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The Use of Artificial Intelligence in Modern Food Production

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***Abstract*—Food systems everywhere are being squeezed from several directions at once: a population that keeps climbing, weather that no longer behaves the way historical records suggest it should, soils that are quietly losing fertility, and supply chains that have grown too complex to manage on spreadsheets and instinct alone. Artificial intelligence (AI) has become one of the more consequential responses to this squeeze, not because it replaces good agronomy or sound engineering, but because it lets producers, processors, and distributors act on patterns in data that would otherwise go unnoticed until it was too late to matter. This paper looks at how AI technologies—machine learning, computer vision, natural language processing, robotics, and the Internet of Things (IoT)—are being put to use across five stages of the food production value chain: planning and farm inputs, crop and livestock production, harvesting and processing, packaging and distribution, and retail. Drawing on recent industry and academic sources, it works through the more established use cases first—yield forecasting, precision irrigation, pest and disease detection—before turning to newer and less settled ground: autonomous machinery, machine-vision quality inspection, predictive maintenance, and traceability. Along the way it includes diagrams of the underlying technology stack and the flow of data across the value chain, plus a short summary of reported market and adoption figures. The final sections are more critical in tone, considering the technical, economic, and regulatory friction that still stands between where AI adoption is today and where it would need to be for the benefits to reach smaller producers as well as large ones.**

***Index Terms*—Agri-food systems; artificial intelligence; computer vision; food processing; food safety; machine learning; precision agriculture; supply chain.**

I. INTRODUCTION

By most projections, the world's population will approach 9.7 billion by 2050, and food production will need to climb well above 2005–2007 levels to keep pace—with the steepest increases required in exactly the regions that can least afford input-heavy farming [4]. That would be a hard enough problem on its own. Add in soils that are degrading, water that is becoming scarcer and more expensive, and post-harvest losses that never seem to shrink no matter how many awareness campaigns are run, and it becomes clear that simply farming more land, or pouring on more fertiliser, is not a workable answer for most of the world. It is against this backdrop that artificial intelligence has moved from a research curiosity to a genuinely practical tool: not because it is a silver bullet, but because it is good at exactly the thing this problem demands—finding usable signal inside enormous, messy streams of agronomic, environmental, and operational data faster than any human team could.

It helps to be clear about what "AI in food production" actually refers to, because it is not one technology but a loose family of them. Machine learning, deep learning-based computer vision, natural language processing, robotics, and the Internet of Things all show up somewhere along the chain that runs from seed selection to the shelf, and they rarely work in isolation—a modern harvesting robot, for instance, is really a computer-vision system, a control system, and a fleet of sensors working together. Industry commentary in 2026 tends to frame this as a turning point: a shift away from AI as a passive advisory tool, offering suggestions a human then acts on, toward what is increasingly called "physical AI"—systems that sense field or plant-floor conditions and act on them with comparatively little human involvement [2], [4].

The remainder of this paper works through the value chain shown in Fig. 1, stage by stage, drawing on recent peer-reviewed reviews and industry reporting rather than speculation. Later sections turn to the underlying technology stack, a summary of what is currently known about adoption and investment, and—perhaps most usefully—an honest look at what is still standing in the way of AI reaching smaller producers and not just the largest, best-capitalised operations.

A. What This Paper Sets Out to Do

Rather than attempt to cover every possible application, this paper focuses on five things: mapping the principal AI applications across the value chain from farm input to consumer; describing the data, modelling, action, and outcome layers that most of these applications share; summarising what is currently reported about adoption and investment; being reasonably candid about the technical, economic, and ethical friction that limits broader and more equitable adoption; and, finally, pointing toward where the field seems to be heading next.

II. AI IN PRE-PRODUCTION PLANNING AND FARM-LEVEL PRODUCTION

If there is one corner of the agri-food system where AI has had time to mature, it is precision agriculture: the practice of applying inputs—water, fertiliser, seed, pesticide—in the right amount, in the right place, at the right time, rather than treating an entire field as a single uniform unit [5], [9]. None of this started with AI. GPS guidance, variable-rate application, and soil mapping were already reshaping farming decades ago. What machine learning and computer vision have done is sharpen the precision of these older tools and extend them into territory that used to require a trained eye and years of experience to judge correctly.

A. Crop Monitoring, Forecasting, and Resource Management

Satellite and drone imagery, fed into models trained alongside IoT soil and weather sensors, now do a great deal of the early watching that farmers once had to do on foot. The point of this is not novelty for its own sake—it is that these systems can catch nutrient deficiency, water stress, or an odd patch in the canopy well before it would be visible to a person walking the rows, which turns a blanket response (spray the whole field, irrigate the whole field) into a targeted one. In practice, this has translated into more efficient water and fertiliser use, and yield forecasts accurate enough that some operations now feed them directly into procurement and breeding decisions rather than treating them as a rough guide [9].

B. Pest and Disease Detection

Recognising a diseased leaf, an early-stage pest infestation, or a weed hiding among a crop is exactly the kind of pattern-recognition task computer vision is good at, and deep learning models trained on drone, fixed-camera, or handheld imagery are now doing much of this recognition work [1]. The value is less in the detection itself and more in the timing: catching a problem while it is still small and localised allows for a targeted response instead of a scheduled, calendar-driven spraying regime, which in turn tends to mean fewer chemicals used overall and less crop lost to problems that were simply caught too late.

C. Livestock Monitoring

The same logic extends to livestock. Sensors tracking movement, body temperature, and feeding behaviour give AI systems enough signal to flag early indicators of illness or distress—often before a herd manager would notice anything wrong on a routine walkthrough [5]. Feeding regimes can be adjusted on the same data, with the dual aim of protecting animal welfare and keeping productivity where it needs to be.

D. Autonomous Field Machinery

The furthest edge of this trend is autonomous machinery: tractors, sprayers, and harvesting robots that combine computer vision, GPS, and robotic control to carry out field operations with a human present mostly to supervise rather than to operate. Industry commentators have taken to describing this as the shift from "digital agronomy," where AI simply informs a human decision, to "autonomous agronomy," where the system itself perceives conditions, reasons about them, and acts. It is not a small undertaking—more than seventy companies were reported in 2026 to be building the underlying pieces (data infrastructure, simulation environments, foundation models, observability tools) that this kind of "physical AI stack" requires, which gives some sense of how much infrastructure sits behind what looks, from the outside, like a single self-driving tractor [4].

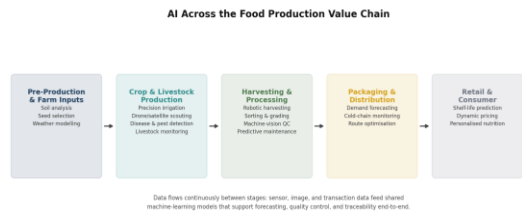

Fig. 1. AI applications mapped across the five stages of the food production value chain.

III. THE AI TECHNOLOGY STACK UNDERLYING FOOD SYSTEMS

Pull apart almost any of the applications described so far and a similar structure tends to appear underneath, sketched out in Fig. 2. At the bottom sits a data layer—the raw material coming in from IoT sensors, satellite and drone imagery, RFID tags, blockchain ledgers, and weather or market feeds. That data feeds a modelling layer, where machine learning, computer vision, NLP, and predictive analytics turn raw signal into something usable: a forecast, a classification, a recommendation. From there, an action layer takes the model's output and does something with it, whether that is directing a robot, adjusting a variable-rate sprayer, sorting produce on a line, or simply surfacing a recommendation on a dashboard for a human to act on. What ties the whole stack together is the outcome layer at the top—the actual point of doing any of this, which is higher yield, lower input use, safer food, less waste, and supply chains that can be traced rather than guessed at [1].

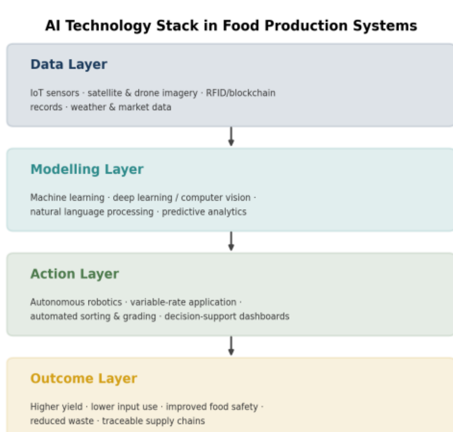

Fig. 2. The four-layer AI technology stack common to modern food production systems.

A. Core Techniques

Table I summarises the principal AI techniques used across the value chain, their representative use cases, and the data on which they typically depend [1], [5].

TABLE ICore AI Techniques Used in Food Production

AI Technique	Representative Use Cases	Primary Data Inputs
Machine Learning (ML)	Yield/demand forecasting, price prediction, shelf-life estimation	Structured sensor, weather, and market data
Computer Vision / Deep Learning	Defect and contaminant detection, sorting and grading, pest/disease ID	Camera, drone, and satellite imagery
Natural Language Processing (NLP)	Regulatory document analysis, agronomist advisory chatbots	Text data, reports, compliance filings
Robotics & Autonomous Systems	Harvesting, weeding, variable-rate spraying, autonomous vehicles	Sensor fusion, GPS, computer vision
IoT & Sensor Networks	Environmental and cold-chain monitoring, livestock biometrics	Temperature, humidity, motion, RFID

IV. AI IN HARVESTING, PROCESSING, AND QUALITY CONTROL

Once a crop leaves the field or an animal leaves the farm, the questions change. It is no longer about optimising growth but about handling, inspecting, and moving product fast enough to keep a processing line running, without letting anything unsafe or substandard through. AI has found a natural home here too, though for slightly different reasons than at the farm level—the pressure in a processing plant is speed as much as accuracy.

A. Machine-Vision Inspection

Of everything discussed in this paper, machine vision is probably the single most widely deployed food-safety application of AI at present [7]. The setup is conceptually simple: high-speed cameras feed a trained classification model that looks for surface defects, foreign material, shape irregularities, discoloration, or a failed seal on packaging, and it has to do this in the handful of milliseconds a product spends in front of the camera on a fast-moving line. Getting the timing right is genuinely hard—a system that is a fraction too slow either lets defective product through or starts flagging good product by mistake. Even so, reported deployments now cover fresh produce grading, poultry and meat processing, baked goods and snacks, and packaged beverages, with some vendors claiming defect-detection accuracy that matches or beats a trained human inspector.

B. Predictive Maintenance and Process Optimisation

Inspection is the visible part, but a fair amount of the value also comes from what happens behind the scenes. Models trained on historical sensor and maintenance logs can flag equipment that is likely to fail before it actually does, which matters enormously on a line where an hour of unplanned downtime can be expensive [10]. Looking across large volumes of process and visual data over time can also surface less obvious connections—a particular defect that keeps showing up alongside a particular machine setting, for example—which plants can then use to fine-tune reliability and cut down on wasted energy.

C. Shelf-Life and Spoilage Prediction

A more understated but arguably just as valuable use of AI is shelf-life prediction. Rather than relying on a fixed date stamped at the point of packaging, models that track temperature, humidity, and storage conditions throughout a product's journey can estimate spoilage risk with much finer resolution, which feeds directly into better inventory decisions and, ideally, less food thrown away simply because a static label was overly cautious or wrong [10].

D. Regulatory and Compliance Applications

AI is not confined to the plant floor, either—it is starting to show up inside the regulatory bodies that oversee food safety. Some agencies have deployed systems that pull together inspection records, submissions, and compliance data from dozens of separate sources into a single platform, supporting document analysis and search across repositories that would otherwise take a human team weeks to work through [6], [8]. It is worth being precise about what this is and is not: these are tools built for regulators, not for individual plants, and they sit alongside rather than replace plant-level controls.

V. AI IN DISTRIBUTION, TRACEABILITY, AND RETAIL

By the time a product is ready to leave the plant, the problem AI is solving has shifted again—now it is mostly about logistics and accountability. Demand-forecasting models try to line up production and inventory with what people will actually buy, which sounds simple but is one of the more persistently difficult problems in retail, and getting it wrong in either direction means either empty shelves or wasted stock. Route-optimisation tools work a related angle, pulling in traffic, weather, and delivery-schedule data in something close to real time to shave time, cost, and emissions off transportation. Traceability is arguably where the technology earns its keep most visibly: pairing AI with IoT devices, RFID tags, and blockchain ledgers means that when something does go wrong, a contamination source can be traced and a recall issued far faster than it could be with paper trails and phone calls, and consumers get more honest visibility into where their food actually came from [11]. Closer to the consumer, the same underlying techniques show up as dynamic pricing, personalised nutrition suggestions, and markdown decisions timed to a product's actual, rather than assumed, shelf life.

VI. REPORTED ADOPTION AND INVESTMENT TRENDS

Money tends to move ahead of headlines, so investment activity is a reasonable proxy for how quickly AI is actually being adopted in food and agriculture, as opposed to how much it is being talked about. On that measure, the picture looks genuinely active: agtech companies are reported to have raised roughly US$7 billion in 2025 alone, with precision-agriculture deals outnumbering crop-input and enhancement deals for the first time [3]. Machine learning alone is estimated to make up about half of the current AI-in-agriculture market. Geographically, North America leads with an estimated 36% share, Europe is active without leading, and Asia-Pacific is described as the fastest-growing region, driven largely by export demand and urbanisation. Looking specifically at precision agriculture, one market estimate puts the compound annual growth rate at around 20% for the 2026–2035 period [3]—a figure worth treating as one analyst's projection rather than a settled fact, but a useful order-of-magnitude signal all the same.

Figs. 3 and 4 turn these numbers into something easier to read at a glance, though a caveat belongs here: only a handful of the data points behind them are actual reported statistics. Fig. 3 takes the reported 2025 investment figure as its anchor and extends it forward using the ~20% CAGR mentioned above, purely to illustrate what that growth rate would look like over time—it is not a third-party forecast and should not be read as one. Fig. 4 does something similar with the regional breakdown: only the North America share (~36%) is a reported number, and the rest of the chart distributes the remainder in a way that is consistent with the qualitative pattern described in current reporting (Europe active, Asia-Pacific growing fastest), rather than reflecting a specific published split [3].

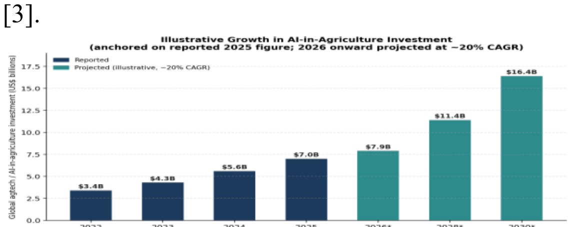

*Fig. 3. Illustrative growth trend in AI-in-agriculture investment, anchored on the reported 2025 figure (~US$7B) and the reported ~20% CAGR for the AI-in-precision-agriculture market (2026–2035). Years marked * are illustrative projections, not third-party forecasts.*

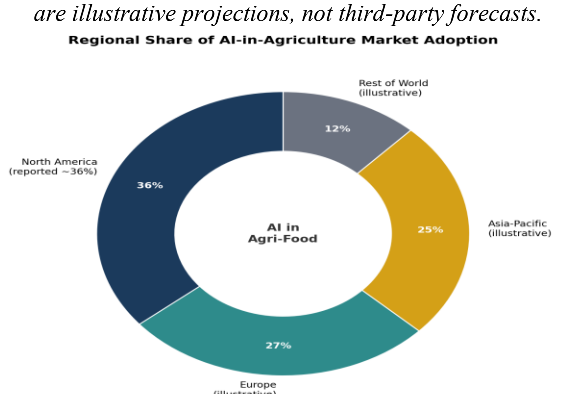

Fig. 4. Regional distribution of AI-in-agriculture market adoption. Only the North America figure (~36%) is a reported statistic; other regional shares are illustrative, consistent with qualitative reporting of relative adoption pace.

A. Representative Deployments

Numbers only tell part of the story, so it is worth grounding this in a handful of concrete, reported examples of what these deployments actually look like in practice (Table II).

TABLE II Representative Reported AI Deployments

Application Area	Description	Source Type
Poultry & meat processing	Computer-vision tracking of cuts through processing lines for consistency and yield	Reported industry deployment (large-scale poultry processor) [7]
Food traceability	AI combined with blockchain to track food origin and authenticity across supply chains	Reported industry platform [11]
Produce quality assessment	AI-based assessment of produce quality and spoilage prediction to reduce waste	Reported agtech startup deployment [9]
Distribution logistics	AI-optimised delivery routing using traffic, weather, and schedule data	Reported logistics-technology deployment [11]
Regulatory data platforms	Consolidated AI platform for inspection, compliance, and submission data across a food regulator	Reported 2026 regulatory-agency rollout [6], [8]

None of this is meant as an exhaustive inventory—it is simply a cross-section, drawn from recent industry reporting, meant to show the range of maturity across different parts of the value chain rather than to endorse any particular vendor or platform.

VII. CHALLENGES AND LIMITATIONS

It would be easy, reading the sections above, to come away thinking the hard problems are mostly solved and what remains is just a matter of rolling the technology out further. That is not really the case.

Several genuine obstacles still stand between the current state of adoption and something broader, more reliable, and more evenly distributed.

A. Data Quality, Access, and Ownership

An AI model is only ever as good as what it was trained on, and farm-level data has a habit of being messy: fragmented across different vendors' systems, recorded inconsistently from one season to the next, or simply owned by a third-party equipment or software provider under terms the farmer never fully read [9]. This is not a minor technical footnote—it shows up repeatedly in the precision-agriculture literature as one of the most persistent barriers to adoption, right alongside cost.

B. Cost of Entry and the Digital Divide

Sensors, connectivity, and compatible machinery all cost money up front, and that cost does not scale down neatly for a smaller operation. The practical effect is that AI-enabled precision agriculture and automated processing remain, for now, considerably more accessible to large, capital-rich operations than to smallholder farmers [3]—which is an awkward irony, given that the regions needing the largest gains in food production are often the ones least able to afford the entry price.

C. Technical Constraints in Real-Time Inspection

On a fast-moving processing line, a machine-vision system has only milliseconds to capture an image, run inference, and decide whether to reject a product—and any delay in that chain either lets a defect through or rejects something perfectly fine. Industry analysis tends to group the underlying difficulty into five recurring areas: the raw latency problem itself, a shortage of well-labelled training data (and the class-imbalance issues that come with it), environmental variability inside a real food factory that a lab-trained model never saw, the headache of integrating new AI tools with legacy equipment that was never designed for them, and the layer of regulatory compliance specific to food safety that sits on top of all of it [7].

D. Workforce Impact

There is also the human side of this, which deserves to be stated plainly rather than glossed over. As harvesting, sorting, and inspection become more automated, there are legitimate questions about what happens to the people who used to do that work, alongside a real need for new skills—people who can manage data pipelines, supervise these systems, and maintain the models running underneath them. Most current industry commentary frames AI as something that augments human inspectors and agronomists rather than replacing them outright, largely because ambiguous cases still need a human judgement call, and someone still has to be accountable when a safety-critical decision goes wrong [8]. Whether that framing holds up as the technology matures further is, honestly, an open question.

E. Accountability, Bias, and Regulatory Uncertainty

The more AI systems are trusted with food-safety-critical decisions, the more questions of liability and bias start to matter. A model trained mostly on common crop varieties or the most frequently seen contamination types may simply perform worse on the less common ones—an uncomfortable failure mode precisely because it tends to be invisible until something slips through. Regulators are beginning to adopt AI tools of their own for compliance work, which is a promising sign, but comprehensive, harmonised rules governing how AI should be validated and held accountable in food-safety contexts are, in most jurisdictions, still very much a work in progress [6], [8].

VIII. FUTURE DIRECTIONS

Predicting exactly where any fast-moving technology will land is a risky business, but a few trajectories already look reasonably likely to shape the next phase of AI adoption in food production [3], [4]:

- A continued push toward autonomous agronomy—less AI-as-advisor, more physical systems that sense, reason, and act in the field or plant with a shrinking need for human supervision.
- The emergence of foundation models built specifically for agriculture: large, pre-trained systems adaptable across different crops, regions, and languages, which could meaningfully lower the data and cost barriers currently keeping smallholder farmers on the sidelines.
- Deeper integration between AI, IoT, and blockchain to deliver traceability that runs genuinely end to end, from farm to consumer,

rather than in the patchy, partial form it often takes today.

- A shift toward AI applications that optimise for sustainability alongside yield—balancing carbon and water footprint against output, rather than treating yield as the only metric that matters.
- Regulatory frameworks that evolve alongside the technology rather than trailing years behind it, addressing how AI-driven food-safety decisions get validated, who is liable when they go wrong, and how they get audited after the fact.

IX. CONCLUSION

What began, not so long ago, as an experimental add-on to a handful of large farming operations has become something closer to a foundational layer across the entire food production value chain—sharpening how inputs get used, catching pests, disease, and contamination earlier than a human easily could, tightening up processing and logistics, and making it possible to actually trace a product's path from farm to consumer instead of just claiming to. Investment and adoption figures suggest this is not a passing trend but something that will keep deepening over the rest of the decade, with the industry visibly moving toward more autonomous, "physical AI" systems. Whether that translates into the outcomes that actually matter—real gains in food security, less waste, more sustainable use of increasingly scarce resources—depends less on the technology itself and more on whether the harder problems get addressed alongside it: messy and poorly owned data, the cost of entry for smaller producers, the technical demands of doing all this reliably in real time, a workforce transition handled with some care, and regulation that keeps pace rather than lagging years behind. None of that happens automatically. It will take continued research, honest reporting of what deployments actually achieve (not just what they promise), and policy that is designed with smallholders in mind from the outset rather than as an afterthought.

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