Critical AI Use Cases in Manufacturing & Motion

Realizing AI-powered innovation with MongoDB Atlas

Table of Contents

AI in Manufacturing and Motion

The integration of Artificial Intelligence (AI) within the manufacturing and automotive industry is transforming the conventional value chain, presenting a spectrum of opportunities. Leveraging Industrial IoT, companies now collect extensive data from assets, paving the way for analytical insights and unlocking novel AI use cases. AI's impact in manufacturing spans the entire manufacturing lifecycle, from AI-driven product design optimization to streamlined planning, procurement, and supplier collaboration. The challenge lies in managing diverse data sources and formats, necessitating a streamlined infrastructure to avoid siloed data and collaboration bottlenecks. The ability for modern manufacturers to innovate quickly using AI is only made possible by easy-to-use, real-time data analytics tools that enable informed decision-making.

During manufacturing, recording data with embedded sensors in machinery creates opportunities for process optimization, but the influx of time series data also poses data storage challenges. AI applications can enhance efficiency by analyzing production data to predict equipment failures, or enable quality inspection through computer vision techniques.

As products move through the value chain, real-time data becomes crucial for supply chain management, logistics, shop floor information and customer relationship enhancement. AI aids in offering value-added demand forecasting, inventory management, predictive maintenance as well as enhanced customer services. In advanced automotive scenarios like autonomous driving, AI processes vast sensor data to map vehicle surroundings and drive real-time actions.

Throughout the manufacturing value chain, data-related challenges contribute to inefficiencies, quality issues, and delays. The ever pressing need for capturing, transforming, and providing the right data to AI models remains critical. MongoDB Atlas, a flexible developer data platform, is the key enabler for innovation, enhancing production efficiency, and ensuring competitiveness in an industry marked by rapid evolution. The marriage of AI and MongoDB's versatile platform promises a transformative journey for manufacturers, navigating the complexities of a dynamic landscape with agility and precision.

Smart Supply Chain

Inventory Optimization

Demand Forecasting

Logistics Optimization

Smart Factory

Predictive Maintenance

Quality Control and Defect Detection

Production Optimization

Smart Products & Services

Personalized Product Recommendations

Autonomous Driving

Smart After Sales Support

MongoDB

Inventory Management and Optimization

Modern manufacturing supply chains are complex interconnected systems. Efficient supply chains are able to control operational costs and ensure on-time delivery to customers. Inventory optimization and management is a key component in achieving these goals. While maintaining higher inventory levels allow for suppliers to deal with unexpected fluctuations in demand, they come with higher inventory holding costs that may be passed on to customers. Thus, every player in the supply chain is motivated to strike a balance between inventory levels to maximize profitability and competitive advantage in the market. Effective inventory management mitigates the risk of 'bullwhip effect', where sudden demands can disrupt the supply chain costs and performance.

For manufacturers, to manage and optimize inventory levels, the first step is to maintain an accurate and real-time view of inventory levels across multiple plants, warehouses, and suppliers. This is absolutely essential because without having visibility into current inventory levels, it is impossible to optimize.

The second step is to reduce inventory carrying costs while still ensuring that the required parts and materials are available to ship out when needed. Finally, the data from multiple customers needs to be aggregated and analyzed despite being in different formats, each with its own unique lead times and order quantities.

Efficient inventory management for manufacturers presents complex data challenges, primarily in forecasting demand accurately and optimizing stock levels. One issue routinely faced is the variability and unpredictability of customer demand patterns, making it difficult to anticipate inventory needs.

Managing diverse data streams from sales records, production schedules, supplier information, and market trends poses a data integration challenge. The spread of data across multiple systems and locations (on-prem systems, cloud regions etc.) can lead to data silos and hinder visibility into overall inventory levels and movements. Finally, when there is sparse historical inventory data available, then traditional ML models may suffer in accuracy.

AI Potential

One of the most significant applications of AI in inventory management is in demand forecasting. AI algorithms can be used to analyze complex datasets to predict future demand of products or parts. Improvement in demand forecasting accuracy is crucial for maintaining optimal inventory levels. AI-based time series forecasting can assist in adapting to rapid changes in customer demand.

Once the demand is known, AI can play a pivotal role in stock optimization. By analyzing historical sales data and market trends, manufacturers can determine the most efficient stock levels. AI systems can also place orders automatically based on predicted demand and targeted stock levels. This automation not just saves time but also reduces human error. Finally, AI utility can be extended to supplier selection and relationship management. By analyzing supplier performance data, AI based software can assist in choosing the right suppliers who will meet the company's quality, delivery and cost requirements.

On top of all this existing potential, Generative AI can help with generating seasonally adjusted demand patterns. It can help with creating scenarios and simulate supply chain disruptions, enabling better contingency planning. Finally, manufacturers may explore using Generative AI to generate synthetic data to supplement limited historical data.

MongoDB Solution

MongoDB Atlas provides a flexible, scalable, and highly available developer data platform for managing inventory data. The document data model can handle complex inventory structures and hierarchies, making it easy to manage inventory across multiple plants and suppliers.

At the warehouse, the inventory can be scanned using a mobile device. This data is persisted in Atlas Device SDK and synced with Atlas using Device Sync. Atlas Device Sync provides an offline-first seamless mobile experience for inventory tracking, making sure that inventory data is always accurate in Atlas.

Once data is in Atlas, it can serve as the central repository for all inventory-related data which includes stock, supplier and customer information, bill of materials and production line data. This repository becomes the source of data for inventory management AI applications. This approach removes data silos and improves visibility into overall inventory levels and movements.

However, the challenge of poor or sparse data at the source systems may still remain. Research is going on the ability of LLMs to generate synthetic data for industrial applications. Manufacturers can take advantage of Atlas Vector Search to feed in right historical data as context to the LLM to generate acceptable synthetic data. They can take multimodal content such as product descriptions and specifications, customer feedback and reviews and inventory notes, vectorize them and store vector embeddings alongside the operational data in MongoDB Atlas. This allows them to supercharge their inventory optimization using Gen AI. They can easily categorize products based on their seasonal attributes, cluster products with similar seasonal demand patterns and provide context to the foundation model to improve the accuracy of synthetic inventory data generation.

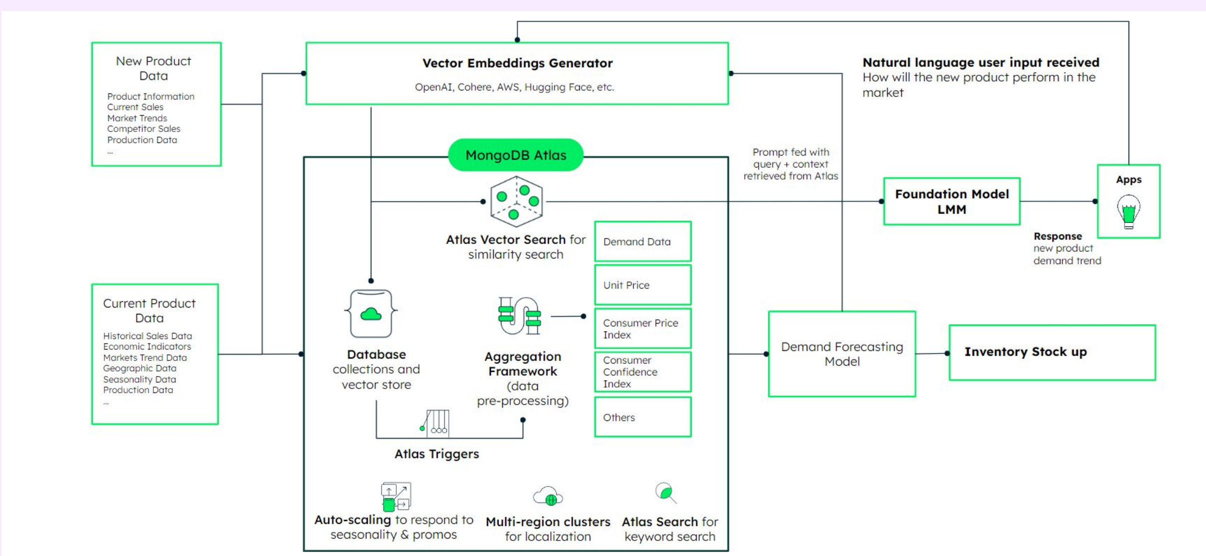

Figure 2. Blueprint for Gen AI powered inventory management system using MongoDB

Predictive Maintenance

Conventional maintenance strategies include reactive, preventive, and predictive maintenance. The most basic approach to maintenance is reactive, also known as run-to-failure maintenance planning. In the reactive maintenance strategy, assets are deliberately allowed to operate until failures actually occur. The assets are maintained on an as-needed basis. The disadvantage is that it becomes challenging to anticipate maintenance resources (e.g., manpower, tools and replacement parts) that will be needed for repairs. In preventive maintenance, systems or components are replaced based on a conservative schedule to prevent commonly occurring failures.

Although preventive maintenance allows for more consistent and predictable maintenance schedules, it can be expensive to execute because of frequent replacement of components or parts before their end-of-life. To reduce the high costs of preventive maintenance, predictive maintenance is an important strategy in which maintenance actions are scheduled based on equipment performance or conditions other than time. The objective of predictive maintenance is to determine the condition of in-service equipment, and ultimately to predict the time at which a system or a component will no longer meet desired functional requirements. If applied correctly, predictive maintenance can increase equipment uptime by up to 20%.

Customer Spotlight

[Read how Grainger innovates with MongoDB and Machine Learning.]

However there are certain challenges in building a predictive maintenance strategy for factory assets/machines. Manufacturing processes generate vast amounts of highly complex and sometimes noisy data from sensors, machines, and other sources, making it challenging to identify the root cause of issues. Additionally, machine diagnostics often require the integration of diverse data types, such as text reports, visual data from cameras, sensor readings, and historical records. Combining and analyzing these data modalities to identify root causes can be a complex task. There is a need to create a structure that can encapsulate this diverse data and is adaptable for different machines.

AI Potential

To implement predictive maintenance, data is first collected from IoT sensors installed on machinery or equipment. This data includes various parameters such as temperature, vibration, pressure, and operational metrics. The collected data is preprocessed to remove outliers and filter out unrelated data. The data is also divided into training and test sets. AI/ML algorithms, such as regression models, decision trees, or neural networks, are then applied to the preprocessed data to train predictive models. Once the models are trained, they are deployed on site, to perform inference on the incoming data at the edge. The models continuously analyze incoming sensor data and upon detecting anomalies or deviations from normal operating conditions, alerts are generated to notify maintenance personnel. Based on these alerts, maintenance actions can be planned and executed proactively, minimizing downtime and optimizing equipment reliability and performance.

On top of this typical AI flow, there is tremendous potential for Generative AI in predictive maintenance applications. A RAG architecture can be deployed to generate or curate the data preprocessor removing the need for specialized data science knowledge. The domain expert can provide the right prompts and context for the LLM. Once the maintenance alert is generated by an AI model, Gen AI can come in again to generate a repair strategy, taking spare parts inventory data, maintenance budget and personal availability into consideration. Finally the repair manuals can be vectorized and used to power a chat bot application that guides the technician in performing the actual repair.

MongoDB Solution

MongoDB Atlas provides a number of relevant features that help our manufacturing clients implement predictive maintenance in their shop floors.

MongoDB documents are inherently flexible while allowing data governance when required. Since machine health prediction models require not just sensor data but also maintenance history and process parameters, the document model is a perfect fit to model such disparate data sources.

During the maintenance and support process of a physical product, information such as product information, replacement parts documentation, labor times, damage codes, repair instructions etc. needs to be available at all times and easily accessible by support staff. Full text search capabilities provided by Atlas can be integrated with the support portal and help staff in retrieving information from Atlas clusters with ease. Atlas Vector Search helps with implementation of RAG architecture that will be the key in generating the repair plan.

Finally, usage of a flexible data platform opens up possibilities for using additional data sources for the AI model. Flexible data platforms working together with AI algorithms can help generate insights from diverse data types, including images, video, audio, geospatial data, and more. Atlas Vector Search stands out as a foundational element for effective and efficient Gen AI powered predictive maintenance models. A major European automotive manufacturer is using Atlas to explore ways of simplifying engine diagnostics. Audio files are recorded from engines which can then be vectorized and searched to retrieve similar cases. Once the cause is identified, they can leverage RAG to implement a chatbot interface that the technician can interact with and get context aware step by step guidance on how to perform the repair. Figure 3 shows how audio based diagnostics setup can be created using a normal USB fan. The QR code in Figure 3 points to a github repo which contains the code for the solution.

Customer Spotlight

[Read how Dongwha establishes Industry 4.0 facilities using MongoDB]

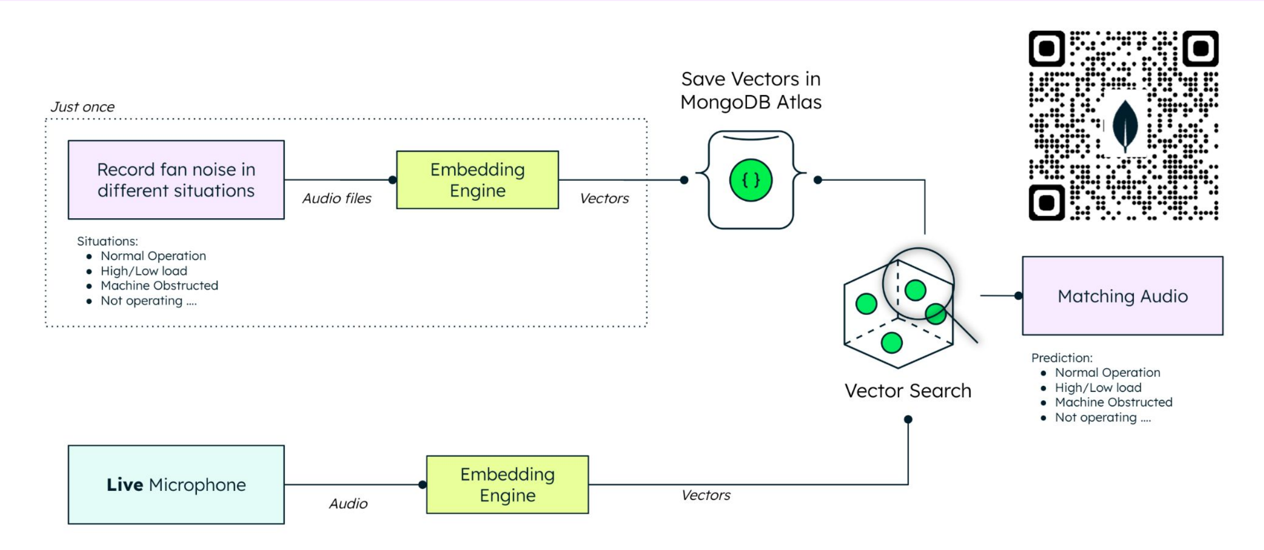

Figure 3. Audio-based anomaly detection with MongoDB Atlas. Scan the QR code to set it up yourself!

Autonomous Driving

As vehicles transform into connected vehicles, automotive manufacturers are transforming their business models into software-first organizations. The data generated by connected vehicles is used to create better driver assistance systems and paves the way for autonomous driving applications. It has to be noted that the journey toward autonomous vehicles is not just about building reliable vehicles but harnessing the power of connected vehicle data to create a new era of mobility that seamlessly integrates cutting-edge software with vehicle hardware.

The ultimate goal of autonomous vehicle makers is to produce cars that are safer than human-driven vehicles. Since 2010, investors have poured over 200 billion dollars into autonomous vehicle technology. Even with this large amount of investment, it is very challenging to create fully autonomous vehicles that can drive safer than humans. Some experts estimate that the technology to achieve level 5 autonomy is about 80% developed but the last 20% will be extremely hard to achieve and will take a lot of time to perfect. Unusual events such as extreme weather, wildlife crossings, and highway construction are still enigmas for many automotive companies to solve.

AI Potential

The answer to these challenges is not straightforward. AI-based image and object recognition still has a long way to go to deal with uncertainties on the road.

However, one thing is certain, automotive manufacturers need to make use of data captured by radar, LiDAR, camera systems, and the whole telemetry system in the vehicle in order to train their AI models better. A modern vehicle is a data powerhouse. It constantly gathers and processes information from onboard sensors and cameras. The Big Data generated as a result presents a formidable challenge, requiring robust storage and analysis capabilities. Additionally, time series data needs to be analyzed in real-time and decisions have to be made instantaneously in order to guarantee safe navigation. Furthermore, ensuring data privacy and security is also a hurdle to cross since self-driving vehicles need to be shielded from cyber attacks as such an attack can cause life-threatening events.

The development of high-definition (HD) maps to help the vehicle 'see' what is on the road also poses technical challenges. Such maps are developed using a combination of different data sources such as Global Navigation Satellite Systems (GNSS), radar, IMUs, cameras, and LiDAR. Any error in any one of these systems aggregates and ultimately impacts the accuracy of the navigation. It is required to have a data platform in the middle of the data source (vehicle systems) and the AI platform to accommodate and consolidate this diverse information while keeping this data secure. The data platform should be able to preprocess this data as well as add additional context to it before using it to train or run the AI modules such as object detection, semantic segmentation, and path planning.

MongoDB Solution

MongoDB can play a significant role in addressing aforementioned data-related challenges posed by autonomous driving. The document model is an excellent way to accommodate diverse data types such as sensor readings, telematics, maps metadata, and model results. New fields to the documents can be added at run time, enabling developers to easily add context to the raw telemetry data. MongoDB's ability to handle large volumes of unstructured data makes it suitable for the constant influx of vehicle-generated information.

MongoDB is not only an excellent choice for data storage but also provides comprehensive data pre-processing capabilities through its aggregation framework. Its support for time series window functions allows data scientists to produce calculations over a sorted set of documents. Time series collections also dramatically reduce storage costs. Column compression significantly improves practical compression, reduces the data's overall storage on disk, and improves read performance. MongoDB offers robust security features such as role-based access control, encryption at rest and in transit, comprehensive auditing, field-level redaction and encryption, and down to the level of client-side field-level encryption that can help shield sensitive data from potential cyber threats while ensuring compliance with data protection regulations.

For challenges related to effectively storing and querying HD maps, MongoDB's geospatial features can aid in querying location-based data and also combining the information from maps with telemetry data fulfilling the continuous updates and accuracy requirements for mapping. Furthermore, MongoDB's horizontal scaling or sharding allows for the seamless expansion of storage and processing capabilities as the volume of data grows. This scalability is essential for handling the data streams generated by fleets of self-driving vehicles.

Once the data is in MongoDB Atlas, the Spark or Kafka connector can be used to connect to external AI engines so that new AI models can be trained. Atlas Search is a key component of the solution because it provides a performant search engine to allow data scientists to iterate their perception AI models.

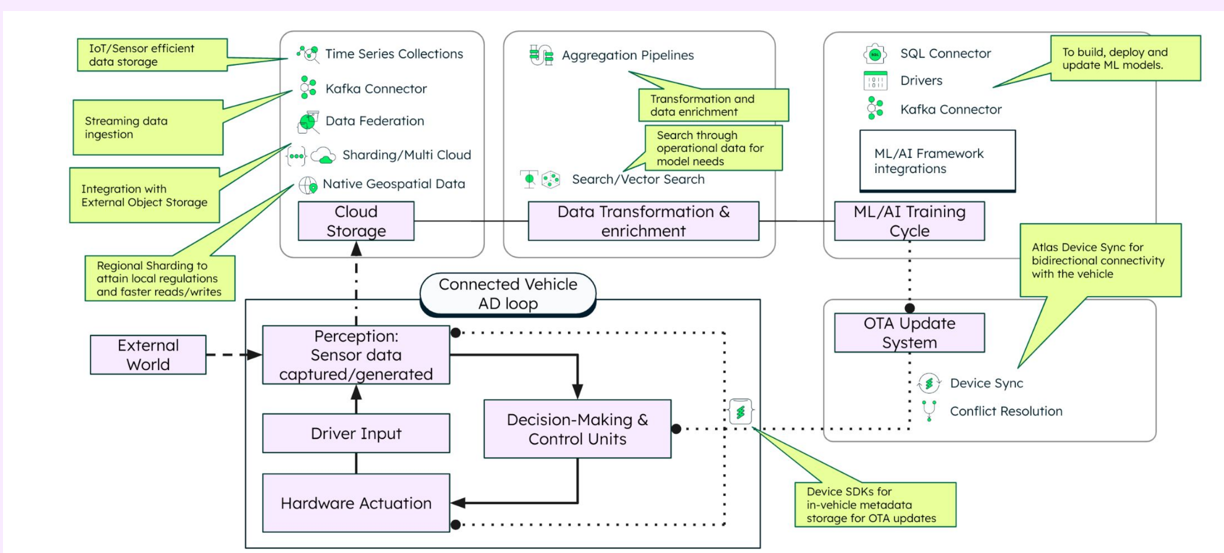

Figure 4. MongoDB Atlas role in Autonomous Driving

Finally, Atlas Device Sync can be used to send configuration updates to the vehicle advanced driving assistance system. Figure 4 shows the various components of MongoDB in an autonomous driving loop.

Other Notable Use Cases

AI plays a critical role in fulfilling the promise of Industry 4.0. There are numerous other use cases of AI that can be enabled by MongoDB Atlas. Some of them are listed below.

Customer Spotlight

Watch Toyota Connected North America's innovative approach to Connected Vehicle Safety

Logistics Optimization

AI can help optimize routes resulting in reduced delays, and enhanced efficiency in day to day delivery operations.

Quality Control and Defect Detection

Computer or machine vision can be used to identify irregularities in the products as they are manufactured. This ensures that product standards are met with precision.

Production Optimization

By analyzing time series data from sensors installed on production lines, waste can be identified and reduced thereby improving throughput and efficiency.

Smart After Sales Support

Manufacturers can utilize AI-driven chatbots and predictive analytics to offer proactive maintenance services, troubleshooting, and personalized assistance to customers.

Next Steps with MongoDB

Connect with our Manufacturing & Motion Experts

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For more information and resources

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