Database Management Systems for Artificial Intelligence: Comparative Analysis of PostgreSQL and MongoDB

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Abstract

The rapid evolution of artificial intelligence (AI) has amplified the need for efficient database management systems (DBMS) to handle the growing volume, variety, and velocity of data. PostgreSQL, a robust relational database, and MongoDB, a leading NoSQL solution, are two widely adopted DBMSs in AI applications, each offering unique advantages. This paper provides a comprehensive comparative analysis of PostgreSQL and MongoDB, focusing on their suitability for AI use cases. Key evaluation criteria include data modeling, query complexity, scalability, ACID compliance, indexing, and integration with AI frameworks. PostgreSQL excels in scenarios requiring strict data consistency, complex querying, and structured data, making it ideal for financial modeling, scientific research, and feature engineering. Conversely, MongoDB's schema-less design, horizontal scalability, and native support for semi-structured data align with real-time analytics, IoT, and evolving AI datasets. The study highlights that the choice between the two databases depends on specific project requirements and proposes hybrid approaches to leverage their complementary strengths. This analysis aims to guide AI practitioners in making informed database decisions to optimize performance, scalability, and flexibility in AI systems.

Keywords

Artificial Intelligence (AI), PostgreSQL, MongoDB, Database Management Systems (DBMS), Scalability, Data Modeling, Query Optimization

1. Introduction

The rapid advancement of artificial intelligence (AI) has led to an exponential increase in data generation and consumption, necessitating robust database management systems (DBMS) to efficiently handle, process, and analyze vast amounts of information. Among the myriad of DBMS options available, PostgreSQL and MongoDB have emerged as prominent choices for AI applications, each offering unique strengths and capabilities (Özsu & Valduriez, 1999).

PostgreSQL, a powerful relational DBMS, is renowned for its adherence to ACID (Atomicity, Consistency, Isolation, Durability) principles, extensive feature set, and ability to handle complex queries (Obe & Hsu, 2017). Its strong support for structured data and advanced indexing techniques makes it particularly suitable for AI projects requiring strict data integrity and sophisticated analytical operations (Sharma et al., 2012).

Conversely, MongoDB, a leading NoSQL database, offers a flexible document-based data model that excels in managing semi-structured and unstructured data commonly encountered in AI applications (Chodorow, 2019). Its horizontal scalability and ability to handle large volumes of diverse data types align well with the dynamic nature of AI datasets and real-time analytics requirements (Győrödi et al., 2015).

The choice between PostgreSQL and MongoDB for AI projects often depends on specific use cases, data characteristics, and performance requirements. While PostgreSQL's relational model provides strong consistency and complex query capabilities, MongoDB's schema-less design offers greater flexibility and scalability for evolving data structures (Nayak et al., 2013). This comparative analysis aims to explore the strengths, limitations, and optimal use cases of PostgreSQL and MongoDB in the context of AI applications. By examining factors such as data modeling, query performance, scalability, and integration with AI frameworks, this study seeks to provide insights that can guide database selection decisions for AI researchers and practitioners.

2. Literature Review

Győrödi et al. (2015) compared MongoDB, a NoSQL database, with MySQL, a relational database, focusing on insertion, selection, and data aggregation performance. The study found MongoDB excels in insertion speed, particularly with large datasets, while MySQL performs better in complex queries and joins. MongoDB's flexibility with unstructured data and horizontal scalability make it advantageous for big data applications. This study offers empirical evidence for comparing NoSQL and relational databases, providing a framework applicable to evaluating PostgreSQL and MongoDB for AI applications.

Nayak et al. (2013) categorize NoSQL databases into key-value stores, document databases, column-oriented, and graph databases, explaining core concepts and highlighting scalability and flexibility advantages. They contrast NoSQL with relational databases, noting NoSQL's performance benefits with unstructured data. This foundational overview is valuable for understanding MongoDB's role within NoSQL and its comparison with relational systems like PostgreSQL. By exploring the fundamental differences, this article helps researchers decide which database system suits specific AI tasks like data storage and retrieval.

Sharma et al. (2018) analyze SQL and NoSQL databases, covering their architecture, data models, and evolution. They highlight SQL's strengths in consistency, complex queries, and ACID compliance, contrasting with NoSQL's scalability and suitability for unstructured data. The paper also compares various NoSQL types, including MongoDB, discussing ideal use cases. This balanced perspective on SQL and NoSQL provides context for evaluating PostgreSQL and MongoDB, offering insights into their respective strengths for tasks like machine learning, data preprocessing, and real-time analytics.

Yu et al. (2024) provides pivotal insights into the application of deep learning and distributed learning techniques, offering a valuable foundation for future research. Chang's research demonstrates a masterful integration of LightGBM and PCA technologies with the SMOTEENN strategy, yielding outstanding performance in classification and prediction tasks. Building upon Chang's research findings, people have substantially enhanced our model's processing efficiency by incorporating his innovative data handling approaches, thereby achieving significant performance gains.

Li et al. (2024) introduces a novel and well-structured framework that redefines large language model architectures, incorporating advanced modular design and optimization techniques, setting a new benchmark for innovation in LLM Development. Li also introduces a novel combination of Bayesian optimization with channel and spatial attention mechanisms, significantly advancing image classification performance and setting a new benchmark for future model improvements in deep learning.

3. PostgreSQL and MongoDB Explanation

PostgreSQL is an advanced, open-source relational database management system (RDBMS) that has gained significant popularity in the field of artificial intelligence due to its robust features and reliability. Originally developed at the University of California, Berkeley, PostgreSQL has evolved into a powerful database solution that adheres to SQL standards while offering numerous extensions and advanced capabilities. PostgreSQL offers a comprehensive set of features that make it well-suited for AI applications. Its ACID compliance ensures data integrity, while support for advanced data types and indexing techniques enhances its ability to handle complex AI-related data structures and queries. The implementation of Multi-Version Concurrency Control allows for efficient simultaneous database access, and its extensibility enables customization for specific AI needs. PostgreSQL's full-text search capabilities further support natural language processing tasks. In the context of AI, these features translate to advantages such as strong data integrity, support for complex queries and analysis, reliable transactional support, and scalability for handling large datasets, making it a powerful choice for many AI workloads that require structured data management and sophisticated analytical capabilities.

MongoDB is a popular, open-source NoSQL database that has gained traction in the AI community due to its flexibility and scalability. Developed by MongoDB Inc., it is classified as a document-oriented database, which stores data in flexible, JSON-like documents called BSON (Binary JSON). MongoDB offers a set of features that are particularly advantageous for AI applications dealing with diverse and rapidly evolving data. Its flexible, schema-less document model allows for easy adaptation to changing data requirements, which is crucial in the dynamic field of AI. MongoDB's design for horizontal scalability through sharding makes it capable of handling the massive datasets often encountered in AI and machine learning projects. The database's high-performance read and write operations, coupled with its support for various indexing types and a powerful aggregation framework, make it well-suited for real-time AI systems and big data processing. Features like GridFS for efficient large file storage further enhance its utility for AI applications dealing with multimedia data. In the AI context, MongoDB's flexibility, scalability, performance, JSON-like structure, and geospatial capabilities make it an excellent choice for applications involving diverse data types, real-time analytics, and location-based analysis, particularly in scenarios where data structures are less rigid and may evolve over time.

Both PostgreSQL and MongoDB have their strengths in the context of AI applications. The choice between them often depends on the specific requirements of the project, such as data structure, scalability needs, consistency requirements, and the nature of the AI algorithms being employed.

4. PostgreSQL and MongoDB Comparison

Data Model and Schema Flexibility

- PostgreSQL:

- Uses a rigid, predefined schema based on the relational model.
- Enforces data integrity through constraints, foreign keys, and data type validation.
- Well-suited for structured data with clear relationships.

- MongoDB:

- Employs a flexible, schema-less document model.
- Allows for dynamic schema changes without downtime.
- Ideal for semi-structured or unstructured data common in AI applications.

PostgreSQL's structured approach is beneficial for AI projects requiring strict data consistency and complex relationships. However, MongoDB's flexibility can be advantageous for projects with evolving data requirements or diverse data types, which is often the case in AI research and development.

Query Language and Complexity

- PostgreSQL:

- Uses standard SQL with extensive support for complex queries, joins, and subqueries.
- Offers powerful query optimization capabilities.
- Supports window functions and common table expressions (CTEs) for advanced analytics.

- MongoDB:

- Uses a custom query language based on method chaining and JSON-like syntax.
- Provides an aggregation framework for complex data transformations and analysis.
- Limited support for joins compared to relational databases.

PostgreSQL's SQL support makes it superior for complex analytical queries often required in AI data preprocessing and analysis. MongoDB's query language, while less expressive for complex operations, offers simplicity and aligns well with document-based data structures commonly used in AI applications.

Scalability and Performance

- PostgreSQL:
  - Primarily designed for vertical scaling (adding more resources to a single server).
  - Offers excellent performance for complex queries and transactions.
  - Can handle large datasets but may face challenges with extremely high write loads.
- MongoDB:
  - Built for horizontal scaling through sharding.
  - Excels in write-heavy workloads and can handle massive datasets across distributed systems.
  - May sacrifice some consistency for improved performance and scalability.

MongoDB's horizontal scalability makes it more suitable for AI applications dealing with big data or requiring high write throughput. PostgreSQL, while scalable to a certain extent, is better suited for AI projects that prioritize data consistency and complex query performance over extreme scalability.

ACID Compliance and Data Consistency

- PostgreSQL:
  - Fully ACID compliant, ensuring strong data consistency.
  - Supports multi-version concurrency control (MVCC) for handling simultaneous transactions.
  - Ideal for applications requiring strict data integrity and transactional reliability.
- MongoDB:
  - Offers tunable consistency levels, from eventual consistency to strong consistency.
  - Provides atomic operations at the document level.
  - May sacrifice some consistency for improved performance and scalability.

PostgreSQL's strong ACID compliance makes it preferable for AI applications that require absolute data consistency, such as financial modeling or critical decision-making systems. MongoDB's flexible consistency model can be advantageous for AI applications that prioritize availability and partition tolerance over strict consistency, such as real-time recommendation systems or social network analysis.

Indexing and Query Optimization

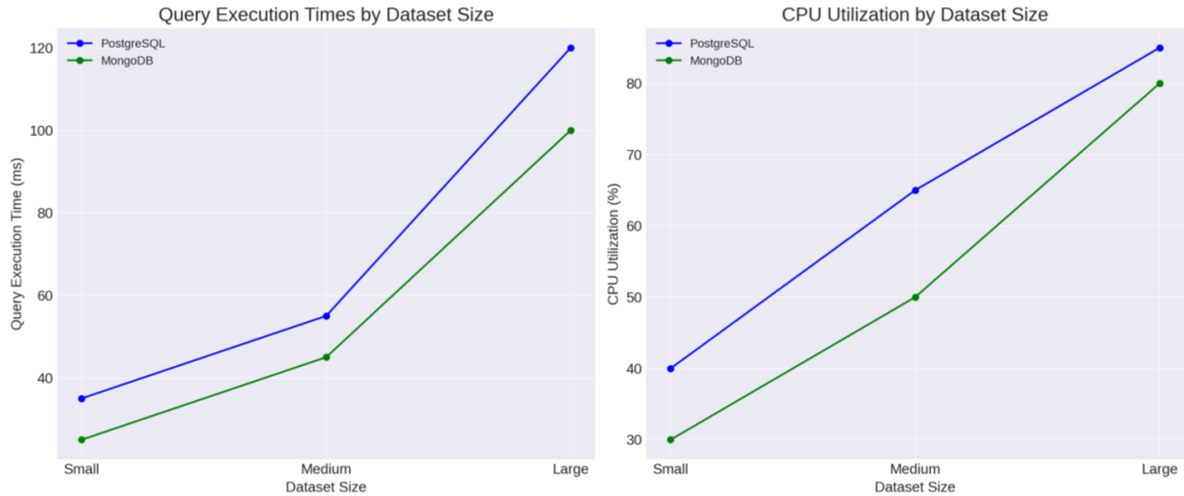
- PostgreSQL:

- Supports various index types, including B-tree, Hash, GiST, and GIN.
- Offers a sophisticated query planner and optimizer.
- Allows for partial and expression indexes.

- MongoDB:

- Provides multiple index types, including single field, compound, multi-key, and text indexes.
- Supports geospatial indexing for location-based queries.
- Offers query optimization using covered queries and index intersection.

Both databases offer robust indexing capabilities, but their strengths differ. PostgreSQL's advanced indexing and query optimization are particularly beneficial for complex analytical queries in AI applications. MongoDB's indexing features, especially geospatial indexing, can be advantageous for AI projects involving location-based data or text analysis.



Support for Unstructured Data and AI-specific Features

- PostgreSQL:

- Offers extensions for handling JSON and other semi-structured data types.
- Supports full-text search capabilities.
- Can integrate with AI libraries through extensions and procedural languages.

- MongoDB:

- Native support for JSON-like documents and nested data structures.
- Provides a flexible model for storing and querying unstructured data.
- Offers built-in support for geospatial queries and text search.

MongoDB's native support for semi-structured and unstructured data makes it particularly well-suited for AI applications dealing with diverse data types, such as text analysis, image processing, or IoT data. PostgreSQL, while capable of handling such data through extensions, excels in scenarios where the data has a more defined structure and relationships.

Integration with AI Frameworks and Tools

- PostgreSQL:

- Can integrate with popular AI frameworks through database connectors and APIs.
- Supports in-database machine learning through extensions like MADlib.
- Works well with data analysis tools like Pandas and Jupyter Notebooks.

- MongoDB:

- Offers native drivers for many programming languages used in AI development.
- Integrates easily with document-oriented AI frameworks and NoSQL-based tools.
- Provides connectors for big data processing frameworks like Apache Spark.

Both databases can integrate well with AI frameworks and tools. PostgreSQL's strength lies in its compatibility with traditional data analysis tools and support for in-database machine learning. MongoDB's advantage is its natural fit with document-oriented AI workflows and big data processing frameworks.

5. Conclusions

The comparison between PostgreSQL and MongoDB in the context of AI applications reveals that both databases have their strengths and are suited for different aspects of AI development and deployment. The choice between them depends largely on the specific requirements of the AI project at hand. PostgreSQL excels in scenarios that require:

- Strong data consistency and ACID compliance
- Complex querying and data analysis
- Structured data with clear relationships
- Advanced indexing and query optimization for analytical workloads
- Integration with traditional data analysis tools and in-database machine learning

These characteristics make PostgreSQL particularly suitable for AI applications in fields such as financial modeling, scientific research, and any domain where data integrity and complex analytical queries are paramount. Its ability to handle sophisticated data relationships and support for advanced SQL features can greatly benefit feature engineering and data preprocessing tasks in machine learning pipelines. On the other hand, MongoDB shines in scenarios that prioritize:

- Flexibility in data modeling and schema design
- Horizontal scalability for handling big data
- High-performance read and write operations
- Native support for semi-structured and unstructured data
- Geospatial data processing and real-time analytics

These features make MongoDB an excellent choice for AI applications dealing with diverse and evolving data types, such as social media analytics, IoT data processing, content management systems, and real-time recommendation engines. Its scalability and performance characteristics are particularly beneficial for AI systems that need to handle large volumes of data or require real-time processing.

It's important to note that the boundaries between relational and NoSQL databases are becoming increasingly blurred, with PostgreSQL adding support for JSON and other NoSQL-like features, and MongoDB improving its support for complex queries and consistency models. This convergence suggests that future AI applications may benefit from hybrid approaches or multi-model databases that combine the strengths of both paradigms.

In conclusion, the selection between PostgreSQL and MongoDB for AI applications should be based on a careful analysis of the project's specific requirements, including:

- Data structure and consistency needs
- Scalability and performance demands
- Query complexity and analytical requirements
- Integration with existing AI frameworks and tools
- Long-term flexibility and maintainability considerations

By weighing these factors, developers and data scientists can make an informed decision that best supports their AI initiatives. In some cases, a hybrid approach using both databases for different aspects of the AI system may provide the optimal solution, leveraging the strengths of each database where they are most beneficial. As AI continues to evolve, database management systems will likely adapt further to meet the unique challenges posed by AI applications. Both PostgreSQL and MongoDB are actively developing features to better support AI workloads, and staying informed about these advancements will be crucial for making the best database choices in future AI projects.

References

1. Özsu, M. T., & Valduriez, P. (1999). Principles of distributed database systems (Vol. 2). Englewood Cliffs: Prentice Hall.
2. Xu, Y., Cai, Y., & Song, L. (2023). Latent fault detection and diagnosis for control rods drive mechanisms in nuclear power reactor based on GRU-AE. IEEE Sensors Journal, 23(6), 6018-6026.
3. Obe, R. O., & Hsu, L. S. (2017). PostgreSQL: up and running: a practical guide to the advanced open source database. " O'Reilly Media, Inc.".
4. Weng, Y., & Wu, J. (2024). Fortifying the Global Data Fortress: A Multidimensional Examination of Cyber Security Indexes and Data Protection Measures across 193 Nations. International Journal of Frontiers in Engineering Technology, 6(2), 13-28.
5. Sharma, V., & Dave, M. (2012). Sql and nosql databases. International Journal of Advanced Research in Computer Science and Software Engineering, 2(8).
6. Xu, Y., Cai, Y. Z., & Song, L. (2023). Anomaly Detection for In-core Neutron Detectors Based on a Virtual Redundancy Model. IEEE Transactions on Instrumentation and Measurement.
7. Bradshaw, S., Brazil, E., & Chodorow, K. (2019). MongoDB: the definitive guide: powerful and scalable data storage. O'Reilly Media.
8. Győrödi, C., Győrödi, R., Pecherle, G., & Olah, A. (2015, June). A comparative study: MongoDB vs. MySQL. In 2015 13th international conference on engineering of modern electric systems (EMES) (pp. 1-6). IEEE.
9. Nayak, A., Poriya, A., & Poojary, D. (2013). Type of NOSQL databases and its comparison with relational databases. International Journal of Applied Information Systems, 5(4), 16-19.
10. Liu, S., Yan, K., Qin, F., Wang, C., Ge, R., Zhang, K., ... & Cao, J. (2024). Infrared Image Super-Resolution via Lightweight Information Split Network. arXiv preprint arXiv:2405.10561.
11. Jiang, H., Qin, F., Cao, J., Peng, Y., & Shao, Y. (2021). Recurrent neural network from adder's perspective: Carry-lookahead RNN. Neural Networks, 144, 297-306.
12. Li, Z., Wang, B., & Chen, Y. (2024). Knowledge Graph Embedding and Few-Shot Relational Learning Methods for Digital Assets in USA. Journal of Industrial Engineering and Applied Science, 2(5), 10-18.
13. Xue, J., Jiang, N., Liang, S., Pang, Q., Yabe, T., Ukkusuri, S. V., & Ma, J. (2022). Quantifying the spatial homogeneity of urban road networks via graph neural networks. *Nature Machine Intelligence*, *4*(3), 246-257.
14. Wang, B., Chen, Y., & Li, Z. (2024). A novel Bayesian Pay-As-You-Drive insurance model with risk prediction and causal mapping. Decision Analytics Journal, 13, 100522.
15. Li, Z., Wang, B., & Chen, Y. (2024). Incorporating economic indicators and market sentiment effect into US Treasury bond yield prediction with machine learning. Journal of Infrastructure, Policy and Development, 8(9), 7671.
16. Zhu, W., & Hu, T. (2021, July). Twitter Sentiment analysis of covid vaccines. In 2021 5th International Conference on Artificial Intelligence and Virtual Reality (AIVR) (pp. 118-122).
17. Zhao, Y., & Gao, H. (2024). Utilizing large language models for information extraction from real estate transactions. arXiv preprint arXiv:2404.18043.
18. Chen, Y., Zhao, J., Wen, Z., Li, Z., & Xiao, Y. (2024, March). TemporalMed: Advancing Medical Dialogues with Time-Aware Responses in Large Language Models. In Proceedings of the 17th ACM International Conference on Web Search and Data Mining (pp. 116-124).
19. Deng, T., Shen, G., Qin, T., Wang, J., Zhao, W., Wang, J., ... & Chen, W. (2024). Plgslam: Progressive neural scene represenation with local to global bundle adjustment. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 19657-19666).
20. Qiao, G., Liu, G., Poupart, P., & Xu, Z. (2024). Multi-modal inverse constrained reinforcement learning from a mixture of demonstrations. Advances in Neural Information Processing Systems, 36.

21. Wang, R., Chen, X., Khalilian-Gourtani, A., Chen, Z., Yu, L., Flinker, A., & Wang, Y. (2020, April). Stimulus speech decoding from human cortex with generative adversarial network transfer learning. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 390-394). IEEE.
22. Weng, Y., Wu, J., Kelly, T., & Johnson, W. (2024). Comprehensive Overview of Artificial Intelligence Applications in Modern Industries. arXiv preprint arXiv:2409.13059.
23. Liang, X., & Chen, H. (2019, August). HDSO: A High-Performance Dynamic Service Orchestration Algorithm in Hybrid NFV Networks. In 2019 IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS) (pp. 782-787). IEEE.
24. Luo, D. (2024). Quantitative Risk Measurement in Power System Risk Management Methods and Applications.
25. Liang, X., & Chen, H. (2024, July). One cloud subscription-based software license management and protection mechanism. In Proceedings of the 2024 International Conference on Image Processing, Intelligent Control and Computer Engineering (pp. 199-203).
26. Hu, Z., Lei, F., Fan, Y., Ke, Z., Shi, G., & Li, Z. (2024). Research on Financial Multi-Asset Portfolio Risk Prediction Model Based on Convolutional Neural Networks and Image Processing. Applied Science and Engineering Journal for Advanced Research, 3(6), 39-50.
27. Liang, X., & Chen, H. (2019, July). A SDN-Based Hierarchical Authentication Mechanism for IPv6 Address. In 2019 IEEE International Conference on Intelligence and Security Informatics (ISI) (pp. 225-225). IEEE.
28. Lin, Z., Wei, D., Jang, W. D., Zhou, S., Chen, X., Wang, X., ... & Pfister, H. (2020). Two stream active query suggestion for active learning in connectomics. In Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XVIII 16 (pp. 103-120). Springer International Publishing.
29. Chen, X., Wang, R., Khalilian-Gourtani, A., Yu, L., Dugan, P., Friedman, D., ... & Flinker, A. (2024). A neural speech decoding framework leveraging deep learning and speech synthesis. Nature Machine Intelligence, 1-14.
30. Qiao, G., Jiang, H., & Min, Y. (2022, May). Research on Vehicle Distance Recognition System Based on Machine Learning and OpenCV. In 2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI) (pp. 334-337). IEEE.
31. Yang, D., Li, M. M., Fu, H., Fan, J., & Leung, H. (2020). Centrality graph convolutional networks for skeleton-based action recognition. arXiv preprint arXiv:2003.03007, 2.
32. Li, M., Belzile, B., Imran, A., Birglen, L., Beltrame, G., & St-Onge, D. (2023, August). From assistive devices to manufacturing cobot swarms. In 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN) (pp. 234-240). IEEE.
33. Zhang, W., Ao, Q., Guan, Y., Zhu, Z., Kuang, D., Li, M. M., ... & Xiao, M. (2022). A novel diagnostic approach for the classification of small B-cell lymphoid neoplasms based on the NanoString platform. Modern Pathology, 35(5), 632-639.
34. Qiao, G., Quan, G., Qu, R., & Liu, G. (2025). Modelling Competitive Behaviors in Autonomous Driving Under Generative World Model. In European Conference on Computer Vision (pp. 19-36). Springer, Cham.
35. Deng, T., Wang, Y., Xie, H., Wang, H., Wang, J., Wang, D., & Chen, W. (2024). Neslam: Neural implicit mapping and self-supervised feature tracking with depth completion and denoising. arXiv preprint arXiv:2403.20034.
36. Xie, T., Wan, Y., Zhou, Y., Huang, W., Liu, Y., Linghu, Q., ... & Hoex, B. (2024). Creation of a structured solar cell material dataset and performance prediction using large language models. Patterns, 5(5).
37. Yu, C., Xie, X., Huang, Y., & Qiu, C. (2024, October). Harnessing llms for cross-city od flow prediction. In Proceedings of the 32nd ACM International Conference on Advances in Geographic Information Systems (pp. 384-395).

38. Weng, Y., & Wu, J. (2024). Leveraging Artificial Intelligence to Enhance Data Security and Combat Cyber Attacks. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, 5(1), 392-399.
39. Xu, W. J., Shang, W. Y., Feng, J. M., Song, X. Y., Li, L. Y., Xie, X. P., ... & Liang, B. M. (2024). Machine learning for accurate detection of small airway dysfunction-related respiratory changes: an observational study. Respiratory Research, 25(1), 286.
40. Yadav, S., Yu, C., Xie, X., Huang, Y., & Qiu, C. (2024, October). Protecting Vehicle Location Privacy with Contextually-Driven Synthetic Location Generation. In Proceedings of the 32nd ACM International Conference on Advances in Geographic Information Systems (pp. 29-41).
41. Qiu, C., Liu, R., Pappachan, P., Squicciarini, A., & Xie, X. (2024). Scalable Optimization for Locally Relevant Geo-Location Privacy. arXiv preprint arXiv:2407.13725.
42. Xie, T., Wan, Y., Lu, K., Zhang, W., Kit, C., & Hoex, B. (2023, December). Tokenizer Effect on Functional Material Prediction: Investigating Contextual Word Embeddings for Knowledge Discovery. In AI for Accelerated Materials Design-NeurIPS 2023 Workshop.
43. Wan, Y., Ajith, A., Liu, Y., Lu, K., Grazian, C., Hoex, B., ... & Foster, I. (2024). SciQAG: A Framework for Auto-Generated Scientific Question Answering Dataset with Fine-grained Evaluation. arXiv preprint arXiv:2405.09939.
44. Deng, T., Liu, S., Wang, X., Liu, Y., Wang, D., & Chen, W. (2023). Prosgnerf: Progressive dynamic neural scene graph with frequency modulated auto-encoder in urban scenes. arXiv preprint arXiv:2312.09076.
45. Yu, C., Jin, Y., Xing, Q., Zhang, Y., Guo, S., & Meng, S. (2024). Advanced User Credit Risk Prediction Model using LightGBM, XGBoost and Tabnet with SMOTEENN. arXiv preprint arXiv:2408.03497.
46. Deng, T., Xie, H., Wang, J., & Chen, W. (2023). Long-term visual simultaneous localization and mapping: Using a bayesian persistence filter-based global map prediction. IEEE Robotics & Automation Magazine, 30(1), 36-49.
47. Weng, Y., & Wu, J. (2024). Big data and machine learning in defence. International Journal of Computer Science and Information Technology, 16(2), 25-35.
48. Chen, Y., Xiao, Y., Li, Z., & Liu, B. (2023). XMQAs: Constructing Complex-Modified Question-Answering Dataset for Robust Question Understanding. IEEE Transactions on Knowledge and Data Engineering.
49. Tan, L., Liu, S., Gao, J., Liu, X., Chu, L., & Jiang, H. (2024). Enhanced self-checkout system for retail based on improved YOLOv10. arXiv preprint arXiv:2407.21308.
50. Liu, X., Yu, Z., Tan, L., Yan, Y., & Shi, G. (2024). Enhancing Skin Lesion Diagnosis with Ensemble Learning. arXiv preprint arXiv:2409.04381.
51. Hsieh, Y. T., Li, Z., & Pompili, D. (2024, April). A Lightweight Hybrid Analog-Digital Spiking Neural Network for IoT. In 2024 20th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT) (pp. 249-253). IEEE.
52. Wang, Y., Zhao, J., & Lawryshyn, Y. (2024). GPT-Signal: Generative AI for Semi-automated Feature Engineering in the Alpha Research Process. In Proceedings of the Eighth Financial Technology and Natural Language Processing and the 1st Agent AI for Scenario Planning (pp. 42-53).
53. Zhao, J., Ding, Y., Jia, C., Wang, Y., & Qian, Z. (2024). Gender Bias in Large Language Models across Multiple Languages. arXiv preprint arXiv:2403.00277.
54. Peng, H., Ran, R., Luo, Y., Zhao, J., Huang, S., Thorat, K., ... & Ding, C. (2024). Lingcn: Structural linearized graph convolutional network for homomorphically encrypted inference. Advances in Neural Information Processing Systems, 36.
55. Zhou, T., Zhao, J., Luo, Y., Xie, X., Wen, W., Ding, C., & Xu, X. (2024). Adapi: Facilitating dnn model adaptivity for efficient private inference in edge computing. arXiv preprint arXiv:2407.05633.
56. Jin, C., Che, T., Peng, H., Li, Y., & Pavone, M. (2024). Learning from teaching regularization: Generalizable correlations should be easy to imitate. arXiv preprint arXiv:2402.02769.

57. Fu, Z., Wang, K., Xin, W., Zhou, L., Chen, S., Ge, Y., ... & Zhang, D. (2024). Detecting Misinformation in Multimedia Content through Cross-Modal Entity Consistency: A Dual Learning Approach.
58. Xin, W., Wang, K., Fu, Z., & Zhou, L. (2024). Let Community Rules Be Reflected in Online Content Moderation. arXiv preprint arXiv:2408.12035.
59. Weng, Y., Cao, Y., Li, M., & Yang, X. (2024). The Application of Big Data and AI in Risk Control Models: Safeguarding User Security. International Journal of Frontiers in Engineering Technology, 6(3), 154-164.
60. Peng, H., Xie, X., Shivdikar, K., Hasan, M. A., Zhao, J., Huang, S., ... & Ding, C. (2024, April). Maxk-gnn: Extremely fast gpu kernel design for accelerating graph neural networks training. In Proceedings of the 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2 (pp. 683-698).
61. Zhao, J., Qian, Z., Cao, L., Wang, Y., & Ding, Y. (2024). Bias and toxicity in role-play reasoning. arXiv preprint arXiv:2409.13979.
62. Hsieh, Y. T., & Pompili, D. (2024, March). A Bio-inspired Low-power Hybrid Analog/Digital Spiking Neural Networks for Pervasive Smart Cameras. In 2024 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops) (pp. 678-683). IEEE.
63. Chen, J., Mao, C., Sha, G., Sheng, W., Fan, H., Wang, D., ... & Zhang, Y. (2024). Reinforcement learning based two-timescale energy management for energy hub. *IET Renewable Power Generation*, *18*(3), 476-488.
64. Hsieh, Y. T., Anjum, K., Huang, S., Kulkarni, I., & Pompili, D. (2021, October). Hybrid analog-digital sensing approach for low-power real-time anomaly detection in drones. In 2021 IEEE 18th international conference on mobile ad hoc and smart systems (MASS) (pp. 446-454). IEEE.
65. Liu, X., & Wang, Z. (2024). Deep learning in medical image classification from mri-based brain tumor images. arXiv preprint arXiv:2408.00636.
66. Liang, J., Li, S., Cao, B., Jiang, W., & He, C. (2021). Omnilytics: A blockchain-based secure data market for decentralized machine learning. arXiv preprint arXiv:2107.05252.
67. Tan, Z., Beigi, A., Wang, S., Guo, R., Bhattacharjee, A., Jiang, B., ... & Liu, H. (2024). Large language models for data annotation: A survey. arXiv preprint arXiv:2402.13446.
68. Song, Y., Arora, P., Varadharajan, S. T., Singh, R., Haynes, M., & Starner, T. (2024, April). Looking From a Different Angle: Placing Head-Worn Displays Near the Nose. In Proceedings of the Augmented Humans International Conference 2024 (pp. 28-45).
69. Kang, Y., Song, Y., & Huang, S. (2024). Tie Memories to E-Souvenirs: Personalized Souvenirs with Augmented Reality for Interactive Learning in the Museum. Preprints, doi:10.20944/preprints202410.1536.v1
70. Kang, Y., Zhang, Z., Zhao, M., Yang, X., & Yang, X. (2022, October). Tie Memories to E-souvenirs: Hybrid Tangible AR Souvenirs in the Museum. In Adjunct Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (pp. 1-3).
71. Tan, Z., Zhao, C., Moraffah, R., Li, Y., Kong, Y., Chen, T., & Liu, H. (2024). The Wolf Within: Covert Injection of Malice into MLLM Societies via an MLLM Operative. arXiv preprint arXiv:2402.14859.
72. Wang, Z., Yan, H., Wang, Y., Xu, Z., Wang, Z., & Wu, Z. (2024). Research on autonomous robots navigation based on reinforcement learning. arXiv preprint arXiv:2407.02539.
73. Dan, H. C., Lu, B., & Li, M. (2024). Evaluation of asphalt pavement texture using multiview stereo reconstruction based on deep learning. Construction and Building Materials, 412, 134837.
74. Gong, Y., Zhang, Q., Zheng, H., Liu, Z., & Chen, S. (2024, September). Graphical Structural Learning of rs-fMRI data in Heavy Smokers. In 2024 4th International Conference on Computer Science and Blockchain (CCSB) (pp. 434-438). IEEE.

75. Zhai, H., Gu, B., Zhu, K., & Huang, C. (2023). Feasibility analysis of achieving net-zero emissions in China's power sector before 2050 based on ideal available pathways. Environmental Impact Assessment Review, 98, 106948.
76. Tao, Y., Wang, Z., Zhang, H., & Wang, L. (2024). Nevlp: Noise-robust framework for efficient vision-language pre-training. arXiv preprint arXiv:2409.09582.
77. Fei, Y., He, Y., Chen, F., You, P., & Zhai, H. (2019). Optimal Planning and Design for Sightseeing Offshore Island Microgrids. In E3S Web of Conferences (Vol. 118, p. 02044). EDP Sciences.
78. Gu, B., Zhai, H., An, Y., Khanh, N. Q., & Ding, Z. (2023). Low-carbon transition of Southeast Asian power systems–A SWOT analysis. Sustainable Energy Technologies and Assessments, 58, 103361.
79. Liu, Z., Zhang, Q., Zheng, H., Chen, S., & Gong, Y. (2024). A Comparative Study of Machine Learning Approaches for Diabetes Risk Prediction: Insights from SHAP and Feature Importance.
80. Dan, H. C., Yan, P., Tan, J., Zhou, Y., & Lu, B. (2024). Multiple distresses detection for Asphalt Pavement using improved you Only Look Once Algorithm based on convolutional neural network. International Journal of Pavement Engineering, 25(1), 2308169.
81. Dang, B., Ma, D., Li, S., Qi, Z., & Zhu, E. (07 2024). Deep learning-based snore sound analysis for the detection of night-time breathing disorders. Applied and Computational Engineering, 76, 109–114. doi:10.54254/2755-2721/76/20240574
82. Xiang, J., & Guo, L. (2022). Comfort Improvement for Autonomous Vehicles Using Reinforcement Learning with In-Situ Human Feedback (No. 2022-01-0807). SAE Technical Paper.
83. Liu, D., Waleffe, R., Jiang, M., & Venkataraman, S. (2024). Graphsnapshot: Graph machine learning acceleration with fast storage and retrieval. arXiv preprint arXiv:2406.17918.
84. Gong, Y., Zhang, Y., Wang, F., & Lee, C. H. (2024). Deep Learning for Weather Forecasting: A CNN-LSTM Hybrid Model for Predicting Historical Temperature Data. arXiv preprint arXiv:2410.14963.
85. C. Yan, J. Wang, Y. Zou, Y. Weng, Y. Zhao, and Z. Li, "Enhancing credit card fraud detection through adaptive model optimization," ResearchGate, doi:10.13140/RG.2.2.12274.52166, May 2024.
86. Sui, M., Zhang, C., Zhou, L., Liao, S., & Wei, C. (2024). An ensemble approach to stock price prediction using deep learning and time series models.
87. Mo, K., Chu, L., Zhang, X., Su, X., Qian, Y., Ou, Y., & Pretorius, W. (2024). DRAL: Deep reinforcement adaptive learning for multi-UAVs navigation in unknown indoor environment. arXiv preprint arXiv:2409.03930.
88. Dong, Y., Yao, J., Wang, J., Liang, Y., Liao, S., & Xiao, M. (2024, August). Dynamic fraud detection: Integrating reinforcement learning into graph neural networks. In 2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS) (pp. 818-823). IEEE.
89. Liu, D., & Jiang, M. (2024). Distance Recomputator and Topology Reconstructor for Graph Neural Networks. arXiv preprint arXiv:2406.17281.
90. Fang, X., Si, S., Sun, G., Sheng, Q. Z., Wu, W., Wang, K., & Lv, H. (2022). Selecting workers wisely for crowdsourcing when copiers and domain experts co-exist. *Future Internet*, *14*(2), 37.
91. Liu, D., Jiang, M., & Pister, K. (2024). LLMEasyQuant--An Easy to Use Toolkit for LLM Quantization. arXiv preprint arXiv:2406.19657.
92. Ding, T., & Xiang, D. (2024). Irregularity Inspection using Neural Radiance Field. *arXiv preprint arXiv:2408.11251*.
93. Liu, D. (2024). Contemporary Model Compression on Large Language Models Inference. arXiv preprint arXiv:2409.01990.
94. Xiang, J., Chen, J., & Liu, Y. (2023). Hybrid Multiscale Search for Dynamic Planning of Multi-Agent Drone Traffic. Journal of Guidance, Control, and Dynamics, 46(10), 1963-1974.
95. Luo, D. (2024). Decentralized Energy Markets: Designing Incentive Mechanisms for Small-Scale Renewable Energy Producers.
96. Xiang, J., Xie, J., & Chen, J. (2023). Landing Trajectory Prediction for UAS Based on Generative Adversarial Network. In AIAA SCITECH 2023 Forum (p. 0127).

97. Dang, B., Zhao, W., Li, Y., Ma, D., Yu, Q., & Zhu, E. Y. (2024). Real-Time Pill Identification for the Visually Impaired Using Deep Learning. 2024 6th International Conference on Communications, Information System and Computer Engineering (CISCE), 552–555. doi:10.1109/CISCE62493.2024.10653353
98. Ma, D., Yang, Y., Tian, Q., Dang, B., Qi, Z., & Xiang, A. (08 2024). Comparative analysis of X-ray image classification of pneumonia based on deep learning algorithm algorithm. doi:10.13140/RG.2.2.35973.77285
99. Li, Y., Zhao, W., Dang, B., Yan, X., Gao, M., Wang, W., & Xiao, M. (2024). Research on Adverse Drug Reaction Prediction Model Combining Knowledge Graph Embedding and Deep Learning. 2024 4th International Conference on Machine Learning and Intelligent Systems Engineering (MLISE), 322–329. doi:10.1109/MLISE62164.2024.10674360
100. Dan, H. C., Huang, Z., Lu, B., & Li, M. (2024). Image-driven prediction system: Automatic extraction of aggregate gradation of pavement core samples integrating deep learning and interactive image processing framework. Construction and Building Materials, 453, 139056.
101. Wang, Z., Zhu, Y., Li, Z., Wang, Z., Qin, H., & Liu, X. (2024). Graph neural network recommendation system for football formation. Applied Science and Biotechnology Journal for Advanced Research, 3(3), 33-39.
102. Liu, X., & Wang, Z. (2024). Deep learning in medical image classification from mri-based brain tumor images. arXiv preprint arXiv:2408.00636.
103. Wang, Z., Tao, Y., & Ma, D. (2024). A multiscale gradient fusion method for edge detection in color images utilizing the cbm3d filter. arXiv preprint arXiv:2408.14013.
104. Tan, Z., Zhao, C., Moraffah, R., Li, Y., Wang, S., Li, J., ... & Liu, H. (2024). " Glue pizza and eat rocks"--Exploiting Vulnerabilities in Retrieval-Augmented Generative Models. arXiv preprint arXiv:2406.19417.
105. Fang, X., Si, S., Sun, G., Wu, W., Wang, K., & Lv, H. (2022, August). A Domain-Aware Crowdsourcing System with Copier Removal. In International Conference on Internet of Things, Communication and Intelligent Technology (pp. 761-773). Singapore: Springer Nature Singapore.
106. Tan, Z., Chen, T., Zhang, Z., & Liu, H. (2024, March). Sparsity-guided holistic explanation for llms with interpretable inference-time intervention. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 38, No. 19, pp. 21619-21627).
107. Zhou, Q., Guo, S., Pan, J., Liang, J., Guo, J., Xu, Z., & Zhou, J. (2024). Pass: Patch automatic skip scheme for efficient on-device video perception. IEEE Transactions on Pattern Analysis and Machine Intelligence.
108. Liang, J., Pang, R., Li, C., & Wang, T. (2024, July). Model extraction attacks revisited. In Proceedings of the 19th ACM Asia Conference on Computer and Communications Security (pp. 1231-1245).
109. Liu, X., Liang, J., Tang, L., You, C., Ye, M., & Xi, Z. (2024). Buckle Up: Robustifying LLMs at Every Customization Stage via Data Curation. arXiv preprint arXiv:2410.02220.
110. Luo, D. (2024). Enhancing Smart Grid Efficiency through Multi-Agent Systems: A Machine Learning Approach for Optimal Decision Making.
111. Liu, X., Yu, Z., & Tan, L. (2024). Deep Learning for Lung Disease Classification Using Transfer Learning and a Customized CNN Architecture with Attention. arXiv preprint arXiv:2408.13180.
112. Chen, Y., Yuan, Y., Liu, P., Liu, D., Guan, Q., Guo, M., ... & Xiao, Y. (2024, March). Talk Funny! A Large-Scale Humor Response Dataset with Chain-of-Humor Interpretation. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 38, No. 16, pp. 17826-17834).
113. Luo, D. (2024). Optimizing Load Scheduling in Power Grids Using Reinforcement Learning and Markov Decision Processes. *arXiv preprint arXiv:2410.17696*.
114. Chen, Y., Xiao, Y., & Liu, B. (2022, May). Grow-and-Clip: Informative-yet-Concise Evidence Distillation for Answer Explanation. In 2022 IEEE 38th International Conference on Data Engineering (ICDE) (pp. 741-754). IEEE.

115. Zhao, Y., & Liu, F. (2024). A survey of retrieval algorithms in ad and content recommendation systems. arXiv preprint arXiv:2407.01712.
116. Hu, T., Zhu, W., & Yan, Y. (2023, December). Artificial intelligence aspect of transportation analysis using large scale systems. In Proceedings of the 2023 6th Artificial Intelligence and Cloud Computing Conference (pp. 54-59).
117. Zhu, W. (2022, July). Optimizing distributed networking with big data scheduling and cloud computing. In International Conference on Cloud Computing, Internet of Things, and Computer Applications (CICA 2022) (Vol. 12303, pp. 23-28). SPIE.
118. Yan, Y. (2022). Influencing Factors of Housing Price in New York-analysis: Based on Excel Multi-regression Model.
119. Li, K., Wang, J., Wu, X., Peng, X., Chang, R., Deng, X., ... & Hong, B. (2024). Optimizing automated picking systems in warehouse robots using machine learning. arXiv preprint arXiv:2408.16633.
120. Li, X., Ma, Y., Huang, Y., Wang, X., Lin, Y., & Zhang, C. (2024). Integrated Optimization of Large Language Models: Synergizing Data Utilization and Compression Techniques.
121. He, L., Wang, X., Lin, Y., Li, X., Ma, Y., & Li, Z. (2024). BOANN: Bayesian-Optimized Attentive Neural Network for Classification.
122. Li, K., Chen, J., Yu, D., Dajun, T., Qiu, X., Jieting, L., ... & Ni, F. (2024). Deep reinforcement learning-based obstacle avoidance for robot movement in warehouse environments. arXiv preprint arXiv:2409.14972.
123. Li, Z., Wan, B., Mu, C., Zhao, R., Qiu, S., & Yan, C. (2024). AD-aligning: Emulating human-like generalization for cognitive domain adaptation in deep learning. arXiv preprint arXiv:2405.09582.
124. Li, K., Liu, L., Chen, J., Yu, D., Zhou, X., Li, M., ... & Li, Z. (2024). Research on reinforcement learning based warehouse robot navigation algorithm in complex warehouse layout. arXiv preprint arXiv:2411.06128.
125. Li, Y., Xiong, H., Wang, Q., Kong, L., Liu, H., Li, H., ... & Yin, D. (2023). Coltr: Semi-supervised learning to rank with co-training and over-parameterization for web search. IEEE Transactions on Knowledge and Data Engineering, 35(12), 12542-12555.
126. Wu, W. (2024). Alphanetv4: Alpha mining model. *arXiv preprint arXiv:2411.04409*.
127. Li, Y., Xiong, H., Kong, L., Wang, Q., Wang, S., Chen, G., & Yin, D. (2023, August). S2phere: Semi-supervised pre-training for web search over heterogeneous learning to rank data. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (pp. 4437-4448).
128. Hu, Z., Lei, F., Fan, Y., Ke, Z., Shi, G., & Li, Z. (2024). Research on Financial Multi-Asset Portfolio Risk Prediction Model Based on Convolutional Neural Networks and Image Processing. Applied Science and Engineering Journal for Advanced Research, 3(6), 39-50.
129. Li, Y., Xiong, H., Kong, L., Zhang, R., Xu, F., Chen, G., & Li, M. (2023). MHRR: MOOCs Recommender Service With Meta Hierarchical Reinforced Ranking. IEEE Transactions on Services Computing.
130. Xu, L., Liu, J., Zhao, H., Zheng, T., Jiang, T., & Liu, L. (2024). Autonomous navigation of unmanned vehicle through deep reinforcement learning. arXiv preprint arXiv:2407.18962.
131. Liu, H., Shen, Y., Zhou, C., Zou, Y., Gao, Z., & Wang, Q. (2024). TD3 Based Collision Free Motion Planning for Robot Navigation. arXiv preprint arXiv:2405.15460.
132. Li, Y., Xiong, H., Kong, L., Sun, Z., Chen, H., Wang, S., & Yin, D. (2023, December). MPGraf: a Modular and Pre-trained Graphformer for Learning to Rank at Web-scale. In 2023 IEEE International Conference on Data Mining (ICDM) (pp. 339-348). IEEE.
133. Li, Z., Wang, B., & Chen, Y. (2024). A contrastive deep learning approach to cryptocurrency portfolio with us treasuries. Journal of Computer Technology and Applied Mathematics, 1(3), 1-10.
134. Pang, Q., & Yang, H. (2024). A distributed block chebyshev-davidson algorithm for parallel spectral clustering. *Journal of Scientific Computing*, *98*(3), 69.