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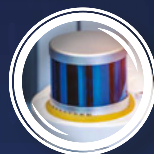

Three Decades of MACHINE VISION

30 YEARS OF INSIGHTS

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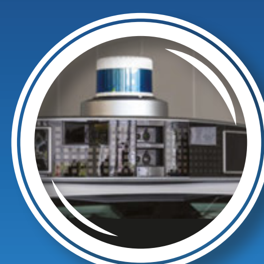

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Looking Back To Look Ahead

As we celebrate the 30th anniversary of VSD in 2026, this special print edition at Vision Stuttgart invites you to reflect on three decades of machine vision innovation and to envision the exciting future ahead.

A good place to start is with Senior Editor Jim Tatum's lead story "Experts Look Back on 30 Years of Machine Vision" (page 6), where we hear from several of our advisory board members.

David L. Dechow, one of the abovementioned experts, explores how traditional machine learning techniques can enhance industrial machine vision systems in his article "Leveraging Machine Learning Tools" (page 10).

Tatum also wrote about a pixel that can create and analyze images simultaneously in "Dual-Function Pixel for Advanced Imaging" (page 14) and about"Vision Language Models (VLMs) Explained" (page 18).

Turn to page 15 for a piece I wrote about a robotic weeding system that combines machine vision with adaptive AI, real-time decision-making, and durable manipulators to deliver scalable and efficient weed control.

Our 2026 Worldwide Industrial Camera Directory begins on page 20.

Looking ahead, 2027 promises expanded coverage of physical AI technologies, where vision stands as the gateway to embedded intelligence and edge computing, aligning with the convergence of perception systems and on-device AI that we're already seeing in industrial automation.

Cheers to 30 years, and here's to many more!

Sharon Spielman
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Interact Analysis on AI, Robotics, and Global Market Shifts

At Automate 2026, *Vision Systems Design* had an opportunity to sit with Jonathan Sparkes, lead analyst for machine vision at Interact Analysis, and talk about the machine vision industry—its current market drivers, technological innovations, and what lies ahead over the next several years.

Sharon Spielman/VSD

Jonathan Sparkes is lead analyst for machine vision at Interact Analysis.

AI and 3D Imaging Accelerate MV Adoption

Sparkes pointed out that camera technology remains a core growth area within machine vision, noting the increasing adoption of stereo and time-of-flight cameras, which offer the dual benefits of lower cost and simpler deployment compared to traditional 2D cameras. These are widely used in mobile robotics, inspection, and bin-picking applications. As Sparkes put it, "We're forecasting and seeing higher growth in stereo cameras and time-of-flight cameras, where there's a lower price point and an easier opportunity to deploy a 3D camera."

Complementing this, the rise of deep learning and AI-powered software plays a big role in reducing barriers for end users and easing integration challenges for manufacturers. He noted the software's role as "offering that opportunity for incremental growth across right now, and then across the next few years."

The show itself reflected these shifting dynamics, with companies showcasing incremental advances such as higher-resolution sensors, improved bandwidth, and faster interface speeds. According to Sparkes, these improvements allow more cost-effective camera deployments while expanding capabilities for broader inspection tasks.

Global Growth, Rising Competition

Regarding recent supply chain concerns, Sparkes's research with leading vendors over the first six months in 2026 found limited disruptions. Although geopolitical tensions—like those related to the Iran conflict—could introduce risks in semiconductor manufacturing or helium availability, the current consensus is optimistic: "People are saying they're not seeing any constraints or huge adverse effects right now." Yet he advises stakeholders to monitor the situation, given its fluid nature.

Geographically, China continues to emerge as an innovation powerhouse in machine vision, quickly designing and manufacturing advanced high-resolution cameras and aggressively expanding in Asia-Pacific and European markets. Sparkes said, "The growth of Chinese vendors...is huge right now," creating challenges for established American and European players. Meanwhile, Eastern Europe—particularly Poland—and Turkey stand out as rising hubs for automation investment. Turkey's position as a gateway between Asia and Europe fuels innovation, while India's growing industrial base is enabling greater machine vision adoption after years of cost-driven hesitance.

New Regulations, New Business Models

The regulatory environment pertaining to data privacy, AI ethics, and cybersecurity remains a developing challenge. Responses among companies vary, with some viewing regulations like Europe's Cyber Resilience Act as serious business threats, while others maintain a more cautious stance about the timeline and impact. "I think it's still probably...a few years away people need to really have that in their mind," he said. Ethical concerns around AI use and data handling mirror this uncertainty, with companies adopting differing approaches.

Business models in machine vision are also changing. Subscription-based software licensing and usage-driven pricing models have gained traction recently. Sparkes explained how companies are exploring monetization strategies tied to operational metrics, such as "how many picks are done, whether that's by month [or by year]." There is speculation around integrating vision technology into broader robot-as-a-service (RaaS) offerings in mobile robotics.

On the market structure, Sparkes sees ongoing fragmentation with many niche application providers. While large-scale mergers have been limited mostly to smaller acquisitions like the late-April Exosens' purchase of hyperspectral specialist Emberion, the industry's diversity creates fertile ground for future consolidation. "There's always a space for a new company to...enter the market with a good solution," he said.

Robotics Integration Drives Growth

Intersecting technologies like robotics, IoT, and 5G are major enablers for machine vision innovation. Cameras increasingly serve as safety sensors in robotics applications, enhancing operational security in manufacturing and logistics environments. Sparkes stressed that evolving network capabilities open new deployment possibilities in complex settings, driving incremental market growth.

Regarding sustainability, Sparkes said its prominence as a market driver has waned somewhat due to diminishing government incentives and changing policy priorities globally. Still, energy use—particularly in relation to rising costs in Europe—remains an important consideration. "It's not necessarily just the cost of deploying a vision system...but how much energy is it using?" he said, noting growing industry interest in monitoring and managing energy consumption alongside performance.

His advice for OEMs and system integrators is straightforward: differentiation and diversification are becoming essential. With mounting price pressure on commoditized cameras, particularly from Chinese manufacturers, companies are increasingly turning to software, services, and integrated solutions to create value. Many are also expanding into new markets, including defense applications such as drones and surveillance. "A lot of companies are now pivoting or at least serving that industry that perhaps hadn't planned to a few years ago."

Jane Heffner Elected President of the International Federation of Robotics

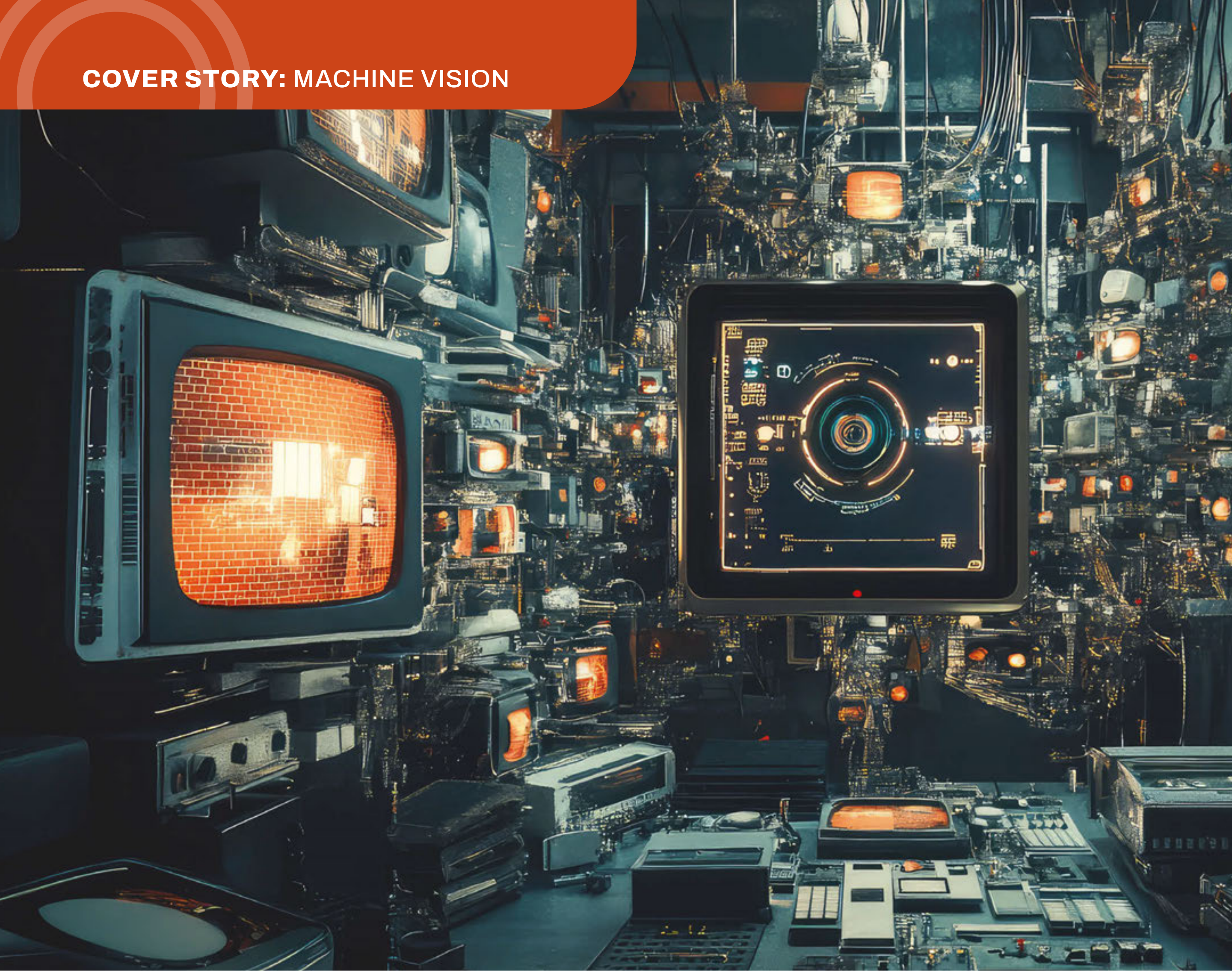
Jane Heffner has been elected president of the International Federation of Robotics (Frankfurt, Germany), a non-profit organization that promotes and represents the robotics industry globally. The election results were announced in an IFR press release on July 2.

Heffner currently serves as global vice president of channel communication at Teradyne Robotics (North Reading, MA). With more than 20 years of leadership experience in robotics, automation, automotive, and aerospace, Heffner will continue in her role at Teradyne while she serves as president of IFR.

Heffner succeeds outgoing president Takayuki Ito of Fanuc Corporation, who was elected in 2024.

"I would like to express my sincere gratitude to Takayuki Ito for his outstanding leadership and dedication," Heffner said in a statement following her election. "The global robotics industry is at an important inflection point, driven by rapid advancements in artificial intelligence and automation. We will continue to build on the excellent work that Takayuki has done as ambassador of the global robotics industry."

The IFR is focused on a number of goals and initiatives for the robotics industry, according to the IFR website. Goals include accelerating global adoption, advancing AI-driven automation, promoting safe and responsible deployment, supporting sustainability, and helping to address labor shortages across industries. Through initiatives ranging from robotics market research and international collaboration to diversity programs and standards development, the IFR is working to achieve those goals, according to the website.In addition to Heffner, the IFR elected a new vice president. Adrien Brouillard is executive president of the robotics division of Stäubli (Pfäffikon, Zurich, Switzerland), where he has worked in leadership roles, including global head of business for general industry and customer services, for more than 15 years.



Experts Look Back on 30 Years of Machine Vision

BY JIM TATUM

Vision Systems Design celebrates a major milestone in 2026: 30 years of covering the machine vision and imaging industry.

VSD began as a spin-off of sister publication *Laser Focus World*. While machine vision may seem like a specialty market to some, it is in fact a robust, growing, multi-billion-dollar industry that clearly merits a publication dedicated exclusively to its coverage.

Still, 30 years is a long time, and too often the present can seem a little slow—even static—until it becomes the past.

Looking back offers a valuable reminder of just how far the industry has come.

A quick AI search will instantly generate a reasonably accurate timeline of machine vision's evolution. In brief, research into image processing and pattern recognition—the foundations of applications such as automated inspection—began in the 1950s and 1960s. Industrial adoption accelerated in the 1980s and 1990s, while neural networks and deep learning expanded machine vision's capabilities by 2010. Today, AI-powered platforms continue to push applications to new levels.

Such an exercise is helpful, if for no other reason than it illustrates that the sheer power, not to mention convenience, of

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technology has advanced, almost unimaginably so, from just a few years ago. But a much more interesting exercise is to see the past, present, and future through the knowledgeable eyes, deep experience, and informed viewpoint of people who have seen the timeline unfold—first person and in real time.

With that in mind, *Vision Systems Design* reached out to its editorial advisory board and asked them to take a quick gander in both their personal rear-view mirrors and crystal balls and share a few thoughts and reflections. Specifically, VSD wanted to hear their takes on such technology areas as automated inspection, SWIR/non-visible imaging, and AI.

The following board members weighed in: Tom Brennan, president of Artemis Vision; David L. Dechow, principal vision systems engineer with Arthur G. Russell Company; Dr. Rex Lee, president and CEO of Pyramid Imaging; John Merva, retired industry consultant, JJMerva & Associates; Dr. Daniel Lau, IEEE Fellow, professor of electrical and computer engineering and the director of graduate studies in electrical engineering at the University of Kentucky; William Schramm, president, PVI Systems; and Matthew Wilton, director, AIET Group UAE.

Machine Vision Then…

"The machine vision and automated imaging environment has changed significantly in three decades," says Dechow, "Technologies, and even markets, were vastly different."Some of the technologies now considered mainstream options, such as AI, non-visible imaging sensors and InGaAs sensors were not yet commercially viable or simply did not exist in 1996, he notes.

Lee says, "Looking back 30 years in our industry feels like looking back to the stone ages," he says. More specifically, he recalls that "the industry was very narrow and specialized. Components were expensive and proprietary with practically no standards. I remember selling 1MP cameras for close to $10,000 and the LVDS cables all custom fit for whichever frame grabber was going to be used. Cables could cost over $800 and take many weeks for delivery. CMOS cameras didn't exist; everything was CCD."

Merva says he remembers that by 1996 application specifics were becoming more of a common requirement when it came to developing applications such as inspection systems.

"Early on, machine vision customers expected the vision system to detect all defects similarly to how a human would," Merva says. "Customers often expected vision systems to do more and more as system installation and buy-off progressed. A well-written specification, including samples of good and bad parts mitigated these problems."

Wilton adds to this, pointing out that "30 years ago, automated inspection was a tightly engineered solution to a narrowly defined problem. The camera, lighting and part presentation were fixed, processing power limited and the result was a simple pass or fail. The system did its job, but operated in isolation from the wider production process."

Camera, Lighting, Application

The past three decades have seen dramatic changes in camera technologies, Dechow says. The rise of CMOS sensors, yielding higher speeds and resolutions, and the availability of a variety of high-speed and reliable image transfer protocol standards such as GigEVision, USBVision, Camera Link, and CoaXpress, all supported by GeniCam, which is another standard that revolutionized imaging, he says.

In addition, quality, efficient illumination using LED lighting has substantially increased the success of vision applications, Dechow adds, further noting that SWIR and non-visible imaging cameras and systems have become standard components benefiting many machine vision applications.

Brennan agrees, noting that "AI, CMOS imaging, thermal imaging and LEDs are probably the biggest technologies of the last 30 years. They've opened tons of doors for new applications."

"And, automated inspection has become almost a requirement in manufacturing rather than just something to be considered," Dechow adds.

Lau says that much progress has been made over the last 30 years in visible and non-visible imaging, Market demand generally drives improvement, advancement, and scalability. That said, while non-visible options are much more affordable than they once were, they are still more expensive than visible imaging cameras, he says.

"Visible-light cameras are inexpensive, high-resolution, and capable of high frame rates because they are built on the same silicon CMOS manufacturing lines used for mainstream computer chips," Lau says.

SWIR cameras, by contrast, require different light-sensitive material, usually indium gallium arsenide (InGaAs), that have to be manufactured on specialized, lower-volume production lines and bonded to separate silicon readout chips. Consequently, these extra manufacturing steps increase cost, reduce yield, and limit resolution, leaving SWIR cameras typically significantly more expensive than visible-light systems, Lau says.

Nonetheless, Lau says, SWIR imaging does offer capabilities that visible cameras do not. For example, SWIR can see through fog, smoke, dust, many plastics, and even silicon, while also distinguishing between materials that appear identical to the human eye. These advantages have made SWIR valuable for a variety of applications, from defense and semiconductor inspection to materials sorting, agricultural grading, and scientific imaging.

Since its commercial emergence in the 1990s, InGaAs-based SWIR technology has steadily improved through advances in detector performance, room-temperature operation, and machine-vision integration, helping expand its use despite its premium cost.

"SWIR stayed expensive because it was shut out of the silicon manufacturing that visible imaging relied on," Lau says. "Over the past 30 years, it has steadily worked its way toward that manufacturing base that over the next 30 will further be driven by AI's demand for richer data, turning SWIR from a specialized, costly tool into something far more affordable and widely used."Schramm notes that advances in imaging have brought one of the most significant changes in automated inspection in the past 30 years.

"SWIR stayed expensive because it was shut out of the silicon manufacturing that visible imaging relied on."

"Beyond the obvious benefits of increased resolution and speed of acquisition, one of the most significant changes has been the development of vision utilized in 3D profiling applications," Schramm says. "There have been multiple technologies that have been developed to help do 3D scanning, such as variations of triangulation via stereo vision, structured light, time of flight scanners (and) LiDAR."

Wilton notes that inspection has evolved to become a source of manufacturing knowledge.

"Modern systems retain images, link results to individual parts or batches, monitor variation and identify process drift," Wilton says. "Rule-based vision remains highly effective for clearly defined tasks, while AI extends what can be automated where defects vary in shape, texture or appearance. It also helps classify defects and reveal patterns across production data that individual inspection results would otherwise miss."

Wilton also notes that machine vision has also moved into metrology.

"Better optics, higher-resolution sensors, structured light, laser profiling and 3D cameras now allow dimensional and surface measurements to be made automatically within inline processes," Wilton says. "Manufacturers can measure more parts, more often, and see variation as it develops."

What about AI?

Dechow notes that AI had been around for a few decades by 1996 but had very little impact on automated imaging.

"Perhaps most visibly, AI became a prominent part of the landscape around 2014 with the development of the technique

Vision system David Dechow worked on in the 1990s.
David Dechow

called deep learning with convolutional neural networks," he says. But by 1996, the only broadly successful use of AI in inspection he recalls had already happened in the 1980s with the development of imaging systems that could read handwritten characters.

Merva says he does remember Acuity Imaging releasing its Mentor product around that time.

"As far as I know, this was the first product to utilize neural networks, the predecessor to AI," he says. "Mentor had a couple of weaknesses but nevertheless ushered in the technology for detecting vaguely described rejects."

One area that has also evolved over time for machine vision, especially in inspection systems, is lighting. Merva said that in 1996, he was general manager of RVSI, which had acquired Northeast Robotics, and was one of two companies providing LED lighting in machine vision applications at the time.

"All lights were red because red LEDs were practically the only ones available," Merva says. "It turned out that red worked really well with the camera sensors response of that time. Lighting geometry was a unique feature offered only by NER. DOALs and Cloudy Day illumination (diffuse lighting techniques) solved applications that were previously not doable. We created the first illumination for machine vision training to help our distributors properly recommend products and help customers understand why illumination geometry mattered."

What Is the Future of Machine Vision?

The general consensus seems to be that machine vision is, for the most part, evolving largely as expected.

"The industry is following a traditional evolutionary path for technology—proprietary products evolve to products adhering to standards," Lee says. "Increased usage drives lower pricing. Increased technology development will yield higher resolutions, higher light sensitivities, and smaller SWAP-size, weight and lower power consumption."

Brennan says that over the next one-to-three decades, he expects to see, "a lot of the current hardware commoditizing and more solutions-oriented companies ascending." Nonetheless, he also says he sees opportunities in hardware.

"For instance, there are huge opportunities to re-invent the flat sensor, traditional lens, traditional frame/exposure concept," Brennan says. "The Lytro was before its time, but I see a need for a versatile image- anything-at-any-depth sensor. I think you'll also see a more fragmented market of purpose built devices from commodity hardware."

Lee notes that until recently, hardware development has seen the most frequent changes over the past 30 years.

"Software, which has been required for implementation of a machine vision solution, has been slower to evolve," he says. "However, the advent of AI has dramatically changed that. I believe AI adoption for pattern recognition, analysis and action will be the primary driver for next generation machine vision solutions for at least the next decade."

Nonetheless, Lee says he believes the continued lowering of costs and SWAP of hardware and the adoption of AI will create more use of swarms of imagers.

Schramm pointed out that the addition of AI and increased computing power will advance development of increasingly better real time 3D measurement systems.

"The intelligence and decision-making ability of the vision systems will, of course, grow alongside the sensor technology resulting in systems that can be trained with much higher-level input than is used today. The systems will be able to continuously improve themselves by 'on-the-job training' as they are able to make use of more data," Schramm says.

Lau says that in the case of SWIR/non-visible imaging, market demand may be an important driver, but AI will be the accelerant. SWIR imaging remains more expensive than visible-light imaging, but its unique capabilities *continued on page 33*

Practical Machine Vision: Leveraging Machine Learning Tools

This article explores how traditional machine learning techniques can enhance industrial machine vision systems, emphasizing practical implementation, algorithm selection, and workflow considerations for improved inspection performance.

BY DAVID L. DECHOW

Practical and effective machine learning tools for machine vision are widely available, even to engineers who are not data scientists. Machine learning has been integral to machine vision for many years, and its role extends well beyond deep learning. If you work in industrial machine vision, you may already be using machine learning tools that aren't explicitly identified as such. This article looks at what machine learning means in a machine vision context and where it can most effectively improve inspection performance and system capability.

In this example, a GMM-based model is used for simple fruit classification. The selected features are object circularity and area, though additional features such as color could be added to improve robustness. The key point is that the classifier can be trained and tuned with relatively little manual effort, making it a practical option for straightforward sorting or inspection tasks. *Images and test algorithms copyright MVTec*

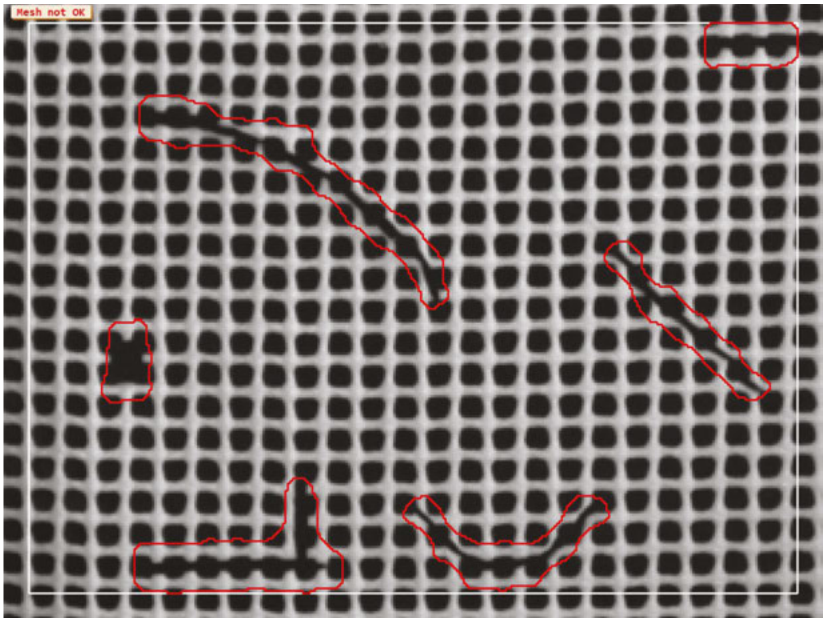
ML and large-scale data analysis are central to the productivity and flexibility goals associated with smart factories, smart manufacturing, and Industry 4.0. This discussion, however, focuses specifically on the practical use of machine learning for machine vision inspection in industrial automation applications.

What Is Machine Learning and How Is It Used for Machine Vision?

At a basic level, machine learning (ML) is a branch of artificial intelligence (AI) and is closely related to data science. In practice, what matters for machine vision is that ML allows systems to learn classification or prediction behavior from data instead of relying entirely on hard-coded rules.

Deep learning is a well-known subset of machine learning and one of the most frequently discussed ML techniques. Here, however, the focus is on traditional machine learning: algorithms that learn and operate without the advanced multilayer neural networks used in deep learning.

Traditional machine learning uses statistical algorithms to build models that analyze data and generate predictions or classifications without requiring every relevant characteristic to be explicitly programmed. Data scientists research, refine, and tune these algorithms, while machine vision engineers select, train, and deploy them for specific applications. Although deep learning may be the most familiar and widely adopted ML approach, traditional ML algorithms remain well suited to many machine vision tasks and, in some cases, can outperform deep learning in efficiency or practicality. Let's start with a high-level overview of machine learning.



In this example, an SVM classifier is trained on feature vectors derived from images to detect random defects. Here, the nominal mesh pattern shows some variation, but consistent texture information can still be extracted from acceptable images using specific convolution operations. Anomalies that fall outside the trained texture distribution are then classified by the SVM as defects. For industrial users, one advantage is speed: this type of statistical analysis is typically very fast, often taking only a few milliseconds. *Images and test algorithms copyright MVTec*

Machine learning algorithms are commonly grouped by how they are trained and how they use data. The primary categories are:

- **Supervised learning:** learns from labeled data.
- **Unsupervised learning:** identifies patterns and groupings in unlabeled data.
- **Reinforcement learning:** learns by interacting with changing inputs and outcomes.

A fourth category, *semi-supervised learning*, is sometimes included. In addition, some algorithms, including deep learning methods and certain regression techniques, can span more than one category. All of these categories are important, but machine learning tools used in machine vision and image analysis most often rely on supervised learning which will be the main focus here.

Supervised learning algorithms most commonly perform one of two tasks: classification or regression. Classification predicts discrete labels for input data, as in object identification or defect detection from trained images. Regression is used when the output is continuous or variable, for example when estimating the remaining operating life of a mechanical component from machine data. As the name implies, supervised learning algorithms use labeled training data to learn mappings from inputs to outputs by comparing predictions against known results. The resulting learned representation, or model, is then used to make predictions on new data and can be refined over time.

The range of machine learning algorithms continues to expand. A comprehensive treatment of these methods and their implementation is beyond the scope of this article; however, the following examples are representative of techniques encountered in practical machine vision applications. Some widely used ML data-analysis tools are not especially well suited to image or feature classification and are therefore omitted here, although they may remain appropriate in selected cases.

Linear, logistic, and polynomial regression—These methods fit linear or polynomial functions to a dataset for prediction or classification. Logistic regression can support relatively simple classification tasks and may be used in limited image-classification scenarios.

Support vector machines (SVM)—SVMs classify data that are not linearly separable by projecting them into higher-dimensional feature spaces. They are well suited to feature classification, image classification, and OCR.

Decision trees—This method classifies data using rules learned from training data and organized in a tree structure with multiple binary decision nodes. It is useful for relatively simple classification problems.

k-nearest neighbors (k-NN)—This straightforward classifier stores features and class labels from the training set, then classifies new data based on the nearest examples using selected distance metrics. In some segmentation contexts it is treated as supervised learning, but related techniques can also be used for unsupervised clustering. k-NN is often effective for general feature classification and OCR.

Gaussian mixture models (GMM)—Also referred to in some contexts as Bayesian classifiers, GMMs can be used in supervised or unsupervised settings and support clustering applications similar to those associated with k-NN. They are effective in some segmentation tasks and can also be useful for texture analysis and anomaly detection, although they may be limited by the number and quality of available features.

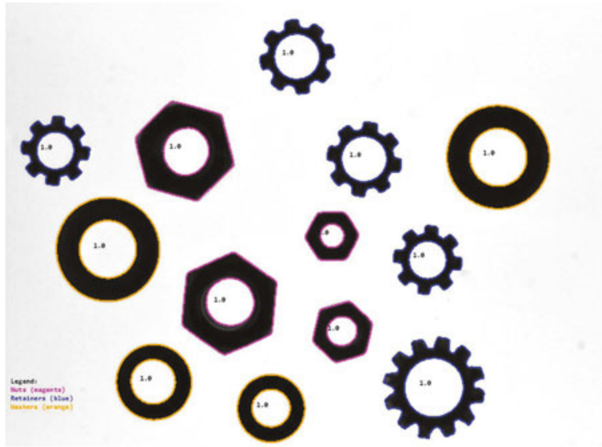
Multilayer perceptrons (MLP)—MLPs are relatively simple artificial neural networks that are related to, but distinct from, deep learning architectures such as convolutional neural networks (CNNs). They typically use one to three hidden layers. MLPs perform well on data that are difficult to separate linearly and are generally leaner and easier to deploy than deep learning models, although they are less powerful for highly complex tasks.

Are you already using traditional machine learning without calling it that? In some cases, perhaps yes. For example, one could make a reasonable case that pattern matching, one of the most widely used machine vision tools, exhibits machine-learning-like behavior because it is trained from input data and used to classify image features. Likewise, simple regressions and convolution-based operations in other machine vision algorithms are closely related to ML concepts.

Traditional Machine Learning and Deep Learning

A natural question is whether deep learning should be used for every machine vision application. Generally, the answer is no: machine vision tasks are often well constrained and well defined, so identifying the relevant features with basic algorithms does not justify the added complexity or computational cost of deep learning.

Traditional machine learning methods for automated imaging generally require less training data and substantially less processing power than deep learning. Many ML tools can be trained in seconds or minutes. Their outputs are also typically easier to characterize, analyze, and debug, whereas deep learning results are often difficult to interpret directly. In addition, commercial machine vision libraries and open-source packages such as OpenCV and scikit-learn provide a wide range of ML tools that can often be deployed without cloud



This example shows classification of simple objects using a k-NN classifier. By evaluating multiple geometric data points associated with the parts, the system can be trained and deployed without exhaustive rules-based programming. In this case, execution is more efficient than either pattern matching or deep learning, which highlights where traditional ML can offer a practical middle ground. *Images and test algorithms copyright MVTec*

infrastructure or subscription-based services. The tradeoff is that traditional ML usually requires more manual feature engineering, more direct involvement during training and retraining, and more structured input data than deep learning.

Deep learning is most effective in applications that are highly complex, nonlinear, or subjective. As a result, its computing and processing requirements are typically higher. Training DL models generally requires larger image datasets, but often less manual engineering than traditional ML. Continuous learning and retraining are possible, although they still may require human oversight and time. In some deployments, both training and inference are performed using cloud-based resources.

In practice, traditional machine learning is often the stronger choice when classification or segmentation problems are well defined, constrained, and characterized by features with limited variability, as is common in many machine vision applications. Deep learning is generally the preferred approach when detection or segmentation is highly complex, ambiguous, or strongly dependent on context.

A Practical Workflow for Implementation

The general workflow for implementing machine learning is straightforward and maps well to many machine vision tasks:

- Collect images that represent the features of interest, reserving separate sets for training and testing.

- Select an appropriate algorithm, recognizing that multiple candidates may need to be evaluated.
- Train the model using input data prepared in the form required by the selected algorithm.
- Evaluate performance, retrain as needed, and deploy.

One part of this process may be less familiar: prepared input data. Unlike many conventional machine vision tools, and unlike most deep learning methods, some ML algorithms do not work directly on raw image data. Instead, they use structured numerical inputs, often called feature vectors. These features describe the objects to be classified or segmented. For these algorithms, feature selection matters: the input data must be chosen carefully so the model can reliably distinguish among classes. Useful features may include geometric descriptors, texture measures, grayscale values, or color information. The same type of feature data used for training is then used during inference.

That leads to another practical question: why not simply program rules that check each part for the characteristics that identify it? In some cases, that is the right approach. But machine learning becomes valuable when many features are needed to separate several possible classes, especially when variation within those classes overlaps. In those situations, a reliable rules-based algorithm can be difficult to design, validate, and maintain. Adding a new class may also require significant rework.

> Deep learning is most effective in applications that are highly complex, nonlinear, or subjective.

Once trained, machine learning algorithms can classify complex input data automatically and can be retrained as new objects or operating conditions are introduced, subject to the limits of the selected method. To be clear, some ML algorithms are trained directly on image data. In those cases, only segmented and/or labeled images or features are required for training.

David L. Dechow is a VSD contributing editor and editorial advisory member. He is an engineer, programmer, and technologist widely recognized as an expert and thought leader in integration of machine vision and rleated technologies. Dechow is principal vision systems engineer for the Arthur G. Russell Company.

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ETH Zurich Develops Dual-Function Pixel for Advanced Imaging

This technology can allow control over light's intensity, phase, and polarization, opening new possibilities for high-information-content imaging applications.

BY JIM TATUM

136499475 | Subbotina | Dreamstime.com

Researchers at ETH Zurich (Zurich, Switzerland) have developed a pixel that can create and analyze images simultaneously.

Pixels, the basic building blocks of imaging, have traditionally been able to either control light to display an image, such as in a television screen or computer monitor, or analyze light to form an image, such as in a camera sensor.

The team, led by David Norris, a professor at ETH Zurich's Optical Materials Engineering Laboratory, published their peer reviewed findings in the scientific journal "Nature" and recently announced the development in an ETH Zurich press release. While the research is still in the early stages, the team has introduced capabilities that were not previously possible, Norris said.

"We can generate and sense light with full control over the light's intensity, phase, and polarization," he said. "In particular, we have made individual pixels. One of the next steps is to try to make arrays of such pixels."

The team's results are based on a fundamental physical effect known as the interference of light waves, which refers to how light waves originating from different points on a surface overlap when that surface scatters light. The shape of that surface determines oscillation phases. If those phases are equal, the light waves reinforce each other. If they are opposed, the waves cancel out.

According to the press release, Norris and his team used this effect to precisely control light with wave-shaped sculpted surfaces. For steering, the pixel—that is, the area on the chip where the material has been processed—first transforms the incoming light into a surface wave propagating along the surface of the chip. At a different point within the pixel, the surface wave is scattered back out of the material as a light wave. Through interference of the light waves, patterns and images can be created. Using mathematical Fourier analysis, the researchers can calculate what these images will look like and what kind of surface pattern is needed for a specific image.

> "We can generate and sense light with full control over the light's intensity, phase, and polarization."

"This pixel can help detect and generate light with much higher information content," Norris said. "It can potentially image using intensity contrast, phase contrast, and polarization contrast."

The team's research is still in early stages, which means they have not yet determined for what applications the technology might ultimately be useful. However, Norris said he believes it could benefit a number of imaging applications.

"If collecting or generating light with much higher information content is important, there is no other way to do it," Norris said.

Rethinking Weed Control in Modern Agriculture

Combining machine vision and adaptive manipulators, AgriPass's autonomous platform offers scalable, efficient weed management tailored for small to medium farms, promoting environmental health.

BY SHARON SPIELMAN

Weed control remains a persistent challenge in agriculture, directly impacting crop yields and global food security. Traditional approaches—widespread herbicide use, intensive soil tillage, and manual labor—are increasingly unsustainable. Herbicides contribute to resistance and environmental toxicity, tillage accelerates soil erosion, and labor shortages limit the viability of manual weeding.

AgriPass addresses these limitations with an autonomous robotic solution built on adaptive, AI-driven machine vision. The AgriPass RHIC (robot of human-inspired cultivation) AI weeding system is designed to replicate human weeding precision while enabling scalable, consistent operation in the field.

Human-Inspired Cultivation, Mechanized

AgriPass is grounded in the concept of "human-inspired cultivation." As CEO Liron Yanay told *Vision Systems Design*, the system performs "a simple mechanical action, just like hand hoeing by a crew," but with automation and speed.

The robotic platform uses multiple independent manipulators, or "hands," each capable of making discrete, real-time weeding decisions. Operating with precision comparable to human workers,

AgriPass's RHIC, robot of human-inspired cultivation, AI weeding machine is seen being demonstrated in a field in Central Valley, Calif.
Images courtesy of AgriPass

these manipulators exceed manual labor in both speed and consistency.

Vision-Guided Decision Intelligence

At the heart of the system is its machine vision architecture. Cameras mounted approximately 60 cm above the soil capture a continuous video stream of the field. The system relies on off-the-shelf cameras that are integrated and optimized for reliable operation in challenging outdoor conditions, Yanay said.

This visual data feeds AI models that perform detailed semantic analysis—not just distinguishing crops from weeds but also identifying specific weed types. This level of classification is critical, as different weed morphologies require different removal strategies. As Yanay noted, “Some have wide leaves, and you need to cut them differently.”

The image stream is processed by an onboard edge computing system capable of real-time inference. This allows the platform to make immediate decisions: whether a robotic hand should engage, how deep it should cultivate, or when it should avoid disturbing a nearby crop.

Maintaining crop integrity is a core requirement. The system achieves less than 3% crop disturbance by combining precise segmentation with adaptive control logic. As Yanay described, the robot can “decide to skip a crop...or clean around it.” Each manipulator operates independently, Yanay said, “really like managing a crew on one solution.”

Data, Mechanics, and Field Performance

Building robust AI models required extensive and diverse field data. AgriPass collected training datasets from multiple regions, including California, Ohio, Florida, Italy, and Israel, capturing a wide range of soil types—from sandy to heavily compacted.

This geographic and seasonal diversity enables the models to generalize effectively across environments. “Since December 2024, we were constantly in the field... and insisted on multi-state operation,” Yanay said, stressing the importance of varied data in achieving reliable performance.

The robotic manipulators translate machine vision insights into physical action. After evaluating multiple designs, the team selected a “T1” hoe shape that balances effective weed removal with minimal soil disruption.

The manipulators are engineered for speed and adaptability across varying soil conditions. Encased for durability, they maintain performance even when encountering differences in soil density, enabling consistent operation in real-world environments.

Liron Yanay, CEO of AgriPass, has rapidly advanced the RHIC, robot of human-inspired cultivation, AI weeding machine from prototype to field operations and commercial momentum.

Accessibility was a key design consideration. The system is built to serve small- and medium-sized farms, which often face barriers to adopting advanced agricultural technologies.

To accelerate deployment, the platform is currently diesel-powered and self-propelled. This decision prioritizes the core weeding technology, with the option to transition to alternative power systems in the future.

Sustainability, Programmability, and Operator Control

Results from the privately held industrial group FYELD trials show the system achieves approximately 80% to 85% weed removal without herbicides, while reducing soil disturbance by 70% to 80%.

These improvements extend beyond weed control. Reduced soil disruption helps retain moisture, preserve soil biology, and minimize carbon release. As Yanay

Building robust AI models required extensive and diverse field data. AgriPass collected training datasets from multiple regions, including this regenerative farm in Florida.

explained, “Less disruption in the soil means we release less carbon, keep more moisture, and preserve the biome—the worms and soil life.” These factors contribute to up to 20% improved water retention and increased resilience to climate variability.

The system is designed for dynamic, field-level programmability. Farmers can adjust parameters in real time, including how closely the system operates around crops or the tolerance for specific weed types.

“A farmer can say, ‘I want you to go closer to the crop,’ or ‘keep 1-2 cm away,’ or ‘don’t come close at all,’” Yanay explained. This flexibility allows operators to tailor performance to specific crops, field conditions, and management strategies.

Balancing Performance and Compute Constraints

A key engineering challenge was balancing the computational demands of real-time vision processing with the constraints of field deployment. Development evolved from laptop-based systems to more advanced embedded computing as hardware matured.

This approach leverages edge computing to continuously refine the balance between model complexity, latency, and power consumption—ensuring the system remains both high-performing and practical for in-field use.

Scaling the Platform, Designing for Real-World Use

AgriPass continues to refine its technology, with plans to scale the platform for larger agricultural operations by 2027. This expansion will involve replicating the modular vision-guided architecture across wider beds while preserving its selective, adaptive capabilities.

The company is also exploring the extension of its machine vision and AI platform into adjacent agricultural applications beyond weed control.

Yanay emphasized the importance of close collaboration with end users during development. “Try to really get into the world of your client,” she advised, noting that long-term partnerships with design collaborators were critical to success.

Continuous field validation and user-centric design ensure the technology aligns with the realities of agricultural environments—where variability, durability, and usability are essential to adoption.

Vision Language Models (VLMs) Explained

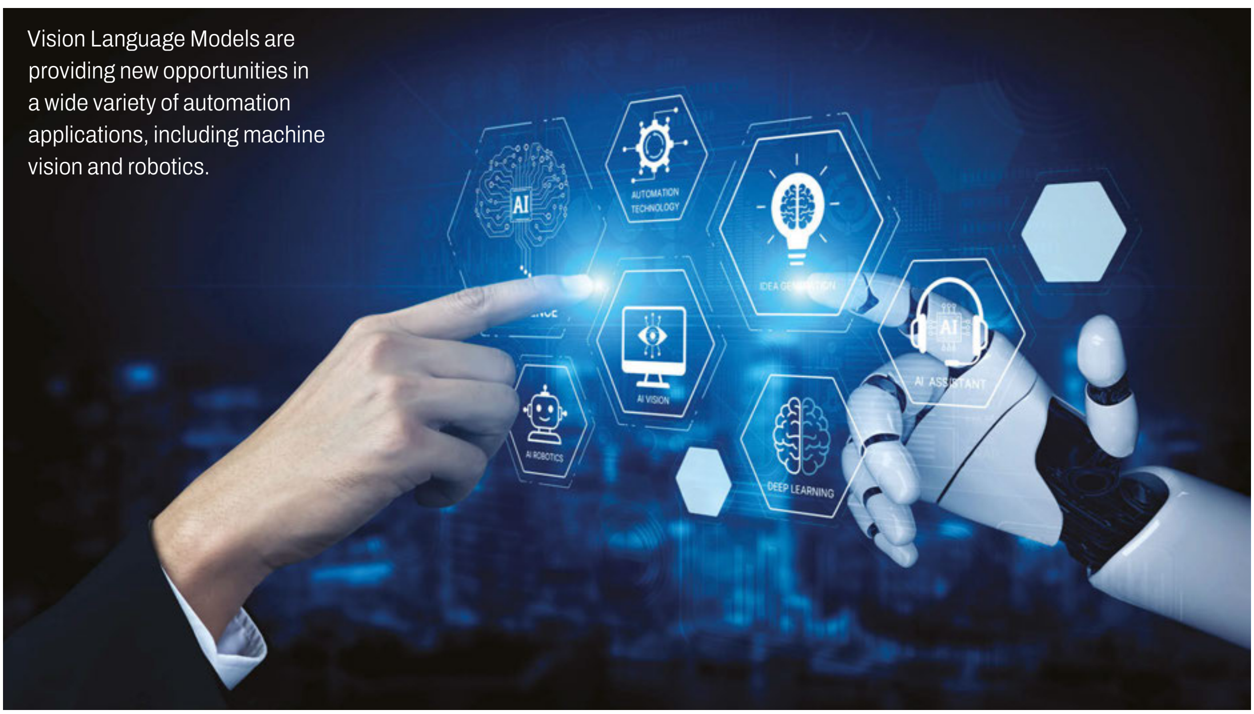
From real-time operator guidance to autonomous inspection, VLMs can advance factory floor automation.

BY JIM TATUM

Robots that can actually think and make decisions? Inspection systems that not only know what's wrong, but why? These are but a couple of applications possible with vision language model (VLM) technology, says Dijam Panigrahi. co-founder/COO of GridRaster (Mountain View, CA, USA), a company that specializes in spatial AI and extended reality. VLM, a next-generation AI technology that combines visual data and natural language to analyze and understand visual scenes, reason, and make decisions, is starting to gain traction in manufacturing technologies, such as machine vision and robotics. In fact, VLMs are already successfully operating in manufacturing settings such as factory floors, enabling robots to go beyond a programmed repetitive task and instead actually look at a complex manufactured component, reason about what they see against learned expert behavior and documented standards, and make quality decisions autonomously. Nonetheless, while the technology shows great promise, there is an initial reluctance to adopt VLM technology, says Panigrahi. "When anything new comes along, I think we as humans are just resistant to change," Panigrahi says. "I see this (VLM) as a tool, basically. People who are able to utilize this tool will be more effective, and in the long run, I think they would be the most desired workers or operators employers will seek."

What Is a VLM and How Does It Work?

A VLM is a type of artificial intelligence model that processes both visual data and natural language, learning a shared representation of a given scene that allows the system to reason across both modalities at once, Panigrahi says. Because the real world is multimodal,



Vision Language Models are providing new opportunities in a wide variety of automation applications, including machine vision and robotics.

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VLMs are multimodal by design—combining vision, text, and contextual cues the way humans do to understand environments and act within them. "VLMs are your whole understanding with the eyes, right?" Panigrahi says A VLM is trained so that images and text are aligned within the same scene to enable the model to answer questions about images, follow visual instructions, generate descriptions, and perform reasoning grounded in visual evidence, Panigrahi says. Data sources for training VLMs can include real sensor data, such as data that comes from cameras, synthetic data from digital twins, and edge-case and failure scenarios. The VLM is not a replacement for legacy machine vision, but rather an augmentation of it, Panigrahi says. For example, a legacy vision system automated inspection application may be designed to determine whether a weld is faulty, or a drilled hole is the correct prescribed size for a product, while a VLM is designed to be able to analyze that information and produce advice as to why the weld might be faulty or the hole is the wrong size—because it has been trained with information defined with prompts and context. In other words, the VLM learns how a human describes and interprets what they see. "You feed all the instructions to the VLM, give it the visual cue of the expert doing that job or doing the repair, assembly, installation, deinstallation, whatever the task you're doing is," Panigrahi says. "The model now completely understands what it should be." VLMs not only add an interpretive facet to a legacy machine vision system but can help a human employee operate at a higher level of job competence, even if the employee has limited experience working that job, Panigrahi says. "Now, somebody who is doing, say, assembly work in real time can get active task guidance that says, okay, do this," he says. And, if the operator does make a mistake, the VLM can flag that mistake and provide instructions/information as to how to fix the mistake and perform the action correctly. "If you have that expert knowledge in the VLM, it provides you a medium that anyone of almost any skill set—maybe they are just one year into it, doesn't matter—they can access that expert knowledge on the go, right? That's the beauty of it; it's almost like it converts everybody into an expert."

Addressing VLM Challenges

While VLMs are becoming more scalable as technology advances and costs decrease, there are still challenges to address, Panigrahi says. For one, VLMs require huge amounts of data, and that data often needs to be specific to the given working environment. For example, GridRaster does work for such entities as the U.S. Air Force and the U.S. Dept. of Defense. "A lot of these environments are very unique—it's not like the VLMs that are available have been trained in those kinds of environments," Panigrahi says. "So, the challenge is how do you train for that specific domain?" Because real-world data, especially in those environments, can be limited, synthetic data generated from real-world data via a digital twin can be utilized to train the VLM, he says. Hand in hand with the challenge of acquiring the data to train the VLM is the challenge of providing enough computer power to handle that data quickly and accurately, without generating false positives or creating latency. In order to run, VLMs need huge computing power to give accurate results. "How much (power) does one model consume? And how do you do that in an industrial setting? How do you put that kind of computer power in those settings?" Fortunately, computer technology is advancing, he says, noting examples such as NVIDIA's DGX Spark, a desktop-sized computer designed for building, tweaking, and operating large AI models locally, then easily move them to a data center or the cloud.

CAMERA MANUFACTURERS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
A&B Software New London, CT, US; 860-823-8301; http://www.ab-soft.com; sales@ab-soft.com								
GigESim GigE Vision simulator	—	C+M	—	≤200 Mpixels	—	Ethernet, GigE, Dual GigE, 5 GigE, 10 GigE, 25GigE, 100 GigE	—	≤100,000
Active Silicon Ltd. Langley, UK; 44-1753-650600; www.activesilicon.com; sales@activesilicon.com								
Harrier 10x AF-Zoom Camera	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, 3G/HD-SDI, USB/HDMI, HDMI, IP H.264	60	—
Harrier 10x AF-Zoom Camera Global Shutter	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, USB/HDMI, IP H.264	60	—
Harrier 30x AF-Zoom Camera Global Shutter	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, USB/HDMI, IP H.264	30, 60	—
Harrier 40x AF-Zoom Camera	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, 3G/HD-SDI, USB/HDMI, HDMI, IP H.264	60	—
Harrier 55x AF-Zoom Camera	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, 3G/HD-SDI, USB/HDMI, HDMI, IP H.264	30	—
Alkeria Srl Cascina, (PI), Italy; 39-050-778-060; www.alkeria.com; sales@alkeria.com								
CELERA One	CMOS	C+M	Area array	2–12 MPixels	NIR, VIS	USB3	175	—
NOTA	CMOS	C+M	Area array	2–12 MPixels	VIS	USB3	161	—
CELERA P	CMOS	M	Area array	5-12 MPixels	VIS	Dual-USB3	154	—
NECTA	CMOS	C+M	Line scan	2–8K	VIS	USB3	—	95 kHz
NECTA X	CMOS	C+M	Line scan	4–16K	VIS	USB3.1 Gen2	—	95 kHz
Allied Vision Technologies GmbH Stadtroda, Germany; 49-36428-677-0; www.alliedvision.com; info@alliedvision.com								
Alvium USB3 and CSI-2	CMOS, InGaAs	C+M	Area array	0.3–24.6 MPixels	NIR, UV, VIS, VSWIR	USB3, MIPI CSI-2	≤691	—
Mako	CCD & CMOS Versions	C+M	Area array	0.3–12.4 MPixels	NIR, VIS	GigE	≤286	—
Manta	CCD & CMOS Versions	C+M	Area array	0.3–24.6 MPixels	NIR, VIS	GigE	≤286	—
Prosilica GT	CCD & CMOS Versions	C+M	Area array	1.2–31.4 MPixels	NIR, VIS	GigE	≤53.7	—
Goldeye	InGaAs	M	—	0.1–1.3 MPixels	SWIR, VSWIR, XSWIR	Camera Link, GigE	≤344	—
Alta Vision Systems LLC Westbrook, CT, US; 860-604-5808; https://www.altavisionsystems.com; info@altavisionsystems.com								
Cognex 3900 series	CMOS	C+M	Area array	1.6–25 MP (MegaPixel)	IR, UV	Ethernet	21–125	—
Cognex 8900 Insight Series	CMOS	C+M	Area array	0.5–5 MP (Mega Pixel)	IR, UV	Ethernet	21–142	—
Basler AG Ahrensburg, Germany; 49-4102-463-500; www.baslerweb.com; sales.europe@baslerweb.com								
Basler ace 2	CMOS	C+M	Area array	640 × 512–5328 × 4608	SWIR, VIS, UV	GigE, 5GigE, USB3, CXP-12	≤240	—
Basler racer 2	CMOS	C+M	Line scan	—	VIS	GigE, 5GigE, CXP-12	—	≤240 kHz
Basler dart	CMOS	C+M	Area array	720 × 540–4208 × 3120	VIS	GigE, USB3, BCON for MIPI	≤523	—
Basler boost	CMOS	C+M	Area array	1936 × 1464–13376 × 9528	VIS	CXP-12	≤400	—
Basler ToF Camera	CMOS	M	Area array	640 × 480	NIR	GigE	30	—
Baumer Optronic GmbH Radeberg, Germany; 49-3528-4386-0; www.baumer.com/vision; sales.cc-vt@baumer.com								
CX/CX.I cameras	CMOS	C+M	Area array	720 × 540–5312 × 4592	POL, SWIR, UV, VIS	GigE, 5 GigE, USB3, Digital I/O, power outputs	≤318	—
CX.XC cameras	CMOS	C+M	Area array	656 × 520–5312 × 4600	SWIR, VIS	GigE, USB3, Digital I/O	≤237	—

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
Baumer Optronic GmbH Radeberg, Germany; 49-3528-4386-0; www.baumer.com/vision; sales.cc-vt@baumer.com								
LX series	CMOS	C+M	Area array	800 × 608–9344 × 7000	NIR, UV, VIS	10GigE, 25 GigE, Dual GigE, GigE, Camera Link, Digital I/O, power outputs	≤1622	—
IX series	CMOS	C+M	Area array	1280 × 800	VIS	GigE, Digital I/O	≤50	—
QX series	CMOS	M	Area array	5328 × 4608	VIS	50GigE, Digital I/O, power outputs	≤101	—
Canon Medical Components USA Inc. Irvine, CA, USA; 810-357-5022; https://mcu.canon/vsd; vsd-sales@mcu.canon								
SV-2000 Video Borescope Tablet Console or CCU	CMOS	C	Area array	400 × 400, 720 × 720	VIS	HDMI, USB 3.0	—	30 Hz
JCS-HR5U One-piece 1080p with USB	CMOS	C	Area array	1920 × 1080	VIS	HDMI, USB 3.0	—	59.94 Hz
IK-HD5UM 3CMOS, 1080p 2-Piece Remote Head	CMOS	C+M	Area array	1920 × 1080	NIR, VIS	3G-SDI, DVI, USB 3.0, RS-232	—	50, 59.94 Hz
Ultra HD IK-4K, 3-Chip Ultra HD 4K Video Camera (2-Piece Remote Head)	CMOS	C	Area array	3840 × 2160, 1920 × 1080	VIS	4- 3G-SDI, RS-232	—	59.94 Hz
JCT-TF5G/7G	CMOS	C	Area array	728 × 544, 1456 × 1088	VIS	Camera Link, PoCL	—	59.4 MHz
CMICRO Corp. Takamatsu, Kagawa, Japan; 81-87-869-8310; www.cmicro.co.jp/en; support@cmicro.co.jp								
RSB400H	CMOS	C	Line scan	4096 × 3	VIS	Camera Link, CoaXPress	—	21.4 kHz
FXS800A	CMOS	M	Line scan	8192	VIS	CoaXPress	—	72.4 kHz
NDB100H	InGaAs	M	Line scan	1024 × 2	SWIR	Camera Link, GigE	—	40 kHz
NHA200H	InGaAs	M	Line scan	2048	SWIR	Camera Link	—	40 kHz
HMM16KP-X9	CMOS	C+M	Line scan	16384 × 4	VIS, NIR	CoaXPress	—	61 kHz
Cubert GmbH Ulm, Germany; 49-177-788636-9; https://cubert-hyperspectral.com/en; sales@cubert-gmbh.de								
ULTRIS X20	CMOS	C	Area array	410 × 410	Hyperspectral, NIR, VIS, UV	GigE	8	—
ULTRIS X20 Plus	CMOS	C+M	Area array	1886 × 1886	Hyperspectral, NIR, VIS, UV	Dual GigE	4	—
ULTRIS 5	CMOS	C	Area array	290 × 275	Hyperspectral, NIR, VIS	GigE	45	—
ULTRIS SWIR 1	InGaAs	C	Area array	200 × 200	Hyperspectral, SWIR	USB3	80	—
ULTRIS XMR	CMOS	C	Area array	1000 × 1000	Hyperspectral, NIR, VIS	USB3	17	—
Cognex Natick, MA, USA; 508-650-3000; www.cognex.com; news@cognex.com								
In-Sight 3800 Vision System	CMOS	C+M	Area array	≤5MP (2448 × 2048)	VIS	Ethernet	200	—
In-Sight 2800 Vision System	CMOS	C+M	Area array	≤2MP (1920 × 1080)	VIS	Ethernet	—	≤45 Hz
Emergent Vision Technologies Inc. Port Coquitlam, BC, Canada; 866-780-6082; www.emergentvisiontec.com; sales@emergentvisiontec.com								
EROS 10GigE	CMOS	C+M	Area array	0.33–24.5 MP	VIS, SWIR, UV	10GigE	30–711	—
BOLT 25GigE	CMOS	C+M	Area array	0.5–127.4 MP	VIS, NIR, UV	25GigE	17–1594	—
ZENITH 100GigE	CMOS	C+M	Area array	2.5–152 MP	VIS	100GigE	14–3462	—
PACE 10GigE	CMOS	C+M	Line array	4K × 2, 8K × 4, 8K × 16, 16K × 2, 16K × 16, 9K 256 TDI	VIS	10GigE	—	70–172 kHz (single line), 23–57 kHz (tri-rate)
ACCEL 25GigE	CMOS	C+M	Line array	8K × 4, 8K × 16, 9K 256 TDI, 16K × 2, 16K × 16	VIS	25GigE	—	120–304 kH (single line), 60–100 kHz (tri-rate)

CAMERA MANUFACTURERS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
e-con Systems Fremont, CA, USA; 408-766-7503; www.e-consystems.com; camerasolutions@e-consystems.comw								
e-CAM85_CUHSB	CMOS	C	—	—	VIS	GigE	60	—
RouteCAM_CU86	CMOS	C	—	—	VIS	GigE	30	—
STURDeCAM88_ CUOAGX	CMOS	C	—	—	VIS	GMSL2	30	—
See3CAM_37CUGM	CMOS	C	—	—	VIS	USB 3.2/2.0	72	—
See3CAM_CU83	CMOS	C	—	—	VIS	USB 3.2/2.0	30	—
EPIX, Inc. Buffalo Grove, IL, 60089-6934, US; 847-465-1818; http://www.epixinc.com; acp@epixinc.com								
SV1C45/SV1M45	CMOS	C+M	Area array	1280 × 960 GLOBAL SHUTTER	VIS	LVDS	45	—
SV5C10/SV5M10	CMOS	C+M	Area array	2592 × 1944	VIS	LVDS	10	—
SV9C10	CMOS	C	Area array	3488 × 2616	VIS	LVDS	6.6	—
SV10C6/SV10M6	CMOS	C+M	Area array	3840 × 2764	VIS	LVDS	6	—
SV15C5	CMOS	C	Area array	4608 × 3288	VIS	LVDS	5	—
Exosens Leuven, Belgium; 32-16-38-99-00; https://www.exosens.com/brands/xenics; advancedimaging@exosens.com								
Manx series	InGaAs	M	Line scan	2048 × 1	SWIR	CoaXPress	256	—
Cheetah+ series	InGaAs	M	Area array	640 × 512	SWIR	CoaXPress	1700	—
Wildcat+ series	InGaAs	M	Area array	640 × 512	SWIR	Camera Link, USB3	220	—
Dione series	Microbolometer	M	Area array	320 × 240, 640 × 480, 1024 × 786, 1280 × 1024	LWIR	16bit DV/MIPI CSI-2/ USB/UVC	60	—
Crius series	Microbolometer	M	Area array	640 × 480, 1280 × 1024	LWIR	CL/SDI/DF40/MIPI CSI-2	60	—
EVK DI Kerschhaggl GmbH Raaba, Austria; 43-316-461-664, www.evk.biz; office@evk.biz								
EVK HELIOS EQ32	InGaAs	C+M	Line Scan	—	Hyperspectral	GigE	—	446 Hz (@full/248 bands)–3.8 kHz (ROI)
EVK HELIOS EC32	InGaAs	C+M	Line Scan	—	Hyperspectral	GigE	—	447 Hz (@full/248 bands)–3.8 kHz (ROI)
EVK HELIOS EC64	InGaAs	C+M	Line Scan	—	Hyperspectral	GigE	—	>700 Hz @full (248 bands)
Hamamatsu Corp. Bridgewater, NJ, USA; 908-231-0960; www.hamamatsu.com; photonics@hamamatsu.com								
High Speed InGaAs Camera (C15333-10E)	InGaAs	M	Line scan	1024 × 1	SWIR	GigE	40 klps	40 kHz
VGA InGaAs Camera (C12741-03)	InGaAs	M	Area array	320 × 256	SWIR	USB3	216	—
RGBNIR multiline Camera (C16006)	CMOS	C+M	Line scan	8192 × 4	NIR, VIS	Camera Link	20 × 4 klps	—
Compact InGaAs Camera (C15853-02)	InGaAs	M	Line scan	1024 × 1	SWIR	USB 3.1 Gen1	40 klps	15 MHz
InGaAs Camera (C16741-40U)	InGaAs	M	Area array	1280 × 1024	VIS, SWIR	USB	71.53	—
Headwall Photonics Inc. Bolton, MA, USA; 978-353-4100; www.headwallphotonics.com; sales@headwallphotonics.com								
Hyperspec SWIR 640	MCT	C+M	Line Scan	—	Hyperspectral, SWIR	CameraLink	—	—
Hyperspec MV.C VNIR	CMOS	C+M	Line Scan	—	Hyperspectral, NIR, VIS	USB 3.1	—	—
Hyperspec MV.C NIR Imaging System	InGaAs	C+M	Line scan	—	Hyperspectral, NIR	Ethernet	—	—

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Please visit www.vision-systems.com/directory for the comprehensive online company listings.

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
HySpex by NEO Oslo, Norway; 47-40-00-18-58; www.hyspex.com; hyspexsales@neo.no								
Baldur S-384N	MCT	M	Line scan	—	Hyperspectral, SWIR	Camera Link, LVDS, 5V/12V/24V TTL	650	—
Baldur S-640iN	InGaAs	M	Line scan	—	Hyperspectral, NIR, SWIR	GigE, LVDS, 5V/12V/24V TTL	500	—
Baldur V-1024N	CMOS	M	Line scan	—	Hyperspectral, NIR, VIS	Camera Link	1000	—
IDS Imaging Development Systems GmbH Obersulm, Germany; 49-7134-96196-0; www.ids-imaging.com; info@ids-imaging.com								
uEye CP camera series	CMOS	C+M	Area array	800 × 600–5328 × 4608	NIR, VIS	Digital I/O, GigE, USB3	≤410	—
uEye LE camera series	CMOS	C+M	Area array	1280 × 1024–3552 × 3552	NIR, VIS	Digital I/O, GigE, USB3	≤235	—
uEye XCP-E camera series	Event Based	M	Area array	1280 × 720	VIS	Digital I/O, USB3	>10,000	—
uEye XLS-E camera series	Event Based	M	Area array	1280 × 720	VIS	Digital I/O, USB3	>10,000	—
uEye Live camera series	CMOS	C	Area array	1920 × 1080	VIS	Digital I/O, GigE	30	—
Nion 3D Time of Flight camera	ToF	M	Area array	1280 × 960	NIR	GigE	30	—
uEye FA camera series	CMOS	C+M	Area array	800 × 600–5328 × 4608	NIR, VIS	Digital I/O, GigE	≤226	—
uEye SE camera series	CMOS	C+M	Area array	800 × 600–5328 × 4608	NIR, VIS	Digital I/O, GigE, USB3	≤739	—
uEye Warp10 camera series	CMOS	C+M	Area array	2464 × 2056–8200 × 5468	VIS	Digital I/O, GigE	≤248	—
uEye ACP camera series	CMOS	C+M	Area array	800 × 600–5336 × 3692	VIS	Digital I/O, GigE	≤409	—
uEye XC camera series	CMOS	C	Area array	4200 × 3120	VIS	USB3	30	—
uEye XCP camera series	CMOS	C+M	Area array	1936 × 1096–5136 × 3856	NIR, VIS	USB3	≤102	—
uEye XLE camera series	CMOS	C+M	Area array	1920 × 1200–5136 × 3856	NIR, VIS	USB3	≤102	—
uEye XLS camera series	CMOS	C+M	Area array	1936 × 1096–5136 × 3856	NIR, VIS	USB3	≤102	—
uEye XS camera series	CMOS	C	Area array	2592 × 1944	VIS	USB2	15	—
IDS NXT malibu/oslo AI camera series	CMOS	C	Area array	2048 × 1536–3840 × 2160	VIS	Digital I/O, GigE	30	—
IDS NXT rio/rome AI camera series	CMOS	C+M	Area array	1456 × 1088–3088 × 2076	VIS	Digital I/O, GigE	≤34	—
Ensenso C/CR 3D cam-era series	CMOS	C+M	Area array	2472 × 2064	VIS	GigE	≤10	—
Ensenso N 3D camera series	CMOS	C	Area array	1936 × 1216	NIR, VIS	GigE	≤20	—
Ensenso XR 3D camera series	CMOS	C	Area array	1456 × 1088–2448 × 2048	VIS	GigE	≤5	—
IMPERX Boca Raton, FL, USA; 561-989-0006; www.imperx.com; sales@imperx.com								
AI1-P1911 CMOS Cheetah Camera	CMOS	C	Area array	—	NIR	GigE Vision w/ PoE	—	—
P67-C1911 Cheetah Camera	CMOS	C+M	Area array	1944 × 1472	NIR	GigE Vision w/ PoE	40	—
2.86 MP CLF-C1921 CMOS Cheetah Camera	CMOS	C+M	Area array	1944 × 1472	NIR	Camera Link Full	174	—
P67-C2010 Cheetah Camera	CMOS	C+M	Area array	2064 × 1544	NIR	GigE Vision PoE	36	—
P67-C2820 Cheetah Camera	CMOS	C+M	Area array	2856 × 2848	NIR	GigE Vision PoE	14.8	—
SFP-C3240 Cheetah Camera	CMOS	C+M	Area array	3200 × 2208	NIR	10 GigE Vision fiber	152.3	—

CAMERA MANUFACTURERS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
IMPERX Boca Raton, FL, USA; 561-989-0006; www.imperx.com; sales@imperx.com								
CXP-1640 Cheetah Camera	CMOS	C+M	Area array	1632 × 1248	NIR	CoaxPress	434.2	—
SDI-C2010 Cheetah Camera	CMOS	C+M	Area array	1920 × 1080	NIR	HD-SDI	60	—
CXP-C9440 Cheetah Camera	CMOS	C+M	Area array	9344 × 7000	NIR	CoaxPress	34.7	—
SFP-C5341 Cheetah Camera	CMOS	C+M	Area array	5312 × 3040	NIR	10 GigE Vision fiber	56.6	—
CLF-C5420-T Cheetah Camera	CMOS	C+M	Area array	5472 × 3084	NIR	Camera Link Full	32	—
P67-C4510 Cheetah Camera	CMOS	C+M	Area array	4512 × 4512	NIR	GigE Vision w/ PoE	5.9	—
POE-C2410Y/Z Polarization Cheetah Camera	CMOS	C+M	Area array	2464 × 2056	NIR	GigE Vision w/ PoE	22	—
CLF-C2420Y/Z Polarization Cheetah Camera	CMOS	C+M	Area array	2464 × 2056	NIR	Camera Link Full	97	—
CLM-P0620I-T SWIR Puma Camera	CMOS	C+M	Area array	656 × 520	SWIR	Camera Link Medium	254	—
POE-P0620I SWIR Puma Camera	CMOS	C+M	Area array	656 × 520	SWIR	GigE Vision w/ PoE	137	—
CLM-P0620I SWIR Puma Camera	CMOS	C+M	Area array	656 × 520	SWIR	Camera Link Medium	254	—
CLM-P1320I-T SWIR Puma Camera	CMOS	C+M	Area array	1296 × 1032	SWIR	Camera Link Medium	132	—
POE-P1320I-T SWIR Puma Camera	CMOS	C+M	Area array	1296 × 1032	SWIR	GigE Vision w/ PoE	132	—
CLM-P1320I SWIR Puma Camera	CMOS	C+M	Area array	1296 × 1032	SWIR	Camera Link Medium	132	—
POE-P1320I SWIR Puma Camera	CMOS	C+M	Area array	1296 × 1032	SWIR	GigE Vision w/ PoE	71.4	—
CLF-P2021I-T SWIR Puma Camera	CMOS	C+M	Area array	2080 × 1544	SWIR	Camera Link Full	139	—
POE-P2021I-T SWIR Puma Camera	CMOS	C+M	Area array	2080 × 1544	SWIR	GigE Vision w/ PoE	37.4	—
CLF-P2520I-T SWIR Puma Camera	CMOS	C+M	Area array	2592 × 1544	SWIR	Camera Link Full	88	—
POE-P2520I-T SWIR Puma Camera	CMOS	C+M	Area array	2592 × 1544	SWIR	GigE Vision w/ PoE	22.5	—
Instrument Systems GmbH Munich, Germany; 49-8945-4943-0; www.instrumentsystems.com; sales@instrumentsystems.com								
LumiTop X30 AR Imaging Colorimeter	CMOS	C	Area array	31 Mpixel	VIS	CoaXPress	—	—
LumiTop X150 Imaging Colorimeter	CMOS	C	Area array	150 Mpixel	VIS	CoaXPress	—	—
LumiTop X30 Low-Luminance Imaging Colorimeter	CMOS	C	Area array	31 Mpixel	VIS	CoaXPress	—	—
LumiTop 5300 Imaging Colorimeter	CMOS	C	Area array	24 Mpixel	VIS	GigE	—	—
VTC 2400 IR Far-Field Camera	CMOS	M	Area array	5 Mpixel	IR	Ethernet	—	—
IO Industries Inc. London, ON, Canada; 519-663-9570; www.ioindustries.com; sales@ioindustries.com								
Redwood 210G230-CQ	CMOS	C+M	Area array	5120 × 4096	VIS	CoaXPress over Fiber	230	—
Redwood HS 105S112-CQ	CMOS	C+M	Area array	10,240 × 10,240	VIS	CoaXPress over Fiber	112	—
Volucam 245D60-V	CMOS	C+M	Area array	5312 × 4608	VIS	10GigE, HD-SDI	60	—
Victorem 4KSDI-Mini	CMOS	C+M	Area array	4096 × 2160	VIS	HD-SDI	60	—
8KSDI	CMOS	C+M	Area array	8192 × 4320	VIS	HD-SDI	60	—

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
iX Cameras Ltd. Woburn, MA, USA; 339-645-0778; www.ix-cameras.com; info@ix-cameras.com								
i-SPEED 511	CMOS	C+M	Area array	1920 × 1080	NIR, UV, VIS	Ethernet, GigE, HDMI, HD-SDI, Proprietary, USB3	100–1,000,000	10 GPx/s
i-SPEED 514	CMOS	C+M	Area array	1920 × 1080	NIR, UV, VIS	Ethernet, GigE, HDMI, HD-SDI, Proprietary, USB3	100–1,000,000	13 GPx/s
i-SPEED 717	CMOS	C+M	Area array	2072 × 1536	NIR, UV, VIS	Proprietary	2.45 million	17 GPx/s
i-SPEED 721	CMOS	C+M	Area array	2072 × 1536	NIR, UV, VIS	Proprietary	2.45 million	21 GPx/s
i-SPEED 727	CMOS	C+M	Area array	2072 × 1536	NIR, UV, VIS	Proprietary	2.45 million	27 GPx/s
JADAK, a Novanta Co. North Syracuse, NY, USA; 315-701-0678; www.jadaktech.com; info@jadaktech.com								
Allegro LW-AL-CMV2000	CMOS	C+M	Area array	2048 × 1024	NIR, VIS	GigE, USB3	300	—
Allegro LW-AL-CMV12000	CMOS	C+M	Area array	4096 × 3072	NIR, VIS	GigE, USB3	50	—
Allegro LW-AL-IMX172	CMOS	C+M	Area array	4000 × 3000	VIS	GigE, USB3	35	—
Mini Camera	CMOS	C+M	Area array	1280 × 800	VIS	USB2, RS-232	60	—
JAI San Jose, CA, USA; 408-383-0300; www.jai.com; camerasales.americas@jai.com								
Go-X Series	CMOS	C+M	Area array	2.3–24.5 MPixels	VIS	GigE, 5GigE, CoaXPress, USB3	4–112	—
Spark Series	CMOS	C+M	Area array	5–45 MPixels	VIS	Camera Link, Camera Link Extended, Camera Link Full, GigE, CoaXPress, USB3	9–253	—
Apex Series	CMOS	C	Area array	1.6–3.2 MPixels	VIS	Camera Link, Camera Link Extended, Camera Link Full, GigE, 5GigE, 10GigE, USB3	12–126	—
Fusion Series	CMOS	C+M	Area array	1.6–3.2 MPixels	Multispectral, NIR, VIS	GigE, 5GigE, 10GigE	107–226	—
Sweep+ Series	CMOS	C+M	Line scan	2048 × 1, 4096 × 1, 8192 × 1	Multispectral, NIR, VIS	GigE, 5GigE, 10GigE, Fiber Optic	—	16–97 kHz
KEYENCE Corp. of America Itasca, IL, USA; 888-539-3623; www.keyence.com/usa; marketing@keyence.com								
VS-C2500X	CMOS	C+M	Area array	5120 × 5120	VIS	Proprietary	—35	
VS-L1500X	CMOS	C+M	Area array	4400 × 3296	VIS	Proprietary	—44	
CA-HF6400	CMOS	C+M	Area array	8192 × 7808	VIS	Proprietary	—17.4	
CA-HL08MX	CMOS	M	Line scan	1 × 8192	VIS	Proprietary	97.7 kHz—	
XT-060	CMOS	C+M	—	3072 × 3072	VIS	Proprietary	— —	
Konica Minolta (Radiant Vision Systems) Redmond, WA, USA; 425-844-0152; www.radiantvisionsystems.com; info@radiantvs.com								
ProMetric I61 Imaging Colorimeter	CMOS	C+M	Area array	9568 × 6380	NIR, VIS	GigE, 10 GigE	— —	
ProMetric I16-G Imaging Colorimeter	CMOS	C+M	Area array	5312 × 3032	NIR, VIS	Ethernet 1000	— —	
ProMetric Y61 Imaging Photometer	CMOS	M	Area array	9568 × 6380	NIR, VIS	10 GigE	— —	
ProMetric Y16-G Imaging Photometer	CMOS	M	Area array	5312 × 3032	NIR, VIS	Ethernet 1000	—	—
LUCID Vision Labs, Inc. Burnaby, BC, Canada; www.thinklucid.com; sales@thinklucid.com								
Atlas25 - 25GigE Camera with RDMA	CMOS	C+M	Area array	≤5320 × 4600	VIS	25GigE	≤176.2	25 Gbps
Atlas10 SWIR Camera with Sony SenSWIR	SWIR	M	Area array	≤2560 × 2048	SWIR	10GigE, PoE	≤158.7	1,250 MB/s
Triton10 - 10GigE Camera with RDMA	CMOS	C+M	Area array	≤9344 × 7000	VIS	10GigE, PoE	≤205	1,250 MB/s

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LUCID Vision Labs, Inc. Burnaby, BC, Canada; www.thinklucid.com; sales@thinklucid.com								
Helios2+ Chroma RGB-D Time-of-Flight Camera	ToF	RGB-D	Area array	640 × 480	3D ToF	GigE, PoE	30	125 MB/s
Triton2 EVS Event-Based Camera	Event Based	NA	Area array	1280 × 720	Event-based	2.5GigE, PoE	NA	300 MB/s
Mega Speed Corp. Minnedosa, MB, Canada; 204-867-3767; www.megaspeedusa.com; sales@megaspeedusa.com								
Mega Speed MS180K	CMOS	C+M	Area array	4K	Vis	10 Gige	1000	—
Mega Speed MS140K	CMOS	C+M	Area array	1920 × 1080–64 × 16	VIS	GigE	35–225,000	—
Mega Speed MS130K-R	CMOS	C+M	Area array	1920 × 1080–640 × 16	VIS	GigE	2100	—
Mega Speed MAX V2	CMOS	C+M	Area array	1920 × 1080–640 × 16	VIS	GigE	2000–200,000	—
Mega Speed MAX V3	CMOS	C+M	Area array	1920 × 1080–640 × 16	VIS	GigE	3000–512,000	—
Opto Engineering Mantova, (MN), Italy; 39-0376-699111; www.opto-e.com; press@opto-e.com								
ITALA G series	CMOS	C+M	Area array	728 × 544–6480 × 4860	VIS	GigE	3.7–296.5	—
ITALA G.EL series	CMOS	C+M	Area array	1456 × 1088–5328 × 4608	VIS	GigE	4.8–74.2	—
ITALA G.SWIR series	CMOS	M	Area array	1296 × 1032	SIR, VIS	GigE	87.8	—
ITALA G.IP series	CMOS	C+M	Area array	728 × 544–5328 × 4608	VIS	GigE	4.8–296.5	—
ITALA G.EL.IP series	CMOS	C+M	Area array	1456 × 1088–5328 × 4608	VIS	GigE	4.8–74.2	—

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Pembroke Instruments, LLC San Francisco, CA 94127, US; 650-550-8618; https://pembrokeinstruments.com/swir-cameras; sales@pembrokeinstruments.com								
SenS 1920 SWIR Camera	InGaAs	—	Area array	1920 × 1080	SWIR	Camera Link, CoaXPress 2.0, Ethernet, GigE, USB3	40	—
IRSX I-640	Microbolometer	M	Area array	640 × 512	LWIR	Ethernet, GigE	30	—
Zephir 2.5e	MCT	M	Area array	640 × 512	SWIR	Camera Link, USB3	240	—
Photron USA Inc. San Diego, CA, USA; 858-684-3555; www.photron.com; image@photron.com								
FASTCAM Nova S	CMOS	C+M	Area array	1024 × 1024		10GigE, Ethernet	18,750	10-bit, 12-bit
FASTCAM Orion	CMOS	C+M	Area array	1280 × 1024		10GigE, Ethernet	31,250	12-bit
FASTCAM Mini R5-4K	CMOS	C+M	Area array	4096 × 2304		10GigE, Ethernet	1250	12-bit, 36-bit
FASTCAM MH6	CMOS	C+M	Area array	1920 × 1080		GigE, Ethernet, USB3	1000	8-bit, 24-bit
Pharsighted E9-150S	CMOS	C+M	Area array	640 × 480		10GigE, Ethernet	489,000	9-bit
PHYTEC Messtechnik GmbH Mainz, Germany; 49-6131-9221-0; www.phytec.de; contact@phytec.de								
VM-016-M	CMOS	C+M	Area array	1280 × 800	VIS	MIPI CSI-2	60	—
VM-017-L	CMOS	C+M	Area array	2592 × 1944	VIS	FPD-Link III	60	—
VM-017-M	CMOS	C+M	Area array	2592 × 1944	VIS	MIPI CSI-2	60	—
VM-020-L	CMOS	C+M	Area array	1920 × 1200	VIS	FPD-Link III	96	—
VM-020-M	CMOS	C+M	Area array	1920 × 1200	VIS	MIPI CSI-2	120	—
Pixelink Ottawa, ON, Canada; 613-247-1211; www.navitar.com/product/pixelink-cameras; sales.pixelink@ametek.com								
PL-U451SWIR	CMOS	M	Area array	1280 × 1024	SWIR	USB3	113	—
PL-U7620	CMOS	C+M	Area array	5472 × 3648	VIS	USB3	20	—
PL-U795B	CMOS	C+M	Area array	2448 × 2048	VIS	USB3	75	—
PL-U753 (HDR)	CMOS	C+M	Area array	1936 × 1464	VIS	USB3	141	—
PL-U752	CMOS	C+M	Area array	1920 × 1200	VIS	USB3	162	—
RDI Technologies/Fastec Imaging Corp. San Diego, CA, USA; 858-592-2342; www.fastecimaging.com; sales.fastec@rditechnologies.com								
HS7 High-Speed Camera	CMOS	C+M	Area array	1920 × 1080	VIS	Digital I/O, Ethernet, 2.5GigE, USB 3.2, USB4, TB4	2500 (10 bits)	6180 MHz
HS5 High-Speed Camera	CMOS	C+M	Area array	2560 × 2048	VIS	Digital I/O, Ethernet, 2.5GigE, USB 3.2, USB4, TB5	253 (12 bits)	1898 MHz
TS5 Handheld High-Speed Camera	CMOS	C+M	Area array	2560 × 2048	VIS	Digital I/O, Ethernet, GigE, USB 1.0/2.0	253	1325 MHz
Fastec IL5	CMOS	C+M	Area array	2560 × 2048	VIS	Digital I/O, Ethernet, GigE, USB 1.0/2.0	253	1325 MHz
Schäfter+Kirchhoff GmbH Hamburg, Germany; 49-40-853-997-0; www.sukhamburg.com; info@sukhamburg.de								
SK4k-U3DR7C	CMOS	C	Line scan	4096 × 2 Bayer Pattern	VIS	USB3	—	43.4 kHz
SK8k-U3DR4	CMOS	M	Line scan	8192 × 1	VIS	USB3	—	43.4 kHz
SK2048_HA	CCD	M	Line scan	2048 × 1	VIS	USB3, GigE Vision, Camera Link	—	52.63 kHz
SK2048U3HU	CMOS	M	Line scan	2048 × 1, 12.5 × 500 µm²	VIS	USB3	—	7.14 kHz
SK4096U3HW	CMOS	M	Line scan	4096 × 1, 7 × 200 µm²	VIS	USB3	—	2.38 kHz
SICK Inc. Bloomington, MN, USA; 952-941-6780; www.sickusa.com; info@sick.com								
InspectorP61x	CMOS	M	Area array	1.2 Mpixel	NIR, VIS	Serial, Ethernet, Fieldbus	≤70	—
Inspector83x	CMOS	C	Area array	1.3- 5.1 Mpixel	NIR, VIS	Serial, Ethernet, Fieldbus	≤70	—
Inspector85x	CMOS	M	Area array	5-12 Mpixel	NIR, VIS	Serial, Ethernet, Fieldbus	≤70	—
Ruler3000	CMOS	M	Line scan	3202, 560 × 832 px 0 datapoint/ profile		Ethernet, GigEvision	—	—

CAMERA MANUFACTURERS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
SPECIM Spectral Imaging Ltd. Oulu, Finland; 358-10-4244-400; www.specim.com; info@specim.com								
Specim FX10	CMOS	M	Line scan	1024 × 224	Hyperspectral, NIR, VIS	Camera Link / GigE Vision	330 (full), 9900 (1 band)	—
Specim FX17	InGaAs	M	Line scan	640 × 224	Hyperspectral, NIR	Camera Link / GigE Vision	670 (full), 15,000 (4 bands)	—
Specim FX19	InGaAs	M	Line scan	640 × 224	Hyperspectral, NIR	GigE Vision	527 (full)	—
Specim FX50	InSb	M	Line scan	640 × 154	MWIR	GigE Vision	377	—
Specim FX120	MCT	M	Line scan	100 × 160	Hyperspectral, LWIR	GigE Vision	240 (full)	—
SWIR Vision Systems Inc. Morrisville, NC, USA; 919-248-0032; www.swirvisionsystems.com; sales@swirvisionsystems.com								
Acuros CQD 1280 eSWIR Camera	Colloidal Quantum Dot (CQD)	M	Area array	1280 × 1024	IR, Multispectral, NIR, SWIR, VIS	GigE, USB3	90	—
Acuros CQD 1920 eSWIR Camera	Colloidal Quantum Dot (CQD)	M	Area array	1920 × 1080	IR, Multispectral, NIR, SWIR, VIS	GigE, USB3	60	—
Acuros CQD 640 SWIR Camera	Colloidal Quantum Dot (CQD)	M	Area array	640 × 512	IR, Multispectral, NIR, SWIR, VIS	GigE, USB3	280	—
Acuros CQD 1280 SWIR Camera	Colloidal Quantum Dot (CQD)	M	Area array	1280 × 1024	IR, Multispectral, NIR, SWIR, VIS	GigE, USB3	90	—
Acuros CQD 1920 SWIR Camera	Colloidal Quantum Dot (CQD)	M	Area array	1920 × 1080	IR, Multispectral, NIR, SWIR, VIS	GigE, USB3	60	—
Teledyne DALSA Waterloo, ON, Canada; 519-886-6000; www.teledynevisionsolutions.com; tdi_sales.americas@teledyne.com								
Calibir GX	Microbolometer	M	Area array	640 × 480	LWIR	GigE	30, 60	—
MicroCalibir	Microbolometer	M	Area array	640 × 480	LWIR	USB2	60	—
Falcon4-CLHS	CMOS	M	Area array	2240 × 1248, 4480 × 2496, 6144 × 6144, 8192 × 8192	VIS	Camera Link HS	1200, 609, 330, 120, 90	—
Genie Nano-CL	CMOS	C+M	Area array	2448 × 2048, 2464 × 2056, 4112 × 2176, 4096 × 4096, 5112 × 5112	NIR, VIS	Camera Link, Camera Link Full	35,141, 88, 64, 45, 30	—
Genie Nano-CXP	CMOS	C+M	Area array	4096 × 4096, 5120 × 5120, 6144 × 6144, 8192 × 8192	NIR, VIS	CoaXPress	120, 80, 40, 30	—
Teledyne e2v, a business unit of Teledyne Digital Imaging US Inc Chestnut Ridge, NJ, USA; 845-425-2000; teledynevisionsolutions.com; e2v-imaging.us@teledyne.com								
OctoPlus OCT	CMOS	M	Line scan	2048 × 1	NIR	Camera Link, USB3	—	20, 80, 130, 250 kHz
Teledyne FLIR ISS Richmond, BC, Canada; 604-242-9937; www.flir.com/mv; mv-sales@flir.com								
Blackfly S USB	CMOS	C+M	Area array	0.4–24.5 MPixels	VIS	USB3	15–522	—
Dragonfly S	CMOS	C+M	Area array	5 MPixels	VIS	USB3	49	—
LT Series	CMOS	C+M	Area array	1.7-31.4 MPixels	VIS	USB3	15–162	—
Firefly S	CMOS	C+M	Area array	0.4–1.6 MPixels	VIS	USB3	60–121	—
Blackfly S Board Level	CMOS	C+M	Area array	1.6–20 MPixels	VIS	USB3, GigE	10–226	—

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Teledyne FLIR LLC Wilsonville, OR, USA; 877-773-3547; www.flir.com; sales@flir.com								
FLIR A6260 SWIR	InGaAs	C+M	Area array	640 × 512	SWIR	GigE, SDI	0.0015–125 Hz (180 Hz burst)	125 Hz (full), 25,614 Hz (max)
FLIR A6750 Series	InSb, Strained-Layer Superlattice	C+M	Area array	640 × 512	LWIR, MWIR	GigE, SDI	0.0015–125 Hz	125 Hz (full), 4175 Hz (max)
FLIR A8580 Series	InSb, Strained-Layer Superlattice	C+M	Area array	1280 × 1024	LWIR, MWIR	GigE, CoaXPress, SDI	0.0015–45 Hz (GigE), 60 Hz (CXP)	60 Hz (full), 3709 Hz (max)
FLIR X6980 Series	InSb, Strained-Layer Superlattice	C+M	Area array	640 × 512	LWIR, MWIR	GigE, CoaXPress, Camera Link, SDI, HDMI	0.0015–1004 Hz	1004 Hz (full), 29,133 Hz (max)
FLIR X8580 Series	InSb, Strained-Layer Superlattice	C+M	Area array	1280 × 1024	LWIR, MWIR	GigE, CoaXPress, Camera Link, SDI, HDMI	~0.5–181 Hz	181 Hz (full), 6026 Hz (max)
Toshiba Teli Corp. Tokyo, Japan; 81-42-589-8771; www.toshiba-teli.co.jp/en/; teli-global@toshiba-teli.co.jp								
EX670AM Series, EX370BMG-X	CMOS	C+M	Area array	8192 × 8192, 6144 × 6144	VIS	CoaXPress2 (CXP-12 Quad)	64.5, 120	4329, 4530 MB/s
DDU2607M / DDU1607M / DDU1207M series	CMOS	C+M	Area array	5120 × 5120, 4000 × 4000, 4096 × 3000	VIS	Dual USB3 (10Gbps)	28.3, 47, 62	742, 752, 750 MB/s
DU1207M / DU657M Series	CMOS	C+M	Area array	4096 × 3000, 2560 × 2560	VIS	USB 5Gbps	32, 55	393, 360 MB/s
F246B-10 / F204B-10 / F162B-10 / F123B-10 / F81B-10 / F50B-10 Series	CMOS	C+M	Area array	5328 × 4608, 4512 × 4512, 5328 × 3040, 4096 × 3008, 2848 × 2848, 2448 × 2048	VIS	USB 10Gbps (Type-C)	37, 44, 56, 73, 112, 180	902, 908, 899, 907, 896, 908 MB/s
BU2409M / BU1208M / BU805M / BU502M Series	CMOS	C+M	Area array	5328 × 4608, 4096 × 3000, 2840 × 2840, 2448 × 2048	VIS	USB 5Gbps	15, 31, 46, 75	367, 393, 371, 376 MB/s
BU1207M / BU505M / BU302M / BU160M / BU040M Series	CMOS	C+M	Area array	4096 × 3000, 2448 × 2048, 2048 × 1536, 1440 × 1080, 720 × 540	VIS	USB 5Gbps	31, 75, 120, 240, 523	393, 376, 377, 373, 203 MB/s
BU406M Series, BU205M	CMOS	C+M	Area array	2048 × 2048, 2048 × 1088	NIR, VIS	USB 5Gbps	90, 170	377, 379 MB/s
BU300M Series	CMOS	C+M	Area array	2048 × 1536	VIS	USB 5Gbps	63	198 MB/s
BU238M Series	CMOS	C+M	Area array	1920 × 1200	VIS	USB 5Gbps	165	380 MB/s
BU132M	CMOS	M	Area array	1280 × 1024	VIS	USB 5Gbps	61	80 MB/s
BU2006M / BU1203MC / BU602M Series	RS-CMOS	C+M	Area array	5472 × 3648, 4000 × 3000, 3072 × 2048	VIS	USB 5Gbps	19, 30, 60	379, 360, 384 MB/s
BG505LM / BG302LM / BG160M / BG040M Series	CMOS	C+M	Area array	2448 × 2048, 2048 × 1536, 1440 × 1080, 720 × 540	VIS	GigE	22, 36, 72, 291	110, 113, 112, 113 MB/s
BG300M Series	CMOS	C+M	Area array	2048 × 1536	VIS	GigE	36	113 MB/s
BC505LM / BC302LM / BC160M / BC040M Series	CMOS	C+M	Area array	2448 × 2048, 2048 × 1536, 1440 × 1080, 720 × 540	VIS	Camera Link, PoCL (Base/3taps)	36, 56, 148, 523	180, 177, 230, 203 MB/s
CSC6M100CMP11, CSC6M100BMP11	CMOS	C+M	Area array	2560 × 2560	VIS	Camera Link, PoCL (Full)	99.2	650 MB/s
CSCS60BM18	CMOS	M	Area array	1280 × 1024	VIS	PoCL (Base)	61	80 MB/s

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CAMERA MANUFACTURERS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
Vieworks Co., Ltd. Anyang-si, Gyeonggi-do, South Korea; 82-70-7011-6161; https://vision.vieworks.com; sales@vieworks.com								
VC, VCS Series	CMOS	C+M	Area array	2,048 × 1088–14, 192 × 10,640	NIR, VIS	CoaXPress, CoaXPress-over-Fiber, 10GigE, Camera Link	1000	—
VP Series	CMOS	C+M	Area array	5120 × 5120–24,000 × 12,000	VIS	CoaXPress, Camera Link	35.4	—
VL Series	CMOS	C+M	Line Scan	2048 × 2–16,384 × 2	VIS	CoaXPress, 5GigE, 10GigE, Camera Link	—	200 kHz
VTS Series	CMOS	M	TDI	4640 × 256–23,456 × 384	VIS, UV	CoaXPress, CoaXPress-over-Fiber	—	1000 kHz
VNP Series	CMOS	C+M	Area array	23,760 × 18,012–48,000 × 24,000	VIS	CoaXPress	30	—
Vision Components GmbH Ettlingen, Germany; 49-7-2432-16723; www.vision-components.com; sales@vision-components.com								
VC MIPI Camera Modules	CMOS	C+M	Area array	≤5496 × 3672	NIR, VIS	MIPI CSI-2 + trigger	≤530	6 Gbit
VC MIPI Blue Line	CMOS	C+M	Area array	≤3536 × 3536 (2–12.5 MP)	NIR, VIS	MIPI CSI-2 (2/4/8-Lane)	60–97	—
VC EvoCam	CMOS	C+M	Area array	3.2 MP (IMX900 GS, konfigurierbar)	VIS, NIR	GigE, USB, PCIe, Digital I/O, Trigger/ Flash	—	—
VC MIPI Multiview Cam	CMOS	C+M	Area array	≤1280 × 800	NIR, VIS	MIPI CSI-2 + trigger	60–230	—
VC nano Z / pro Z Series (SoC Smart Cameras)	CMOS	C+M	Area array	≤1920 × 1200	NIR, VIS	Digital I/O, Ethernet/ GigE, RS-232/422	≤230	—
XIMEA Münster, NRW, Germany; 49-251-202-408-0; www.ximea.com; info@ximea.com								
High-Speed Cameras with up to 3700 Fps (xiB-64)	CMOS	C+M	Area array	1280 × 864–9344 × 7000 (1.1–65.4 Mpixel)	NIR, VIS	Digital I/O, Fiberoptic, PCIe, Proprietary	3709 (1.1 Mpixel)–71 (65.4 Mpixel)	64 Gbps
Multiple Camera Platform (xiX / xiSwitch)	CMOS	C+M	Area array	816 × 624–9344 × 7000 (0.4–65.4 Mpixel)	NIR, UV, VIS	Digital I/O, PCIe, Proprietary	≤752	10–64 Gbps (model-dependent)
Embedded Vision Cameras (xiX)	CMOS	C+M	Area array	1936 × 1216, 2064 × 1544, 2464 × 2056, 4112 × 2176, 4112 × 3008	NIR, UV, VIS	Digital I/O, PCIe, Proprietary	166, 218, 165, 95, 69	10–20 Gbps
xiMU, MU196	CMOS	C+M	Area array	5120 × 3840	NIR, VIS	Digital I/O, USB3	14	5 Gbps
xiMU, MU050	CMOS	C+M	Area array	2592 × 1960	NIR, VIS	Digital I/O, USB3	30	5 Gbps
xiMU, MU051	CMOS	C+M	Area array	2472 × 2064	NIR, VIS	Digital I/O, USB3	48	5 Gbps
xiC, Sony Pregius Gen 1+2, 2.3-12.4 Mpixel Camera	CMOS	C+M	Area array	1936 × 1216, 2064 × 1544, 2464 × 2056, 4112 × 2176, 4112 × 3008	NIR, VIS	Digital I/O, USB3	163, 121, 76, 43, 31	5 Gbps
xiC, Sony Pregius S Gen 4, 5.1-24.5 Mpixel Camera	CMOS (BSI)	C+M	Area array	2472 × 2064, 2856 × 2848, 4128 × 3008, 5328 × 3040, 4512 × 4512, 5328 × 4608	NIR, VIS	Digital I/O, USB3	72, 46, 30, 23, 18, 15	5 Gbps
xiQ, compact 1.3-4.1 Mpixel Camera	CMOS	C+M	Area array	1280 × 1024, 2048 × 1088, 2048 × 2048	NIR, VIS	Digital I/O, USB3	210, 169, 90	5 Gbps
xiX, small - Sony Pregius Gen 1+2	CMOS	C+M	Area array	1936 × 1216, 2064 × 1544, 2464 × 2056, 4112 × 2176, 4112 × 3008	NIR, VIS	Digital I/O, PCIe, Proprietary	166, 218, 165, 95, 69	10–20 Gbps
xiX, small - Sony Pregius Gen 3 (incl. UV model)	CMOS	C+M (UV: M)	Area array	816 × 624, 1608 × 1104, 1944 × 1472, 3216 × 2208, 2856 × 2848 (UV)	NIR, UV, VIS	Digital I/O, PCIe, Proprietary	752, 257, 174, 74, 87 (UV)	10–20 Gbps

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
XIMEA Münster, NRW, Germany; 49-251-202-408-0; www.ximea.com; info@ximea.com								
xiX, small - Sony Pregius S Gen 4	CMOS (BSI)	C+M	Area array	2472 × 2064, 2856 × 2848, 4128 × 3008, 5328 × 3040, 4512 × 4512, 5328 × 4608	NIR, VIS	Digital I/O, PCIe, Proprietary	133, 88, 61, 45, 35, 30	10–20 Gbps
xiX-Xtreme, with detached sensor head (Sony Pregius S)	CMOS (BSI)	C+M	Area array	5328 × 3040, 4512 × 4512, 5328 × 4608	VIS	Digital I/O, Fiberoptic, PCIe	160, 110, 107	32 Gbps
xiX-XL, 61-245.7 Mpixel with detached sensor head	CMOS (BSI)	C+M	Area array	9568 × 6380, 11,648 × 8742, 13,408 × 9528, 14,176 × 10,640, 19,200 × 12,800	VIS	Digital I/O, Fiberoptic, PCIe	17, 8.7, 20, 6.2, 10	32 Gbps
xiX-XL, MX2457 (Sony IMX811, 245.7 Mpixel flagship)	CMOS (BSI)	C+M	Area array	19,200 × 12,800	VIS	Digital I/O, Fiberoptic, PCIe	10	32 Gbps
xiX-XL, MX1276 (Sony IMX661, 127.7 Mpixel global shutter)	CMOS	C+M	Area array	13,408 × 9528	VIS	Digital I/O, Fiberoptic, PCIe	20	32 Gbps
xiJ, Scientific cooled sCMOS	sCMOS	M	Area array	2048 × 2048	NIR, Soft X-ray/XUV, UV, VIS	Digital I/O, PCIe, USB3	≤73	5 Gbps (USB3); PCIe option
MX377, large-format scientific sCMOS	sCMOS (BSI/ FSI)	M	Area array	6200 × 6144	NIR, UV, VIS	Digital I/O, PCIe	48	32 Gbps
xiSPEC, Hyperspectral	CMOS, spectral filters	M (spec-tral)	Line scan/Area array	2048 × 5 (line scan); 2.2 Mpixel mosaic (4×4 VIS, 5×5 NIR)	Hyperspectral, 460–960 nm (16/24/150 bands)	Digital I/O, PCIe, USB3	170 (USB3), 338 (PCIe)	5–10 Gbps
Zhejiang MRDVS Technology Co., Ltd. Hangzhou City, China; 86-13370882355; www.mrdvs.com; service@mrdvs.com								
S10	3D	C	Area array	240 × 160	IR	Digtal I/O, Ethernet	20	—
S10 Ultra	3D	C	Area array	240 × 160	IR	Digtal I/O, Ethernet	20	—
M4 Mega	3D	C	Area array	640 × 480	IR	Digtal I/O, Ethernet	25	—
V2 Pro	3D	C	Area array	1920 × 1080	IR	Digtal I/O, Ethernet, CAN	20	—
Zivid Oslo, Norway; 47-21022472; www.zivid.com; marketing@zivid.com								
Zivid 2	3D	C+M	Area array	1944 × 1200	VIS	10GigE	10	—
Zivid 2+	3D	C+M	Area array	2448 × 2048	VIS	10GigE	10	—
Zivid 2+ R-series	3D	C+M	Area array	2448 × 2048	VIS	10GigE	10	—

CAMERA DISTRIBUTORS

Product	Sensor type	Color/ Mono	Scan type	Image format	Spectrum digitized	Interface	Frame/s	Data rate
1stVision Inc. Andover, MA, USA; 978-474-0044; www.1stvision.com; info@1stvision.com								
Allied Vision Goldeye SWIR GigE and Camera Link Series	InGaAs	M	Area array	320 × 256, 640 × 480	SWIR	Digital I/O, Ethernet, GigE, Camera Link	344	106 MB/s
Allied Vision, area scan cameras, Alvium 10GigE, GigE, Camera link and USB3 Series	CMOS	C+M	Area array	VGA–31 MPixels	NIR, VIS	Digital I/O, Ethernet, GigE, USB3, MIPI-CSI2	≥1000	400 MB/s
IDS Imaging 10GigE, 5GigE, GigE, and USB3 Series	CMOS	C+M	Area array	VG–45 MPixels	NIR, VIS	Digital I/O, Ethernet, GigE, 5 GigE, 10 GigE, USB3	396	500 MB/s
Teledyne Dalsa Linea GigE, 5GigE, and Camera Link Line Scan Series	CMOS	C+M	Line scan	2048 × 1–32, 768 × 1	NIR, SWIR, VIS	Digital I/O, Ethernet, 10GigE, GigE, 5 GigE, Camera Link	—	≥80 kHz
Teledyne Dalsa Genie Nano GigE, 5GigE, Camera Link, and CoaXpress Series	CMOS	C+M	Area array	VGA–67 MPixels	LWIR, NIR, VIS	Digital I/O,Ethernet, GigE, 5 GigE, 10 GigE	≥1000	1608 MB/s
Active Silicon Ltd. Langley, UK; 44-1753-650600; www.activesilicon.com; sales@activesilicon.com								
Tamron MP3010M-EV	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, HDMI, USB 3, 3G/HD-SDI, HD-VLC, CVBS, H.264	60	—
Sony FCB-EV9500L	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, USB 3, HDMI, 3G/HD-SDI, HD-VLC, CVBS, H.264	60	—
Sony FCB-EV9520L	CMOS	C+M	Area array	1920 × 1080	VIS	LVDS, USB 3, HDMI, 3G/HD-SDI, HD-VLC, CVBS, H.264	60	—
RMA Electronics, Inc. Hingham, MA, US; 781-749-9700; http://rmaelectronics.com; ronjr@rmaelectronics.com								
Allied Vision	CMOS	C+M	Area array	≤19,200 × 12,800	NIR, SWIR, UV, VIS	CoaXPress 2.0, GigE, 5 GigE,10 GigE, 100 GigE, MIPI CSI-2, USB3	≤671	—
The Imaging Source	CMOS	C+M	Area array	≤5320 × 4600	VIS	GigE, USB3	≤539	—
Systematic Vision Corp. Ashland, MA, USA; 508-532-1116; www.systematicvision.com; bill@systematicvision.com								
SVS-Vistek FXO Series	CMOS	C+M	Area array	5–24 MPixels	NIR, VIS	CoaXPress 2.0, 10 GigE	259	—
Princeton Infrared 1280MVCam	InGaAs	M	Area array	1280 × 1024	NIR, SWIR, VIS	Camera Link	100	—
Photonfocus MV8-D8424-G01-GT	CMOS	C+M	Area array	8424 × 6032	VIS	10GigE	24	—
Photonfocus MV4 Series	CMOS	C+M	Area array	1.3–65 MPixels	NIR, UV, VIS	GigE, 10GigE	80,000	—
Photonfocus MV3 Series	CMOS	C+M	Area array	0.1–0.3 MPixels	NIR, UV, VIS	Camera Link, GigE	344	—

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continued from 9 often justify the cost, he says. In fact, AI could dramatically increase demand for SWIR because AI systems benefit from access to new types of image data beyond traditional RGB imagery.

Because SWIR reveals information about materials, tissues, and objects that visible cameras cannot capture, it may become an important tool for advancing AI applications in healthcare, agriculture, autonomous systems, materials science, and industrial inspection. Also, emerging technologies such as quantum-dot and thin-film photodiode sensors aim to eliminate expensive production steps while offering smaller pixels and broader spectral sensitivity.

“Vision will no longer sit at the end of manufacturing; it will become one of the senses through which industry understands and controls itself."

“If these approaches succeed, SWIR sensors could follow the same cost-reduction path that made visible cameras ubiquitous, creating a cycle of lower prices, broader adoption, increased investment, and further innovation,” Lau says.

Wilton says he believes computer vision will evolve far beyond the inspection systems of today, with advances in AI, robotics, and sensing enabling production of machines capable of perception, interpretation, and response to less structured environments.

“Vision will no longer sit at the end of manufacturing; it will become one of the senses through which industry understands and controls itself,” Wilton says.Dechow says that, while interesting and potentially disruptive innovations always come along, he believes the industry will continue to develop steadily, largely driven by market forces.

“Bottom line is that the needs of the marketplace and the benefits provided always dictate what technologies take their place as standard choices for implementation,” he says.

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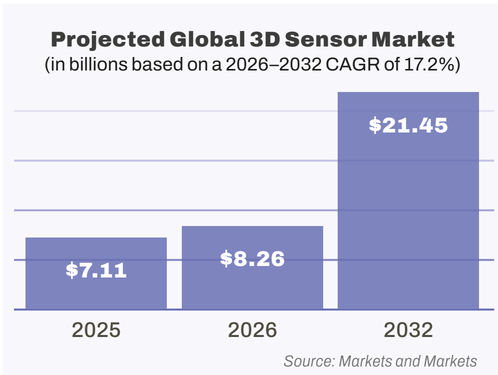
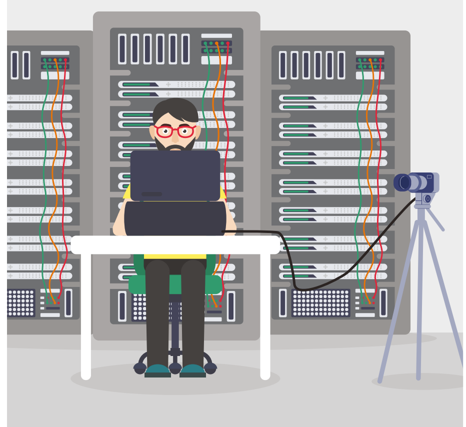
ToF Powers Next-Gen Vision

The growth of the 3D sensor market is being accelerated by the expansion of automated technologies and spatial data processing across industries, according to a report by Markets and Markets, which is leading to an increase in depth-sensing modules per individual device. As resolution requirements increase and device architectures become compact, traditional stereoscopic vision approaches are being replaced, according to the research. Manufacturers are adopting advanced technologies such as vertical cavity surface emitting laser (VCSEL) arrays, time of flight (ToF) modules, and backside illuminated (BSI) architectures, according to the report. Emerging applications include autonomous vehicles, artificial intelligence integration, medical diagnostics, and smart manufacturing. By type, the image sensor segment is estimated to lead the market during the forecast period. By technology, the time of flight segment is projected to grow at the fastest CAGR of 18.6% during the forecast period.



Did You Know?

The Massachusetts Institute of Technology developed an image analysis system that would eventually control a robotic arm for industrial applications. In 1966, MIT's Marvin Minsky asked his student Gerald Jay Sussman to spend his summer vacation trying to connect a camera to a computer, and so a mathematical description of what the camera's eye captures was born. Source: mv-center.com



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Focus & Find

Solve the VSD-related anagrams to reveal the letters for the final message. Each circled letter is used just once.

VSD site members will find the answer here: vision-systems.com/55390753

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