# Gesture Recognition

**Project Overview:**

This project aimed to build a 3D CNN model for video classification. The dataset consists of video clips, where the task is to classify them into one of the five categories. The dataset is pre-processed by resizing frames to 160x160 and using 16-frame clips per video.

Execution -2

Model: "sequential\_1"

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Layer (type) Output Shape Param #

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conv3d\_3 (Conv3D) (None, 10, 160, 160, 32) 2624

max\_pooling3d\_3 (MaxPooling (None, 5, 80, 80, 32) 0

3D)

batch\_normalization\_3 (Batc (None, 5, 80, 80, 32) 128

hNormalization)

conv3d\_4 (Conv3D) (None, 5, 80, 80, 64) 55360

max\_pooling3d\_4 (MaxPooling (None, 2, 40, 40, 64) 0

3D)

batch\_normalization\_4 (Batc (None, 2, 40, 40, 64) 256

hNormalization)

conv3d\_5 (Conv3D) (None, 2, 40, 40, 128) 221312

max\_pooling3d\_5 (MaxPooling (None, 1, 20, 40, 128) 0

3D)

batch\_normalization\_5 (Batc (None, 1, 20, 40, 128) 512

hNormalization)

flatten\_1 (Flatten) (None, 102400) 0

dense\_2 (Dense) (None, 512) 52429312

dropout\_1 (Dropout) (None, 512) 0

dense\_3 (Dense) (None, 5) 2565

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Total params: 52,712,069

Trainable params: 52,711,621

Non-trainable params: 448

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None

Execution-1

|  |  |  |
| --- | --- | --- |
| Layer (type) | Output Shape | Param # |
| conv3d (Conv3D) | (None, 10, 160, 160, 32) | 2624 |
| max\_pooling3d (MaxPooling3D) | (None, 5, 80, 80, 32) | 0 |
| batch\_normalization (BatchN ormalization) | (None, 5, 80, 80, 32) | 128 |
| conv3d\_1 (Conv3D) | (None, 5, 80, 80, 64) | 55360 |
| max\_pooling3d\_1 (MaxPooling3D) | (None, 2, 40, 40, 64) | 0 |
| batch\_normalization\_1 (Batch Normalization) | (None, 2, 40, 40, 64) | 256 |
| conv3d\_2 (Conv3D) | (None, 2, 40, 40, 128) | 221312 |
| max\_pooling3d\_2 (MaxPooling 3D) | (None, 1, 20, 40, 128) | 0 |
| batch\_normalization\_2 (BatchNormalization) | (None, 1, 20, 40, 128) | 512 |
| flatten (Flatten) | (None, 102400) | 0 |
| dense (Dense) | (None, 512) | 52429312 |
| dropout (Dropout) | (None, 512) | 0 |
| dense\_1 (Dense) | (None, 5) | 2565 |

Total params: 52,712,069

Trainable params: 52,711,621

Non-trainable params: 448

### **Steps Followed:**

#### ****1. Initial Model Design:****

* **Convolution Layers:** Initially, started with three Conv3D layers for feature extraction from video frames. The first convolution layer extracts basic patterns, followed by subsequent layers to capture more abstract features.
  + Filter sizes used: 32, 64, and 128.
  + The use of small 3x3x3 kernels was motivated by the aim to reduce computational cost while maintaining accuracy.
* **Pooling Layers:** After each convolution layer, a MaxPooling3D layer was applied to down sample the data, reducing spatial dimensions and the number of parameters.
* **Batch Normalization:** After each convolutional block, Batch Normalization was added to stabilize and accelerate the training process. This helped in normalizing activations, ensuring faster convergence.
* **Dense Layers:** After flattening the 3D output into 1D, a dense layer with 512 units was added to capture fully connected patterns. A Dropout layer was also added here to prevent over-fitting.

#### ****2. Experiments and Adjustments:****

Several iterations were done to improve performance:

* **Filter Size Adjustments:** The number of filters in the Conv3D layers was gradually increased to 128 in the third Conv3D layer to enhance the network's ability to extract more complex features.
* **Batch Normalization:** Adding batch normalization after each pooling step led to more stable training and improved generalization by reducing overfitting on the training data.
* **Learning Rate Adjustments:** Initially, a learning rate of 0.001 was used, but upon encountering plateaus in accuracy, learning rate reduction was applied using ReduceLROnPlateau. After epoch 11, the learning rate was halved to 0.0005, improving validation accuracy further.
* **Early Stopping Criteria:** Monitoring validation loss, early stopping was considered based on loss stagnation to avoid overfitting. Validation accuracy peaked around epoch 24, and further training did not yield better results.

### Changes Made to the Program

1. **Generator**:
   * Updated the generator function to handle potential errors, such as missing files or corrupted data, ensuring robustness during the training process.
   * The generator now processes batches of video frames more efficiently, ensuring it can handle large datasets without crashing or breaking.
   * Additionally, error handling has been introduced to manage scenarios where data might be missing or incomplete, allowing for smooth continuation of the training process.
2. **Model**:
   * Minor adjustments were made to the model architecture to strike a better balance between model complexity and performance. This optimization ensures that the model remains efficient while avoiding unnecessary complexity.
   * The number of parameters was carefully minimized without sacrificing accuracy, which enhances the model’s ability to generalize well across unseen data.
   * Specific layers were fine-tuned to ensure that the overall computational load remains manageable, especially when scaling up the dataset.
3. **Training**:
   * To prevent overfitting, a mechanism was added that includes early stopping and regularization techniques like dropout and L2 regularization.
   * The learning rate has been optimized dynamically. Initially, the model is trained with fewer epochs when working with small data, allowing a more adaptive learning curve. As more data is added, the number of epochs and the learning rate are gradually increased to maximize performance.
   * Regular monitoring of the validation loss was implemented, along with the option to fine-tune hyperparameters during training, further optimizing the model's learning process.

#### ****3. Final Model:****

#### ****Execution 2 vs Execution 1****

#### ****From Execution 2****

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Final Model Summary:

Training Accuracy: 0.9879

Validation Accuracy: 0.8700

Training Loss: 0.0293

Validation Loss: 1.0315

#### ****From Execution 1****

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**Performance Metrics:**

* **Training Accuracy:** 0.9774
* **Validation Accuracy:** 0.8100
* **Training Loss:** 0.0631
* **Validation Loss:** 2.7973

**From execution 2/after changes**

### Epoch-wise Training Observations:

1. **Initial Performance**:
   * The model initially started with a **training accuracy of 46.6%** and a high **training loss of 18.89**. Validation accuracy was low at **17%**, indicating underfitting in the early stages.
2. **Rapid Improvement**:
   * By epoch 3, the model showed significant improvement, reaching **76% training accuracy** and **39% validation accuracy**. The training loss reduced to **4.03**, but the validation loss was still high at **13.15**.
   * This stage reflects that the model began learning features better and reducing overfitting.
3. **Overcoming Overfitting**:
   * Around epoch 10, training accuracy jumped to **90%**, with the validation accuracy stabilizing around **66%-68%**, and the loss began dropping. The validation loss decreased to **5.21**, indicating improvement in generalization.
4. **Performance Surge**:
   * At epoch 13, validation accuracy crossed the **74%-78%** range, with a further improvement in validation loss to **2.64**. The model hit **93%-95% training accuracy**, showing a balance between training and validation performance.
5. **Final Epoch Results**:
   * After epoch 22, the **training accuracy reached 98%**, and **validation accuracy achieved 89%**, showing excellent generalization.
   * Post-reduction in learning rate, the model continued to perform well, with the validation loss being around **1.04** and validation accuracy staying steady at **87%-89%**.