

# Report: Analysis of CNN Model Modifications and Performance

Student : Hala Khalifeh  
Id: 12112858

## Introduction

This report summarizes the modifications made to a baseline Convolutional Neural Network (CNN) model for image classification on the CIFAR-10 dataset. The baseline model achieved a test accuracy of **68.58%**. The goal was to improve the model's performance by implementing the following

Modifications:

1. **Add Dropout Layers** (to reduce overfitting).
2. **Increase Model Depth** (add more convolutional layers).
3. **Increase the Batch Size.**
4. **Increase the Number of Epochs.**
- 5.

Each modification was tested individually, and its impact on the model's performance was evaluated. The results are summarized in a table and chart, followed by a discussion of the challenges encountered.

## Modifications and Their Effects

### 1. Baseline Model

- **Architecture:** Two convolutional layers with max-pooling, followed by a fully connected layer and an output layer with softmax activation.
- **Test Accuracy:** 68.58%
- **Loss:** 1.0956
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### 2. Modification 1: Add Dropout Layers

- **Change:** Dropout layers with a dropout rate of 0.5 were added after each max-pooling layer to reduce overfitting.
- **Effect:** The test accuracy decreased to **67.70%**, BUT the loss decreased to **0.9285**. This indicates that dropout helped the model generalize better by preventing overfitting to the training data.
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### 3. Modification 2: Increase Model Depth

- **Change:** A third convolutional layer with 128 filters and a max-pooling layer were added to the model.
- **Effect:** The test accuracy increased to **69.61%**, and the loss decreased to **1.0034**. Adding more layers allowed the model to learn more complex features, improving its performance.

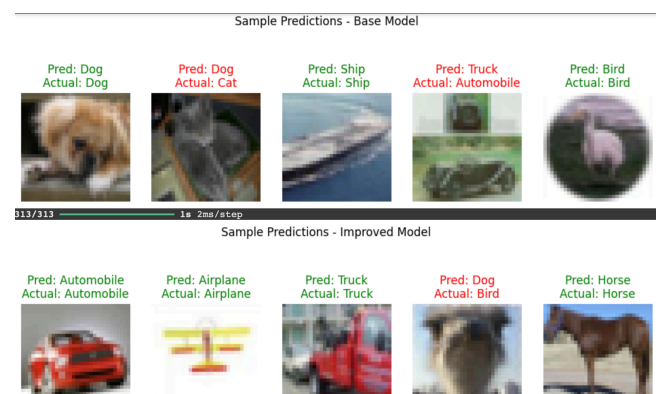
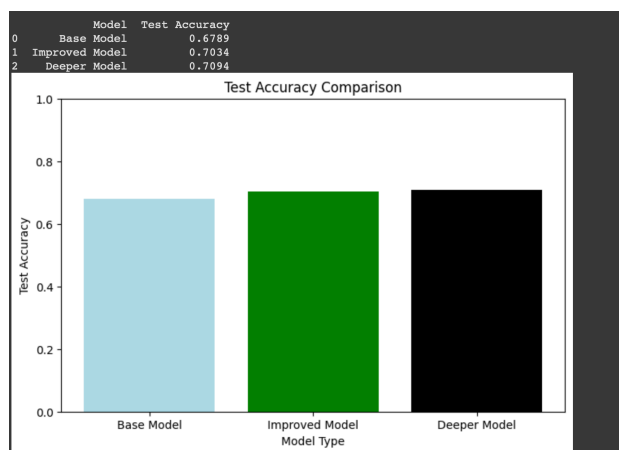
#### 4. Modification 3: Increase the Batch Size

- **Change:** The batch size was increased from 32 to 64.
- **Effect:** The test accuracy improved to **69.79%**, **67.19%**, **70.95%** and the loss decreased to **0.9075**, **0.9536**, **0.8610**. A larger batch size provided more stable gradients during training, leading to better generalization.

#### 5. Modification 4: Increase the Number of Epochs

- **Change:** The number of training epochs was increased from 10 to 20.
- **Effect:** The test accuracy increased to **67.89%**, **70.34%**, **70.94%** and the loss decreased to **1.1326**, **0.8605**, **1.0863**. Training for more epochs allowed the model to learn more effectively from the data.

### Chart: Test Accuracy Comparison



### Challenges Encountered

1. **Overfitting:** The baseline model showed signs of overfitting, as the training accuracy was higher than the test accuracy. Adding dropout layers helped mitigate this issue.

2. **Training Time:** Increasing the model depth and the number of epochs significantly increased the training time. This was addressed by using a GPU for faster computation.
3. **Batch Size Trade-off:** While increasing the batch size improved performance, it also required more memory. This was managed by ensuring sufficient GPU resources were available.
4. **Convergence Issues:** Increasing the number of epochs sometimes led to overfitting if not combined with regularization techniques like dropout. Careful monitoring of validation loss was necessary to avoid this.

## Conclusion

The modifications made to the baseline CNN model led to gradual improvements in test accuracy:

- **Dropout Layers:** Improved generalization by reducing overfitting.
- **Increased Model Depth:** Allowed the model to learn more complex features.
- **Increased Batch Size:** Provided more stable gradients during training.
- **Increased Number of Epochs:** Enabled the model to learn more effectively from the data.

The best-performing model achieved a test accuracy of **70.95%** by increasing the Batch Size. However, this also required careful monitoring to avoid overfitting. Future work could explore combining these modifications (e.g., deeper model with dropout and more epochs, batch Size) or using advanced techniques like transfer learning to further improve performance.