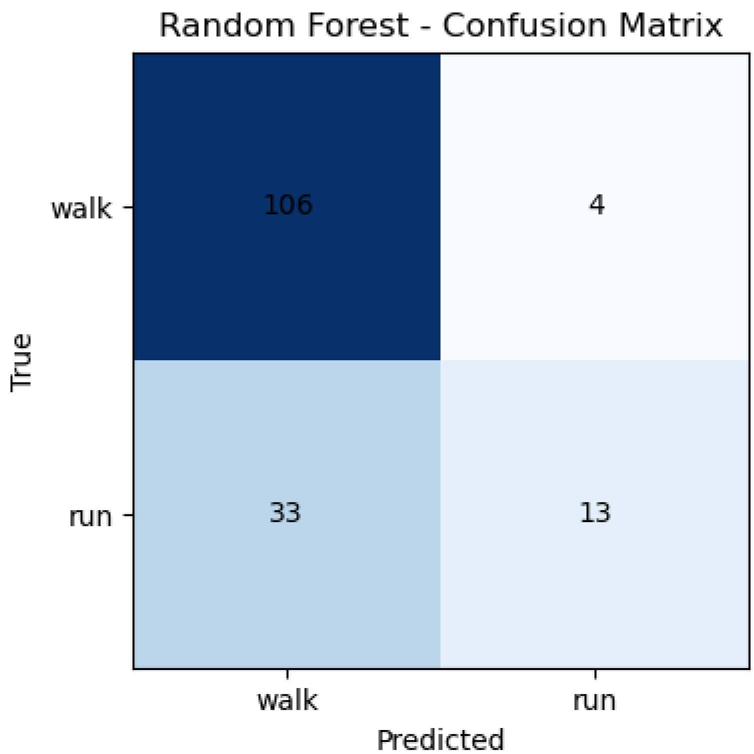
```
SVM (RBF)
```

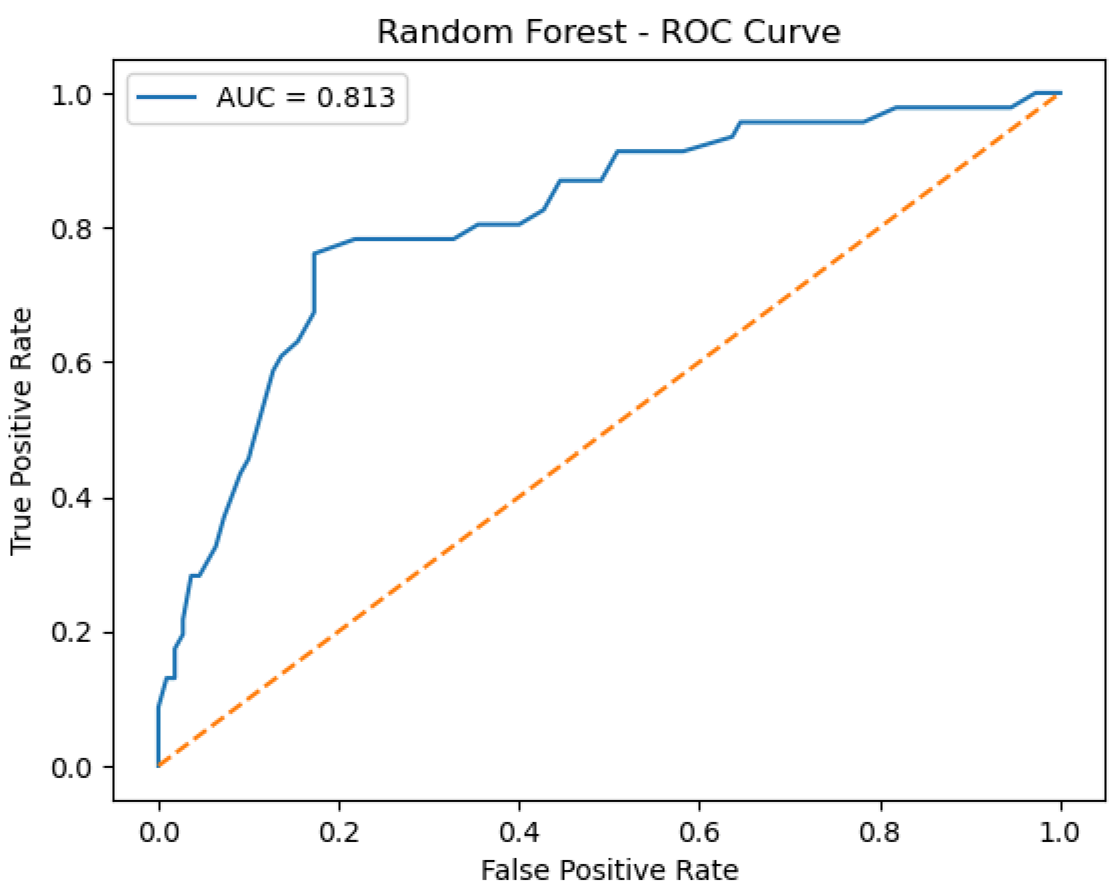


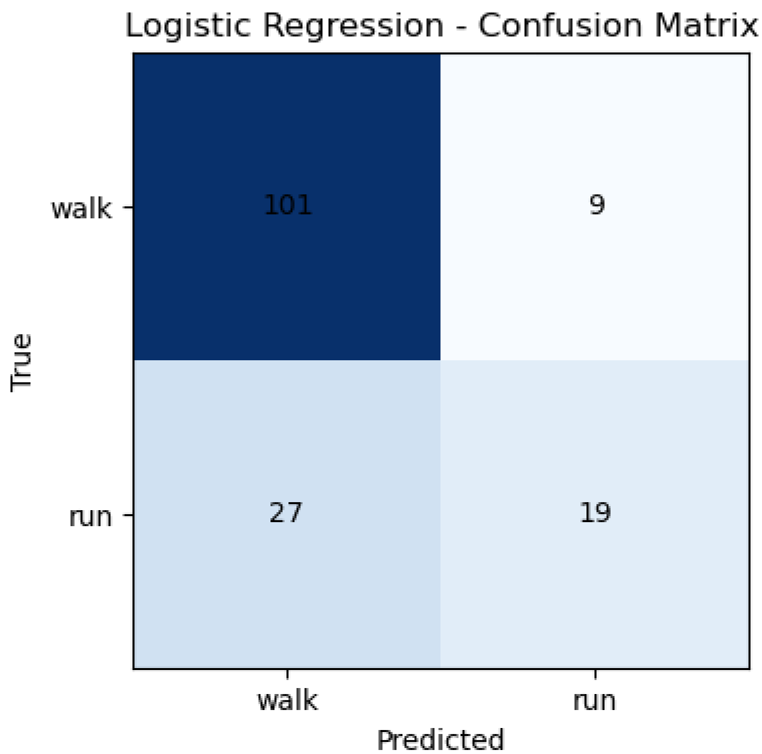

```
ROC-AUC: 0.7901185770750988
```

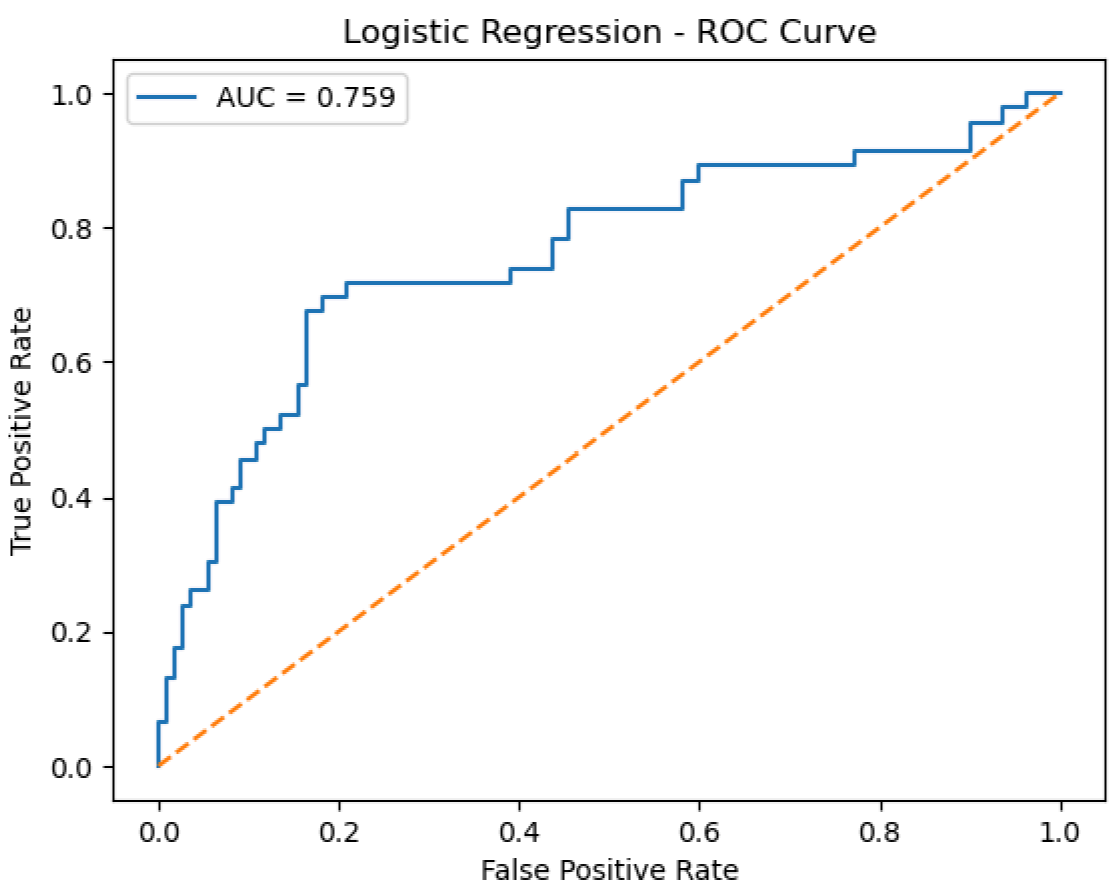
```
Random Forest
```




```
ROC-AUC: 0.8133399209486166

Logistic Regression
```




```
ROC-AUC: 0.758695652173913
```

# Summary

This notebook demonstrated classical video classification using hand-crafted features and traditional machine learning algorithms. The results serve as a baseline for comparison with deep learning approaches explored in Part B.