

Project Overview

The project involves developing a machine learning model for image classification using the CIFAR-100 dataset. The CIFAR-100 dataset is a collection of 60,000 32x32 color images in 100 classes, with 600 images per class. The goal is to train a model that can accurately classify these images into their respective classes.

Model Development

The initial approach involved building a Convolutional Neural Network (CNN) from scratch. The model architecture included several layers such as Conv2D, BatchNormalization, MaxPool2D, Dropout, and Dense layers. Despite the complex architecture and the use of techniques such as batch normalization and dropout to prevent overfitting, the model's performance was not satisfactory.

To improve the model's performance, transfer learning was then employed using the ResNet50 architecture. The last five layers of the ResNet50 model were retrained, and two Dense layers were added at the end. Despite these modifications, the model still did not yield the desired improvements in accuracy.

Cross-Validation

To further enhance the model's performance, K-Fold Cross Validation was implemented. This technique involves dividing the dataset into 'k' subsets and training the model 'k' times, each time using a different subset as the validation set. This method is often used to get a more robust estimate of model performance.

However, even after implementing K-Fold Cross Validation, the model's performance did not improve significantly. The model achieved high accuracy on the training data but did not generalize well to unseen data, indicating overfitting.

Conclusion and Future Directions

Despite several attempts to improve the model's performance, including modifying the model architecture, employing transfer learning, and implementing K-Fold Cross Validation, the desired level of accuracy was not achieved. This suggests that further modifications and optimizations are needed.

Future work could involve experimenting with different model architectures, activation functions, and regularization techniques. Other pre-trained models could also be explored for transfer learning. Additionally, more advanced techniques for preventing overfitting, such as early stopping or different data augmentation strategies, could be employed. Lastly, tuning the hyperparameters of the model, such as the learning rate of the optimizer, could potentially lead to improvements in model performance.

Overall, while the results of the project were not as expected, valuable insights and learnings were gained, which will inform future efforts in developing high-performing image classification models. The project also highlighted the importance of continual iteration and experimentation in machine learning model development. Despite the challenges encountered, the project provided a valuable opportunity to apply and deepen understanding of key concepts in machine learning and image classification.