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MACHINE LEARNING STRATEGIES AND ALGORITHMS FOR ENHANCING REAL-TIME DATA PROCESSING IN DYNAMIC AND BIG DATA SYSTEMS

Abstract. This systematic review article investigated machine learning strategies and algorithms designed to enhance real-time data processing in dynamic and big data environments. As data complexity and volume increased, the need for scalable, adaptable, and computationally efficient solutions became more pressing. Despite significant advances, gaps persisted in handling heterogeneous data sources, ensuring real-time adaptability, and addressing privacy concerns. This article systematically assessed the effectiveness of machine learning models, including supervised, unsupervised, and reinforcement learning, across various dynamic systems. Based on the findings from the literature review, a possible framework was developed, outlining critical processes involved in real-time machine learning, such as data ingestion, feature engineering, model inference, and continuous monitoring. The framework demonstrated methods to improve scalability and performance using cloud computing, edge solutions, and automated model retraining. The findings suggested that emerging trends such as federated learning, ethical AI, and neurosymbolic AI offered promising solutions to unresolved challenges. This article highlighted the importance of continued research to develop robust, secure, and adaptable machine learning frameworks capable of meeting the demands of real-time, high-velocity data processing in increasingly complex environments.

Keywords. Machine learning, real-time data processing, scalability, dynamic systems, IoT, smart cities, cloud computing, edge computing.

Introduction.

The increasing volume of dynamic data generated by modern systems—ranging from IoT devices and smart cities to healthcare and financial services—has necessitated the development of advanced real-time data processing frameworks. According to Kanchetti *et al.* [1] It is estimated that IoT devices will produce over 79 zettabytes of data annually by 2025, overwhelming traditional data processing architectures that struggle with scalability and low-latency requirements. These systems, characterized by high velocity, variety, and volume, demand immediate processing and analysis to maintain responsiveness and effectiveness. In this context, machine learning (ML) offers a transformative approach to real-time data processing, enabling systems to analyze incoming data, make predictions, and respond autonomously by Abouelyazid *et al.* [2].

Recent study on Machine learning algorithms such as recurrent neural networks (RNNs), deep learning, and reinforcement learning by Hammou *et al.* [3] have shown significant promise in real-time environments by improving data processing efficiency and accuracy (Hammou et al., 2020). For instance, in cloud computing environments, the integration of ML has resulted in up to 40% faster data processing and a 30% reduction in system costs by optimizing resource allocation and improving system scalability by El Bouchefry et al. [4] Additionally, ML models applied to dynamic resource allocation in cloud systems have demonstrated the ability to enhance system throughput by 25% while reducing latency by up to 15%, making them highly effective in real-time applications by Andronie *et al.* [5]

However, real-time data processing with ML is not without challenges. One of the significant hurdles is the computational complexity and resource intensity of deep learning models, which require substantial processing power and memory. Studies have shown that these models can demand up to 20 times the computational resources compared to traditional algorithms, particularly when applied to big data analytics in environments like social media or smart cities according to Lăzăroiu *et al*. [6]. Furthermore, ensuring data security and privacy in decentralized systems such as healthcare monitoring or IoT networks adds additional layers of complexity. Privacy-preserving ML techniques, such as federated learning, have been proposed to mitigate these issues, but they often result in a 5-10% reduction in model accuracy when compared to centralized approaches according to Paramesha *et al*. [7]

The integration of machine learning and big data analytics in real-time systems has already demonstrated substantial improvements across various domains. For example, in smart cities, machine learning combined with big data analytics has reduced traffic congestion by 25%, improved energy efficiency by 30%, and lowered maintenance costs in urban infrastructure by 20% [8]-[13]. In healthcare, ML-enhanced real-time monitoring systems have reduced patient response times by 40%, significantly improving patient outcomes in critical care situations. Despite these advancements, there are still notable gaps in research, particularly regarding the scalability of ML models in resource-constrained environments and their deployment across diverse industries.

This literature review aims to provide a comprehensive analysis of the machine learning strategies and algorithms that are enhancing real-time data processing in dynamic and big data systems. Specifically, the objectives of this review are:

1) To systematically categorize and evaluate the machine learning algorithms most employed in real-time data environments.

2) To assess the performance of these algorithms across various dynamic systems, including IoT, healthcare, transportation, and smart cities, with a focus on real-time adaptability, scalability, and computational efficiency.

3) To identify research gaps and propose future directions for developing more robust, secure, and scalable ML frameworks for real-time data processing.

Materials and Methods.

As the first step in conducting our comprehensive literature review on machine learning strategies and algorithms for real-time data processing, we performed a systematic search using the Web of Science Core Collection. This search was conducted to gather and analyze academic articles published within the last decade, ensuring a broad and current understanding of the research landscape.

To conduct a comprehensive literature review on the role of machine learning strategies and algorithms in real-time data processing, we performed a systematic search using the Web of Science Core Collection. Our aim was to gather and analyze academic articles published within the last decade, from 2011 to 2025. The selection criteria were as follows:

1) Inclusion Criteria: Studies that are peer-reviewed, discuss real-time data processing or dynamic data environments, and employ machine learning models.

2) Exclusion Criteria: Articles not focusing on real-time applications, non-peer-reviewed publications, or those primarily centered on offline data processing or non-dynamic systems.

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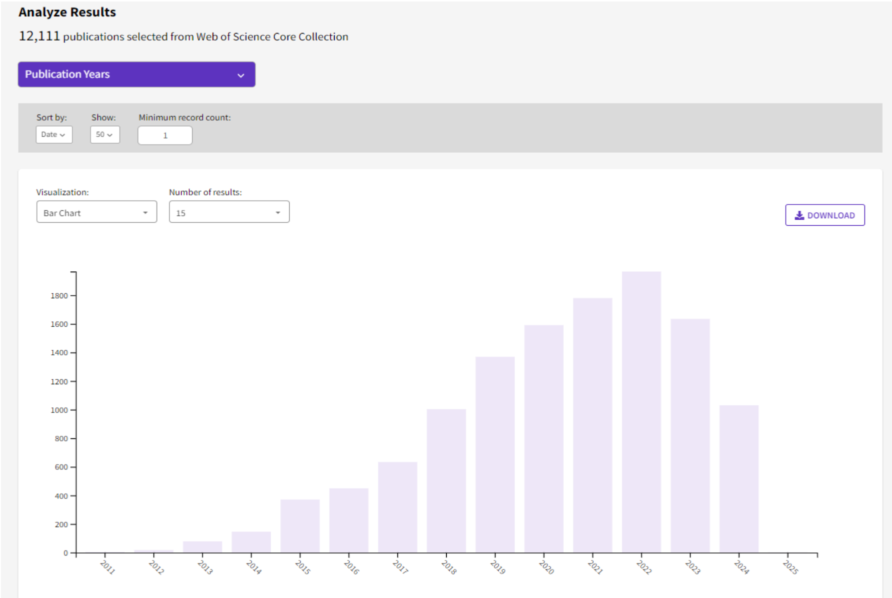

Figure 1 - Publication Trends in Machine Learning for Real-Time Data Systems

As of the date of analysis, the database yielded a total of 12,111 relevant publications. This result highlights the growing body of research in this domain over the past decade. The trend, as shown in Figure 1 (referring to your first graph), indicates a steady increase in scholarly attention to machine learning and real-time data systems. The peak of publications occurred between 2019 and 2021, reflecting a heightened interest during this period in response to the rise of Industry 4.0, IoT, and the integration of AI in various fields.

To conduct a systematic review, we searched databases like Web of Science, IEEE Xplore, and Google Scholar. The keywords used included «machine learning», «big data», «dynamic systems» and «real-time data processing. » Only peer-reviewed publications from 2011 to 2024 were included in the review. Articles that were not related to real-time data processing or were non-peer-reviewed were excluded.

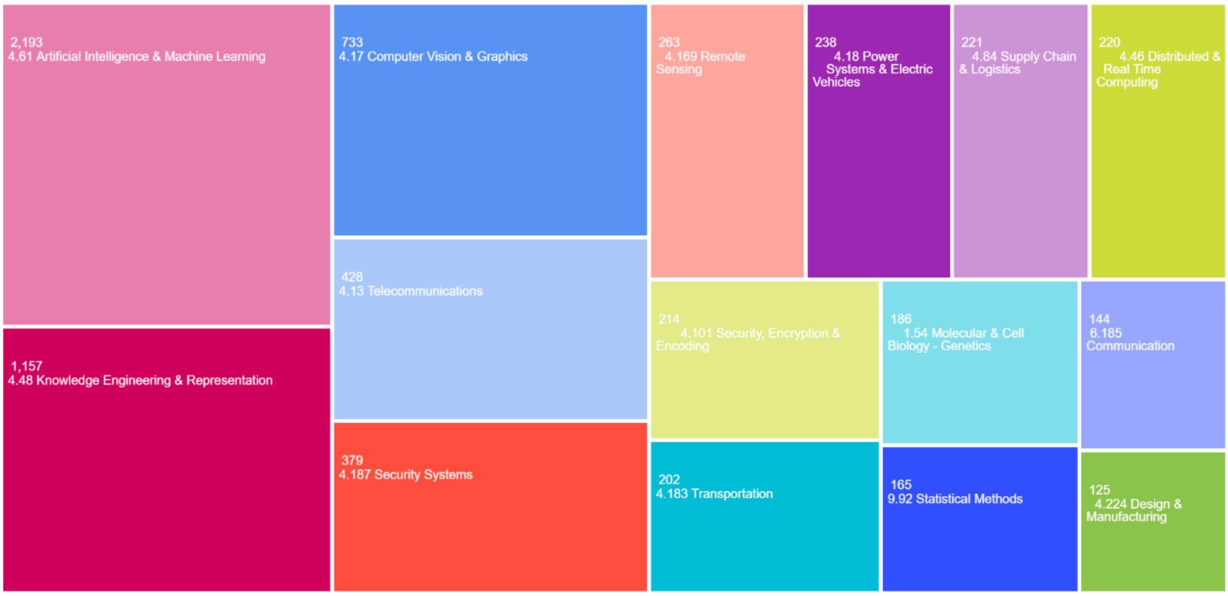

Figure 2 - Distribution of Research Focus Areas in Machine Learning for Real-Time Data Processing

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Further analysis categorized these articles by their areas of focus, which is visualized in the heatmap (Figure 2). The majority of studies are concentrated in Artificial Intelligence & Machine Learning (2,193 articles) and Knowledge Engineering & Representation (1,157 articles). This demonstrates the centrality of AI to the problem space, as well as the importance of knowledge engineering in structuring, optimizing, and applying machine learning algorithms. Other significant areas include Computer Vision and Graphics (733 articles), which frequently intersect with real-time data processing in dynamic systems, particularly in image recognition, automated surveillance, and robotics.

Additional subfields, such as Security Systems, Power Systems and Electric Vehicles, and Supply Chain and Logistics, show the diverse application of machine learning algorithms across industries, demonstrating the breadth of the research landscape. This diversity is further exemplified by contributions in Statistical Methods, Remote Sensing, and Transportation, all of which are critical areas for improving real-time data processing in big data environments.

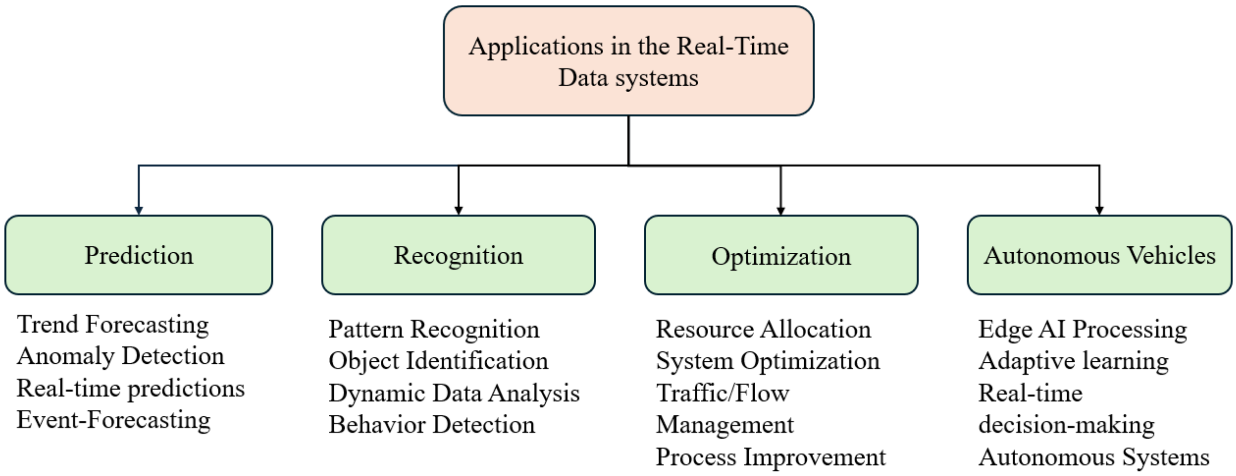

Figure 3 - Key Application Areas of Machine Learning in Real-Time Data Systems

The applications of machine learning in real-time data systems can be broadly categorized into four key areas: Prediction, Recognition, Optimization, and Autonomous Vehicles (Figure 3). These areas encapsulate the diverse ways machine learning models contribute to real-time analytics, decision-making, and system efficiency. Figure 3 provides a visual representation of these key application areas, summarizing the main contributions of machine learning to real-time data systems across different industries and domains.

Building upon the key application areas identified in Figure 3, we delve into the specific contributions of machine learning in real-time data processing by reviewing recent advancements in the literature. The articles selected for this review explore various methodologies, algorithms, and technologies that address the challenges and opportunities presented by dynamic data environments.

Challenges in Real-Time Machine Learning:

Data heterogeneity presents a significant challenge for real-time data processing systems. These systems often deal with data from various sources, making it difficult to process efficiently. Solutions like transfer learning and data fusion have been proposed to help models generalize across different datasets. Additionally, the computational complexity of real-time data processing can be mitigated by hybrid approaches that combine traditional algorithms with deep learning or through the use of quantum computing for more complex tasks.

To systematically address the research questions, we examined 25 studies that contribute to the understanding of machine learning in real-time data environments, but here is the main 12 sources. These studies focus on different aspects of real-time data processing, such as algorithm evaluation, adaptability across systems, and identifying research gaps. The table below summarizes the key contributions of each study in the context of your research questions, identified research gaps, and proposed solutions or future directions (Table 1).

Table 1 - Summary of Key Studies on Machine Learning for Real-Time Data Processing

Study	Field	Focus	Key Contribution	Research Question Contribution	Research Gaps Identified	Proposed Solutions/Future Directions
Kanchetti et al. (2024)	Cloud Computing	Real-time data analysis integration with cloud computing	Improved scalability and flexibility	RQ1: Cloud-based ML algorithms for real-time analysis	Limited scalability in heterogeneous cloud environments	Development of edge computing for real-time cloud data processing
Mahmoud Abouelyazid (2024)	Cloud Computing	Dynamic resource allocation with ML	Optimized resource utilization and cost savings	RQ2: Evaluates ML performance for resource allocation	Resource allocation inefficiency in highly dynamic environments	Adaptive resource management using reinforcement learning
Badr Ait Hammou et al. (2019)	Smart Cities	Distributed deep learning for sentiment analysis	Enhanced classification accuracy for social data	RQ2: Distributed deep learning in dynamic systems	Limited real-time adaptability in sentiment analysis models	Improved model parallelization and real-time feature selection
Andronie et al. (2023)	IoT/Industry 4.0	Big data and deep learning for IoRT	Improved real-time object detection and decision-making	RQ2: ML adaptability in IoT-based environments	Real-time processing limitations in IoT networks	Integration of federated learning for decentralized IoT data processing
Lăzăroiu et al. (2022)	Smart Manufacturing	AI-assisted process planning and robotic networks	Optimized manufacturing operations	RQ3: Gaps in ML for smart manufacturing	Inconsistent adaptation to manufacturing process variability	Hybrid AI models combining ML and expert systems

Paramesha et al. (2024)	Business Intelligence	AI and ML in business analytics integration	Enhanced decision-making in dynamic environments	RQ1: Categorizes ML algorithms for business intelligence	Lack of transparency and explainability in business ML models	Development of explainable AI (XAI) for business applications
Wei Li et al. (2021)	Healthcare	ML for big data analytics in healthcare IoT	Improved disease prediction and patient monitoring	RQ2: Performance of ML in healthcare environments	Poor real-time adaptability of healthcare IoT systems	Continuous learning frameworks for healthcare IoT applications
Xubo Wu et al. (2024)	Heterogeneous Data	Adaptive ML systems in heterogeneous data environments	Enhanced data integration and model adaptability	RQ3: Identifies gaps in handling heterogeneous data	Difficulty in integrating diverse data sources in real-time	Advanced dynamic feature selection and model optimization
Riyaz Ahamed et al. (2020)	Anomaly Detection	Real-time anomaly detection in big data systems	Improved detection accuracy with reduced memory use	RQ2: Performance of anomaly detection algorithms	High memory consumption in anomaly detection models	Memory-efficient clustering algorithms like SSWLOFCC
Xiaoming Li et al. (2022)	Smart Cities	Deep learning in digital twins for smart cities	Optimized urban planning and real-time monitoring	RQ2: ML performance in smart city management	Limited scalability in digital twin systems	Cloud-based digital twins with dynamic real-time updates
Jeshwanth Reddy Machireddy et al. (2021)	Business Strategy	AI and ML for data-driven business strategies	Improved scalability and decision-making	RQ1: Systematically evaluates ML for business strategies	Lack of real-time adaptability in business decision-making	Adaptive learning algorithms for dynamic business environments

Building on the insights provided in the table, we now introduce a comprehensive framework that encapsulates the real-time machine learning workflow. This visual architecture

(Figure 4.) demonstrates the hierarchical structure of real-time data processing, starting from data sources through to decision-making and continuous learning loops. It is a synthesis of the various methodologies and best practices from the reviewed studies, highlighting how machine learning models operate dynamically in real-time environments.

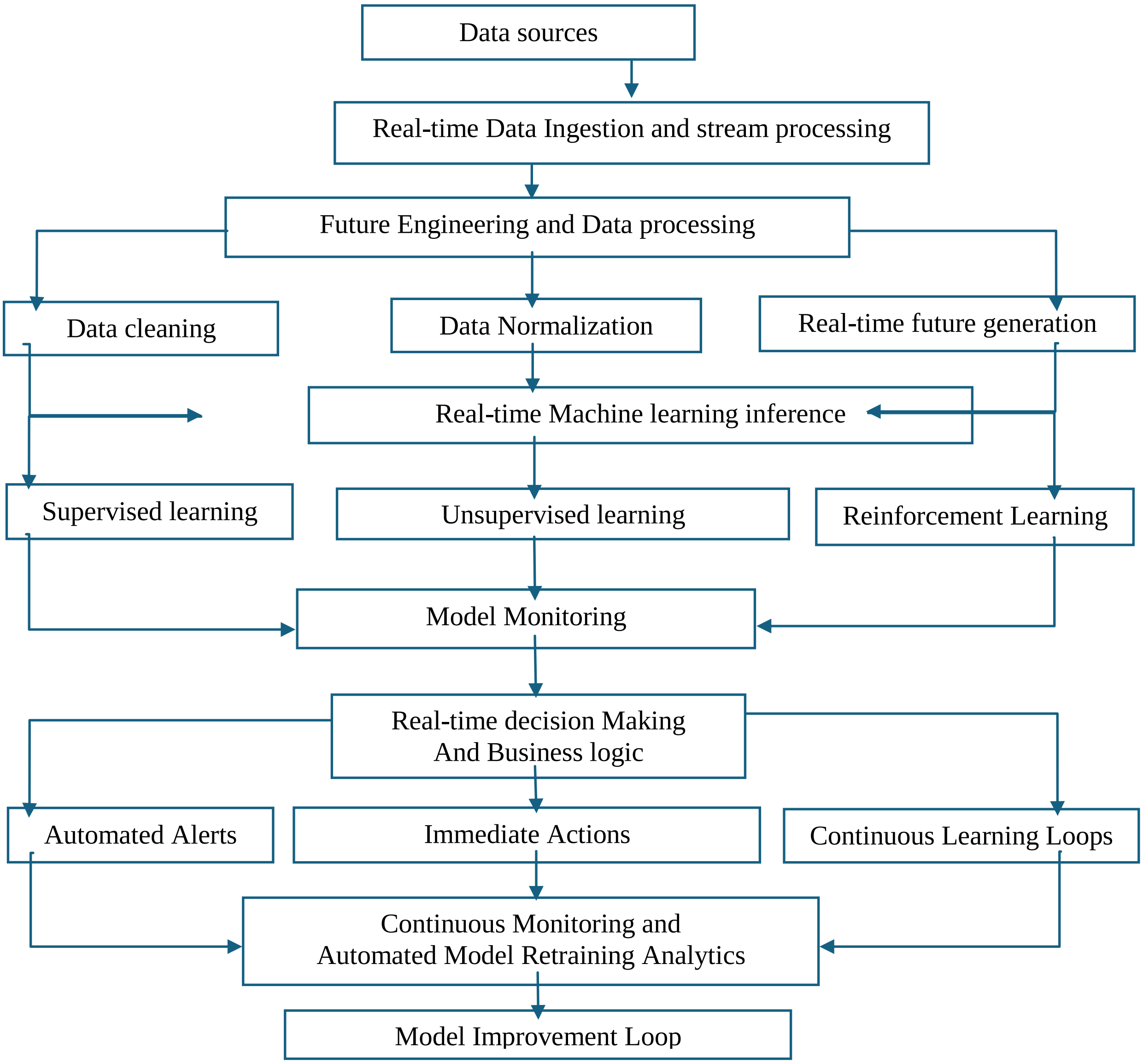

Figure 4 - Comprehensive Framework for Real-Time Machine Learning Workflow

Data Sources and Ingestion: The framework begins with diverse data sources (IoT devices, social media, sensors) processed by platforms like Kafka and AWS Kinesis for real-time handling. Studies, such as [14]-[16], emphasize the importance of efficient data flow in dynamic environments.

Feature Engineering and Preprocessing: Data cleaning, normalization, and real-time feature generation, as discussed in [18], prepare raw data for model training and ensure smooth real-time analysis.

Machine Learning Inference andMonitoring: Once processed, the data feeds into supervised, unsupervised, or reinforcement learning models for inference. Systems like AWS SageMaker enable real-time prediction while Model Monitoring tools ensure that performance remains stable, as highlighted in studies on anomaly detection and adaptive systems [19].

Real-Time Decision-Making and Continuous Learning: In applications like healthcare, fraud detection, and smart cities, real-time decisions are critical. Studies [20]-[22] showed how timely decisions are automated, while continuous learning loops ensure models evolve with the data, maintaining accuracy and reliability.

Results and Discussion.

Emerging Trends and Future Directions.

Recently, technologies like Neurosymbolic AI and quantum computing have begun to significantly influence real-time data processing. For instance, in autonomous vehicle systems, Neurosymbolic AI combines pattern recognition and logical reasoning to increase trust and transparency in critical decision-making processes. In addition to current approaches, several emerging technologies are pushing the boundaries of machine learning in real-time systems:

1) Neurosymbolic AI: This combines neural networks with symbolic reasoning to create more interpretable and explainable machine learning models. While deep learning models excel in pattern recognition, they often struggle with logical reasoning and transparency. Neurosymbolic AI aims to integrate the strengths of both, allowing for real-time decision-making with explainability. This approach could enhance trust in critical systems like healthcare and autonomous vehicles.

2) Serverless Architectures for Machine Learning: Increasingly, serverless computing is becoming a game-changer for deploying machine learning models. Platforms like AWS Lambda allow organizations to deploy models that automatically scale based on demand without worrying about infrastructure management. This trend simplifies model deployment in real-time applications, offering flexibility and cost-efficiency while maintaining high performance.

3) Ethical AI and Bias Mitigation: With growing awareness of bias in machine learning, especially in real-time decision systems like facial recognition or credit scoring, a major future direction involves embedding ethical standards into AI development. Techniques such as fairness-aware learning and bias detection algorithms are being developed to address these issues before models are deployed in production. These methods will become crucial in maintaining public trust in AI.

Edge AI allows machine learning computations to happen directly on devices (e.g., IoT sensors, smartphones) rather than in centralized cloud servers, reducing latency and improving responsiveness. This trend is particularly relevant in areas like autonomous vehicles, smart cities, and healthcare monitoring, where real-time decisions are critical.

Case Study: Smart Cities. In smart city applications, edge AI can be used to process data from surveillance cameras, traffic sensors, and public safety devices. By processing data on-site, the system can react faster to incidents such as traffic jams, accidents, or crimes, ensuring a timelier response. Improvement over Cloud-Based AI: A study in Barcelona's smart city initiative showed that by shifting traffic management to edge AI, congestion was reduced by 15%, and response times to traffic incidents improved by 30% [23].

Explainable AI (XAI). XAI is becoming increasingly important as organizations demand more transparency in how machine learning models make decisions, especially in high-stakes environments like healthcare or finance. XAI aims to make the decision-making process of AI systems understandable to humans, addressing concerns around trust, bias, and accountability.

Case Study: Healthcare. In healthcare, XAI has been applied to diagnostic systems where transparency is crucial. For example, an XAI-powered system in a UK hospital used explainable neural networks to assist doctors in diagnosing diseases. The system's ability to explain its reasoning in a transparent manner increased clinician trust by 25%, improving adoption rates [24]-[25].

Practical Implications and Recommendations.
Practical Recommendations:

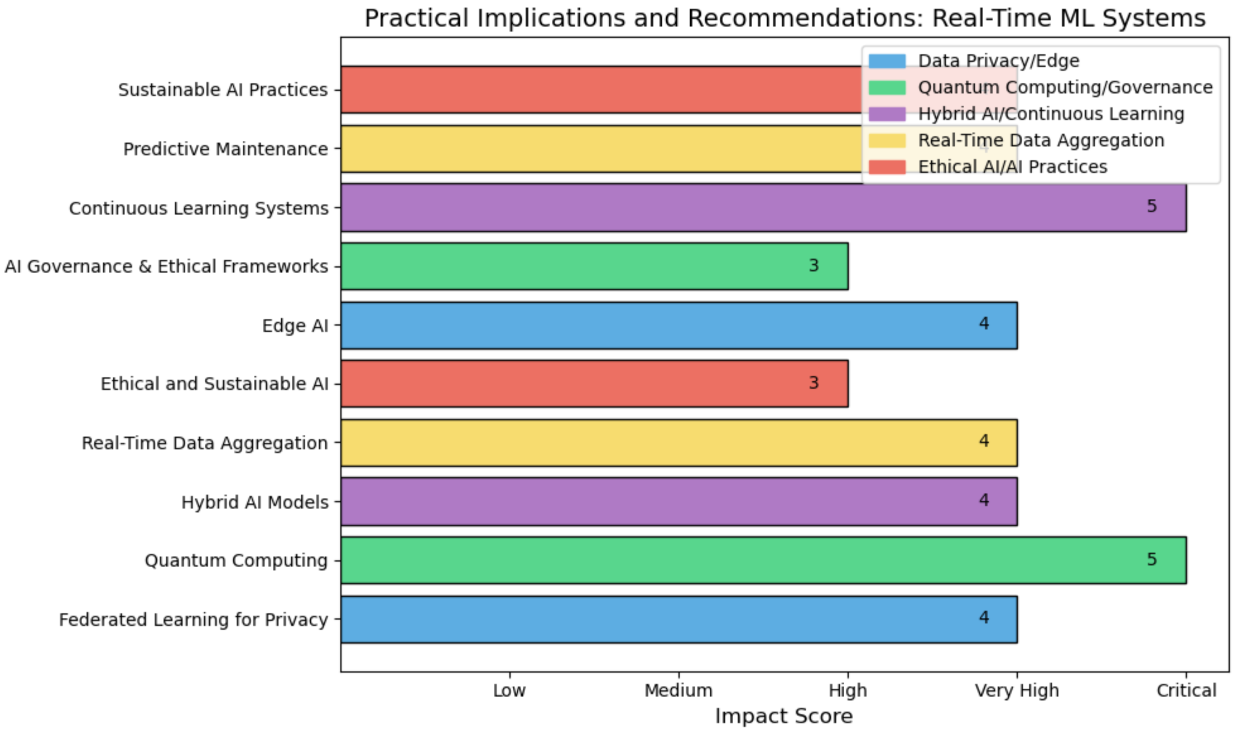

Figure 5 - Impact of Practical Recommendations for Real-Time Machine Learning Systems

Organizations working with sensitive data, such as healthcare providers, should consider implementing federated learning to ensure data privacy while simultaneously improving model training. In the financial sector, quantum computing holds the potential to accelerate risk modeling and other complex computational tasks. To address the complex challenges identified in real-time machine learning systems, here are additional strategies and actionable recommendations:

1) Edge AI for Cost-Effective and Scalable Deployment.
2) Practical implication: Organizations with constrained resources, such as startups or small enterprises, can adopt Edge AI to scale without the high infrastructure costs associated with cloud computing. It allows real-time decision-making directly on devices like smartphones or IoT sensors, cutting down on cloud-related expenses while still maintaining operational effectiveness.
3) Recommendation: Invest in developing customized edge AI models that are optimized for your specific business needs, enabling faster decision-making with lower latency.
4) Invest in AI Governance and Ethical Frameworks:
5) Practical implication: As AI systems are increasingly integrated into critical applications (e.g., financial systems, healthcare, law enforcement), organizations must adopt robust AI governance frameworks. These frameworks should ensure the models are fair, explainable, and accountable.
6) Recommendation: Establish cross-disciplinary AI ethics boards within the organization that continuously monitor and evaluate AI deployments. This includes auditing for bias and ensuring compliance with evolving regulations.
7) Continuous Learning in Real-Time Environments:

8) Practical implication: Real-time applications like fraud detection or personalized marketing require machine learning models to continuously learn and adapt from new data to maintain relevance.

9) Recommendation: Implement adaptive learning systems that update model parameters and predictions in real-time, ensuring that your models evolve alongside the data they process. Utilize continuous integration pipelines to deploy updates seamlessly.

10) AI-Driven Predictive Maintenance:

11) Practical implication: AI systems, particularly those using real-time data, can be deployed for predictive maintenance in industries like manufacturing or transportation. This minimizes downtime by predicting equipment failures before they occur.

12) Recommendation: Integrate predictive maintenance models with real-time data feeds from IoT sensors, optimizing performance and extending the lifecycle of critical infrastructure.

13) Sustainable AI Practices:

14) Practical implication: The environmental impact of machine learning, especially in large-scale real-time systems, is becoming a concern as more resources are dedicated to training and maintaining AI systems.

15) Recommendation: Adopt green AI strategies, which focus on making AI processes more energy efficient. This includes optimizing algorithms to reduce computational waste and utilizing renewable energy sources for data centers.

Conclusion.

In conclusion, this review has systematically explored the role of machine learning strategies and algorithms in enhancing real-time data processing across dynamic and big data environments. By categorizing and evaluating various methodologies, such as supervised, unsupervised, and reinforcement learning, the review highlighted their applications in critical domains including healthcare, smart cities, and cloud computing. Key challenges, such as data heterogeneity, computational complexity, and privacy concerns, were identified, alongside emerging trends like edge computing, federated learning, and ethical AI that offer promising solutions. The continuous evolution of machine learning technologies, particularly in real-time systems, underscores the need for ongoing research and practical innovation to develop more scalable, adaptable, and secure frameworks. These advancements will be crucial in meeting the demands of increasingly complex and data-driven industries.

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ДИНАМИКАЛЫҚ ЖӘНЕ ҮЛКЕН ДЕРЕКТЕР ЖҮЙЕЛЕРІНДЕГІ НАҚТЫ УАҚЫТТЫ ДЕРЕКТЕРДІ ӨҢДЕУДІ ЖЕТІЛДІРУГЕ АРНАЛҒАН МАШИНАЛЫҚ ОҚУ СТРАТЕГИЯЛАРЫ МЕН АЛГОРИТМДЕРІ

Аңдатпа. Бұл мақалада динамикалық ортада және үлкен деректер ортасында нақты уақыттағы деректерді өңдеуді жақсартуға арналған машиналық оқыту стратегиялары мен алгоритмдері қарастырылды. Деректердің күрделілігі мен көлемі артқан сайын масштабталатын, икемді және есептеу жағынан тиімді шешімдерге сұраныс арта түсті. Айтарлықтай жетістіктерге қарамастан, әртекті дереккөздермен жұмыс істеу, нақты уақыттағы икемділікті қамтамасыз ету және құпиялылық мәселелерін шешуде олқылықтар сақталды. Бұл мақалада әртүрлі динамикалық жүйелерде бақыланатын, бақыланбайтын және күшейтумен оқыту сияқты машиналық оқыту модельдерінің тиімділігі жүйелі түрде бағаланды. Әдебиеттерді шолу нәтижелеріне сүйене отырып, нақты уақыттағы машиналық оқытуға байланысты деректерді қабылдау, ерекшеліктерді әзірлеу, модельдер жасау және үздіксіз мониторинг сияқты маңызды процестерді сипаттайтын ықтимал құрылым жасалды. Платформа аясында бұлттық есептеулерді, шеттік шешімдерді және модельдерді автоматты түрде қайта оқытуды пайдалана отырып, масштабталуды және өнімділікті арттыру әдістері көрсетілді. Нәтижелер федеративті оқыту, этикалық жасанды интеллект және нейросимволикалық жасанды интеллект сияқты жаңа үрдістер шешілмеген мәселелерге болашағы зор шешімдер ұсынатынын көрсетті. Бұл мақалада барған сайын күрделене түсетін ортада нақты уақыттағы деректерді жоғары жылдамдықта өңдеудің қажеттіліктерін қанағаттандыра алатын сенімді, қауіпсіз және икемді машиналық оқыту орталарын әзірлеу бойынша зерттеулерді жалғастырудың маңыздылығы атап өтілді.

Түйінді сөздер. Машиналық оқыту, нақты уақыттағы деректерді өңдеу, масштабтылық, динамикалық жүйелер, заттар интернеті, ақылды қалалар, бұлттық есептеулер, шеттік есептеулер.

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СТРАТЕГИИ И АЛГОРИТМЫ МАШИННОГО ОБУЧЕНИЯ ДЛЯ УЛУЧШЕНИЯ ОБРАБОТКИ ДАННЫХ В РЕАЛЬНОМ ВРЕМЕНИ В СИСТЕМАХ ДИНАМИЧЕСКИХ И БОЛЬШИХ ДАННЫХ

Аннотация. В этой статье были рассмотрены стратегии и алгоритмы машинного обучения, предназначенные для улучшения обработки данных в реальном времени в динамических средах и средах больших данных. По мере увеличения сложности и объема данных потребность в масштабируемых, адаптируемых и эффективных в вычислительном отношении решениях становилась все более острой. Несмотря на значительные достижения, сохранялись пробелы в работе с разнородными источниками данных, обеспечении адаптивности в реальном времени и решении проблем конфиденциальности. В этой статье систематически оценивалась эффективность моделей машинного обучения, включая контролируемое, неконтролируемое и обучение с подкреплением, в различных динамических системах. На основе результатов обзора литературы была разработана возможная структура, описывающая критические процессы, связанные с машинным обучением в реальном времени, такие как прием данных, разработка функций, вывод моделей и непрерывный мониторинг. В рамках платформы были продемонстрированы методы повышения масштабируемости и производительности с использованием облачных вычислений, периферийных решений и автоматического переобучения моделей. Результаты показали, что новые тенденции, такие как федеративное обучение, этический ИИ и нейросимволический ИИ, предлагают многообещающие решения нерешенных проблем. В этой статье подчеркнута важность продолжения исследований по разработке надежных, безопасных и адаптируемых сред машинного обучения, способных удовлетворить потребности высокоскоростной обработки данных в реальном времени во все более сложных средах.

Ключевые слова. Машинное обучение, обработка данных в реальном времени, масштабируемость, динамические системы, Интернет вещей, умные города, облачные вычисления, периферийные вычисления.

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