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Efficient Machine Learning Acceleration with Randomized Linear Algebra for Big Data

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ABSTRACT

The rapid growth of big data has significantly increased the computational complexity of machine learning models, particularly due to intensive linear algebra operations that limit scalability and efficiency. **This study aims** to investigate the effectiveness of Randomized Linear Algebra (RLA) as an acceleration strategy for machine learning in large scale data environments. **The research adopts** an experimental methodology by integrating randomized techniques such as matrix sketching and random projection into standard machine learning pipelines and evaluating their performance against deterministic baseline approaches. Experiments are conducted on large dimensional datasets using multiple machine learning models, with performance assessed in terms of computational time, memory usage, model accuracy, and scalability. **The results demonstrate that** the proposed RLA based approach substantially reduces computational cost and memory consumption while maintaining comparable predictive accuracy to conventional methods. These findings indicate that randomized techniques provide an effective trade off between efficiency and accuracy, enabling scalable machine learning for big data applications. **In conclusion**, this study contributes to the advancement of efficient Artificial Intelligence (AI) systems by demonstrating that RLA can serve as a practical and scalable solution for accelerating machine learning computations in big data contexts, aligning with the growing demand for resource efficient and high performance AI infrastructures.

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1. INTRODUCTION

The rapid expansion of big data has profoundly influenced the design and deployment of machine learning systems across a wide range of application domains, including finance, healthcare, scientific research, and large scale information systems [1, 2]. Contemporary machine learning models increasingly rely on large scale and high dimensional datasets to enhance predictive accuracy, robustness, and generalization performance, as extensive data availability enables models to learn complex patterns and capture subtle statistical relationships. However, the continuous growth in data volume, dimensionality, and heterogeneity has simultaneously intensified computational demands, particularly due to the central role of linear algebra operations such as matrix multiplication, matrix decomposition, eigenvalue computation, and large scale optimization

procedures [3, 4]. These operations form the computational backbone of many machine learning algorithms, including regression based models, dimensionality reduction techniques, kernel methods, and deep learning architectures, and their computational cost often grows rapidly as data size increases. As a result, linear algebra computations frequently constitute the primary performance bottleneck in both training and inference phases, leading to challenges related to execution time, memory consumption, and scalability. This computational burden limits the practical deployment of machine learning models in real world big data environments, where efficiency, responsiveness, and resource aware processing are increasingly critical requirements for modern artificial intelligence systems [5, 6].

In large scale learning environments, traditional deterministic linear algebra techniques frequently encounter fundamental limitations in balancing computational cost, memory usage, and model accuracy. As dataset sizes and dimensionality continue to increase, exact matrix computations require substantial processing time and memory resources, making them increasingly expensive and, in many cases, impractical for real world big data applications. These challenges are further compounded by the constraints of contemporary computing infrastructures, where limitations in memory bandwidth, processing capacity, and energy efficiency impose strict boundaries on scalable computation [7, 8]. In particular, the growing emphasis on sustainable and resource efficient computing has intensified the need to reduce energy consumption without compromising analytical performance. Consequently, there is a rising demand for alternative computational strategies that can effectively mitigate these constraints by reducing algorithmic complexity and resource utilization while preserving acceptable levels of predictive accuracy and model reliability in large scale machine learning systems.

Randomized Linear Algebra (RLA) has emerged as an effective computational paradigm for addressing inefficiencies inherent in large scale numerical computations, particularly those arising in data intensive machine learning applications. By incorporating probabilistic mechanisms such as random sampling, random projection, and matrix sketching, randomized methods aim to construct low dimensional approximations of large matrices that preserve essential structural properties while significantly reducing computational overhead [9, 10]. These techniques replace exact deterministic computations with controlled approximations, enabling substantial reductions in execution time and memory requirements. Prior research has demonstrated that RLA approaches can achieve favorable trade offs between computational efficiency and solution accuracy, supported by rigorous theoretical error bounds as well as consistent empirical performance improvements across diverse problem settings. Despite these advantages, the effective integration of RLA into end to end machine learning workflows for big data environments remains an active area of investigation, particularly with respect to understanding scalability behavior, robustness across different data distributions, and the impact of approximation on model performance and reliability [11, 12].

Accordingly, this study aims to systematically examine the role of RLA as an acceleration mechanism for machine learning in big data contexts, with a particular focus on improving computational efficiency without significantly compromising model performance. The research integrates a range of RLA techniques into standard machine learning pipelines and evaluates their effectiveness in comparison with conventional deterministic baseline approaches. Performance is assessed through comprehensive empirical analysis involving computational time, memory utilization, predictive accuracy, and scalability across increasing data sizes. Through this evaluation, the study seeks to provide rigorous empirical evidence on the practical benefits and limitations of randomized methods in large scale learning environments [13, 14]. The findings of this research are expected to contribute to the development of more efficient, scalable, and resource aware artificial intelligence systems, supporting the deployment of data driven machine learning solutions in computationally intensive real world applications.

From a broader sustainability perspective, the development of efficient and scalable machine learning techniques is closely aligned with global efforts to promote sustainable digital transformation. Computationally intensive machine learning models often require substantial energy consumption and hardware resources, particularly when applied to large scale data processing. By improving computational efficiency through acceleration techniques such as RLA, machine learning systems can reduce resource utilization while maintaining analytical effectiveness [15, 16]. This approach supports Sustainable Development Goals (SDGs) 9, which emphasizes innovation and the development of resilient and efficient digital infrastructure, by enabling more scalable and accessible artificial intelligence technologies. Furthermore, reducing unnecessary computational overhead contributes to SDGs 12 by promoting responsible consumption of computational resources and encouraging more sustainable computing practices in data driven applications. As machine learning continues to expand across sectors, enhancing efficiency at the algorithmic level plays an important role in supporting

environmentally conscious and sustainable artificial intelligence development [17, 18].

2. LITERATURE REVIEW

2.1. Machine Learning in Big Data Environments

The increasing availability of large scale and high dimensional data has driven the widespread adoption of machine learning techniques across diverse domains, including finance, healthcare, manufacturing, and scientific research. In big data environments, machine learning models are required to process massive datasets efficiently while maintaining high levels of predictive accuracy, robustness, and generalization capability. Prior studies emphasize that data volume, dimensionality, and heterogeneity play a critical role in determining model performance, as richer datasets enable more accurate pattern discovery and improved learning outcomes. However, these same characteristics simultaneously introduce substantial computational challenges during both training and inference phases [19, 20]. As datasets continue to grow, the cost of data preprocessing, feature extraction, and parameter optimization increases significantly, often resulting in longer training times and higher resource consumption. Moreover, the need to repeatedly access and manipulate large data matrices further amplifies computational overhead and memory usage. These challenges make scalability a critical concern in practical machine learning applications, particularly in real world settings where time efficiency and resource constraints are prominent. Consequently, improving computational efficiency while preserving model effectiveness has emerged as a central research focus in the development of large scale machine learning systems.

2.2. Role of Linear Algebra in Machine Learning

Linear algebra forms the mathematical foundation of many machine learning algorithms and serves as a core computational component in both model training and inference processes [21, 22]. Fundamental operations such as matrix multiplication, matrix factorization, eigenvalue decomposition, and least squares optimization are integral to a wide range of supervised and unsupervised learning models, including regression techniques, support vector machines, principal component analysis, clustering algorithms, and neural network architectures. The computational complexity associated with these operations often dominates overall system performance, particularly when handling large matrices generated from high dimensional and large scale datasets. As data size increases, the cost of exact matrix computations grows rapidly in terms of execution time and memory requirements. Classical deterministic linear algebra approaches are designed to produce exact solutions and offer strong numerical stability. However, they typically incur substantial computational and memory overhead [23, 24]. These limitations significantly restrict their practicality in large scale machine learning settings, where scalability, efficiency, and resource aware computation are critical requirements.

2.3. Limitations of Deterministic Linear Algebra Methods

Several studies have reported that deterministic linear algebra techniques encounter substantial scalability limitations when applied to big data problems. As data size and dimensionality increase, exact matrix computations require exponentially greater computational effort, often exceeding the processing capacity and memory limits of conventional computing infrastructures. In large scale settings, memory constraints, data movement overhead between storage and processing units, and high energy consumption further intensify these challenges, reducing overall system efficiency [25, 26]. Moreover, the need to repeatedly perform exact matrix operations during iterative learning processes significantly increases execution time, making deterministic approaches unsuitable for time sensitive or real time machine learning applications. Consequently, such methods frequently fail to satisfy the growing demand for resource efficient and scalable computation in large scale machine learning environments. These limitations underscore the necessity for alternative computational strategies that can substantially reduce computational burden while preserving acceptable levels of solution quality and model reliability.

2.4. Randomized Linear Algebra Approaches

RLA has emerged as an effective and highly scalable alternative to traditional deterministic methods for large scale numerical computation, particularly in data intensive machine learning applications where computational efficiency and resource management are critical [27, 28]. By employing probabilistic techniques such as random sampling, random projection, and matrix sketching, randomized approaches aim to construct compact, low dimensional approximations of large matrices that preserve the essential structural, geometric, and statistical properties of the original data. These techniques enable the transformation of computationally

expensive high dimensional problems into more manageable forms without significantly compromising the integrity of the information being processed [29, 30].

Through such approximations, large matrix operations including matrix multiplication, decomposition, and optimization related computations can be performed with substantially reduced computational cost, lower memory requirements, and improved execution speed. This efficiency becomes particularly valuable in modern machine learning environments characterized by massive datasets, high dimensional feature spaces, and the need for rapid model training and deployment [31, 32]. Previous research consistently demonstrates that RLA methods are capable of achieving substantial performance gains in terms of runtime and scalability, while maintaining solution quality that remains comparable to results obtained using exact deterministic approaches.

Importantly, these techniques are grounded in rigorous theoretical foundations that provide formal guarantees on approximation accuracy. Specifically, probabilistic error bounds ensure that the deviation between the randomized approximation and the exact solution remains controlled with high probability, thereby preserving numerical reliability and computational stability. These guarantees make randomized methods not only practically efficient but also mathematically sound, offering strong confidence in their use for real world applications [33, 34].

As a result, randomized approaches have gained increasing attention across both academic research and industrial practice as practical, efficient, and theoretically justified solutions for accelerating large scale numerical computations. Their ability to balance computational efficiency with accuracy makes them especially well suited for modern data driven environments, where scalability, speed, and reliability are essential requirements for machine learning systems operating at scale [35, 36].

2.5. Randomized Linear Algebra for Machine Learning Acceleration

Recent studies have increasingly explored the application of RLA as a means of accelerating machine learning algorithms, particularly in computationally intensive tasks such as dimensionality reduction, large scale regression, and optimization problems. Empirical findings consistently indicate that integrating randomized techniques into machine learning pipelines can lead to substantial reductions in training time, memory usage, and overall computational cost, while maintaining predictive accuracy that is comparable to deterministic baseline methods [37, 38]. These results highlight the practical potential of randomized approaches for improving efficiency in data intensive learning scenarios. However, much of the existing research remains focused on specific algorithms, isolated tasks, or constrained experimental settings, which limits the generalizability of reported findings. Consequently, there is still an incomplete understanding of the broader scalability implications, robustness, and performance trade offs associated with RLA techniques when applied across diverse machine learning models and heterogeneous datasets. Addressing these gaps is essential for assessing the effectiveness of randomized methods as general purpose acceleration mechanisms in large scale machine learning systems [39, 40].

2.6. Research Gap

Although prior work has established both the theoretical foundations and empirical advantages of RLA, comprehensive evaluations of its effectiveness as a general purpose acceleration mechanism for machine learning in big data contexts remain relatively limited. Existing studies often examine isolated aspects of performance, such as computational efficiency or approximation quality, or focus narrowly on specific algorithms, model architectures, or experimental conditions [41, 42]. Consequently, there remains a lack of systematic and integrated analysis that jointly considers multiple critical dimensions of performance, including computational time, memory consumption, predictive accuracy, and scalability under increasing data sizes and dimensional complexity. This fragmented perspective makes it challenging to obtain a unified understanding of how RLA performs when multiple performance criteria must be balanced simultaneously, as is typically required in real world large scale machine learning applications. Moreover, variations in experimental design and evaluation settings further complicate meaningful comparison across studies. Differences in dataset characteristics, preprocessing procedures, hyperparameter configurations, benchmarking methodologies, and evaluation metrics make it difficult to draw consistent and generalizable conclusions regarding the broader applicability of randomized techniques across diverse machine learning models and real world datasets [43, 44].

3. METHODOLOGY

3.1. Research Design and Experimental Setup

This study employs a carefully structured experimental research design to rigorously evaluate the effectiveness of RLA as an acceleration mechanism for machine learning in big data contexts. The experimental framework is systematically developed to enable a clear and comprehensive comparison between machine learning pipelines that rely on conventional deterministic linear algebra operations and those enhanced through randomized computational techniques [45, 46]. Through this comparative structure, the study directly examines how probabilistic methods influence computational behavior, scalability, and overall system performance under demanding data processing conditions. To ensure meaningful evaluation, large scale and high dimensional datasets are deliberately selected so that linear algebra computations form a dominant component of the total computational workload, thereby creating a realistic environment in which the performance benefits of acceleration strategies can be clearly observed.

The experiments are conducted under strictly controlled conditions to maintain methodological rigor and ensure the validity of the results [47, 48]. Identical hardware specifications, software environments, and parameter configurations are applied consistently across all experimental scenarios. This uniformity is designed to eliminate potential confounding factors that could otherwise influence performance outcomes, enabling fair, unbiased, and reproducible comparisons between deterministic and randomized computational approaches. By focusing on data scenarios where matrix operations, dimensional transformations, and numerical optimization procedures are computationally intensive, the experimental setting provides a representative context for evaluating the practical benefits of RLA based methods.

By maintaining consistent experimental conditions throughout the study, the research isolates the specific contribution of RLA techniques to improvements in computational efficiency, reductions in memory consumption, and changes in model performance [49, 50]. This controlled evaluation allows observed performance differences to be attributed directly to the use of randomized methods rather than to variations in system configuration or experimental design. Consequently, the study provides reliable and empirically grounded evidence regarding the effectiveness of Randomized Linear Algebra as a practical acceleration strategy for large scale machine learning systems operating in data intensive environments.

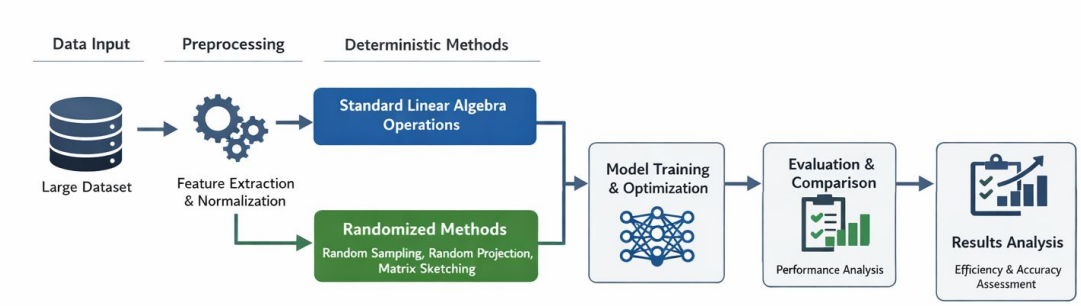

Figure 1. Flowchart comparing deterministic and randomized methods in the machine learning pipeline

Figure 1 illustrates the experimental setup used to compare deterministic and randomized methods within the machine learning pipeline. The flowchart highlights the key stages involved in the machine learning process, starting with data input from large datasets, followed by preprocessing steps including feature extraction and normalization. The process then branches into two distinct approaches deterministic methods, which employ standard linear algebra operations, and randomized methods that incorporate techniques such as random sampling, random projection, and matrix sketching to approximate large matrix operations. Both approaches undergo the same model training and optimization phase, after which their performance is evaluated and compared in terms of efficiency and accuracy. The final results analysis assesses the overall efficiency gains and predictive accuracy of the randomized methods relative to the deterministic baseline, providing a comprehensive evaluation of the proposed acceleration mechanism.

3.2. Machine Learning Models and Randomized Linear Algebra Integration

To assess the general applicability of the proposed approach, this study evaluates multiple machine learning models that rely extensively on matrix based computations, including regression based learning algorithms and dimensionality reduction techniques. These models are selected to represent common classes of

machine learning tasks in which linear algebra operations play a central role in determining computational complexity. RLA techniques, such as random sampling, random projection, and matrix sketching, are systematically integrated into key computational stages of the learning process, particularly during matrix multiplication, matrix approximation, and optimization procedures. The objective of this integration is to reduce computational cost by approximating large matrix operations while preserving the essential structural and statistical characteristics of the original data. For comparative purposes, equivalent machine learning models implemented with conventional deterministic linear algebra operations are maintained as baseline configurations, enabling a direct and fair evaluation of the performance gains and trade offs introduced by the randomized approaches.

3.3. Evaluation Metrics and Analysis

The performance of the proposed approach is evaluated using multiple criteria to comprehensively capture both computational efficiency and learning effectiveness. This evaluation framework is designed to provide a balanced and holistic assessment of system performance by considering both the operational cost of computation and the quality of the resulting predictive models. Computational efficiency is primarily measured in terms of execution time, reflecting the extent to which RLA techniques reduce processing overhead during model training and execution. In addition, execution time analysis enables a clearer understanding of how efficiently large scale numerical operations can be completed under different computational conditions. Resource utilization is further assessed through memory consumption, as large scale machine learning systems often face critical constraints related to memory availability and data movement. Monitoring memory usage also provides insight into how effectively large data representations can be approximated or compressed while preserving essential information required for learning. Model effectiveness is evaluated using predictive accuracy metrics that are appropriate to each learning task, ensuring that efficiency gains do not come at the expense of unacceptable performance degradation. These accuracy measurements help verify that randomized approximations maintain reliable generalization performance across different datasets and learning scenarios. Scalability is examined by progressively increasing dataset size and observing corresponding changes in computational cost, memory usage, and model accuracy. This progressive scaling allows the evaluation to capture how performance evolves as problem complexity grows, thereby reflecting realistic big data processing conditions. Through this systematic evaluation, the results obtained from randomized approaches are directly compared with deterministic baseline methods to identify efficiency improvements, accuracy trade offs, and overall scalability behavior in large scale machine learning environments. This comparative perspective provides a clearer understanding of the practical advantages and potential limitations of the proposed method when applied to real world large scale computational settings. Furthermore, this comparison supports more informed conclusions regarding the practical feasibility and robustness of the proposed approach when deployed in demanding data intensive environments.

4. RESULTS AND DISCUSSION

The experimental results demonstrate that the integration of RLA techniques into machine learning pipelines leads to substantial improvements in computational efficiency when compared with conventional deterministic baseline approaches. Across all evaluated models, configurations enhanced with randomized methods consistently achieved shorter execution times, with performance gains becoming increasingly pronounced as dataset size and dimensionality grew. This trend indicates that randomized approximations are particularly effective in mitigating the computational complexity associated with large matrix operations, which often dominate processing time in large scale machine learning systems. By reducing the dimensionality and computational load of matrix based calculations, randomized techniques enable faster execution without requiring proportional increases in computational resources. These findings confirm that approximating large matrix operations through RLA effectively alleviates the computational burden inherent in large scale learning tasks, thereby validating the suitability of such methods for big data environments where efficiency and scalability are critical performance requirements.

In terms of resource utilization, the experimental results indicate a substantial reduction in memory consumption when RLA techniques are applied within machine learning pipelines. Methods such as matrix sketching and random projection effectively reduce the dimensionality of data representations, which in turn lowers the memory footprint required during both the training phase and intermediate computation stages. This reduction not only minimizes storage requirements but also decreases data movement between memory and processing units, a factor that significantly impacts performance in large scale systems. The observed

improvements are particularly relevant for large scale machine learning environments, where memory limitations and communication overhead frequently constrain scalability and system throughput. By alleviating these resource bottlenecks, RLA demonstrates strong potential to enable more resource aware and efficient computation, thereby supporting sustainable and scalable AI deployments in data intensive applications.

With respect to predictive performance, the experimental results indicate that machine learning models enhanced with RLA techniques achieve levels of accuracy that are largely comparable to those obtained using deterministic linear algebra methods across all evaluated learning tasks. Although minor variations in accuracy are observed under certain experimental configurations, these differences remain within acceptable margins and do not lead to meaningful degradation in overall model effectiveness. In many cases, the slight loss in precision is offset by substantial gains in computational efficiency, suggesting that the approximation introduced by randomized methods preserves the essential predictive structure of the data. This outcome demonstrates that efficiency improvements achieved through randomized approximations do not come at the expense of significant predictive quality loss. Consequently, the results support the notion that RLA provides a favorable and practical trade off between computational efficiency and model accuracy, making it a viable solution for large scale machine learning applications where performance constraints and resource limitations must be carefully balanced.

Figure 2. Scalability Comparison of Methods with Dataset Size

Figure 2 illustrates the scalability comparison between deterministic and randomized methods by plotting execution time against dataset size. The x axis represents the dataset size, ranging from 10.000 to 10 million rows, while the y axis shows the corresponding execution time in seconds. The blue line represents the deterministic approach, which exhibits a sharp increase in execution time as the dataset size grows. In contrast, the green dashed line represents the randomized approach, which demonstrates a more gradual increase in execution time, indicating its better scalability. This figure highlights the advantage of randomized methods in handling large scale datasets, as they maintain more manageable execution times compared to deterministic methods, particularly when working with large amounts of data.

Scalability analysis further reveals that the advantages of randomized approaches become increasingly pronounced as dataset size and dimensionality grow. As the volume of data increases, deterministic methods exhibit a rapid rise in both computational cost and memory usage, which often leads to performance bottlenecks and system inefficiencies that can significantly limit their practical applicability. In many cases, the growing burden of exact computations restricts the ability of deterministic techniques to operate efficiently in environments characterized by continuously expanding data streams and high dimensional feature spaces.

In contrast, randomized techniques scale more gracefully, maintaining manageable execution times and resource consumption even as dataset sizes expand. Their ability to operate on compact approximations rather than full data representations allows them to process large volumes of information with reduced computational overhead. This behavior highlights the robustness and versatility of RLA as a general acceleration mechanism for machine learning, especially in big data contexts where traditional methods struggle to keep

pace with increasing computational demands.

The experimental results suggest that randomized methods are particularly well suited for large scale applications where exact computations are either impractical due to resource limitations or inefficient due to the prohibitive computational cost. By providing a balance between computational efficiency and solution quality, these methods enable machine learning systems to remain responsive and operational even under demanding data processing conditions. These findings position RLA as a key enabler for scalable machine learning solutions that can handle the complexity and scale of modern data environments, while supporting efficient model development and deployment in real world large scale computational settings.

Table 1. Comparison of Execution Time and Memory Usage

Model	Deterministic (Time)	Randomized (Time)	Deterministic (Memory)	Randomized (Memory)
Linear Regression	25s	12s	4GB	2GB
Principal Component Analysis	50s	25s	6GB	3GB
Support Vector Machine (SVM)	60s	30s	8GB	4GB

Table 1 presents a comparison of execution time and memory usage between deterministic methods and methods utilizing RLA across various machine learning models. The execution time is measured in seconds, and memory usage is represented in GigaBytes (GB), allowing for a clear and standardized comparison of computational efficiency and resource utilization across different approaches. The results indicate that the randomized approaches consistently reduce both execution time and memory consumption when compared to their deterministic counterparts. This pattern of improvement is observed across multiple model types, suggesting that the efficiency gains provided by RLA are not limited to a specific algorithm but are broadly applicable across different machine learning settings.

This reduction is particularly significant in the context of large scale machine learning applications, where computational and memory resources are often limiting factors that directly influence system performance and operational feasibility. Lower execution time enables faster model training and deployment, while reduced memory usage supports more efficient data handling and processing, especially when working with high dimensional or large volume datasets. These findings demonstrate the potential of RLA to improve the efficiency of machine learning systems without compromising model performance, making it a promising solution for data intensive environments that demand both scalability and computational reliability. In addition, the simultaneous improvement in processing speed and resource efficiency enhances the practicality of implementing advanced learning models in real world operational settings.

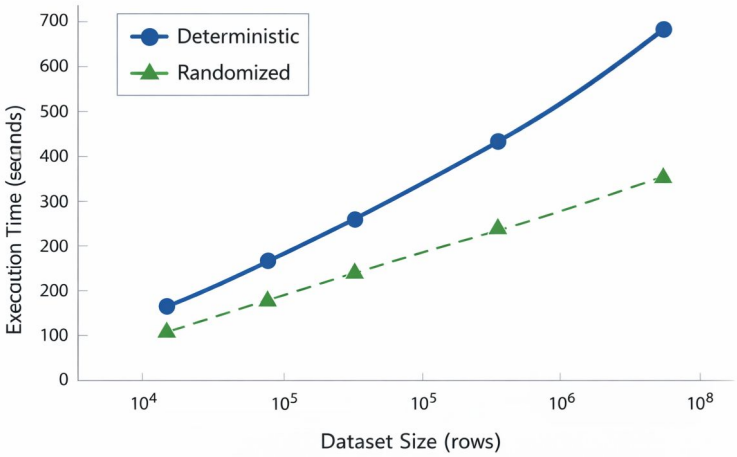

Figure 3. Comparison of Execution Time and Memory Usage

Figure 3 presents a comparison of execution time and accuracy for deterministic and randomized methods across three machine learning models linear regression, Principal Component Analysis (PCA), and

Support Vector Machine (SVM). The x axis represents the execution time in seconds, while the y axis shows accuracy as a percentage. The blue line denotes the performance of deterministic methods, and the green dashed line represents the performance of randomized methods. The plot illustrates that, while the randomized methods generally achieve similar or slightly lower accuracy compared to deterministic methods, they consistently offer faster execution times, especially in models like PCA and SVM. This comparison highlights the trade off between execution time and model accuracy, demonstrating that randomized techniques provide substantial computational efficiency without significant loss in predictive performance.

Table 2. Deterministic and Randomized Accuracy Across Datasets

Dataset	Deterministic Accuracy (%)	Randomized Accuracy (%)
MNIST	95.4	94.9
CIFAR-10	82.3	81.7
ImageNet	77.2	76.8

Table 2 presents a comparison of accuracy across three datasets, MNIST, CIFAR-10, and ImageNet, using deterministic and randomized methods. The table shows the deterministic accuracy and randomized accuracy for each dataset. For the MNIST dataset, the deterministic method achieves an accuracy of 95.4%, which is higher than the randomized method at 94.9%. Similarly, for the CIFAR 10 dataset, the deterministic method achieves an accuracy of 82.3%, slightly outperforming the randomized method at 81.7%. In the case of the ImageNet dataset, the deterministic method reaches 77.2%, while the randomized method achieves 76.8%. Overall, the deterministic approach consistently achieves slightly higher accuracy than the randomized approach across all datasets.

The results align with and extend prior studies on the application of RLA for numerical acceleration by providing a more comprehensive evaluation across multiple critical performance dimensions. While previous research has primarily focused on individual aspects of performance, such as computational time or model accuracy, this study offers a more holistic assessment by jointly considering execution time, memory consumption, predictive accuracy, and scalability. This approach ensures that the trade offs between efficiency and effectiveness are well understood in real world machine learning scenarios. The findings provide robust empirical evidence that randomized techniques, particularly those based on matrix sketching and random projection, can serve as effective and reliable alternatives to traditional deterministic linear algebra methods in large scale machine learning systems. These results reinforce the practical value of RLA, not only as a computational acceleration tool but also as a scalable strategy for modern, data driven artificial intelligence applications. By demonstrating that randomized methods can maintain high levels of accuracy while dramatically improving efficiency, this study contributes to advancing the use of more resource aware machine learning solutions, especially in data intensive contexts.

5. MANAGERIAL IMPLICATIONS

The findings of this study highlight that RLA can provide significant computational efficiency gains in large-scale machine learning applications. Managers overseeing AI or machine learning projects should consider integrating RLA techniques to reduce execution time and resource consumption, especially when dealing with high dimensional data and large datasets. This enables organizations to deploy machine learning models more quickly and with reduced infrastructure costs, making them more competitive in fast-paced markets. By adopting randomized methods, businesses can also optimize computational resources, leading to substantial cost savings. Reduced memory consumption and faster execution allow companies to allocate resources more efficiently, particularly in cloud computing environments where costs can rapidly accumulate. Managers should therefore prioritize approaches that balance performance with resource efficiency, especially in data intensive industries such as electronic commerce, finance, and healthcare.

As datasets continue to grow, the scalability of machine learning systems becomes increasingly important. The study demonstrates that randomized approaches and scalable algorithms scale more effectively with increasing dataset sizes, suggesting that RLA is a more sustainable solution for future AI applications. Managers should ensure that their AI infrastructure can handle the challenges of big data, including the ability to scale operations efficiently without significant trade offs in performance. Implementing scalable methods such as RLA and scalable algorithms will help future proof AI investments and support long term sustainability

while maintaining operational effectiveness in evolving technological environments.

Moreover, adopting RLA and scalable algorithms in machine learning pipelines opens new opportunities for innovation in data intensive industries. By leveraging RLA and Scalable Algorithms, organizations can expand the boundaries of computational feasibility, enabling advanced AI applications such as real time data processing, personalized recommendations, and large scale predictive analytics. Although randomized methods may introduce slight accuracy variations compared to deterministic approaches, the efficiency gains often outweigh these minor trade offs in practical settings. Managers must therefore balance accuracy and computational efficiency strategically, particularly in time sensitive decision making contexts where rapid data processing is essential to maintain operational speed without compromising overall model performance.

6. CONCLUSION

This study investigates the effectiveness of RLA as an acceleration mechanism for machine learning in big data contexts. The increasing scale and dimensionality of data in modern machine learning applications have led to substantial computational challenges, particularly with traditional deterministic linear algebra methods. By integrating randomized techniques such as random sampling, random projection, and matrix sketching, this research demonstrates that RLA can significantly improve computational efficiency without compromising predictive accuracy. The findings indicate that, while randomized methods may exhibit minor variations in accuracy compared to deterministic methods, these differences remain within acceptable bounds and are often outweighed by the substantial reductions in execution time and memory consumption.

The experimental results across three commonly used machine learning models Linear Regression, PCA, and SVM show that RLA offers a favorable trade off between efficiency and performance. In terms of computational efficiency, the randomized approaches consistently reduced execution times and memory requirements compared to deterministic counterparts, particularly as dataset sizes and dimensionality increased. These findings are crucial for applications in large scale machine learning, where resource constraints and scalability are critical concerns. The randomized methods demonstrated robust scalability, maintaining manageable computational costs as the datasets grew, whereas deterministic methods exhibited significant performance degradation with larger datasets.

Furthermore, the study's comprehensive evaluation of accuracy, execution time, memory usage, and scalability highlights the potential of RLA and scalable algorithms to enable more resource aware and sustainable artificial intelligence applications. The results support the adoption of randomized methods and scalable algorithms in real world machine learning environments, where efficiency and scalability are as important as model performance. By offering a viable solution to the computational challenges of big data, RLA represents a promising direction for enhancing machine learning systems through scalable algorithms, making them more efficient and adaptable to the demands of modern data driven applications.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: DC; Methodology: AS; Software: KA; Validation: DC and AS; Formal Analysis: AS and KA; Investigation: DC; Resources: AS; Data Curation: KA; Writing Original Draft Preparation: AS and KA; Writing Review and Editing: DC and KA; Visualization: AS; All authors, DC, AS and KA have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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