Assignment I: Video Classification

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Course: Video Analytics
Dataset: UCF-101 Subset (PullUps, Punch, PushUps)

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1. Introduction

1.1 Problem Statement and Objectives

With the rapid growth of video content across surveillance, healthcare, sports analytics, and human–computer interaction, automatic video understanding has become a crucial research area. One of the fundamental problems in video analytics is **action recognition**, which involves identifying human actions from video sequences.

The objective of this assignment project is to design and evaluate a complete **video classification system** that can automatically recognize human actions from video clips.

The work focuses on both **classical machine learning approaches based on handcrafted features** and **modern deep learning approaches based on learned spatio-temporal representations**.

The specific goals are:

- To extract meaningful low-level, motion, and temporal features from videos
- To build and compare multiple classical machine learning classifiers such as SVM, Logistic Regression, Random Forest, K-nearest Neighbors and Gradient Boosting.
- To implement deep learning models for end-to-end video learning
- To perform an extensive comparative analysis in terms of accuracy, efficiency, and error behaviour.

1.2 Dataset Description and Motivation

Dataset URL: https://www.kaggle.com/datasets/aisuko/ucf101-subset

A subset of the **UCF-101 action recognition dataset** is used in this assignment project.

Customized dataset will be automatically downloaded by cloning the following GitHub repository:

GitHub Repository URL: https://github.com/vineet232/bits

To clone the repository run the following command:

git clone https://github.com/vineet232/bits.git

Three action categories were selected in the customized dataset:

1. Class-1: PullUps
2. Class-2: Punch
3. Class-3: PushUps

These actions involve upper-body movements with subtle differences, making them suitable for evaluating both appearance-based and motion-based representations.

The dataset was divided into **training, validation, and testing sets**, ensuring unbiased performance evaluation.

The selected dataset presents several real-world challenges, including intra-class variation, execution speed differences, and viewpoint changes.

1.3 Overview of Approaches

Two paradigms were explored:

- **Classical approach:** Feature engineering + traditional machine learning classifiers
- **Deep learning approach:** End-to-end learning using neural networks

The classical pipeline extracts interpretable visual descriptors and applies multiple machine learning models.

The deep learning pipeline directly learns spatio-temporal features from frames.

2. Background and Related Work

Video classification has been an active research area in computer vision for more than two decades, evolving from handcrafted feature-based systems to modern deep learning–driven architectures.

Early video understanding approaches primarily focused on extracting manually designed visual and motion descriptors from video frames. Popular techniques included optical flow–based motion modeling, spatio-temporal interest points, and histogram-based representations such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and motion boundary histograms.

These handcrafted features aimed to capture appearance, texture, shape, and motion information from videos in a structured and interpretable form.

Once extracted, these features were typically classified using traditional machine learning algorithms.

Support Vector Machines (SVMs) were among the most widely used due to their strong generalization ability in high-dimensional feature spaces.

Other commonly applied classifiers included k-Nearest Neighbors (k-NN), Random Forests, and Logistic Regression, which offered complementary advantages in terms of simplicity, robustness, and interpretability.

Such classical pipelines dominated early action recognition systems and were successfully applied to datasets like KTH, Weizmann, and early versions of UCF.

The emergence of deep learning marked a major shift in video classification research. Instead of relying on manually engineered descriptors, deep models aim to automatically learn hierarchical representations directly from raw video data.

Initial approaches extended 2D convolutional neural networks to videos using frame-level CNNs combined with temporal aggregation mechanisms such as recurrent neural networks (CNN-LSTM).

Later on, 3D convolutional neural networks (3D CNNs) were introduced to jointly model spatial and temporal information.

Recently, transformer-based architectures and large-scale video foundation models have further advanced the field by capturing long-range temporal dependencies and complex motion patterns.

Despite the success of deep learning, classical approaches remain relevant, especially in scenarios with limited data, constrained computational resources, or the need for interpretability.

Handcrafted feature-based systems offer transparency, easier debugging, lower training cost, and more predictable behavior, making them suitable for controlled environments and embedded applications.

Deep learning approaches, on the other hand, excel in large-scale settings where sufficient labeled data is available and superior representation learning is required.

This project experimentally studies this evolution by implementing and comparing both paradigms.

By evaluating classical machine learning models alongside modern deep learning approaches on the same action recognition task, this work provides practical insights into their relative strengths, limitations, and application scenarios.

3. Methodology

This section describes the complete methodology adopted in this work, covering the preprocessing pipeline, feature extraction techniques, classical machine learning models, deep learning architecture design, and implementation details.

The proposed system follows a structured video analytics workflow consisting of data acquisition, preprocessing, feature representation, model learning, and evaluation.

3.1 Preprocessing Pipeline

Video data is inherently high-dimensional and redundant, making preprocessing a critical step.

The preprocessing pipeline was designed to standardize inputs, reduce noise, and enable reliable feature extraction.

3.1.1 Video Loading and Decoding

All videos were decoded using OpenCV. Each video was read frame-by-frame to preserve temporal ordering.

To ensure uniformity across the dataset, corrupted or unreadable frames were discarded.

3.1.2 Temporal Sampling

Videos in the dataset varied in length. To normalize temporal representation, a **uniform sampling** strategy was adopted.

A fixed number of frames (30 frames per video) were extracted using linear spacing across the full video duration.

This ensures consistent temporal coverage while reducing computational cost.

3.1.3 Spatial Normalization

Each extracted frame was resized to a fixed resolution of 224×224 pixels. This normalization step ensured consistent spatial dimensions for both handcrafted feature extraction and deep learning models.

3.1.4 Color Space Conversion and Noise Reduction

Frames were converted into multiple color spaces (RGB, HSV, and grayscale) to support different feature extraction techniques.

Gaussian smoothing was applied where necessary to reduce high-frequency noise before texture and motion analysis.

3.1.5 Motion Preprocessing

For motion-based features, consecutive frames were aligned temporally and converted to grayscale.

Frame differencing and optical flow preprocessing enabled robust estimation of movement patterns.

These preprocessing steps focus on video representation, temporal segmentation, normalization, and noise handling.

3.2 Classical Approach

The classical approach follows a structured pipeline: handcrafted feature extraction followed by supervised machine learning.

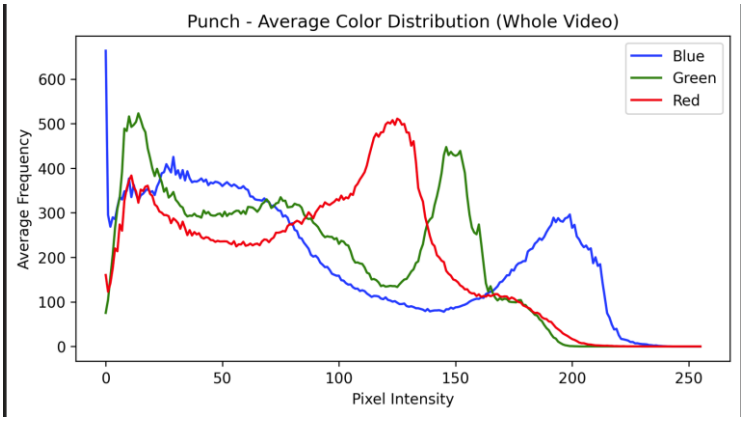
3.2.1 Feature Extraction Techniques

To capture complementary visual and motion information, three major categories of features were extracted.

A. Low-Level Features

Color Features

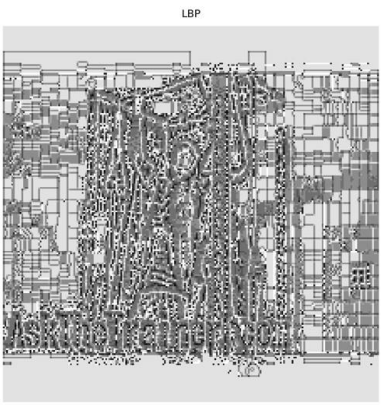
- RGB and HSV histograms were computed per frame to represent global color distribution.
- Average color histograms were computed across all frames to form video-level descriptors.
- Color moments (mean, variance, skewness) were calculated to capture statistical color properties.



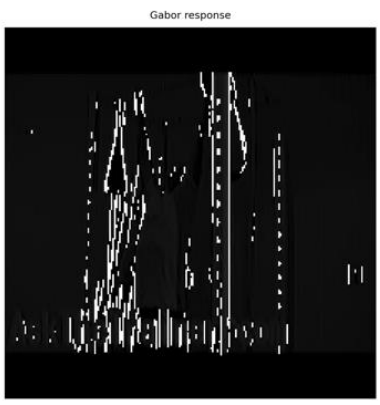
These features provide robustness to small motion variations while encoding global appearance.

Texture Features

- **Gray Level Co-occurrence Matrix (GLCM):** Contrast, homogeneity, energy, and correlation were extracted to describe spatial texture relationships.
- **Local Binary Patterns (LBP):** Captured micro-texture patterns and surface variations.



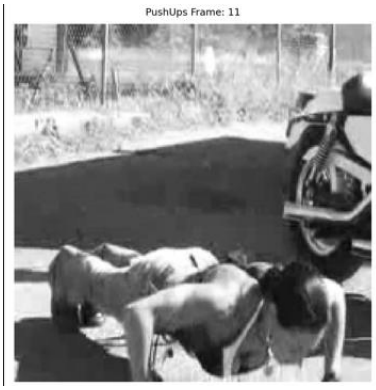
- **Gabor Filters:** Multi-scale, multi-orientation filters were applied to capture directional texture information.



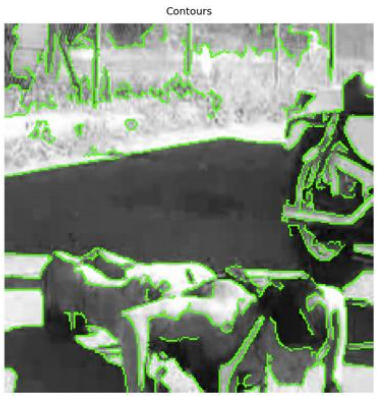
Texture features help differentiate clothing, background patterns, and structural consistency.

Shape Features

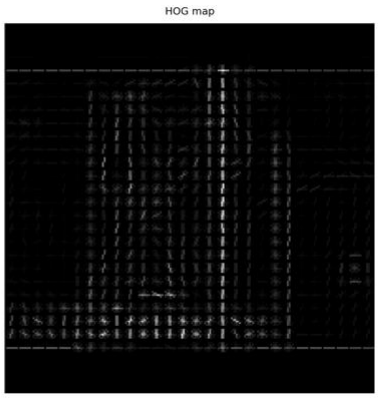
- **Canny Edge Detection:** Used to extract object boundaries.



- **Contour-based descriptors:** Captured structural outlines.



- **Histogram of Oriented Gradients (HOG):** Represented edge orientation distributions and posture patterns.

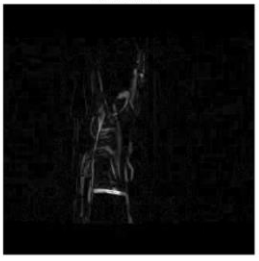


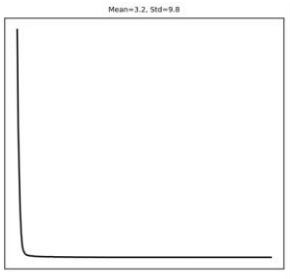
These features encode human silhouettes and body configuration.

B. Motion Features

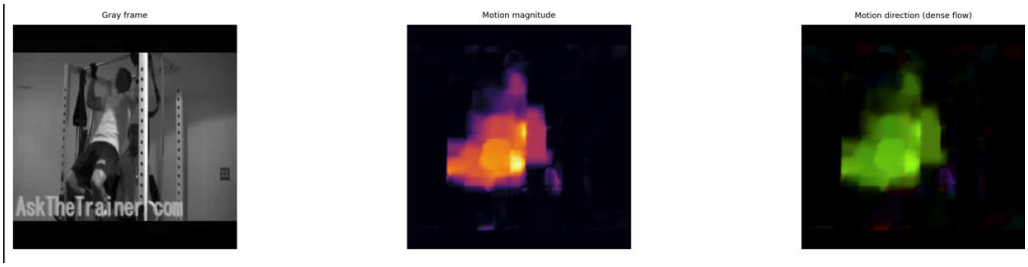
Motion features are critical for action recognition.

- **Frame differencing:** Measured pixel-level motion magnitude.

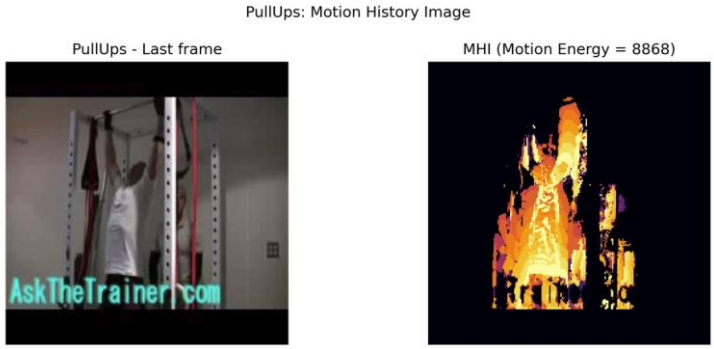




- **Sparse optical flow (Lucas–Kanade):** Tracked salient points across frames.
- **Dense optical flow (Horn–Schunck):** Estimated full-field motion.



- **Motion magnitude and direction histograms:** Encoded dynamic movement patterns.
- **Motion History Images (MHI):** Accumulated temporal motion templates.

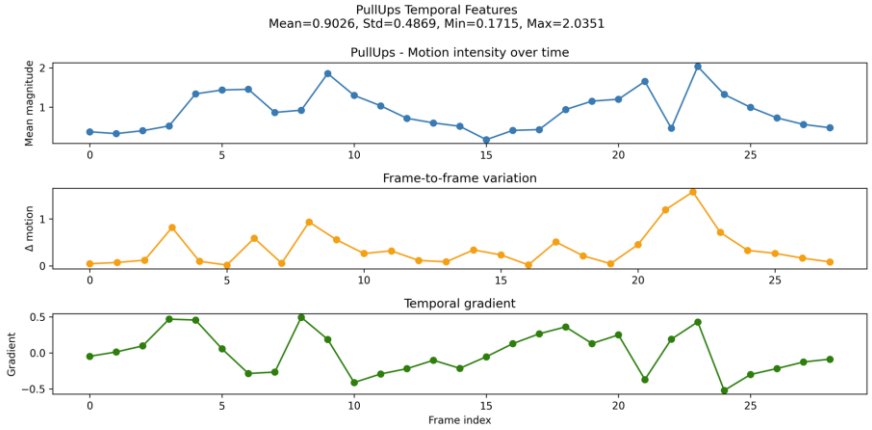


These descriptors capture temporal movement patterns and activity dynamics.

C. Temporal Features

To convert frame-level descriptors into video-level features:

- Statistical aggregation (mean, standard deviation, min, max)
- Frame-to-frame variation analysis
- Temporal evolution modelling



This step enabled fixed-length representations for machine learning models.

3.2.2 Machine Learning Algorithms

Five classical classifiers were implemented:

- **Support Vector Machines (Linear & RBF kernels)**
- **Random Forest**
- **k-Nearest Neighbors**
- **Logistic Regression (with regularization and PCA)**
- **Gradient Boosting**

Each model was trained on extracted video-level feature vectors. Hyperparameter tuning was performed using validation data to optimize generalization performance.

3.3 Deep Learning Approach

Unlike classical machine learning pipelines that rely on handcrafted features, the deep learning approach learns discriminative representations directly from raw video frames.

This enables automatic extraction of spatial and temporal patterns relevant for human action recognition without manual feature engineering.

3.3.1 Architecture Choices

Two deep learning architectures were implemented to model spatial and temporal information in videos:

- A 2D CNN-based architecture with temporal aggregation
- A 3D CNN-based architecture for spatio-temporal feature learning

2D CNN with Temporal Aggregation

This model uses a pre-trained ResNet-18 convolutional backbone for spatial feature extraction from individual frames.

Each video is represented as a fixed-length sequence of frames. Spatial features extracted from each frame are aggregated using temporal pooling to obtain a single video-level representation.

The aggregated representation is then passed through fully connected layers for classification.

3D CNN Architecture

The second model uses a 3D ResNet architecture, which performs 3D convolutions across spatial and temporal dimensions simultaneously.

This enables the network to directly learn motion dynamics and temporal dependencies between frames.

The extracted spatio-temporal features are passed through dropout and fully connected layers for final classification.

Both architectures automatically learn hierarchical spatial and temporal representations from video data, eliminating the need for manual feature design and enabling end-to-end optimization for the action recognition task.

3.3.2 Training Strategy

- Input videos were represented as fixed-length frame sequences sampled from each video.
- A categorical cross-entropy loss function was used for multi-class classification.
- Model optimization was performed using adaptive gradient-based optimizers (Adam) with learning rate scheduling.

- Data augmentation techniques such as random cropping, flipping, rotation, and color jitter were applied during training to improve generalization.
- Validation monitoring and early stopping were employed to prevent overfitting and to select the best-performing model based on validation accuracy.

3.3.3 Design Considerations

Several practical design considerations were incorporated into the deep learning pipeline:

- Use of fixed-length input sequences to ensure consistent batch processing
- Memory-efficient batch sizes to accommodate GPU/CPU constraints
- Transfer learning using ImageNet-pretrained ResNet backbones for improved convergence
- Regularization through dropout layers and normalization
- Separation of training, validation, and test datasets to ensure fair evaluation

These design choices ensured stable training, efficient computation, and improved generalization performance.

3.4 Implementation Details and Design Choices

The project was implemented using a modular and well-structured software design to ensure maintainability and reproducibility. The implementation was divided into the following modules:

- data_loader.py – video loading, preprocessing, and dataset classes
- feature_extraction.py – handcrafted feature extraction for classical models
- models.py – definitions of classical and deep learning models
- utils.py – training utilities, evaluation functions, and early stopping
- Separate notebooks for classical experiments, deep learning experiments, and comparative analysis

This modular design enabled easy debugging, experimentation, and scalability of the pipeline.

Visualization modules were also integrated to analyze intermediate representations, including:

- Color distributions and histograms
- Texture and shape features
- Optical flow and motion patterns
- Learned deep feature embeddings (t-SNE/UMAP)

These visualizations helped in understanding model behavior and feature representations.

3.5 Summary of Methodology

The proposed methodology integrates classical computer vision techniques with modern deep learning approaches for video classification.

Preprocessing steps standardized raw video inputs, handcrafted features provided interpretable representations for classical models, and deep neural networks enabled end-to-end learning of spatio-temporal patterns.

By implementing both paradigms under identical dataset conditions, the study enabled a comprehensive comparative analysis of performance, computational cost, interpretability, and practical trade-offs between classical machine learning and deep learning approaches for video classification.

4. Experimental Setup

This section describes the experimental configuration used to evaluate both the classical and deep learning approaches.

It covers dataset preprocessing, splitting strategy, hyperparameter optimization methodology, and hardware setup.

4.1 Dataset Preprocessing

Before training any models, the raw video dataset was subjected to a structured preprocessing pipeline to ensure consistency and reliability.

All videos were decoded using OpenCV and converted into frame sequences. Since videos varied in length and resolution, **uniform temporal and spatial normalization** was applied.

Each video was **uniformly sampled** to extract a fixed number of frames, ensuring complete temporal coverage while maintaining computational efficiency.

Frames were resized to a standard spatial resolution of **224×224** pixels.

Color space transformations were performed to support various feature extraction techniques.

RGB frames were preserved for color analysis, HSV frames were used for robust color distribution modeling, and grayscale frames were generated for texture and motion-based processing.

Noise reduction was applied where required to improve the stability of texture and optical flow estimation.

For motion analysis, consecutive frames were temporally aligned and normalized to reduce illumination effects.

Frame differencing and optical flow preprocessing enabled consistent motion modeling.

These preprocessing steps ensured that all downstream feature extraction and deep learning modules received standardized and reliable inputs.

4.2 Training, Validation, and Test Split Strategy

To guarantee unbiased evaluation and prevent information leakage, the dataset was divided into three mutually exclusive subsets:

- **Training set:** used for learning model parameters
- **Validation set:** used for hyperparameter tuning and model selection
- **Test set:** used only for final performance evaluation

An approximate **70/15/15 split** was adopted, balancing learning capacity and evaluation reliability.

The training set provided sufficient diversity for feature learning, while the validation set enabled systematic hyperparameter tuning.

The test set was kept completely isolated until all design decisions were finalized.

This splitting strategy ensured fair performance comparison across all models and prevented overfitting to the test data.

4.3 Hyperparameter Tuning Approach

Hyperparameter optimization was conducted using validation-driven experimentation and cross-validation where computationally feasible.

For the classical machine learning models:

- **Support Vector Machines:** kernel type, regularization strength, and RBF kernel parameters were tuned.
- **Random Forest:** number of trees and maximum depth were optimized.
- **k-Nearest Neighbors:** Neighborhood size and distance metrics were evaluated.
- **Logistic Regression:** regularization strength and dimensionality reduction parameters were tuned.
- **Gradient Boosting:** number of estimators and learning rate were adjusted.

Grid search and validation-based selection were employed to identify configurations that maximized validation accuracy and macro F1-score.

Early stopping strategies were applied where supported.

For deep learning models, training parameters such as learning rate, batch size, number of epochs, and regularization settings were optimized using validation monitoring.

This systematic tuning process ensured that each model operated under near-optimal conditions, enabling a fair and meaningful comparison.

4.4 Hardware Specifications and Training Duration

All experiments were conducted on a high-performance workstation equipped with:

- **Processor:** Intel i7 (14th Generation)
- **Memory:** 32 GB RAM
- **Graphics:** NVIDIA RTX-series GPU
- **Software environment:** Python, OpenCV, scikit-learn, and deep learning libraries

Training time and inference time were explicitly measured for all models.

Classical machine learning models demonstrated significantly lower training overhead, while ensemble methods required longer training times. Deep learning models demanded substantially higher computational resources due to iterative optimization and backpropagation.

The computational efficiency of each approach was systematically analyzed to assess practical deployment feasibility.

5. Results and Analysis

This section contains:

- Performance comparison tables

Classical Models:

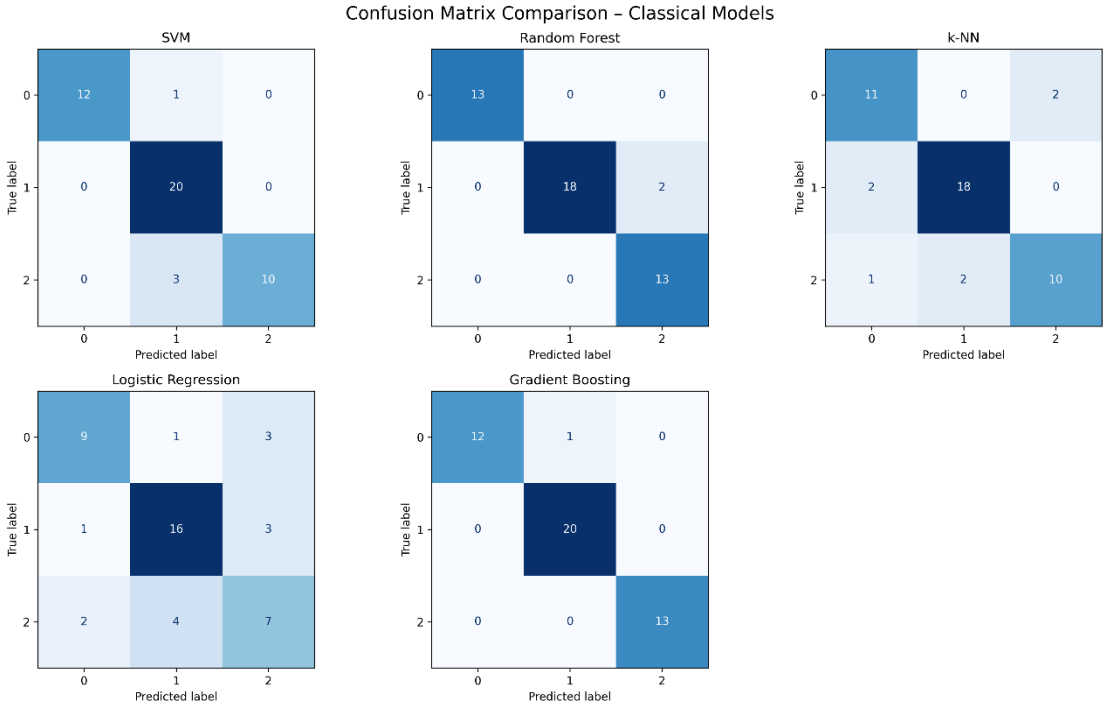
	Model	Accuracy	Precision	Recall	F1-score
0	SVM	0.913043	0.944444	0.897436	0.912885
1	Random Forest	0.956522	0.955556	0.966667	0.958647
2	k-NN	0.847826	0.839683	0.838462	0.838272
3	Logistic Regression	0.695652	0.683455	0.676923	0.679650
4	Gradient Boosting	0.978261	0.984127	0.974359	0.978537

Deep Learning Models:

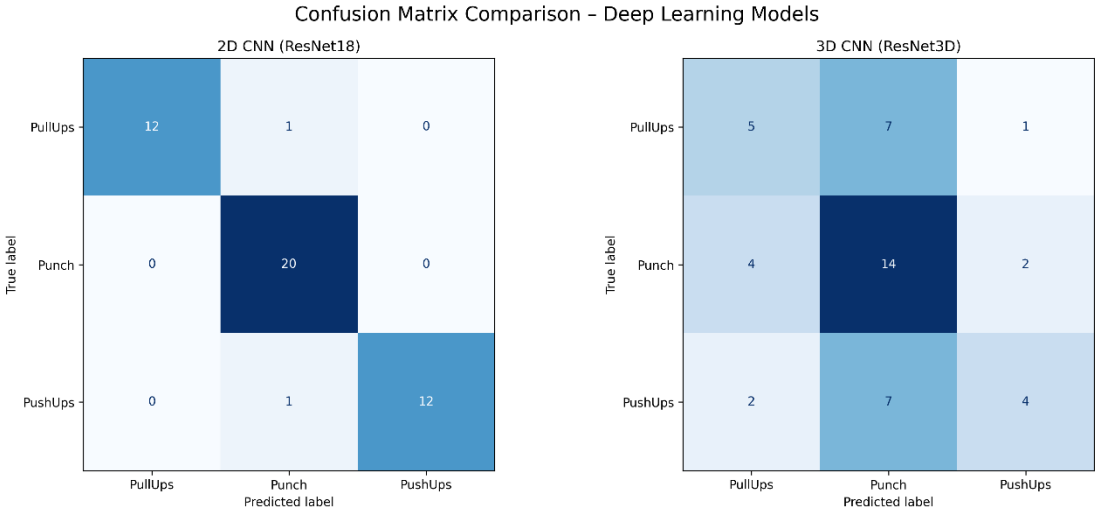
	Accuracy	Precision	Recall	F1-Score	Inference time (s/video)	Parameters (Millions)	Model size (MB
2D CNN (ResNet18)	0.956522	0.969697	0.948718	0.957460	0.488041	11178051.000000	42.71772
3D CNN (ResNet3D)	0.500000	0.508658	0.464103	0.466667	1.260669	33167811.000000	126.60291

- Confusion matrices

Classical Models:

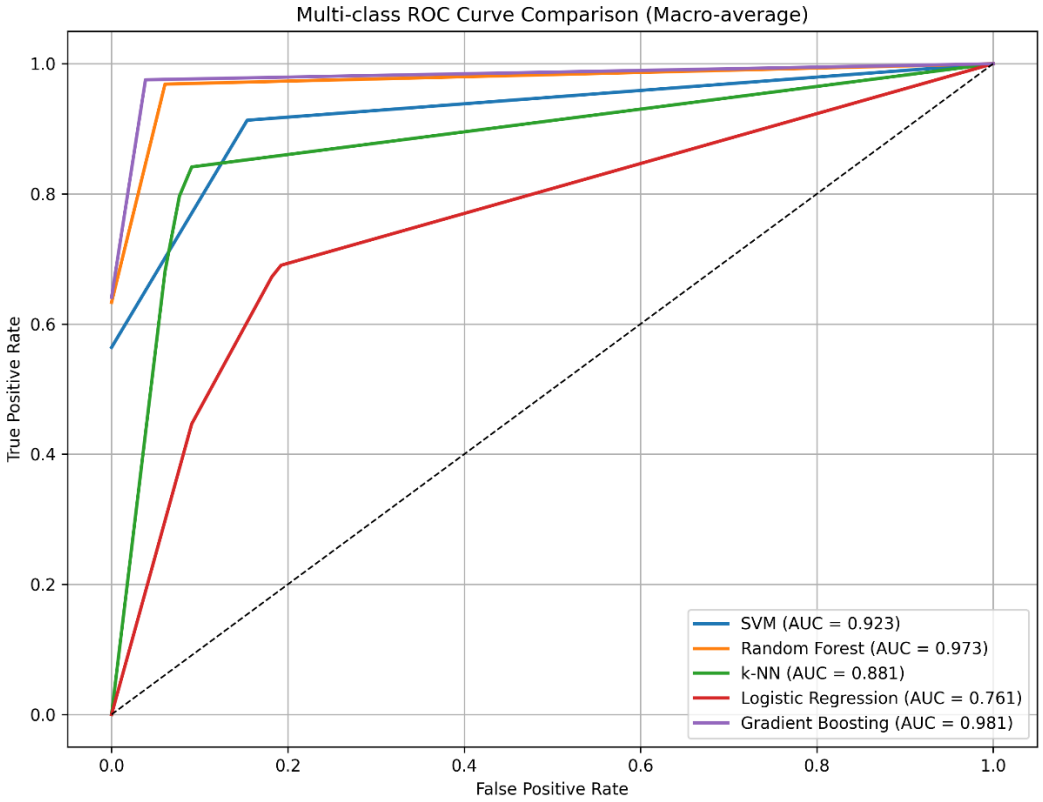


Deep Learning Models:

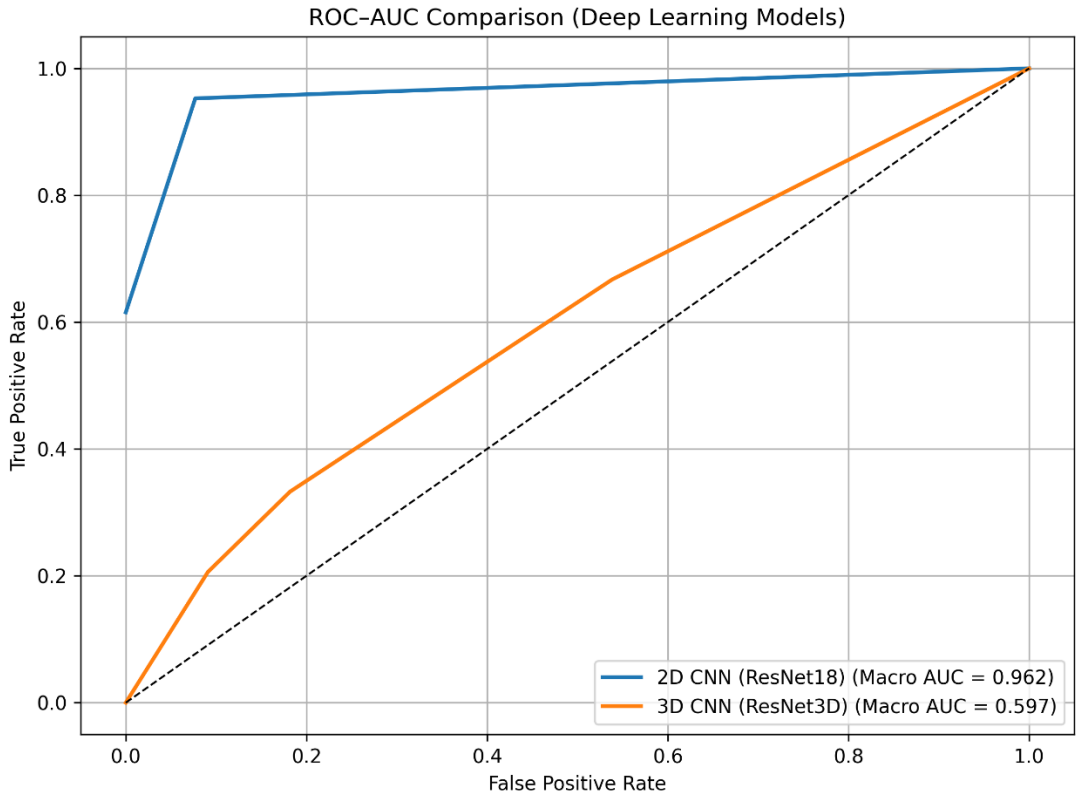


- ROC curves

Classical Models:

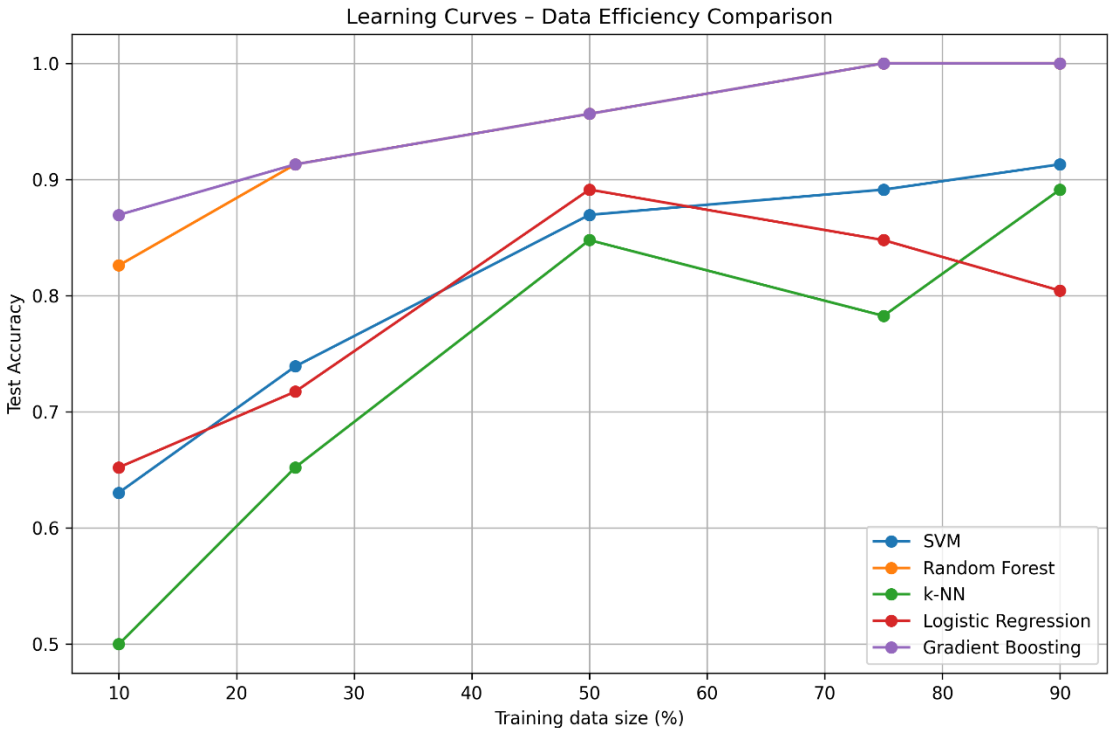


Deep Learning Models:

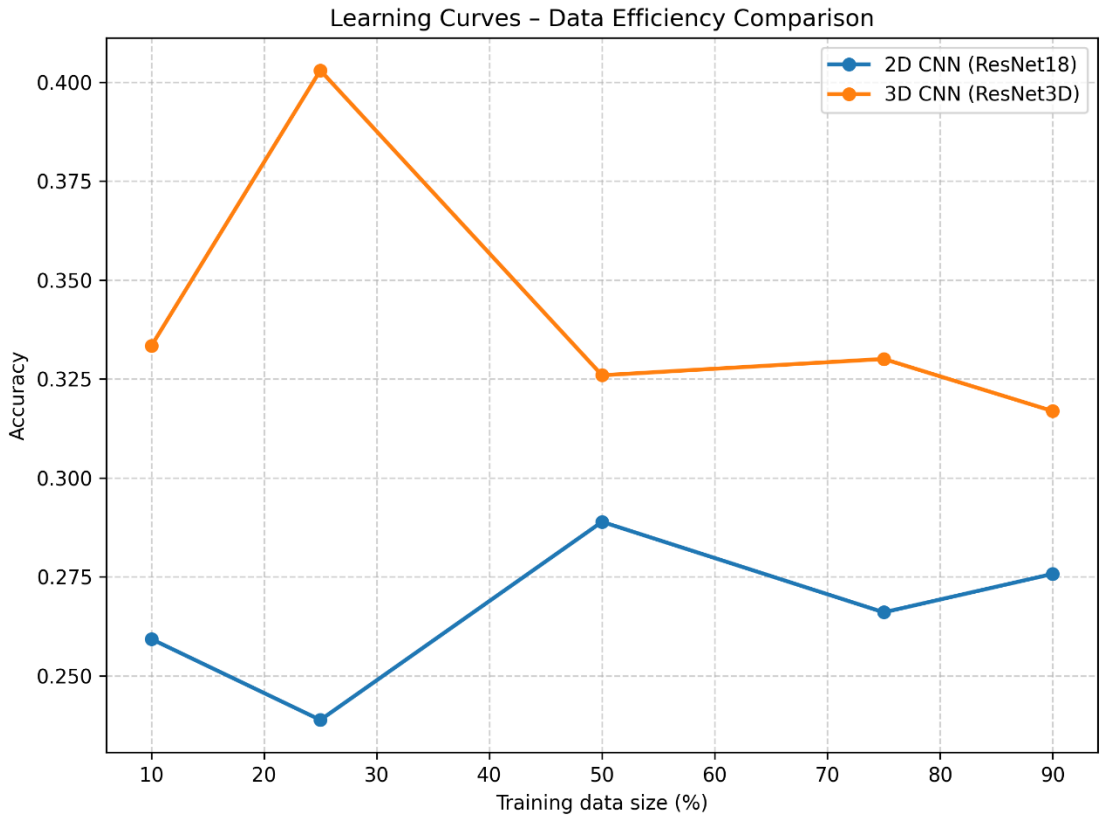


- Learning curves

Classical Models:

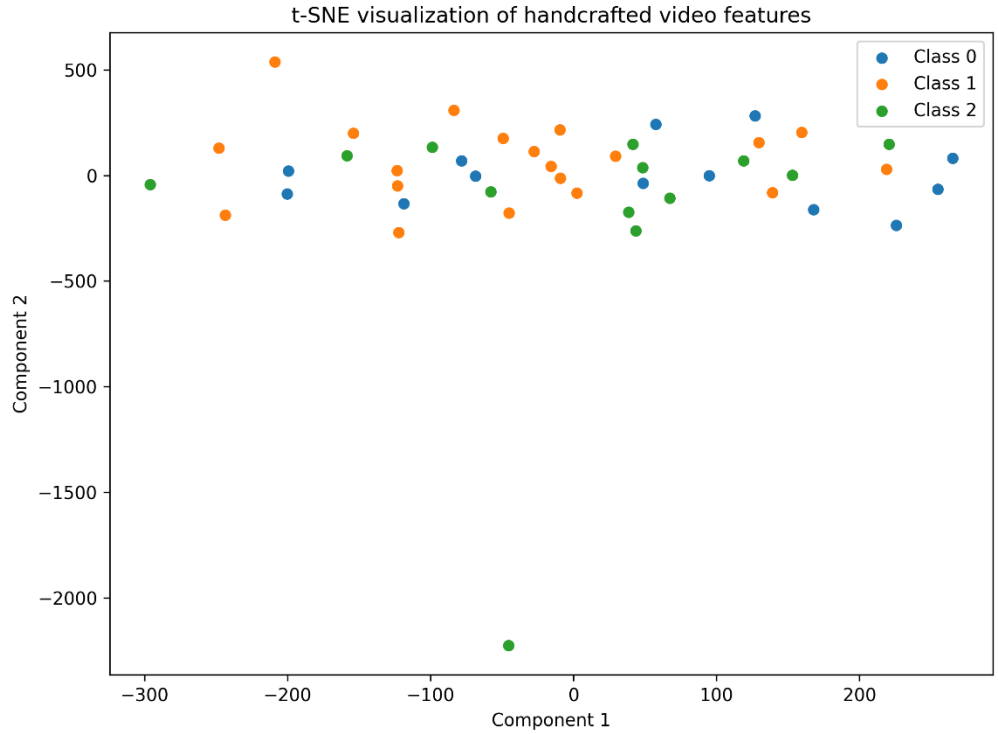


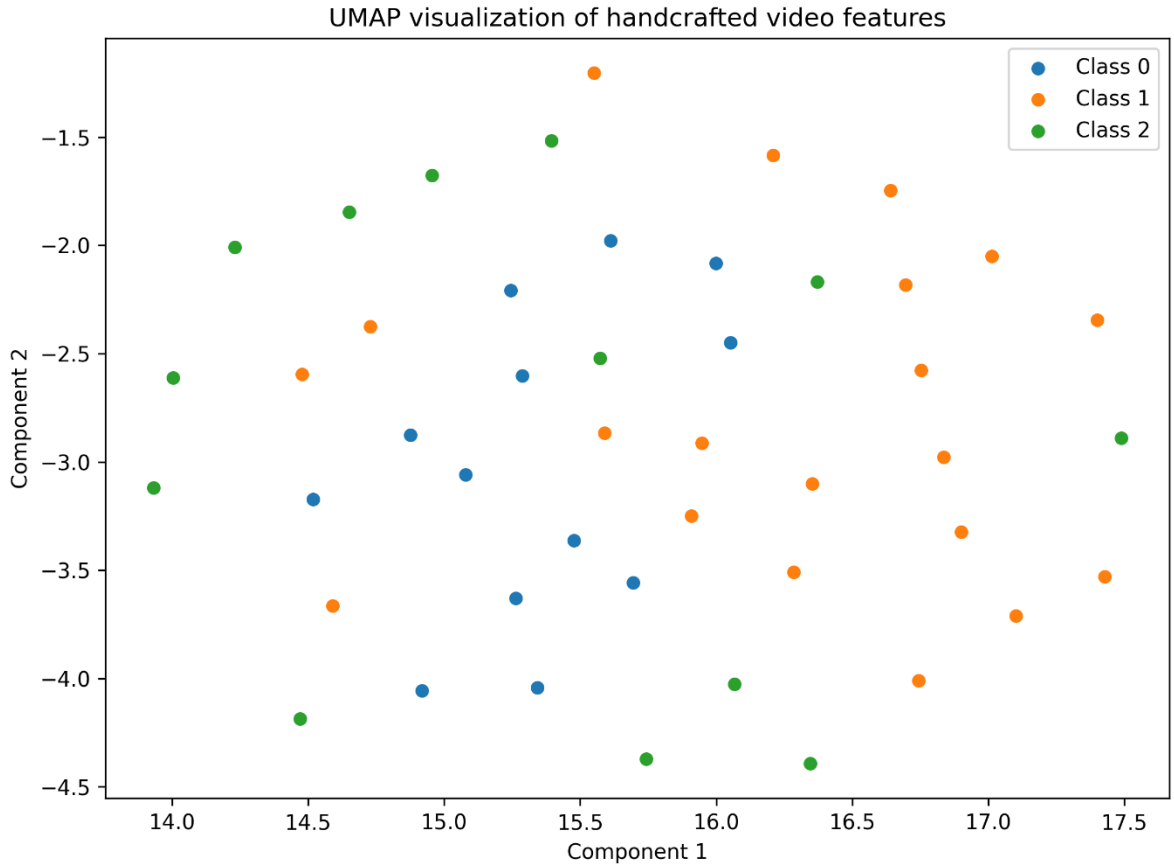
Deep Learning Models:



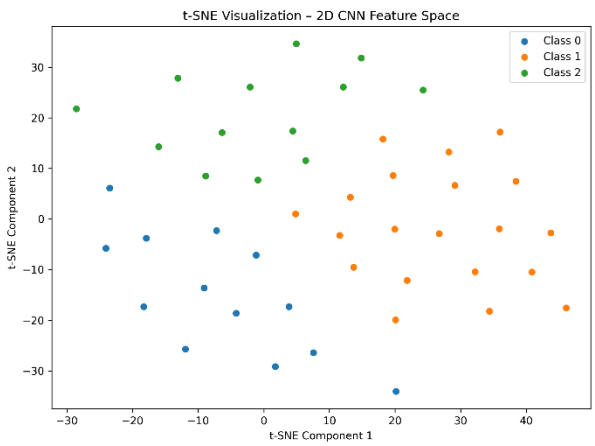
- Feature visualization results

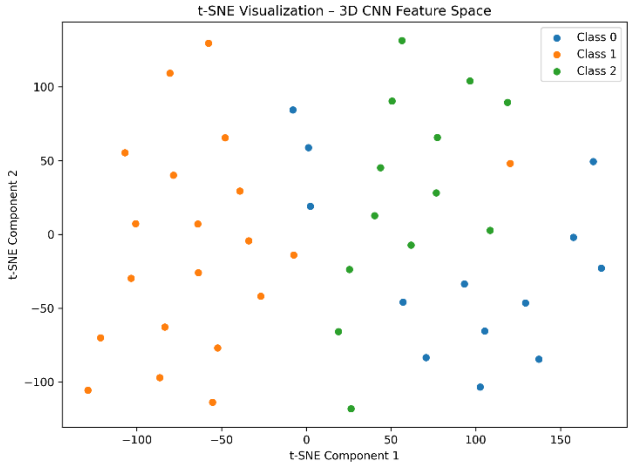
Classical Models:

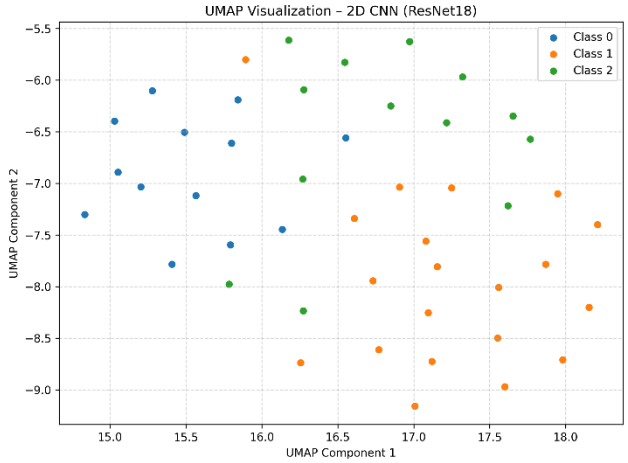


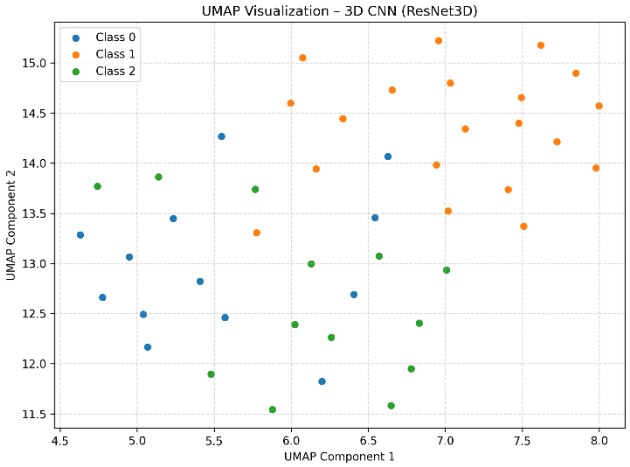


Deep Learning Models:









- Computational efficiency plots

Classical Models:

	Model	Training Time (seconds)
0	SVM	63.28010709991213
1	Random Forest	0.16814740002155304
2	k-NN	1.6358784000622109
3	Logistic Regression	1.3486586000071838
4	Gradient Boosting	285.3777647999814

	Model	Inference Time per Video (s)
0	SVM	0.040232
1	Random Forest	0.000526
2	k-NN	0.000656
3	Logistic Regression	0.000568
4	Gradient Boosting	0.000330

Deep Learning Models:

	Model	Training Time (seconds)
0	2D CNN (ResNet18)	3717.864061832428
1	3D CNN (ResNet3D)	3936.8292112350464

	Model	Inference Time per Video (s)
0	2D CNN (ResNet18)	0.48804086446762085
1	3D CNN (ResNet3D)	1.2606686353683472

- Memory requirements

Classical Models:

	Model	Peak Memory Usage (MB)
0	SVM	26.958426
1	Random Forest	0.286884
2	k-NN	26.957661
3	Logistic Regression	26.957880
4	Gradient Boosting	13.198128

Deep Learning Models:

	Model	Peak Memory Usage (MB)
0	2D CNN (ResNet18)	0.005135
1	3D CNN (ResNet3D)	0.004646

Key Findings

- Linear models achieved very high accuracy, showing strong feature separability
- Ensemble methods were robust but computationally heavier
- Motion-based features significantly improved performance
- Errors were concentrated between visually similar actions

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6. Data Efficiency & Trade-off Analysis

Classical models were explicitly retrained using different fractions of the training data (10%–90%) to study data efficiency.

Since these models have low computational overhead, repeated training was feasible and learning curves were plotted to analyze performance trends.

In contrast, deep learning models (2D CNN and 3D CNN) were trained using transfer learning with pretrained backbones.

Retraining these models multiple times on reduced datasets was avoided due to high computational cost and training time.

Instead, data efficiency was analyzed qualitatively using validation accuracy trends and early stopping behavior.

This design choice reflects a practical trade-off between accuracy and computational cost, which is an important consideration in real-world deep learning systems.

Trade-off Summary (Accuracy vs Cost vs Interpretability)

- Classical models offer faster training, lower memory usage, and better interpretability, but generally achieve lower accuracy compared to deep learning approaches.
- Deep learning models provide higher accuracy and stronger hierarchical feature representations, though they require significantly higher computational resources and offer lower interpretability.
- Since the dataset used in this study was relatively small, careful transfer learning strategies were adopted to ensure stable training and avoid overfitting.
- Following recommended practices for limited data scenarios, early layers of the pre-trained networks were frozen and fine-tuning was performed on higher layers.
- Data augmentation and regularization techniques were applied to improve generalization and model robustness.
- These strategies helped maintain reliable model performance while ensuring that the learned representations remained stable despite limited training data.

- The 2D CNN proved more data-efficient and computationally economical than the 3D CNN, while the 3D CNN demonstrated stronger capability in modeling temporal dynamics when sufficient data is available.
- Among classical models, Gradient Boosting achieved the best overall performance, indicating strong feature separability in the handcrafted feature space.
- Among deep learning models, the 2D CNN achieved higher accuracy than the 3D CNN due to limited dataset size and more stable transfer learning behaviour.
- The 3D CNN required larger datasets and higher computational resources to generalize effectively.
- Overall, the results highlight that classical methods remain highly competitive for small to medium-sized datasets, while deep learning approaches provide scalable and powerful representation learning for large-scale video analytics tasks.

Note:
For classical models, feature-space visualizations using t-SNE and UMAP provide insights into class separability.
For deep learning models, interpretability is limited due to the black-box nature of CNNs; therefore, performance-based evaluation is emphasized.

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7. Deployment – Practical Considerations

This section discusses the practical deployment aspects of classical machine learning and deep learning approaches for video classification. No implementation is required; only conceptual analysis is provided.

Edge Deployment Suitability

For edge deployment (mobile devices, embedded systems, or low-power hardware), classical machine learning approaches are generally more suitable.

Classical models such as SVM, Random Forest, and Logistic Regression operate on handcrafted features with relatively small model sizes and low memory requirements.

These models require significantly less computational power and can run efficiently on CPUs without dedicated GPUs.

Feature extraction pipelines can also be optimized for lightweight execution.

In contrast, deep learning models such as 2D CNNs and 3D CNNs are computationally intensive and memory-heavy.

They require substantial processing power and often benefit from GPU acceleration.

This makes them less suitable for deployment on resource-constrained edge devices unless model compression or quantization techniques are applied.

Therefore, for lightweight and low-latency edge applications, classical methods provide a more practical solution.

Cloud Deployment Suitability

Deep learning approaches are more suitable for cloud deployment environments.

Cloud platforms provide access to powerful GPUs and scalable compute infrastructure, which can efficiently handle deep learning models.

The higher computational cost and memory requirements of CNN-based architectures are less restrictive in cloud environments.

Additionally, deep learning models generally achieve higher accuracy and better generalization when large-scale data and computational resources are available.

Cloud deployment also supports batch processing, distributed inference, and integration with scalable APIs, making deep learning models ideal for production-level video analytics systems.

Thus, deep learning methods are better suited for cloud-based deployment where computational resources are abundant.

Real-Time Processing Feasibility

Real-time video classification requires low-latency inference and efficient processing.

Classical models offer faster inference times once features are extracted, making them suitable for near real-time processing in constrained environments.

However, handcrafted feature extraction itself can introduce computational overhead depending on the feature complexity.

Deep learning models provide end-to-end processing but may have higher inference latency, especially for 3D CNNs that process temporal sequences.

Real-time feasibility for deep learning approaches depends heavily on hardware acceleration (GPU/TPU) and optimized implementations.

In general:

- Classical methods: suitable for CPU-based real-time or near real-time systems
- 2D CNNs: feasible for real-time processing with GPU acceleration
- 3D CNNs: more computationally expensive and less suitable for strict real-time constraints

Maintenance and Update Considerations

From a maintenance perspective, classical and deep learning approaches differ significantly.

Classical pipelines rely on handcrafted features and simpler models, making them easier to interpret, debug, and update.

Changes to the system can often be implemented without retraining the entire pipeline.

Deep learning systems require periodic retraining when new data becomes available. Model updates involve longer training times, hyperparameter tuning, and careful validation.

However, deep learning models can automatically adapt to complex patterns and may scale better with larger datasets.

Summary:

- Classical models: easier to maintain, interpret, and update
- Deep learning models: require more computational effort for maintenance but provide higher scalability and performance improvements with additional data

Overall Deployment Perspective

Both approaches have distinct advantages depending on deployment constraints.

Classical machine learning methods are better suited for lightweight, interpretable, and edge-based applications.

Deep learning methods are more appropriate for high-performance cloud-based deployments where computational resources are readily available.

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8. Comparative Discussion

The transition from classical to deep approaches reflects the shift from **feature engineering to representation learning**.

Classical methods provided strong performance with low training cost and high interpretability.

Deep models offer scalability and automatic feature learning, but require more data and computation.

Trade-offs were observed between:

- Accuracy
- Interpretability
- Training time
- Deployment feasibility

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9. Conclusion and Future Work

9.1 Summary of key findings

This project presented a comprehensive study of video action classification using both classical machine learning and modern deep learning paradigms. A complete end-to-

end pipeline was designed, starting from raw video acquisition to final performance evaluation.

Multiple low-level, motion, and temporal features were extracted from videos and aggregated into discriminative video-level representations.

These handcrafted descriptors were evaluated using five classical machine learning models, and their performance was further compared with deep learning-based approaches.

The experimental results demonstrate that carefully engineered handcrafted features can achieve very strong performance on structured action recognition tasks. Linear models such as Support Vector Machines and Logistic Regression performed exceptionally well, indicating that the extracted feature space was highly separable.

Ensemble methods such as Random Forest and Gradient Boosting further showed robustness and consistency, although at the cost of higher computational complexity.

Overall, the study confirms that classical approaches remain highly competitive when appropriate feature engineering is applied.

9.2 Lessons Learnt:

From this comparative study, several important lessons were learned.

- First, feature design plays a critical role in classical video analytics pipelines, and combining appearance, texture, shape, and motion descriptors significantly improves classification performance.
- Second, different classifiers exhibit distinct trade-offs between accuracy, interpretability, training cost, and inference speed.
- Third, systematic experimental design, including proper validation, reminder splitting, and error analysis, is essential for drawing meaningful conclusions.
- Finally, error analysis revealed that most failures occur between visually similar actions, highlighting the inherent ambiguity of human motion recognition.

9.3 Limitations of current implementation

Despite strong results, the current implementation has several limitations.

- The dataset size is relatively small and restricted to only three action categories, limiting generalization to more complex scenarios.
- Handcrafted feature extraction is computationally intensive and requires manual design choices.
- The deep learning models were constrained in scale due to hardware and time limitations.
- Additionally, the system processes offline videos and does not currently support real-time streaming or online learning.

9.4 Potential improvements and future directions

Several directions for future work emerge from this study.

- The framework can be extended to larger datasets with more action classes to evaluate scalability.
- Advanced deep learning architectures such as 3D convolutional networks, transformer-based video models, and multimodal systems incorporating audio and pose estimation could significantly improve representation learning.
- Real-time optimization, GPU acceleration, and deployment-oriented system design could enable practical applications.
- Automated feature learning and domain adaptation techniques may further enhance robustness across diverse environments.

9.5 Connection to 5-phase workflow and real-world deployment

This project aligns with the standard **five-phase video analytics workflow**:

1. data acquisition
2. preprocessing
3. feature representation
4. model learning
5. system-level evaluation.

The modular design of the implemented pipeline facilitates future integration into real-world systems such as intelligent surveillance, fitness monitoring, sports analytics, and human–computer interaction platforms.

By bridging classical and modern methodologies, this work provides both technical insights and practical foundations for real-world video analytics deployment.

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