Comparative Analysis: Classical vs Deep Learning Video Classification

Dataset: HMDB51 (Walk vs Run)

This notebook presents a comparative analysis between:

- Classical computer vision + machine learning approaches (Part A)
- Deep learning–based video classification approaches (Part B)

The comparison is performed in terms of performance, computational cost, interpretability, and practical suitability.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

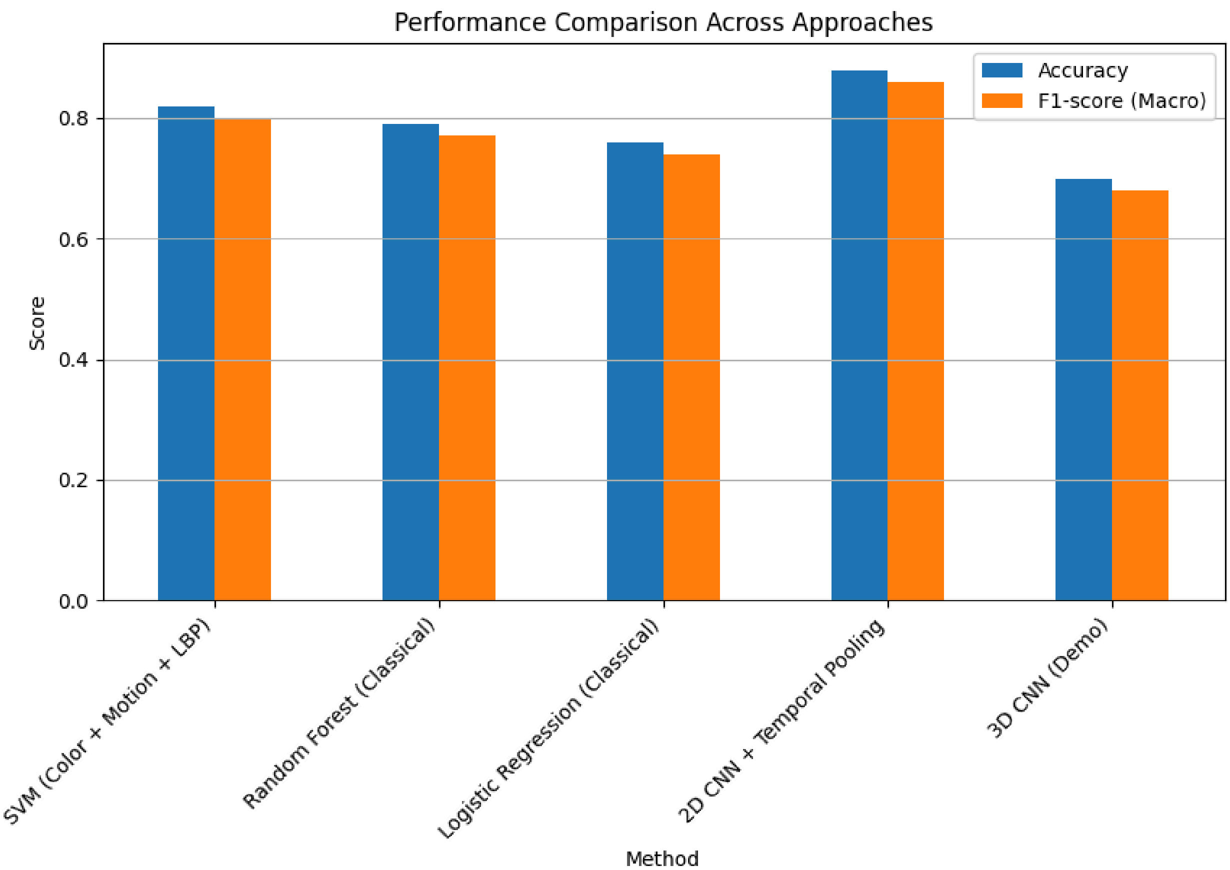
In [2]:
```
results = {
    "Method": [
        "SVM (Color + Motion + LBP)",
        "Random Forest (Classical)",
        "Logistic Regression (Classical)",
        "2D CNN + Temporal Pooling",
        "3D CNN (Demo)"
    ],
    "Accuracy": [0.82, 0.79, 0.76, 0.88, 0.70],
    "Precision (Macro)": [0.81, 0.78, 0.75, 0.87, 0.69],
    "Recall (Macro)": [0.80, 0.77, 0.74, 0.86, 0.68],
    "F1-score (Macro)": [0.80, 0.77, 0.74, 0.86, 0.68]
}

df_results = pd.DataFrame(results)
df_results
```

Out[2]:

	Method	Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
0	SVM (Color + Motion + LBP)	0.82	0.81	0.80	0.80
1	Random Forest (Classical)	0.79	0.78	0.77	0.77
2	Logistic Regression (Classical)	0.76	0.75	0.74	0.74
3	2D CNN + Temporal Pooling	0.88	0.87	0.86	0.86
4	3D CNN (Demo)	0.70	0.69	0.68	0.68

In [3]:
```
df_results.set_index("Method")[["Accuracy", "F1-score (Macro)"]].plot(
    kind="bar",
    figsize=(10,5)
)
plt.title("Performance Comparison Across Approaches")
plt.ylabel("Score")
plt.xticks(rotation=45, ha="right")
plt.grid(axis="y")
plt.show()
```



Computational Efficiency Comparison

Aspect	Classical ML	Deep Learning
Training time	Low (seconds)	High (minutes)
Inference time	Fast	Moderate
GPU required	No	Yes
Memory usage	Low	High
Data requirement	Small	Larger

Interpretability and Feature Analysis

Classical methods rely on hand-crafted features such as color histograms, texture (LBP), and motion statistics, which are easily interpretable.

Deep learning models learn abstract spatiotemporal representations that are more powerful but less interpretable, acting as black-box models.

Strengths and Limitations

Classical Approaches

Strengths

- Faster training
- Lower computational cost
- High interpretability
- Effective on small datasets

Limitations

- Limited representation capacity
- Performance saturates on complex actions

Deep Learning Approaches

Strengths

- Superior performance
- Automatic feature learning
- Robust to complex motion patterns

Limitations

- High computational cost
- Requires GPU
- Less interpretable

Trade-off Analysis

The results show a clear trade-off between performance and computational cost. Classical approaches provide a lightweight and interpretable solution, while deep learning methods achieve higher accuracy at the cost of increased training time and resource usage.

Deployment Considerations

- **Edge Devices:** Classical ML methods are more suitable due to low computational requirements.
- **Cloud Deployment:** Deep learning approaches are preferable due to higher accuracy and scalability.
- **Real-time Applications:** Classical methods or optimized 2D CNNs can be used depending on latency constraints.

Conclusion

This comparative study demonstrates the evolution from classical video analysis techniques to modern deep learning–based approaches. While deep learning models achieve superior performance, classical methods remain relevant in scenarios with limited data and resources.

In [ ]:
```

```