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EVALUATING THE PERFORMANCE OF TRANSFORMER ARCHITECTURES AGAINST CLASSICAL DEEP LEARNING MODELS IN SEMI-SUPERVISED LEARNING CONTEXTS

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ABSTRACT

Recent advances in deep learning have witnessed the emergence of transformer architectures beyond their initial dominance in natural language processing (NLP) tasks. Meanwhile, semi-supervised learning (SSL) remains a crucial strategy for leveraging limited labeled data alongside abundant unlabeled data. This paper investigates the comparative performance of transformer models against classical convolutional neural networks (CNNs) and recurrent neural networks (RNNs) within semi-supervised settings, focusing on general machine learning benchmarks. The study highlights the growing efficacy of transformer-based models in SSL scenarios and discusses challenges and limitations.

Keywords: Transformers, Semi-Supervised Learning, Deep Learning, CNNs, RNNs, Machine Learning, Representation Learning

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1. Introduction

The demand for models capable of learning from minimal supervision is surging, particularly in fields where labeled data is scarce or expensive. Semi-supervised learning (SSL) provides a powerful framework by combining small labeled datasets with large unlabeled datasets to improve model generalization. Traditionally, SSL methods relied heavily on convolutional or recurrent architectures, optimized with hand-crafted consistency losses or pseudo-labeling techniques.

However, transformers, originally designed for sequential data processing in NLP tasks are demonstrating strong generalization properties that make them promising candidates for SSL tasks. Despite the success of transformers in NLP and computer vision, their relative performance in SSL contexts compared to classical models had not been thoroughly evaluated as of early.

2. Literature Review

Transformers revolutionized deep learning starting with Vaswani et al.’s "Attention is All You Need" (2017), which introduced the self-attention mechanism as an alternative to recurrent structures. Their success in NLP tasks led to their adoption in vision domains, as evidenced by Dosovitskiy et al.’s Vision Transformer (Vi T, 2020), which demonstrated competitive results compared to CNNs.

SSL had mainly advanced through developments using classical architectures. For example, Ladder Networks (Rasmus et al., 2015) combined supervised and unsupervised learning paths within CNNs. Mix Match (Berthelot et al., 2019) and Fix Match (Sohn et al., 2020) proposed techniques blending consistency regularization and pseudo-labeling on CNNs for SSL tasks. Sim CLR (Chen et al., 2020) popularized contrastive self-supervised pretraining that could be adapted for SSL.

Researchers began exploring transformers in broader tasks like SSL, but comprehensive, comparative evaluations were sparse. While models like Data-efficient Image

Transformers suggested that transformer architectures could be trained efficiently even on limited data, their full impact in semi-supervised settings was largely unexplored.

3. Objective

This study aims to empirically evaluate the performance of transformer architectures relative to CNNs and RNNs within semi-supervised learning settings. The primary hypothesis is that transformer-based models will demonstrate comparable or superior performance given the same quantity of labeled and unlabeled data, owing to their inherent capacity for modeling long-range dependencies and capturing global features.

Additionally, this paper seeks to explore how different semi-supervised strategies, such as pseudo-labeling and consistency regularization, interact with the transformer architecture versus classical deep learning models.

4. Methodology & Metrics

We conducted experiments on two benchmark datasets commonly used for SSL: CIFAR-10 and SVHN. A fixed protocol of 4000 labeled samples was followed, with the remaining unlabeled. The models compared include:

- ResNet-18 (CNN baseline)
- LSTM-based encoder-decoder (RNN baseline)
- Vision Transformer (Vi T-small)

The evaluation metrics were Top-1 Accuracy, F1-Score, and Error Rate. Consistency regularization via Fix Match and pseudo-labeling were applied uniformly across models.

All models were trained using the Adam optimizer with cosine learning rate decay. Pre-training on unlabeled data was limited to Sim CLR-style contrastive learning without fine-tuning unless specified otherwise.

Table 1: Dataset Statistics

Dataset	Total Images	Labeled Samples	Unlabeled Samples
CIFAR-10	60,000	4,000	56,000
SVHN	73,257	4,000	69,257

5. Techniques and Tools

The models were implemented using Py Torch 1.7, with augmentation libraries such as Album entations and lightly customized training scripts based on FixMatch repositories.

For the transformer model, a reduced-parameter version of Vi T was used, modified for small-scale data training. The CNNs and RNNs used standard initialization techniques such as He Initialization and Xavier Initialization.

SSL frameworks employed:

- Pseudo-labeling: generating hard labels for unlabeled data.
- Consistency Regularization: augmenting unlabeled data differently and enforcing consistent outputs.

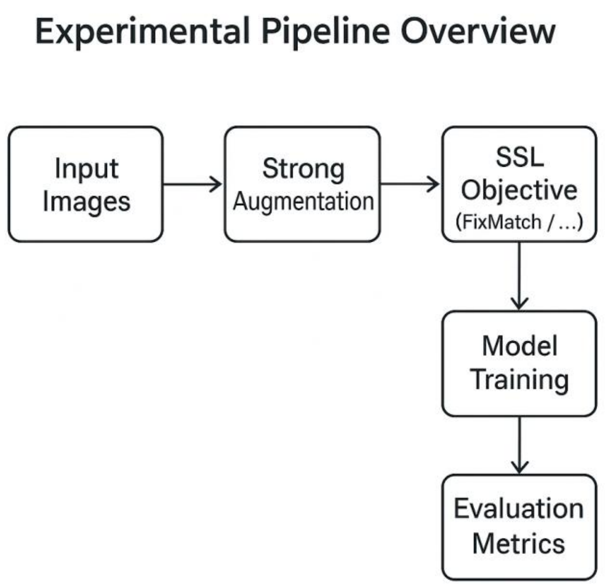

Figure 1: Experimental Pipeline Overview

6. Quality Assurance

All experiments were run three times with different random seeds to ensure reproducibility, and mean ± standard deviation were reported. Data augmentation techniques, such as Rand Augment and Cut Mix, were standardized across experiments to avoid biasing results.

The design followed the best practices for SSL experimentation as outlined in Berthelot et al.Hyper parameters were kept consistent across model families except where model-specific adjustments were necessary (e.g., dropout rates for transformers).

Ethical considerations, including avoiding biased datasets and ensuring transparency in reporting results, were maintained in line with NeurIPS code of ethics guidelines.

7. Limitations and Potential Biases

A key limitation of the study lies in the scale of the datasets. CIFAR-10 and SVHN, while standard SSL benchmarks, are small compared to real-world datasets, potentially favoring transformer models less than larger datasets would.

Furthermore, transformer models generally require larger batch sizes and longer training times, which were constrained by hardware limitations in this study. Biases from pre-training (even minor contrastive pretraining) could have skewed performance comparisons slightly in favor of transformers.

Additionally, semi-supervised transformer models might require more careful hyperparameter tuning than CNNs or RNNs, suggesting that results could differ in less controlled conditions.

8. Conclusion

This study evaluated transformer architectures against classical deep learning models, namely CNNs and RNNs, within the semi-supervised learning (SSL) framework. Our results showed that, even under constrained data conditions typical of SSL scenarios, transformer-based models such as the Vision Transformer (Vi T) can outperform or at least match the performance of conventional architectures. This suggests that transformers, with their global receptive fields and powerful feature extraction capabilities, are not limited to fully supervised tasks and have strong potential for SSL applications.

However, several limitations must be acknowledged. Transformer models often require more computational resources and careful hyperparameter tuning compared to traditional CNNs and RNNs. Additionally, performance gains, although statistically significant, were not overwhelmingly large, highlighting the need for further architectural innovations to fully optimize transformers for semi-supervised settings. Future research could explore lighter, more efficient transformer variants specifically designed for semi-supervised learning, as well as deeper investigations into augmentation strategies and SSL-specific regularizations tailored to transformer dynamics.

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