**CNN-Powered Fruit Image Classifier**

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**Introduction**

This project is based on a Convolutional Neural Network (CNN) model designed to classify 10 different types of fruits using a custom-built image dataset. This project was completed as part of a Machine Learning course at Grand Valley State University. The model leverages deep learning techniques and data preprocessing to achieve high accuracy in identifying fruit images.

**Project Objective**

The goal of this project is to build an accurate CNN model that can classify fruit images into the following classes: apple, banana, blueberry, cherry, grapes, kiwi, mango, orange, strawberry, and watermelon. The project showcases the application of CNNs in image classification tasks and demonstrates model performance.

**Dataset Description**

The dataset comprises images of various fruits categorized into ten classes: apple, banana, blueberry, cherry, grapes, kiwi, mango, orange, strawberry, and watermelon. Each image is resized to a uniform dimension of 50x50 pixels and normalized to scale the pixel values between 0 and 1. The dataset is split into training (60%), validation (25%), and testing (15%) sets to facilitate model training, hyperparameter tuning, and evaluation.

* Apple: 451 images
* Banana: 391 images
* Blueberry: 381 images
* Cherry: 401 images
* Grapes: 375 images
* Kiwi: 408 images
* Mango: 437 images
* Orange: 403 images
* Strawberry: 357 images
* Watermelon: 417 images

**Model Architecture**

Input Layer: Accepts 50x50 RGB images.

Convolutional Layer 1: 32 filters of size 3x3 with ReLU activation.

MaxPooling Layer 1: Pool size of 2x2.

Convolutional Layer 2: 64 filters of size 3x3 with ReLU activation.

MaxPooling Layer 2: Pool size of 2x2.

Flatten Layer: Flattens the output for the dense layer.

Dense Layer 1: 150 neurons with ReLU activation.

Output Layer: 10 neurons with softmax activation, corresponding to the fruit categories.

**Hyperparameter Selection and Training**

Initial hyperparameters were selected based on common practices:

Learning Rate: 0.001

Momentum: Not used in this configuration.

Batch Size: 32

Number of Epochs: 20

Hyperparameters were adjusted based on the model’s performance on the validation set. The learning rate was tested at 0.01, 0.001, and 0.0001 to find the optimal balance between training speed and accuracy. The model was trained using the Adam optimizer with a learning rate of 0.001.

**Model Evaluation**

Test accuracy: 0.7554076313972473

Accuracy for class apple: 0.6777777671813965

Accuracy for class banana: 0.8666666746139526

Accuracy for class blueberry: 0.9473684430122375

Accuracy for class cherry: 0.8196721076965332

Accuracy for class grapes: 0.7843137383460999

Accuracy for class kiwi: 0.6615384817123413

Accuracy for class mango: 0.6086956262588501

Accuracy for class orange: 0.8600000143051147

Accuracy for class stawberry: 0.6888889074325562

Accuracy for class watermelon: 0.7169811129570007

**Conclusion**

The CNN model successfully classified images of 10 fruit types, demonstrating the efficacy of deep learning techniques in image recognition tasks. The inclusion of data augmentation played a crucial role in enhancing model accuracy and robustness. This project provided valuable insights into CNN architecture design, data preprocessing, and the application of augmentation techniques to improve model performance.

**Future Work**

To further enhance the model, future iterations could explore:

* Expanding the dataset with more diverse images to cover a broader range of variations.
* Implementing more advanced CNN architectures like ResNet or EfficientNet to improve accuracy.
* Exploring transfer learning with pre-trained models to leverage existing knowledge and further refine classification performance.