Enhancing Manufacturing Efficiency through Computer Vision and IIoT Integration

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Executive Summary

This white paper outlines how an integrated computer vision and Industrial Internet of Things (IIoT) solution can significantly improve manufacturing quality control and efficiency. It addresses a common challenge in modern manufacturing: subtle production anomalies that escape traditional automated detection and lead to waste, downtime, or product recalls. The paper presents a case study from the Connected Systems Institute's (CSI) advanced manufacturing testbed at the University of Wisconsin–Milwaukee, where a custom machine vision system was deployed to monitor product quality in real-time. Leveraging an edge AI device (NVIDIA Jetson) and cloud analytics (Microsoft Azure), the solution was able to detect defects on a high-speed production line and provide immediate feedback to operators. As a result, previously unnoticed defects were identified and removed early, reducing scrap and improving overall throughput. The following sections discuss the industry context and problem, detail the technology solution and its implementation, report on results and key metrics, and examine the business impact. Finally, the paper provides considerations for replicating this approach in other manufacturing settings, highlighting potential challenges and requirements for success.

Figure 1 University of Wisconsin-Milwaukee CSI

Industry Context

Modern manufacturing is undergoing a digital transformation often referred to as Industry 4.0. This movement integrates physical production equipment with digital technologies such as sensors, connectivity, and intelligent automation. A cornerstone of Industry 4.0 is the Industrial Internet of Things (IIoT), which enables plant-floor devices and machines to communicate data from the production line to enterprise systems and cloud platforms in real time. This connectivity allows for advanced monitoring, data analysis, and adaptive control of manufacturing processes. For example, IIoT systems can track production parameters, equipment status, and product quality continuously, leading to insights that drive efficiency improvements.
However, rapid technological advancement has also created integration challenges, especially for small and medium-sized manufacturers. Many of these firms struggle to seamlessly implement new Industry 4.0 technologies into legacy systems, resulting in communication bottlenecks, inefficiencies, or security vulnerabilities. Moreover, the human factor is significant: there is a well-recognized skills gap shortage of workers with the specialized expertise to deploy, manage, and maintain advanced automation and data analytics systems. This gap can slow down the adoption of cutting-edge solutions on the factory floor. Companies find that while technologies like IIoT and AI promise great benefits, achieving those benefits in practice requires not only capital investment but also workforce development and process changes.

In response to these trends, industry and academia have increasingly collaborated to demonstrate practical solutions and train the next-generation workforce. One example is the Connected Systems Institute (CSI) at UWM, which hosts an Advanced Manufacturing Testbed co-developed with industry leaders (including Rockwell Automation, FANUC, Endress+Hauser, Microsoft, and others). This state-of-the-art facility simulates a modern factory environment and serves as proving ground for Industry 4.0 technologies. Research and pilot projects at CSI focus on areas like IIoT-driven automation, robotics, and data analytics. A key topic of interest and the focus of this white paper is the integration of computer vision with IIoT to enable automated, real-time quality assurance. By experimenting in such an environment, stakeholders can explore how intelligent vision systems might transform manufacturing processes, reduce waste, and increase productivity in real-world settings.

Problem Statement

Even in highly automated production lines, quality control gaps can occur. Advanced robots and machinery perform repetitive tasks with precision, but they may not always detect when something goes wrong in the process. A prime example is the occasional mishandling of products on the line events that might be rare and fleeting yet have significant consequences. In our study environment (the CSI testbed), an intermittent anomaly was observed: robotic arms would sometimes misgrip or jostle small containers (vials) on the line, causing a few to be dropped, crushed, or otherwise damaged. The automated system's internal sensors did not flag these incidents; production would continue as if every item were intact. This blind spot reflects a broader challenge in manufacturing: subtle or rapid anomalies can escape standard detection, leading to downstream issues.

On a real factory floor, undetected defects or mishandled items can disrupt operations and erode profitability. For instance, a dropped or broken vial in a batch might spill contents or contaminate equipment, necessitating cleanup and unplanned downtime. If a damaged product isn't caught and is mixed into finished goods, the entire lot might be compromised. In many industries, especially pharmaceuticals or food & beverage, failing to catch such defects early can result in hazardous products reaching customers, with potentially deadly consequences and massive recalls. Even when safety isn't at stake, shipping substandard products harms customer trust and often forces expensive rework or replacement of goods.

1) Several underlying factors contribute to this quality control gap:

Intermittent Automation Failures:

No matter how advanced, automation systems can experience occasional errors (e.g. a robot's grip slipping). These events may happen in a split second. Traditional sensors or logic controllers might not recognize a brief mishap, especially if the process flow continues normally afterward. In the CSI testbed, about 4% of vials were mishandled over a five-month observation period non-trivial defect rate given high production volume.

2) Inadequate Real-Time Detection:

Existing quality control mechanisms often rely on scheduled inspections, basic sensors, or manual checks. They are not always equipped to catch fast, small-scale irregularities. In our consultations with industry experts, we found that even sophisticated manufacturing lines can have an undetected defect rate of roughly 2–3%. Tiny cracks, minor spills, or momentary misalignments might pass unnoticed if they occur between inspection points or outside sensor parameters. This highlights the need for more intelligent, continuous monitoring systems.

3) Operational and Financial Impact:

Each undetected anomaly directly translates into waste and inefficiency. A mishandled container results in lost material (the product inside becomes scrap) and potentially wasted packaging or ingredients in subsequent processes. Over time, these losses added up, and the data from our testbed suggested that unchecked vial mishandling could lead to significant annual waste costs. Moreover, suppose defects slip through to later stages. In that case, they might cause equipment wear or failures (if, say, a broken piece jams a machine) and degrade inventory accuracy (the system assumes more good products were made than were). In the worst case, defective products reaching customers trigger recalls and legal liabilities, impacting revenue and brand reputation.

Figure 2 CSI's Advanced Manufacturing testbed

In summary, the manufacturing sector faces a critical challenge: **how to detect and address subtle production anomalies in real time** to ensure dependable quality and high efficiency. The problem is not only identifying obvious errors but also spotting those "hidden" flaws that occur sporadically and are easily missed by conventional automation. As the push toward digital manufacturing continues, solving this problem becomes essential for maintaining productivity and competitive advantage.

Technology Solution

To address the quality control gap, a custom computer vision system integrated with IIoT connectivity was developed and deployed in the testbed. The solution adds a layer of intelligent visual inspection to the existing manufacturing line, enabling automatic detection of anomalies as they occur. The design centers on two key technological components: edge-based machine vision and cloud-based analytics.

Edge Vision System: At the core of the solution is a smart camera setup on the production line that monitors each product in real time. In practice, this consists of a high-quality USB industrial camera linked to an NVIDIA Jetson AGX Xavier edge computing device. The Jetson Xavier is a powerful, GPU-accelerated small computer capable of running advanced AI algorithms on-site (at the “edge” of the network). A tailored object detection model (based on the Single Shot Detector MobileNet (SSD MobileNet) architecture) is deployed on the device to analyze each video frame for signs of defects or mishandling. This model was chosen for its balance of speed and accuracy, crucial for keeping up with high-speed manufacturing. When a vial is being handled incorrectly or shows a defect (e.g., cracks, spillage, or an abnormal position), the vision system identifies it within milliseconds. The edge device can then flag the event immediately for response. By performing this analysis locally on the Jetson (rather than sending every frame to the cloud), the system minimizes latency and continues to work even if the internet connection is temporarily lost. This configuration helps prevent material wastage by catching issues the moment they occur on the line.

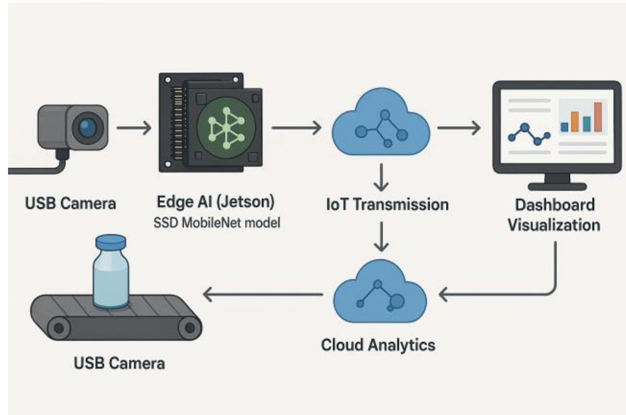

Figure 3 High-level architecture of the computer vision quality control solution, combining an edge AI device

Detection Performance: The machine vision model underwent training and tuning to achieve robust performance in the testbed environment. During evaluation, it demonstrated a high level of accuracy in detecting the target anomalies. Key performance metrics include:

- **Precision:** ~71.9% – meaning when the system reported a defect, roughly 72% of the time it was a true positive (actual anomaly). A solid precision reduces false alarms so operators are not overburdened by unnecessary stops.

- **Recall:** ~93.3% – meaning the system caught approximately 93% of all true defects on the line. High recall is critical in quality control to ensure almost no real issue goes unnoticed.

- **F1 Score:** ~88.9% – the harmonic mean of precision and recall, indicating overall effectiveness of the detection algorithm at an 80% confidence threshold.

These metrics indicate that the vision system performs at a level that meets or exceeds typical industry standards for quality inspection. In other words, the AI is correctly identifying most defects while keeping false alerts to a manageable level. Such performance was achieved through careful model selection (SSD MobileNet proved both agile and effective on the Jetson platform) and iterative testing. (Figure 1 illustrates the architecture of this edge vision system and how it connects to cloud analytics.)

Data Transmission and Cloud Analytics: When the edge vision system detects an anomaly, it doesn't just alert local operators, but it also streams data to the cloud for further analysis. Specifically, the Jetson device sends a packet of information to a Microsoft Azure cloud platform endpoint. This packet can include the timestamp of the event, details about the detected anomaly, and even short video snippets or images of the defect. In Azure, this data enters an advanced analytics pipeline. The cloud infrastructure aggregates and analyzes these events over time, using Azure's powerful data processing and machine learning services. By doing so, it can identify trends or recurring issues and generate predictive insights. For example, cloud analysis might reveal that anomalies happen more frequently on a particular machine or shift, suggesting a preventative maintenance need or operator training opportunity. The cloud platform can also continuously improve the edge detection algorithm by analyzing false positives/negatives and retraining the model with more diverse data. This feedback loop edge detection feeding cloud analysis, which in turn refines edge intelligence, helps boost the accuracy and efficiency of the overall system over the long run. Additionally, having data in the cloud allows management to access dashboard reports on quality performance from anywhere and integrates with broader enterprise quality management systems.

Implementation & Integration

Implementing this computer vision IIoT solution in the CSI advanced manufacturing testbed required careful planning and integration with existing processes. The deployment was carried out as a pilot project over a span of three months in a controlled setting to ensure minimal disruption and to measure outcomes.

Pilot Setup: The edge vision system (camera and Jetson device) was physically installed on the production line of the testbed, focusing on a critical handling point for the vials. The Jetson was configured to interface with the testbed's network so that detection events could be communicated both to on-site personnel and to the Azure cloud. An initial challenge encountered was ensuring that the Jetson's output could trigger alerts within the testbed's control system (which is composed of industrial PLCs and manufacturing execution software). This was solved by integrating Jetson's signals with the testbed's existing alarm/notification system, enabling automatic stoppage or operator alerts when a defect was detected. Concurrently, Azure cloud services were set up to receive anomaly event data from Jetson through a secure IoT messaging protocol.

Integration Process: Once the hardware and connections were in place, the system underwent a series of trials. Approximately **150 vials** (across three different product formulations run on the CSI line) were used in test runs that simulated regular production conditions. During these runs, any time the vision model flagged a vial as damaged or mishandled, the system would log the event and notify operators in real time. Operators and engineers were thus able to witness how the AI "watchdog" functioned alongside the normal automation. The integration allowed the generation of real-time alerts on the factory floor, for example, a light signal or a dashboard pop-up would indicate "Defect detected on Line 1." Additionally, the system sent analytical reports to managers, summarizing the number and types of anomalies detected each shift or day. Crucially, the feedback mechanism provided by this integration enabled **immediate corrective action**. If the system caught a misaligned or broken vial, the line could be paused and the item removed before it caused a spill or got into a finished batch. This immediate response not only prevented that single defect from progressing but also helped the team investigate and address the root cause (for example, if a robot gripper was starting to wear out or mis-calibrate, causing the mishandling). Over the pilot period, the vision system brought **to light several defects that previously went unnoticed** by the standard automation. Each of these detections was an opportunity to fine-tune the equipment and process.

By the end of the integration phase, the system was running smoothly alongside the existing manufacturing line. The pilot demonstrated that a retrofit intelligent vision system can be layered onto a traditional production setup with manageable effort, and without requiring a complete overhaul of the legacy equipment. The key requirements were ensuring network compatibility, developing the interface between the AI system and the line control, and educating the operational staff on the new tool.

Results & Metrics

The implementation of the computer vision and IIoT solution yielded clear improvements in quality control performance and operational efficiency. Both technical metrics and business-related outcomes were recorded:

High Anomaly Detection Accuracy: As noted earlier, the vision model achieved approximately 93.3% recall in detecting defective or mishandled vials, with about 71.9% precision. This means most true defects were caught by the system, drastically reducing the chance of a bad product slipping through. The false alert rate was low enough to be practical on the line. An F1 score of ~88.9% reflects a strong overall balance of catching defects while minimizing noise. These figures represent a significant improvement over baseline manual or periodic inspection performance. In fact, compared to an estimated ~4% defect miss rate before, the automated system recovered most of that lost yield, ensuring that nearly all products leaving the line met quality standards.

Reduced Scrap and Waste: During the pilot, every time a vial was identified as faulty, it was removed before further materials were added or value was lost. By preventing defective units from continuing down the line, the company avoids compounding waste (for example, adding expensive ingredients to a vial that is cracked would be pure waste). Thanks to real-time detection, the scrap rate related to vial mishandling dropped dramatically. In quantitative terms, the previously observed 4% mishandling rate was cut down to well under 1% in the test runs. This implies a potential 75% or more reduction in scrap due to this specific issue. The savings come not just from the containers themselves, but also from conserving the contents and processing resources that would have been wasted on defective units. This directly translates to cost savings.

Improved Throughput and Efficiency: With fewer incidents of undetected defects, the manufacturing line experienced less unexpected downtime. In the past, a broken vial might not have been noticed until it caused a bigger problem (spillage requiring cleanup or a machine jam), forcing a line stoppage. Under the new system, such issues were caught and dealt with proactively. Operators could remove the bad part and resume production quickly, rather than reactively responding to a downstream failure. Over the three-month pilot, the production throughput became more consistent. Although the sample size was limited, the trend suggested that catching and fixing small problems early prevented larger disruptions. This contributes to higher Overall Equipment Effectiveness (OEE), a key manufacturing performance metric, by improving the quality and availability components of OEE.

Data for Process Improvement: All detected anomaly events were logged to the cloud, creating a valuable dataset for engineering analysis. Reviewing this data, the team identified patterns, for instance, noticing that most mishandling events occurred during a specific motion of the robot or with a certain type of vial. These insights are being used to adjust machine parameters and operator procedures to further reduce error rates. In essence, beyond the immediate quality control, the system provided a learning tool for continuous improvement. The company can track quality incidents over time and measure the impact of any process changes on defects. This data-driven approach is a leap forward from previous reliance on anecdotal operator reports or periodic inspections.

Overall, the results from the CSI testbed pilot strongly indicate that an AI-driven vision inspection system, integrated with IIoT connectivity, can elevate manufacturing performance. High detection accuracy was achieved and maintained in real time, and this led to tangible operational benefits like scrap reduction and smoother production runs. In a production environment scaling up from this pilot, even a few percentages points improvement in yield and uptime can translate to substantial annual savings and capacity gains.

Business Impact

Implementing real-time computer vision for quality assurance does more than just improve technical metrics; it delivers concrete business benefits. From the case study results, several key impacts for manufacturing operations and business performance can be identified:

Cost Savings through Waste Reduction: By catching defective products early, the system prevents wasted materials and labor. Every vial removed before mixing or filling saves the cost of ingredients and processing that would have gone into a faulty product. Over time, these savings add up significantly. For example, if a production line handles millions of units per year, eliminating a 3–4% scrap rate means tens of thousands of units saved. This directly lowers the cost of goods sold and improves profit margins. Additionally, reducing scrap aligns with lean manufacturing principles and sustainability goals (less waste disposal and rework).

Protection Against Recalls and Liability: In industries with strict quality requirements, shipping a defective or contaminated product can be extremely costly not only in financial terms (recall logistics, refunds, regulatory fines) but also in damage to brand reputation. An automated vision QA system provides an insurance layer by greatly reducing the likelihood of a bad product reaching customers. This protects the business from the nightmare scenario of a recall or a product failure in the field. For sectors like pharma or food, such protection is invaluable and can preserve market trust.

Improved Production Efficiency and Capacity: Fewer quality incidents mean the production line can run more smoothly with less downtime for troubleshooting issues. The ability to identify and remove a bad part on the fly avoids the need to halt the entire line later when the problem surfaces. This increases the effective throughput of the line, more sellable products are produced per shift when there are fewer interruptions and rejections. In some cases, this might defer or reduce the need for capital investment in additional capacity, as improving quality has the effect of getting a better output from the same line.

Data-Driven Decision Making: The integration of cloud analytics means managers and engineers have access to real-time and historical data on quality performance. This visibility supports better decision-making at the business level. Trends and reports from the system can justify process changes or guide maintenance schedules (e.g., “Machine X is causing 80% of defects, invest in its upgrade”). It also enables quantifying ROI for quality initiatives, for instance, showing how the vision system improved yield by X% and calculating the dollar savings. Having solid data makes it easier for decision-makers to allocate resources and set priorities for continuous improvement projects.

Competitive Advantage and Digital Transformation: Embracing advanced quality control technology sends a message to stakeholders (customers, partners, and even employees) that the company is at the forefront of manufacturing innovation. For customers, this can be a selling point, they can expect more consistent, high-quality products. For the business, it is a step towards full digital transformation, where operations are smarter, more responsive, and more integrated. In a competitive market, the companies that effectively leverage AI and IIoT can differentiate themselves by offering superior quality and reliability. In many cases, this can open new business opportunities or markets that demand stringent quality (for example, being able to meet higher standards could allow entry into medical or aerospace manufacturing contracts).

It is important to note that achieving these business benefits does require investment and strategic alignment. The company must invest in hardware, software, and training for such a system, and ensure that the operations team is prepared to work with it. However, as demonstrated, the payoff comes in the form of operational excellence and risk mitigation. An analysis of this pilot suggests that the return on investment (ROI) for full-scale deployment could be very attractive, especially when considering the avoided costs of poor quality.

Replication Considerations

While the pilot implementation was successful, replicating this computer vision and IIoT solution in other manufacturing settings requires careful consideration of several factors. Organizations looking to adopt a similar approach should be mindful of the following challenges and requirements:

- **Integration with Cloud Platforms:** The Complexity of Setup. One of the primary challenges encountered was connecting the edge system with a cloud service (in our case, Microsoft Azure). Cloud platforms often have complex architectures that require specific configurations, security credentials, and middleware to link with on-premises devices. There was a steep learning curve to ensure that the Jetson edge device could reliably communicate with Azure's IoT services and data storage. Companies with limited cloud computing experience may need to invest in specialist support or training. It's crucial to plan for secure data transmission, proper network configuration (firewalls, protocols), and possibly adapt the solution to whichever cloud provider is in use (AWS, Google Cloud, etc., if not Azure). Early engagement with IT and cloud experts is recommended to smooth this integration.

- **Edge Processing Power:** Hardware selection. The choice of edge computing hardware can make or break the feasibility of real-time vision analytics. In our project, we initially attempted to use the NVIDIA Jetson Nano, an affordable and compact device. However, the Jetson Nano proved underpowered for the computational load of the SSD MobileNet model running in real time. The video processing and inference tasks overwhelmed the Nano, leading to lag and dropped frames. We had to upgrade to the Jetson AGX Xavier, which offers significantly more processing power (both CPU and GPU) and could comfortably handle the model's requirements. This switch entailed additional configuration work and optimization to utilize the new hardware effectively. The lesson for replication is to carefully match your AI model's complexity with the capabilities of the edge device. If the production line speed is very high or the model is complex, you may need higher-end hardware (or even an edge server) to meet the response time needs. Under-spec'd hardware can bottleneck the whole system.

- **Hardware Lifecycle and Availability:** Product longevity. A related consideration is the availability and support for the chosen hardware. Technology evolves quickly; notably, both the Jetson Nano and the Jetson AGX Xavier used in our project have been discontinued by NVIDIA as of 2023. This presents a challenge for scaling up: acquiring more of these units is difficult, and existing units might not receive long-term software support or updates. For future deployments, it will be necessary to identify current hardware alternatives. NVIDIA's Jetson Orin series (such as the AGX Orin or the Orin Nano) are the modern successors, offering even greater performance. Adopting a new device means you may need to refactor some of the software (e.g., drivers, libraries, model optimizations) and thoroughly re-test the system. Ensuring that your solution is not tied to an obsolete platform is important for longevity. It may also be wise to design the system in a modular way so that the edge computing module can be swapped out or upgraded with minimal disruption, should hardware lines be discontinued.

- **Technical Expertise and Training:** Skill requirements. Implementing an AI-powered IIoT solution demands a mix of expertise across domains of computer vision and AI, embedded systems/edge computing, industrial automation, and cloud infrastructure. In our case, success was driven by a team that could cover these areas, but not every manufacturing organization has such a team readily available. There is often a significant learning curve for staff who are unfamiliar with programming AI models or configuring cloud services. Companies aiming to replicate this should consider how to acquire the necessary skills: this could involve hiring specialists, partnering with tech providers or universities, or investing in training programs for current engineers. In addition, once the system is deployed, ongoing support and maintenance are needed (for instance, updating the model if the product changes, or managing cloud costs and security). Establishing a support plan whether through internal capability or external service contracts – is a part of the adoption strategy.

- **Development Time and Customization:** Project timeline. Unlike off-the-shelf inspection equipment, a custom AI vision system requires a development period for data collection, model training, and solution refinement. In our project, initial dataset gathering and model training took a significant amount of time (several weeks for a usable model, and a few months to reach optimal performance with iterative improvements). Each new implementation may need its own model training if the products or defect types differ, which can extend the project timeline. Businesses should be prepared for a phased approach: a proof-of-concept phase, followed by pilot deployment, and then scaling. It's important to manage expectations that while the technology is powerful, it's not a plug-and-play quick fix it involves a custom engineering effort. However, once in place, the system can be a lasting asset, and the experience gained will make future projects faster.

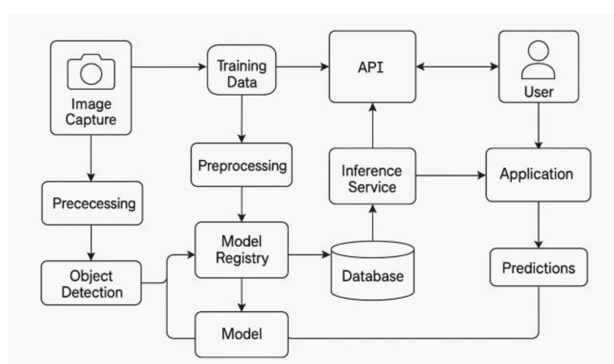

Figure 4 showing a detailed end-to-end wire architecture for image capture and object detection training

In summary, replicating the success of this pilot in a different factory requires addressing cloud integration, ensuring sufficient computing hardware, planning for hardware/software updates, and having the right expertise on board. None of these challenges is insurmountable; many companies have begun to navigate them as part of their digital transformation journeys. The key is planning and knowledge sharing. Learning from pilot projects (such as the one detailed in this paper) can help identify pitfalls early. Manufacturers may also consider starting with a smaller scope (e.g., one production cell or one defect type) to gain confidence before scaling up. By being mindful of the considerations above, an organization can increase the likelihood of smooth adoption and maximize the return from its investment in smart quality control systems.

Conclusion

The case study of integrating computer vision and IIoT in a manufacturing testbed vividly demonstrates the potential benefits of embracing advanced technology for quality assurance and efficiency. By augmenting an automated production line with intelligent vision capabilities, we were able to detect and mitigate issues that traditional systems overlooked. The outcome was a notable reduction in defects and waste, along with more stable and efficient operations, all of which are highly compelling results for any manufacturing enterprise.

This success, however, comes with a nuanced understanding of what it takes to implement such solutions. The project underscored that achieving a high-performance smart manufacturing system isn't just about buying new technology; it requires a combination of the right tools, technical know-how, and strategic planning. Challenges like cloud integration complexities, hardware changes, and skill gaps must be proactively managed. For small and medium-sized manufacturers particularly, the initial investment (in equipment, integration effort, and training) is a significant consideration. It must be weighed against the long-term gains in quality, savings, and competitive edge. The evidence from this pilot suggests that, with proper execution, the long-term business benefits can far outweigh the upfront costs. Early adopters will likely gain a market advantage through superior quality control and data-driven process optimization.

Looking ahead, the landscape of smart manufacturing will continue to evolve. New hardware (such as the latest generation of edge AI devices) and emerging technologies (like 5G connectivity and more sophisticated machine learning algorithms) are steadily lowering barriers and expanding capabilities for factory automation. Future projects building on this work should explore these advancements – for instance, leveraging more powerful yet energy-efficient processors, or integrating predictive maintenance AI models alongside quality control. Additionally, fostering partnerships between industry practitioners, technology providers, and academic research (as exemplified by the CSI testbed collaboration) can accelerate innovation and help disseminate best practices.

In conclusion, enhancing manufacturing efficiency through computer vision and IIoT integration is not only feasible but highly advantageous. It represents a significant step towards the broader goal of digital transformation in manufacturing. Organizations that invest in understanding and deploying these technologies will be better equipped to ensure quality, improve efficiency, and remain resilient in a rapidly advancing industrial era. This white paper has provided a roadmap and insights from a real implementation to guide stakeholders interested in replicating or scaling such solutions. By learning from these insights and remaining adaptable to new developments, manufacturers can confidently navigate the journey toward smarter, more efficient production systems.

References

1. *Liu, Y.-C., Hsu, Y.-L., & Sun, Y.-N. (2010). A Computer Vision System for Automatic Steel Surface Inspection. National Cheng-Kung University, Tainan, Taiwan.*
2. *Wright, A. (n.d.). Building A Better Packaging Machine With Cost-Effective High-Performance Machine Vision Tools. ISTECH, Dover, PA.*
3. *Agin, G. J. (1980, May). Industrial Computer Inspection Vision Systems and Assembly. Carnegie-Mellon University. IEEE Computer, 11.*
4. *Soldani, D. (2020). 5G AI-Enabled Automation. DOI: 10.1002/9781119471509.w5gref225*
5. *Mahmood, A., Beltramelli, L., Abedin, S. F., Zeb, S., Mowla, N. I., Hassan, S. A., Sisinni, E., & Gidlund, M. (Year). Industrial IoT in 5G-and-Beyond Networks: Vision Architecture and Design Trends. IEEE.*
6. *Lin, H.-D., Lin, W.-T., & Tsai, H.-H. (Year). Automated Industrial Inspection of Optical Lenses Using Computer Vision. Department of Industrial Engineering and Management, Chaoyang University of Technology, Taichung 41349, Taiwan; Department of Marketing, Mays Business School, Texas A&M University, College Station, TX 77843, USA.*
7. *Liu, Y.-C., Hsu, Y.-L., & Sun, Y.-N. (Year). A Computer Vision System for Automatic Steel Surface Inspection. Computer Science and Information Engineering, National Cheng-Kung University, Tainan, Taiwan R.O.C..*
8. *Sudharsan, B. (Year). AI Vision: Smart Speaker Design and Implementation with Object Detection Custom Skill and Advanced Voice Interaction Capability.*

Appendix

Figure 5 Labeled data from testbed

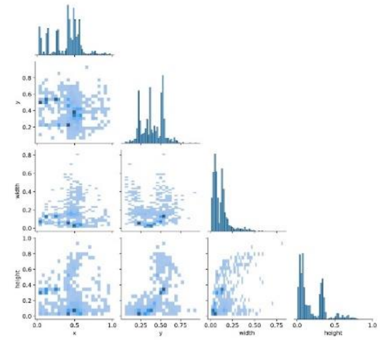

Figure 7 Chart data

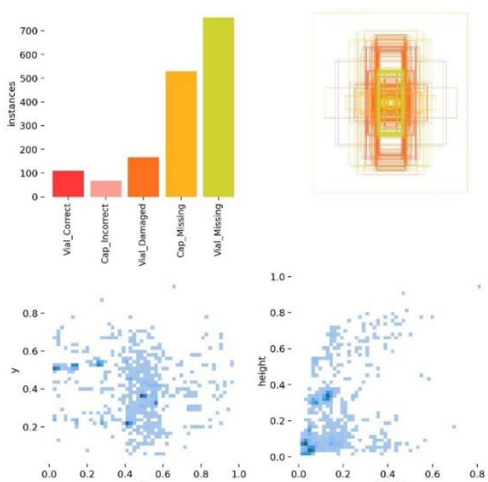

Figure 6 Distribution data