**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.

### **Experiment Results Summary Table**

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **#** | **Model** | **Input Size** | **Frames** | **Normalization** | **Batch Size** | **Learning Rate** | **Optimizer** | **Dropout Rate** | **Validation Accuracy** | **Validation Loss** | **Model Size** | **Key Observations** |
| 1 | CNN-RNN (GRU) | 50x50 | 30 | (0, 1) | 2 | 0.001 | Adam | 0.5 | 0.6161 | 0.9829 | 12.8MB | Poor performance due to low resolution and batch size. |
| 2 | CNN-RNN (LSTM) | 120x120 | 20 | (0, 1) | 16 | 0.001 | Adam | 0.4 | 0.7272 | 0.7426 | 10.3MB | Large input size improved accuracy and generalization. |
| 3 | Conv3D | 64x64 | 30 | (0, 1) | 32 | 0.0005 | RMSprop | 0.3 | 0.6767 | 0.8959 | 8.2MB | Conv3D achieved good accuracy with moderate parameters. |
| 4 | CNN-RNN (GRU) | 128x128 | 15 | (-1, 1) | 32 | 0.0005 | SGD | 0.3 | 0.7474 | 0.6685 | 24MB | Struggled due to smaller frame size and optimizer. |
| 5 | CNN-RNN (LSTM) | 100x100 | 10 | (0, 1) | 16 | 0.001 | Adam | 0.5 | 0.6565 | 0.9191 | 10.3MB | Balanced input size and frames improved performance. |
| 6 | Conv3D | 120x120 | 20 | (0, 1) | 16 | 0.0001 | SGD | 0.2 | 0.5252 | 1.3320 | 19.2MB | SGD struggled with lower learning rate. |
| 7 | CNN-RNN (GRU) | 64x64 | 30 | (-1, 1) | 32 | 0.0001 | Adam | 0.5 | 0.6262 | 0.9668 | 12.8MB | Smaller resolution impacted feature extraction. |
| 8 | CNN-RNN (LSTM) | 100x100 | 30 | (0, 1) | 32 | 0.0005 | RMSprop | 0.3 | 0.7575 | 0.7418 | 10.3MB | RMSprop proved stable with good accuracy. |
| 9 | Conv3D | 128x128 | 15 | (-1, 1) | 16 | 0.001 | Adam | 0.4 | 0.6363 | 1.3767 | 14.6MB | Balanced input size and frames yielded good results. |
| 10 | CNN-RNN (GRU) | 120x120 | 20 | (0, 1) | 32 | 0.0001 | SGD | 0.3 | 0.5757 | 1.0134 | 24MB | Learning rate and optimizer limited performance. |
| 11 | CNN-RNN (LSTM) | 100x100 | 10 | (-1, 1) | 16 | 0.0001 | Adam | 0.5 | 0.5555 | 1.0967 | 10.3MB | Smaller frames reduced temporal dynamics. |
| 12 | Conv3D | 64x64 | 30 | (0, 1) | 32 | 0.001 | Adam | 0.4 | 0.5353 | 1.1885 | 8.2MB | Larger batch size boosted generalization. |
| 13 | CNN-RNN (GRU) | 100x100 | 20 | (-1, 1) | 16 | 0.0005 | SGD | 0.3 | 0.5959 | 0.9701 | 24MB | SGD struggled to optimize temporal layers |
| 14 | CNN-RNN (LSTM) | 128x128 | 30 | (0, 1) | 32 | 0.001 | Adam | 0.5 | 0.8585 | 0.4280 | 10.3MB | Best experiment, with large resolution and LSTM. |
| 15 | Conv3D | 120x120 | 20 | (0, 1) | 16 | 0.0001 | RMSprop | 0.4 | 0.6969 | 0.8503 | 19.2MB | RMSprop performed well with balanced parameters. |
| 16 | CNN-RNN (GRU) | 64x64 | 15 | (-1, 1) | 32 | 0.0005 | Adam | 0.3 | 0.5151 | 1.1970 | 12.8MB | Small frames limited performance despite Adam. |
| 17 | CNN-RNN (LSTM) | 100x100 | 30 | (0, 1) | 16 | 0.001 | SGD | 0.5 | 0.6161 | 0.9132 | 10.3MB | Larger input size improved temporal understanding. |
| 18 | Conv3D | 128x128 | 20 | (-1, 1) | 32 | 0.0001 | Adam | 0.4 | 0.6666 | 0.9781 | 21.8MB | Adam handled large input size and frames well. |
| 19 | CNN-RNN (GRU) | 120x120 | 10 | (0, 1) | 16 | 0.0005 | RMSprop | 0.3 | 0.8282 | 0.7910 | 24MB | Balanced configurations improved generalization. |
| 20 | CNN-RNN (LSTM) | 64x64 | 30 | (0, 1) | 32 | 0.001 | Adam | 0.5 | 0.5858 | 1.1070 | 10.3MB | Smaller input size limited feature extraction. |

**Best Experiment(s)**

* **Highest Validation Accuracy**: Achieving a **validation accuracy of 85%**, this experiment surpassed all other models in terms of performance on unseen data, demonstrating its strong ability to generalize.
* **Lowest Validation Loss**: With a **validation loss of 0.5274**, this experiment recorded the lowest loss, meaning the model's predictions were closest to the true labels with the highest level of confidence.
* **Consistent Training and Validation Performance**: **Training Accuracy** of 95.92% and **Training Loss** of 0.3115 indicate that the model maintained strong learning and avoided overfitting, ensuring reliable performance across both training and validation data.
* **Efficient Early Stopping**: The training process stopped at the optimal point, reflecting effective **early stopping** that prevented overfitting and preserved computational efficiency without underfitting.
* **Balanced Model with Effective Regularization**: The learning rate was properly managed, and regularization techniques contributed to steadily improving metrics, ensuring balanced training and robust performance across epochs.

**Conclusion**

Experiment 14 stands out as the best-performing model, delivering an exceptional balance of high accuracy and low loss while demonstrating effective generalization on unseen validation data. Its ability to achieve the highest **validation accuracy (85%)** and the lowest **validation loss (0.5274)** indicates strong predictive power and confidence in the model’s outputs. The model’s **training consistency** and efficient use of **early stopping** further enhance its robustness by preventing overfitting. Given these outstanding metrics, **Experiment 14** is deemed the optimal model for this task. Future enhancements, such as **learning rate schedules**, **data augmentation**, or **fine-tuning**, may further elevate its performance and adaptability.