Abstract

Recent advancements in machine learning (ML) and deep learning (DL) have advanced the capabilities of analytical models, achieving unprecedented accuracy and efficiency in a wide array of domains. These models, characterized by their depth and ability to learn hierarchical features, set new standards in fields ranging from natural language processing to computer vision. However, their reliance on extensive, diverse datasets to train effectively introduces significant challenges in environments where data is scarce or constrained by privacy, safety, or rarity. To address this issue, approaches such as few-shot learning and transfer learning prove effective, allowing models to learn from limited examples and leverage knowledge from related tasks to improve performance. Despite their promise, these strategies encounter limitations related to model adaptability, dataset diversity, and task specificity.

This study explores the efficacy of task similarity when applying transfer learning for deep object detection, investigating whether investments in domain-specific datasets and models offer significant advantages under conditions of data scarcity. Through empirical analysis, two base models, one with low task similarity and another with high task similarity, are compared in a series of transfer learning and few-shot learning experiments. The findings of this study indicate that while task similarity substantially improves model convergence and the accuracy of predictions, the advantages diminish as the amount of training data increases. These results highlight the potential benefits of developing domain-specific datasets, particularly when data is scarce, yet also emphasize the necessity for broader research into task similarity and its application across domains facing similar challenges.