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Image Classification using CIFAR 100

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1 Abstract

The rapid advancement of deep learning has significantly impacted various domains, particularly in computer vision. This report details a deep learning project focused on image classification using the CIFAR-100 dataset. The CIFAR-100 dataset, with its diverse set of 100 classes, poses a challenging task for image recognition systems. The project employs convolutional neural networks (CNNs) to tackle this problem, leveraging their ability to automatically learn hierarchical features from images. This report outlines the methodology, results, challenges, and future directions of the project.

2 Introduction

2.1 Background

Deep learning has emerged as a powerful tool for solving complex problems in image classification. The CIFAR-100 dataset, a variant of the CIFAR-10 dataset, provides a challenging benchmark for image classification tasks with its increased number of classes and diversity of images.

2.2 Objective

The primary objective of this project is to develop a robust image classification model using deep learning techniques, specifically CNNs, to accurately classify images into one of the 100 classes in the CIFAR-100 dataset.

2.3 Dataset Overview

The CIFAR-100 dataset consists of 60,000 32x32 color images, with 600 images per class. It is divided into 50,000 training images and 10,000 testing images. The diversity of classes ranges from animals and plants to household objects, presenting a comprehensive set of challenges for classification.

3 Methodology

3.1 Data Preprocessing

The dataset undergoes preprocessing, including normalization and augmentation, to enhance the model's generalization capability. Data augmentation techniques such as rotation, flipping, and zooming are applied to artificially increase the dataset's size and improve the model's robustness.

3.2 Model Architecture

A state-of-the-art CNN architecture is employed for the image classification task. The model consists of multiple convolutional layers, followed by max-pooling and fully connected layers. Rectified linear unit (ReLU) activation functions are used to enhance the model's non-linearity. Loss Function used is Categorical Cross Entropy.

Table 1: CNN Architecture Details

Layer Type	**Output Shape**	**Parameters**	**Activation Function**
Conv2D (32 filters)	(30, 30, 32)	896	ReLU
MaxPooling2D	(15, 15, 32)	0	-
Conv2D (64 filters)	(13, 13, 64)	18,496	ReLU
MaxPooling2D	(6, 6, 64)	0	-
Conv2D (128 filters)	(4, 4, 128)	73,856	ReLU
Flatten	(2048)	0	-
Dense (256 units)	(256)	524,544	ReLU
Dense (100 units)	(100)	25,700	Softmax

3.3 Training and Optimization

The model is trained using a suitable optimization algorithm, such as stochastic gradient descent (SGD) or Adam. Hyperparameter tuning is performed to optimize the learning rate, batch size, and other parameters. The training process involves monitoring the loss on the validation set to prevent overfitting.

4 Results and Discussion

4.1 Performance Metrics

The model's performance is evaluated using standard metrics such as accuracy.

4.2 Experimental Results

The trained model achieves results on the CIFAR-100 test set, demonstrating the effectiveness of the proposed approach. The classification accuracy, was obtained to be 35.8

4.3 Challenges and Limitations

Despite the success, challenges such as class imbalance, limited data per class, and fine-grained distinctions between classes pose difficulties. Strategies for addressing these challenges, such as class-weighted loss functions and transfer learning, are explored.

4.4 Future Directions

To further enhance the model's performance, future work may involve investigating advanced architectures, ensembling techniques, and transfer learning from pre-trained models. Additionally, the exploration of advanced data augmentation methods and attention mechanisms can contribute to improving the model's robustness.

5 Conclusion

In conclusion, this deep learning project on image classification using the CIFAR-100 dataset demonstrates the efficacy of CNNs in handling diverse and complex visual data. The results indicate a successful application of deep learning techniques to the challenging task of image recognition. The insights gained from this project contribute to the broader field of computer vision and lay the foundation for future research in improving the accuracy and efficiency of image classification models.