



Deploying AI at the Edge and Beyond

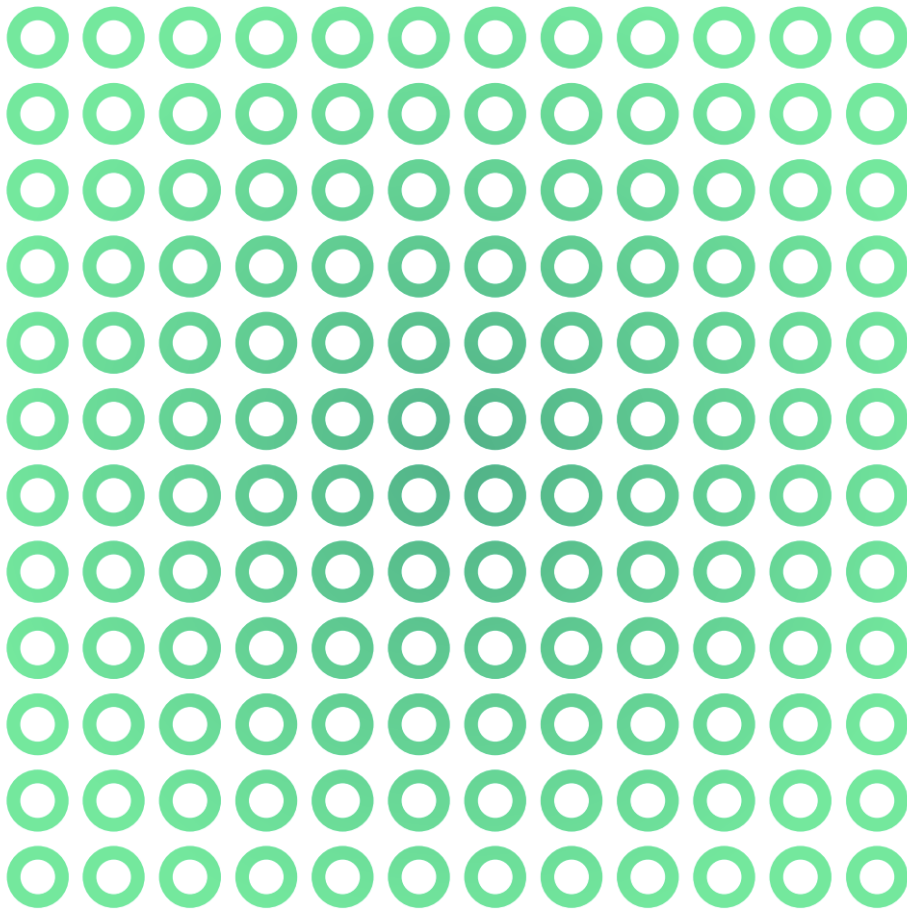
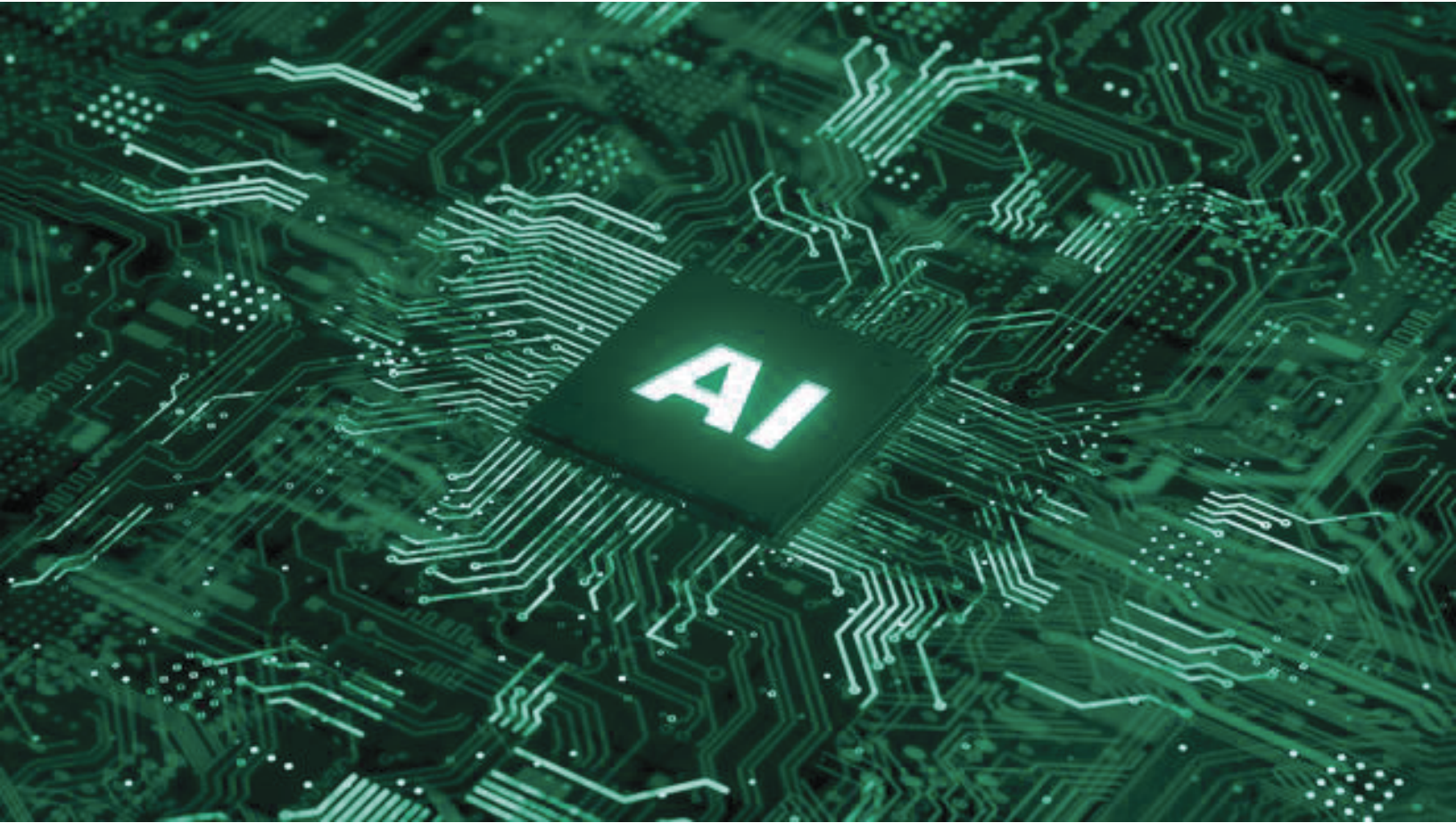


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Deploying AI at the Edge and Beyond

Deploying AI (artificial intelligence) at the edge is revolutionizing operations across many industries. In the manufacturing space, it offers significant advantages for operations, such as driving efficiency, reducing costs, optimizing production, and improving overall product quality. However, integrating new technology with existing processes and systems can be challenging and is the primary cause for slow adoption.

To keep pace with technological advancements, it's crucial to implement scalable AI tools that deliver tangible results while ensuring reliability and security.

This white paper presents the traditional uses of AI, the challenges manufacturers face with AI implementations, and how NI's software offers the best-in-class solution for quick deployment, seamless integration, and advanced analytics.

A Brief History of Artificial Intelligence

With recent hype about generative AI capabilities, it's easy to lose sight of the fact that AI technology has been around for decades, powering everyday software tools such as email spam filters, search engines, and chatbots.

The Evolution of AI (in a Nutshell)

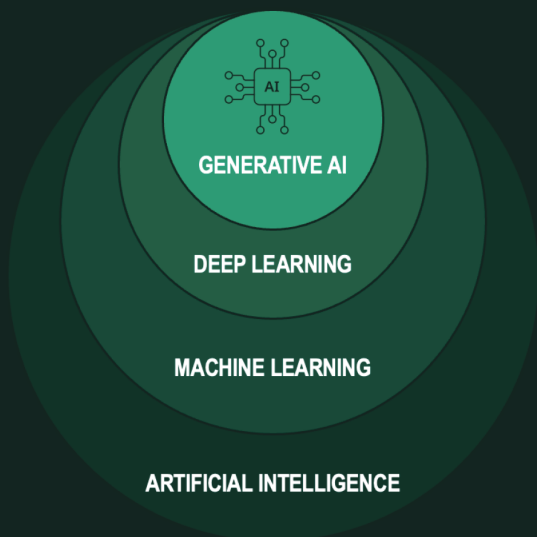
AI is the simulation of human intelligence in machines that are programmed to think and learn like humans. AI is used widely across various industries and applications, driving significant advancements in automation and software capabilities.

Machine Learning (ML) is a subset of AI that enables machines to learn from existing data to improve decisions or predictions. ML algorithms analyze patterns in data, weigh expected outcomes, and make predictions based on this inference of data. Over time, these algorithms continuously improve their accuracy.

Deep learning is a further subset of ML that uses artificial neural networks to process and analyze information. Although many advanced ML models use deep learning techniques, the term ML is often used broadly, encompassing general ML methods and specific deep learning applications.

Generative AI significantly advances the accessibility of AI with its ability to create new content and images based on conversational prompts from the user. Using machine learning techniques, generative AI can produce new and creative outputs. Its remarkable capabilities have drawn widespread attention while raising valid concerns about misinformation, privacy, security, and intellectual property.

Evolution of AI



GENERATIVE AI

Machine-generated written, visual, and auditory content is created based on conversational prompts from the user.

DEEP LEARNING

A machine learning (ML) technique that uses layers of neural networks to process data and make decisions. The term ML is often used broadly to include deep learning applications.

MACHINE LEARNING

Subset of AI that enables machines to learn from existing data and improve upon that data to make decisions or predictions.

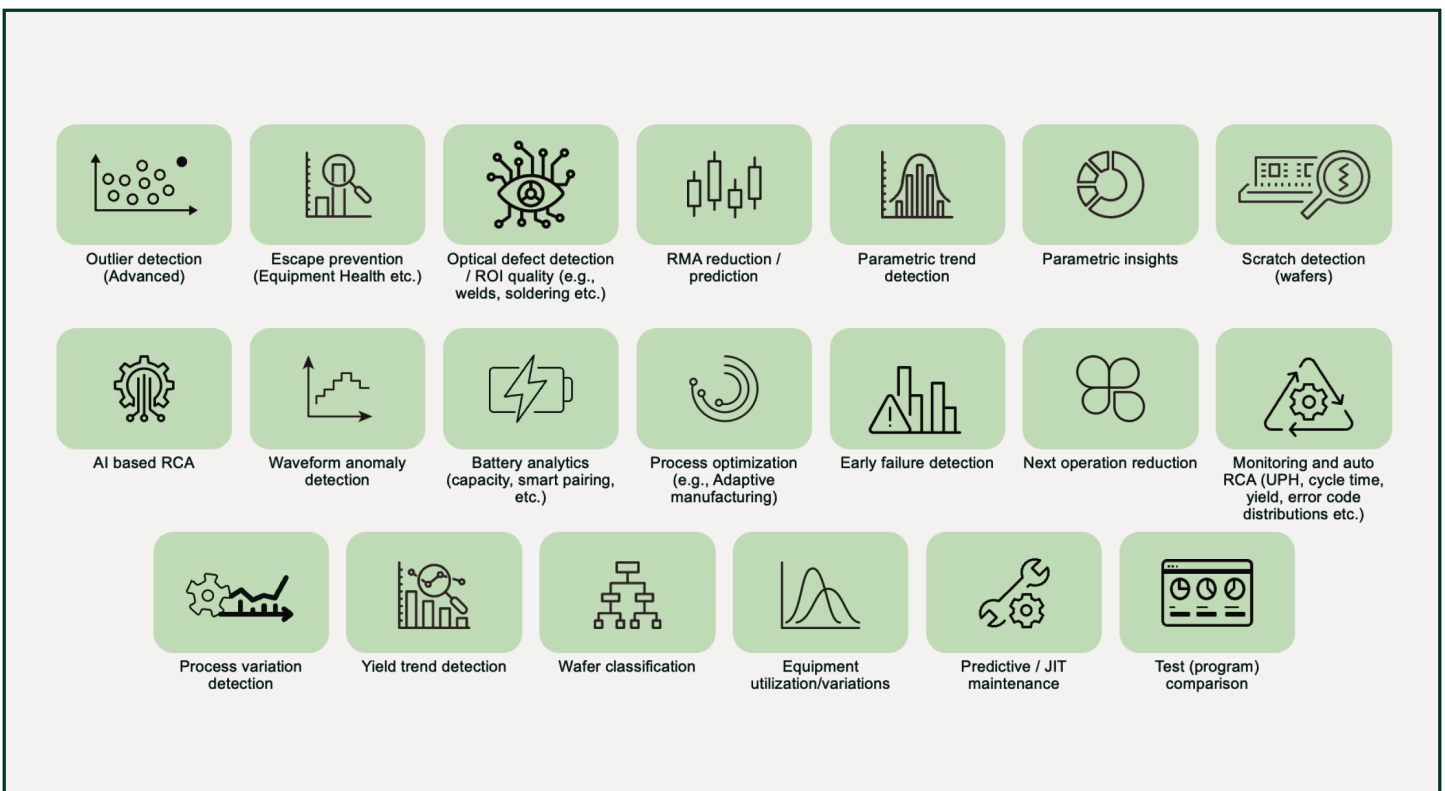
ARTIFICIAL INTELLIGENCE

The field of computer science that seeks to create intelligent machines that can replicate or exceed human intelligence.

Traditional AI Use Cases in Manufacturing

In the manufacturing sector, some organizations already leverage AI and ML to enhance quality and productivity across multiple production lines and locations. Because manufacturing operations are often distributed, AI is often deployed and utilized at the edge and centrally.

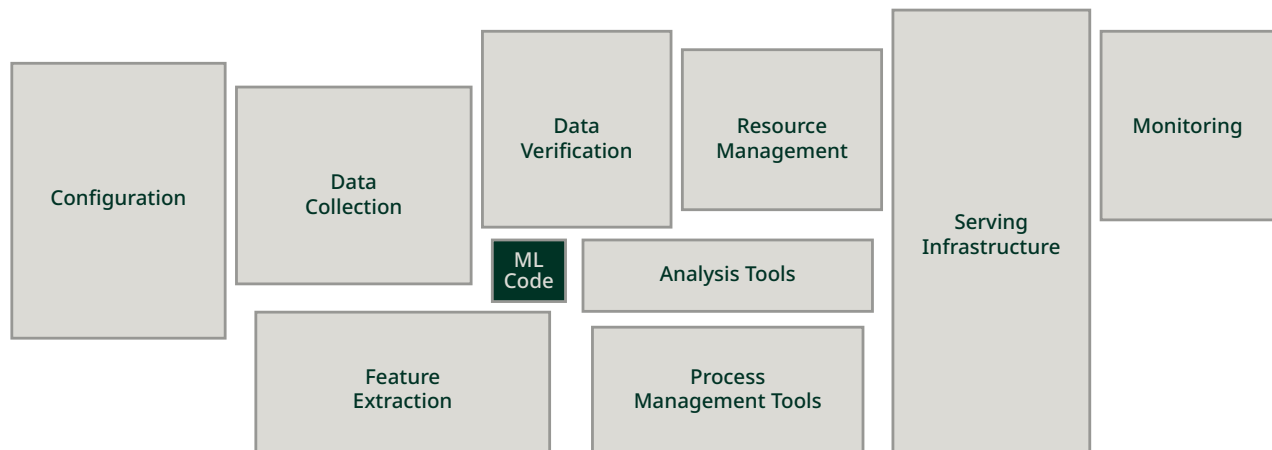
In edge AI deployments, advanced analytics can identify process variations and predict maintenance requirements before human detection is possible. Additionally, ML models can evaluate images to inspect for quality defects in real-time. Over time, user feedback helps improve the reliability of these models, making them essential for optimizing manufacturing efficiency and product quality.



Complexities of Wider AI Deployment in Manufacturing

Broader and more advanced AI adoption in manufacturing has the potential to transform operations; however, it has proven challenging for most manufacturers.

While implementing ML algorithms may seem like a coding challenge, multiple considerations and hidden complexities exist when integrating AI tools with existing infrastructure. The following graphic from Google reveals how ML code is typically just a small piece in a larger puzzle of infrastructure and data requirements.



Understanding and addressing these elements is critical to ensure AI's smooth and scalable integration into operations.

Configuration

Aligning with the specific needs and requirements of the manufacturing environment, including system parameters, hardware and software setups, network configurations, and integration points with existing systems.

Complexities: Requires in-depth knowledge of AI/ML technologies and the specific manufacturing processes to ensure proper alignment and functionality; these issues are compounded with distributed and outsourced manufacturing.

Data Collection

Gathering raw data from various sources, such as sensors, test equipment, IoT devices, machine logs, operational databases, and manual inputs.

Complexities: Ensuring accurate and timely data collection, handling large volumes of data, dealing with diverse data sources, and maintaining data integrity.

Data Verification

Ensuring the accuracy, quality, consistency, and reliability of collected data through cleaning, validation, removal of duplicates, and error detection.

Complexities: Identifying and correcting errors in large datasets, dealing with missing or inconsistent data, aligning data from different facilities and processes, and verifying data against multiple sources.

Feature Extraction

Transforming raw data into meaningful and useful features that ML models can use by identifying relevant variables, generating new variables through transformations, and selecting the most significant features.

Complexities: Requires domain expertise to identify the right features, handle high-dimensional data, and ensure that features are representative of the underlying processes.

Machine Resource Management

Managing the computational resources required to train and run ML models, such as CPU/GPU allocation, memory management, storage optimization, and network bandwidth.

Complexities: Balancing resource usage to optimize performance and cost, scaling resources to handle large workloads, and ensuring high availability and reliability.

Process Management Tools

Aligning the tools and systems to streamline the processes involved in implementing AI and ML in manufacturing, such as workflow management systems, versioning, deployment, automation tools, and project management software.

Complexities: Integrating new tools and processes with existing processes, managing dependencies between tasks, and ensuring efficient and scalable processes.

Analysis Tools

Statistical analysis software, visualization tools, and business intelligence platforms are used to analyze data and interpret the results of ML models.

Complexities: Off-the-shelf analysis tools might not fit the manufacturing requirements; therefore, selecting the right tools for the job and integrating with the right data sources is critical to ensure the analyses are accurate and actionable.

Serving Infrastructure (Hosting)

Appropriate servers, databases, APIs, and load balancers must be in place to deploy and serve ML models in a production environment.

Complexities: Ensuring low latency and high throughput, managing deployments and updates (particularly in siloed, outsourced manufacturing plants,) and handling failures and recovery.

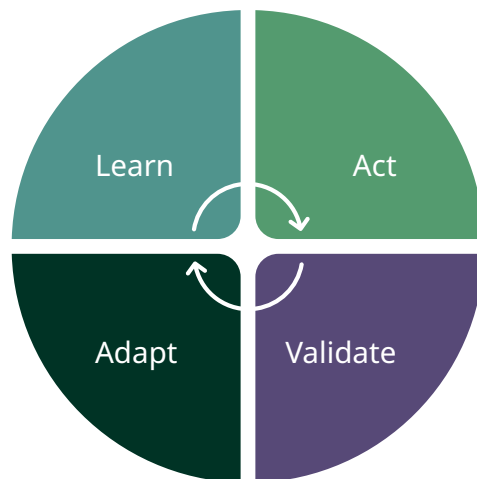
Monitoring

Continuously tracking the performance and behavior of ML models and the systems they interact with, including monitoring tools, alerting systems, and performance dashboards.

Complexities: Setting up comprehensive monitoring to detect issues in real-time, distinguishing between normal and anomalous behavior, and maintaining monitoring systems without introducing significant overhead or consuming resources.

A Framework for ML Adoption

The machine learning lifecycle is a framework that enables manufacturers to manage complexity by deploying and adapting ML use cases with a proactive approach.



The framework ensures that ML models are well-trained, deployed responsibly, continuously monitored, and updated as conditions evolve. It is an ongoing cycle of learning, acting, validating, and adapting to achieve optimal business results.

Learn

The learning phase begins with data collection and pre-processing. Adequate data points and clean data are critical for training accurate models. After applying the algorithm and training the model, results are validated to fine-tune parameters and prevent overfitting.

What is Overfitting?

Overfitting occurs when an ML algorithm models noise and outliers in training data as significant patterns, missing underlying trends and leading to poor performance when using new data. Statistical techniques and human oversight can mitigate overfitting.

Retrieving data from multiple sources, organizing it, aligning formats, and extracting specific features can be laborious. The key to success is streamlining and automating data collection and pre-processing.

Act

Integrating the model into a production environment may involve using APIs, microservices, or embedding the model into applications. Seamless integration with systems and workflows is critical to achieving optimal accuracy, gaining efficiencies, and driving user adoption.

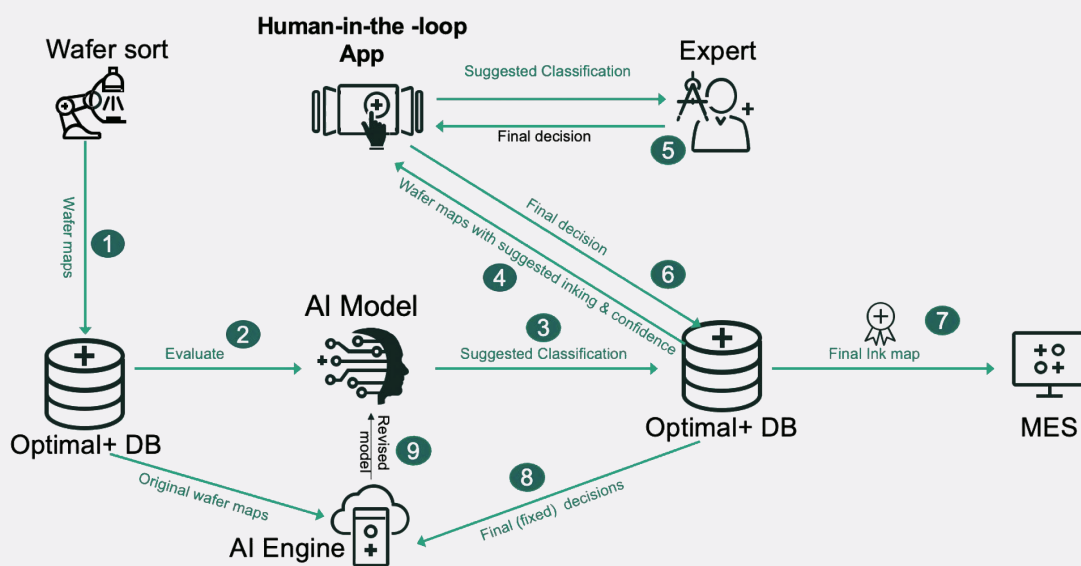
Depending on the current systems, equipment, and workflows, integrating ML models into production can be a huge undertaking. Legacy infrastructure and complex “plumbing” can complicate and prevent smooth implementations, resulting in disjointed systems and/or project scope creep. Multiple factories, distributed manufacturing, and outsourced supply compound these issues. Thorough operational and IT planning upfront will yield dividends in quicker results and long-term scalability.

Validate

Ongoing monitoring is critical to detect issues or drifts in accuracy. A human-in-the-loop provides oversight to analyze the errors, understand the model's limitations, and identify opportunities for improvement. Metrics and impact assessments verify if AI is delivering the expected outcomes and build confidence in AI tools and processes.

Human-in-the-loop (HITL)

Human-in-the-loop (HITL) is critical to ensuring that the ML algorithm is always expert-led by having an expert validate the suggested classification by the model. Some organizations may start with 100% human validation and then scale back to sampling after gaining confidence. The human decision drives the outcome classification and feeds into the AI engine to revise the ML model for improved future performance.



Streamlined workflows and systems for ongoing validation are critical elements. Data from disparate systems must continually be monitored to ensure seemingly unrelated technology changes don't cause unexpected problems. Ideally, production ML model monitoring should be automated, highlighting anomalies to avoid taking time away from new projects and innovations.

Adapt

To stay relevant and continue to deliver results, ML models must be updated and retrained to eliminate errors, incorporate new trends, and account for changes in production processes. User feedback and new data play crucial roles in fine-tuning models to improve accuracy over time.

Inevitably, changing conditions cause models to become stale, and the model needs to be retrained on new data. Ongoing monitoring and metrics provide an early warning of retraining requirements to ensure peak performance.

Choosing the Right Software Solutions

A common software and data environment is essential for reducing complexity and following the machine learning lifecycle, ensuring data integrity and system efficiency. Advanced software solutions offer a flexible data platform, an open architecture, contextual insights, and ML model monitoring.

Data Platform

The application should support data collection and verification from multiple data sources. Advanced systems allow data management at the edge or centrally. This affords organizations ultimate flexibility to manage diverse data types, optimize machine resource management, ensure real-time responsiveness, and maintain system scalability and security.

Open Architecture

A seamless and interoperable test environment is vital for extensibility. Software built with an open, well-documented architecture fosters smooth integration and configuration with infrastructure, hardware, and other software. This design maximizes flexibility and future-proofs the environment, allowing for the effortless addition of new tools, technologies, and capabilities as requirements evolve.

Contextual Insights

Test-centric software with domain expertise and feature extraction is key for contextualizing insights and presenting specialized schemas, maximizing the benefits from engineer to enterprise. By converging test data and non-test data from design, validation, and production into a unified application environment, advanced software solutions deliver comprehensive insights to break down silos, streamline operations, and accelerate innovation.

ML Model Monitoring

Monitoring is crucial to validating and adapting ML models in the machine learning lifecycle to ensure peak performance. Automated monitoring functionality takes the guesswork out of maintaining ML models. Metrics detect significant drifts and deviations, offering an objective early warning that ML models must be updated or retrained.

Take AI to the Edge and Beyond

NI's high-precision hardware and powerful software enable organizations to meet the testing demands of today and into the future.

NI SystemLink and NI Optimal+ platforms support validation and production at every stage, offering flexibility and quick deployment. Engineers are empowered with expert-led solutions that are AI-enhanced to accelerate processes and enable smarter decision-making while keeping the engineer in the loop. Data is traceable and secure, providing the confidence to innovate without compromise.

The platforms enable rapid AI deployment at the edge and beyond to achieve faster, more accurate results. Scalable solutions foster collaboration and innovation from engineer to enterprise while accommodating future requirements.

No matter where you are in your AI journey, we have the solutions to help you get started and succeed.

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