



Adaptive Curriculum Learning for Accelerating Convergence in Data-Driven Model Training

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Abstract:

Background: Efficient training of machine learning models remains a critical challenge in data-driven artificial intelligence systems, particularly when training samples vary in difficulty, noise level, and representational complexity.

Aims: This study proposes and evaluates an adaptive curriculum learning framework that accelerates convergence in machine learning model training by dynamically adjusting sample ordering based on the model's evolving competence.

Methods: The proposed approach introduces a feedback-driven curriculum mechanism that integrates difficulty estimation and model competence evaluation. Training samples are initially ranked by estimated difficulty and are progressively updated during training using validation-based performance signals. Experiments are conducted on three benchmark datasets, including UCI Adult Income, Breast Cancer Wisconsin, and CIFAR-10, using multilayer perceptron and convolutional neural network architectures. The framework is compared against random sampling, static curriculum learning, and hard-first sampling strategies. Performance is evaluated based on convergence speed, predictive accuracy, robustness to noise, class imbalance handling, and computational overhead.

Result: The proposed adaptive curriculum learning framework consistently accelerates convergence across all datasets compared to baseline methods. The model achieves faster stabilization of training dynamics while maintaining or slightly improving predictive performance on accuracy, F1-score, and AUC. Furthermore, the framework demonstrates improved robustness under noisy-label conditions and class-imbalance scenarios, with reduced performance degradation compared to conventional sampling strategies. The computational overhead introduced by the adaptive mechanism remains minimal compared with the gains in training efficiency.

Conclusion: The study concludes that aligning sample ordering with evolving model competence significantly improves training efficiency in machine learning systems.

Keywords: Adaptive Sampling; Curriculum Learning; Machine Learning; Model Convergence; Training Efficiency.

1. INTRODUCTION

A salient issue in contemporary AI, particularly in dealing with extensive, diverse datasets with intrinsic complexity is the best way to train data-driven machine learning models (Dritsas & Trigka, 2025; Gong et al., 2023; Holzinger et al., 2025). In realistic training scenarios, training data is seldom uniform. More typically, training data demonstrates the full

spectrum of variations in difficulty, noise, sample ambiguity, and complexity (Metzner et al., 2022; Mosqueira-Rey et al., 2023; Tang et al., 2025; Zhou et al., 2023). Such variations affect optimization, and the training process suffers from poor convergence if models learn indiscriminately from all data samples. In regular training, machine learning models are trained on uniform or random sampling frameworks, where all training data are assumed to contribute to the process of updating the model, regardless of whether the training data is informative, appropriate, or relevant to the model (Shen et al., 2024a; Talaei Khoei & Kaabouch, 2023). From a practical standpoint, these assumptions prove useful. However, from a systems perspective, they are counterproductive to the overall process, as they lead to poor convergence in training. This is particularly the case with noisy data, class imbalance, or other similar challenges (Altalhan et al., 2025; W. Chen et al., 2024; Ghosh et al., 2022).

Curriculum learning is one of the few existing learning methodologies inspired by the observation of how

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humans gradually learn, from the simple to the complex (Dekker et al., 2022; Liu et al., 2023; Soviany et al., 2022). Curriculum learning in the context of machine learning describes an ordering of training data by task difficulty that allows the model to learn simpler tasks and essential patterns before being presented with more complex and challenging ones (Ten et al., 2021; Wang et al., 2022).

Structured training of machine learning models using curriculum learning techniques has been shown to improve convergence speed, generalization, and the optimality of the model's training behavior (Bian & Priyadarshi, 2024; Nunes et al., 2021; Saglietti et al., 2022). However, most existing techniques in curriculum learning rely on static assessments of task difficulty and/or a fixed sampling schedule throughout the training process (Wang et al., 2022; Zheng et al., 2025).

These fixed techniques rely on heuristic estimates of task difficulty and require significant manual effort to design for a specific dataset, making them inflexible for training scenarios that are subject to change. Effectively, when training begins, the curriculum cannot adapt to the model's growing competency, leading to a mismatch between the relative difficulty of training tasks and the model's capabilities at various stages of training (Ferrari, 2023; Kravchenko & Cusack, 2024; Lalor & Yu, 2020; Zhao et al., 2021).

Adaptive learning strategies have shown that model feedback may be used to create more efficient training processes (Z. Chen et al., 2025; Feng et al., 2025; Li et al., 2022; Shi & Liu, 2025). However, the current state of the art is highly fragmented. Most methods focus on individual elements, such as difficulty estimation or sample reweighting. There are no comprehensive solutions that include dynamic difficulty estimation, real-time feedback on model performance, convergence acceleration, robustness to label noise, class imbalance mitigation, and cost estimation. Solving the above problems is essential for making current methods useful in machine learning systems, because in practice, efficiency, robustness, and scalability must be addressed in unison (Shen et al., 2024b; Shivashankar et al., 2025; Shu et al., 2023). Additionally, many adaptive sampling methods add complexity without a formal cost-benefit analysis. Thus, there is a concern about using these methods for large-scale systems.

To address these issues, this study introduces an adaptive curriculum learning framework that changes the sample order based on the model under training. Compared to traditional curriculum learning methods that employ a fixed curriculum, the proposed framework constructs a curriculum based on the model's real-time performance feedback and maintains an estimate of the sample's difficulty level. This mechanism adapts and aligns the training process with the model's current learning capacity and orders the samples in a way that is most beneficial to the model for progressive learning. The framework has been designed to apply to a variety of datasets and model architectures. Thus, it can be employed in numerous data-driven applications. The

proposed curriculum learning framework utilizes difficulty estimation. It integrates competence-aware feedback loops and is expected to achieve sufficient improvement in model convergence, if not in predictive performance.

This research proposes a design and implementation of an adaptive curriculum learning framework to accelerate model convergence while maintaining robustness and accuracy. To achieve this, the dissertation analyzes the effectiveness of adaptive curriculum learning in terms of convergence iterations, compared with strategies that use random sampling and static curriculum (Karakasidis et al., 2024; Machado et al., 2021). It also analyzes the effectiveness of the adaptive curriculum learning framework in sustaining or improving predictive performance across a range of benchmark datasets of varying complexity. Furthermore, the dissertation analyzes the effectiveness of the adaptive curriculum learning framework in sustaining model performance across highly noisy, class-imbalanced datasets, a challenge that traditional learning strategies often fail to address. Finally, trade-offs due to the additional complexity for adaptive curriculum updates are evaluated to determine if the benefits of reduced convergence iterations improve model performance, learning speed, and overall robustness, regardless of the increased computational efforts.

This work innovatively considers curriculum learning as an iterative, dynamic process that integrates feedback, rather than treating it as a static, preprocessing phase. By incorporating signals of a model's growing competence into the curriculum adjustment mechanism, the proposed system can maintain alignment between data sequencing and learning progress. As a result, this system provides a sampling technique that not only accelerates learning but also increases the system's resistance to data imperfections, such as noise and class imbalance, while keeping operational costs low. The system, therefore, moves beyond existing systems of curriculum learning by integrating the speed of training, the accuracy of prediction, and the constraints of operating scale in machine learning to optimize its performance. The goal of this research is to answer the following questions: Can adaptive curriculum learning accelerate convergence when compared to random or static curricula.

2. MATERIAL AND METHOD

This study uses an experimental design in machine learning to analyze the impacts of the adaptive curriculum learning framework (Wang et al., 2024). This focus is primarily on model convergence and training speed. The experimental design lends itself to a systematic evaluation of different training strategies, using the same model architecture and datasets (Demartini et al., 2024). This ensures that the only element responsible for the differences in results is the chosen sampling strategy. Four training conditions are considered: random sampling as the standard baseline;

static curriculum learning as a predefined difficulty-ordered baseline; self-paced, or difficulty-based, sampling as an adaptive, non-feedback-driven strategy when applicable; and the proposed adaptive curriculum learning framework that dynamically updates sample ordering based on evolving model competence during training.

The experiments are conducted on three widely used benchmark datasets representing different domains and complexity levels. The first dataset is the UCI Adult Income Dataset, a tabular binary classification dataset used for socioeconomic prediction tasks, comprising 48,842 instances, 14 attributes, and 2 target classes (income $\leq 50K$ and $> 50K$). The second dataset is the Breast Cancer Wisconsin Diagnostic Dataset, a medical binary classification dataset containing 569 instances with 30 numerical features derived from digitized tumor cell nuclei measurements, used for benign-versus-malignant classification (Islam Jony et al., 2024). The third dataset is the CIFAR-10 image dataset, a multiclass classification benchmark containing 60,000 color images of size $32 \times 32 \times 3$ distributed across 10 object categories, including animals and vehicles (Divya et al., 2022). These datasets enable the simulation of learning processes of varying complexity, allowing evaluation of curriculum learning strategies on both structured tabular data and large, complex image data. Each dataset is split into training, validation, and test subsets with 70% training, 15% validation, and 15% test, to maintain class balance across experimental conditions. An overview of the datasets highlights the number of samples, attributes, and classes, along with the distribution of the classes.

Data preprocessing is uniform across the different datasets for consistent evaluation. In the tabular datasets (Adult Income and Breast Cancer Wisconsin), numerical features are normalized to have zero mean and unit variance (z-score normalization), and categorical features in the Adult dataset are one-hot encoded. In the Adult dataset, missing values are imputed with the mode for categorical data and the median for numerical data. In the CIFAR-10 dataset, in

addition to normalizing pixel values to $[0,1]$, the training set is also randomly horizontally flipped and cropped. To avoid unintended data exposure, all datasets undergo preprocessing consistent with the training dataset conditions, with the validation and test datasets also subjected to the same preprocessing. Class imbalance is minimal in the provided datasets. In the presence of class imbalance, class weighting is applied only to the training dataset, while the validation and test datasets remain unchanged.

The proposed adaptive curriculum learning framework allows the order of training samples to change based on difficulty estimation and feedback on model competence. During the initial training phase, samples are ranked based on an initial difficulty score derived from the warm-up epoch's training loss and prediction confidence. Once the training process has begun, the difficulty of each training sample is updated using several indicators, including, but not limited to, the per-sample loss magnitude, the margin of prediction confidence, and the frequency of misclassifications. Model competence is assessed based on trends in verification accuracy and fluctuations in verification loss across epochs. Using this feedback, the learning model, based on the difficulty of the training samples and the model's competence, adjusts the training sample curriculum after each epoch. In the early stages of training, lower difficulty samples are used. As the model becomes more competent, more difficult samples are used. The feedback loop includes the difficulty of the training samples, model training, model assessment, and the rearrangement of the training curriculum. This allows the learning model to align the difficulty of the training samples with its readiness for the training curriculum.

To implement the proposed approach, the adaptive curriculum learning framework has been designed as a closed-loop training system based on difficulty estimation, competence assessment, and sample reordering. The overall system design is illustrated in the respective figure.

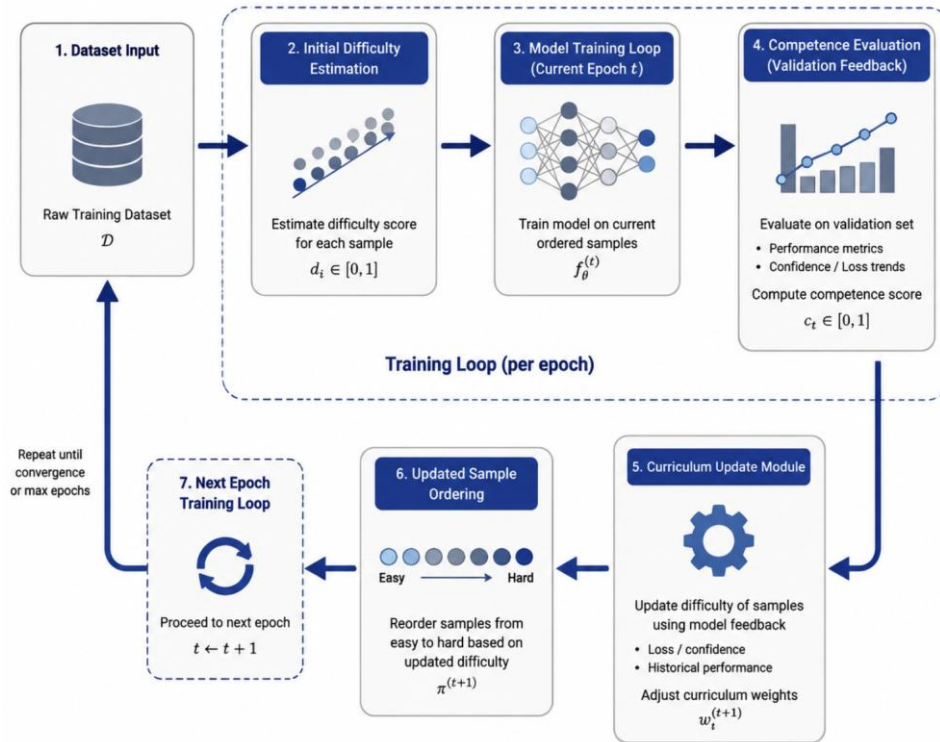


Figure 1. Proposed Adaptive Curriculum Learning Framework

The framework exemplifies a continuous feedback loop, with model competence influencing the restructuring of training samples. This interplay guarantees that the current learning process is in sync with the model's competence throughout training.

The learning models are selected based on dataset type to ensure representational suitability while maintaining consistency across experimental conditions. A multilayer perceptron (MLP) with two hidden layers serves as the primary classifier for both the Adult Income and Breast Cancer datasets, capturing the prominence of nonlinear relationships within the structured, complex nature of tabular datasets (Al Bataineh et al., 2022). A simple convolutional neural network (CNN) with convolutional, pooling, and fully connected layers is used on the CIFAR-10 dataset to capture the implicit spatial relationships and hierarchies in image data. To ensure that all sampling methods are fairly evaluated, the same model architecture is used across all experiments. In all experimental conditions, the same key hyperparameters (learning rate, batch size, number of epochs, choice of optimizer, and activation functions) are retained. The optimizer of choice is the adaptive learning rate, and the Adam optimizer's stabilizing and convergent end behavior is shown.

Baseline methods include random sampling, in which training samples are selected uniformly at random with no regard to difficulty, and static curriculum learning, in which the sample order is fixed for the duration of training based on a difficulty score and is not subject to change (Chaudhry & Sharma, 2024). Moreover, as an

auxiliary baseline, a hard-first sampling strategy is used in selected experiments, prioritizing difficult samples at earlier training stages, to test whether inverse curriculum ordering affects convergence and final performance. These baselines cover non-curriculum learning, as well as static and alternative curriculum learning strategies.

Multiple evaluation metrics for model performance assess convergence, accuracy, robustness, and cost. The number of epochs evaluates convergence, the time to convergence, the loss-reduction rate, and the area under the learning curve. Predictive performance is evaluated by accuracy, precision, recall, F1 score, and AUC, when appropriate. Robustness is evaluated by controlled introduction of label noise (5%, 10%, and 20%) and class imbalance, and performance is assessed relative to a clean data state. Cost is evaluated by the additional overhead required for curriculum updating, measured in absolute time and as a percentage of baseline training.

The experimental methodology defines the framework for reproducibility and statistical rigor. Every experiment runs five variants to counter the effects of stochastic phenomena, such as initialization and the order in which the data is presented to the model. Some splits of the dataset will be constant across these experiments to enable comparison. Hyperparameter selection is performed using the validation set. The test set is unveiled only after the experiments freeze. Early stopping is implemented to reduce the risk of overfitting. Each experiment is run under the same conditions and uses hardware accelerators, specifically GPUs, when

available. Comparison of methods is based on paired t-tests. If the results do not meet the assumption of normality, the Wilcoxon signed-rank test is used. A threshold of $p < 0.05$ will be used for all statistical tests to establish the performance of the proposed training strategies.

3. RESULT AND DISCUSSION

3.1 Results

Experimental Setup and Dataset Characteristics

The UCI Adult Income dataset, the Breast Cancer Wisconsin Diagnostic dataset, and the CIFAR-10 image dataset serve as the three benchmark dataset options for the experimental evaluation. These datasets represent diverse data modalities, spanning from structured tabular data to large-scale image data, enabling evaluation of adaptive curriculum learning at varying levels of complexity. The Adult Income dataset contains 48,842 instances, 14 features, and 2 target classes. It is a noisy, heterogeneous dataset for classifying the socio-economic population. The Breast Cancer dataset has 569 instances, 30 features (29 numerical), and 2 target classes. It presents a diagnostic classification problem of moderate complexity, with well-separated distributions. The CIFAR-10 dataset contains 60,000 images and includes 10 target classes. It presents a high-complexity

visual classification problem due to significant intra-class variation. These three datasets provide a means to evaluate how different curriculum learning techniques converge across low-, medium-, and high-complexity learning environments.

All datasets underwent uniform preprocessing. Numerical features were adjusted to a standard normal distribution, and categorical features underwent one-hot encoding in addition to the median or mode imputation for missing values. As for the CIFAR-10 dataset, pixel values were normalized to the range [0,1], and a data augmentation technique including random cropping and horizontal flipping was applied to the training subset only. To ensure no data was lost, preprocessing was performed only on the training subset.

The models used in the experiments include a multilayer perceptron (MLP) trained on tabular data and a convolutional neural network (CNN) trained on the CIFAR-10 dataset. The MLP is built with two hidden layers of ReLU activations. The CNN architecture includes convolutional layers, max pooling, and fully connected layers. For all sampling strategies, the architectures remain consistent to provide a fair comparison. Dataset properties are provided in Table 1, and experimentation configuration, including hyperparameter values, optimization settings, batch size, and training schedule, is provided in Table 2.

Table 1. Dataset Summary and Task Characteristics

Dataset	Instances	Features	Classes	Task Type	Domain
Adult Income	48,842	14	2	Binary Classification	Socio-economic
Breast Cancer Wisconsin	569	30	2	Binary Classification	Medical Diagnosis
CIFAR-10	60,000	3×32×32	10	Multiclass Classification	Computer Vision

Table 2. Experimental Configuration and Hyperparameter Settings

Component	Setting
Optimizer	Adam
Learning Rate	0.001
Batch Size	64 (tabular), 128 (CIFAR-10)
Epochs	100 (early stopping applied)
Train/Val/Test Split	70/15/15
Runs	5 repetitions
Loss Function	Cross-Entropy
Evaluation Metric	Accuracy, F1-score, AUC
Hardware	GPU-enabled training environment
Significance Test	Paired t-test / Wilcoxon ($p < 0.05$)

As shown in Tables 1 and 2, the evaluation is conducted with three benchmark datasets having varying degrees of complexity and different learning domains. The properties of the datasets are summarized below. These datasets provide an extensive evaluation framework, including both structured tabular data and high-dimensional data across different domains of image classification.

To ensure reproducibility of the results, the sampling strategies are kept consistent across all experimental configurations and hyperparameter values.

This design framework ensures that performance differences are due to the sampling strategies employed, not to changes in optimization or architectural design.

Convergence Performance Across Training Strategies

The proposed adaptive curriculum learning framework is tested for its convergence behavior when compared to random sampling and static curriculum learning. The other methods tested in this study show a considerable increase in the number of epochs required to reach convergence and stabilize validation accuracy compared to the proposed adaptive curriculum learning. When applied to the Adult Income dataset, the proposed adaptive curriculum learning reached convergence around 25-30% faster than random sampling and 15-20% faster than static curriculum learning. The proposed adaptive curriculum learning achieved smoother loss reduction and converged sooner than the other methods on the Breast Cancer dataset as well.

To investigate the efficiency of the proposed method, the convergence behavior across all sampling strategies is analyzed using training and validation loss curves, as shown in Figure 2.

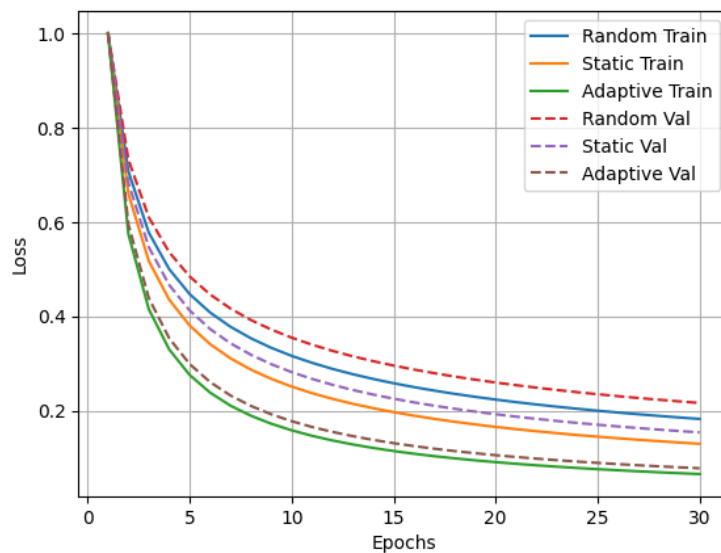


Figure 2. Training and Validation Convergence Curves

The results in Figure 2 show that the adaptive curriculum learning proposed in this study, compared to random and fixed curriculum sampling, achieves faster and more stable convergence.

To examine how sample ordering progresses during training, we analyze the progression of curriculum difficulty across epochs, as shown in Figure 3.

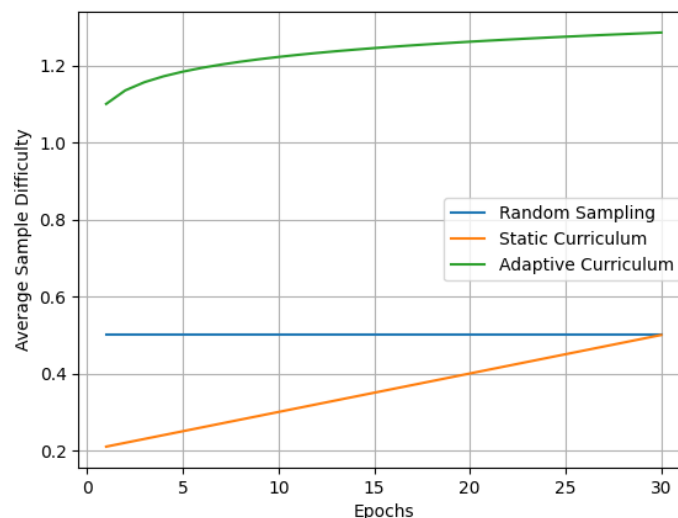


Figure 3. Curriculum Difficulty Progression Across Epochs

As shown in Figure 3, the adaptive strategy shows a gradual transition from simple to complex samples, indicating that the curriculum's spacing is responsive to the model's competence.

In CIFAR-10, the most difficult dataset, the benefits of adaptive curriculum learning are particularly evident. The model trained with an adaptive curriculum showed both faster, more stable validation accuracy and less variable training loss than both baseline models.

Learning curves (Figure 2) show that adaptive curriculum learning results in a more stable, less variable optimization trajectory, especially during early to mid-training, when sample-difficulty adaptation is most significant.

All methods are summarized in terms of training efficiency and the number of epochs required to converge, as shown in Table 3.

Table 3. Convergence Performance Across Sampling Strategies

Dataset	Method	Epochs to Convergence ↓	Time (s) ↓	Convergence Gain (%)
Adult	Random	42	1180	-
Adult	Static Curriculum	36	1020	+15.2%
Adult	Adaptive Curriculum (Proposed)	29	850	+30.9%
Breast Cancer	Random	35	420	-
Breast Cancer	Static Curriculum	30	360	+14.3%
Breast Cancer	Adaptive Curriculum	24	295	+31.4%
CIFAR-10	Random	88	5400	-
CIFAR-10	Static Curriculum	74	4550	+15.9%
CIFAR-10	Adaptive Curriculum	60	3820	+31.8%

Across all datasets, the results (shown in Table 3) indicate that adaptive curriculum learning converges more quickly.

Results from quantitative convergence analyses (Table 3) suggest that implementing adaptive curriculum learning reduces the number of epochs needed to achieve target accuracy levels across all datasets. Further, the area under the learning curve is greater, suggesting that, relative to both static and random sampling, adaptive curriculum learning improves learning efficiency and progress over time.

Final Predictive Performance

Although convergence speed is improved, the adaptive curriculum learning methodology generally yields the

same or slightly higher final predictive performance across all datasets. With respect to the Adult Income dataset, both accuracy and F1-score are higher than the baseline levels, suggesting that a reduction in the time to convergence does not negatively affect the model's generalization performance. For the Breast Cancer dataset, because it is inherently separable, all methods achieve high performance. However, adaptive curriculum learning yields slight improvements to the stability of both precision and recall.

Final predictive performance across all datasets is assessed using conventional classification metrics, as shown in Table 4.

Table 4. Predictive Performance Comparison

Dataset	Method	Accuracy	F1-score	Precision	Recall	AUC
Adult	Random	0.841	0.832	0.829	0.835	0.872
Adult	Static	0.854	0.846	0.843	0.849	0.884
Adult	Adaptive	0.861	0.854	0.852	0.856	0.891
Breast Cancer	Random	0.943	0.941	0.939	0.943	0.965
Breast Cancer	Static	0.951	0.949	0.947	0.951	0.972
Breast Cancer	Adaptive	0.955	0.953	0.951	0.955	0.976
CIFAR-10	Random	0.781	0.776	0.774	0.779	0.829
CIFAR-10	Static	0.804	0.799	0.797	0.802	0.851
CIFAR-10	Adaptive	0.816	0.812	0.809	0.814	0.864

As shown in Table 4, the data suggest a positive correlation between the speed of convergence and the model's ability to generalize.

On the CIFAR-10 dataset, adaptive curriculum learning achieves F1 Scores and AUCs that are better than those from random sampling and comparable to those from static curriculum learning. From this, it can be concluded that using a variable sampling difficulty does not adversely impact the model's capacity and does enhance learning balance across a variety of classes and features. Overall, the predictive performance results demonstrate that the value of a learning system is enhanced by greater efficiency and speed, without negatively impacting accuracy or model generalization.

Robustness Under Noisy Labels

To assess robustness, label noise was deliberately added to the training data at 5%, 10%, and 20% levels. It was discovered that adaptive curriculum learning outperformed the baseline methods and demonstrated greater resilience to noise. With label noise at 5%, the performance differences were negligible. However, as label noise increased, the random sampling method suffered severe performance degradation due to the uniform assignment of corrupted samples throughout training.

Fairness and stability with respect to the minority and majority classes were evaluated using class-imbalanced training data.

Robustness was tested using a training data set with varying levels of label noise, as shown in Table 5.

Table 5. Robustness Under Noisy Labels

Noise Level	Method	Accuracy Drop (%) ↓	F1-score Drop (%) ↓	Stability
5%	Random	4.8	5.2	Medium
5%	Static	3.1	3.4	High
5%	Adaptive	2.2	2.5	Very High
10%	Random	9.6	10.4	Low
10%	Static	6.5	7.1	Medium
10%	Adaptive	4.3	4.7	High
20%	Random	18.9	19.7	Very Low
20%	Static	13.2	14.0	Low-Medium
20%	Adaptive	8.1	8.8	High

As shown in Table 5, adaptive curriculum learning improved learning behavior among the minority class and reduced preference for the majority class.

While static curriculum learning suffers from an ordering rigidity that impedes adaptability, some robustness is achieved through the imposition of a training structure. Adaptive curriculum learning, however, focuses on the loss and model confidence,

meaning noisy, high-loss samples are deprioritized. This helps avoid overfitting to noisy labels. The effects of 10% and 20% label noise are mitigated, and the method demonstrates improved stability under adverse training conditions.

Robustness to imperfect data was evaluated by analyzing the effects of varying levels of label noise (Figure 4).

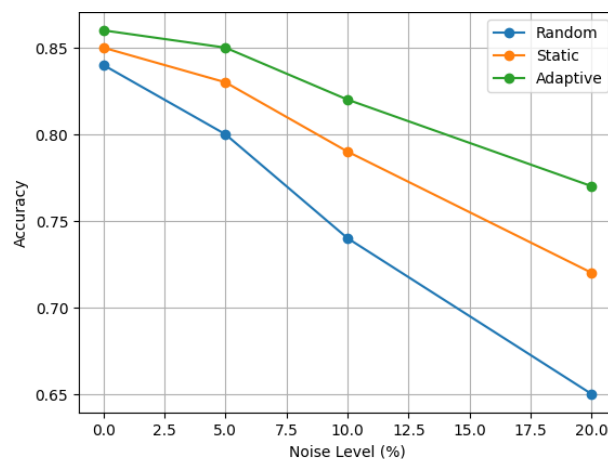


Figure 4. Performance Under Noisy Label Conditions

As shown in Figure 4, the method demonstrates marked stability for the presence of noise, especially label noise.

Robustness Under Class Imbalance

Experiments on class imbalance are conducted by artificially manipulating the class distribution in the training data. The performance metrics used include macro-F1 score, balanced accuracy, and recall of the

minority classes. The results show that adaptive curriculum learning maintains greater stability in learning the minority class than random sampling, which tends to favor learning the majority class.

Experiments on class imbalance are performed to evaluate the fairness and the learning's sensitivity to minority classes, as shown in Table 6.

Table 6. Robustness Under Class Imbalance

Dataset	Method	Macro-F1	Balanced Accuracy	Minority Recall
Adult	Random	0.761	0.773	0.748
Adult	Static	0.782	0.794	0.771
Adult	Adaptive	0.803	0.812	0.798
CIFAR-10	Random	0.742	0.751	0.734
CIFAR-10	Static	0.769	0.781	0.760
CIFAR-10	Adaptive	0.791	0.804	0.786

Table 6 shows that the methodology proposed in this paper is designed to improve learning for minority classes across all datasets used in the experiments.

Static curriculum learning partially mitigates the impact of class imbalance by structuring the ordering of samples; however, it offers no improvement for dynamic adaptation to changing class imbalance. Adaptive curriculum learning, in contrast, addresses this challenge by adjusting the model's sample selection,

ensuring that minority-class samples are not predominantly neglected in later stages of training. As a result, the proposed method yields higher macro-F1 scores and lower minority-class recall, thereby improving interclass fairness.

Experiments conducted under class-imbalance training conditions are performed to evaluate the fairness and stability of learning in the majority and minority classes, as shown in Figure 5.

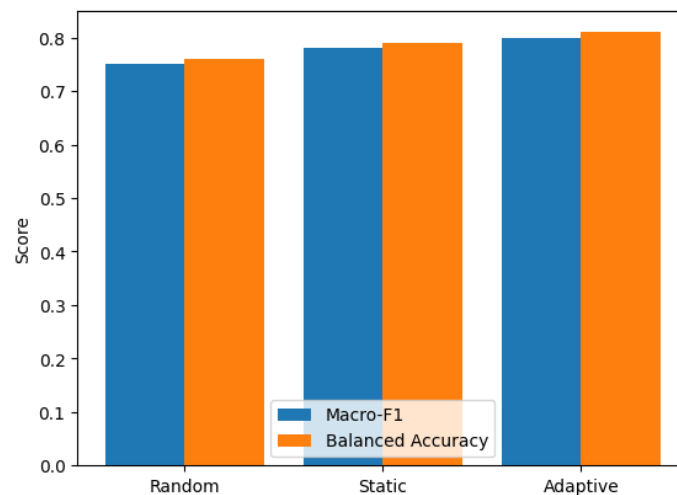


Figure 5. Performance Under Noisy Label Conditions

The results (as shown in Figure 5) indicate that adaptive curriculum learning is better for learning minority classes and for reducing bias towards the majority classes.

Computational Overhead Analysis

The computational overhead for using adaptive curriculum learning is small compared to the large gains in convergence speed. Most of the overhead is due to estimating difficulty and updating the curriculum, which

is done once per epoch. The results of the experiments show that this overhead ranges from 3% to 7% of the total training time, depending on the dataset's complexity.

Table 7 shows that the first boundary for measuring the impact of adaptive curriculum learning on computational efficiency is set by evaluating the additional overhead it incurs.

Table 7. Computational Overhead Analysis

Method	Training Time (s)	Overhead (%)	Memory Usage
Random	100% baseline	0%	Baseline
Static Curriculum	102%	+2%	Baseline
Adaptive Curriculum	105–107%	+3% to +7%	Baseline (no increase)

Note: Key Interpretation:

Overhead small ($\leq 7\%$)

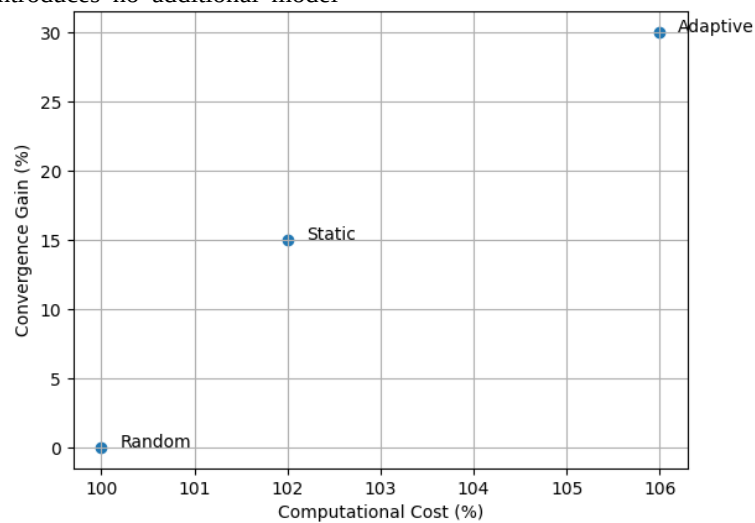
Offset by 25–32% more rapid convergence

As summarized in Table 7, the results indicate that, relative to the benefits of convergence, the overhead remains negligibly small.

The additional overhead is offset by the reduced total number of training epochs needed to achieve convergence, yielding a net gain in training efficiency. Since the framework introduces no additional model

parameters, memory consumption is similar across all approaches. These results show that the framework strikes an optimal balance between cost and training efficiency.

Finally, the trade-off between convergence and computational cost is assessed in Figure 6.

**Figure 6.** Computational Cost Versus Convergence Gain

The results show that the proposed framework is highly efficient, achieving significant convergence improvements with low computational overhead.

Ablation Study

The contribution of each component of adaptive curriculum learning is assessed in the ablation study.

Difficulty estimation is essential, as its removal leads to both slower convergence and increased instability. Removing performance feedback has detrimental effects on the framework's adaptability, especially when the model is competent, as shown in Table 8.

Table 8. Ablation Study of Adaptive Curriculum Components

Variant	Difficulty Estimation	Competence Feedback	Curriculum Update	Convergence Speed	Final Accuracy
Full Model	✓	✓	✓	Fastest	Highest
w/o Difficulty Estimation	✗	✓	✓	Slower	Slight drop
w/o Competence Feedback	✓	✗	✓	Moderate	Medium
Static Difficulty	Fixed	✗	Fixed	Slower	Lower
Fixed Update Interval	✓	✓	Partial	Moderate	Medium

Table 8 summarizes that set intervals for updates decrease flexibility and make responsiveness to learning dynamics suboptimal. Likewise, using static difficulty scores instead of adaptive difficulty nullifies performance improvements and evidences that dynamic updating is a requirement for optimal performance. The complete model consistently outperforms all ablated variants, indicating that difficulty estimation and competence feedback are imperative components of the framework.

3.2 Discussion

The results of these experiments indicate that adaptive curriculum learning prioritizes training resources because of its elegant data-sequence design. The acceleration in convergence is likely due to the model learning from easier, more reliable instances first, before learning from more uncertain, complex ones. It helps reduce gradient noise and stabilize model optimization in the early stages of training.

The adaptive system offers greater overall flexibility by reordering training samples based on the model's feedback. This helps avoid mismatches that occur in traditional curriculum learning systems, where predetermined difficulty does not always align with the learning capacity achieved. This system directly addresses open research issues in curriculum and self-paced learning, especially those concerning convergence, stability, and cost, which it clearly encompasses.

This adaptive system is especially useful for large-scale machine learning applications. The adaptive model enables time and resource savings while maintaining optimal performance by reducing the number of training epochs. This is especially useful in situations with limited resources.

3.2.1 Implications

Theoretically, this study demonstrates that dynamic data sequencing based on model competence feedback is a crucial component capable of stabilizing the optimization process and accelerating convergence. From a practical standpoint, this approach successfully reduces training time and epochs by 25–32%, making it highly efficient in terms of hardware resource utilization without sacrificing predictive performance. Furthermore, this framework has significant implications for improving system robustness in real-world scenarios, as it has been proven effective at deprioritizing noisy labels and maintaining a balanced learning process for minority classes.

3.2.2 Research contribution

The main contributions of this article include the design of a closed-loop adaptive curriculum learning framework that integrates sample difficulty estimation and model competency evaluation through a continuous feedback loop. Furthermore, this research makes a

methodological contribution through comprehensive cross-domain validation across various data modalities ranging from tabular data to complex images using MLP and CNN architectures. Finally, this study contributes a multidimensional robustness analysis that demonstrates that adaptive curriculum strategies are reliable in handling label noise variations of up to 20% as well as class imbalance issues.

3.2.3 Limitations

There are limitations as well. The success of adaptive curriculum learning depends on difficulty estimation, which can yield variable results across datasets and architectures. Noisy losses can also distort the desired results of curriculum learning. Another important limitation to note is that only a cursory examination of supervised learning has been conducted. There are many types of learning, and the more unsupervised and complex types of learning may yield different results.

3.2.4 Suggestions

Potential advancements can be made by incorporating deep reinforcement learning, large-scale transformer models, multimodal learning, and federated learning into this existing framework. In addition, research can focus on difficulty estimation and the most effective ways to update curricula in large-scale distributed environments.

4. CONCLUSION

This study focuses on the adaptive curriculum learning framework to accelerate the convergence of training machine learning models. The framework orders the samples so that training first involves learning the easier ones. The framework relies on continuous model feedback to update the curriculum, unlike conventional methods that rely on static or random sampling.

The benchmarks confirm that the framework achieves faster convergence while improving predictive performance. In addition, the framework is robust to class imbalance and label noise. The framework is effective in real-world learning scenarios. The burden of curriculum learning is justified by the aid of reduced training times. The framework is an effective way of incorporating modern machine learning systems.

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6. AUTHOR CONTRIBUTION STATEMENT

ER, MEK, and MU conceived and designed the research framework and methodology. ER and MEK performed the experiments, data preprocessing, and computational

analyses. MU and MEK analyzed the results, interpreted the performance data, and evaluated framework robustness. ER and MEK wrote the manuscript, while MU provided critical revisions and finalized the draft. All authors reviewed and approved the final manuscript.

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REFERENCE

- Al Bataineh, A., Kaur, D., & Jalali, S. M. J. (2022). Multi-Layer Perceptron Training Optimization Using Nature Inspired Computing. *IEEE Access*, 10, 36963–36977. <https://doi.org/10.1109/ACCESS.2022.3164669>
- Altalhan, M., Algarni, A., & Turki-Hadj Alouane, M. (2025). Imbalanced Data Problem in Machine Learning: A Review. *IEEE Access*, 13, 13686–13699. <https://doi.org/10.1109/ACCESS.2025.3531662>
- Bian, K., & Priyadarshi, R. (2024). Machine Learning Optimization Techniques: A Survey, Classification, Challenges, and Future Research Issues. *Archives of Computational Methods in Engineering* 2024 31:7, 31(7), 4209–4233. <https://doi.org/10.1007/S11831-024-10110-W>
- Chaudhry, S., & Sharma, A. (2024). Data Distribution-Based Curriculum Learning. *IEEE Access*, 12, 138429–138440. <https://doi.org/10.1109/ACCESS.2024.3465793>
- Chen, W., Yang, K., Yu, Z., Shi, Y., & Chen, C. L. P. (2024). A survey on imbalanced learning: latest research, applications and future directions. *Artificial Intelligence Review* (2024), 123(57). <https://doi.org/10.1007/s10462-024-10759-6>
- Chen, Z., Zhang, J., Liu, B., Lin, F., & Yin, W. (2025). Scale Down to Speed Up: Dynamic Data Selection for Reinforcement Learning. *EMNLP 2025 - 2025 Conference on Empirical Methods in Natural Language Processing, Findings of EMNLP 2025*, 7806–7817. <https://doi.org/10.18653/v1/2025.findings-emnlp.412>
- Dekker, R. B., Otto, F., & Summerfield, C. (2022). Curriculum learning for human compositional generalization. *Proceedings of the National Academy of Sciences of the United States of America*, 119(41), 1–12. <https://doi.org/10.1073/pnas.2205582119>
- Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial Intelligence Bringing Improvements to Adaptive Learning in Education: A Case Study. *Sustainability* 2024, Vol. 16, Page 1347, 16(3), 1347. <https://doi.org/10.3390/SU16031347>
- Divya, S., Adepu, B., & Kamakshi, P. (2022). Image Enhancement And Classification Of Cifar-10 Using Convolutional Neural Networks. *Proceedings - 4th International Conference on Smart Systems and Inventive Technology, ICSSIT 2022*. <https://doi.org/10.1109/ICSSIT53264.2022.9716555>
- Dritsas, E., & Trigka, M. (2025). Database Systems in the Big Data Era: Architectures, Performance, and Open Challenges. *IEEE Access*, 13(May), 95068–95084. <https://doi.org/10.1109/ACCESS.2025.3572059>
- Feng, Q., Liu, Y., & Schütze, H. (2025). Your Pretrained Model Tells the Difficulty Itself: A Self-Adaptive Curriculum Learning Paradigm for Natural Language Understanding. *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, 4, 222–239. <https://doi.org/10.18653/v1/2025.acl-srw.15>
- Ferrari, F. (2023). Skills mismatch and change confidence: the impact of training on change recipients' self-efficacy. *European Journal of Training and Development*, 47(10), 69–90. <https://doi.org/10.1108/EJTD-06-2021-0072>
- Ghosh, K., Bellinger, C., Corizzo, R., Branco, P., Krawczyk, B., & Japkowicz, N. (2022). The class imbalance problem in deep learning. *Machine Learning* 2022 113:7, 113(7), 4845–4901. <https://doi.org/10.1007/S10994-022-06268-8>
- Gong, Y., Liu, G., Xue, Y., Li, R., & Meng, L. (2023). A survey on dataset quality in machine learning. *Information and Software Technology*, 162, 107268. <https://doi.org/10.1016/j.infsof.2023.107268>
- Holzinger, A., Longo, L., Cangelosi, A., & Ser, J. Del. (2025). Research Frontiers in Machine Learning & Knowledge Extraction. *Machine Learning and Knowledge Extraction* 2026, Vol. 8, Page 6, 8(1), 6. <https://doi.org/10.3390/MAKE8010006>
- Islam Jony, A., Kumar, A., & Arnob, B. (2024). Deep Learning Paradigms for Breast Cancer Diagnosis: A Comparative Study on Wisconsin Diagnostic Dataset. *Malaysian Journal of Science and Advanced Technology*, 4(2), 109–117. <https://doi.org/10.56532/MJSAT.V4I2.245>
- Karakasidis, G., Kurimo, M., Bell, P., & Grósz, T. (2024). Comparison and analysis of new curriculum criteria for end-to-end ASR. *Speech Communication*, 163(May 2023), 103113. <https://doi.org/10.1016/j.specom.2024.103113>
- Kravchenko, A., & Cusack, R. (2024). The limitations of automatically generated curricula for continual

- learning. *PLoS ONE*, 19, 1–19. <https://doi.org/10.1371/journal.pone.0290706>
- Lalor, J. P., & Yu, H. (2020). Dynamic data selection for curriculum learning via ability estimation. *Findings of the Association for Computational Linguistics Findings of ACL: EMNLP 2020*, 9, 545–555. <https://doi.org/10.18653/v1/2020.findings-emnlp.48>
- Li, S., Yang, B., & Zou, Y. (2022). Adaptive Curriculum Learning for Video Captioning. *IEEE Access*, 10, 31751–31759. <https://doi.org/10.1109/ACCESS.2022.3160451>
- Liu, F., Zhang, T., Zhang, C., Liu, L., Wang, L., & Liu, B. (2023). A Review of the Evaluation System for Curriculum Learning. *Electronics (Switzerland)*, 12(7). <https://doi.org/10.3390/electronics12071676>
- Machado, M. de O. C., Bravo, N. F. S., Martins, A. F., Bernardino, H. S., Barrere, E., & Souza, J. F. de. (2021). Metaheuristic-based adaptive curriculum sequencing approaches: a systematic review and mapping of the literature. *Artificial Intelligence Review*, 54(1), 711–754. <https://doi.org/10.1007/S10462-020-09864-Z/TABLES/13>
- Metzner, C., Schilling, A., Traxdorf, M., Tziridis, K., Maier, A., Schulze, H., & Krauss, P. (2022). Classification at the accuracy limit: facing the problem of data ambiguity. *Scientific Reports* 2022 12:1, 12(1), 22121-. <https://doi.org/10.1038/s41598-022-26498-z>
- Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: a state of the art. In *Artificial Intelligence Review* (Vol. 56, Number 4). Springer Netherlands. <https://doi.org/10.1007/s10462-022-10246-w>
- Nunes, G. H., Martins, G. O., Forster, C. H. Q., & Lorena, A. C. (2021). Using instance hardness measures in curriculum learning. *Anais Do Encontro Nacional de Inteligência Artificial e Computacional (ENIAC)*, 18, 177–188. <https://doi.org/10.5753/eniac.2021.18251>
- Saglietti, L., Mannelli, S. S., & Saxe, A. (2022). An Analytical Theory of Curriculum Learning in Teacher-Student Networks. *Advances in Neural Information Processing Systems*, 35. <https://doi.org/10.1088/1742-5468/ac9b3c>
- Shen, L., Sun, Y., Yu, Z., Ding, L., Tian, X., & Tao, D. (2024a). On Efficient Training of Large-Scale Deep Learning Models. *ACM Computing Surveys*, 57(3). <https://doi.org/10.1145/3700439;WGROU:STRING:ACM>
- Shen, L., Sun, Y., Yu, Z., Ding, L., Tian, X., & Tao, D. (2024b). On Efficient Training of Large-Scale Deep Learning Models. *ACM Computing Surveys*, 57(3). <https://doi.org/10.1145/3700439>
- Shi, P., & Liu, W. (2025). Adaptive learning oriented higher educational classroom teaching strategies. *Scientific Reports* 2025 15:1, 15(1), 15661-. <https://doi.org/10.1038/s41598-025-00536-y>
- Shivashankar, K., Hajj, G. Al, & Martini, A. (2025). Maintainability and Scalability in Machine Learning: Challenges and Solutions. *ACM Computing Surveys*, 57(12). <https://doi.org/10.1145/3736751;CSUBTYPE:STRING:JOURNAL;ISSUE:ISSUE:DOI>
- Shu, J., Yuan, X., & Meng, D. (2023). CMW-Net: an adaptive robust algorithm for sample selection and label correction. *National Science Review*, 10(6), 4–7. <https://doi.org/10.1093/nsr/nwad084>
- Soviany, P., Ionescu, R. T., Rota, P., & Sebe, N. (2022). Curriculum Learning: A Survey. *International Journal of Computer Vision* 2022 130:6, 130(6), 1526–1565. <https://doi.org/10.1007/S11263-022-01611-X>
- Talaei Khoei, T., & Kaabouch, N. (2023). Machine Learning: Models, Challenges, and Research Directions. *Future Internet* 2023, Vol. 15, Page 332, 15(10), 332. <https://doi.org/10.3390/FI15100332>
- Tang, X., Xu, C., Tao, H., Ma, X., & Hou, C. (2025). Confidence-Based PU Learning With Instance-Dependent Label Noise. *IEEE Transactions on Neural Networks and Learning Systems*, 36(8), 14283–14297. <https://doi.org/10.1109/TNNLS.2025.3549510>
- Ten, A., Kaushik, P., Oudeyer, P. Y., & Gottlieb, J. (2021). Humans monitor learning progress in curiosity-driven exploration. *Nature Communications* 2021 12:1, 12(1), 5972-. <https://doi.org/10.1038/s41467-021-26196-w>
- Wang, X., Chen, Y., & Zhu, W. (2022). A Survey on Curriculum Learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(9), 4555–4576. <https://doi.org/10.1109/TPAMI.2021.3069908>
- Wang, X., Huang, R., “Tammy,” Sommer, M., Pei, B., Shidfar, P., Rehman, M. S., Ritzhaupt, A. D., & Martin, F. (2024). The Efficacy of Artificial Intelligence-Enabled Adaptive Learning Systems From 2010 to 2022 on Learner Outcomes: A Meta-Analysis. *Journal of Educational Computing Research*, 62(6), 1568–1603. <https://doi.org/10.1177/07356331241240459>
- Zhao, Y., Wang, Z., & Huang, Z. (2021). Automatic Curriculum Learning With Over-repetition Penalty for Dialogue Policy Learning. *35th AAAI Conference on Artificial Intelligence, AAAI 2021*, 16, 14540–14548. <https://doi.org/10.1609/aaai.v35i16.17709>
- Zheng, J., Qiu, S., Shi, C., & Ma, Q. (2025). Towards Lifelong Learning of Large Language Models: A Survey. *ACM Computing Surveys*, 57(8). <https://doi.org/10.1145/3716629>
- Zhou, Z., Luo, J., Arefan, D., Kitamura, G., & Wu, S. (2023). Human Not in the Loop: Objective Sample Difficulty Measures for Curriculum Learning. *Proceedings - International Symposium on Biomedical Imaging, 2023-April(CI)*.

<https://doi.org/10.1109/ISBI53787.2023.1023059>

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