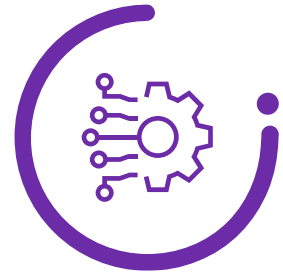


Computer Vision Driven Outcomes – The Data Scientist Viewpoint



Publication date:

October 2023

Author(s):

Bradley Shimmin, Chief Analyst, AI & Data Management

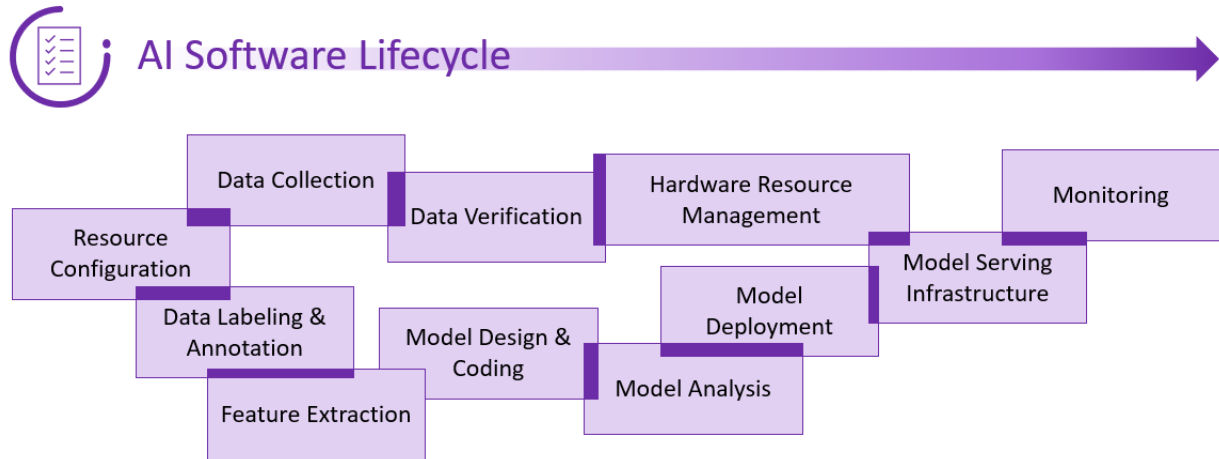
Tackling computer vision complexity through data integration and a little help from AI

Two concerns keep data scientists awake at night: data and technical debt. More specifically, a lack of access to high quality data that must be freed from isolated data siloes, and the unwanted accrual of technical debt stemming from that same access to high quality data. At a minimum these two interlinked and unfortunately enduring issues can slow development and drive up solution costs. And in the extreme they can entirely derail even the best planned and funded projects.

Such concerns plague all IT practitioners seeking to build AI outcomes. But they are uniquely acute within the realm of computer vision, where huge amounts of valuable information streams constantly from IoT sensors, cameras, marketing/sales software, customer resource management (CRM) systems and other business apps. Unfortunately, most of this valuable information remains trapped within these systems or departmental data warehouses, many of which were originally designed to bring analytical data together but now serve as a complexity-inducing roadblock -- a roadblock that currently dominates most of the ML development lifecycle (see Figure 1).

Two concerns keep data scientists awake at night:...a lack of access to high quality data that must be freed from isolated data siloes, and the unwanted accrual of technical debt stemming from that same access to high quality data.

Figure 1: Data access, processing, and verification make up the brunt of a typical ML development project.



Source: Omdia

What is it about data silos that makes it so difficult for data scientists to gathering the data necessary to create a viable computer vision solution? Before data scientists can actual do data science (i.e., working with data), they must first embark on data integration journey.

- **Identifying and evaluating all necessary data sources.** This can be tricky, as different sources will contain data that varies in accuracy, completeness, reliability, consistency, and timeliness.
- **Assessing the legal and compliance requirements** that must be addressed before a single byte can move out of an established data silo. This can prove to be a great challenge when multiple suppliers/partners are involved.
- **Designing a data integration plan** that encapsulates and harmonizes what are often very complex data models specific to each data source.
- **With the integration plan, building physical data pipelines capable of reaching into and extracting the necessary data.** Note that these pipelines must be built to stand the test of time, enduring not just connectivity issues but organizational changes and of course inevitable upstream data model adds/moves/changes.

Even more difficult is the task of bringing this data into the hardware and software infrastructure specific to a computer vision solution. Creating a centralized data warehouse is crucial, as it can serve as a central point of management for all computer vision project data, no matter where it originates. But it's not enough to create a centralized data warehouse - it must be able to house and make accessible the many different data types (both structured and unstructured) used within a computer vision solution in a way that can create a positive impact on the broader business. Finally, it must be able to help bring the output to decision makers themselves, in a form that they can understand and act upon.

This is what companies are after when they invest in computer vision -- rapid access to insights that can serve as both a protection against unanticipated change and an effective way to create a competitive advantage. It is no wonder when asked to describe their two-year investment plans, 41% of data

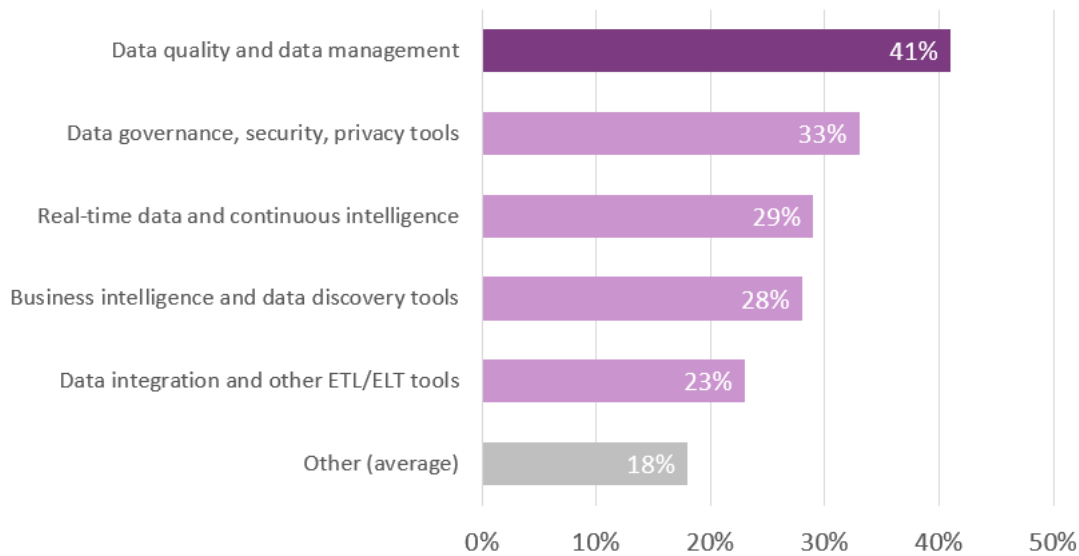
scientists named data quality and data management as their number one priority (see Figure 2). High quality data serves as the literal foundation upon which data scientists build. Without that, the whole solution will not provide the desired results – no matter how elegantly designed and executed.

Figure 2: Data quality and management takes top trumps.



What are your top data and analytics investment priorities over the next 24 months?

Select top three.



Source: Omdia

Example: Putting data science to work in retail

To illustrate the importance of building a solid data foundation for computer vision, consider the retail industry. Today, retailers must operate across many different points of contact. For that reason, forward-thinking retailers are increasingly turning toward computer vision as a means of engaging directly with their customers, whether digitally or physically.

Leveraging combined data from numerous data sources, often employing real-time information, retailers are building a unified, centralized computer vision management platform capable of conducting wall-to-wall retail store services. For example, with in-store shopping, this platform could be used for digital signage to provide immediate access to shopping assistance, personalized and dynamic promotions, discounts, and recommendations.

Conversely, a continuing market shift toward online ordering for curbside pickup or at-home delivery is creating a new kind of hub for retailers, that’s highly automated and highly personalized to serve as both a fulfillment and customer experience center. Omdia expects this new autonomous store to play a critical role in the retail computer vision marketplace, reaching \$331m dollars in revenue by 2027.

This ability to leverage computer vision in both worlds (online and in-store) has become a market-defining factor.

Not surprisingly these new kinds of personalized shopping experiences demand a new approach to data, leveraging computer vision data at scale and also breaking down silos between disparate departments. Only in this way can retailers create a true 360-degree view of their customers, improving customer outcomes through insight-driven, contextual responses to customer needs whether online or in-store.

How can companies break down their data silos and set their data scientists free to truly leverage computer vision data in support of customer 360 efforts? Perhaps surprisingly, a recent market trend is toward more capable data warehouses that can centralize, curate, and manage data at the edge, data center and cloud. Such a warehouse can more rapidly, securely, and affordably ingest, tag/annotate, store, and query video data. Not all data needs to be centralized, but the learning model and access to the results can be – so users have a consistent experience and know where to find insight.

Once combined under a single analytical roof, these disparate data assets can then be accessed through a unified API in support of many use cases ranging from predictive restocking algorithms to virtual “try on” booths.

Enter generative AI

Data centralization can certainly help ensure the success of computer vision projects, even for companies just beginning to explore its numerous and multifaceted opportunities. But there are other helpful measures emerging. Consider the current market trend surrounding generative AI (GenAI) and large language models (LLMs) in particular. LLMs dominate the news cycle and remain very much hype for now, evolving so rapidly that enterprise customers are struggling to keep up with daily innovations and challenges specific to LLMs.

Quite the opposite is true for computer vision, which has already positively transformed businesses across a wide spectrum of industries, driving customer engagement, supporting key sustainability efforts, and enhancing operations. Still, there are lessons to be learned from the whirlwind of GenAI. GenAI actually holds great promise for computer vision practitioners, promising to help with key functions such as:

- **Code generation:** LLMs are great at turning declarative statements into working functions and even full-fledged applications such as data integration pipelines.
- **API navigation:** LLMs trained on API calls and database schemas can help not just build but maintain complex data pipelines, performing root cause analysis, documenting data sources, and validating data itself.
- **Data creation and annotation:** LLMs can readily create synthetic data, making them the perfect companion for data scientists looking to work with sensitive data. And they are adept at labeling image data, which can help speed up this costly step in the computer vision lifecycle.

Computer vision...has already positively transformed businesses across a wide spectrum of industries, driving customer engagement, supporting key sustainability efforts, and enhancing operations.

While still in their infancy, these and many more LLM-enhanced automation and augmentation capabilities will eventually play a crucial role in helping data scientists focus on what they were hired for -- doing data science.

Conclusions

For computer vision data scientists in particular, this means accelerating data integration, preparation, validation, annotation, and tagging workflows. And when combined with a solid approach to data integration within a flexible data warehouse, they can free companies all together from having to worry about accruing technical debt in integrating data silos, allowing them to instead focus on business outcomes and accelerating AI development efforts across the company.



One recommendation in this journey is that enterprises should **invest in data science as an engineering endeavor**. Advances in AI-led automation and human augmentation have brought data science forward to the point where enterprises can begin to view AI outcomes as an engineering rather than a data science problem. That is, companies should invest in expertise specific to the integration and orchestration of systems, data, and AI resources rather than hiring to build AI outcomes from scratch. Again, this underscores the importance of building a computer vision architecture that prioritizes data integration and curation, where centralized models and results can be accessed and understood by decision makers, as this will greatly accelerate AI development efforts across the company.

Finally, enterprises should partner wisely – crucial because finding a good technology partner capable of simplifying the front end process can help companies overcome what Omdia has found to be the biggest hurdle to the adoption of any AI-based solution, namely the complexity of AI itself and the difficulties involved in integrating AI into the business.

To read more recommendations and insight to the market, readers should view the full whitepaper: [Practical Computer Vision from the further reading list below](#).

Appendix

Further reading

[Practical Computer Vision - Whitepaper](#)

[Beyond the platform](#) - by Dell Technologies and Intel

[Leading the industry with an outcomes-based process for computer vision](#) - by Dell Technologies and Intel

Author(s)

Bradley Shimmin, Chief Analyst, AI & Data Management

Bradley.Shimmin@Omdia.com



Omdia Commissioned Research

This piece of research was commissioned by Dell Technologies and Intel.

Citation policy

Request external citation and usage of Omdia research and data via citations@omdia.com.

Omdia consulting

We hope that this analysis will help you make informed and imaginative business decisions. If you have further requirements, Omdia's consulting team may be able to help you. For more information about Omdia's consulting capabilities, please contact us directly at consulting@omdia.com.

Copyright notice and disclaimer

The Omdia research, data and information referenced herein (the "Omdia Materials") are the copyrighted property of Informa Tech and its subsidiaries or affiliates (together "Informa Tech") or its third party data providers and represent data, research, opinions, or viewpoints published by Informa Tech, and are not representations of fact.

The Omdia Materials reflect information and opinions from the original publication date and not from the date of this document. The information and opinions expressed in the Omdia Materials are subject to change without notice and Informa Tech does not have any duty or responsibility to update the Omdia Materials or this publication as a result.

Omdia Materials are delivered on an "as-is" and "as-available" basis. No representation or warranty, express or implied, is made as to the fairness, accuracy, completeness, or correctness of the information, opinions, and conclusions contained in Omdia Materials.

To the maximum extent permitted by law, Informa Tech and its affiliates, officers, directors, employees, agents, and third party data providers disclaim any liability (including, without limitation, any liability arising from fault or negligence) as to the accuracy or completeness or use of the Omdia Materials. Informa Tech will not, under any circumstance whatsoever, be liable for any trading, investment, commercial, or other decisions based on or made in reliance of the Omdia Materials.

CONTACT US

[omdia.com](https://www.omdia.com)

customersuccess@omdia.com