Data-Centric Machine Learning: Enhancing Performance through Intelligent Data Curation

[1] Laiba Qaisar, [2] Ifrah Ikram
[1] University of Gujrat, Pakistan
[2] COMSATS University Islamabad, Pakistan
Corresponding E-mail: laibaqaisar006@gmail.com

Abstract

In the evolving landscape of artificial intelligence, the emphasis on model-centric optimization has overshadowed the importance of data quality. Data-centric machine learning (DCML) challenges this narrative by shifting the focus from fine-tuning model architectures to improving the quality, consistency, and relevance of the data used to train these models. This research paper investigates the transformative impact of intelligent data curation on the performance of machine learning systems. We explore the principles and practices of DCML, evaluate various data curation techniques such as data augmentation, labeling optimization, deduplication, and error correction, and present experimental results showcasing performance improvements across multiple benchmark datasets. The findings underscore the critical role of high-quality data in achieving robust, reliable, and interpretable machine learning models.

Keywords: Data-centric AI, machine learning, data curation, data quality, intelligent labeling, dataset optimization, model performance, data preprocessing

I. Introduction

The explosive growth of machine learning applications across industries has spotlighted the need for high-performance models capable of generalizing well in real-world scenarios. Traditional practices in machine learning have prioritized architectural innovation and model complexity under the assumption that better models will yield better results [1]. However, this model-centric paradigm often fails to address the root cause of suboptimal performance—poor data quality. Data-centric machine learning (DCML) represents a fundamental shift in approach, advocating for systematic improvements in data quality to enhance model performance. The focus is no longer solely on tweaking hyperparameters or

experimenting with deeper neural networks but on ensuring that the data fed into these models is clean, representative, and labeled with high fidelity [2].

In DCML, the success of a machine learning project is viewed as being heavily dependent on the underlying dataset. Noisy, inconsistent, and poorly labeled data can significantly deteriorate model outcomes, regardless of the algorithm's sophistication. This realization has led researchers and practitioners to explore techniques for intelligent data curation, such as automated labeling tools, data validation frameworks, and data auditing practices. These methods aim to refine and enrich the dataset to reflect the true distribution of the problem space, thereby enabling models to learn more effectively and avoid overfitting to irrelevant patterns or outliers [3]. As the complexity of real-world problems increases, the challenge of collecting and managing high-quality data becomes even more pronounced. For instance, in healthcare or autonomous driving, the quality of annotations and the diversity of data samples can mean the difference between success and catastrophic failure. DCML advocates for a meticulous, iterative, and human-in-the-loop approach to dataset construction, where domain knowledge, statistical insights, and machine-assisted tools converge to build datasets that are not only accurate but also comprehensive and fair. This paper aims to dissect these principles and illustrate their utility through empirical evaluations.

Despite growing interest in DCML, there remains a lack of structured frameworks that quantify the improvements resulting from data-centric interventions. Many organizations still underestimate the cost and impact of low-quality data, relegating it to the realm of data engineering rather than treating it as a core part of the AI development process. This gap between research and practice necessitates a detailed analysis of the tangible benefits that DCML can offer in different application domains [4]. Our work seeks to bridge this gap by providing both theoretical insights and experimental validations. To achieve this, we structure the remainder of this paper as follows: we begin by reviewing existing literature and identifying key components of intelligent data curation. We then describe our experimental setup and methodology for assessing data quality and its influence on model performance. Finally, we present results that highlight the performance gains achieved through specific data-centric interventions and conclude by discussing the broader implications for AI development pipelines.

II. Literature Review

Over the last decade, data has grown exponentially in volume, but not necessarily in value or quality. The earliest efforts to address data issues in machine learning stemmed from data cleaning and preprocessing techniques in statistical analysis. These methods, while effective to a degree, were often ad hoc and not scalable to large, dynamic datasets. The rise of big data and deep learning further exposed the limitations of traditional data handling practices. It became evident that model performance gains plateaued without corresponding improvements in data quality. Consequently, researchers began to formalize the concept of data-centric AI as a disciplined field of study. Recent work by Andrew Ng and his colleagues has popularized the term "data-centric AI," emphasizing the need for consistent labeling, class balance, and sample diversity. Their research highlights several critical data curation strategies, including the use of error analysis tools, labeling instructions refinement, and sampling strategies to ensure adequate representation of edge cases [5]. These strategies aim to address both random noise and systematic bias in datasets, improving the model's ability to generalize to unseen data. Moreover, the field has witnessed the emergence of platforms like Snorkel and Cleanlab, which automate parts of the data curation process and integrate seamlessly with model training pipelines.

A growing body of evidence supports the claim that improvements in data quality yield better returns than complex model tuning. For instance, studies in image classification have shown that refining mislabeled images in the training set led to more significant performance boosts than switching from a baseline CNN to a state-of-the-art architecture. Similar results have been observed in NLP tasks such as sentiment analysis and named entity recognition, where clarifying ambiguous labels and expanding underrepresented categories yielded measurable improvements in accuracy and F1 scores. Despite these successes, challenges remain. Many datasets used in academic research are static and curated manually, making it difficult to assess the value of iterative data-centric interventions. In contrast, industry datasets are often dynamic, messy, and labeled under time constraints, creating opportunities for real-time data curation and continuous learning. Research has only recently started to explore the impact of continuous feedback loops, where model errors inform subsequent data corrections. This iterative, feedback-driven paradigm aligns well with the goals of DCML and deserves further exploration [6].

In parallel, ethical considerations such as fairness, accountability, and transparency are being integrated into data curation practices. Biased data not only reduces model performance but also perpetuates harmful social outcomes. Techniques like subgroup analysis, de-biasing algorithms, and diverse sampling are being incorporated into data-centric pipelines to mitigate these risks. These developments underscore the interdisciplinary nature of DCML, blending machine learning, statistics, human-computer interaction, and ethics into a unified framework.

III. Methodology

To evaluate the impact of intelligent data curation on machine learning performance, we conducted experiments across three domains: image classification, sentiment analysis, and fraud detection. Each domain featured its own publicly available benchmark dataset—CIFAR-10 for images, IMDB Reviews for sentiment, and Credit Card Fraud Detection from Kaggle. These datasets were chosen for their diversity, common usage in ML benchmarking, and varying data quality challenges. We created baseline models for each task using standard architectures: ResNet18 for CIFAR-10, LSTM for IMDB, and Random Forest for fraud detection.

The baseline performance was measured using the raw datasets without any curation. We then introduced specific data-centric interventions aimed at improving data quality. These included correcting mislabeled data using Cleanlab, augmenting underrepresented classes with domain-specific techniques (e.g., image rotation, synonym replacement), deduplicating overlapping entries, and refining class definitions in the labeling guidelines. For each intervention, we retrained the model from scratch and evaluated the performance using standard metrics such as accuracy, F1 score, precision, and recall. To isolate the effect of data quality, we kept the model architecture, hyperparameters, and training procedure constant throughout the experiments [7]. We also conducted ablation studies to assess the individual contribution of each data-centric strategy. For example, we examined the performance boost from just correcting labels, or from applying augmentation alone, before applying all improvements together. This helped quantify the marginal impact of each curation method.

Additionally, we introduced synthetic noise into the datasets by randomly flipping a percentage of labels or inserting duplicates, and then applied our data curation techniques to

recover performance. This stress-testing approach helped validate the robustness of data-centric methods in the face of imperfect data. We recorded the difference between noisy and curated performance to determine recovery efficiency. The experiments were executed on a standard ML pipeline using Python, TensorFlow, and PyTorch. All results were averaged over five runs to account for variance[8]. A human-in-the-loop framework was also incorporated for label refinement, involving annotators guided by enhanced labeling manuals to re-evaluate ambiguous cases. The entire experiment aimed to simulate realistic scenarios encountered in industry workflows where data is far from pristine.

IV. Results and Discussion

Our experiments revealed compelling evidence supporting the data-centric approach. For the CIFAR-10 image classification task, baseline accuracy using uncurated data was 87.2%. After correcting approximately 4% mislabeled samples, deduplicating 3.5% of the dataset, and introducing balanced augmentation, the final accuracy improved to 91.3%. This gain, achieved without altering the model architecture, reinforces the central tenet of DCML—that better data leads to better models. In the IMDB sentiment analysis task, we observed an F1 score increase from 84.7% to 88.9% after enhancing labeling consistency and incorporating domain-specific synonym augmentation. The manual correction of ambiguous labels, guided by revised annotation guidelines, played a significant role in resolving class confusion and improving the model's semantic understanding. Moreover, the improved label distribution reduced variance across test splits, leading to more stable training dynamics [9].

The fraud detection task showcased a significant increase in precision, from 62.4% to 75.1%, primarily due to the removal of duplicates and the injection of synthetically generated fraud patterns into underrepresented regions of the feature space. The refined dataset helped the Random Forest classifier better learn rare fraud signals, which are typically drowned out in imbalanced datasets [10]. In ablation studies, label correction alone yielded 1.8–2.6% improvement across all tasks, while data augmentation and deduplication contributed an additional 2–3%. The highest gains occurred when all techniques were combined, underscoring the cumulative effect of multiple curation strategies. Notably, human-in-the-loop methods were found to be time-consuming but provided the most substantial improvements in terms of label quality and edge case representation.

Interestingly, synthetic noise experiments highlighted the resilience of DCML strategies. When 10% of labels were corrupted, performance dropped by over 8% in all models [11]. After applying data-centric recovery methods, up to 90% of the original performance was restored. This suggests that DCML practices are not only proactive but also effective in reactive correction of noisy datasets, making them valuable in dynamic and uncertain data environments [12].

V. Conclusion

This research confirms that intelligent data curation is a powerful lever for enhancing machine learning performance, often surpassing the gains achieved through complex model modifications. Through systematic interventions—such as label refinement, deduplication, augmentation, and human-in-the-loop validation—data-centric machine learning transforms raw data into a strategic asset that drives model reliability, robustness, and fairness. Our experiments across diverse domains underscore that even modest improvements in data quality can lead to substantial performance gains, particularly in real-world scenarios where data is messy and unbalanced. As machine learning systems become increasingly integrated into critical applications, adopting a data-centric mindset is not just beneficial—it is essential.

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