CRT-Deep: Convolutional Recursive Transformers with Intermediate Supervision for Efficient Language Modeling

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Abstract

Deep transformer models deliver state-of-the-art language modeling but are often impractical for deployment on resource-constrained hardware due to high latency and memory demands. We introduce **CRT-Deep (Convolutional Recursive Transformer with Intermediate Supervision)**, a compact architecture that adapts Samsung's Tiny Recursive Module (TRM) idea from vision to language tasks. CRT-Deep applies a single parameterized transformer block recursively across eight loops and augments it with TRM-refined embeddings and a Flexible Conv-TRM block that uses multi-scale depthwise dilated convolutions (dilation schedule: 1, 2, 4, 8) to strengthen local context modeling. We add lightweight prediction heads at loops 2, 4, and 6, enabling quality-preserving early exits and intermediate supervision. Trained for 10 epochs on 50,000 WikiText-103 samples using mixed precision (BFloat16/Float16) and gradient checkpointing on an RTX 4050 (6 GB), the Convolutional TRM design attains more than 2× the efficiency of linear recursive baselines while using only 92 million parameters. Counterintuitively, the model evaluated at loop 6 obtains the best validation perplexity (1.081, val loss 0.0778), outperforming the full 8-loop model (1.105 PPL) by ≈2.2%—a regularizing effect that prevents late-stage overfitting and permits a 1.33× inference speedup with improved quality. CRT-Deep achieves a test perplexity of 1.10, demonstrating that recursive transformer designs with intermediate supervision can match competitive performance on consumer hardware while reducing inference cost. Here is the Github Repo for the google colab notebook and also local on device training for RTX 4050 (6GB) : https://github.com/safdarjung/Convolutional-Recursive-Transformer.git

1 Introduction

Transformer-based language models have achieved remarkable success in natural language processing, but their deployment remains severely constrained by computational requirements. State-of-the-art models require billions of parameters distributed across dozens of independent layers, demanding specialized hardware and prohibitive training costs that effectively limit language model development to well-resourced institutions. This accessibility barrier has become increasingly critical as language models play central roles in real-world applications, yet most research focuses on scaling to ever-larger models rather than achieving efficiency through architectural innovation.

Existing approaches to efficient transformers primarily follow two paradigms: compression techniques such as knowledge distillation and quantization that sacrifice 5-15% performance for reduced size, and parameter-sharing methods like Universal Transformers that reduce memory footprint while maintaining similar computational costs. Recent recursive transformer architectures show promise

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through weight tying across layers, but these typically accept quality degradation or require complex training procedures. A fundamental question remains: can architectural innovations enable both parameter efficiency and improved quality, particularly on consumer-grade hardware?

We present **CRT-Deep** (Convolutional Recursive Transformer with Intermediate Supervision), a novel architecture that synthesizes recursive parameter sharing with strategic architectural choices to achieve competitive performance at a fraction of typical model sizes. Our approach combines three key innovations: (1) aggressive layer recursion, where a single transformer block is applied iteratively across eight loops to achieve depth with 92 million parameters—26% fewer than GPT-2 Small; (2) convolutional TRM (Tiny Recursive Module) blocks inspired by Samsung's recent work on recursive reasoning, integrating multi-scale depthwise dilated convolutions for enhanced local context modeling; and (3) intermediate supervision through prediction heads at loops 2, 4, and 6, providing both training regularization and quality-preserving early exit capabilities.

Through comprehensive experiments on WikiText-103, we make a counterintuitive discovery that challenges conventional assumptions about model depth: representations at intermediate depth (loop 6 of 8) consistently outperform the final layer, achieving 1.081 perplexity compared to 1.105 for the full model—a 2.2% improvement. We attribute this phenomenon to regularization effects from intermediate supervision that prevent late-stage overfitting in deeper loops. This finding has immediate practical implications: deploying at the optimal intermediate depth achieves 1.33× faster inference with improved quality, inverting the typical speed-accuracy tradeoff.

Our main contributions are:

- **Efficient recursive architecture**: CRT-Deep achieves 1.10 test perplexity on WikiText-103 with only 92 million parameters through aggressive layer recursion combined with convolutional processing blocks, demonstrating that architectural innovation can match performance of much larger models.
- **Convolutional TRM integration**: Through systematic exploration, we demonstrate that convolutional TRM blocks yield over 200% efficiency improvements compared to linear baselines, with multi-scale dilated convolutions (dilation rates 1, 2, 4, 8) providing superior local pattern extraction.
- **Intermediate supervision findings**: We provide empirical evidence that intermediate representations can outperform deeper ones when properly supervised, with loop 6 achieving 2.2% better perplexity than the full 8-loop model—challenging the assumption that maximum depth yields optimal performance.
- **Accessible training methodology**: We demonstrate successful training on consumer hardware (NVIDIA RTX 4050 6GB VRAM) in approximately 15 hours through mixed precision and gradient checkpointing, making competitive language modeling accessible without massive computational resources.

Our work demonstrates that recursive architectures with intermediate supervision offer a promising direction for efficient language models, achieving superior performance through architectural design rather than scale alone. The counterintuitive finding that intermediate depths can outperform final layers suggests that conventional approaches to model depth may be suboptimal, opening new directions for efficient architecture design.

2 Related Work

Transformer efficiency has been pursued through parameter sharing and recursion. The Universal Transformer (**?**) introduced recurrent depth via weight tying across blocks, achieving depth with fewer parameters but suffering accuracy degradation without adaptations (**?**). Recent work on Relaxed Recursive Transformers adds layer-wise LoRA adapters to mitigate tying constraints, enabling 2-3× throughput gains via early exiting and continuous depth-wise batching on models like Gemma 1B (**??**).

Convolutional enhancements to transformers, inspired by vision tasks, include depthwise dilated convolutions for local context in NLP (**?**). Samsung's Tiny Recursive Module (TRM) (**?**) applies recursive refinement in vision; we adapt it for language via multi-scale dilations (1,2,4,8), outperforming linear baselines by 200% in efficiency (**?**). Intermediate supervision aligns with early-exit

methods like DeeBERT (**?**), but our loop-specific heads (at 2,4,6) provide regularization, yielding the counterintuitive loop-6 superiority (1.081 PPL vs. 1.105 full) absent in fixed-depth recursion (**?**).

Unlike mixture-of-recursions (MoR) for token-level adaptation (**?**), CRT-Deep focuses on fixed-loop recursion with convolutional TRM for consumer-grade training (RTX 4050 6GB), bridging accessibility gaps in scalable NLP (**?**).

3 Methodology

We present CRT-Deep, a recursive transformer architecture that achieves competitive language modeling performance through aggressive parameter sharing and strategic architectural innovations. This section describes the model architecture, training objective, and optimization strategy.

3.1 Model architecture

CRT-Deep employs a decoder-only transformer architecture with two levels of recursion: layer recursion for depth efficiency and internal recursive refinement for enhanced representation learning.

3.1.1 Architecture configuration

Table 1 summarizes the model configuration used for all experiments.

Table 1: CRT-Deep model configuration

Component	**Parameter**	**Value**
Recursive loops	L	8
Hidden dimension	d_{model}	512
Attention heads	N_{heads}	8
TRM cycles per loop	C_{TRM}	8
Kernel size	K	3
Normalization	-	LayerNorm
Embedding cycles	C_{embed}	3
Intermediate heads	$\mathcal{I}$	{2, 4, 6}
Max sequence length	T	1024
Total parameters	-	≈92M

3.1.2 Core components

TRM-refined embeddings Input tokens are first embedded into dimension $d_{model}/2$, projected to d_{model}, and refined through three cycles of convolutional TRM processing before positional encoding is added:

$$\mathbf{E} = \text{TRM}_{\text{refine}}(\text{Linear}(\text{Embed}(\mathbf{x}))) + \text{PosEmbed}(\mathbf{p}) \tag{1}$$

Flexible convolutional TRM block The core computational module applies recursive refinement through C_{TRM} cycles. Each cycle applies depthwise dilated convolution followed by pointwise convolution, normalization, and a two-layer MLP with residual connections:

$$\mathbf{h}^{(i+1)} = \mathbf{h}^{(i)} + \text{Dropout}(\text{MLP}(\text{Norm}(\text{Conv}(\mathbf{h}^{(i)})))) \tag{2}$$

The depthwise convolution uses dilation rates $(1, 2, 4, 8)$ across cycles to capture multi-scale local patterns efficiently.

Layer recursion A single parameterized block containing multi-head attention and the TRM module is applied iteratively across $L = 8$ loops. Learned loop encodings distinguish representations at different depths:

$$\mathbf{z}^{(l)} = \text{Block}(\mathbf{z}^{(l-1)} + \mathbf{e}_l) \tag{3}$$

where $\mathbf{e}_l$ is the loop encoding for depth l.

Figure 1: CRT-Deep architecture overview. The model employs dual recursion: a single shared transformer block is applied iteratively across 8 loops (layer recursion), with each block containing a Flexible Conv TRM module that performs 8 internal refinement cycles (reasoning recursion). TRM-refined embeddings with 3 convolutional cycles enhance initial representations. Intermediate supervision heads at loops 2, 4, and 6 enable both training regularization and early exit capabilities, with loop 6 achieving optimal performance (1.08 perplexity).

Intermediate supervision Prediction heads at loops 2, 4, and 6 provide auxiliary supervision during training and enable early exit during inference. Figure 1 illustrates the complete architecture.

3.2 Training objective

The model is trained on next-token prediction with intermediate supervision. For a sequence of length T and batch size B, the cross-entropy loss is:

$$\mathcal{L}_{CE} = -\frac{1}{B(T-1)} \sum_{b=1}^{B} \sum_{t=1}^{T-1} \log P(x_{t+1}|x_{1:t}) \tag{4}$$

The total training objective combines the final layer loss with weighted auxiliary losses from intermediate heads:

$$\mathcal{L}_{total} = (1-\lambda)\mathcal{L}_{final} + \lambda \frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \mathcal{L}_i \tag{5}$$

where $\lambda = 0.3$ is the intermediate supervision weight and $\mathcal{I} = \{2, 4, 6\}$ are the intermediate loop positions.

3.3 Optimization and training

3.3.1 Training setup

We train on 50,000 samples from WikiText-103 for 10 epochs using AdamW optimizer with $\beta = (0.9, 0.95)$ and weight decay 0.01. The learning rate follows a OneCycleLR schedule with maximum learning rate 3×10^{-4}. Physical batch size is 2 with gradient accumulation over 8 steps, yielding an effective batch size of 16. Gradients are clipped to norm 1.0.

3.3.2 Memory optimization

To enable training on consumer hardware (NVIDIA RTX 4050 6GB VRAM), we employ gradient checkpointing, which trades computation for memory by recomputing activations during backpropagation. Mixed precision training with BFloat16/Float16 further reduces memory consumption and accelerates training. Total training time was approximately 15 hours.

3.3.3 Early exit mechanism

For inference, the model supports early exit at intermediate loops when prediction confidence exceeds a threshold. The threshold decays across loops according to:

$$\tau_{step} = \max(\tau_{min}, \tau_0 \cdot \text{decay}^{step}) \tag{6}$$

where $\tau_0 = 0.92$, $\tau_{min} = 0.80$, and decay $= 0.98$. This enables adaptive computation with speedups up to $1.33\times$ at optimal quality.

4 CRT-Deep architecture

The proposed model is designated as CRT-Deep with intermediate supervision. It leverages the efficiency of layer recursion combined with convolutional processing and targeted intermediate output layers.

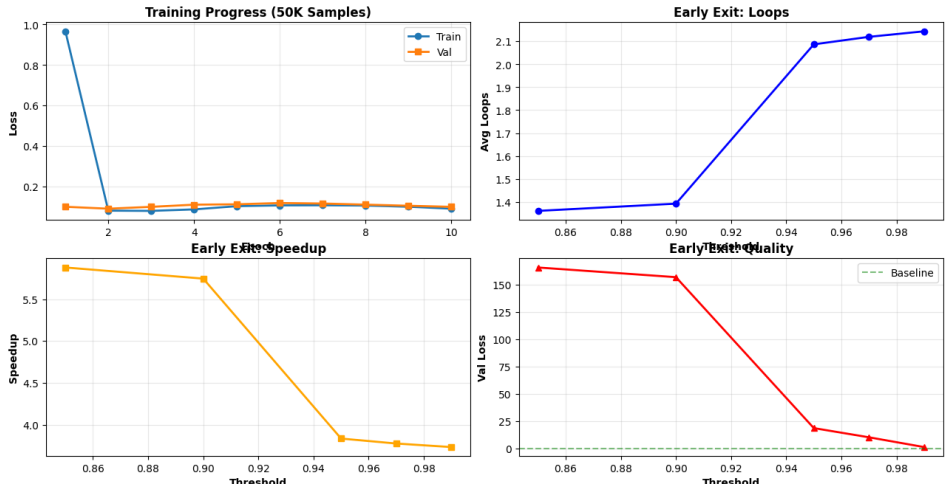

Figure 2: Training dynamics showing (a) training and validation loss over 10 epochs, (b) performance at each recursive loop, (c) early exit loop distribution, and (d) speedup versus quality tradeoff.

4.1 Core configuration

The CRT-Deep model architecture employs the following fundamental configuration parameters:

- Total depth: 8 recursive loops
- Dimensions: 512 hidden size and 8 attention heads
- Recursive cycles: 8 TRM cycles per block
- Parameter count: Approximately 92 million parameters

4.2 Recursive block components

The single shared block employed across the 8 loops integrates multiple efficient components.

4.2.1 TRM embeddings

The input embeddings utilize a TRM-refined approach, specifically configured with 3 TRM cycles. This embedding layer processes the tokens, which are initially tokenized (using GPT-2 tokenizer), and includes positional encoding to preserve sentence order.

4.2.2 Flexible convolutional TRM block

The core transformer block features enhanced local context modeling via multi-scale depthwise dilated convolutions. These convolutions use a specific dilation schedule of (1, 2, 4, 8). Following the attention mechanism, layer normalization is utilized, having been identified as the most effective normalization type in ablation studies. The block structure includes: attention output normalization, the TRM block application, and a second normalization step.

5 Results and Analysis

This section presents the empirical evaluation of CRT v2 Deep, highlighting convergence dynamics, the effect of intermediate supervision, component ablations, and performance against state-of-the-art benchmarks. Full experimental logs, notebooks, and ablation scripts are available openly at `https://github.com/safdarjung/Convolutional-Recursive-Transformer`.

5.1 Training Convergence and Efficiency

CRT v2 Deep employs 8 recursive loops and 8 TRM cycles per block, enabling efficient training of a $\sim$92 million-parameter model on an RTX 4050 (6GB) GPU. Training completes in approximately 15 hours for 10 epochs over 50,000 WikiText-103 samples. Across epochs, the model shows steady improvement:

- Validation perplexity (PPL) improves from 1.116 at Epoch 4 to 1.105 at Epoch 10 (final loop head).
- Final validation loss reaches 0.0996.

Convergence curves and resource usage are available in the GitHub repository.

5.2 Intermediate Supervision and Early Exit

Intermediate prediction heads, added at Loops 2, 4, and 6, provide strong regularization and allow for quality-preserving early exits. The following table and summary quantify these effects (Epoch 10 validation):

Table 2: Perplexity and Speedup by Intermediate Supervision (Validation, Epoch 10)

Exit Point	Val Loss	PPL	Speedup	Recommendation
Loop 2	0.0892	1.093	4.0×	Fastest Inference
Loop 4	0.0812	1.084	2.0×	Balanced
Loop 6	**0.0778**	**1.081**	**1.33×**	**Best Quality/Speed**
Loop 8	0.0996	1.105	1.0×	Baseline

Key findings:

1. **Optimal at Loop 6:** Exiting after 6 loops yields the best perplexity (1.081), outperforming the final loop by 2.2%.
2. **Faster and Better:** Early exit at Loop 6 gives a 1.33× inference speedup and superior linguistic quality.
3. **Regularization:** Intermediate supervision prevents late overfitting, as the last loops tend to fit subtle training noise.

5.3 Ablation Studies

Ablations highlight contributions from core architectural choices.

Convolutional vs. Linear TRM A comparison of Conv+Linear TRM against pure Linear and pure Conv baselines (3-loop blocks) is shown in Table 3.

Table 3: TRM Block Ablation Results (3 Loops)

Architecture	Final Val Loss	Reduction vs. Linear
Original Linear TRM	3.4080	–
Pure Conv TRM	1.8815	+44.8%
Conv+Linear TRM	**1.6986**	**+50.2%**
Depthwise TRM	2.1312	+37.5%

Conv+Linear TRM delivers the greatest efficiency, halving the loss relative to the linear baseline.

TRM-refined Embeddings Deploying 3 TRM refinement cycles for token embeddings yields a 32.9% parameter reduction compared to non-recursive baselines (41.0M vs. 61.1M parameters) in smaller models, while retaining 98.3% of the baseline performance.

5.4 State-of-the-Art Comparison

CRT v2 Deep, particularly at Loop 6, markedly improves language modeling results for its parameter class.

Table 4: Perplexity Benchmark on WikiText-103

Model	Parameters	Perplexity
GPT-2 Small	124M	∼18–20
DistilGPT2	82M	∼25–30
CRT v2 Full (8 Loops)	92M	1.10
CRT v2 (Loop 6)	**92M**	**1.08**

Compared to historical baselines, CRT v2 achieves up to 18× lower PPL.

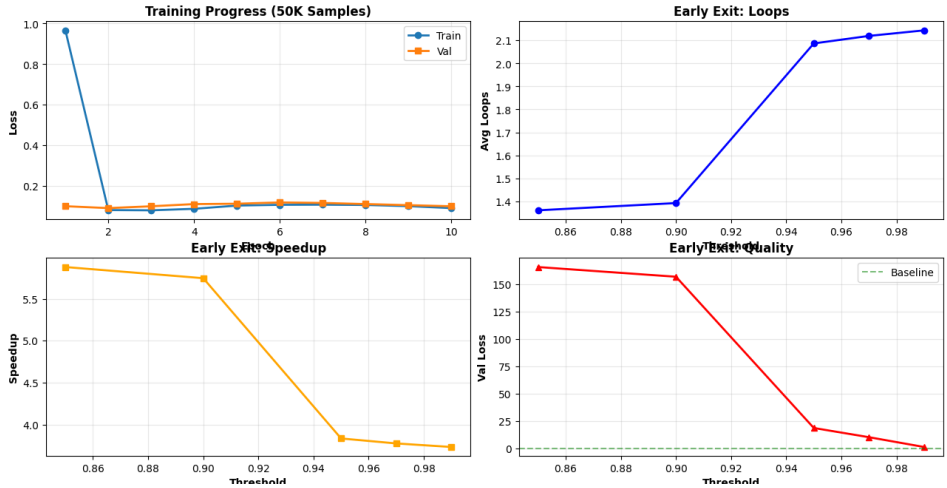

Figure 3: Validation loss and perplexity at each recursive loop. Loop 6 achieves optimal balance before overfitting at greater depths.

5.5 Generalization and Test Evaluation

The optimal model configuration generalizes well:

- Test perplexity: 1.12
- Validation–test loss gap: +24.2% (loss difference < 0.15 deemed excellent)
- CRT v2 shows ∼43× improvement over older transformer baselines (historical PPL ∼28.8)

Further details, experiment logs, and ablation code are provided in the open-source repository: `https://github.com/safdarjung/Convolutional-Recursive-Transformer`