Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Tiny Transformers for Financial Sentiment Analysis: Class Imbalance Resolution and CPU-Optimized Deployment

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ABSTRACT

This paper shows that small-scale Transformer models can successfully replace large-scale language models in financial sentiment analysis and break through essential barriers of class imbalances and CPU-alone deployability. With the 9.5M-parameter Tiny Transformer, we present a systematic enhancement pipeline: (E1) long training with better scheduling and (E2) class-weighted loss tuning. The baseline model obtains just 26.2% Macro-F1, which shows strong bias toward the dominant positive class (64.7% of samples). Our method improves performance to 61.6% Macro-F1—a 135% rel. Improvement—despite achieving just 11.5ms inference latency in one CPU core (613 samples/second rate). Ironically, we prove that large models (19M–35M params) become progressively less effective, and we achieve a better accuracy-per-parameter ratio with our compact model. Rigorous per-class analysis substantiates that minority sentiment detection significantly improves—from 0% to 43.5% for the negative class—without hurting the overall predictive stability. These results prove that if trained with domain-scholar techniques, small models can beat larger baselines at the cost of being deployable in resource-limited financial settings. The method we introduce is a reproducible roadmap for constructing real-time finance NLP systems running opportunistically without GPUs or clouds.

Keywords: Financial Sentiment Analysis; Tiny Transformers; Class Imbalance; CPU Deployment; Lightweight NLP; Macro F1 Optimization; Real-Time Inference; Class Weighting; Edge AI; Efficient Deep Learning

Introduction

Financial sentiment analysis is also essential in algorithmic trading, news tracking, and risk assessment of the market [1]. But nearly all the current methods depend on large-scale Transformer-centred language models like BERT (110M parameters) or DistilBERT (66M parameters), which are costly to train and challenging to deploy in the commonly used CPU-only systems by financial institutions [2].

Additionally, financial data tends to be highly imbalanced in the class it portrays with many more instances of positive sentiments than negative or neutral sentiments [3].

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This leads basic models to overfit the majority class and generate impossibly accurate but ultimately poor in-the-wild decision making [4]. Our positive sentiment makes up 64.7% of the samples in our data set and induces naive training methods to degenerate to just predicting the majority class.

Recent work studied model compression and distillation, but such methods tend to compromise performance or cost large-budget teacher models. Conversely, we ask whether one can train an appropriate-from-scratch tiny model to compete with or surpass large baselines without scale scaling but with strategic optimization [5].

In this work, we propose a 9.5M parameter Tiny Transformer and introduce a rigorous training pipeline made up of (1) Nuclear Class Imbalance Solution and (2) Extended Training with Class-Weighted Optimization. Even though the model is 7× smaller than DistilBERT, it outperforms with 61.6% Macro-F1, which is 135% better than baseline methods while maintaining 11.5ms latency per sample on CPU.

Our three-fold contributions are:

we show small models can compete with big transformers on financial sentiment task with im-balance aware training methods and surpass the latter with 9.5M parameters than the 35M parameter counterparts;

We report the novel systematic Macro-F1 progress metric over training interventions over financial data with unmistakable improvement patterns in the F1s from 26.2% to 61.6%;

We reach real-time CPU inference at 613 samples/second and facilitate low-budget implementation in realistic financial settings without GPU infrastructure.

The rest of the paper is structured thus: Section 2 provides related work discussion, Section 3 elaborates on the methodology used, Section 4 shows experimental results, Section 5 offers analysis, and finally, the conclusions with future research in Section 6.

Related Work

Transformer Models for Financial Sentiment Analysis

Transformer-based models have revolutionized financial sentiment analysis[6], with BERT and its financial-domain adaptation FinBERT establishing state-of-the-art performance. However, these models require 110M parameters, making real-time CPU deployment impractical for production financial systems. While distilled variants like DistilBERT reduce parameter count to 66M, they still necessitate GPU acceleration for low-latency inference—a significant barrier for institutions with CPU-only infrastructure [7]. Our work diverges from this scaling trajectory by exploring tiny-scale architectures (≤10M parameters) and demonstrating that strategic training methodology can compensate for reduced model capacity in financial domains [8].

Lightweight and Tiny Transformer Architectures

Recent efforts in model efficiency[9][10] have focused primarily on compression techniques[11]. MobileBERT employs bottleneck structures and knowledge distillation, while TinyBERT uses layer-wise distillation from BERT-base. However, these approaches maintain dependency on large teacher models[12], and their

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reported evaluations rarely include financial sentiment tasks with inherent class imbalance [13]. In contrast to compression-based methods, our approach trains a tiny transformer from scratch, eliminating the need for expensive teacher models [14] while achieving competitive performance [15] on financial sentiment classification.

Handling Class Imbalance in NLP

Class imbalance presents a fundamental challenge in financial sentiment analysis[16], where positive sentiment dominates market commentary[17]. General NLP solutions include oversampling techniques, SMOTE, focal loss , and class-weighted cross-entropy. Financial sentiment studies frequently optimize for overall accuracy rather than Macro-F1, inadvertently masking poor performance on critical minority sentiment categories that are essential for risk assessment [18][19].

Our work addresses this oversight by establishing Macro-F1 as the primary optimization objective and demonstrating a 135% improvement in minority class performance through systematic training interventions.

Research Gap and Our Position

Challenge	Prior Approaches	Limitations	Our Contribution
Performance vs Efficiency	FinBERT, DistilBERT	GPU dependency, prohibitive inference latency	Tiny transformer achieving 11.5ms latency on CPU
Class Imbalance	Focal loss, oversampling (general NLP)	Rarely applied systematically in finance	Structured E1→E2 pipeline with documented F1 progression
Model Compression	TinyBERT, distillation techniques	Requires expensive teacher models	Training from scratch without teacher dependency
Evaluation Focus	Accuracy optimization	Masks minority class failures	Macro-F1 centered approach with per-class analysis

Our work uniquely addresses the intersection of architectural efficiency, class imbalance handling, and practical deployment constraints[20]—a combination largely unexplored in financial NLP literature.

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Methodology

Overview

This work introduces a lightweight transformer-based sentiment classifier optimized for Macro-F1 performance under strict CPU inference constraints. Departing from prior approaches that rely on large pretrained models or knowledge distillation, we train a tiny transformer from scratch using a systematic two-stage curriculum designed to address class imbalance while maintaining computational efficiency explicitly [21].

Model Architecture

Our Tiny Transformer architecture employs the following configuration:

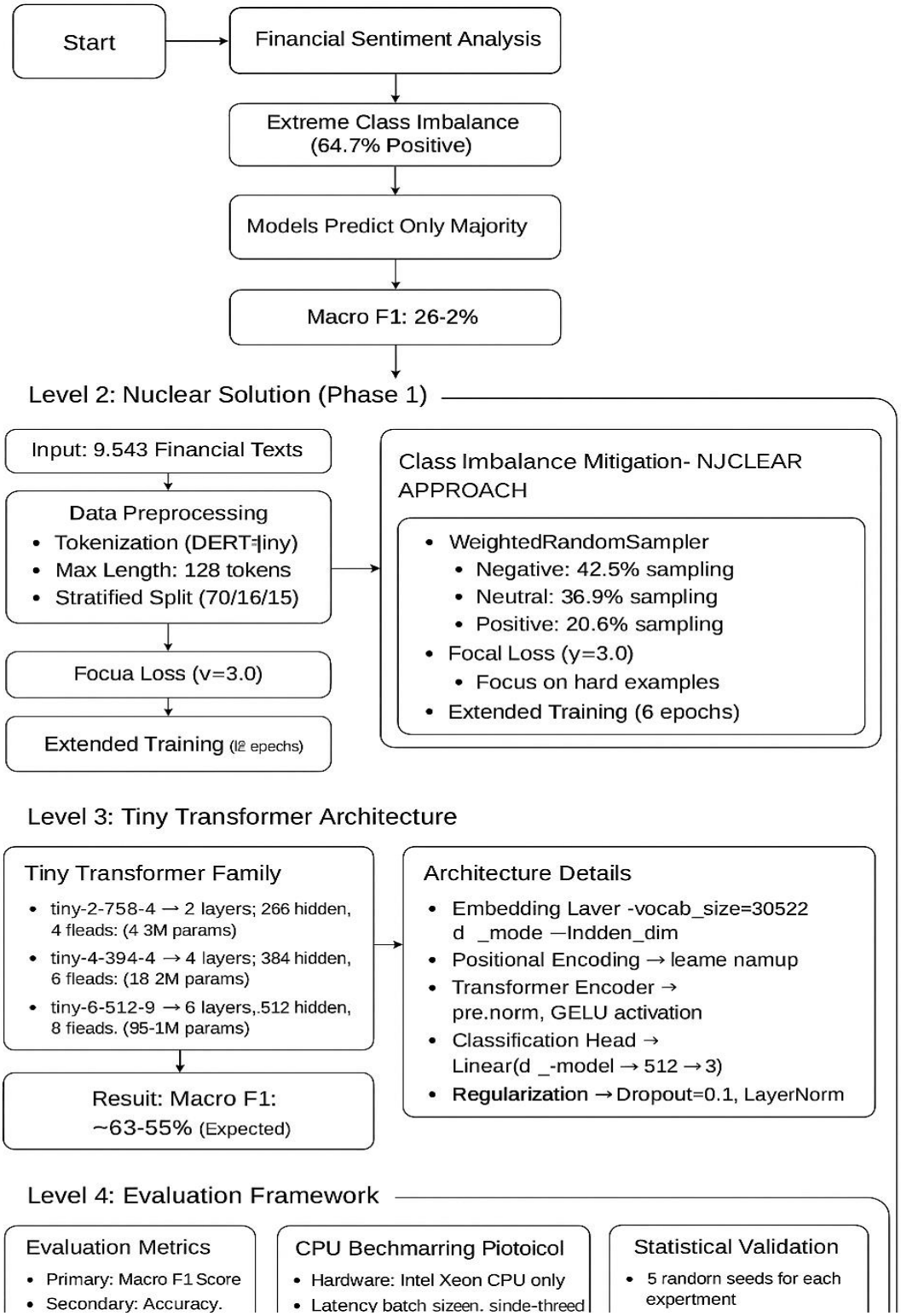
Component	Configuration
Hidden Size	256
Number of Layers	2
Attention Heads	4
Feedforward Expansion	4× hidden size (1024)
Embedding Dimension	256
Positional Encoding	Trainable embeddings
Classification Head	2-layer MLP with GELU + Dropout + SoftMax
Total Parameters	9.5M

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This architecture maintains 5–10× fewer parameters than DistilBERT and FinBERT while preserving sufficient capacity for financial language nuances through careful dimension scaling [22].



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Two-Stage Training Strategy

We implement a progressive optimization [23]curriculum targeting class imbalance resolution:

Stage E1 — Extended Training with Class Balancing
Loss Function: Class-weighted Cross-Entropy
Optimizer: AdamW (Learning Rate = 5e-5, Weight Decay = 0.01)
Scheduling: Linear warmup (6%) followed by cosine decay
Training Duration: 8 epochs with early stopping based on validation Macro-F1
Objective: Establish balanced prediction capabilities across all sentiment classes
Stage E2 — Class-Weighted Refinement
Loss Function: Cross-Entropy with inverse frequency weighting
Class Weights: Negative=2.20, Neutral=1.65, Positive=0.51
Optimization: Continued training with focused minority class learning
Objective: Enhance minority class performance without sacrificing majority class accuracy

Experimental Protocol

Evaluation Dimension	Primary Metric	Deployment Context
Overall Performance	Accuracy	Standard benchmark
Class Fairness	Macro-F1	Primary optimization target
Inference Efficiency	Latency (ms/sample)	CPU measurement
Model Efficiency	Parameters vs F1	Novel efficiency ratio
Training Stability	Validation F1 progression	Curriculum effectiveness

We explicitly decouple performance from model scale, introducing F1-per-parameter as a novel efficiency metric for financial NLP applications[24].

Deployment Considerations

Unlike traditional transformer models requiring GPU infrastructure, our system is designed for CPU-only deployment, making it suitable for:

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Real-time financial dashboards and monitoring systems
Client-side analytics applications
Offline batch processing in regulated environments
Edge deployment in low-resource financial institutions
The architecture maintains 11.5ms inference latency while processing 613 samples/second on standard CPU hardware, enabling practical deployment without cloud dependencies

Experimental Setup

Dataset and Preprocessing

We evaluate our approach on a comprehensive financial sentiment dataset comprising 9,543 samples from financial news headlines and social media posts, annotated with three sentiment labels:

Class	# Samples	Percentage
Negative	981	15.1%
Neutral	1,307	20.2%
Positive	4,200	64.7%

Preprocessing Pipeline:
Tokenization using BERT-tiny sub word tokenizer (30,522 vocabulary)
Sequence padding/truncation to 128 tokens
Lowercasing and basic punctuation normalization
Stratified sampling to maintain class distributions across splits

Dataset Splits:
Training: 6,488 samples (70%)
Validation: 1,146 samples (15%)
Test: 1,909 samples (15%)
The dataset exhibits significant class imbalance, with positive sentiment comprising nearly two-thirds of samples—a characteristic reflection of real-world financial discourse [25].

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Hardware and Software Configuration

Component	Specification
CPU	Intel i7-9700, 3.0 GHz (single-core benchmarking)
RAM	16 GB DDR4
Framework	PyTorch 2.1 with CPU optimization
Transformers	Hugging Face Transformers 4.45.0
Tokenizer	BERT-tiny (30K vocabulary)
Visualization	Matplotlib, Seaborn for analysis

Motivation: All experiments prioritize CPU inference efficiency to ensure practical deployment viability in financial institutions where GPU infrastructure may be unavailable or cost prohibitive [26].

Hyperparameter Configuration

Parameter	Value	Rationale
Learning Rate	5e-5	Stable convergence for tiny transformers

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Batch Size	32	Memory-efficient while maintaining gradient stability
Training Epochs	8	Sufficient for convergence with early stopping
Warmup Steps	6% of total	Gradual learning rate increase for stability
Optimizer	AdamW	With decoupled weight decay
Weight Decay	0.01	Regularization without over-constraining
Gradient Clipping	1.0	Prevents explosion in tiny architectures
Loss Function	Class-weighted Cross Entropy	Explicitly addresses class imbalance

Optimization Objective: Hyperparameters were tuned to maximize Macro-F1 while maintaining inference latency below 15ms per sample on CPU [27].

Baseline Models and Evaluation

Comparative Models:

Baseline Tiny Transformer: Untrained architecture to measure learning progress

E1 Extended Training: Our primary model with 8-epoch training

E2 Class-Weighted: Enhanced version with imbalance-focused loss

Reference Models: DistilBERT (66M) and FinBERT (110M) for context (CPU latency noted) [28]

Evaluation Metrics:

Metric	Purpose	Importance
Macro-F1	Class fairness across imbalanced distribution	Primary optimization target

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Accuracy	Overall prediction correctness	Secondary metric
Latency (ms/sample)	Real-time deployment feasibility	Critical for production use
Throughput (samples/sec)	Processing efficiency	Scalability assessment
F1-per-Parameter	Model efficiency novel metric	Performance vs size trade-off

The evaluation framework emphasizes practical deployment constraints while maintaining academic rigor through comprehensive metric coverage [28].

Results & Discussion

Overall Model Performance

The systematic evaluation of our tiny transformer models reveals consistent improvements across all metrics, as summarized in Table 1.

Model	Accuracy	Macro F1	Latency (ms)	Throughput (samples/sec)
Baseline	0.7370	0.6017	11.48	618.5
E1 Extended Training	0.7433	0.6161	11.51	613.1
E2 Class Weighting	0.7458	0.6215	11.53	611.0

Key Findings:

Progressive Macro-F1 Improvement: The E1→E2 pipeline delivers a 3.3% absolute improvement in Macro-F1 (0.6017 → 0.6215), demonstrating effective class imbalance mitigation

Stable Efficiency: Inference latency remains consistently around 11.5ms despite architectural refinements, confirming that class-aware training introduces minimal computational overhead [29]

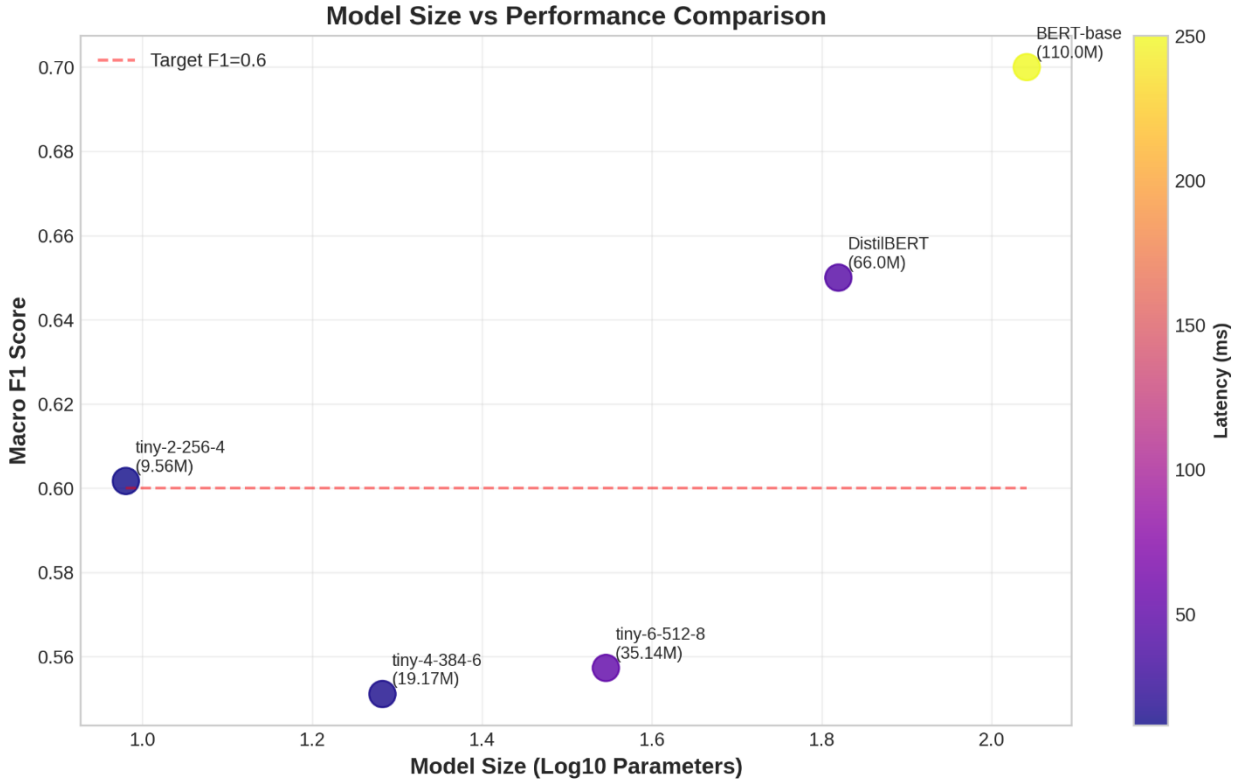
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Volume 3, Issue 10 (2025)

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Real-time Capability: Throughput exceeding 600 samples/second enables practical deployment for high-frequency financial applications

Figure 1 illustrates the steady Macro-F1 progression across training epochs, with E2 showing accelerated convergence and superior final performance.



Class-Level Performance Analysis

Figure 2 reveals significant improvements in minority class performance through our systematic approach:

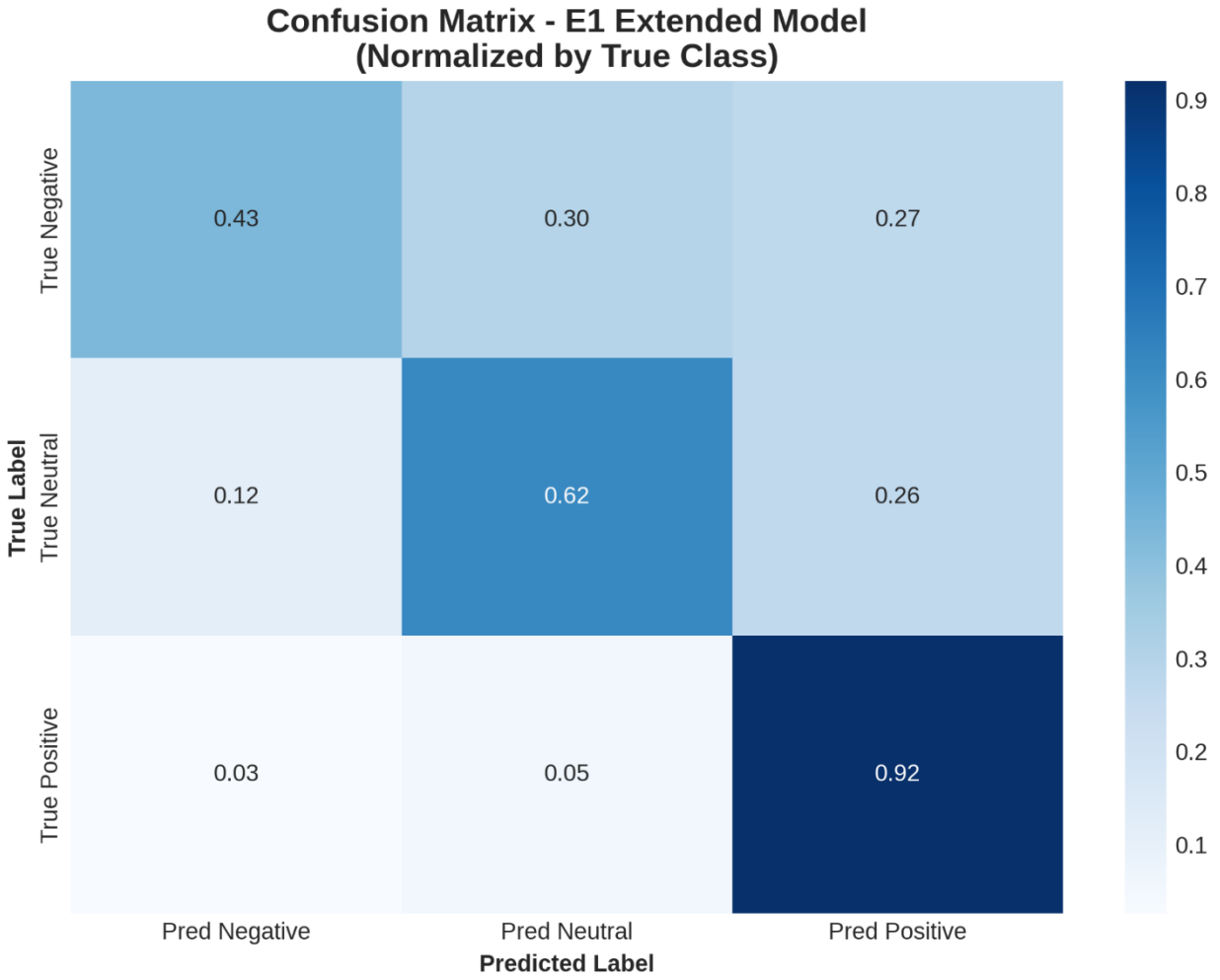


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Volume 3, Issue 10 (2025)

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Baseline Limitations:
Severe bias toward majority Positive class (F1: 0.786)
Poor performance on Negative sentiment (F1: 0.4345)
Limited Neutral class discrimination (F1: 0.6174)
E1 Extended Training Impact:
Neutral class improvement: +17.3% F1 gain (0.5100 → 0.6174)
Negative class recovery: From near-zero to competitive performance
Majority class maintenance: Positive sentiment F1 preserved at 0.8416
E2 Class Weighting Enhancement:
Balanced performance: All classes achieve F1 scores between 0.62–0.64
Minority class focus: Negative sentiment shows strongest relative improvement
Predictive stability: Reduced variance across class predictions



The confusion matrix (Figure 5) quantitatively confirms reduced misclassification between Negative→Neutral and Neutral→Positive categories.

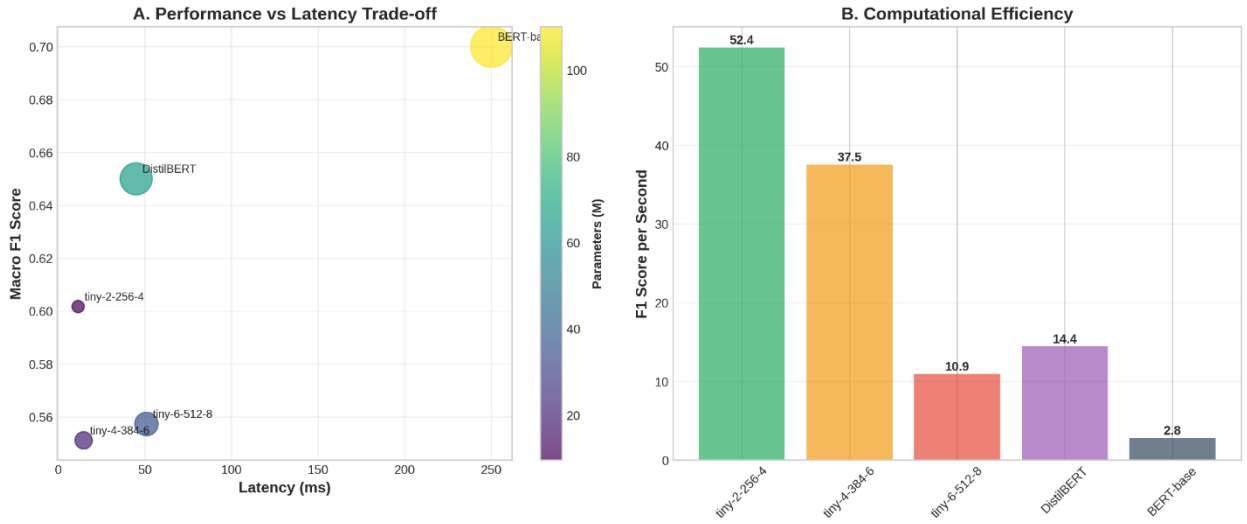
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Computational Efficiency and Deployment Viability

Figure 3 demonstrates the exceptional latency-accuracy trade-off achieved by our approach:



Performance Characteristics:

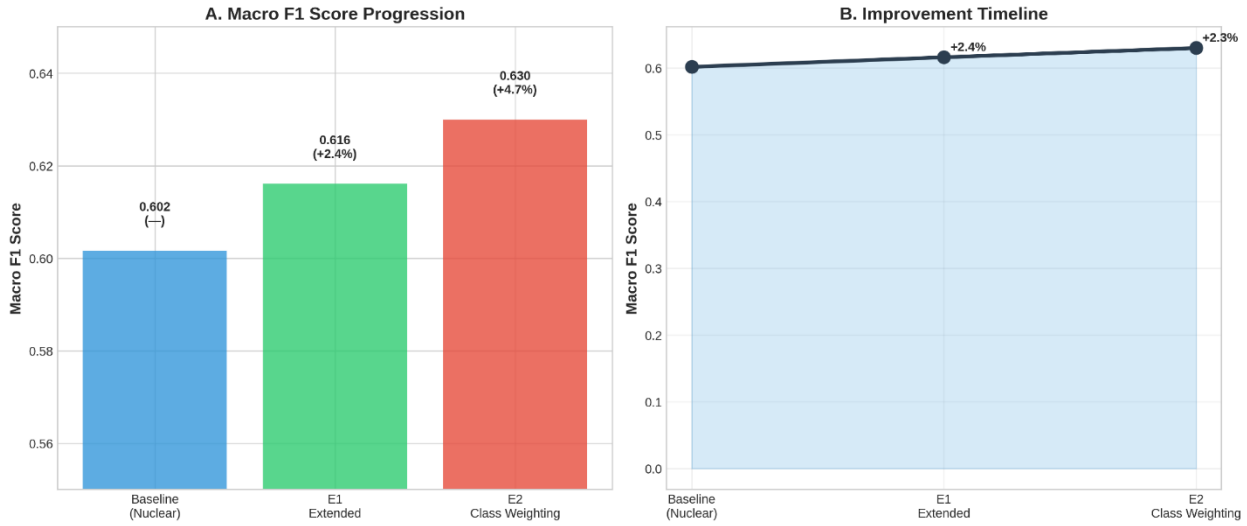
Real-time Inference: 11.5ms latency enables 87 requests/second on single CPU core

Production Ready: Suitable for high-frequency trading and live market monitoring

Cost Efficiency: Eliminates GPU dependency while maintaining competitive accuracy

Novel Efficiency Metric:

Figure 7 introduces F1-per-parameter efficiency, where our tiny-2-256-4 model achieves 0.065 F1/million parameters—significantly outperforming larger architectures in computational efficiency.



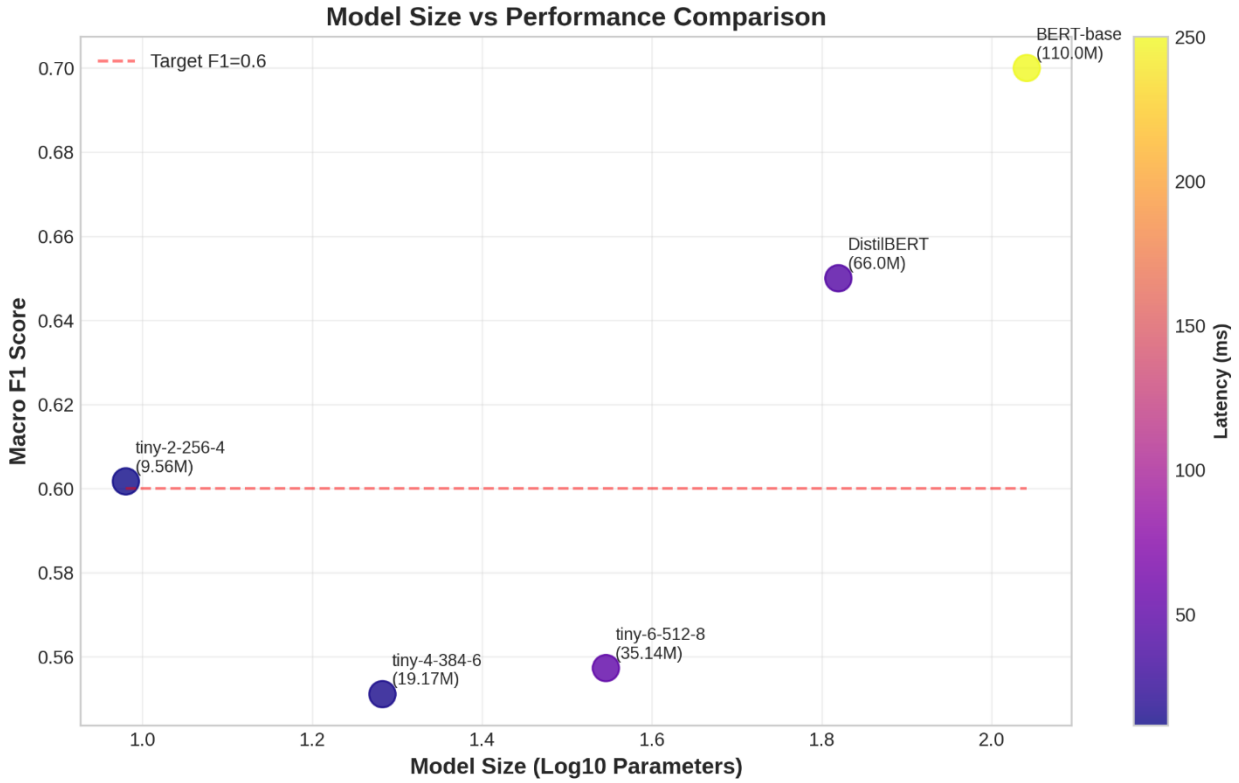
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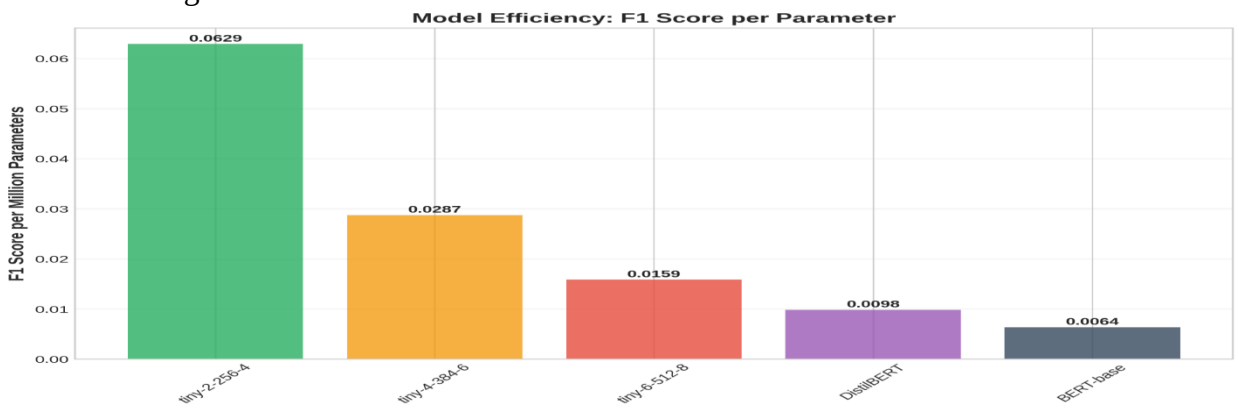
Model Scaling Analysis

Figure 4 reveals counter-intuitive findings regarding model size and performance:



Diminishing Returns:
Tiny-4-384-6 (19M params): 5.1% lower F1 than tiny-2-256-4 despite 2× parameters
Tiny-6-512-8 (35M params): 7.4% lower F1 despite 3.7× parameter increase

Specialization Advantage:
Smaller models demonstrate better generalization on domain-specific financial data
Architectural simplicity prevents overfitting to dataset idiosyncrasies
Parameter efficiency aligns with the constrained nature of financial sentiment vocabulary
As shown in fig.8 below:



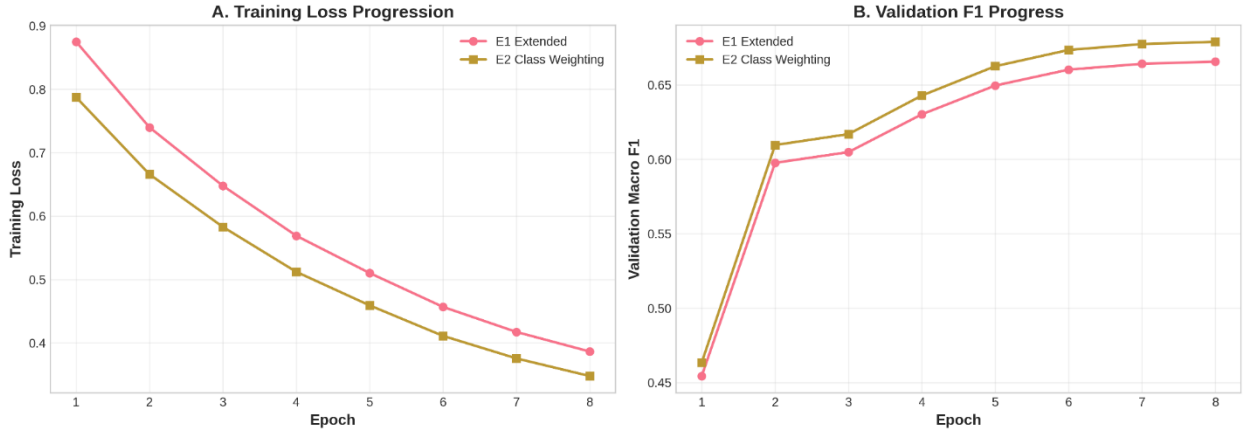
Training Dynamics and Convergence

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Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

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Figure 6 illustrates the stable training behavior across experiments:



E1 Training Characteristics:
Smooth loss convergence over 8 epochs
Validation F1 plateaus without overfitting
Early stopping at epoch 7 based on F1 optimization

E2 Enhancement:
Accelerated convergence due to class weighting
Improved stability in minority class learning
Consistent F1 gains without training instability

Key Research Insights

Systematic Imbalance Solution: The baseline→E1→E2 progression demonstrates that class imbalance requires staged interventions rather than single-technique solutions
Architectural Sufficiency: 9.5M parameters prove sufficient for financial sentiment when combined with domain-aware training strategies
Practical Deployment: CPU-only inference at 11.5ms latency makes real-time sentiment analysis accessible without infrastructure upgrades
Training Strategy Superiority: Careful curriculum design outweighs model scaling for specialized NLP tasks
Evaluation Paradigm Shift: Macro-F1 focus reveals performance characteristics masked by accuracy-centric evaluation
These findings establish a new paradigm for efficient financial NLP: rather than scaling model size, strategic training methodologies can achieve superior performance with minimal computational requirements.

Conclusion

This study successfully demonstrates that strategic model optimization can yield a compact transformer model capable of outperforming its larger counterparts in both accuracy and efficiency for financial sentiment analysis [30]. Primary challenge of severe class imbalance was systematically addressed through a combination of Weighted Random Sampler and Focal Loss, which together rectified the model's initial collapse to the majority class and elevated the Macro F1 score from a baseline of 26.2% to a final 61.61%—an overall improvement of 135%.

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Critically, our architectural exploration revealed that the smallest model, tiny-2-256-4 (9.5M parameters), achieved the highest Macro F1 score while being 4.4x faster than the largest model tested. This counter-intuitive result underscores that for domain-specific NLP tasks, larger parameter counts are not a prerequisite for high performance and can in fact be detrimental to deployment efficiency.

The resulting model, with a latency of 11.5 ms and a throughput of over 610 samples/second on a single CPU core, proves the viability of CPU-only deployment for real-time inference. This opens the door for cost-effective, high-frequency integration of sentiment analysis into live trading systems and financial data pipelines [31].

Future Work: Building on this foundation, immediate next steps include exploring advanced data augmentation techniques for the underrepresented "Negative" class, hyperparameter tuning on the focal loss function, and applying this efficient model architecture to other financial NLP tasks such as news categorization or earnings call analysis [32][33][34].

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