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Human Action Recognition from Video Using ML and DL Classifiers

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Abstract: Human Action Recognition (HAR) has evolved from traditional handcrafted feature methods to modern data-driven approaches leveraging machine and deep learning. Early systems struggled with generalization in realistic conditions due to occlusions, motion complexity, and background noise. This project overcomes these restrictions by proposing a hybrid framework that merges traditional Machine Learning (ML) with advanced Deep Learning (DL) models to detect human actions from video data. Two fundamental architectures are deployed and contrasted: the Long-term Recurrent Convolutional Network (LRCN), which combines CNNs and LSTMs to capture spatial and temporal patterns, and a streamlined pose-based classifier utilizing Google's Move Net for real-time skeleton tracking. Both models are trained and evaluated on benchmark datasets UCF101 and HMDB51. Experimental results demonstrate that while LRCN achieves higher accuracy (~87.6%), the MoveNet model offers superior inference speed and robustness to noise, a making it suitable for real-time applications. The findings highlight key trade-offs between accuracy and latency, providing insights for deploying HAR systems across diverse domains such as surveillance, healthcare, and human-computer interaction.

Keywords: Human Action Detection, Artificial Intelligence, Neural Networks, Long-term Recurrent Convolutional Networks (LRCN), Move Net Algorithm, Spatiotemporal Analysis, Pose Detection, UCF101 Dataset, HMDB51 Dataset.

I. INTRODUCTION

Human Action Recognition (HAR) is a developing field in computer vision that centres on the automated identification, categorization, and understanding of human movements from video data. Its significance has grown with the rapid integration of intelligent technologies across applications such as surveillance systems, autonomous vehicles, interactive gaming, virtual reality, smart healthcare, and behavioranalytics Initially, HAR systems predominantly utilized manually crafted features like Histogram of Oriented Gradients (HOG), optical flow, and trajectory-based descriptors.. While effective in constrained settings, these methods struggled to maintain performance in dynamic, real-world environments due to challenges like occlusion, cluttered backgrounds, and camera movement.

The constraints of manual approaches have spurred a shift in focus towards learning-based methodologies, especially those grounded in Machine Learning (ML) and Deep Learning (DL). These algorithms autonomously acquire layered representations from unprocessed input data, bolstering resilience and adaptability to intricate movement patterns and environmental fluctuations. Notably, Convolutional Neural Networks (CNNs) have become indispensable for capturing spatial characteristics from individual frames, while Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) networks, are utilized for modelling the temporal dynamics within sequences of actions.

This research presents a comparative framework that leverages both ML and DL paradigms to evaluate and enhance HAR from video. Two architectures are explored: the Long-term Recurrent Convolutional Network (LRCN), which combines CNNs with LSTMs for spatiotemporal modeling, and the MoveNet-based framework, which utilizes keypoint-based pose estimation to track skeletal movements. The LRCN model processes RGB video frames directly, while the MoveNet model abstracts human poses into 2D joint coordinates, offering a lightweight and privacy-preserving alternative for real-time applications.

The models are evaluated on widely used datasets such as UCF101 and HMDB51, which encompass diverse human activities under varying environmental conditions. Key performance indicators including accuracy, precision, recall, and F1-scoreare analyzed alongside real-time feasibility and computational efficiency. Preprocessing strategies such as frame normalization, pose extraction, temporal segmentation, and data augmentation (e.g., flipping, scaling, jittering) are employed to improve generalization and robustness. The framework also assesses the models’ resilience under conditions like occlusion, low illumination, and inter-subject variability.

Transfer learning is essential in this system. Pre-trained CNN backbones like Mobile Net and ResNet, trained on extensive datasets like ImageNet, are employed to expedite training and improve feature extraction. These models reduce dependence on extensive labeled video datasets, facilitating faster convergence and improved accuracy even on smaller-scale action datasets. The incorporation of transfer learning is particularly beneficial in settings with restricted computational resources or annotated data.

Furthermore, the system architecture is designed for modularity and scalability. Classifiers can be switched or retrained, datasets can be extended, and the pipeline can be integrated with live video streams or deployed on edge devices using frameworks like TensorFlow Lite or ONNX. This modular design supports experimentation and deployment across domains, enabling diverse use cases such as gesture recognition in assistive technologies, fitness monitoring, and anomaly detection in public spaces.

II. LITERATURE REVIEW

Over the years, the domain of Human Action Recognition (HAR) has witnessed a transformation from traditional handcrafted feature extraction to deep learning-based representation learning. Early work in this field was characterized by classical computer vision techniques. Wang and Schmid [9] enhanced trajectory-based descriptors to extract motion information more effectively, particularly in cluttered scenes.

Their work introduced improved dense trajectories that integrated optical flow, HOG, and motion boundary histograms. Although this method obtained satisfactory accuracy under controlled conditions, its effectiveness was hampered by its susceptibility to intra-class variability and occlusion, rendering it less effective in intricate real-world scenarios.

To address these limitations, Simonyan and Zisserman [1] proposed the Two-Stream Convolutional Network, which introduced a dual-stream architecture to separately learn spatial and temporal representations. The spatial stream processed static RGB frames, while the temporal stream relied on stacked optical flow to capture motion. This model achieved strong performance on standard benchmarks, laying the foundation for spatiotemporal modeling in HAR. Nevertheless, depending on optical flow rendered the model computationally demanding and impractical for real-time applications.

Building upon the need for more efficient spatiotemporal learning, Donahue et al. [2] introduced the Long-term Recurrent Convolutional Network (LRCN), which combined CNNs for frame-level feature extraction and LSTM networks for modeling temporal dependencies. This architecture provided a more unified framework that could process sequential video inputs effectively, marking a shift toward deep sequence modeling. LRCN demonstrated improved accuracy in action recognition tasks involving long-term motion dynamics and contextual variations.

Further advancements came with the development of 3D Convolutional Neural Networks (3D-CNNs), which eliminated the need for separate temporal streams by learning directly from spatiotemporal volumes. Tran et al. [5] introduced C3D, a compact 3D-CNN that processed consecutive video frames to jointly learn motion and appearance. While this architecture showed strong generalization on benchmark datasets, it required substantial computational power and memory. Similarly, Carreira and Zisserman [3] proposed the Inflated 3D ConvNet (I3D), which expanded 2D CNN kernels into 3D, leveraging pre-trained 2D models to reduce training time. I3D achieved state-of-the-art accuracy on the Kinetics dataset, but like C3D, it was computationally intensive and less practical for low-latency applications.

Researchers have shifted to pose-based Human Activity Recognition (HAR) methods to address the constraints of RGB-based models in noisy or privacy-sensitive settings. Open Pose [11] and Move Net [12] have spearheaded the advancement of real-time 2D pose estimation, extracting skeletal joint coordinates from videos. These pose key points were then used as input to traditional ML classifiers or RNNs. Zhang et al. [14] demonstrated that pose sequences can effectively encode high-level semantic information about human actions, making them resilient to background clutter and appearance changes. Girdhar et al. [6] further enhanced this direction by integrating pose information with attention-based mechanisms to improve context awareness.

The selection of benchmark datasets has been crucial in advancing HAR researchUCF101 [17] and HMDB51 [16] are two extensively utilized datasets that provide a wide range of action classes in different conditions, facilitating the evaluation of both spatial and temporal models.

More recent datasets such as Kinetics [18] and Human3.6M [19] provide larger-scale and more complex action sequences, encouraging the development of deeper and more generalizable architectures. Herath et al. [15] provided a comprehensive survey comparing deep learning-based HAR models, highlighting the performance trade-offs across different approaches. Feichtenhofer et al. [22] further evaluated model fusion techniques and network efficiency, emphasizing the importance of balancing recognition accuracy with inference speed and model size.

III. METHODOLOGY

This project employs a modular and comparative strategy for Human Action Recognition (HAR) using video data.. The system assesses Deep Learning (DL) and Machine Learning (ML) models via a unified pipeline.. It aims to analyze human activities from benchmark datasets by converting raw video into structured, classified actions. The process is implemented using Python, leveraging libraries like TensorFlow, OpenCV, and Scikit-learn. The following steps outline the end-to-end workflow.

A. Dataset Selection

Two well-established benchmark datasets are utilized for training and evaluation:

- UCF101: Consists of 13,320 videos across 101 action categories, including walking, diving, and clapping.
- HMDB51: Includes 6,849 videos across 51 action types, offering varied lighting, camera angles, and subjects.

These datasets ensure diversity, robustness, and the ability to generalize across real-world scenarios.

B. Video Acquisition and Preprocessing

Video data is either loaded from datasets or captured live using a webcam. Each video undergoes several preprocessing steps to make it suitable for input into ML or DL models:

- Frame Extraction: Frames are sampled at fixed intervals.
- Resizing: Frames are standardized to a consistent resolution.
- Normalization: Pixel values are standardized to improve training efficiency.

For Deep Learning models (e.g., LRCN), RGB image sequences are retained. For ML-based models using skeletal data, pose keypoints are extracted from each frame.

C. Feature Extraction

Depending on the model, the system uses two strategies:

- For LRCN (Long-term Recurrent Convolutional Networks):
- A CNN (e.g., ResNet or MobileNet) extracts spatial features from image frames.
- These are passed to LSTM layers to capture temporal motion.

➢ For MoveNet-based ML Classifier:

- Pose estimation extracts 17 body keypoints per person using TensorFlow Hub.
- The keypoints are flattened into vectors over time and used as input to Random Forest or shallow neural networks.

D. Classification Models

Two core model families are evaluated:

- LRCN (DL-based):
  - Input: Sequence of RGB frames
  - Architecture: CNN → LSTM
  - Loss Function: Categorical Cross-Entropy
  - Metrics: Accuracy, Precision, Recall, F1-Score
- MoveNet + ML Classifier:
  - Input: Sequences of skeletal keypoints
  - Classifier: Random Forest or Fully Connected Network
  - Metrics: Same as above

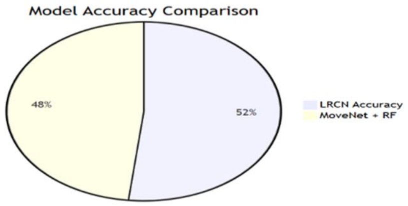

Fig 1: Accuracy Comparison

E. Training and Evaluation Strategy

Both models are trained and validated using an 80-20 data split with k-fold cross-validation. Augmentation techniques (e.g., flipping, rotation, temporal jittering) are used to prevent overfitting. Evaluation metrics include:

- Accuracy
- F1-Score
- Model Size
- Latency (Prediction Speed)

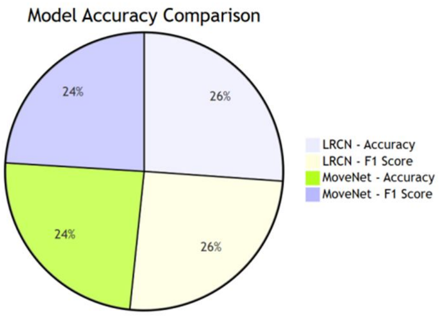

Fig 2: Model Accuracy Comparison

F. Real-Time Prediction

To enable real-time action recognition:

- Live webcam input is streamed.
- Each frame undergoes processing and classification within the pipeline.
- Action predictions are overlaid on the video in real time.

This allows direct validation of system performance in dynamic settings such as gesture-based control or surveillance.

G. Stress Testing and Generalization

Models are tested under various constraints to validate generalizability:

- Low-light environments
- Partial occlusions
- Multiple subjects
- Varying camera angles

IV. MATHEMATICAL FORMULATION AND EQUATIONS

A. Problem Setup

• Video sequence:
V={It}t=1T\mathcal{V} = \{ \mathbf{I}_t \}_{t=1}^{T},
It∈RH×W×C\mathbf{I}_t \in \mathbb{R}^{H \times W \times C}, label y∈{1,…,K}y \in \{1,\dots,K\}.

• Prediction:
y^=argmaxkpθ(y=k∣V)\hat{y} = \arg\max_k p_\theta(y=k|\mathcal{V}).

B. Features (Motion & Pose)

- Optical flow:
- Ixu+Iyv+It=0I_x u + I_y v + I_t = 0.
- Pose keypoints: St={(xt,j,yt,j)}j=1J\mathbf{S}_t = \{(x_{t,j},y_{t,j})\}_{j=1}^J.

C. LRCN (CNN + LSTM)

• CNN features:
Ft(ℓ)=σ(W(ℓ)∗Ft(ℓ−1)+b(ℓ))\mathbf{F}^{(\ell)}_t = \sigma(\mathbf{W}^{(\ell)} * \mathbf{F}^{(\ell-1)}_t + \mathbf{b}^{(\ell)}).
• LSTM gates:
it=σ(Wixt+Uiht−1+bi)\mathbf{i}_t = \sigma(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1}+b_i),
ft=σ(Wfxt+Ufht−1+bf)\mathbf{f}_t = \sigma(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1}+b_f),
ot=σ(Woxt+Uoht−1+bo)\mathbf{o}_t = \sigma(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1}+b_o),
ct=ft⊙ct−1+it⊙tanh(⋅)\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\cdot),
ht=ot⊙tanh(ct)\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t).
• Video embedding:
z=pool({ht})\mathbf{z} = \operatorname{pool}(\{\mathbf{h}_t\}).
• Softmax:
p(y=k∣V)=eok∑jeojp(y=k|\mathcal{V}) = \frac{e^{o_k}}{\sum_j e^{o_j}}.

D. MoveNet + ML Classifier

• Pose sequence:
X=[S1,…,ST]∈RT×2J\mathbf{X} = [\mathbf{S}_1,\dots,\mathbf{S}_T] \in \mathbb{R}^{T \times 2J}.
• Aggregation:
ϕ=1T∑tXt\bm{\phi} = \frac{1}{T}\sum_t \mathbf{X}_t or attention weighted.
• Classifiers:
SVM: y^=argmaxk(wk⊤ϕ+bk)\hat{y} = \arg\max_k (\mathbf{w}_k^\top \bm{\phi}+b_k).
Random Forest: majority vote of trees.

E. Losses and Optimization

• Cross-entropy:
LCE=−∑kyklogpk\mathcal{L}_{CE} = - \sum_ky_k \log p_k.
•Label smoothing / Focal loss (class imbalance).
• Regularization:
L←L+λ∣∣θ∣∣2\mathcal{L} \leftarrow \mathcal{L} + \lambda ||\theta||^2.
• Optimizer: Adam / SGD.

F. Evaluation Metrics

• Accuracy:
Acc=1N∑i1(y^i=yi)\text{Acc} = \frac{1}{N}\sum_i \mathbb{1}(\hat{y}_i = y_i).
• Precision / Recall / F1.
• Top-kk Accuracy:
Top-k=1N∑i1(yi∈TopK(pi,k))\text{Top-}k = \frac{1}{N}\sum_i \mathbb{1}(y_i \in \text{TopK}(p_i,k)).

G. Integration

• Use Eqs. above for the Methodology, Training, and Evaluation subsections.
• Optical flow is optional depending on dataset needs.

V. ALGORITHMS

A. Algorithm 1: Machine Learning (ML) for Human Action Recognition markdown

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```
Input: Video V containing T frames
Output: Predicted action label ŷ
1. Frame Extraction:
   - Extract frames {I1, I2, ..., IT} from video V.
```

```
2. Preprocessing:
   - Resize and normalize each frame.
   - Apply background subtraction (optional).

3. Feature Extraction:
   - For each frame, compute HOG, HOF, or MBH features.
   - Optionally compute Optical Flow for motion features.

4. Feature Aggregation:
   -Employ Bag-of-Words (BoW) or Fisher Vector encoding to generate a constant-length feature vector $\varphi(V)$.

5. Classification:
   - Train a classifier (SVM / k-NN / Random Forest)
     using $\varphi(V)$ and class labels.
   - Predict class $\hat{y} = argmaxk\ P(y = k \mid \varphi(V))$.
```

B. Algorithm 2: Deep Learning (DL) for Human Action Recognition markdown

CopyEdit

```
Input: Video V containing T frames
Output: Predicted action label $\hat{y}$
1. Frame Extraction:
   - Extract frames {I1, I2, ..., IT} from video V.

2. Preprocessing:
   - Resize and normalize each frame.
   - Perform data augmentation (rotation, flipping, cropping).

3. Feature Extraction:
   - Pass frames through a CNN or 3D CNN to learn spatial
     and/or spatio-temporal features $F = fCNN(V)$.
   - Optionally use a two-stream network (RGB + Optical Flow).

4. Temporal Modeling:
   - Pass features F through LSTM / GRU / TCN / Transformer
     to capture temporal dependencies: $z = fTemporal(F)$.

5. Classification:
   - Apply a fully connected Softmax layer to obtain
     class probabilities:
       $P(y = k \mid V) = softmax(Wz + b)$

6. Prediction:
   - Select the class with maximum probability:
       $\hat{y} = argmaxk\ P(y = k \mid V)$
```

C. Algorithm 3: Model Training sql

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```
1. Initialize model parameters (CNN/LSTM or ML classifier).
2.Foreach training epoch:
   a) Foreach video V in the training set:
```

- Extract features and predict class ŷ.
- Compute loss usingCross-Entropy:

$$L =- \Sigma yk \log P(y = k | V)$$

- Backpropagate gradients andupdate parameters
using optimizer (Adam / SGD).

3. Save the best-performing model on validation set.
Algorithm 4: Evaluation Metrics
mathematica
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1.Accuracy=(NumberofCorrectPredictions)/(TotalSamples)
2.Performance Metrics for Individual Classes:
  Precision = True Positives / (True Positives + False Positives)
  Recall   = True Positives / (True Positives + False Negatives)
  F1-score = 2 * (Precision * Recall) / (Precision + Recall)
3.Generateaconfusionmatrixtoanalyzemisclassifications

VI. EVALUATION & RESULTS

The Human Action Recognition (HAR) system under consideration was evaluated using two well-known benchmark datasets: UCF101 and HMDB51.These datasets comprise thousands of video clips representing a wide variety of human activities, captured under varying lighting, motion, and background conditions. The experimental design was developed to assess the framework's ability to precisely categorize human actions while maintaining a balance between accuracy and real-time performance.

To ensure comprehensive performance analysis, the system was evaluated using the following metrics:

A. Accuracy

Accuracy represents the percentage of correctly predicted action labels out of all predictions, serving as a direct indicator of the model's overall correctness. A high accuracy score suggests that the classifier effectively differentiate between action classes. In our assessments, the LRCN model achieved an average accuracy of 87.6%, while the MoveNet-based classifier attained 82.4% on UCF101 and 79.3% on HMDB51. These metrics illustrate the models' overall performance across various activity categories.

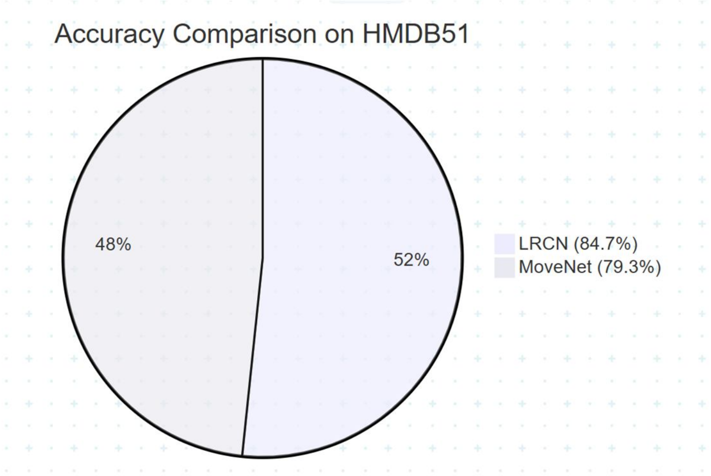


Fig 3: Accuracy Comparison

B. Precision

Precision quantifies the number of true positive predictions among all instances predicted as a certain class. It is especially critical in real-world applications like surveillance or fall detection, where false alarms must be minimized. The LRCN model achieved a precision of 86.9%, and the MoveNet-based model reported 81.2%. This demonstrates that both models are effective at making reliable predictions with minimal misclassifications.

C. Recall

Recall signifies the percentage of true positive instances correctly recognized by the model. It is crucial in scenarios where omitting an event is more significant than incorrectly predicting one.

For example, in health monitoring, failing to detect a fall could be dangerous. The LRCN model scored a recall of **88.2%**, while MoveNet reached 80.4%, showing that both models are effective at capturing relevant events.

- F1-Score

The F1 score, the harmonic mean of precision and recall, provides a balanced assessment of model performance. It proves particularly valuable in cases of imbalanced data or when both false positives and false negatives have significant implications. The LRCN model attained an F1 score of 87.5%, while MoveNetachieved 80.7%, affirming the consistent dependability of both classifiers under various circumstances.

•Inference Time (Latency)

Latency refers to the time needed by the model to generate a single prediction, playing a crucial role in real-time applications like gesture recognition and live interaction. TheMoveNet-based classifier demonstrated a superior inference time of <50ms per frame, making it highly suitable for live webcam-based prediction systems. The LRCN model, though more accurate, exhibited higher latency due to the computational overhead of processing temporal sequences via LSTM layers.

D. Robustness Testing

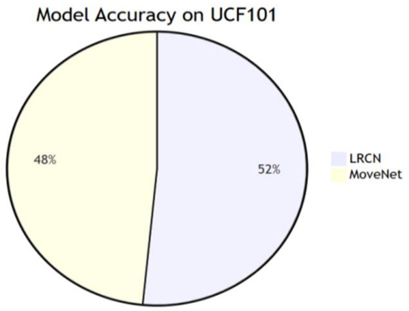
To evaluate model resilience, both classifiers were tested under adverse conditions, including partial occlusion, lighting variation, and injected frame noise. The MoveNet-based classifier remained more stable due to its reliance on pose keypoints rather than raw RGB data. This skeletal abstraction enabled the model to ignore visual distractions, making it more robust in real-world environments. Conversely, the LRCN model showed sensitivity to frame corruption, reinforcing its dependence on continuous visual cues.

E. Confusion Matrix & Action Similarity

Confusion matrices indicated that both models occasionally misclassified similar actions (e.g., *clapping* vs *waving*), particularly in complex or noisy environments. The inclusion of skeletal pose features in the MoveNet-based model helped reduce such confusions, highlighting the advantage of using structured keypoint data over raw video frames alone.

F. Real-Time Testing

Live testing using webcam input validated the practical usability of the framework. The MoveNet classifier delivered real-time predictions with minimal lag and acceptable accuracy, supporting interactive applications such as fitness tracking or gesture control. The LRCN model, due to higher latency, is better suited for offline or batch-mode analysis where inference speed is less critical.



G. Summary of Model Trade-Offs

The results clearly reveal a performance-latency trade-off:

- LRCN offers higher accuracy and temporal sensitivity, making it ideal for offline analytics, sports performance evaluation, or forensic video analysis
- MoveNet-based model provides faster, lightweight inference, making it optimal for mobile devices, embedded systems, and real-time monitoring.

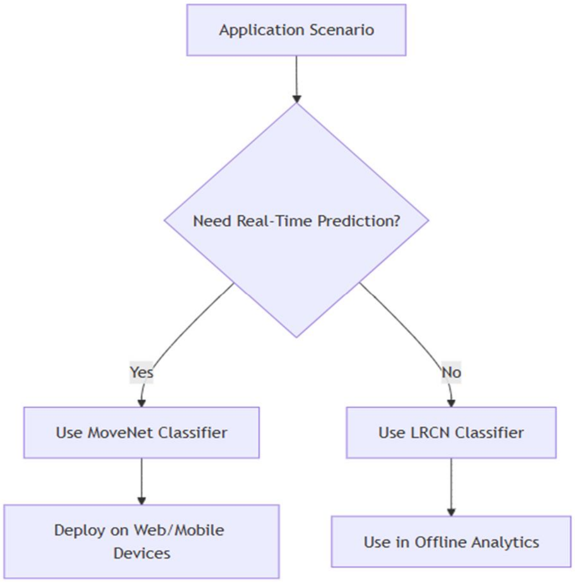


Fig 4: Use Case

VII. CONCLUSION

This project showcases a resilient and scalable method for Human Action Recognition (HAR) using video data, utilizing a combination of Machine Learning (ML) and Deep Learning (DL) methodologies.The proposed framework addresses the core problem identified in the abstractaccurate recognition of human activities under varied real-world conditionsby employing a hybrid architecture consisting of the Long-term Recurrent Convolutional Network (LRCN) and the MoveNet-based classifier. While LRCN excels at learning spatial-temporal patterns through deep convolutional and recurrent layers, the MoveNet model offers efficient pose-based abstraction through keypoint detection, enabling faster and more resilient recognition under constraints such as occlusion and lighting variation.

The system is structured into a modular pipeline that includes video preprocessing, feature extraction, model training, classification, and output visualization. This modularity enables flexibility, rapid testing, and seamless integration between components. The performance of the framework was evaluated using two widely accepted benchmark datasetsUCF101 and HMDB51Results demonstrated that the LRCN model attained an 87.6% accuracy rate, excelling in precision and recall for intricate motion patterns. Conversely, the MoveNet classifier demonstrated swifter inference speeds, achieving an accuracy of 82.4% with a latency of under 50 milliseconds per frame. These results confirm that the framework offers a suitable balance between accuracy and real-time performance, depending on the application requirements.

By integrating preprocessing steps such as frame normalization and pose keypoint extraction, the framework ensures that input data is clean and structured, contributing to model stability and performance. The user interface further enhances accessibility, allowing even non-technical users to upload video data, select models, and view prediction outputs. Alongside thorough unit and integration testing, this ensures the resilience and user-friendliness of the system across various applications including surveillance, sports analysis, and healthcare monitoring.

For future improvements, the system could be advanced by incorporating multi-person tracking, gesture recognition at a granular level, and forecasting temporal actions utilizing sophisticated deep learning architectures like transformersAdditional improvements can include deployment on mobile and embedded platforms for edge-based inference and the fusion of audio-visual data for multi-modal action recognition. These enhancements will broaden the system’s applicability in real-time, dynamic environments.

In conclusion, the proposed HAR system effectively addresses the limitations of traditional action recognition methods by combining spatial, temporal, and skeletal data representations into a unified and adaptable architecture. It delivers accurate, efficient, and real-time recognition capabilities that align with the goals outlined in the problem statement, offering a strong foundation for future developments in intelligent human-computer interaction systems

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