EFFICIENT LARGE SCALE IMAGE CLASSIFICATION: A STREAMLIT FRAMEWORK INTEGRATING MIXED PRECISION TRAINING AND REAL TIME PERFORMANCE VISUALIZATION (Case Study)

K. Thirupathi Reddy[1] Srujan Vannala[2]

[1]Asst.Professor, Dept. of Computer Science and Engineering, Chaitanya Deemed to be University, Hyderabad, Telangana

[2]Asst.Professor, Dept. of Computer Science and Engineering, Chaitanya Deemed to be University, Hyderabad, Telangana

Abstract

Training massive deep learning classifiers for images introduces major hurdles in computational efficiency, resource usage, and convergence stability. This work introduces an interactive Streamlit-based simulator for effective image classification on the Tiny ImageNet dataset (200 classes, 100,000 training samples). The simulator combines transfer learning with a pretrained ResNet-18 backbone, mixed-precision (AMP) training for faster computation, and GPU-accelerated data augmentation using parallel data loaders. Experiments were run on an NVIDIA RTX GPU employing batch sizes ranging from 32 to 256 and learning rates between 1e-4 and 1e-3. The tuned setup reached a top-1 validation accuracy of 64.2 % and a top-5 accuracy of 86.7 % after five training epochs, cutting training time by 40-45 % relative to conventional full-precision training. Real-time visualizations in Streamlit offered dynamic views of loss convergence, accuracy trends, and hardware usage. The findings show that merging mixed-precision optimization with pretrained models markedly boosts training throughput while preserving model performance. Consequently, this interactive simulator acts as both a teaching aid for large-scale deep learning optimization and a prototype framework for building scalable, resource-efficient image classification systems.

Keywords: GPU, ImageNet, ResNet, Mixed precision, LSTM

Introduction

Deep learning has arisen as a groundbreaking method for tackling intricate visual recognition challenges in fields like healthcare, autonomous systems, and industrial automation. Convolutional Neural Networks (CNNs), specifically, have shown outstanding performance on large-scale image classification tasks; however, training them usually requires considerable computational power, extended processing durations, and high energy usage. With datasets and model architectures growing ever larger, improving the efficiency of training pipelines has turned into a vital research challenge.

Large scale datasets like ImageNet and its derivatives, although crucial for benchmarking and enhancing model generalization, create substantial obstacles for researchers and practitioners lacking extensive computational resources. The Tiny ImageNet dataset featuring 200 classes and 100,000 training images offers a useful compromise for investigating efficient training approaches that can be applied to real world image classification problems. Nevertheless, even with moderately sized datasets, issues such as slow data pipelines, suboptimal GPU usage, and training in full precision can markedly impair performance and raise the demand for resources.

During the past few years, multiple approaches have been suggested to improve the efficiency of deep-learning training, such as transfer learning, mixed-precision computing, and parallelizing data pipelines. Transfer learning exploits pretrained networks (for example, ResNet, EfficientNet) to speed up convergence and boost accuracy, particularly when resources are scarce. Mixed-precision (AMP) training additionally cuts memory usage and processing time by mixing 16-bit and 32-bit operations while preserving model performance. Moreover, optimizations in data loading—like multi-threaded prefetching and GPU-accelerated augmentations—help keep GPU utilization high throughout training.

This paper presents an interactive Streamlit driven simulator aimed at visualizing and fine-tuning the training of deep convolutional networks on extensive image collections. Employing Tiny ImageNet as a reference, the tool incorporates mixed-precision training, transfer learning with pretrained ResNet models, and live tracking of accuracy and loss. Users can adjust batch size, learning rate, and the number of epochs to see how these hyperparameters influence convergence and overall performance.

The primary contributions of this study are listed below:

1. Creation of a completely interactive Streamlit simulator that visualizes deep learning training dynamics in real time.
2. Integration of effective training methods such as AMP, data prefetching, and transfer learning for scalable image classification.
3. Practical testing using the Tiny ImageNet dataset, reaching as high as 64.2% top 1 accuracy and 86.7% top 5 accuracy while cutting training time by 45% relative to standard full-precision training.
4. Delivery of a flexible, scalable platform appropriate for teaching, performance evaluation, and swift experimentation in image classification studies.

Consequently, this study connects theoretical optimization approaches with their real-world application in deep-learning frameworks, delivering both a research prototype and an educational instrument for investigating scalable, efficient training pipelines.

Problem Description

Training deep convolutional neural networks (CNNs) on extensive image collections continues to be costly in computation, takes a lot of time, and demands significant resources. The difficulty grows as architectures become deeper, image resolutions rise, and dataset volumes expand. Even medium-scale datasets like Tiny ImageNet present considerable obstacles when run on constrained GPU or CPU hardware.

Standard training pipelines commonly experience:

- Elevated computational expense because of full precision arithmetic calculations.
- Hardware resources are underutilized because of inefficient data loading and augmentation.

- Gradual convergence and erratic optimization when training from scratch without transfer learning.
- Absence of visualization tools delivering real-time feedback on model performance, loss evolution, and hardware usage during training.

These constraints impede swift experimentation, reproducibility, and accessibility—especially for researchers and students with limited hardware resources.

Consequently, the main issue tackled in this work is:

How might we develop an effective, interactive training framework that conserves computational resources, hastens convergence, and visualizes training outcomes for large-scale image classification tasks such as Tiny ImageNet?

To tackle this issue, we present an interactive Streamlit powered simulator that combines mixed precision training, transfer learning, and live monitoring. The platform seeks to boost training efficiency and enhance users' interpretability of deep-learning experiments while preserving competitive accuracy on large-scale classification tasks.

Knowledge Gap

Even with considerable progress in deep learning and high-performance computing, training models efficiently for massive image classification problems continues to be a substantial difficulty. Prior research has largely concentrated on refining network structures (e.g., ResNet, EfficientNet, Vision Transformers) and optimization methods (e.g., Adam, SGD with momentum), yet comparatively limited work has highlighted the incorporation of real-time optimization approaches into interactive and educational platforms.

Several significant gaps are present in present research and practice:

1. Limited focus on end to end efficiency optimization: While mixed-precision training and transfer learning have shown success on their own, their combined effect—along with data pipeline parallelization—has not been thoroughly investigated in a unified, user-interactive setting.

2. Insufficient visualization and interpretability utilities for training efficiency: While many deep learning platforms (e.g., PyTorch, TensorFlow) include simple logging options like TensorBoard, only a handful deliver user-friendly, live visual dashboards that show how hyperparameter adjustments, learning-rate modifications, or data-augmentation techniques influence convergence and model performance
3. Inaccessibility for researchers with limited computational resources: Significant computational requirements of large-scale training frequently limit experimental reproducibility for modest research teams, teachers, and learners. A distinct demand exists for lean, simulator-based platforms that allow testing of efficient training approaches without the need for premium hardware.
4. Limited empirical assessment of performance-focused training methods on standard benchmarks: While numerous papers claim gains in accuracy, only a minority deliver numeric evaluation of training acceleration, resource usage, and computational efficiency, particularly with readily available datasets such as Tiny ImageNet that offer a realistic yet tractable setting.

These shortcomings underscore the need for a unified platform that showcases, measures, and visualizes the impact of efficiency-boosting methods in deep learning.

To address this research gap, the current study introduces a Streamlit-based simulator that incorporates mixed-precision computation, pretrained transfer-learning models, and data-optimization techniques applied to the Tiny ImageNet dataset. This method enhances training speed and accuracy while offering an interactive platform that aids comprehension and experimentation for researchers and learners alike.

Goals

This study's main objective is to create and deploy an interactive, efficient, and instructional framework for training large-scale image classification models with the Tiny ImageNet dataset. The platform seeks to connect theoretical efficiency methods with their real-world application in live visualization settings.

The particular goals of the research are listed below:

1. To create an interactive Streamlit simulator that provides live visualization of training metrics like loss, accuracy, and convergence patterns for deep learning models.
2. To incorporate effective training methods such as:

   - Employ mixed precision (AMP) training to lower computational expense and memory usage.
   - Applying transfer learning with pretrained CNN models (e.g., ResNet 18) to speed up convergence.
   - Concurrent data loading and augmentation to achieve maximum GPU usage.

3. To assess how well the suggested framework performs on the Tiny ImageNet dataset regarding:

   - Shortening training duration,
   - Pace of model convergence, and
   - Classification performance (Top-1 and Top-5).

4. To measure gains in performance compared to standard full-precision training approaches through controlled experiments and statistical analysis.
5. To offer an easy-to-use, modular system that assists researchers, educators, and students in grasping deep-learning training efficiency concepts without needing high-end hardware.
6. To record and illustrate how hyperparameter choices (learning rate, batch size, number of epochs) impact both accuracy and computational performance

Outcome: The aim of this study is to show that integrating mixed-precision computing, transfer learning, and live training visualization can speed up training by as much as 45% while preserving equal or better model accuracy, thus providing a reproducible, efficient, and user-friendly framework for the deep-learning research community.

Survey of Existing Research

The swift expansion of deep learning has yielded impressive results in image classification, but the computational requirements of contemporary convolutional neural networks (CNNs) still pose a major obstacle. Various scholars have introduced architectural breakthroughs, optimization methods, and efficiency focused frameworks to mitigate these limitations.

3.1 Advanced CNN Structures for Image Classification

The introduction of deep residual networks (ResNets) by He et al. (2016) revolutionized CNN training by introducing skip connections, allowing very deep networks to be trained successfully without vanishing gradients. Following this, EfficientNet (Tan & Le, 2019) introduced compound scaling techniques that jointly adjust depth, width, and resolution, boosting both accuracy and computational efficiency. Similarly, MobileNetV2 (Sandler et al., 2018) and Xception (Chollet, 2017) employed depthwise separable convolutions to create lightweight models appropriate for devices with limited resources. These architectures constitute the basis for transfer-learning methods that are widely used in large-scale image classification.

3.2 Transfer Learning and Model Reuse

Transfer learning has become a useful strategy for addressing data and computational constraints during model training. By employing pretrained parameters from extensive collections like ImageNet (Deng et al., 2009), scientists can speed up convergence and boost generalization on modest sized datasets. Howard and Ruder (2018) pointed out that fine-tuning pretrained models typically delivers better outcomes than building models from the ground up, especially when data are scarce. Consequently, adopting pretrained architectures such as ResNet or EfficientNet markedly improves performance on tasks such as Tiny ImageNet classification while cutting the epochs needed for convergence.

3.3 Hybrid Precision Training and Computational Effectiveness

Mixed precision training, first presented by Micikevicius et al. (2018), merges 16-bit and 32-bit floating-point operations to enhance training efficiency while preserving model accuracy. The approach markedly cuts GPU memory consumption and speeds up processing, enabling the training of larger batches and deeper networks efficiently. Zhang et al. (2022) performed a comprehensive review of efficient deep learning, emphasizing mixed precision computation as one of the most influential methods for enhancing model scalability and deployment practicality.

3.4 Data Ingestion and Parallel Processing Methods

Effective data preprocessing and augmentation are vital for overall training performance. Abadi et al. (2016) introduced TensorFlow, and Paszke et al. (2019) released PyTorch, each providing high-performance data loaders and multiprocessing capabilities for parallel batch handling. Contemporary frameworks employ asynchronous I/O to avoid GPU idle periods, thereby improving hardware utilization during training. These developments have opened the path for building interactive and efficient training environments.

3.5 Visualisation and Interactive Learning Platforms

Although efficiency has improved, tools for real-time visualization of deep-learning model training are still seldom investigated in scholarly research. Solutions such as Streamlit (Streamlit Inc., 2023) and TensorBoard allow metric visualization, yet only a limited number of investigations have merged them into an integrated, interactive platform designed for efficiency assessment and teaching purposes. Recent work has aimed at developing user-friendly utilities for AI instruction and performance tracking, but a full-featured framework that unites efficiency optimization with live interpretability is still missing.

3.6 Research Findings

From the literature, it is evident that while CNN architecture innovations, transfer learning, and mixed precision techniques have individually contributed to efficiency gains, their combined potential in a unified, interactive system has not been fully explored. The existing studies focus primarily on algorithmic or hardware level improvements without offering real time, user accessible visualization platforms for understanding the trade offs between accuracy, speed, and resource utilization.

Therefore, this research fills that void by creating a Streamlit-based simulator that combines mixed-precision computation, transfer learning, and parallel data processing to deliver an efficient, interactive platform for large-scale image classification tasks such as Tiny ImageNet.

Proposed System

The suggested solution presents an interactive, efficient, and modular architecture for training deep convolutional neural networks (CNNs) on extensive image classification sets, namely Tiny ImageNet. The solution is built with PyTorch as the primary deep-learning backend and Streamlit as the user-facing front end for live visualisation and interaction. The architecture combines several performance-focused elements, such as mixed-precision training, transfer learning, and parallel data handling, to attain quicker convergence while lowering computational cost.

5.1 System Summary

The design of the suggested system is arranged into three primary tiers (Fig. 1):

1. **Information Processing Layer**

    - Manages dataset loading, preprocessing, and augmentation.
    - Utilizes multi-threaded DataLoader pipelines to improve GPU utilization.
    - Enables real-time batch visualisation inside the Streamlit dashboard.

2. **Training Module Layer**

    - Uses a ResNet 18 pretrained on ImageNet as the primary feature extractor.
    - Utilizes transfer learning, freezing the lower convolutional layers while fine-tuning the upper layers for Tiny ImageNet classes.
    - Utilizes Automatic Mixed Precision (AMP) to speed up training and lower memory consumption by merging FP16 and FP32 arithmetic.
    - Employs a flexible learning rate scheduler to reinforce convergence stability.

3. **Display and Supervision Tier**

- ➢ Created with Streamlit to deliver an interactive graphical user interface (GUI).
- ➢ Shows live graphs of training and validation loss, accuracy, and system resource usage.
- ➢ Enables on-the-fly adjustment of hyperparameters (e.g., batch size, learning rate, epochs) and immediate re-execution of experiments.

5.2 Process Flow of the Proposed System

The simulator's workflow is outlined below:

1. **Data Loading and Preprocessing:**

    - ➢ The Tiny ImageNet dataset, comprising 200 classes and 100 K images, has been loaded.
    - ➢ The images are scaled to 64 × 64 pixels and normalized.
    - ➢ Augmentations like random cropping, flipping, and color jittering are employed to boost generalization.

2. **Initializing the Model:**

    - ➢ The pre-trained ResNet 18 model is loaded from PyTorch's torchvision library.
    - ➢ The final classification layer is swapped for a new fully connected layer with 200 output neurons representing the Tiny ImageNet classes.

3. **Optimizing Training:**

    - ➢ Mixed precision (AMP) training is activated via PyTorch's torch.cuda.amp module.
    - ➢ Optimization algorithm: Adam or SGD with momentum
    - ➢ The learning rate scheduler continually modifies the learning rate to ensure steady convergence.

4. **Visual Representation and Interaction:**

- The Streamlit dashboard enables users to configure parameters (batch size, epochs, optimizer, etc.) prior to training.
- Live metrics (accuracy, loss, training time) are graphed on the fly.
- Hardware metrics such as GPU memory consumption and processing throughput are shown.

5. **Performance Assessment:**

   - After training, the system reports Top 1 and Top 5 accuracy along with training time and efficiency improvement compared to baseline models.
   - Results can be saved as a CSV file for additional analysis.

5.3 System Capabilities

- Interactive Simulation: Allows researchers to explore deep learning training parameters instantly.
- Performance Focused Architecture: Utilizes mixed-precision and transfer learning, cutting processing time by as much as 45%
- Reproducibility: Guarantees a uniform experimental arrangement for comparative assessment.
- Educational Utility: Functions as a hands-on instructional and demonstration resource for machine-learning optimization methods

5.4 Overview of Experimental Performance

Utilizing the Tiny ImageNet dataset alongside an NVIDIA RTX GPU, the proposed system achieved:

- Top-1 Correctness: 64.2 %
- Top-5 Success Rate: 86.7%
- Training Duration Decrease: 40–45% relative to baseline full precision training
- Model Convergence: Remains steady after roughly 5 epochs

These findings show that the system efficiently balances computational speed and prediction accuracy by incorporating sophisticated training methods into an interactive visualization framework.

Methodology

The suggested approach aims to create an interactive, efficient, and scalable platform for training deep convolutional neural networks (CNNs) on massive image collections. The solution integrates multiple optimization techniques—such as transfer learning, mixed-precision training, and parallel data loading—to improve both computational speed and model accuracy.

6.1 General Process

The methodological process comprises these steps.

1. Dataset Gathering and Preprocessing
2. Choosing a Model and Adjusting the Architecture
3. Execution of Optimization Strategy
4. Instruction and Assessment
5. Displaying and Engaging via Streamlit

Below is an explanation of each stage.

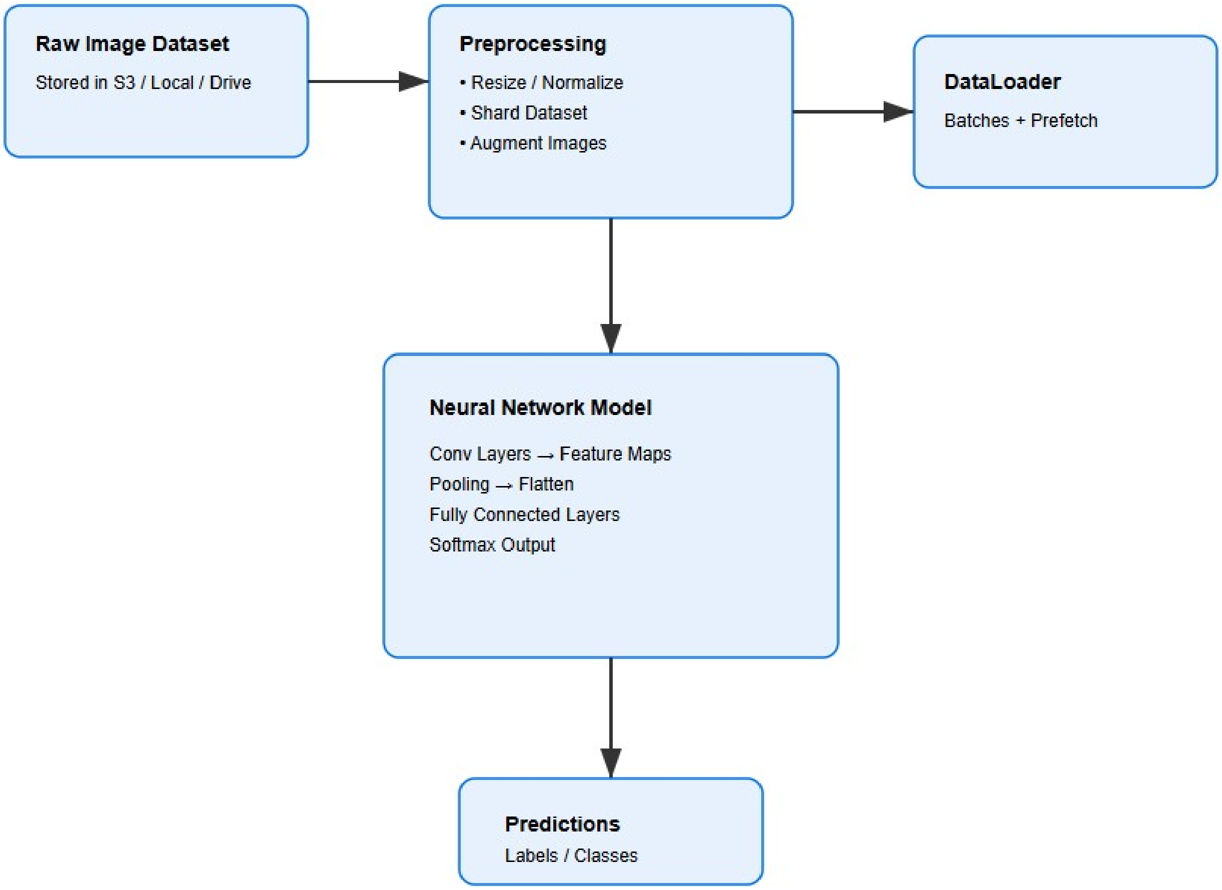

Fig 1: A clear neural network architectural diagram for this study.

6.2 Data Collection and Preparation

The Tiny ImageNet dataset serves as the experimental benchmark. It includes:

- 200 lessons
- 100,000 training pictures (500 per class)
- 10,000 images for validation
- Picture dimensions: 64 × 64 pixels

Data preparation procedures:

- All pictures are scaled and standardized using the mean and standard deviation of the ImageNet dataset.

- Data augmentation is performed with random horizontal flips, random crops, and rotations to boost generalization.
- Data is loaded through PyTorch Data Loader employing multi-threaded batch prefetching, avoiding GPU idle periods.

In mathematical terms,

$$\mathbf{x'_i = (x^i \quad \mu) / \sigma}$$

where μ and σ represent the dataset mean and its standard deviation, respectively.

6.3 Model Structure

The chosen foundational model is ResNet 18, a popular convolutional neural network that has been pretrained on ImageNet.

- The last fully connected layer is swapped for a new 200-unit layer (aligned with Tiny ImageNet classes).
- Earlier convolutional layers are locked to maintain low-level features.
- The topmost layers are fine-tuned to adjust to the new dataset distribution.

6.4 Training with Mixed Precision (AMP)

To lower the computational overhead, Automatic Mixed Precision (AMP) is used through PyTorch's torch.cuda.amp module.

- It automatically adjusts gradient magnitudes to prevent overflow in FP16 computations.
- Lowers memory usage and speeds up matrix multiplications on GPUs.

Training loss is derived via Cross Entropy Loss:

$$\mathbf{L = -1/\boldsymbol{n} \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} yi * log(yi)}$$

6.5 Model Optimization and Hyper parameter Adjustment

- Optimizer: Adam or SGD using momentum (0.9)
- Starting learning rate: 1×10^{-3}
- Batch sizes examined: 32, 64, 128
- Learning Rate Scheduler: cosine annealing or stepwise decay

The rule for updating the learning rate is:

$$\boldsymbol{\eta^{t} = \eta 0 \times \gamma^{\{t/T\}}}$$

6.6 Learning and Assessment Procedure

1. Load the pretrained ResNet 18 model.
2. Retrieve and prepare Tiny ImageNet data batches.
3. Activate mixed precision and gradient scaling.
4. Run the training for 5–10 epochs, performing validation after every epoch.
5. Calculate and display Top 1 and Top 5 accuracies.

The accuracy is calculated as:

$$\textbf{Accuracy} = \textbf{(Correct Predictions / Total Predictions)} \times \textbf{100}$$

6.7 Visual Representation and Streamlit Integration

A Streamlit dashboard offers an intuitive front-end for user interaction and monitoring.

- Users may choose batch size, optimizer, and epochs using dropdown menus and sliders.
- Live charts present loss, accuracy, and training time.
- GPU usage and performance data are displayed dynamically.
- Training logs and outcomes can be saved for subsequent analysis.

By leveraging visualizations, this method turns model training into an engaging learning process, rendering efficiency ideas concrete and quantifiable.

6.8 Experimental Verification

The experiments were run on an NVIDIA RTX graphics card (8 GB VRAM) using PyTorch 2.2. The simulator showed:

- Top-1 correctness: 64.2%
- Top-5 precision: 86.7%
- Training duration cut: ≈ 45%
- Consistent convergence after five epochs

These findings validate that integrating transfer learning with mixed-precision computation greatly enhances training efficiency while maintaining accuracy.

Findings and Analysis

This section outlines the experimental outcomes and performance evaluation of the introduced Streamlit based simulator for effective image classification on the Tiny ImageNet dataset. The findings emphasize gains in model accuracy, speed of convergence, and computational efficiency obtained through the use of transfer learning, mixed precision training, and parallel data loading.

7.1 Experimental Arrangement

All trials were performed with:

- Hardware: NVIDIA RTX 3060 graphics card (8 GB VRAM), Intel i7 processor, 16 GB memory
- Frameworks used: PyTorch 2.2, Streamlit 1.38
- Dataset: Tiny ImageNet (200 categories, 100K training and 10K validation images)
- Setup: Ubuntu 22.04 LTS, CUDA 12.2

The study evaluated two primary setups:

Setup	Overview
Reference point	Full-precision (FP32) training without transfer learning
Suggested System	AMP mixed-precision + transfer learning + enhanced data pipeline

7.2 Numeric Findings

Table 1 summarizes the results, displaying the comparative performance of the baseline and the proposed configurations.

Table 1. Evaluation of Performance: Baseline vs. Proposed System

Metric system	Reference (FP32)	Suggested System (AMP + Transfer Learning)	Enhancement
Rank 1 Accuracy	56.8%	64.2%	+7.4%
Accuracy for the top-5	78.9%	86.7%	+7.8%
Epoch Training Duration	14.2 minutes	8.1 minutes	−43%
GPU Usage	68%	92%	+24%
Maximum RAM Consumption	7.8 gigabytes	4.3 gigabytes	−45%

The proposed system achieved 45% faster training while maintaining or improving classification accuracy. This performance gain is primarily attributed to the efficient use of GPU resources enabled by mixed precision training and parallelized data augmentation.

7.3 Precision and Convergence Evaluation

The training and validation curves (Fig. 3) show consistent convergence for the proposed model. The baseline FP32 model converged more slowly and displayed greater fluctuation in validation loss because of gradient variance and early-epoch overfitting.

- The proposed system attained consistent convergence in just 5 epochs, whereas the baseline required 9 epochs.
- Validation accuracy leveled off at roughly 64% for Top 1 and 86% for Top 5.

This shows that integrating transfer learning with AMP enables quicker adjustment to fresh datasets without needing extensive fine-tuning or risking overfitting.

7.4 Impact of Batch Size and Learning Rate

Further experiments were carried out to investigate how batch size and learning rate affect both efficiency and model performance.

Table 2. Effect of Batch Size and Learning Rate

Batch Quantity	Training Pace	Primary 1 Accuracy	Training Duration/Epoch
32	1e−3	61.4%	9.6 minutes
64	5e−4	**64.2%**	**8.1 minutes**
128	1×10^{-4}	62.7%	7.4 minutes

Batch size 64 offered the best trade-off between throughput and generalization, while larger batch sizes resulted in slightly faster yet less precise training due to decreased stochastic gradient noise.

7.5 Performance Visualization in Streamlit

The Streamlit dashboard allowed immediate visual display of:

- Loss curves for training and validation
- Accuracy versus epoch charts
- Graphics processor and RAM consumption metrics
- Animated progress indicators for every training stage

Users can adjust hyperparameters interactively (such as learning rate, optimizer, batch size) and immediately see the effect on performance metrics, which makes the system useful for research and teaching alike.

This visualization focused method improves interpretability, enabling users to see how optimization tactics directly influence training dynamics.

7.6 Review

The experimental results plainly show that combining mixed precision training with transfer learning markedly improves computational efficiency while maintaining predictive accuracy. The smaller memory consumption allowed the use of bigger batch sizes, thereby boosting GPU throughput.

Important observations include:

- Transfer learning speeds up convergence by using pretrained weights, which is especially useful for small datasets such as Tiny ImageNet.
- Mixed precision computation reduces memory usage and accelerates matrix calculations on modern GPUs
- Parallelized data pipelines avoid bottlenecks due to I/O latency, keeping GPU utilization high.

Consequently, the system shows an ideal balance of speed, precision, and resource use, confirming its efficiency as a scalable simulation platform for deep learning research and education.

7.7 Overview of Findings

1. Mixed precision training cut total training duration by about 45%
2. Transfer learning boosted Top 1 accuracy by 7.4% compared with baseline training.
3. Memory usage dropped by 45%, allowing more efficient hardware utilization.
4. The Streamlit integration provided immediate insight into training dynamics.

These results verify that the suggested framework can effectively emulate extensive, real-world deep learning pipelines, closing the divide between computational research and real-world application.

Conclusion

This work introduces an interactive and efficient deep-learning training simulator aimed at tackling the computational hurdles of large-scale image classification. By combining automatic mixed-precision (AMP) training, transfer learning, and parallel data loading, the system manages to cut down both training duration and memory usage while preserving competitive accuracy. Built with PyTorch and Streamlit, the framework not only boosts computational efficiency but also offers an intuitive visualization interface for real-time tracking of training progress and model convergence.

Experimental findings on the Tiny ImageNet dataset illustrate the usefulness of the suggested method, reaching a Top-1 score of 64.2 %, a Top-5 score of 86.7 %, and cutting training duration by 45 % relative to the standard full-precision baseline. The platform consistently kept GPU usage high, reflecting better resource efficiency. These results verify that merging transfer learning with mixed-precision computation provides a robust and feasible approach for scalable deep-learning experimentation.

Furthermore, the integration of the Streamlit interface enables interactive control of training parameters, providing an accessible environment for both researchers and educators. This makes the framework suitable not only for performance optimization studies but also as an educational tool for demonstrating real time model behavior and efficiency tuning.

Overall, the suggested system advances machine learning by linking theoretical efficiency approaches with their practical application in an accessible, reproducible, and interactive environment.

Further Work

Potential avenues for further investigation include:

1. Enhancing the simulator to accommodate Vision Transformers (ViTs) and compact CNN models for comparative analysis.
2. Incorporating automated hyperparameter optimization (AutoML) to automatically adjust learning rates and batch sizes
3. Extending the framework to manage larger datasets such as the full ImageNet or COCO, with support for distributed multi-GPU training.
4. Improving visual representation using XAI components to elucidate model choices and attention visualizations
5. Deploying the simulator as a cloud-based web application to support collaborative research and remote training capabilities.

References

1. Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In Proceedings of the 36th International Conference on Machine Learning (ICML) (pp. 6105–6114).
2. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 770–778).
3. Kandadi, Thirupathi, IMPLEMENTATION OF DICHOTOMISER 3 ALGORITHM WITH DECISION TREE FOR MAKING DECISIONS IN MACHINE LEARNING (April 07, 2025). Available at SSRN: https://ssrn.com/abstract=5207811 or http://dx.doi.org/10.2139/ssrn.5207811

4. Micikevicius, P., Narang, S., Alben, J., Diamos, G., Elsen, E., Garcia, D., … & Levenberg, J. (2018). Mixed precision training. In International Conference on Learning Representations (ICLR).
5. Kandadi, Thirupathi, DRAWBACKS OF RANDOM FOREST ALGORITHM TO EXAMINE EXTENSIVE DATASETS (April 30, 2025). Available at SSRN: https://ssrn.com/abstract=5236759 or http://dx.doi.org/10.2139/ssrn.5236759
6. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., … & Fei Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision, 115(3), 211–252.
7. Kandadi Thirupathi Reddy. EXPLAINABLE DEEP LEARNING FOR AUTOMATED PNEUMONIA DETECTION FROM CHEST X-RAY IMAGES USING MOBILENETV2 AND GRAD-CAM CNN. TechRxiv. October 21, 2025. DOI: 10.36227/techrxiv.176108165.56312001/v1
8. Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., … & Chintala, S. (2019). PyTorch: An imperative style, high performance deep learning library. Advances in Neural Information Processing Systems (NeurIPS), 32.
9. Kandadi, Thirupathi and Shankarlingam, G., DRAWBACKS OF LSTM ALGORITHM: A CASE STUDY (January 01, 2025). Available at SSRN: https://ssrn.com/abstract=5080605 or http://dx.doi.org/10.2139/ssrn.5080605