BASIC CNN AND RESNET50 PERFORMANCE COMPARISON ON SMALL DATASET

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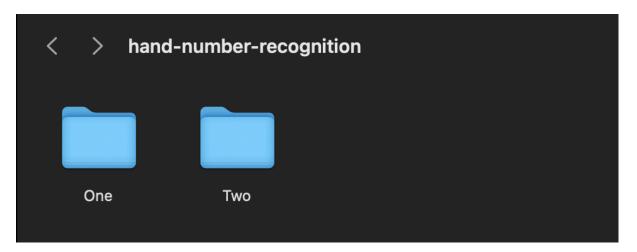
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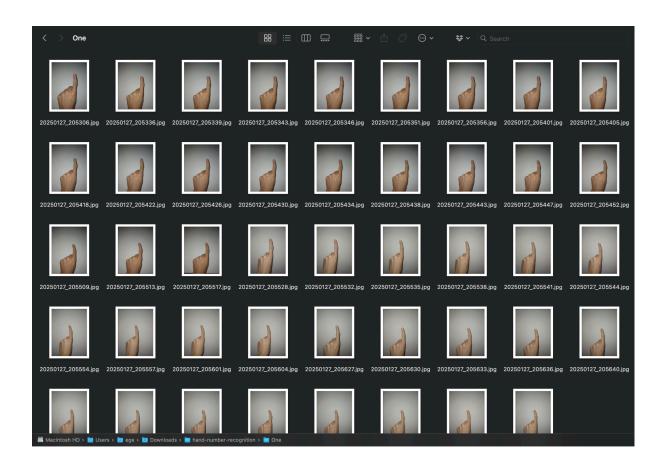
Introduction

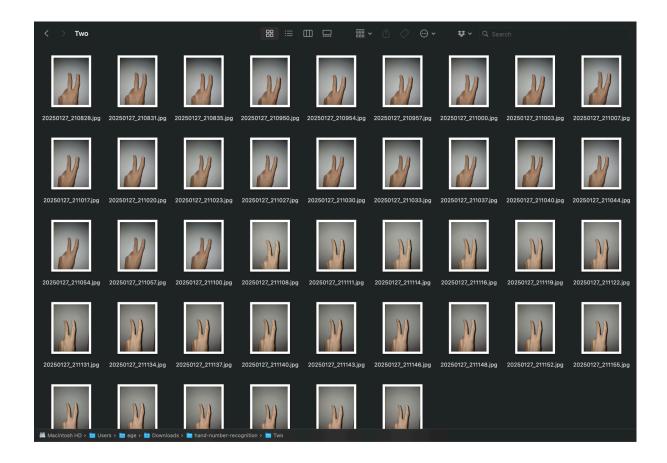
In this project we will compare two Convolutional Neural Networks' performance on small dataset: a basic 7-layer CNN model and the ResNet50 which were trained to recognize hand gestures representing the numbers 1 and 2.

Data Collection

The dataset for this project was created by manually gathering images corresponding to the two classes under study. Images were captured using a smartphone camera and organized into two folders, each representing a class. The images were preprocessed to have a consistent size and format suitable for input into both models. To improve the robustness of the dataset, data augmentation techniques such as rotation and flipping were applied, increasing the diversity of training samples.







Model Design

Basic CNN Model

The first model is a sequential CNN with the following architecture:

1. Convolutional Layers:

- Layer 1: 32 filters, 3x3 kernel, ReLU activation, followed by 2x2 max pooling.
- Layer 2: 64 filters, 3x3 kernel, ReLU activation, followed by 2x2 max pooling.
- Layer 3: 128 filters, 3x3 kernel, ReLU activation, followed by 2x2 max pooling.
- Layer 4: 128 filters, 3x3 kernel, ReLU activation, followed by 2x2 max pooling.
- Layer 5: 128 filters, 3x3 kernel, ReLU activation, followed by 2x2 max pooling.
- 2. **Flattening Layer**: Converts the 3D feature maps into a 1D vector.

3. Dense Layers:

- Dense Layer 1: 64 units with ReLU activation.
- Dense Layer 2: Output layer with 1 unit and sigmoid activation for binary classification.

ResNet50 Model

The second model uses the pre-trained ResNet50 model as a feature extractor. It consists of:

- 1. **Pretrained Model**: The ResNet50 architecture pre-trained on the ImageNet dataset.
- 2. **Global Average Pooling Layer**: Reduces the dimensionality of feature maps from the ResNet50 output.
- 3. **Prediction Layer**: A dense layer with 1 unit and sigmoid activation for binary classification.

The ResNet50-based model leverages transfer learning to adapt the pre-trained weights to the dataset at hand.

Training

Training and validation sets were split from the dataset. 80% of data is used for training, 20% of the data used for validation. Followings are used at training process:

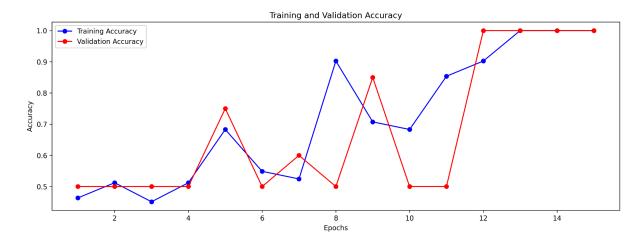
Batch size: 16Epochs: 15

• Loss Function: Binary cross-entropy

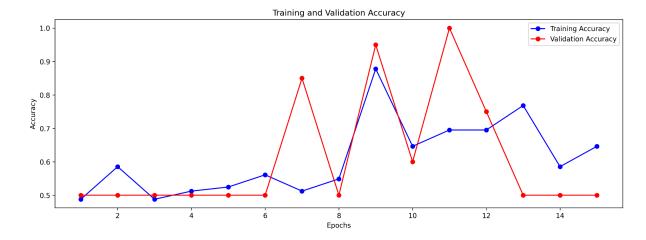
• Optimizer: Adam

Results

Accuracy:

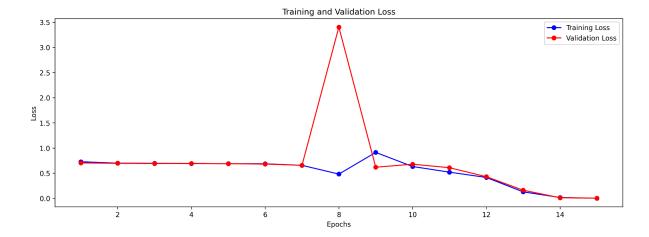


Accuracy of Basic CNN

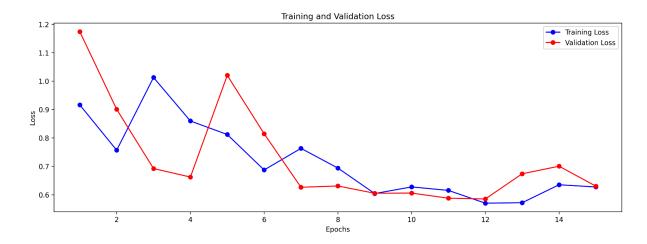


Accuracy of ResNet50

Loss:

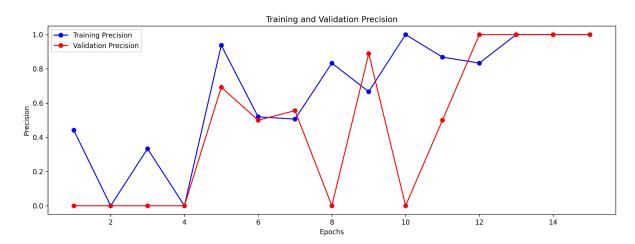


Loss of Basic CNN

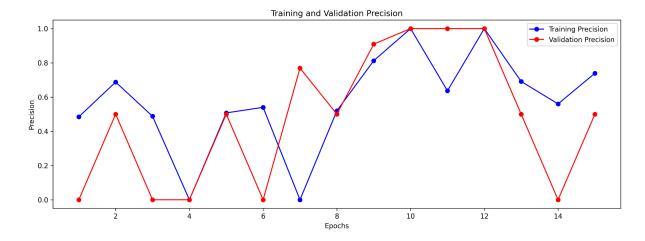


Loss of ResNet50

Precision:

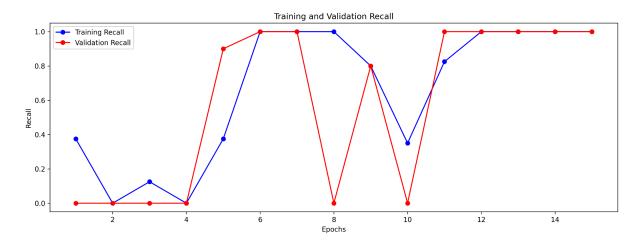


Precision of Basic CNN

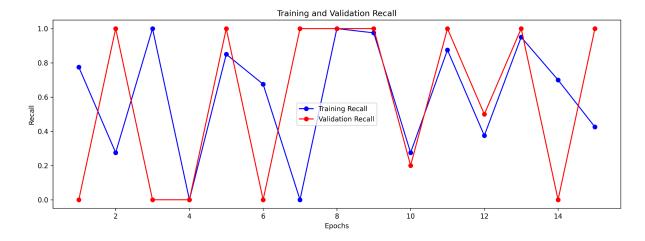


Precision of ResNet50

Recall:



Recall of Basic CNN



Recall of ResNet50

Conclusion

We can observe that the basic CNN demonstrates greater stability and achieves better accuracy for this specific task compared to ResNet50. This suggests that the simpler architecture of the basic CNN is more effective at capturing the dataset's features.