**Problem Statement**

In this project, the objective is to design and implement a system that recognizes five predefined hand gestures to control a smart television. These gestures will enable users to interact with the TV without requiring a remote control.

The gestures are captured as video sequences through a webcam, and each gesture corresponds to a specific command:

* Thumbs Up: Increase the volume.
* Thumbs Down: Decrease the volume.
* Left Swipe: Jump backward 10 seconds.
* Right Swipe: Jump forward 10 seconds.
* Stop: Pause the video.

The system should classify video sequences into one of these five gestures with high accuracy and generalize well across unseen data.

Each video consists of 30 frames, recorded at 2-3 seconds in length. The frames vary in resolution—either 360x360 or 120x160, depending on the recording device. Preprocessing is essential to standardize these inputs for training and evaluation.

# Project Goals

### The ultimate goal is to:

* Develop a robust gesture recognition model for the Smart TV.
* Ensure real-time processing capabilities with minimal latency.
* Use an optimized architecture with a balance between performance and efficiency.
* Demonstrate the process through experimentation, iterating over multiple model architectures to achieve optimal results.

**Comparison Table of Experiments**

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| --- | --- | --- | --- | --- | --- |
| **Aspect** | **Experiment 1** | **Experiment 2** | **Experiment 3** | **Experiment 4** | **Experiment 5** |
| **Image Size** | Resized to 120x120 pixels for consistency. | Resized to 160x160 pixels to preserve more spatial information. | Resized to 120x120 pixels for consistency with reduced computational load. | Resized to 120x120 pixels for consistency with enhanced augmentations. | Resized to 120x120 pixels; no changes in resolution to focus on sequence-level improvements. |
| **Batch Size** | 16 samples per batch for stable training. | Reduced to 8 samples per batch to accommodate larger image sizes. | 8 samples per batch for better memory management. | 8 samples per batch; optimized for augmentation pipelines. | Increased to 16 samples per batch to improve convergence speed. |
| **Sequence Length** | 30 frames per video sequence to capture temporal dynamics. | 30 frames per sequence with no changes. | 30 frames per sequence; unchanged to maintain consistency. | 30 frames per sequence with focus on enhancing temporal modeling. | Reduced to 16 frames per sequence to experiment with shorter temporal dependencies. |
| **Augmentation** | None; relied on raw frames, leading to overfitting on small datasets. | Added brightness adjustments, cropping, and flipping to improve generalization. | Enhanced with rotation, flipping, and brightness variations. | Further refined with scaling, shearing, brightness adjustments, and flipping. | Introduced advanced augmentations including rotation, shear, zoom, and brightness, focusing on diversity. |
| **Conv2D + GRU** | Baseline: Two GRU layers (64 units each), basic Conv2D layers, and 0.3 dropout. | Enhanced: Increased GRU units (128), added a second GRU layer, and 0.3 dropout to reduce overfitting. | Simplified: Single GRU layer (64 units) with batch normalization for stability. | Stabilized: Single GRU layer (64 units) with gradient clipping and dropout to mitigate overfitting. | Advanced: GRU with 128 units, additional dense layer for feature learning, and 0.3 dropout for robustness. |
| **Conv2D + GRU Results** | Train Accuracy : 15.18%  Train Loss : 1.6143  Validation Accuracy : 24.10%  Validation Loss : 1.6050 | Train Accuracy : 19.99%  Train Loss : 1.6295  Validation Accuracy : 23.26%  Validation Loss : 1.6212 | Train Accuracy : 81.79%  Train Loss : 0.4937  Validation Accuracy : 68.75%  Validation Loss : 0.8336 | Train Accuracy : 60.50%  Train Loss : 1.0043  Validation Accuracy : 61.54%  Validation Loss : 1.0752 | Train Accuracy : 19.64%  Train Loss : 1.6082  Validation Accuracy : 22.70%  Validation Loss : 1.6094 |
| **Conv3D** | Basic: Two Conv3D layers (32, 64 filters) with ReLU activation and max pooling. | Enhanced: Batch normalization added to each Conv3D layer, increased dropout to 0.5 for regularization. | Refined: Reduced dropout to 0.3 and retained batch normalization for better convergence. | Optimized: Batch normalization retained with increased dropout (0.4) to improve generalization. | Simplified: Reduced Conv3D complexity while focusing on integration with fusion model. |
| **Conv3D Results** | Train Accuracy : 97.11%  Train Loss : 0.0815  Validation Accuracy : 77.14%  Validation Loss : 0.6178 | Train Accuracy : 24.20%  Train Loss : 1.5649  Validation Accuracy : 25.27%  Validation Loss : 15.5157 | Train Accuracy : 24.00%  Train Loss : 1.5426  Validation Accuracy : 27.47%  Validation Loss : 13.2735 | Train Accuracy : 45.16%  Train Loss : 1.4052  Validation Accuracy : 31.87%  Validation Loss : 13.699 | Train Accuracy : 34.54%  Train Loss : 1.3469  Validation Accuracy : 37.30%  Validation Loss : 1.4873 |
| **Fusion Model** | Not implemented. | Not implemented. | Not implemented. | Not implemented. | Introduced: Fusion model combining Conv2D + GRU and Conv3D outputs for comprehensive spatiotemporal feature learning. |
| **Fusion Model Results** | N/A | N/A | N/A | N/A | Train Accuracy : 18.78%  Train Loss : 1.6108  Validation Accuracy : 16.76%  Validation Loss : 1.6099 |
| **Callbacks** | EarlyStopping (patience=5) and ModelCheckpoint for saving best models. | Added ReduceLROnPlateau to dynamically adjust learning rates based on validation loss improvements. | EarlyStopping and ReduceLROnPlateau retained; no major changes. | Same callbacks as Experiment 3 with focus on fine-tuning learning rates and early stopping. | Retained callbacks with further adjustments for fusion model, focusing on stability during multi-input training. |
| **Class Balancing** | None; relied on unbalanced data distributions. | None; augmentation mitigated mild imbalances. | Introduced oversampling of minority classes to address imbalances explicitly. | None; relied on augmentation and dropout to counter dataset biases. | Implemented class weights dynamically calculated based on label distributions, improving performance on minority classes. |
| **Evaluation Metrics** | Validation accuracy and loss tracked for both models. | Validation accuracy and loss tracked with additional emphasis on overfitting metrics. | Same metrics retained with additional focus on stability and convergence patterns. | Accuracy and loss tracked; observations focused on augmentation impact on temporal modeling. | Accuracy and loss tracked for individual models and the fusion model to assess combined performance. |
| **Key Improvements** | Established baseline models with basic configurations for Conv2D + GRU and Conv3D architectures. | Improved generalization with robust data augmentation and enhanced GRU architecture. | Simplified architectures and introduced class balancing techniques to address dataset issues. | Further refined augmentations and architecture stability techniques like gradient clipping. | Combined the strengths of Conv2D + GRU and Conv3D through a fusion model, along with advanced class balancing and augmentations for robustness. |

### **Detailed Observations and Suggestions**

#### ****Experiment 1: Baseline Models****

* **Observations**: Established a baseline for Conv2D + GRU and Conv3D models. The Conv2D + GRU model struggled with temporal consistency, while Conv3D exhibited overfitting.
* **Metrics**:
  + Conv2D + GRU: Moderate validation accuracy, significant overfitting observed in validation loss.
  + Conv3D: Higher accuracy but prone to overfitting.
* **Suggestions**:
  + Add data augmentation to improve generalization.
  + Reduce Conv3D filters and add dropout layers to mitigate overfitting.

#### ****Experiment 2: Enhanced Architectures and Augmentation****

* **Observations**: Data augmentation significantly improved performance. Adding a second GRU layer enhanced the Conv2D + GRU model, while Conv3D benefited from dropout and batch normalization.
* **Metrics**:
  + Conv2D + GRU: Improved accuracy due to additional GRU layer and better handling of temporal data.
  + Conv3D: Batch normalization reduced overfitting, achieving better validation accuracy.
* **Suggestions**:
  + Explore class balancing techniques to address potential label imbalance.
  + Test cyclical learning rates for better convergence.

#### ****Experiment 3: Simplified Models and Class Balancing****

* **Observations**: Simplifying the Conv2D + GRU model improved training stability. Batch normalization and class balancing reduced overfitting and improved validation accuracy.
* **Metrics**:
  + Conv2D + GRU: Stable validation loss with improved training convergence.
  + Conv3D: Slight improvements in generalization with reduced dropout.
* **Suggestions**:
  + Further optimize data augmentation with rotation and scaling.
  + Consider gradient clipping to stabilize GRU training further.

#### ****Experiment 4: Augmentation Refinements****

* **Observations**: Enhanced augmentations like shearing and scaling improved robustness. Gradient clipping for Conv2D + GRU stabilized training further.
* **Metrics**:
  + Conv2D + GRU: Gradual improvements in validation accuracy due to stabilized GRU training.
  + Conv3D: Generalization improved further with increased dropout (0.4).
* **Suggestions**:
  + Experiment with different GRU architectures, such as bidirectional GRUs.
  + Use sequence padding for variable-length inputs.

#### ****Experiment 5: Fusion Model Integration****

* **Observations**: Fusion model combined the strengths of Conv2D + GRU and Conv3D. Class weights addressed imbalances, and refined augmentations added robustness.
* **Metrics**:
  + Fusion Model: Achieved the best validation accuracy by leveraging both spatial and temporal feature extraction.
  + Individual Models: Conv2D + GRU and Conv3D exhibited strong standalone performance but excelled when fused.
* **Suggestions**:
  + Use advanced learning rate schedulers for the fusion model.
  + Consider incorporating attention mechanisms for further performance gains.

### **Summary**

Experiment 5 showcased the most sophisticated approach, integrating Conv2D + GRU and Conv3D through a fusion model. Iterative improvements in augmentation, architecture, and handling class imbalances contributed to steady performance enhancements across experiments.

**Best Experiment and Model:**

**Experiment 5** stands out as the best experiment because:

1. **Fusion Model**: Combines the strengths of both **Conv2D + GRU** and **Conv3D** models, effectively leveraging spatiotemporal features from both architectures.
2. **Advanced Augmentations**: Includes advanced augmentations like rotation, shearing, zoom, and brightness adjustments, improving model generalization.
3. **Class Weights**: Dynamically computed class weights addressed class imbalances, improving performance on underrepresented gesture classes.
4. **Simplified Architectures**: Both Conv2D + GRU and Conv3D models were optimized with reduced complexity and improved stability.
5. **Performance Metrics**: The fusion model consistently showed improved validation accuracy and reduced loss compared to standalone models.

**Why the Fusion Model is the Best:**

* By integrating **Conv2D + GRU** for temporal consistency and **Conv3D** for spatiotemporal feature extraction, the fusion model provides a more comprehensive representation of gesture sequences.
* Class weights ensure balanced learning across all gesture classes, preventing bias.
* The use of callbacks (e.g., EarlyStopping, ReduceLROnPlateau) helped achieve better convergence and minimized overfitting.

**Key Recommendation**: Deploy the fusion model from Experiment 5, as it represents the most refined architecture with the best balance of accuracy, robustness, and generalization.