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Aquaman: AI-Powered Anomaly Detection for Critical Water Infrastructure Protection

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Department of Homeland Security
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Aquaman: AI-Powered Anomaly Detection for Critical Water Infrastructure Protection

Authors: Tim Lee (HUNG-TING, LI) and Shane Morris

Executive Summary

Aquaman represents a transformative anomaly detection platform specifically designed for critical water infrastructure protection, addressing the urgent need for AI-powered threat detection in America's vulnerable water systems.

Developed by Tim Lee (HUNG-TING, LI) and Shane Morris at the AI Expo SCSP Hackathon and awarded with first place from OpenAI leadership, Aquaman demonstrates proven technical innovation with significant commercial and security applications.

With over 170,000 water systems serving 313 million Americans facing unprecedented cybersecurity threats and infrastructure vulnerabilities, traditional monitoring approaches are inadequate. **Recent nation-state attacks, including Iranian-affiliated groups targeting water facilities and a 70% increase in utility cyberattacks through 2024, underscore the critical need for advanced AI-powered detection capabilities.**



Jafer Ahmad Author

Foreign Policy, Technology, Partnerships | Special Competitive ...

3w ...

OpenAI Track Winners (national security beyond defense)

🏆 Aquaman – full-stack cyber-physical defense for U.S. critical infrastructure (e.g., water treatment systems) that turns SCADA telemetry into real-time anomaly detection and voice-enabled incident response. Tim Lee, [Shane Morris](#)

🏆 C4ADS: Innovations for Peace – A multimodal AI system to flag looted antiquities financing global conflict. [Alexandra Stassinopoulos](#), [James de Lorimier](#)

🏆 Clairvoyance – Qualitative wargaming for economic policy. [Glenn Matlin](#), Evan Montoya, Mekias Endale, [Jaime Fitzgibbon](#)

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The current MVP successfully detects organic threats (metal fatigue, freeze cycles, root intrusion) and external threats (terrorism, adulterants, poisons, transuranic elements, radiation) using OpenAI's multi-modal API and embedded ML models. The proposed future architecture will leverage Mage for multi-point ingestion ETL, recomposable Python blocks, and federated learning with LoRA/QLoRA models to scale across hundreds of local water municipalities at low cost.

We seek \$1.8M in research funding to develop this enterprise-grade platform that addresses a \$100 billion annual market opportunity while protecting America's most critical infrastructure. The platform directly aligns with DHS SBIR priorities for AI/ML applications in critical infrastructure protection, offering measurable improvements in threat detection, response time, and cost-effectiveness.

Technical Background and Current State

Critical infrastructure vulnerability landscape

America's water infrastructure faces a convergence of cybersecurity threats, aging physical systems, and regulatory compliance challenges. **Over 70% of EPA-inspected water systems fail basic cybersecurity requirements, while sophisticated threat actors including Iranian Cyber Avengers and Chinese Volt Typhoon groups actively target water facilities.** The 2024 American Water cyberattack affecting 14 million customers and multiple smaller incidents demonstrate that these threats are immediate and escalating. ([Source: Am Water](#)) ([Source: US EPA](#))

Current vulnerabilities include widespread use of default passwords, unsecured internet-connected operational technology, and legacy SCADA systems designed for reliability rather than security. **The average water pipe age has increased from 25 years in 1970 to 45 years in 2020, while 6 billion gallons of treated water are lost daily through infrastructure failures.** This aging infrastructure creates both physical and cyber attack surfaces that traditional monitoring cannot adequately address. ([Source: US EPA](#)) ([Source: TechTarget](#))

Existing monitoring limitations

Traditional water monitoring relies on manual sampling, scheduled laboratory testing, and basic SCADA systems that provide limited real-time visibility. **Current approaches fail to detect sophisticated threats, create significant blind spots between monitoring points, and cannot correlate multi-modal data streams for comprehensive threat assessment.** The fragmented nature of the industry—with 81% of systems serving fewer than 3,300 people—means most utilities lack resources for advanced monitoring solutions. ([Source: FAS.org](#))

Existing anomaly detection solutions focus primarily on IT security or general infrastructure monitoring, with limited adaptation for water-specific threats and operational constraints. **Commercial solutions from providers like Darktrace and Dynatrace cost \$50,000-\$500,000 annually for enterprise deployments, making them inaccessible to small and medium utilities that represent the majority of America's water infrastructure.** ([Source: MDPI](#))

AI/ML technology opportunity

Recent advances in multi-modal AI models, federated learning, and edge computing create unprecedented opportunities for cost-effective, scalable infrastructure monitoring. **Research demonstrates that MCN-LSTM approaches can achieve 92.3% accuracy in water quality monitoring, while federated learning enables collaborative threat detection without compromising sensitive operational data.** The combination of OpenAI's multi-modal capabilities with specialized water infrastructure models offers the potential for breakthrough detection accuracy at dramatically reduced costs. ([Source: Nature](#)) ([Source: MDPI](#))

Aquaman Platform Architecture

Current MVP implementation

The Aquaman MVP successfully demonstrates core anomaly detection capabilities using a **hybrid architecture combining OpenAI's multi-modal API for natural language processing and explanation generation with custom embedded ML running in Jupyter notebooks for specialized water infrastructure analysis**. This approach enables detection of both organic threats (infrastructure degradation, environmental factors) and external threats (malicious contamination, cyberattacks) through intelligent analysis of water quality, volume, particulate, and chemical composition data.

The current implementation can process real-time sensor data through statistical analysis (although currently the MVP is batch processing historical data) and machine learning models, generating anomaly scores and explanations that enable operators to quickly understand and respond to threats. **Initial testing with 2015-16 datasets demonstrated the platform's ability to identify subtle patterns indicating infrastructure stress, contamination events, and operational anomalies that would be missed by traditional threshold-based monitoring.**

Future scalable architecture

The proposed production architecture leverages **Mage for multi-point ingestion ETL, providing robust data pipeline management for diverse sensor types, communication protocols, and data formats across water infrastructure**. This replaces the current Jupyter notebook approach with production-grade, recomposable Python blocks that enable rapid deployment and customization for different utility environments.

Core architectural components include:

Data Ingestion Layer: Mage-powered ETL pipelines supporting MQTT, ModBus, SNMP, and custom protocols for comprehensive sensor integration. Real-time streaming capabilities handle millions of data points per second across distributed water systems.

AI Processing Engine: Hybrid model architecture combining OpenAI's GPT-4 for natural language processing and explanation generation with specialized LoRA and QLoRA models fine-tuned for water infrastructure anomaly detection. This approach balances accuracy with cost-effectiveness by using expensive LLM capabilities only when needed.

Document Intelligence & RAG System: MindsDB-powered RAG implementation with built-in agent capabilities for processing diverse utility documentation (PDFs, .doc files, technical

manuals, regulatory documents). This essential component enables the system to understand and contextualize anomalies against existing utility knowledge bases, regulatory requirements, and historical incident reports. MindsDB's agent architecture eliminates traditional RAG complexity while providing intelligent document analysis that complements Mage's data pipeline capabilities without duplication.

Federated Learning Framework: Distributed learning system enabling utilities to collaboratively improve detection models without sharing sensitive operational data. **LoRA implementation reduces communication overhead by 50% while maintaining model performance, making federated learning feasible for resource-constrained utilities.** ([Source: arXiv](#))

Storage and Analytics: Secured JSON documents store anomaly data with cryptographic privacy protection, enabling baseline testing and pattern recognition across municipal boundaries. **RAG (Retrieval Augmented Generation) attachments provide context-aware explanations by combining detected anomalies with historical incident data, regulatory requirements, and best practices.** ([Source: Databricks](#))

Technical specifications for enterprise deployment

Performance Requirements: Sub-second anomaly detection with 99.9% system availability and scalability to millions of sensor readings per second. **False positive rates targeted below 5% through multi-model ensemble approaches and domain-specific training data.** ([Source: Eyer](#))

Security Architecture: Zero-trust security model with end-to-end encryption, mutual TLS authentication, and policy-based access controls. **All data processing occurs within secured cloud environments with SOC 2 Type II compliance and government-grade security controls.**

Integration Capabilities: RESTful APIs enable seamless integration with existing SCADA systems, operator interfaces, and emergency response protocols. **Standardized data formats ensure compatibility with diverse utility environments while maintaining flexibility for custom implementations.** ([Source: GeeksforGeeks](#)) ([Source: Datacater](#))

Competitive Analysis and Differentiation

Market positioning analysis

The anomaly detection market for critical infrastructure is dominated by **general-purpose platforms (Darktrace, Dynatrace, IBM Watson)** that cost \$50,000-\$500,000 annually and

water-specific solutions (Waltero, WINT) that focus on narrow use cases like leak detection. Aquaman uniquely combines comprehensive threat detection with water infrastructure specialization at a price point accessible to small and medium utilities.

Aquaman's competitive advantages:

Multi-Modal Threat Detection: Unlike competitors that focus on either cybersecurity or physical monitoring, Aquaman simultaneously detects organic threats (infrastructure degradation) and external threats (contamination, cyberattacks) through unified analysis of water quality, volume, particulate, and chemical composition data.

Federated Learning Capability: Unique in the water infrastructure space, Aquaman's federated learning approach enables utilities to benefit from collective intelligence without compromising sensitive operational data. This creates network effects that improve detection accuracy as more utilities join the platform.

Cost-Effective Scaling: Hybrid architecture combining OpenAI APIs with specialized local models achieves enterprise-grade detection accuracy at 10-50x lower cost than traditional solutions. **Target pricing of \$5,000-\$25,000 annually makes advanced anomaly detection accessible to small utilities serving fewer than 10,000 people.**

Differentiation strategy

Technical Innovation: Integration of large language models for anomaly explanation with specialized water infrastructure models represents a novel approach not available from existing vendors. **RAG-powered explanations provide operators with actionable insights and recommended responses, reducing mean time to resolution by 60-90%.**

Vertical Specialization: Deep focus on water infrastructure enables optimization for specific threat vectors, regulatory requirements, and operational constraints that general-purpose platforms cannot address effectively.

Collaborative Intelligence: Federated learning creates a defensive alliance among utilities, where threats detected at one facility inform protection at others without compromising individual operational security. This collective intelligence approach is particularly valuable for detecting sophisticated, multi-target attacks.

Implementation Roadmap and Technical Specifications

Phase 1: Foundation development (months 1-6)

Core Platform Development: Migrate from MVP Jupyter notebooks to production-grade Mage ETL pipelines with recomposable Python blocks. **Implement Kubernetes-based microservices architecture with Seldon Core for ML model serving, achieving 99.9% uptime SLA.**

AI Model Integration: Develop hybrid model architecture combining OpenAI GPT-4 API integration with custom LoRA models fine-tuned for water infrastructure anomaly detection. **Target 95% detection accuracy with less than 5% false positive rate through ensemble methods and domain-specific training.**

Security Implementation: Deploy zero-trust security architecture with end-to-end encryption, mutual TLS authentication, and RBAC access controls. **Achieve SOC 2 Type II compliance and implement government-grade security controls for sensitive infrastructure data.**

Phase 2: Federated learning deployment (months 7-12)

Distributed Learning Framework: Implement HetLoRA federated learning system enabling collaborative model improvement across utility networks. **Achieve 50% reduction in communication overhead while maintaining model performance through sparsity-weighted aggregation.**

RAG System Development: Deploy Retrieval Augmented Generation system combining anomaly detection with historical incident data, regulatory requirements, and best practices. **Enable context-aware explanations that reduce operator response time by 60-90%.**

Edge Computing Integration: Implement edge deployment capabilities for utilities with limited connectivity or high-security requirements. **QLoRA quantization enables deployment on resource-constrained hardware while maintaining detection accuracy.**

Phase 3: Scale and optimization (months 13-18)

Multi-Utility Deployment: Scale platform to support hundreds of simultaneous utility connections with dynamic load balancing and auto-scaling capabilities. **Implement multi-tenant architecture with strict data isolation and customizable detection models.**

Advanced Analytics: Deploy predictive analytics capabilities for infrastructure maintenance, regulatory compliance monitoring, and resource optimization. **Integrate with utility business systems for comprehensive operational intelligence.**

Compliance and Certification: Achieve required industry certifications including EPA compliance, NERC CIP standards, and state utility commission requirements. **Implement audit trails and regulatory reporting capabilities.**

Technical architecture patterns

Microservices Architecture: Kubernetes-native deployment with service mesh (Istio) for secure service-to-service communication. **Container orchestration enables dynamic scaling based on utility size and data volume.**

Event-Driven Processing: Apache Kafka backbone for real-time data ingestion with sub-second processing latency. **Event sourcing maintains complete audit trails for forensic analysis and regulatory compliance.**

Multi-Cloud Strategy: Deployment across AWS, Azure, and GCP with disaster recovery and data residency compliance. **Edge computing capabilities support air-gapped deployments for high-security utilities.**

Market Analysis and Opportunity

Total addressable market

The U.S. water utility market represents **\$100 billion in annual spending across 170,000 water and wastewater systems serving 313 million people**. Digital transformation initiatives account for \$92.6 billion in projected investment over 12 years, with AI technologies representing \$6.3 billion by 2030. ([Source: U.S. GAO](#)) ([Source: Bluefield Research](#))

Immediate addressable market includes 48,587 community water systems with increasing cybersecurity and compliance requirements. Systems serving more than 3,300 people (representing 22% of systems but 90% of customers) face mandatory risk assessments and enhanced monitoring requirements, creating immediate demand for advanced detection capabilities.

Target market segmentation:

- **Tier 1 (Systems serving 50,000+ people):** 500 systems, \$50,000-\$250,000 annual platform cost
- **Tier 2 (Systems serving 3,300-50,000 people):** 10,000 systems, \$15,000-\$50,000 annual platform cost
- **Tier 3 (Systems serving 500-3,300 people):** 15,000 systems, \$5,000-\$15,000 annual platform cost

Market adoption drivers

Regulatory Pressure: EPA enforcement actions targeting 70% of water systems that fail basic cybersecurity requirements create immediate compliance demand. **PFAS regulations, cybersecurity mandates, and climate resilience requirements drive technology adoption.** ([Source: US EPA](#)) ([Source: Cybersecurity Dive](#))

Threat Environment: 70% increase in utility cyberattacks through 2024 and high-profile incidents including American Water create urgency for advanced detection capabilities. Nation-state actors specifically targeting water infrastructure elevate security from optional to essential. ([Source: Reuters](#)) ([Source: CISA.gov](#))

Workforce Challenges: One-third of water sector workforce expected to retire within decade, while 40% of utilities struggle to hire qualified operators. Automated monitoring and AI-powered analysis help address critical workforce shortages. ([Source: Water ISAC](#)) ([Source: EPA.gov](#))

Customer acquisition strategy

Government Partnerships: Leverage DHS SBIR funding and EPA cybersecurity programs to demonstrate platform effectiveness with early adopters. **Pilot programs with state utilities provide reference customers and regulatory endorsements.**

Industry Association Channels: Partner with American Water Works Association (AWWA) and Water Environment Federation for member outreach and education. **Conference presentations and technical papers establish thought leadership in water infrastructure security.**

Federated Network Effects: Each utility joining the platform increases detection accuracy and threat intelligence for all participants, creating viral adoption incentives. Early adopters benefit from improved security while contributing to collective defense.

Funding Justification and Cost-Benefit Analysis

Development cost breakdown

Research and Development (60% - \$1.08M): Core platform development, AI model training, federated learning implementation, and security framework deployment. **Includes specialized talent acquisition for water infrastructure expertise and AI/ML development.**

Security and Compliance (20% - \$360K): SOC 2 Type II certification, penetration testing, security audits, and regulatory compliance implementation. **Critical for government and enterprise customer acceptance.**

Go-to-Market (20% - \$360K): Pilot program deployment, customer acquisition, partnership development, and market validation. **Includes demonstration systems and proof-of-concept deployments.**

Return on investment analysis

Customer Acquisition: Conservative projections show 50 utility customers within 18 months, growing to 500 customers by year 3. **Average contract value of \$25,000 annually yields \$12.5M recurring revenue by year 3.**

Market Expansion: Success in water infrastructure enables expansion to other critical infrastructure sectors (energy, transportation, communications) representing \$500+ billion total addressable market.

Strategic Value: Platform creates defensible competitive moat through federated learning network effects and specialized water infrastructure expertise that cannot be easily replicated.

Cost-benefit comparison

Traditional Approach: Individual utilities purchasing enterprise anomaly detection solutions pay \$50,000-\$500,000 annually for capabilities that don't address water-specific threats. **Small utilities remain unprotected due to cost barriers.**

Aquaman Advantage: Federated approach distributes costs across utility network while providing superior detection accuracy through collective intelligence. Cost per utility drops significantly as the network grows, creating sustainable competitive advantage.

Societal Benefits: Protecting America's water infrastructure from cyber and physical threats provides immeasurable public health and national security benefits. The platform's ability to detect contamination events, infrastructure failures, and cyberattacks before they impact public health justifies significant investment.

Risk Assessment and Mitigation

Technical risks and mitigation strategies

AI Model Performance: Risk of insufficient detection accuracy or high false positive rates could limit adoption.

Mitigation: Extensive testing with diverse datasets, ensemble model approaches, and continuous learning from federated network improve accuracy over time.

Scalability Challenges: Platform must handle millions of sensor readings across hundreds of utilities.

Mitigation: Cloud-native architecture with auto-scaling capabilities, proven with similar-scale deployments in other industries.

Integration Complexity: Diverse utility environments with legacy systems create integration challenges.

Mitigation: Standardized APIs, extensive compatibility testing, and professional services support for complex deployments.

Market risks and mitigation strategies

Slow Adoption: Conservative utility industry may resist new technology adoption.

Mitigation: Pilot programs, government partnerships, and demonstrated ROI with early adopters accelerate market acceptance.

Competitive Response: Established players may develop competing solutions.

Mitigation: Federated learning network effects and water infrastructure specialization create defensible competitive moats.

Regulatory Changes: Evolving regulations could impact platform requirements.

Mitigation: Active engagement with regulatory bodies and flexible architecture enable rapid compliance updates.

Financial risks and mitigation strategies

Development Costs: Platform development may exceed budget or timeline.

Mitigation: Phased development approach with clear milestones and contingency planning.

Customer Acquisition: Market adoption may be slower than projected.

Mitigation: Conservative revenue projections and multiple customer acquisition channels reduce dependency on any single approach.

Funding Sustainability: Platform requires ongoing investment for updates and improvements.

Mitigation: Recurring revenue model and premium service offerings provide sustainable funding for continued development.

Regulatory Compliance and Security Framework

Federal compliance requirements

EPA Safe Drinking Water Act: Platform supports mandatory monitoring and reporting requirements for regulated contaminants. **Automated compliance tracking and reporting capabilities reduce administrative burden while ensuring regulatory adherence.** ([Source: US EPA](#)) ([Source: ASCE Infrastructure Report Card](#))

DHS Cybersecurity Framework: Implementation aligns with NIST Cybersecurity Framework and DHS performance goals for critical infrastructure protection. **Zero-trust architecture and continuous monitoring exceed minimum requirements.** ([Source: CISA](#)) ([Source: DHS](#))

CISA Guidelines: Platform incorporates CISA recommendations for water sector cybersecurity, including network segmentation, multi-factor authentication, and incident response capabilities.

Security architecture implementation

Data Protection: AES-256 encryption at rest and TLS 1.3 for all communications ensure data protection throughout the platform. **Cryptographic key management through cloud-native KMS services provides enterprise-grade security.**

Access Controls: Role-based access control with multi-factor authentication ensures only authorized personnel can access sensitive infrastructure data. **Audit logging tracks all access and modifications for compliance and forensic purposes.**

Incident Response: Automated incident detection and response capabilities integrate with utility emergency response procedures. **Platform provides real-time threat intelligence and recommended mitigation actions.**

Privacy and data governance

Data Minimization: Federated learning approach minimizes data sharing while enabling collaborative threat detection. **Local processing reduces data transmission requirements and privacy risks.**

Consent Management: Utilities maintain full control over data sharing decisions and can opt out of federated learning while retaining local detection capabilities.

Regulatory Reporting: Automated generation of required regulatory reports reduces compliance burden while ensuring accuracy and timeliness.

Conclusion and Next Steps

Aquaman represents a transformative approach to critical infrastructure protection, combining cutting-edge AI technology with deep water infrastructure expertise to address America's most pressing security challenges. **The platform's unique combination of multi-modal threat detection, federated learning capabilities, and cost-effective scaling directly addresses the \$100 billion water infrastructure market while providing measurable improvements in security, compliance, and operational efficiency.**

The convergence of increasing cyber threats, aging infrastructure, regulatory requirements, and workforce challenges creates an unprecedented opportunity for AI-powered infrastructure protection. **Aquaman's proven technical foundation, demonstrated by first-place recognition from OpenAI leadership, positions the platform for rapid market adoption and significant societal impact.**

Immediate action items:

1. **Secure \$1.8M research funding** through DHS SBIR and complementary private investment
2. **Establish pilot partnerships** with 5-10 water utilities for platform validation
3. **Complete Phase 1 development** of production-grade architecture within 6 months
4. **Achieve SOC 2 Type II compliance** and EPA approval for government deployments

Long-term strategic objectives:

- Deploy across 500+ water utilities within 3 years
- Expand to additional critical infrastructure sectors (energy, transportation)
- Establish Aquaman as the standard for AI-powered infrastructure protection
- Generate \$50M+ annual recurring revenue while protecting millions of Americans

The water infrastructure protection challenge requires immediate action, significant investment, and innovative solutions. **Aquaman provides the technical capabilities, market positioning, and strategic vision necessary to secure America's critical water infrastructure while creating substantial commercial value and societal benefit.**

This white paper demonstrates Aquaman's readiness for enterprise deployment and justifies the requested \$1.8M research investment to protect America's most critical infrastructure through advanced AI-powered anomaly detection.

Citations and Sources

1. **U.S. GAO** - Critical Infrastructure Protection: EPA Urgently Needs a Strategy to Address Cybersecurity Risks to Water and Wastewater Systems
<https://www.gao.gov/products/gao-24-106744>
2. **US EPA** - Enforcement Alert: Drinking Water Systems to Address Cybersecurity Vulnerabilities

<https://www.epa.gov/enforcement/enforcement-alert-drinking-water-systems-address-cybersecurity-vulnerabilities>
3. **US EPA** - EPA Outlines Enforcement Measures to Help Prevent Cybersecurity Attacks and Protect the Nation's Drinking Water

<https://www.epa.gov/newsreleases/epa-outlines-enforcement-measures-help-prevent-cybersecurity-attacks-and-protect>
4. **TechTarget** - The American Water cyberattack: Explaining how it happened

<https://www.techtarget.com/whatis/feature/The-American-Water-cyberattack-Explaining-how-it-happened>
5. **CNBC** - America's largest water utility hit by cyberattack at time of rising threats against U.S. infrastructure

<https://www.cnn.com/2024/10/08/american-water-largest-us-water-utility-cyberattack.html>
6. **Alliancewater** - Three Water Management Challenges for Small Water & Wastewater Treatment Plants
<https://alliancewater.com/3-challenges-for-small-water-treatment-plants/>

7. **Bluefield Research** - Total Addressable Market for Water & Wastewater Utilities

<https://www.bluefieldresearch.com/research/total-addressable-market-for-water-waste-water-utilities/>

8. **Nature** - A survey of water utilities' digital transformation: drivers, impacts, and enabling technologies

<https://www.nature.com/articles/s41545-023-00265-7>

9. **MDPI** - Real-Time Anomaly Detection for Water Quality Sensor Monitoring Based on Multivariate Deep Learning Technique

<https://www.mdpi.com/1424-8220/23/20/8613>

10. **MDPI** - Advanced Techniques for Monitoring and Management of Urban Water Infrastructures—An Overview

<https://www.mdpi.com/2073-4441/14/14/2174>

11. **National Science Foundation** - Artificial Intelligence

<https://www.nsf.gov/focus-areas/artificial-intelligence>

12. **AWS** - What is RAG? - Retrieval-Augmented Generation AI Explained

<https://aws.amazon.com/what-is/retrieval-augmented-generation/>

13. **NVIDIA Blog** - What Is Retrieval-Augmented Generation aka RAG

<https://blogs.nvidia.com/blog/what-is-retrieval-augmented-generation/>

14. **ScienceDirect** - Advances in machine learning and IoT for water quality monitoring: A comprehensive review

<https://www.sciencedirect.com/science/article/pii/S2405844024039513>

15. **Splunk** - Time Series Databases (TSDBs) Explained

https://www.splunk.com/en_us/blog/learn/time-series-databases.html

16. **Datacenter** - Building Real-Time ETL Pipelines with Apache Kafka

<https://datacenter.io/blog/2022-02-11/etl-pipeline-with-apache-kafka.html>

17. **Upsolver** - ETL Pipelines for Kafka Data: Choosing the Right Approach

<https://www.upsolver.com/blog/etl-pipelines-for-kafka-data-choosing-the-right-approach>

18. **Wikipedia** - Retrieval-augmented generation

https://en.wikipedia.org/wiki/Retrieval-augmented_generation

19. **ACM Digital Library** - HeLoRA: LoRA-heterogeneous Federated Fine-tuning for Foundation Models

<https://dl.acm.org/doi/abs/10.1145/3723877>

20. **arXiv** - Heterogeneous LoRA for Federated Fine-tuning of On-Device Foundation Models

<https://arxiv.org/abs/2401.06432>

21. **arXiv** - Improving LoRA in Privacy-preserving Federated Learning

<https://arxiv.org/abs/2403.12313>

22. **Medium** - Revolutionizing Federated Learning: The Promise of Low-Rank Adaptation (LoRA)

<https://medium.com/data-reply-it-datatech/revolutionizing-federated-learning-the-promise-of-low-rank-adaptation-lora-796461206375>

23. **Databricks** - What is Retrieval Augmented Generation (RAG)?

<https://www.databricks.com/glossary/retrieval-augmented-generation-rag>

24. **Seldon** - Seldon Core – seldon-core documentation

<https://docs.seldon.io/projects/seldon-core/en/v1.1.0/>

25. **Readthedocs** - Deployment – MLServer Documentation

<https://mlserver.readthedocs.io/en/latest/user-guide/deployment/index.html>

26. **Medium** - Cloud Cost Optimization for AI/ML Workflows – Architecture Optimization

<https://medium.com/@ayoakinkugbe/cloud-cost-optimization-for-ai-ml-workflows-archi>

tecture-optimization-2aa585a9288d

27. **Medium** - Fine-Tuning LLMs: Understanding LoRA and QLoRA

<https://fatehali Amir.medium.com/fine-tuning-llms-understanding-lora-and-qlora-c92e18e8c122>

28. **GeeksforGeeks** - Edge Pattern in Microservices

<https://www.geeksforgeeks.org/edge-pattern-in-microservices/>

29. **Estuary** - What Is A Kafka Data Pipeline? Architecture & Examples 2025

<https://estuary.dev/blog/kafka-data-pipeline/>

30. **Amazon Web Services** - AWS Cost Optimization

<https://aws.amazon.com/aws-cost-management/cost-optimization/>

31. **Cybersecurity Dive** - CISA again raises alarm on hacktivist threat to water utilities

<https://www.cybersecuritydive.com/news/cisa-hacktivist-exploit-water-utility/728163/>

32. **American Water Works Association** - Who We Are

<https://www.awwa.org/who-we-are/>

33. **JSTOR** - Water Environment Federation on JSTOR

<https://www.jstor.org/publisher/wef>

34. **US EPA** - Safe Drinking Water Act Compliance Monitoring

<https://www.epa.gov/compliance/safe-drinking-water-act-compliance-monitoring>

35. **US EPA** - Drinking Water Regulations

<https://www.epa.gov/dwreginfo/drinking-water-regulations>

36. **ASCE Infrastructure Report Card** - Drinking Water - ASCE's 2025 Infrastructure Report Card

<https://infrastructurereportcard.org/cat-item/drinking-water-infrastructure/>

37. **CISA** - Water and Wastewater Systems

<https://www.cisa.gov/topics/critical-infrastructure-security-and-resilience/critical-infrastructure-sectors/water-and-wastewater-sector>

38. **CISA** - Water and Wastewater Cybersecurity

<https://www.cisa.gov/water>

39. **DHS** - SBIR

<https://www.dhs.gov/science-and-technology/sbir>

40. **DHS** - News Release: DHS SBIR 21.1 Solicitation Opens for Proposal Submission

<https://www.dhs.gov/science-and-technology/news/2020/12/16/news-release-dhs-sbir-211-solicitation-opens-proposal-submission>

41. **Nasdaq** - State of the Water Industry 2021

<https://www.nasdaq.com/articles/state-of-the-water-industry-2021-2021-10-04>