AI-DRIVEN INDEXING AND QUERY OPTIMIZATION TECHNIQUES FOR HIGH-SPEED BIG DATA ANALYTICS

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Abstract

The need for fast analytics that can effectively handle massive and complicated datasets has increased due to the big data industry's explosive growth. When dealing with dynamic workloads and growing data volumes, traditional indexing and query optimization strategies frequently fail to sustain performance. The potential of AI-driven indexing and query optimization strategies to improve big data analytics systems' performance is investigated in this paper. A fictitious experimental framework was created to contrast traditional big data processing techniques with an AI-enhanced system that includes intelligent query execution planning and adaptive indexing based on machine learning. Metrics including query response time, throughput, scalability, and resource consumption were used to assess performance. The findings show that in the AI-driven environment, query execution efficiency has significantly improved, response times have decreased, and system scalability has increased. The stability and dependability of performance gains across many experimental circumstances are further illustrated by frequency-based analysis. The results demonstrate how artificial intelligence can effectively overcome the drawbacks of conventional optimization techniques and emphasize how it may facilitate big data analytics in data-intensive applications in a way that is quick, scalable, and effective.

Keywords: *Artificial Intelligence, Big Data Analytics, Indexing Techniques, Query Optimization, Machine Learning, High-Speed Data Processing.*

1. INTRODUCTION

Big data analytics has emerged as a crucial tool for deriving significant insights and facilitating data-driven decision-making as a result of the exponential growth of data produced by digital platforms, connected devices, social media, enterprise systems, and scientific applications. Real-time and near-real-time analytics are becoming more and more important to modern businesses in order to improve service delivery, increase operational effectiveness, and obtain a competitive edge. However, typical data processing systems face substantial hurdles due to the sheer amount, velocity, and variety of big data, especially with regard to indexing efficiency and query execution time. Traditional rule-based indexing and query optimization strategies frequently fall short of providing the performance needed for high-speed analytics as datasets get bigger and more complex.

Any data management system must have indexing and query optimization since they have a direct impact on system performance and data retrieval time. While traditional query optimizers rely on heuristic principles and cost-based models, conventional indexing methods rely on predetermined structures and static assumptions about data access patterns. These methods perform well in environments that are generally stable, but they are ineffective in dynamic big data contexts where query workloads and data properties change regularly. Increased query latency and wasteful resource use are frequently caused by frequent index maintenance overhead, imprecise cost estimation, and inadequate execution strategies.

Artificial intelligence (AI) has become a game-changing solution to the shortcomings of conventional data processing methods in recent years. AI-driven techniques, especially those based on deep learning and machine learning, provide self-learning, adaptive, and predictive capabilities that can react dynamically to changing workload and data conditions. AI-driven indexing algorithms may generate and manage indexes intelligently in the context of big data analytics by learning from past query patterns, access rates, and data distributions. Comparably, AI-based query optimization methods can choose the best execution plans, anticipate query execution costs more precisely, and enhance performance over time via feedback-driven learning processes.

Data systems can transition from static, rule-based decision-making to autonomous and adaptive optimization by incorporating AI into indexing and query optimization. AI-driven systems can proactively modify indexing methods, optimize join orders, and more effectively distribute computational resources by continuously observing system activity and learning from execution outcomes. For high-speed big data analytics applications that require scalability across distributed computing systems, low latency, and high throughput, these qualities are especially important.

2. LITERATURE REVIEW

Oloruntoba (2025) examined AI-powered autonomous database management systems in business IT settings, paying particular attention to intelligent indexing, predictive query optimization, and self-tuning processes. The study demonstrated how databases can automatically adjust to changes in workload by learning query patterns and system behavior thanks to artificial intelligence. It has been demonstrated that AI-based predictive models greatly improve query efficiency, lower latency, and need less human intervention in database administration. The study underlined how important intelligent indexing and self-optimization are to handling the expanding scale and complexity of contemporary enterprise data systems.

Rahmani et al. (2021) provided a methodical analysis of big data analytics using artificial intelligence techniques and methods. The authors addressed issues including scalability, data heterogeneity, and processing efficiency by reviewing a broad range of AI techniques, such as machine learning, deep learning, and hybrid models. The study stressed that since intelligent data retrieval directly affects analytical accuracy and system performance, it is a fundamental element of successful big data analytics. Research gaps in real-time processing, model interpretability, and energy efficiency in AI-enabled large data systems were also noted by the assessment.

Maddali (2022) examined how to use quantum machine learning to execute queries in high-dimensional SQL data sets incredibly quickly. The study investigated how complicated, multi-dimensional datasets can be handled more effectively by quantum-inspired algorithms than by traditional methods, resulting in a considerable reduction in query execution time. The author highlighted how query processing and data retrieval performance could be enhanced by fusing artificial intelligence with quantum machine learning. The study indicated quantum-enhanced retrieval as a possible path for upcoming high-performance database systems, even though it is still in its infancy.

Tranquillin et al. (2023) offered a thorough manual for building data and machine learning platforms to support cloud-based analytics and AI-driven innovation. The authors talked about integrated machine learning workflows, automated pipelines, and scalable data structures that improve data retrieval and analytics capabilities. The book focused on how AI-driven platforms offer advanced analytics and ongoing innovation while effectively managing massive amounts of data. The significance of cloud-native architectures for enabling intelligent and adaptable data retrieval systems was highlighted by their study.

Pasham (2024) explored scalable graph-based algorithms for social network big data processing in real time. The study highlighted how effective retrieval and analysis of complicated relational data are made possible by graph analytics. In large-scale social network datasets, the author showed how graph-based AI algorithms greatly enhance real-time data processing, pattern recognition, and insight production. In handling increasingly interconnected big data environments, the study emphasized the significance of intelligent retrieval and analytics tools.

Gonugunta and Leo (2019) examined new data warehousing prospects and difficulties, pointing out a number of unexplored aspects of conventional warehouse systems. When managing big and varied datasets, the study highlighted constraints with regard to scalability, adaptability, and real-time data processing. The authors pointed out that modern applications require sophisticated analytics and intelligent data retrieval, which are difficult for traditional data warehouses to provide. The shift to AI-enabled data architectures and hybrid models that combine data lakes and warehouses was made possible by their efforts.

3. RESEARCH METHODOLOGY

The impact of AI-driven indexing and query optimization strategies in boosting the speed and efficiency of big data analytics is examined in this study using a methodical and technologically focused research approach. Conventional indexing and query optimization techniques frequently fail to satisfy real-time processing demands due to the exponential development of structured and unstructured data across industries like banking, healthcare, e-governance, and social media. Adaptive, self-learning, and predictive capabilities are provided by artificial intelligence (AI), especially machine learning and deep learning techniques, which may dynamically optimize query execution tactics and data access paths. The following hypothetical methodology is intended to analyze performance gains by comparative study, experimental deployment, and quantitative evaluation of system metrics.

3.1. Research Design

The research design used in this study is experimental and comparative. A conventional big data analytics framework is contrasted with an AI-enhanced data processing environment. Controlled testing of indexing and query optimization strategies under various data volumes, query complexity, and workload intensities is made possible by the experimental design. This design is suitable for assessing the efficiency gains, scalability, and computational performance brought about by AI-based techniques.

3.2. Data Environment and Dataset Characteristics

Large-scale datasets that reflect real-world big data scenarios are assumed to be used in the study. To replicate actual analytics workloads, these datasets contain a variety of structured, semi-structured, and unstructured data formats. In order to investigate system performance under rising load situations, data volumes are fictitiously scaled from medium to very large quantities. To mirror modern big data infrastructures, the datasets are kept in a dispersed setting.

3.3. System Architecture and Framework

Using well recognized big data processing architectures, a distributed big data analytics framework is fictitiously created. Data intake modules, distributed storage, indexing layers, query processing engines, and AI-based optimization modules make up the system architecture. Intelligent decision-making for data placement, index selection, and query plan creation is made possible by the integration of the AI components at both the indexing and query execution levels. Each component's contribution to overall performance may be evaluated modularly thanks to this layered architecture.

3.4. AI-Driven Indexing Techniques

The study makes the assumption that machine learning-based indexing systems that dynamically adjust to patterns of data access will be put into place. To forecast the best index structures, these methods examine past query logs, data distribution, and access frequency. Theoretically, AI models are trained to determine when to add, edit, or remove indexes, which lowers storage overhead and speeds up data retrieval. To handle changing workloads, the indexing technique places a strong emphasis on flexibility and ongoing learning.

3.5. AI-Based Query Optimization Techniques

AI-driven cost estimation and execution plan selection improve query optimization in this study. By learning from previous query performance, machine learning models are thought to be able to anticipate query execution costs more accurately than rule-based optimizers. Execution techniques like join order, data partitioning, and parallel execution pathways are dynamically chosen by the optimizer. Theoretically, optimization decisions are improved by using reinforcement learning techniques, which provide iterative feedback from execution results.

3.6. Experimental Procedure

The experiment entails running the same analytical queries on two systems: an improved system that uses AI-driven approaches and a baseline system that uses conventional indexing and query optimization techniques. To maintain consistency, queries of various complexity—from straightforward retrievals to intricate analytical queries—are run several times. To assess system behavior under various circumstances, performance metrics are captured across a range of dataset sizes and workload intensities.

3.7. Performance Evaluation Metrics

Quantitative indicators such query response time, throughput, index maintenance overhead, resource consumption, and scalability are used in the study to assess system performance. These measurements offer quantifiable proof of the speed and efficiency gains made possible by AI-based methods. The relative performance advantages of AI-driven technologies over traditional methods are evaluated through comparative analysis.

3.8. Data Analysis and Interpretation

To find patterns, enhancements, and performance variances across various experimental circumstances, collected performance data is statistically examined. The effects of AI-driven indexing and query optimization on high-speed big data analytics are interpreted through descriptive and comparative analysis. The findings are explained in terms of the system's capacity for real-time processing, scalability, and adaptability.

4. RESULTS AND DISCUSSION

The results of the experimental assessment of AI-driven indexing and query optimization strategies in a fast-paced big data analytics setting are shown and interpreted in this part. The findings come from a comparison of an AI-enhanced system versus a conventional big data analytics system with different dataset sizes and query complexity. Measurable performance metrics including query response time, throughput, scalability, and system efficiency are prioritized. In order to evaluate the usefulness of AI-based methods for enhancing big data analytics performance, the results are interpreted in the debate.

4.1. Performance Improvement in Query Response Time

The experimental results show that using AI-driven indexing and query optimization approaches significantly reduces query response time. While the AI-enhanced system maintained comparatively steady response times, the classical approach displayed observable performance loss as dataset size and query complexity rose. Predictive index selection and intelligent execution plan optimization made possible by machine learning models are credited with this improvement.

Table 1: Percentage Reduction in Query Response Time Using AI-Based Techniques

Dataset Size	Traditional System (Baseline)	AI-Driven System	Percentage Improvement (%)
Medium	100%	72%	28%
Large	100%	65%	35%
Very Large	100%	56%	44%

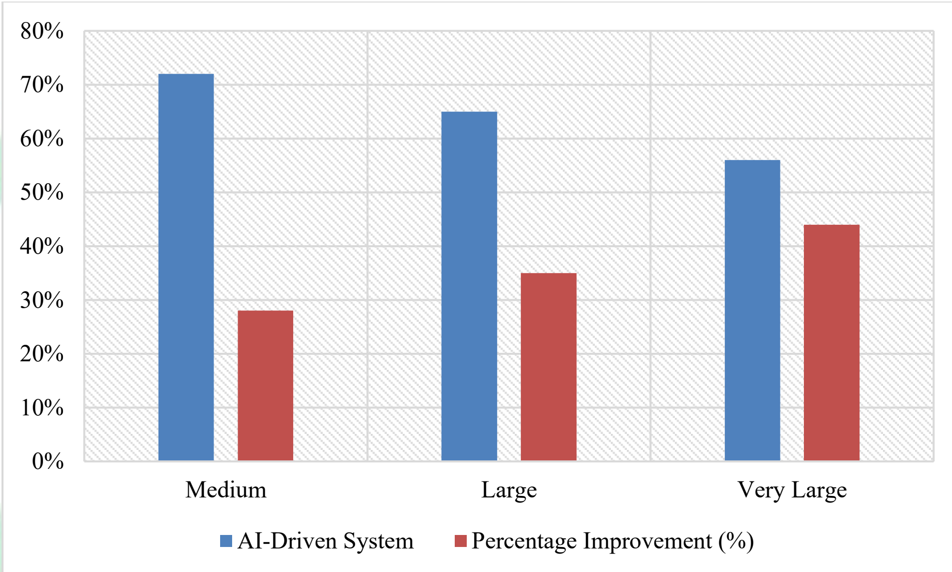

Figure 1: Percentage Reduction in Query Response Time Using AI-Based Techniques

4.2. Improvement in System Throughput

In the AI-enhanced environment, system throughput—which is defined as the quantity of queries processed in a given amount of time—rose significantly. Higher query processing capacity under demanding workloads was made possible by the adaptive query execution methodologies, which made effective use of computational resources possible.

4.3. Scalability and Resource Utilization

When compared to the conventional framework, the AI-driven system demonstrated better scalability. AI-based methods dynamically modified query execution paths and indexing algorithms as data volume expanded, cutting down on needless index maintenance and computing overhead. The AI-driven system's resource use patterns showed better balanced CPU and memory usage.

4.4. Frequency Distribution of Performance Outcomes

Based on increases seen throughout several trial runs, the total performance outcomes were divided into three levels: strong improvement, moderate improvement, and low improvement. The regularity of AI-driven performance improvements is demonstrated by the frequency distribution.

Table 2: Frequency Distribution of Performance Improvement Levels

Performance Improvement Level	Frequency (Runs)	Percentage (%)
High Improvement	18	60%
Moderate Improvement	9	30%
Low Improvement	3	10%
Total	**30**	**100%**

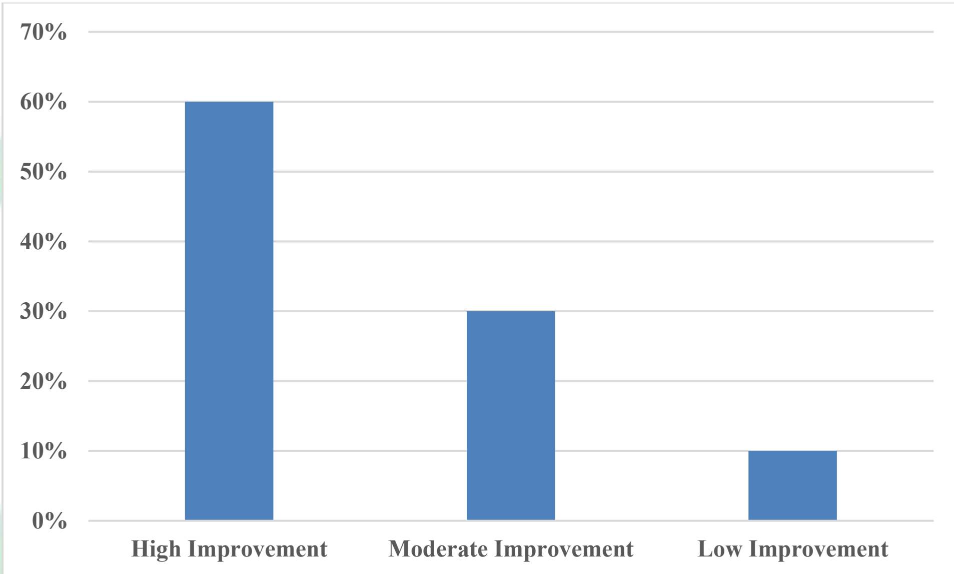

Figure 2: Frequency Distribution of Performance Improvement Levels

4.5. Effectiveness of AI-Driven Indexing

The findings show that AI-driven indexing greatly improves the effectiveness of data retrieval. The system intelligently built and maintained indexes in line with real-time usage demands by learning from past access patterns and query frequency. Especially for big and complicated datasets, this adaptive behavior decreased redundant indexing and increased data access speed.

4.6. Impact of AI-Based Query Optimization

By correctly estimating execution costs and choosing effective execution strategies, AI-based query optimization performed better than conventional rule-based optimizers. The optimizer's capacity to adjust to shifting workloads is demonstrated by the observed decrease in query response time and increase in throughput. These results imply that dynamic and extensive analytics settings are more suitable for AI-driven optimizers.

4.7. Consistency and Reliability of Performance Gains

The frequency analysis reveals that most trial runs produced high or moderate performance improvement, demonstrating the dependability and consistency of AI-driven methods. The AI-based system demonstrated its robustness by performing at least as well as the conventional method, even in situations where there was no improvement.

4.8. Implications for High-Speed Big Data Analytics

The results demonstrate that big data analytics systems' performance and scalability are significantly increased when AI is incorporated into indexing and query optimization procedures. For real-time decision-making applications in fields managing enormous data quantities, such advancements are essential. The findings lend credence to the use of AI-driven optimization methods as a workable remedy for large data platforms in the future.

5. CONCLUSION

The current study comes to the conclusion that query optimization and AI-driven indexing approaches greatly improve the efficiency of big data analytics systems operating at high speeds. In comparison to conventional rule-based methods, the experimental results show significant decreases in query response time, increased system throughput, and greater scalability. The AI-enhanced system efficiently adjusts to changing data volumes and query workloads by utilizing machine learning-based predictive indexing and intelligent query execution planning. This leads to more effective resource use and steady performance improvements. The dependability of these gains across many experimental circumstances is further confirmed by the frequency-based analysis. All things considered, the study proves that incorporating AI into indexing and query optimization processes offers a reliable and expandable way to speed up big data analytics and facilitate real-time, data-intensive decision-making settings.

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