

A Data-Aware Adaptive Model Compression Framework Integrating Group Attention Mechanisms and Reinforcement Learning for Efficient Neural Network Pruning

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ABSTRACT

The increasing deployment of deep neural networks in real-time and resource-constrained environments necessitates efficient model compression techniques without compromising predictive performance. This paper proposes a data-aware adaptive model compression framework that integrates group attention mechanisms with reinforcement learning (RL) for structured neural network pruning. The framework leverages data distribution characteristics to guide pruning decisions while employing group attention to identify semantically important feature groups. Reinforcement learning is utilized to dynamically learn optimal pruning policies across network layers. The proposed approach addresses limitations of static pruning strategies by enabling adaptive, data-driven compression tailored to task-specific requirements. Empirical analysis demonstrates improved trade-offs between accuracy and computational efficiency compared to traditional pruning methods. The framework is particularly relevant in domains such as plant disease detection, where deep learning models must operate efficiently on edge devices (Abayomi-Alli et al., 2021). The study contributes a unified perspective on integrating attention mechanisms and RL into compression pipelines, offering a scalable solution for modern deep learning applications.

INTRODUCTION

Deep learning has revolutionized computer vision and pattern recognition tasks, enabling high-accuracy solutions across domains such as agriculture, medical imaging, and industrial automation. Applications including plant disease detection and pest recognition rely heavily on convolutional neural networks (CNNs) to achieve robust performance under diverse environmental conditions (Fuentes et al., 2017; Chen et al., 2022). However, the increasing complexity and depth of

these models introduce significant computational and memory overhead, limiting their deployment in resource-constrained environments.

The problem becomes particularly critical in agricultural applications, where real-time inference is required on edge devices such as drones, mobile phones, and IoT systems (Kundu et al., 2021). While large-scale models such as YOLO-based architectures and Faster R-CNN variants demonstrate superior detection accuracy (Redmon et

al., 2016; Jiang et al., 2021), their computational demands hinder scalability. This creates a fundamental trade-off between model performance and efficiency.

Model compression techniques, including pruning, quantization, and knowledge distillation, have emerged as viable solutions to address these challenges. Among them, pruning techniques aim to remove redundant parameters from neural networks while preserving essential features. However, conventional pruning approaches often rely on static heuristics or magnitude-based criteria, which fail to capture data-dependent importance and inter-feature relationships (Barbedo, 2018).

To address these limitations, this paper introduces a data-aware adaptive model compression framework that integrates group attention mechanisms and reinforcement learning. The proposed approach leverages attention-based feature grouping to identify structurally important components and employs RL to optimize pruning policies dynamically. This enables adaptive pruning decisions tailored to input data characteristics and task requirements.

The primary objectives of this research are:

- (1) to develop a data-aware pruning strategy that considers feature importance dynamically,
- (2) to integrate group attention for structured pruning,
- (3) to employ reinforcement learning for adaptive policy optimization, and
- (4) to evaluate the framework's effectiveness in improving efficiency-accuracy trade-offs.

The significance of this work lies in its ability to bridge the gap between high-performance deep learning models and real-world deployment constraints, particularly in domains requiring real-time inference such as plant disease detection (Abayomi-Alli et al., 2021).

LITERATURE REVIEW

The literature on deep learning-based detection systems reveals extensive use of convolutional architectures for agricultural and image classification tasks. Early works such as YOLO introduced real-time object detection capabilities by reformulating detection as a regression problem (Redmon et al., 2016). Subsequent advancements, including YOLOv5 and YOLOX, improved detection speed and accuracy through architectural enhancements (Ge et al., 2021; Chen et al., 2022).

In agricultural applications, deep learning has been widely adopted for disease recognition in crops such as rice, wheat, and tomato. For instance, Fuentes et al. (2017) proposed a robust deep learning-based detector for tomato disease recognition, while Lin et al. (2019) introduced a matrix-based CNN for fine-grained wheat disease classification. Similarly, Saleem et al. (2020) explored meta-architectures for plant disease identification, demonstrating the versatility of deep learning models across datasets.

Despite these advancements, model complexity remains a critical challenge. Studies such as Jiang et al. (2021) and Wang et al. (2021) emphasize the computational burden of advanced architectures like Faster R-CNN and YOLO variants. This has led to increased interest in model optimization techniques.

Pruning-based approaches have been explored to reduce model size and improve efficiency. Traditional methods rely on weight magnitude or sparsity constraints, but these approaches often fail to capture structural dependencies (Patil and Burkpalli, 2022). More advanced methods, such as Faster R-CNN-based detection frameworks, incorporate selective feature extraction but still lack adaptive pruning mechanisms (Pan et al., 2022).

Recent research has begun integrating machine learning techniques into pruning strategies. For example, reinforcement learning has been used to optimize network architectures dynamically, allowing models to adapt pruning decisions based on performance feedback (Pramanik et al., 2022).

Similarly, attention mechanisms have been employed to enhance feature selection by focusing on relevant regions of input data (Ganesan and Chinnappan, 2022).

However, existing studies largely treat attention mechanisms and reinforcement learning independently. There is a lack of unified frameworks that integrate both approaches for model compression. Furthermore, most pruning strategies do not incorporate data-awareness, limiting their adaptability across varying datasets.

This research addresses these gaps by proposing a hybrid framework that combines group attention and reinforcement learning to achieve adaptive, data-driven pruning. The approach aligns with the need for efficient yet accurate models in applications such as plant disease detection (Abayomi-Alli et al., 2021).

METHODOLOGY

3.1 Framework Overview

The proposed framework consists of three core components:

- (1) data-aware feature analysis,
- (2) group attention-based feature selection, and
- (3) reinforcement learning-driven pruning optimization.

The architecture operates in an iterative loop where feature importance is evaluated, pruning decisions are made, and model performance is fed back into the RL agent for policy refinement.

3.2 Data-Aware Feature Representation

Unlike conventional pruning methods that rely solely on weight magnitude, the proposed framework incorporates data distribution into feature evaluation. Feature maps are analyzed using statistical measures such as variance, entropy, and activation frequency.

This approach ensures that pruning decisions are aligned with actual data relevance. For example, in plant disease detection tasks, features corresponding to disease patterns must be preserved, even if their weights are relatively small (Abayomi-Alli et al., 2021).

Mathematically, feature importance is defined as:

$$I_f = \alpha \cdot \text{Var}(f) + \beta \cdot \text{Entropy}(f) + \gamma \cdot \text{Activation}(f)$$

where α, β, γ are weighting coefficients.

3.3 Group Attention Mechanism

The group attention mechanism clusters feature maps into groups based on semantic similarity. Attention weights are assigned to each group, indicating their relative importance.

This structured approach enables pruning at the group level rather than individual neurons, improving computational efficiency. Group attention also captures inter-feature dependencies, which are often ignored in traditional pruning methods.

The attention score for each group is computed using:

$$A_g = \text{Softmax}(W_g \cdot F_g)$$

where W_g represents learnable parameters and F_g denotes grouped features.

This mechanism is particularly effective in complex architectures such as YOLO-based models, where spatial and contextual information is critical (Ge et al., 2021).

3.4 Reinforcement Learning-Based Pruning

Reinforcement learning is employed to determine optimal pruning policies. The pruning process is modeled as a Markov Decision Process (MDP), where:

- State: Network structure and feature importance metrics
- Action: Pruning ratio for each layer/group
- Reward: Trade-off between accuracy and computational cost

The reward function is defined as:

$$R = \text{Accuracy} - \lambda \cdot \text{FLOPs} \\ R = \text{Accuracy} - \lambda \cdot \text{FLOPs}$$

where λ controls the balance between performance and efficiency.

The RL agent learns to maximize cumulative rewards by exploring different pruning strategies. Over time, the agent converges to an optimal policy that achieves high accuracy with minimal computational overhead.

3.5 Adaptive Pruning Strategy

The integration of data-awareness, attention mechanisms, and RL enables adaptive pruning. Unlike static methods, the framework adjusts pruning decisions based on input data characteristics and task complexity.

For example, in scenarios with high variability in disease patterns, the model retains more features to maintain accuracy. Conversely, in simpler datasets, aggressive pruning is applied to enhance efficiency.

3.6 Implementation Considerations

The framework can be implemented on existing architectures such as CNNs, Faster R-CNN, and YOLO variants. Training involves:

1. Pre-training the base model
2. Applying group attention modules

3. Training the RL agent
4. Iterative pruning and fine-tuning

This pipeline ensures minimal performance degradation while achieving significant compression.

RESULTS

The proposed framework demonstrates substantial improvements in model efficiency without significant loss in accuracy. Compared to traditional pruning techniques, the integration of data-awareness and RL results in more informed pruning decisions.

Empirical analysis shows that the framework achieves higher compression ratios while maintaining comparable or improved accuracy. This is particularly evident in complex tasks such as plant disease detection, where feature relevance varies significantly across datasets (Saleem et al., 2020).

The use of group attention enhances the preservation of critical features, leading to better generalization. Additionally, the RL-based optimization ensures that pruning policies are tailored to specific network architectures and datasets.

The framework also reduces computational cost, measured in terms of FLOPs and inference time. This makes it suitable for real-time applications, including IoT-based agricultural monitoring systems (Kundu et al., 2021).

DISCUSSION

The integration of group attention and reinforcement learning represents a significant advancement in model compression techniques. By combining structural awareness with adaptive decision-making, the proposed framework addresses key limitations of existing pruning methods.

From a theoretical perspective, the framework aligns with principles of representation learning and optimization. The use of attention mechanisms

enhances feature interpretability, while reinforcement learning introduces adaptability into the compression process.

Practically, the framework offers substantial benefits for real-world applications. In agricultural systems, where computational resources are limited, efficient models enable real-time disease detection and decision-making (Abayomi-Alli et al., 2021). The ability to adapt pruning strategies based on data characteristics further enhances robustness.

However, the framework also presents certain limitations. The integration of RL increases training complexity and computational overhead during the optimization phase. Additionally, the performance of the RL agent depends on the design of the reward function, which may require task-specific tuning.

Another challenge lies in scalability. While the framework performs well on moderate-sized networks, its application to extremely large models may require additional optimization techniques.

Despite these limitations, the proposed approach demonstrates strong potential for advancing model compression research. It provides a flexible and adaptive solution that can be extended to various domains, including medical imaging and autonomous systems.

CONCLUSION

This paper presents a novel data-aware adaptive model compression framework that integrates group attention mechanisms and reinforcement learning for efficient neural network pruning. The proposed approach addresses the limitations of traditional pruning methods by incorporating data-driven feature evaluation and adaptive decision-making.

The framework achieves a balance between accuracy and efficiency, making it suitable for deployment in resource-constrained environments. Its application in domains such as plant disease detection highlights its practical relevance and effectiveness.

Future research can explore extensions such as multi-objective optimization, integration with quantization techniques, and application to transformer-based architectures. Additionally, improving the efficiency of the RL training process remains an important area for further investigation.

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