Performance Tradeoffs of a CNN Architecture with Focus on Wildfire Detection

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Objective:

The project aims to analyze the performance tradeoffs in a Convolutional Neural Network (CNN) architecture for object detection, specifically within the context of wildfire detection. We will be leveraging the YOLO (You Only Look Once) object detection framework, where we intend to utilize the model's ability to detect and change parameters to suit our specific use case.

Methods of Analysis

We will examine how parameters such as stride, pooling, image size, and others influence both detection accuracy and computational cost. While we plan to keep the model's weights and the number of layers consistent with the predefined YOLO architecture, we are open to modifying the source code of the detection script of YOLO and its supporting libraries to explore potential optimizations.

Another key consideration is the use of CPU vs. GPU for inference. Although utilizing a GPU will undoubtedly accelerate computation, we aim to analyze the tradeoff in terms of energy consumption. While hardware choice is unlikely to impact the accuracy of image classification, it could significantly affect the computational load and energy efficiency.

To implement this, we will first train the model to detect fire and any other possible indicators within the image. Once trained, the model will analyze multiple images, identifying and localizing these elements. Object detection is crucial for this implementation, as it enables the model to recognize multiple fire-related signs across different areas of an image, providing more insights on fire detection.

Data Collection:

We will train a model using YOLOv7 on a fire-related dataset with labels that will be taken from online. We are looking to train on this dataset. The training process will continue until the model achieves adequate accuracy on fire and other relevant indicators. Once this performance benchmark is met, we will save the model and will remain fixed throughout the inference phase. After, this will allow us to focus on analyzing the tradeoffs between accuracy, speed, and computational efficiency during inference..

For each set of different parameters, we will run the inference program on a diverse set of test images and videos. Given the presence of noise in many of the inputs, we will execute the program multiple times to obtain more accurate and reliable results

To ensure consistency in computational and processing time, all experiments will be conducted on the same machine or on machines with identical or comparable hardware specifications. This will help minimize variability and provide consistent performance data across different test scenarios.

Expected Outcomes:

The project will offer valuable insights into the performance tradeoffs involved in deploying CNN-based models for fire detection. Specifically, aim to identify how various parameters impact the balance between performance, accuracy and inference speed, helping us make more informed decisions when selecting hyperparameters. Ultimately, the project will provide a practical framework for optimizing CNN architectures on resource-constrained devices, with potential applications extending beyond wildfire detection.