SMART LIVESTOCK FARMING

AI ENTERS THE BARN

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This book was organized and produced with artificial intelligence. It brings together materials collected from major languages around the world.

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CHAPTER 1

Precision Livestock Farming and Livestock DX

1.1

The Digital Transformation of Livestock Farming and the Agriculture 4.0 Paradigm

The scene that follows is a fictional reconstruction based on multiple studies and field reports. It is four in the morning, and the stars have not yet faded above the barn roof. The air inside the cattle barn is cold, and each cow is ruminating in a different posture. No one has arrived yet. In one corner of the milking parlor, a robotic arm stands motionless, quietly waiting for its next turn. Breath blooms white beyond the window, and only the low hum of the cooling unit fills the darkness. Somewhere, a feed trough rattles as it is pushed, and a dog barks once in the distance, then falls silent.

A small device around the neck of the dairy cow in stall 3 flashes blue twice. On the computer screen in the office outside the barn, an alert appears: the cow has spent less time ruminating than usual. Before a human eye has opened, the machine is already guessing what may be happening inside that cow's body.

Ten years ago, a scene like this would have belonged in a science-fiction film. There was a time when a barn manager walked through the cattle shed with a flashlight, checked the cows by eye, and handled manure to gauge their health. Today, high-resolution cameras mounted on the ceiling, microphones that capture sound, and wireless devices attached to necks and ears record the animals' breathing and gait throughout the day.

This movement, in which information and communication technology, the Internet of Things (IoT), and artificial intelligence have reached the very center of the farm, is called the digital transformation (DX) of the livestock industry. People often group it within the broader current known as Agriculture 4.0, but what actually happens inside a barn is much more concrete. It means recognizing every cow, every pig, and every chicken as an individual.

The world's appetite for cattle, pigs, and chickens shows no sign of fading. The Food and Agriculture Organization of the United Nations has projected that by 2050, meat consumption will rise 73 percent from the baseline year and dairy consumption will rise 58 percent. In 2022, about 83 billion terrestrial animals, including chickens, ducks, and pigs, were slaughtered for food. There are limits to the land that can be turned into more fields and paddies, and to the water livestock can drink. Herds and flocks cannot simply keep growing.

The people who have tended barns are growing old, and young workers willing to take over the job rarely appear. At livestock gatherings in rural townships, most faces are elderly, and it is common to find families whose children have moved to the city and never returned. Stories from livestock cooperative offices about recruitment notices left on the wall for months without a single phone call are no longer surprising.

Feed and electricity cost more every year. In countries that rely heavily on imported grain feed, a shift in the exchange rate can make the feed bill lurch. Electricity charges soar with heating in winter and cooling and ventilation in summer. At the same time, government rules requiring reductions in methane and ammonia are becoming steadily more detailed. In national plans for carbon neutrality, livestock farming is singled out as an industry that emits large amounts of methane.

A ruminating cow releases a substantial quantity of methane each day, so measuring and reducing emissions has itself become an indispensable part of livestock management.

When an infectious disease such as foot-and-mouth disease or avian influenza sweeps through, an entire barn can disappear within days. Trucks arriving to carry out culling are no longer an unfamiliar sight at the entrance to a village. There is a clear limit to how many animals a person can inspect by eye, yet the number needing care has long since grown from hundreds to tens of thousands.

The problem is that illness arrives in silence. By the time mastitis or lameness in a dairy cow becomes outwardly visible, the condition is often already well advanced. When the rhythm of a jaw chewing feed slows ever so slightly, the human eye rarely catches the difference. Milk yield drops sharply, and treatment costs snowball. Feeding an entire herd as if pouring the same amount into every trough has the same weakness. Cows that need more feed and cows that need less are served the same ration, so unused feed is discarded, while nitrogen and phosphorus in manure flow into rivers and soil.

Precision Livestock Farming (PLF) is an attempt to move beyond these limits. It is a management approach that uses sensors, cameras, and artificial intelligence to watch the condition and behavior of every individual animal 24 hours a day. In the past, an entire cattle barn, pig house, or poultry house was managed as a single average. Precision livestock farming breaks apart that average and treats cow 17 and cow 18 as two different animals. To borrow an analogy, it is as if a hospital that once treated an entire ward with a single prescription had begun examining the chart of each individual patient.

Consider an example. Cow 17 is a high-yielding animal that produces more than 40 liters of milk a day, so she needs a generous grain ration to avoid losing body condition. Cow 18, by contrast, is older and produces less milk. If she eats the same amount, she gains excess weight and puts strain on her hooves. In the past, both cows would have shared the same trough and received the same mixed feed. In a precision livestock system, a sensor around the neck reads each identification number, and the feeder automatically dispenses a different quantity and blend for each cow.

The situation is similar for pigs raised in groups. In a pig house equipped with an electronic feeder, each sow must enter the feeding stall before feed is dispensed. The machine reads the tag around her neck, releases only the amount suited to her weight and stage of pregnancy, and then opens the gate. This is why pigs raised in the same pen are less likely to diverge into overweight and underweight animals.

The difference between the two approaches is visible from the outside. In the past, a person looked over the animals once or twice a day and wrote observations by hand in a ledger. Today, sensors, cameras, and microphones accumulate data day and night. The center of gravity has shifted from responding after disease appears to predicting and acting before it does.

Precision livestock farming works in three stages: collecting data, analyzing it, and finally supporting human decisions. In the first stage, sensors attached to bodies or installed in the barn, together with cameras and microphones, gather body temperature, sound, and gait. Artificial intelligence reads the data, learns what is normal for that particular animal, and detects signs of departure from that pattern. It can then display a specific message on the farmer's smartphone, such as, "Cow 3's rumination time has fallen 22 percent in one day, suggesting early mastitis," or operate the feed dispenser and ventilation fan on its own.

The screen a farmer sees is not necessarily crowded with complicated graphs. Many systems show the condition of the barn at a glance in three colors: green, yellow, and red. Green means conditions are normal. Yellow signals that closer observation is needed. Red means someone should go there immediately. By turning complicated figures into a single color, this small device allows even older farmers who are not comfortable with computers to survey an entire barn with one smartphone.

The size of the artificial intelligence market for precision livestock farming reveals the speed of this shift. One market research report estimated the market at $2.7 billion in 2025 and $3.45 billion in 2026. It projected that the figure would exceed $8 billion by 2030. The picture is no different in South Korea. The government calls this movement smart livestock farming and has placed it at the center of policy. The Ministry of Agriculture, Food and Rural Affairs drew up the First Basic Plan for Fostering Smart Agriculture, a roadmap running from 2025 to 2029.

The Korea Institute for Animal Products Quality Evaluation began operating a dedicated smart livestock organization in June 2025 and announced the launch of its Smart Livestock Division in January 2026. In May 2026, the Ministry of Agriculture, Food and Rural Affairs appointed young people as Smart Livestock Youth Supporters. The intention was to bring young hands and digital technology into aging farms together. The reason for government action is plain. The countryside has fewer people, while barns have more data.

Policy reporting from actual farm sites likewise shows a growing number of farms installing wirelessly controlled CCTV cameras and estrus detectors.

In a cattle barn equipped with milking robots, cows walk into the milking parlor on their own. The robot reads the identification tag around a cow's neck and retrieves her previous milk yield and udder position. Its arm calculates the coordinates and attaches a milking cup precisely to each teat. Without a human hand, the cow can now be milked two or three times a day whenever she chooses.

A rumen bolus sensor swallowed whole by a cow plays a major role in health monitoring. This small, pill-shaped device measures rumen pH and temperature every few minutes and transmits the readings wirelessly. If the pH remains below a set threshold for a certain period, the system sounds an alert for the risk of acidosis. Across broad pastures, a virtual fence combining a Global Positioning System (GPS) device on a collar with vibration and sound takes the place of barbed wire. The farmer can draw a line on a smartphone map and move, whenever needed, the boundary that the herd must not cross.

For pigs, the ear takes on a large role. Microphones mounted on the ceiling of a pig house isolate coughs from the noise made by thousands of animals. Acoustic analysis systems such as SoundTalks distinguish ordinary squeals from coughs caused by respiratory illness and signal a possible infectious disease before a person notices anything by sight. A device called the Pig Cough Monitor works on the same principle. Cameras replace eyes as well.

An artificial-intelligence recognition technology called YOLO captures three-dimensional images of passing pigs' torsos, estimates their weight without putting them on a scale, and calculates a suitable date for shipment. Another danger is monitored beside a sow with newborn piglets. The crushing of piglets when a large sow shifts her body has long troubled pig farms. Ceiling cameras overlay the sow's posture with the piglets' positions in real time. When a dangerous posture appears, the system sounds an alarm in the pen or wakes the sow with a vibrating device.

Chickens present a different problem. Tens of thousands may crowd into a single poultry house, making individual visual inspection impossible. A camera moving along a ceiling rail records throughout the day whether combs are red or pale and whether the tissue around the eyes is swollen, then passes the images to artificial intelligence. Microphones distinguish pecking from vocalizations and use their pitch and frequency to gauge whether the flock is comfortable or under stress. The sound and video data can also serve as measures of how much feed the birds consume and how much weight they gain.

The machine detects the flock's condition before the sound of human footsteps arrives.

The story of raising productivity and the story of making animals more comfortable may seem to point in different directions. One appears to be about money, the other about well-being. Data accumulated at precision livestock farms, however, points elsewhere. Animals that experienced less stress and received care before becoming ill produced more milk and meat. The numbers confirmed once again that a farmer cannot leave animals sick and still make a profit.

A study of 90 dairy, pig, and poultry farms from 2022 to 2024 found that average raw milk production rose 13.5 percent on dairy farms that adopted precision livestock farming. Daily weight gain on pig farms improved by 15 percent. The feed required to produce 1 kilogram of raw milk fell from 1.5 kilograms to 1.3 kilograms. The feed conversion ratio for pigs declined from 2.6 to 2.2. Because these results pool farms and countries with different conditions, they do not mean that every farm will improve by the same amount.

In the same study, rates of mastitis and lameness in dairy cows fell from 18 percent to 10 percent. Respiratory and digestive diseases in pigs declined from 21 percent to 12 percent. The researchers interpreted the findings as evidence that precise detection and early intervention may reduce the burden of disease. The figures alone, however, do not establish that antibiotic use fell by the same degree.

Human work changed as well. When automated milking robots and feed dispensers take over repetitive tasks, managers can spend more time examining cows and calves that trigger alerts. The study of 90 farms reported that animal-welfare indicators improved within a range of 16 percent to 27 percent after precision livestock farming was introduced. At midday in the height of summer, when the temperature-humidity index inside the barn crosses a threshold, fans spin hard and a fine mist sprays across the cows' backs. Sensors that read temperature and humidity together activate ventilators and misters to reduce the risk of heat stress.

The amount of raw milk loss avoided varies with climate, barn design, and cooling equipment.

Yet none of this is without a shadow. Automated milking robots, three-dimensional cameras, and intelligent ventilation systems require large investments. A single robot can cost as much as constructing a modest new barn. Well-capitalized large farms move ahead, while small farms that support a household cannot reach such equipment. Over time, the gap is more likely to widen than narrow. Government subsidies and equipment rental programs try to fill it, but the structure still tends to favor large farms that can step forward first.

Too many alerts create another problem. If a sensor is overly sensitive or barn noise contaminates its readings, false alarms can make a smartphone ring dozens of times a day. Stories of farmers exhausted by notifications pouring in before dawn and switching their phones to silent mode are not uncommon. That is how even a signal of genuine danger can be dismissed without thought. Recent systems try to reduce the problem by having artificial intelligence rank alerts so that truly urgent signals appear first.

Communication is not always smooth either. Wireless signals in mountain barns frequently drop out, and the thick bodies of cows and pigs can block radio waves. Equipment and software standards differ among companies, so farmers may still have to enter the same information on one company's screen one day and another company's screen the next. Some parts of the industry have only recently begun discussing common data standards to reduce this burden.

One unusually quiet concern is the distance between people and animals. When attention remains fixed on numbers and graphs on a screen, the practiced eye developed by seeing and touching cows directly can grow dull. A line on a graph increasingly replaces the warmth and muscular tremor once felt through fingertips. There is a risk that livestock will come to be seen merely as machines for producing meat and milk. Other farmers say that by leaving repetitive feeding and routine checks to machines, they have gained time to stroke a sick animal for longer.

Return to the barn before dawn. When the manager steps out of the truck and opens the office door, the screen is filled with alerts accumulated overnight. He taps the rumination warning for cow 3 to acknowledge it, but still pulls on his boots and walks into the cattle shed. He places a hand on the cow's flank, watches its breath rise and fall for a long while, and only turns away after looking into its eyes. The machine has noticed the abnormality first, but a person confirms it to the end with both hands.

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1.2

The Four-Layer Architecture of Smart Livestock Systems: Sensing, Transmission, Analysis, and Action

The scene that follows is a fictional reconstruction based on multiple studies and field reports. At five in the morning, everything is still dark when the barn door is pushed open. Several small lights blink in the darkness: the collar sensor around dairy cow 47's neck, the infrared lamp on the ceiling camera, and the indicator on a gas sensor fixed to the wall. The breath drawn in carries the smell of feed mixed with a faint scent of disinfectant. Sawdust rustles underfoot, and another cow lows softly somewhere in the back. Unaware of it all, the cow simply ruminates in front of the trough.

Even then, the device around her neck is continuously measuring her neck movements. Far more invisible calculation than visible activity takes place inside this quiet barn. A signal from the cow's body must pass through four layers before it travels through a server and returns to the fan and feed bin: the precision sensing layer, the high-speed transmission layer, the intelligent decision-making layer, and the automated action layer.

Inside the collar sensor around cow 47's neck are two components no larger than a fingernail. One is an accelerometer that measures movement in three directions, and the other is a gyroscope that measures the angle of rotation. Depending on the device, the accelerometer measures the cow's neck movement anywhere from several to dozens of times each second. At that speed, the system can distinguish by the minute whether the cow has lowered her head, is standing still and ruminating, or is resting on her side. An electronic ear tag supplies her individual number.

Whenever the cow moves through the barn, an antenna beside the doorway automatically reads the number and records which cow stood before the feed bin and when. If beef from the cow later reaches a supermarket shelf, the traceability number on the package can be used to retrieve linked records of the farm, transport, and slaughter. Some farms go a step further and have cattle swallow a pill-shaped rumen bolus sensor. Resting in the stomach, it measures temperature and pH throughout the day and sends the readings wirelessly. Because they are attached to the body or placed inside it, devices like these are called livestock wearable sensors.

Other devices watch a cow without touching her. A three-dimensional camera suspended from the ceiling records continuous video and selects the portions showing the hind legs and hooves for transfer to a computer. These images reveal how much the cow limps as she walks and how much flesh lies along the line from spine to rump. A thermal camera shows areas where surface temperature has risen locally through differences in color. Temperature and humidity sensors, along with ammonia, carbon dioxide, and hydrogen sulfide sensors, measure the air in the barn.

In pig houses, experimental arrays of multiple microphones filter coughs from surrounding noise. Electrical conductivity and somatic cell count readings in the milking parlor serve as supplementary indicators for mastitis risk. No disease is confirmed from a single measurement alone.

Scoring body condition has also become a job for cameras rather than human eyes. A three-dimensional image reads the curve from the spine to the rump and assigns a score on a five-point scale, indicating whether the cow is lean or carries ample flesh. These scores can now be obtained far more often and consistently than under the older method, in which a person felt along the cow's back by hand. The score becomes the first criterion for reformulating the ration.

This precision sensing layer has its own shadows. When manure splashes onto a lens, the camera is as good as blind. A cow may rub against a steel fence until an ear tag falls off. Over time, a sensor can drift from its initial calibration and therefore needs periodic recalibration. In barns with many animals, cows overlap in the camera's view and recognition rates fall. Following the manufacturer's guidance and responding to the degree of contamination, the farm manager cleans the lenses and checks that the tags remain intact. No matter how smart a sensor may be, without that human touch its data slowly begins to lie.

The numbers generated at cow 47's neck do not remain there. They travel by low-power Bluetooth, Zigbee, or the long-range, low-power wireless technology called LoRaWAN to a gateway somewhere in the barn. LoRaWAN can operate for years on a small battery and reach far enough for one gateway to cover a radius of several kilometers. By the end of 2025, more than 125 million devices worldwide were connected to LoRaWAN. An Australian livestock startup fitted grazing cattle with solar-charged ear tags weighing less than 30 grams.

Even without an electrical supply, their positions can be located in real time as long as they remain within gateway range.

Before a signal reaches the gateway, a palm-sized circuit board is the first to gather it. A low-cost, low-power microcontroller called an ESP32 performs this task. When the small board publishes sensor readings as MQTT messages, the gateway subscribes to the designated topic and receives them. Delivery reliability is adjusted through Quality of Service (QoS) settings. Because the board must run for months on a single battery, conserving electricity matters more to it than communication speed.

There is another route that uses a telecommunications network already built by a mobile carrier. This method, called Narrowband Internet of Things (NB-IoT), differs from LoRaWAN because the farm does not need to install its own gateway and the carrier assumes responsibility for communication quality. In effect, the farm borrows the base station already standing nearby, so there is no new tower to erect and no new utility pole to plant. It must, however, pay a monthly communication fee, and mountain barns far from a base station remain vulnerable to weak signals.

LoRaWAN appears to be a practical choice when a farm can install a gateway and wants to run its own monitoring. NB-IoT is more realistic where cellular coverage is already good and the farm prefers to leave management to a carrier.

Large data streams such as camera video are difficult to send through these narrow channels. They require separate, wider communication routes such as Wi-Fi 6, 4G, or 5G. One study tested a dedicated barn gateway combining a Raspberry Pi 5 with a 5G module. In its test environment, latency was 24.0 milliseconds over Wi-Fi, 34.7 milliseconds over 4G, and 38.5 milliseconds over 5G non-standalone mode. The figures can vary with the farm's walls, distance from the base station, and network congestion. One practical option is to send low-power sensor data over LoRaWAN or NB-IoT while routing video separately through Wi-Fi or 5G.

There is no need to insist on only one of the four. On a small farm raising 50 Hanwoo cattle, a single LoRaWAN network may be enough to connect ear tags with temperature and humidity sensors. Conditions differ at a dairy complex with more than 500 cows. Ear-tag signals should travel over LoRaWAN while CCTV footage travels over Wi-Fi or 5G, so the two streams do not impede each other. Where cellular base stations are distant, as in mountain areas, a combination of LoRaWAN and satellite backhaul may work better. On plains near cities, NB-IoT may be the more straightforward choice.

The barn itself creates problems. Steel roofs and concrete walls reflect radio waves, while the thick body of a cow becomes a wall that blocks them. A bolus sensor inside the rumen must send a signal through the cow's torso, so its success rate can fall. The internet may also drop out briefly. Unless the gateway has storage that can hold data even temporarily, the records from that interval disappear.

Numbers that pass through the gateway gather on a server or a small computer in one corner of the barn. Calculation begins there. At first, the data consists only of acceleration values along the x, y, and z axes. Bundled across a day, those values yield an activity index showing how much the cow walked. When the activity index is unpacked again, it reveals bodily conditions such as how long the cow ruminated and whether her gait differs from normal. Combined with livestock science, the data produces a recommended time for artificial insemination or an alert for mastitis risk. Risk scores vary with the model and the farm used for validation.

The signal must climb four successive steps, raw data, index, condition, and judgment, before it becomes language a person can understand.

A cow nearing parturition may begin labor in the middle of the night. No one can sit in the cattle shed and keep watch until morning. When activity and temperature graphs take a curve different from their normal shape, the system sends an alert that calving is near. How many hours of advance warning it can provide varies with the device, breed, and the cow's calving history.

To read images, systems use the real-time visual recognition model YOLO and convolutional neural networks (CNNs) in the ResNet family. They distinguish individual cows and find limping in their gait. Convolutional neural networks are strong at reading complex patterns, while lightweight methods such as k-nearest neighbors (KNN) can run quickly on devices with limited resources. Recurrent neural networks and long short-term memory (LSTM) models read the passage of time and calculate how today's activity may lead to later disease or parturition.

Researchers are also studying ultralight artificial intelligence, known as TinyML, that runs on microcontrollers so diagnosis does not stop when a barn loses its internet connection.

A pig-house study published in 2025 shows another face of this decision-making layer. Space inside a barn is too constrained to place a sensor at every desired point. Researchers first estimated values in empty spaces by blending readings from several sensors according to distance, then applied a time-series model to reduce errors over time. Validation used 34,992 records collected from January through August 2025. The coefficients of determination between calculated and observed values were 0.970 for temperature, 0.978 for humidity, 0.981 for carbon dioxide, and 0.964 for ammonia.

The paper assumed that an ammonia sensor would last approximately eight to twelve months and cost $60 to $120 each. The researchers estimated that replacing some physical sensors with virtual ones could reduce sensor-related costs by 30 percent to 40 percent. The imputed values can also be rendered as a three-dimensional model of the barn on a web screen. By rotating the barn with a mouse, a farmer can see by color which areas have stale air.

The decision-making layer, however, has a weakness: it cannot always explain itself. Even when deep-learning models are accurate, they often cannot say why they reached a particular judgment. A model that exceeds 95 percent accuracy on a research farm may suffer a steep decline when moved to another farm with a different breed, stocking density, or barn design. Trivial environmental changes can trigger dozens of alerts in a day. After notifications sound more than twenty times overnight, the same sound becomes background noise the next day.

Finishing the calculation does not make the barn move by itself. The decision must travel back down a wire, pass through a programmable logic controller (PLC), and reach machinery that physically acts. When the temperature-humidity index (THI) crosses a threshold, ventilation fans increase their speed, while water-fed cooling pads and fine-mist sprayers switch on together. Once the fans begin turning, hot air near the ceiling is pushed out and the reading on the barn thermometer visibly drops. A robot that pushes total mixed ration (TMR) moves feed already placed at the feed bunk closer to the cows.

A fully automated feeding robot that mixes and transports feed can prepare and dispense the formula set for each management group. In the milking parlor, an automatic milking system (AMS) reads a dairy cow's electronic ear tag and begins milking when she enters on her own. If her milk is judged abnormal, an automatic sorting gate opens after milking and directs her into an isolation area.

On pasture, a virtual fence that combines a collar's location signal with a brief electrical stimulus, a method also known as eShepherd, keeps cattle within a boundary without wire. When a cow approaches the boundary, the collar first emits a short warning tone. If she continues after hearing it, a mild electrical stimulus follows. Once a cow learns this sequence through experience, she later turns back at the warning sound alone. On the barn floor, a cleaning robot called a slurry scraper follows a set route and pushes manure away.

Many farms stop before this final action layer. Automation equipment takes the largest share of total barn investment, and the threshold is harder for a small farm to cross. Machinery can halt when a foreign object becomes lodged or a motor overheats, bringing all work in the barn to a standstill. There is another difficulty. If the company that made the milking robot and the company that made the feeder use different communication standards, the two machines operate separately in the same barn without reading each other's data. When a chain breaks or a belt slips, feed stops being distributed and simply piles up.

The milking robot's screen shows data from the milk just collected, but the feeder's screen does not show how much more that cow should eat today. Each screen looks only at its own company's server. Neither sees the other.

Returning to the story of this dairy cow, it takes no more than a few seconds for one neck-movement signal to start a fan. The sensing layer creates the signal and the transmission layer carries it. The decision-making layer interprets it, and the action layer moves the fan and feeder. Once the fan is running, the lower barn temperature is captured again by sensors in the sensing layer and becomes material for the next decision. The four layers make a circle and form a closed loop. To human eyes, it is merely a quiet morning. The first sunlight enters through the eastern window.

The dairy cow still stands before the feed trough, but in the meantime the barn has probably completed this loop again and again. The green light on the collar sensor will blink again tonight.

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1.3

Edge Computing, the Cloud, and Federated Learning

The scene that follows is a fictional reconstruction based on multiple studies and field reports. At three in the morning, a camera lens turns quietly on the ceiling of a dairy barn. The farmer is still under the covers. Inside the barn, only the red light blinking on a sensor beside the feed bin and the sound of the cows breathing remain. The lens takes several pictures each second, capturing their postures, rumination, and gait. Depending on the resolution, compression ratio, and bitrate, one camera can generate several terabytes of video in a month.

If all of that video were carried over the internet to a distant server, the connection at a rural farm would bear a heavy load.

That does not happen in this barn. A small box beside the ceiling camera, the gateway, completes the calculation right there instead of sending the video outside. The method of completing calculations at the very place where data originates, inside the barn's sensors, cameras, and small computers, is called edge computing. A recognition algorithm called YOLO locates each cow, and an artificial-intelligence model that follows determines whether the cow is lying down, chewing feed, or hunching her body in pain. The system can retain the original footage for a set period or delete it immediately, sending only necessary event information outside.

Short messages reach the farmer's smartphone: cow 3 resting, cow 12 suspected of heat stress. What the farmer sees on waking is not a night of accumulated video, but these few lines of summary.

This short latency is tied directly to animal safety. Ventilation fans and misting equipment in a pig house must start as soon as the temperature-humidity index, which combines temperature and humidity, crosses a threshold. On a summer afternoon, the temperature inside a pig house can rise rapidly. Control may be delayed or communication may fail while a signal travels across the internet to a distant server and the answer returns. An edge device judges the sensor signal on site and starts the fan, reducing the burden of this round trip and the risk of a broken connection.

Farms in mountain regions have another worry. Heavy rain can cut communication lines, and wireless signals sometimes fluctuate for days. One Hanwoo farm in a valley in Gangwon Province once remained without internet until the day after a typhoon passed. Even then, automatic feeders, milking robots, and environmental controllers continued to operate. The gateway inside the cattle barn could make decisions and issue commands on its own without the cloud. Even while the internet was down, the farmer could connect a smartphone to the barn's local Wi-Fi network and continue checking the cattle. Cows do not wait for the internet to recover.

Gaps in rural communications are not unique to South Korea. Agricultural machinery companies and telecommunications carriers are working together in many parts of the world to extend Long-Term Evolution and 5G signals to remote farms.

A communication outage is not the only threat to a mountain farm. Several nights a year, a typhoon or lightning strike may cause an entire village to lose power. Then the situation is different. The gateway in the barn can think for itself when the internet is down, but if electricity itself is lost, the small computer stops with it. Cameras, sensors, and screens all go dark. The autonomy of edge computing that endured a severed communication line must once again wait for a human hand in front of a single power cord.

In mountain regions where both the power grid and communications network are fragile, the risk appears to come in two overlapping layers.

The edge device's task resembles filtering information rather than carrying it in full. Instead of sending tens of thousands of sound samples per second or dozens of video frames accumulating each second, it selects moments when behavior changes or a reading crosses a threshold and transmits only a brief signal. Palm-sized computers such as a Raspberry Pi or an ESP32 carry an ultralight artificial-intelligence engine called TinyML. The engine combines readings from accelerometers, thermometers, ammonia sensors, and acidity meters, then identifies signs of abnormality in cattle or pigs at the site.

A single collar sensor simultaneously measures steps, rumination frequency, and temperature. The moment those values diverge from the animal's normal pattern, an alert appears in the app. In a study published in an international journal in 2026, an Edge TPU-equipped, multimodal TinyML system reduced the size of its artificial-intelligence model to as little as one 270th while keeping response time below 80 milliseconds.

Selecting and sending event information instead of large files is called event-based transmission. When model compression and low-power computation are added, the amount of electricity consumed by a small machine also falls. Green AI and Frugal AI are broader perspectives that encompass these savings in computation and energy. CattleML is the name of a lightweight inference device for livestock proposed by a 2026 study. These technologies take different routes toward reducing both the volume of data sent outside the barn and the energy burden on devices at the site.

If the edge supplies an immediate answer inside the barn, cloud computing in a distant data center takes time to draw the larger picture. It gathers summaries from farms across the country and plots weight-gain curves, raw milk production curves, and seasonal feed efficiency over months and years. With one office monitor, a veterinarian can place a farm in Gyeongsang Province beside one in Chungcheong Province and compare where cattle grow better or which feed mixture performs better in winter. A single graph can help assess health without a long drive to a distant farm.

The cloud uses powerful graphics processing units to retrain a vast artificial-intelligence model on millions of records, then sends the refined model back down to the edge devices in the cattle barns. Data rises from below in summarized form, while intelligence descends from above after refinement.

The edge and the cloud have different jobs from the outset. An edge device handles video pouring in at dozens of frames per second and an unbroken stream of sensor readings. Its response is completed in a range from a few milliseconds to a few hundred milliseconds. The cloud handles summaries filtered and sent up from many farms, together with management statistics and medical records, and returns its answer over seconds or minutes. The edge can run alone when the internet is down, but the cloud works only when stable wireless communication continues.

Engineers call this arrangement, in which the field and the center fill each other's gaps, a hybrid edge-cloud architecture.

Yet farmers still carry a weight of concern. They worry that their own feed formulation ratios, financial records, disease histories, and video from inside the barn may fall into the hands of a competitor or a feed company while passing through the cloud. A feed mixture refined over decades is a secret a farmer may cherish like a child. It would be a bitter thing if those numbers wandered somewhere on the internet and flowed into a farm in the next village. This anxiety appears to have slowed the move toward smart livestock farming in practice. Can artificial intelligence become smarter without farmers giving up their data?

This concern has a name: data ownership. The daily output of every cow, precise feed formulation ratios, farm financial records and disease histories, and even video looking into the cattle barn all raise questions. Who owns these data, and how much may be transferred to whom? The boundaries have not yet been fully drawn. Once raw data leaves a farm, it is difficult for the farmer to trace every place it passes and every hand that receives it. This is precisely why federated learning, in which only weights move, has attracted attention.

Federated learning offers one answer. Its principle is unexpectedly straightforward. The data remain on the farm, while the artificial-intelligence model visits the farm, learns, and returns. It resembles an itinerant teacher who visits each classroom and writes down only the lessons learned that day, instead of collecting every student's entire notebook. First, a central server sends the same base model to the edge devices at farm A, farm B, and farm C. Each farm quietly trains the model using only its own cattle data. When training ends, the original records never leave the farm.

Only weight values showing how the model changed travel to the central server. Because these values can also leak information, separate protections such as encryption in transit and secure aggregation are required. The central server statistically averages the numbers arriving from the three farms into one integrated model, then distributes it to every farm again. A disease signal experienced by the herd at farm A may provide the clue that saves a cow at farm C, whose name and face no one at farm A knows.

This averaging procedure has a name of its own. Because it blends numbers from multiple farms into one, engineers call it Federated Averaging (FedAvg). It resembles combining the different test scores of each classroom into one schoolwide average. But if sick cattle are concentrated on one farm and another has only healthy animals, taking the average does not eliminate the bias. In a Non-IID environment, where the character of the data differs from farm to farm, the integrated model's performance may deteriorate.

Recent work adds cryptographic techniques such as blockchain ledgers and zero-knowledge proofs. A zero-knowledge proof establishes that something is true without revealing its contents. The ledger preserves an indelible record of who sent which value and when, allowing a dispute to be traced later. Researchers have also proposed using graph attention neural networks to group similar farms before training, in an effort to reduce differences in the character of data caused by varied rearing environments and animal breeds, the so-called Non-IID problem.

Dairy farms learn first with other dairy farms, while pasture-based Hanwoo farms form their own group before learning.

One experiment applying these methods produced notable results. Communication volume in one round was 4.25 kilobytes, 97.7 percent less than under the comparison method. Under baseline conditions, the accuracy of the integrated model was 96.94 percent. Even when noise was added to 20 percent of the signals, accuracy remained above 90 percent. The experiment, however, used public data, so its findings cannot be assumed to match long-term performance on actual farms.

In March 2026, a federated-learning model that predicts cattle growth curves from weight records was released as an arXiv preprint. The model combines a recurrent neural network with a multilayer perceptron to read growth over time from past weight records. In effect, it borrows data from other farms to estimate how much a calf on a given farm will grow by the next month or the next season. To account for differences in stocking density and feed formulations, the researchers also proposed a personalized approach that adds a farm-specific prediction layer on top of the shared model.

A limitation remains: it is not a peer-reviewed conference paper.

The movement is clear in South Korea as well. The Korea Institute for Animal Products Quality Evaluation has created an organization dedicated to smart livestock farming and operates support programs that connect farms with wearable sensors, environmental sensors, and data standards. It is also pursuing a foundation through which farms, academia, and private companies can use data together. For this plan to take root, however, it cannot avoid the question of who will provide how much data. Federated learning tries to answer that very question: can everyone become smarter together without gathering all raw records in one place?

Of course, holes remain in this net. An edge device inside a barn is a palm-sized object without abundant storage or power. Long exposure to hot, humid air, ammonia gas, and dust can corrode a circuit board or overheat it, leading to faults that distort calculations. Equipment with weak protection against water, dust, and damage to circuitry requires earlier replacement.

The different character of each farm's data is another obstacle. Hanwoo cattle, dairy cows, pigs, and chickens differ in their basic physiology. Even among farms raising the same cattle, stocking density, feed formulation, and barn structure vary. A mountain farm with broad pasture and a plains farm that packs cattle into a narrow barn may raise the same dairy breed but produce data with entirely different shapes. As a result, the model weights trained independently at each farm can diverge sharply. When the central server averages them into one, a paradox can arise in which the integrated model becomes less accurate.

One cycle in which several farms exchange weights is called a round. With each round, the integrated model becomes slightly more refined, until it reaches a point beyond which little changes. How quickly it approaches that point depends on how often and how consistently farms respond to each round. As communication grows lighter, each round takes less time, and the model finds its course sooner.

A remote farm that loses communication for hours disrupts the rhythm of the cycle. In synchronous federated learning, which waits for every participant's response, one slow farm can lengthen the update cycle for all. Actual systems reduce the problem by selecting only some participants, setting response deadlines, or using asynchronous learning that does not wait for a late farm.

Water- and dust-resistant device design and standards that align the different data formats used by farms remain problems pursued by many laboratories.

Outside the cattle barn before dawn, the internet signal still flickers. Even so, the gateway screen lists the condition of 60 cattle, one clean line at a time. Far away, on a server, the few numbers this farm sent last night are quietly mixing with numbers from other farms. The air in the barn remains dark, and the cattle continue to ruminate.

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CHAPTER 2

Multimodal Sensing and Monitoring

2.1

Computer Vision and Object-Detection Algorithms

The scene that follows is a fictional reconstruction based on multiple studies and field reports. At five in the morning, dairy cows stand in line in the narrow passage leading to the milking parlor. The smell of feed and milk mixes in the corridor where their breath rises white. One cow is missing the yellow tag that should be on her right ear. Only a red wound remains where it tore away when she struck her head on a steel fence the day before. The manager shines a flashlight and tries to guess her number by the angle of her horns and the way she walks, relying on the practiced eye.

Behind her, other cows stamp their feet with impatience, and the milking machine beats out its steady sound. Only after passing several similar-looking cows does the manager finally identify the one without a name tag. Unconcerned by the commotion, a ceiling camera traces a rectangular box around each passing cow and quietly places a number beside it instead of a name.

Ear tags punched through the ear, tattoos marked on the skin, and ear notching that removes a piece of the ear's edge have long been standard ways to distinguish cattle, pigs, and sheep. These methods leave a mark on the animal's body. An ear tag may snag on wire mesh or tear away in a collision with another animal, and when mud or manure covers it, the number becomes difficult to read. Losing a tag does not instantly erase the animal's record from the farm ledger, but it creates the work of attaching a replacement and reconnecting the history. Later came electronic ear tags containing radio-frequency identification chips, read by an antenna.

A cow can still be missed if she moves outside the antenna's range. This is why researchers began looking for a way to recognize an animal by sight wherever it walks, without attaching anything to its body.

Accurate identification is not a spectacle. Records showing which cow is pregnant, which one has eaten less than usual over the past three days, and which pig is gaining less weight than its littermates all hang on an individual number. If the number wavers, the records waver with it. A breeding program that selects a bull with strong reproductive performance cannot even begin without accurate individual records. A traceability system that follows an animal from the farm where it was born, through the slaughterhouse, and to the table likewise requires an unshakable individual number at its base.

The same is true of epidemiological work tracing an outbreak back to the farm where it began. Insurance and pedigree records retain official individual numbers and documents, while faces and markings read by a camera become another clue that supports them.

A camera lens avoids the problem without touching the cow's body. Computer Vision (CV) is the field of artificial intelligence that reads shapes and movement in photographs and video. Within it, Object Detection is the technology that finds what is present in an image and where it is located. Deep Learning models read outward features that change little over an animal's lifetime: the bone structure of a cow's face, the positions of eyes, nose, and ears, the arrangement of wrinkles on the muzzle, the pattern of black and white patches across the body, and, in a goat, even the iris pattern in the eye.

Because muzzle wrinkles resemble human fingerprints, they are sometimes called muzzle prints. Research has found that algorithms combining Scale-Invariant Feature Transform (SIFT) with a Convolutional Neural Network (CNN) substantially increase the accuracy of reidentifying the same animal. Once a photograph of the muzzle pattern has been stored, it can be compared again when the same cow passes before the lens, allowing identification within seconds. In breeds with black and white body patches, such as Holsteins, the arrangement of markings alone can distinguish individuals.

In species with dark irises, such as Bengal Black goats, the fine vascular pattern of the iris acts as a fingerprint. Researchers have also combined muzzle recognition with few-shot learning, which can train on only a small number of photographs, for rare breeds from which hundreds of images are difficult to collect. On several farms, systems already send an alert to a manager's phone when a camera discovers an unregistered face. In a pig pen, even when ten piglets pile across one another in a narrow space, the camera strains to preserve the number assigned to each.

From birth onward, a notably small piglet's weight gain among its littermates can be followed every day with that one camera, without attaching a new name tag.

One core algorithm that performs such recognition in real time is YOLO. The name itself means You Only Look Once. Older methods combed through an image repeatedly, examining candidate positions one by one. YOLO divides a single image into a grid and predicts the objects and boundaries at every position in one neural-network computation. People first draw boxes around cattle in each photograph to mark the correct answers. The neural network then compares the boxes it draws with those answers and gradually reduces its error. As the series moved through YOLOv3 and YOLOv5 to YOLOv8, YOLOv11, and YOLOv12, the models became lighter and faster.

Performance in this family is commonly expressed as mean Average Precision (mAP), a score indicating how accurately the model identifies an object's location and class. A benchmark study published in 2025 reported that, in a task treating number markings as individual classes, the YOLOv12m model achieved mAP50 of 0.947 and mAP50-95 of 0.911. In another study recording lactating sows, the YOLOv8l model distinguished standing, lateral lying, and nursing postures with an F1-score above 0.90. A paper also tested a lightweight YOLOv11 model for dairy-cow detection and tracking on low-specification equipment.

Ultralytics previewed YOLO26 in September 2025 and announced its official release in January 2026. The official documentation gives a CPU ONNX inference time of 38.9 milliseconds for YOLO26n. Speed changes with input size, hardware, and runtime. Separate field validation is needed to determine how well this model finds cattle or pigs in a barn.

Considerable human labor is required before one of these models can be put to practical use. Before fixing a camera to the ceiling, researchers visit a barn for months and take thousands of photographs. In each image, they mark by hand the location, breed, and posture of every animal. Unless the collection includes dark and overcast days and images in which rain blurs the markings, the resulting model may perform well only on frontal photographs taken in clear weather.

If YOLO answers where an animal is, neural networks such as ResNet (Residual Network) serve as the backbone that decides what the form represents. As neural networks grow deeper, they can become better at reading fine patterns, but training becomes more difficult and the error may actually increase, a problem known as degradation. ResNet uses a Residual Learning structure with shortcuts that pass information across layers, preventing training from collapsing even as layers deepen. Lower layers recognize lines and light-dark contrast. Middle layers read the texture of hair and the edges of patches.

Higher layers distinguish larger forms such as the overall shape of a face. A ResNet-50 study combining Channel Attention with images from five livestock species and 44 breeds reported breed-identification accuracy of 94.3 percent. Vision Transformer (ViT) models, which encode an image by dividing it into small square patches, have also entered the competition. In a comparative study across 459 classes of cattle images, ResNet18 achieved 95.86 percent accuracy and the Vision Transformer 96.27 percent. For both models, the probability of placing the correct answer among the top five candidates exceeded 99 percent.

Dairy DigiD's Detectron2-based model, which tracks coordinates around the eyes, nose, and ears, recorded an overall weighted F1-score of 0.92. Its class-level F1-scores were 1.00 for pregnant cows and young cattle, 0.96 for mature cows, and 0.94 for dry cows. DGS-YOLO, a pig-specific facial-recognition model published in 2026, was designed to distinguish individuals quickly even inside a crowded pig pen.

Beyond the barn roof, cameras also take to the sky. High-resolution cameras carried by Unmanned Aerial Vehicle (UAV) drones scan broad pastures from tens of meters above and capture scattered livestock in one view. Before sunrise, the sight of a drone rising over dew-covered grass and leaving only the sound of its propellers behind has become a familiar morning scene on many ranches. Counting that once took hours of riding a motorcycle or driving a truck can now end with one short recording. Older methods that brought cattle together on horseback or by truck placed considerable stress on the animals.

A drone can remain high enough not to frighten and scatter them while still finding each one. Research published in 2025 found that, even in pasture video mixing breeds with overlapping appearances, such as Simmental, Holstein, and Brown Swiss, deep-learning models including C-DCNN, Xception, and VGG19 combine body contour, frame, and coat-color patterns to separate breeds and count animals. In the summer of 2026, a company said it had launched multiple drones at once and counted 90,000 cattle on a large ranch in under two hours. The company announced accuracy of 99.997 percent.

That figure was the company's own claim, not a result verified by independent researchers. Whether it remains the same in dense fog or terrain with heavy tree shade still requires observation. In a dark pasture at night, not only fog and shade but the lack of light itself can make shapes impossible to distinguish, so a growing number of farms combine visible cameras with thermal cameras that sense body heat.

Finding a cow in one photograph is an entirely different task from following that moving cow under the same number for ten minutes. The latter is called Multi-Object Tracking (MOT), and algorithms such as DeepSORT and ByteTrack have long performed this role. They work by connecting location information extracted from one frame to the next. An algorithm notes where an animal has just been, calculates where it is likely to appear next, then assigns the same number to the individual nearest that predicted location in a new frame. It checks again by comparing markings and appearance.

On open pasture, where cattle stand apart, this approach works relatively well. In a narrow barn passage or before a feed bunk, conditions are different. Several times a day, the distance between animals shrinks to less than the width of one torso. The moment one animal blocks another, an event known as Occlusion, the calculation begins to fail. When two or three pigs tangle together or climb over one another in a tight pen, the tracker may lose their numbers or swap the identities of two animals entirely. A 2026 study tested a method called Depth-OC-SORT combined with a camera that also reads depth.

The paper noted that conventional tracking methods commonly used in complex barn environments caused ten to twenty identity-switch errors per minute. Overlap is not the only cause. Moisture carrying feed dust and manure residue clings to the lens. Sunlight enters through windows at different angles in the morning and evening, while at night the lights themselves go out. A model trained for one farm, one breed, and one stocking density commonly suffers a sharp loss of recognition when moved unchanged to a neighboring farm with a different barn structure.

A model trained only on dairy-cow images, for example, can become entirely unusable when transferred directly to a pig-house camera. Unless photographs from many farms are evenly mixed in training, this gap is unlikely to close easily. Recognition also remains weaker for categories with few available images, such as pregnant cows or animals just beginning to fall ill. A 2025 review of these difficulties identified occlusion, environmental noise, and differences in rearing conditions among farms as factors that impede multi-object tracking.

To fill the gap, researchers are testing combinations of downward-looking depth cameras and thermal cameras mounted on the ceiling, so an animal can be retained by the outline of its body heat even when its visible markings are hidden.

Back in the passage before dawn, the cow that lost her ear tag now recovers her number simply by walking beneath a camera. The manager no longer needs to hold a flashlight and measure the angle of her horns. A grain of dust on the lens and morning sunlight cutting through the window still disturb the calculation, but before the next cow enters the passage, the system quietly corrects the errors it made this morning.

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2.2

Wearable Sensors and IoT Biometric Data

The scene that follows is a fictional reconstruction based on multiple studies and field reports. At five in the morning, the first thing encountered when the barn door opens is not light but sound. Cows with their noses in the feed bunk chew their rations, and a brief electronic beep slips into the spaces between. As a dairy cow wearing a thick belt around her neck lowers and raises her head, a green light inside it blinks steadily. To a human eye, it is only the motion of a shaking head. To the tiny chip inside the belt, it is a coordinate that changes at every instant.

On a winter morning when breath spreads white and at the height of a sweltering summer day, the light never goes out. Even while people sleep, the belt continues counting how many steps the cow has taken and how many times she has lowered her head.

The chip is called a three-axis accelerometer. It works on the same principle as the component that rotates a smartphone screen when the phone is turned sideways. It measures movement forward and back, side to side, and up and down on three separate axes. When the three figures are overlaid, waveforms reveal whether a cow has lowered her head, is running, or is standing still. Add a gyroscope that measures how quickly the body rotates, and the result is a more sophisticated component known as an inertial measurement unit, or IMU.

Even when the cow thinks she is doing nothing at all, the component on her neck is converting bodily movement into numbers dozens of times per second.

These numbers pass through several stages before reaching a person. The chip in the collar temporarily stores acceleration readings taken at brief intervals, bundles them together every few minutes, and sends them by wireless signal. A receiver installed on the barn roof or in one corner of the yard receives the signal and transfers it to a server through an internet connection. An artificial-intelligence model on the server reads the waveform and distinguishes rumination, feeding, and resting. This arrangement, in which multiple devices exchange signals and form one management network, is called the Internet of Things, or IoT.

The judgment immediately appears as a notification on the farmer's mobile phone. A cow's motion of shaking her head two or three times becomes a sentence in a person's hand within seconds.

The waveform produced as a cow slowly works her jaw from side to side while ruminating differs in shape from the waveform produced as she lowers her head toward the trough and eats rapidly. Rumination creates rounded, slow curves repeated at regular intervals. Feeding produces tightly packed runs of short, pointed waves. When the cow lies on the floor, the value on the vertical axis drops sharply. The moment she stands again, it leaps upward. A healthy dairy cow generally spends 400 to 600 minutes a day ruminating. The server does not rely on one fixed rate of decline.

It considers how far rumination time has fallen from that individual cow's normal baseline and how long the change persists. If the decline continues, it displays an alert for a possible disease such as mastitis or ketosis. The waveform records jaw movements that a person cannot watch all day.

Rumination, feeding, standing, and lying are not the only movements an accelerometer can distinguish. When a cow rubs her body or head hard against a barn post, a virtual fence, or a grooming brush, the waveform takes another form. It is neither the rounded curve of rumination nor the sharp repetition of feeding. Signals jump irregularly at high frequency and crowd into a short interval. Even if a person is standing at the far end of the barn, this signal alone allows the server to determine immediately which cow is scratching herself.

Early sensors identified behavior by comparing accumulated numbers with thresholds. More recently, artificial-intelligence models called convolutional neural networks and long short-term memory algorithms, abbreviated CNN and LSTM, have entered both sensor terminals and servers. Accuracy varies with device placement, the type of behavior, the time window, and the farm environment. Even two results in the 90-percent range can represent tasks of different difficulty, such as distinguishing a standing posture and identifying the moment rumination begins.

These conditions accompany the transformation of a waveform, once no more than the rise and fall of several numbers, into information approaching a daily schedule for an individual cow.

Behavior-classification accuracy of 97 percent means that 3 percent of the observed time windows or behavioral events were misclassified. It cannot be converted into the number of individual animals read incorrectly in a day. Measuring rumination time by the minute presents the same issue. A waveform does not always cut cleanly between the beginning and end of rumination. If a cow makes several stray jaw movements, pauses briefly, and begins chewing again, an error can enter between the actual rumination time and the machine's estimate.

The movements detected by the same accelerometer differ according to where it is attached. A collar sensor reads jaw movement and head angle sensitively, and it remains among the more accurate methods for distinguishing rumination from feeding. An ear-tag sensor responds more readily to an ear flick or head shake, while its light weight places less burden on the cow. A nose-ring sensor can capture the breath and pressure moving through the nostrils and therefore read signals from deeper inside, such as respiratory rate or pulse.

A study that compared sensors at three positions, collar, halter, and ear tag, found that large movements such as walking or standing were distinguished well at every site, but recognition rates diverged sharply by location as the movements became subtler. Choosing where to attach a sensor is therefore not a matter of preference. It is a design decision governed by what one wants to know.

An actual cattle collar contains a low-energy Bluetooth chip or a low-power wide-area wireless chip called LoRa, which carries data to a receiver in the barn. One evaluation of the RUMI collar accelerometer found specificity of 100 percent and sensitivity of 90.9 percent. It was highly effective at identifying cows that were not in estrus and detected roughly nine of every ten cows that were. In other older pedometer studies, the share of alarms triggered when cows were not in estrus ranged from 17 percent to 55 percent. Those data came from different devices and farm conditions and should not be combined with RUMI's results.

An ear tag can also serve as a name tag by incorporating a Radio-Frequency Identification, or RFID, chip. Nose-ring sensors are used on only a small number of farms, but efforts continue to read pressure changes caused by respiration and heartbeat with a thin membrane inside the ring.

Sheep and goats grazing on broad pasture cannot carry heavy equipment. They therefore wear lightweight collars fitted with only a small accelerometer. The rhythm of a sheep's motion as it tears off grass in short bites clearly differs from the motion of raising its head and walking. From this rhythm alone, it is possible to infer which area has been grazed out first and which animal has not eaten enough. Several studies have distinguished feeding, walking, and rumination with one collar. The broader the pasture, the more this tiny device replaces work that would be difficult to perform animal by animal with the human eye.

Paired with an invisible virtual fence, a collar can also use vibration or sound to turn a sheep back when it tries to leave a designated area, a method that is spreading as well.

Pigs face an entirely different problem. Their curious mouths chew whatever catches their attention, so ear tags can be damaged or lost. Electronic pig tags are therefore enclosed in impact-resistant housings, while the accelerometer inside focuses on the posture of a sow as she stands and lies down, and on the speed of those movements. A newborn piglet can be crushed beneath a mother that weighs far more. This is why researchers continue working to read the sow's posture together with the piglet's cry and signal danger. A chewed ear tag lying on a sawdust floor is not an unfamiliar sight on a pig farm.

Beside a piece of plastic marked clearly by teeth, the pig that once owned the tag often has her nose calmly buried in the feed trough.

Some devices enter through a cow's mouth and settle inside the stomach. A cow swallows a ceramic capsule much larger than a pill, and it sinks into the rumen, the first stomach. There it measures temperature and pH and transmits the readings wirelessly. In South Korea, a company called LiveCare has commercialized this type of capsule sensor. In explanatory material issued during the development stage in 2018, the Rural Development Administration gave an accuracy level of about 70 percent for predicting disease, estrus, and parturition, compared with 40 percent for visual observation.

Performance measured under different conditions cannot be applied unchanged to every farm today. The Canadian company Wandering Shepherd states a battery life of ten years for its wireless rumen capsule. That is a manufacturer's specification, not the result of long-term field tracking.

There is a reason so much effort is devoted to a single number, body temperature. During some infectious diseases, heat stress, estrus, and parturition, internal temperature moves before or alongside other signs. When the temperature-humidity index, abbreviated THI, crosses a certain line, a cow may enter heat stress. Sunlight falling on the back or a cold wind striking the flank can easily raise or lower skin temperature. A sensor placed inside the body is less affected by the environment, but temperature alone cannot confirm disease or reproductive status.

Temperature can be measured somewhere other than the stomach. A sensor inserted into the vagina of a cow approaching breeding measures temperature and electrical conductivity, looking for changes that occur during estrus. There are also implantable sensors, small capsules placed under the skin or behind the ear. Such a device reads temperature at its implantation site. To estimate core temperature, its error must be validated against a reference thermometer. The target value is the same, body temperature, but the location determines how often it is measured and how long the device lasts.

Compared with computer vision that uses cameras to examine cattle, body-attached sensors have a clear strength. When lighting grows dark, when cattle block one another, or when an animal moves behind a barn structure, a camera simply misses the movement. A sensor has no such blind spot. Hanging from the neck, attached to the ear, or settled inside the body, it streams signals 24 hours a day wherever the cow walks in the barn and however dark the night becomes. Yet beyond the barn door, a long line of problems remains that this strength alone cannot solve.

All these devices run on one small battery. One manufacturer states that a Bluetooth label using a CR2032 battery can last up to 765 days under conditions of 0 dBm output, a five-second transmission interval, and a disabled three-axis accelerometer. That is a product specification under defined conditions, not a field measurement. A collar sensor may consume more power because it reads its accelerometer dozens of times per second and also transmits wirelessly.

When the batteries run down, hundreds of cows must be restrained so their collars can be removed and the cells replaced. It is not welcome labor for barn workers.

This rate of consumption reflects an unavoidable tradeoff. The more instants an accelerometer samples each second, the denser and more precise the waveforms separating rumination from feeding become, but the faster the battery is depleted. Sampling more sparsely to save the battery reverses the problem. Brief, subtle movements then escape through the gaps between waveforms. Manufacturers cannot avoid this balance when setting sampling intervals, and the result appears directly in battery-replacement cycles and the precision of behavior recognition.

Even a healthy battery does not guarantee that a signal will arrive intact. When cows stand shoulder to shoulder in a narrow cattle barn, their thick, water-filled bodies absorb the radio waves. The collar sends a signal, but nothing reaches the receiver. On a hot summer day, a cow may keep shaking her head to drive off flies. The system can misread this as rumination and issue an alert for a disease that is not there. The same survey found cases in which a cow whose entire gait was disrupted by one lame leg was incorrectly identified as being in estrus.

Another labor-intensive problem is the sensor falling from the body entirely. Cows rub their necks and heads hard against steel fence posts or trees, and the friction can open a collar buckle or tear away an entire ear tag. A four-year Canadian survey followed 2,000 calves, 1,000 growing cattle, and 700 adult cattle. Ear-tag retention exceeded 96 percent in calves but averaged 82 percent in adults. On pig farms, animals biting one another's ears also causes tag loss. When a tag falls off, the history in the farm ledger does not immediately disappear, but the individual must be reconnected to the record.

The act of attaching an ear tag can itself leave a wound. When the ear is pierced, inflammation may spread through the cartilage, and insects such as flies may gather at the wound and aggravate it. A collar is not always safe either. If fastened too tightly, it can rub and strip the skin underneath until an ulcer develops. A device fitted to read an animal's movements may end by leaving a new injury on that body.

Efforts to solve these problems continue. Self-powered collars that harvest electricity from a cow's temperature or movement, and ear tags made from materials that do not break easily when chewed, are being tested in laboratories and as prototypes. Solar-charged collar devices also combine an accelerometer with a temperature sensor to ease the burden of battery replacement. One commercial market survey estimated the livestock wearable-sensor market at $2.18 billion in 2025 and projected an average annual growth rate of 12 percent from 2026 through 2034. The scope and figures vary among research firms.

No clear representative statistic yet shows the adoption rate across all U.S. livestock farms. Still, the hand opening the barn door at dawn first reaches toward the belt around a cow's neck to make sure it remains securely in place.

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2.3

Measuring Without Touch: Thermal Imaging, Spectroscopy, and Sound

The scene that follows is a fictional reconstruction based on multiple studies and field reports. At five in the morning, a thermal camera suspended from the cattle-barn ceiling slowly turns its lens. Around the eyes and at the bases of the ears of sleeping dairy cows, orange forms appear on the screen. Only one cow lying in a corner stall shows a noticeably deeper color. No one has yet opened the barn door. Before the person on duty sits down in the office chair, the server is already turning through the night's images and continuing its calculations alone.

There is a collective name for these technologies. Because they read an animal's condition from signals without touching its body, they are called non-contact, non-invasive biometric measurement technologies. Because they observe the entire farm in fine detail, they also fall under the broad heading of Precision Livestock Farming (PLF). Cameras and microphones watch the barn 24 hours a day, 365 days a year, without fitting an ear tag or collar. While wearable sensors can be lost, rub the skin, and require battery replacement, these technologies perform similar work without hanging anything on the bodies of cattle, pigs, or chickens.

This camera does not touch the cow. It receives infrared energy emitted from the body surface and reflected from the surroundings, then converts it into a surface-temperature map. The colors on the screen are only a palette chosen by the device. Red does not always indicate the same temperature. A cow's eyes, ear bases, udder, and hooves, which appear as black shapes in darkness, emerge as separate temperature regions before an Infrared Thermography (IRT) camera. Surface temperature in areas with abundant blood flow serves as a supplementary indicator of bodily condition.

The value read by the camera is not core body temperature itself, so ambient temperature, humidity, wind, distance, and emissivity must be considered in calibration.

Mastitis can severely disrupt the finances of a dairy farm. When inflammation develops, the surface temperature of an infected udder quarter may change. One study recorded thermal images of dairy cows' eyes and udders as they entered a milking parlor and segmented them with a deep-learning model called CLE-UNet. Compared against somatic cell counts, mastitis classification accuracy was 86.67 percent, sensitivity was 82.35 percent, and the F1 value was 87.5 percent. Because this was a classification study at one point in time, it cannot establish that the condition was detected days before clinical signs.

A thermal alert must be followed by a somatic cell count and veterinary confirmation.

Beyond CLE-UNet, various image-segmentation and object-detection models have been tested to locate eyes and udders. Each model traces contours and identifies temperature regions in a different way. The mere use of multiple models does not reduce misdiagnosis. Sensitivity and specificity must be compared on the same data. Thermal imaging is best treated as a screening device linked to milk testing and clinical observation, not as a definitive diagnosis on its own.

Cattle have limited capacity to release heat through sweat. In hot, humid weather, they pant to drive heat from the body. Thermal cameras are used to measure surface temperature around the eyes and ear bases. Respiratory rate can be measured in another way. One study segmented a cow's torso in ordinary RGB video with DeepLab V3+, then amplified subtle chest movement using Phase-based Video Magnification. It reported average respiratory-rate measurement accuracy of 93.04 percent across 70 videos. In 105 heat-stress videos, the figure was 98.69 percent. Thermal imaging and RGB video can be used together, but they are not the same sensor.

As heat stress intensifies, surface temperature around the eyes and ear bases, respiratory rate, and posture may change together. Artificial intelligence places these signals beside the temperature-humidity index and generates an alert. A judgment based only on one fixed temperature or respiratory rate can miss differences among individuals and seasons. Research continues on heat stress in ruminants such as goats and sheep by combining surface temperature with behavior.

Newborn calves are vulnerable to Bovine Respiratory Disease (BRD). Early in pneumonia, body temperature rises only slightly, a change that is difficult to feel by hand. If the temperatures of the eye and nostril are measured automatically with thermal imaging, a sick calf can be moved aside and treatment begun without forcing a thermometer into its mouth. The isolated calf receives feed separately in a pen away from the group, while antibiotics bring down the inflammation in its body. A similar process occurs around the hoof. Arthritis or hoof inflammation raises the surrounding temperature.

Detecting this change can reveal a problem before the cow begins to limp.

The human eye sees visible light at wavelengths of roughly 400 to 700 nanometers. Multispectral and hyperspectral cameras divide images across multiple wavelength bands, including Near-Infrared (NIR). A multispectral camera selects several bands, while a hyperspectral camera reads more densely spaced bands in a continuous sequence. Differences in reflectance can be used to estimate surface condition, moisture, and material composition. One recording, however, cannot conclusively determine blood oxygen saturation, capillary flow, and edema all at once.

Which physiological indicators can be read depends on the wavelength range and calibration data.

A drone carrying thermal and multispectral cameras together can scan a broad pasture. A study published in 2026 reported accuracy above 90 percent in using drones and artificial intelligence to identify health abnormalities in cattle. The result combined temperature anomalies, movement, and skin problems. It does not mean that wounds and dehydration each achieved the same accuracy. A drone can scan a broad area faster than a person, but the time required varies with ranch area, terrain, and flight regulations.

Researchers have also distinguished chicken breeds by reflectance at different wavelengths. This study, however, did not identify live chicks in a poultry house. It was a food-authenticity study that photographed sections of breast meat from four slaughtered chicken breeds with a hyperspectral camera. It differs in subject and purpose from computer-vision research that reads the comb shape, gait, and position within the flock of live chickens. A line must be drawn between biometric identification conducted with ordinary video and meat-breed identification conducted with spectral images.

Microphone arrays mounted on a pig-house ceiling capture an entirely different signal. Amid the mixed noise of ventilation-fan motors, feed dispensers, and pigs colliding and squealing, artificial intelligence filters out coughs. When sound is unfolded into Mel-Frequency Cepstral Coefficients (MFCC), convolutional neural networks (CNNs) and recurrent neural networks (RNNs) find the trace of a cough. Commercial systems such as the Pig Cough Monitor and SoundTalks use this principle. SoundTalks states that it can signal a respiratory abnormality up to five days earlier than manual inspection.

This early-detection claim is not a performance measure equivalent to 90 percent accuracy in an independent study.

The actual screen displays more than numbers. When an abnormal signal is detected, it shows a short sentence that a person can understand at once, such as, "Pen 3: cough pattern of an early respiratory infection detected." It does not stop at converting sound into numbers. It translates the signal into words a caretaker can read and act upon immediately.

The judgment does not occur only on a large server. More recently, ultralight artificial-intelligence models known as TinyML have been embedded directly in a small chip beside the microphone, allowing sound to be classified instantly without being sent to a server across the internet. The entire process, collecting the signal, filtering noise, and refining it through Digital Signal Processing (DSP), takes place in one small box inside the barn. On a remote farm where the internet is broken or communication is slow, this approach is more dependable.

Coughs are not the only signals. When pigs are ill or stressed, the texture of their cries and breathing may change. Researchers are testing methods that distinguish coughs, screams, and ordinary vocalizations and use them as supplementary indicators of health and welfare. Sound alone cannot confirm a disease. Environmental sensors, video, and a veterinarian's confirmation must follow.

In 2026, the National Institute of Animal Science began field demonstrations of this technology at two pig farms, one in Gimje, North Jeolla Province, and the other in Cheonan, South Chungcheong Province. At the time the demonstration began, the developed models had accuracies of 91.4 percent for detecting activity, 91.3 percent for detecting cough sounds, and 90.0 percent for detecting feeding behavior. These figures were not results produced after the two-farm demonstration was completed. The researchers plan to compare farm records of mortality and stunted pigs with video and audio data to establish early-warning criteria.

Cattle also reveal their condition through their voices. Research continues on using machine learning to classify vocalizations and find signals of estrus, stress, and hunger. Missing the period of estrus lengthens the wait until the next opportunity for pregnancy. Continuous listening for calf coughs can help detect a respiratory abnormality in a group early.

Voice matters to sheep as well. Newborn lambs and ewes distinguish each other's voices amid the sounds of the flock. If a machine learns the features of each individual's call, it opens a path to finding a particular animal's voice within the group. The Cattle Call Monitor, developed for cattle, emerged from a separate line of research. It selects and records estrus vocalizations from a dairy herd, helping the farmer identify the right time for breeding.

Microphones in a poultry house count the sound of pecking and the vibration of swallowing to estimate changes in feeding across the flock. Artificial intelligence also targets coughs in chicks. In a study published in 2026, mAP during training was 92.86 percent, while accuracy in determining cough counts on independent test data was 92.11 percent. Processing one five-second audio segment took about 200 milliseconds. These separate metrics should not be merged into one identification rate. Sheep reveal their grazing condition through the sound of tearing and chewing grass.

Recent researchers have gone further, trying to combine these signals and read the full language of cattle behavior. When vocalizations, movement, temperature, and activity are overlaid, clues become clearer about whether a cow is hungry, ill, or in breeding season. A picture that was blurred when only one signal was visible becomes sharp when multiple signals are superimposed. The work resembles a machine transcribing the condition of an animal that cannot speak in human words.

A barn, however, is not a laboratory. A thermal camera is affected not only by heat emitted from a cow's body but also by surface emissivity and radiant energy reflected from the surroundings. When sunlight entering through a window falls across a cow's back, a healthy animal can be incorrectly classified as heat stressed. Strong ventilation, dried manure and mud on the hide, and condensation on a humid day can all disturb the temperature reading. Settled dust can also make values jump, so a manager must clean the lens.

The same cow is read as a different number simply because winter and summer temperatures differ, requiring thresholds to be calibrated for season and environment.

An error of this kind is called a False Positive. It wrongly reads a healthy cow as sick and increases the labor of managers who must check every alert by eye.

The situation with sound is no different. In pig and poultry houses where large ventilation fans, feed scrapers, and manure-cleaning robots operate, background noise covers animal sounds and lowers the Signal-to-Noise Ratio (SNR). If moisture enters microphones and circuit boards, audio becomes muffled and corrosion may accelerate. Cough-localization research has continued for many years, but reliably identifying which individual coughed in a pen crowded with hundreds of animals remains difficult. A device that monitors the health of an entire group is not the same as a device that diagnoses an individual.

The equipment is costly as well. High-resolution thermal cameras, multispectral sensors, and acoustic-analysis servers require large initial investments. Artificial intelligence processing high-resolution video in real time consumes corresponding amounts of electricity and computing power. For a small farm, the expense is likely to remain a formidable wall.

To fill these gaps, a growing number of recent systems avoid relying on a single camera or microphone. Instead, they combine video, thermal images, and sound on one screen through multimodal data fusion. Algorithms that automatically correct temperature values by incorporating ambient measurements such as the temperature-humidity index, wind speed, and illumination are following. Even so, human footsteps have not disappeared from the barn before dawn. When one number on the screen turns red, confirmation is complete only after a person pulls on boots, walks to the stall, and looks directly at the animal.

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Smart Livestock Farming: AI Enters the Barn

CHAPTER 3

Health and Disease Prediction, Reproduction, and Nutrition

3.1

AI That Detects Illness Before It Shows

The following scene is a fictional reconstruction based on multiple livestock monitoring studies. At 4:30 a.m., while stars still linger above the barn roof, a farmer's phone rings. An alert says that one dairy cow's milk yield, electrical conductivity, and rumination time have strayed from their usual patterns. The farmer pulls on a thick jacket and steps into the still-dark yard. When he walks over with a flashlight, the cow has her nose in the feed trough as usual. She is not limping, and her udder does not appear swollen. After checking the cow's udder and the condition of her milk, the farmer calls a veterinarian.

A sensor alert is not a diagnosis; it is a signal that prompts a person to check sooner.

In the neighboring barn, a different kind of alert appears. Microphones record the pigs' coughs through the night, and AI scans spectrograms that turn those waveforms into images. Coughs that the human ear cannot distinguish from ventilation noise appear to the machine as clear patterns.

Cattle do not say when they are sick. Their body temperature, gait, rumination time, and milk composition speak for them. The problem is that these signals rise and fall with the season, the production stage, and even the day's weather. If a system judges only whether a value at a single moment has crossed a threshold, false alarms ring several times a day. A cow panting on a sweltering afternoon may be flagged as though she has a fever. What really matters is not one day's number but the pattern traced over the past several days and weeks. Data read with their temporal order intact are called time-series data.

On a graph, they form a single line that winds like a mountain ridge, and a dip below its usual path can be a sign of illness.

One AI architecture that reads this flow is the Recurrent Neural Network (RNN). It retains recently seen information and draws on it for the next judgment. Its weakness is that memories fade over time, much as a person's recollection of an event ten days earlier grows hazy. Long Short-Term Memory (LSTM) was designed to correct this weakness. Each cell has three small gates that sort information worth keeping from information that can be forgotten. An LSTM learns the normal patterns of rumination time and movement that a dairy cow has shown over the past several weeks, then pinpoints the moment she departs from them.

If a cow that usually ruminates for around 540 minutes a day falls below 480 minutes on two consecutive days, the LSTM treats the decline as a warning rather than random fluctuation. Newer approaches include bidirectional LSTMs, which read the flow of time in both directions, and LSTM autoencoders, which detect anomalies while compressing and reconstructing normal patterns. Both can find warning signs without a person first reshaping the data by hand.

Another method finds answers through tree-shaped calculations. Is the body temperature above 39.5°C? Did the animal eat less feed than yesterday? It follows one question after another down the branches and arrives at the probability of disease. Random Forest (RF) plants hundreds of these trees and decides by majority vote. One tree can be wrong, but hundreds are less likely to make the same mistake at once. If 270 of 300 trees vote for danger, the final judgment tilts toward danger as well. Gradient Boosted Trees (GBT) grow trees in sequence so that each new tree concentrates on the mistakes missed by the one before it.

XGBoost is a faster and more finely tuned version of this method. Even when dozens of variables such as body temperature, milk yield, somatic cell count, and feed intake are tangled together, these trees extract the probability of disease from the knot.

In remote mountain barns where internet signals are unreliable, sending data to a cloud server is difficult. This has led to technology that completes AI calculations on a chip no larger than a fingernail. It is called Tiny Machine Learning, or TinyML. A study published in 2025 used multiple small computing units together with an auxiliary chip called an edge TPU, shrinking the AI model to 1/270 of its original size while holding response time below 80 milliseconds. That is shorter than the blink of an eye. The result, however, was achieved on research equipment.

More field testing is needed to see whether the same speed and accuracy persist in barns where communications fail.

Mastitis is an inflammation caused when bacteria enter udder tissue, and it has long occupied the first line on dairy farmers' lists of losses. Inflammation can raise sodium and chloride ion concentrations in milk, driving up electrical conductivity and somatic cell count. These changes may appear first in data collected by milking robots and sensors. Yet a 2026 review found that the sensitivity of mastitis detection systems ranged from 26 percent to 98 percent, while specificity ranged from 40 percent to 99.8 percent. Differences among farms and devices are too great to base treatment on an alert alone.

A 2026 study of 2,420 dairy cows on three Sri Lankan farms set a threshold of 353,000 somatic cells per milliliter. When several machine-learning models competed using milk electrical conductivity and parity data, XGBoost recorded 77.3 percent accuracy, and electrical conductivity was the variable that contributed most to the prediction. This figure does not mean that a sensor replaces a veterinarian's diagnosis. It is closer to a supporting signal that helps decide which cow to check first.

Lameness is an abnormal gait caused by hoof inflammation or joint disease, and it pulls down both feed intake and body weight in cattle and pigs. A 3D depth camera suspended over a passage or milking-parlor entrance captures, one by one, the curve of a cow's back, the left-right balance of her stride, and her walking speed. On the screen, as the cow rounds her back like a bow, she subtly shifts her weight onto the sound leg. Studies using cameras and accelerometers have automatically classified these differences, but definitions of lameness and performance metrics vary from one study to another.

Separate validation is needed to determine whether classification accuracy achieved on one farm carries over to other breeds and passageways, and whether the system can warn of lameness several days in advance.

In pig and poultry houses, microphones listen for different sounds. When audio captured by ceiling-mounted microphones is transformed with methods such as Mel-Frequency Cepstral Coefficients (MFCC), coughs and calls leave patterns distinct from ventilation noise. The commercial SoundTalks system converts sounds collected day and night into a respiratory health score displayed on the manager's screen. How many days in advance it detects disease and how accurately it classifies coughs, however, vary with the disease, the farm, and the placement of the equipment.

After receiving an alert, the manager must directly check ventilation and temperature in that pen, observe the pigs' breathing, and decide on treatment with a veterinarian.

Around calving, high-producing dairy cows enter a period when milk production rises sharply and the energy their bodies must expend can exceed the energy available to them. If this imbalance deepens, it can lead to ketosis or ruminal acidosis. A bolus sensor placed in the rumen measures pH and body temperature minute by minute. A single change in pH or rumination time, however, cannot immediately be labeled disease. The duration below the baseline, feed, and parity must be considered together. A Lithuanian study published in 2025 followed 94 Holstein dairy cows on one farm for 21 days after calving.

Random Forest and XGBoost both achieved 100 percent accuracy in this small internal dataset; logistic regression recorded 89.5 percent, decision trees 84.2 percent, and Naive Bayes and support vector machines 78.9 percent. The researchers warned that these results might reflect overfitting and must be rechecked with independent data from multiple farms.

Alerts for these four diseases usually converge on a single screen. On a tablet mounted on the barn wall or in the farmer's smartphone app, each cow appears by number rather than name, with color-coded risks for mastitis, lameness, respiratory illness, and metabolic disorders. Green means safe, yellow means observe, and red means check immediately. For years now, this screen has been what the farmer looks at before seeing the cows upon waking at dawn.

Disease does not decline on its own merely because a sensor sounds early. Results change only when a person checks the cow after an alert, a veterinarian makes a diagnosis, and treatment and husbandry are adjusted. Among the precision livestock systems examined by a 2026 review, few carried an alert through to on-farm decision-making and automated intervention. This is why a high laboratory classification score cannot be connected to lower disease rates, higher milk production, and reduced feed costs in a single chain of cause and effect.

A recital of successes, however, tells only half the story. On a well-managed farm, cases of clinical mastitis or serious disease account for less than 5 percent of the entire dataset. Healthy observations form a mountain while sick cases can be counted on one hand, so AI may become skilled at identifying healthy cows yet miss the animals that are actually sick. This is why the Lithuanian researchers issued their own warning. Among 94 cows, there were only 24 cases of ketosis and 26 cases of acidosis. The figure of 100 percent may be closer to chance than ability. Excessive alerts pose another serious problem.

If slight barn noise or a momentary sensor error produces false alarms several times a day, the farmer gradually becomes numb to notifications and eventually lets a real danger signal pass unheard. A model that approaches 95 percent accuracy on one farm often suffers a sharp decline when transplanted unchanged to a farm with a different breed, feed mixture, barn design, or climate. Equipping every animal with sensors, collars, and rumination monitors is costly as well.

A farm with hundreds of cattle may recover the equipment cost within a few years through lower medication costs and mortality losses, but a small farm with only dozens of cattle hesitates before the upfront expense. Recent research is therefore moving beyond feeding sensor readings alone into algorithms. It is turning toward hybrid approaches that combine established models of bovine physiology with AI, and toward personalized deep-learning systems that relearn baselines in real time for each farm and each animal.

Back in the reconstructed predawn barn, the farmer's fingertips are still resting on the phone. Some of the notifications may be false alarms caused by sensor error or weather. But the next one cannot simply be dismissed. The farmer reads the screen and then walks to the barn to check the cow. This predawn walk back and forth between numbers on a screen and a living cow in the barn is unlikely to disappear soon, no matter how sophisticated AI becomes.

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3.2

Eyes That Read Estrus and Calving

The following is a fictional scene reconstructed from estrus-detection research. In a barn after midnight, one cow paces the passage instead of lying down. She briefly places her forelegs across the back of another cow in the next pen, then immediately steps away. In the dark barn, the eye watching this movement is an infrared camera suspended from the ceiling. Activity recorded by an accelerometer on her neck also rises above its usual curve. A notification on the sleeping manager's phone reports strong signs of estrus and asks that the animal be checked.

The time for artificial insemination is chosen by considering the onset of estrus and the animal's records together, not from a single sensor alert.

Reproductive success determines the livelihood of a livestock farm. Missing the right moment of estrus once delays pregnancy and lengthens the period without milk production, while feed costs continue without pause. If human help arrives late at calving, the mother or calf may die. This management approach, in which signals from every animal are watched around the clock, is called precision livestock farming, or PLF. One person can visually inspect at most a few dozen cattle, while sensors and cameras can capture the movements of hundreds at once.

In rural areas where hiring labor is becoming increasingly difficult, devices that keep watch all night in a person's place are no longer convenient extras. They are becoming indispensable tools.

Inside a cow entering estrus, the reproductive hormone estrogen surges. The changes it produces appear plainly in visible behavior. The cow walks farther and stands longer. She mounts other cows, or stands still instead of moving away when another cow mounts her. On farms, this posture is called standing heat. The other cows ignore the commotion and keep their noses in the feed trough, continuing to ruminate. The cow in estrus, by contrast, shows a sharp drop in eating and rumination time. Against her normal daily baseline, she loses roughly

20 to 40 percent of her rumination time. Quiet changes occur inside the body as well.

Vaginal electrical conductivity shifts slightly, temperatures in the ear and deep in the body rise and fall, and the cow repeatedly makes high-pitched calls that are otherwise unusual. Pigs in the neighboring barn send their own signals. A sow's vulva swells, and she stands firm rather than stepping away when a male approaches and presses against her. None of these behaviors lasts long. They peak at around one day and then subside. A cow that stops ruminating and repeatedly rises to walk is writing the first sentence with her body.

Accelerometers attached to the neck, ear, or ankle turn that sentence into numbers. A sensor records the cow's movement several times each second, and the readings accumulate by day for comparison with her normal activity. When a sudden spike in activity overlaps with a decline in rumination, the algorithm calculates the likelihood of estrus. An indoor positioning system can add where and how long she paced. Models such as Random Forest, support vector machines, and LSTMs read these data. Their results are uneven.

In a 2026 review, the sensitivity of reproductive detection systems ranged from 45 percent to 98 percent and specificity from 70 percent to 99 percent. The number of missed cows and false alarms changed with breed, sensor position, and the standard used to confirm estrus. These systems can reduce the need for a person to watch the barn all night, but no device yet catches every animal.

Finding the right time for artificial insemination is much harder than detecting estrus. The interval between estrus onset and ovulation differs among cows, and semen condition and parity affect conception rates. An algorithm finds the moment when the activity curve peaks, narrowing the onset of estrus, and combines it with past breeding records for the inseminator to review. It does not identify an almost exact two-hour window that works for every cow. Alert times help the inseminator decide the order in which to check mucus, standing heat, and individual history. Those records feed back into the next estrus prediction.

Sensors and video fill one another's gaps, but the final time is set only after a person checks the cow.

Cameras watch herd behavior without collars or ear tags. Systems combining infrared imaging and deep learning can record mounting behavior at night while people sleep. Some neural networks distinguish patterns on each cow's body, assign an identity, and then judge mounting behavior. If the identity is wrong at the first stage, the later judgment is assigned to the wrong cow as well. IATEFF-YOLO was designed to find mounting behavior in dark conditions, and ensemble methods that combine video from two angles are also under study.

A 2026 PLOS ONE study, however, tested three cows in 17 hours and 16 minutes of video recorded over a single day, and only two cows were in estrus. Another 2026 study pairing a YOLO-family neural network with DeepSORT remains at the conference-abstract stage. Video is only one non-contact alternative. Accelerometers, GPS, marking by males, and hormone tests provide other methods for sheep and goats. Research using a 3D convolutional neural network to identify tail wagging in ewes adds one more option.

A cow approaching calving sends signals different from those of estrus. A day or two before giving birth, she spends less time at the feed trough and may separate from the herd to find a corner. She lies down and stands up repeatedly, and lifts her tail more often. A thermal sensor attached to the tail records changes in surface temperature before calving. This is not the same as deep-body temperature and is affected by wind and season. Research has therefore continued to read posture and activity together rather than relying on one temperature line.

Methods that combine temperature and posture changes are being refined in two directions, sensors and video. A tail-mounted temperature and accelerometer device has been tested to predict separate 24-hour and 6-hour periods before calving. A 3D depth camera mounted on the ceiling labels, scene by scene, whether a cow is lying, standing, or lifting her tail. A hidden Markov model follows the sequence in which these states change. Studies have combined trajectories and posture to separate normal calving from cases requiring assistance, but this is not yet a field system that can determine the minute of birth and whether dystocia will occur.

Ushi-Waka and NiLIMo detect scenes in which the amniotic sac or a calf's legs become visible and send a phone alert. Nikon reports 95 percent calving-detection performance for NiLIMo. Product alerts may reduce nighttime rounds, but farm-level validation is needed to show how many minutes of patrol time remain and how much calf survival improves.

The numbers make this technology look nearly flawless, but real barns raise three barriers.

The first is false alarms. A cow suffering from summer heat, mastitis, or lameness may also stop ruminating and pace restlessly. To an algorithm, these movements can be indistinguishable from signs of estrus or calving. On a sweltering afternoon, a cow that cannot stop walking as she searches for a strip of shade may be read by her collar as being in estrus. The surface temperature of a cow's tail also falls in cold winter wind, and the sensor may mistake that chill for a calving signal. If a lame cow repeatedly lies down and rises because of pain, a calving-monitoring algorithm may misread the movement as labor.

When an inseminator rushes to a predawn alert only to find a lame cow rather than one in estrus, the cost of a straw of semen, that day's call-out fee, and the time spent are all wasted. After several days of such false alarms, the manager may pull the blanket back over his head instead of getting up when a notification arrives. Each repeated alert slightly erodes the farmer's trust in the system.

Signals are missed as well. A first-calving heifer behaves quite differently before estrus and calving from a cow that has given birth several times. Some cows show almost no outward sign of estrus, and a single standardized algorithm has difficulty catching this silent heat. A low-ranking cow may be forced aside by others and retreat before she can even show mounting behavior. Individual differences in the expression of estrus are considered one of the obstacles to automated detection. Miss one heat, and the farm must wait almost another three weeks for the next. During that interval, the cow remains nonpregnant and consumes feed.

Every additional day without pregnancy adds directly to feed costs, and the next lactation is pushed back by the same amount. When lost milk production is added, the loss from one cow is by no means small. As the days without milking mount, some farmers begin weighing whether to keep the cow at all. Missing a calving signal carries graver consequences. If a cow struggles alone and the fetus is malpositioned, both mother and calf are at risk. If dawn passes without an alert, the situation may end before anyone has time to intervene.

Equipment durability is another problem. Amniotic fluid, blood, and manure released during calving coat tail-mounted sensors and camera lenses. When a cow rubs her body against a post in the narrow calving stall, a carefully attached sensor may be torn off entirely. If mud and feed debris dry onto the camera lens, the image turns cloudy, and for days the system watches the barn with its eyes half closed. A depleted battery or a corner pen beyond the wireless signal may produce no readings at all. The same trouble returns on winter mornings when frost whitens the lens. Expensive equipment can go silent at precisely the moment it is needed.

Replacing sensors that fall off or fail is costly, and the expense snowballs on farms raising many cattle at once.

Research on the next stage is therefore continuing to shift toward personalized models that learn each animal's past records and adjust the decision threshold to that cow, and toward computer vision that watches without a sensor touching the body. Attempts are underway to draw separate baselines for primiparous and multiparous cows and to define different normal ranges for summer and winter. Lowering equipment costs and making installation easier remain tasks that must be solved alongside this work. Devices from different companies often operate separately because they cannot exchange signals, another problem still awaiting a solution.

Fewer human footsteps circle the barn before dawn, but several more steps remain before those footsteps disappear completely.

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3.3

Cameras That Measure the Body: Body Condition Score and Weight Estimation

The following fictional scene is reconstructed from research on automated body-shape measurement. At 5:00 a.m., cows leaving the milking parlor pass one by one through a narrow passage. Each time a cow walks beneath a box suspended from the ceiling, an indicator light flashes briefly. Light from inside the box scans her back and loin, and a three-dimensional map appears on the office monitor, a field of tens of thousands of red and blue points. Seconds later, the screen displays a body condition score and estimated weight. The cow is already out of the passage and walking toward the feed trough.

She never stepped on a scale, and no human hand touched her body.

Until recently, this score came from a person's fingertips. A manager pressed and rubbed a palm around the cow's tailhead and lumbar vertebrae, judging the thickness of fat and bone, then transferred that sensation to a single number on a clipboard. Weight was measured even more roughly. Cattle or pigs had to be forced onto a scale. Trapped in a narrow passage, an animal frightened by the unfamiliar metal floor might back away or lose its footing and injure a leg. Farmers were not infrequently kicked or pinned beneath an animal's body, suffering injured wrists or broken ribs.

Even for the same cow, scores from different evaluators could differ by nearly half a point. Remeasuring by hand an entire herd of dairy cows whose weights changed often took a full half day. Fatigue made human scores waver, and a score taken in the morning sometimes differed from one taken in the evening. The person who had to trust that score to set the feed ration was left in a bind each time.

Body Condition Score (BCS) compresses the amount of fat and muscle stored in a cow's or pig's body into one number. Standards vary by species and country, but the common scale runs from 1, extremely thin, to 5, obese; some countries and species use a finer scale of nine levels. The score fluctuates most around calving, when lactation has just begun. Stored fat is being converted into milk at a rapid pace. If a dairy cow loses body fat too quickly while producing milk, ketosis and fatty liver can follow, and the probability of the next pregnancy falls.

If she becomes excessively fat before calving, the risk of dystocia and mastitis rises sharply. A discrepancy of just half a point can change her health and reproductive performance for weeks. Nor is the task finished once she gets safely through the few weeks around calving. The curve must be watched as the score rises and falls gradually throughout the roughly ten months of milk production. Only then can the next breeding and the following year's milk yield be estimated. One cow's entire farming year hangs on this single score.

Automated assessment equipment has transferred the sensitivity of human fingertips to cameras and LiDAR. LiDAR calculates distance by measuring the time it takes emitted light to return. Looking down from above a passage, an RGB-D camera such as Intel RealSense or Kinect, or a LiDAR unit, records tens of thousands of coordinates on the animal's surface in the brief moment she passes, creating a point cloud, a three-dimensional map made of points. Each point means nothing by itself, but together tens of thousands reveal the full contours of a cow's back and loin.

Image-segmentation algorithms such as Detectron2 or Mask R-CNN then cut out only the topline, hooks, pins, and tailhead mound. The background, legs, and head disappear from the image, leaving only the curves of the back and hindquarters. The curvature and depth of the selected areas pass to a neural network such as PointNet++, which compresses them into one score. Every calculation finishes before the cow has completely passed through the corridor. Light has taken the place of touch.

A correlation coefficient shows how closely expert and camera scores move together; the closer it is to 1, the more alike they are. Multiple validations have reported values above 0.90. A camera can score cows in the same way every time they enter and leave the milking parlor, tracing a long-term pattern. This does not eliminate disagreement among people or bias among farms. Changes in posture, lighting, and breed can still move the score. A study published in 2026 compared depth images and three-dimensional point clouds from 1,020 dairy cows side by side.

Even after this comparison, the question of whether more three-dimensional information necessarily produces a more accurate score remained open.

A score alone is not enough. Weight must be measured separately as an actual number in kilograms, along with Average Daily Gain (ADG), the amount that number increases each day. These values are needed to set the shipment date and determine how efficiently feed becomes body mass. Identifying animals that gain well on the same feed and those that do not begins with these numbers. A shipment delayed by only a few days leaves the feed consumed during that interval as a direct loss. A camera finds several landmarks on the body of a cow or pig.

In an instant it identifies withers height, body length from shoulder to hip, heart girth, chest depth, and hip width. A person would have taken five separate measurements with a tape. The camera estimates weight from those measurements.

The problem is the distance and angle between camera and animal. The same cow appears larger when she passes close to the camera and smaller when she veers along the edge of the passage. To reduce this error, one camera estimates depth, or two cameras overlap views captured from different angles and calculate true distance. Calibration that assigns centimeters to pixels reduces distortion within a defined imaging range. Change the camera height or lens and the system must be calibrated again; error remains when an animal leans or overlaps another.

After calibration, the body measurements pass through a trained formula once more. Some systems mark landmarks with YOLOv8-Pose and calculate weight with regression models such as XGBoost or LightGBM. Others estimate volume and weight directly from depth images or three-dimensional point clouds. The pipelines differ, but their foundation is the same: train on camera data paired with readings from an actual scale.

In multiple cattle validations, the correlation coefficient between camera estimates and scale readings exceeded 0.90. In a study measuring growing Holstein cattle with LiDAR, heart girth and body length alone were enough to predict weight without a scale. A Korean study of Hanwoo went one step further, using machine learning to predict even the backfat thickness used in carcass grading. It was an attempt to use a camera to estimate, while the animal was still alive, a grade that would otherwise be known only at the slaughterhouse. A Southeast Asian study imaging Bali cattle reported similar results.

Comparable reliability recurred in validation studies that installed cameras on commercial dairy farms rather than in laboratories and followed them for months. Species and countries differed, but the principle was the same: an animal passing beneath a camera became a set of numbers.

A 3D camera mounted on the ceiling of a finishing pig house measures pigs' torso volume and has recorded coefficients of determination from 0.96 to 0.98 in some validations. These figures are high, but error rises when imaging conditions and posture change. On pasture, research has mounted LiDAR and RGB cameras on drones to estimate cattle body dimensions. A 2025 dataset imaged 96 cattle from heights ranging from 8 to 50 meters. The coefficient of determination for weight estimation was about 0.94 when the cattle were standing and fell to about 0.74 when they were lying down.

This is closer to research testing the effects of posture and flight conditions than to equipment that fixes the weight of an entire herd within minutes.

Subtract yesterday's weight from today's and the result is average daily gain. A graph of this increase accumulated over several days determines the shipment date. Pigs growing more slowly than the target curve receive a changed feed mixture and stay for several more days, while pigs outpacing the curve leave for market earlier than planned. Shipping below the target weight reduces product value; feeding an animal after it has finished growing merely leaks away feed costs. In the past, all pigs in a pen were shipped together, so animals that were not yet fully grown went onto the truck as well.

Now each animal's curve can be tracked separately, allowing the fastest-growing pigs in the same pen to be selected first. The rest eat for several more days until they catch up with the curve. Without a struggle on a scale, a single curve on a screen sets the shipment time for each animal.

These numbers show their real worth at the feed trough. When a cow enters an individual feeding station, RFID first identifies her. Weight, milk yield, and body condition score inform the amount of concentrate supplement allotted to that animal. Robots delivering Total Mixed Ration (TMR) generally supply a mixture to groups with similar nutritional needs, not to individual cows. Group TMR and individual concentrate stations are different pieces of equipment.

Precision nutrition may reduce leftover feed and nutrient excretion, but it is too early to say that one body-condition camera lowers feed conversion ratio and methane emissions by a fixed percentage.

The camera cannot read every posture. If a cow arches her back, hangs her head low, crosses her legs, or stands at an angle, her spinal line itself becomes distorted, throwing off both score and weight. A posture that looks awkward to a person remains difficult for a camera too. The lens cannot escape barn dust, mud, manure, or cobwebs. When these cling to its surface, they block the LiDAR signal; when thick clumps of mud stick to an animal's hide, the torso outline itself is captured incorrectly. Such problems are likely to pile up the day after rain.

One camera has difficulty separating individuals when several animals stand overlapping in a narrow pen. Among tangled pigs, an image may not reveal where one animal's back ends and its neighbor's rump begins. A study published in 2026 tried to solve this by overlapping images from multiple camera angles and filtering out calculations that did not agree. Research is continuing on frame-selection techniques that scan only when an animal is standing still, and on dustproof lens covers that keep out dust and manure.

Processing large three-dimensional datasets in real time requires a server with a high-performance graphics processor in the barn, and its cost remains burdensome for small farms. The smaller the farm, the longer it may take to close this gap.

Back in the predawn passage, the cow simply walks toward the feed trough, unaware that she is being imaged. She does not know what the light sweeping across her back is measuring. As the camera takes over work once done by a manager's fingertips, the person remains to press the final button that decides what feed to mix and how much. No one is yet certain what will fill the space left by the vanished sensation of a hand passing over a cow's back. The numbers on the screen, at least, are updated again today without fail.

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CHAPTER 4

Field Applications of AI by Livestock Species

4.1

Dairy Cattle and Hanwoo: Robotic Milking and Virtual Fences

The following is a fictional reconstruction of a day on an automated dairy farm. At 5:00 a.m., the air inside the barn is still cold. One dairy cow leaves the herd and walks toward the milking parlor. As the tag around her neck passes the entrance antenna, the gate opens and she puts her nose into the feed bin. The computer checks when she was last milked and her expected milk yield. The manager is still under the covers, while the cow's number and milking record quietly appear on his phone.

The Automatic Milking System (AMS), commonly called a milking robot, has reversed the old method in which people drove cows into the parlor. It is designed instead to let cows walk in voluntarily when they wish. When the Radio-Frequency Identification (RFID) antenna at the entrance reads the collar tag, the central computer immediately retrieves the time of that cow's last milking and the amount collected. If the milking interval is not yet complete, the gate does not open. She eats a little feed and returns to the herd. If the system judges that enough milk has accumulated, the door opens and she can enter the milking stall.

Under the traditional system, cows were led by people to the parlor twice a day at fixed times. With the robot, they walk in on their own two or three times a day, in step with their bodies' rhythms.

The real work begins when the cow enters the milking stall and stands. A three-dimensional (3D) camera and laser sensors on the end of a robotic arm scan beneath her belly, calculating the udder's curves and the positions of four teats as three-dimensional coordinates. Every cow's udder has a different shape, and each cow stands a little differently when she enters, so the calculation is performed anew every time. Once the coordinates are fixed, rotating brushes or warm-water cups wash and disinfect the teats. The first few drops of milk are then expressed separately to stimulate milk letdown.

Only then does the robotic arm attach four milking cups to the teats one by one. If it cannot find a teat on the first attempt, the arm changes angle and tries again. If failures persist, it flags the cow for manual milking. What looks to the human eye like a few seconds is the result of a camera reading shapes, calculating arm angles, retracing errors, and correcting them repeatedly within a short span.

The four teats are managed separately. A flowmeter measures the milk flow from each teat, and when one empties first, only that cup slips off quietly. A traditional milking machine treats all four teats as a set, so a teat that emptied early could remain under pressure until the others finished. The robot reduces this overmilking and the fixed labor required at dawn and dusk. But changes in the number of cows one worker can manage and in milk yield vary greatly with cows per robot, feed, animal adaptation, and farm layout. Some farms produce more milk as milking frequency rises, but this cannot be treated as a fixed effect for every farm.

Automation has changed not only the cow's day. A person who once had to stand in the parlor at precisely two times each day, morning and evening, can now use those hours to care for calves, revise feed mixtures, or catch up on sleep. In exchange, a new habit has emerged: being unable to put down the smartphone. Checking how many times each cow visited the parlor overnight and whether any animal's yield has fallen can itself interrupt predawn sleep.

The companies that make these robots continue to expand. The Dutch company Lely unveiled the Astronaut A5 Next and Astronaut Max in the summer of 2025. The Max links 18 robots in a single system and targets farms with 500 to 1,100 cows. The Swedish company DeLaval enlarged the milking box in its 2025 VMS 300, giving larger cows more room to enter. The German company GEA's DairyRobot R9500 offers quarter-level milking and compatibility with the M6850 sensor. Official manufacturer materials do not confirm worldwide installed units or annual growth rates.

Lely Hub is not a device for controlling multiple robots; it manages data and cybersecurity between the robot and the internet. Multi-robot operation is handled by Astronaut Max.

The situation in South Korea is different. In February 2022, the Rural Development Administration counted 153 imported milking robots, used by about 2 percent of dairy farms. Official 2023 material mentions about 180 units, so the survey date must be considered with the installation total. A 2022 survey found that raising one dairy cow required 69.22 labor hours a year, of which milking accounted for 27.55 hours, or 39.8 percent. A domestic model developed by the Rural Development Administration and milking-robot specialist DAWOON targets a supply price of about 200 million won, roughly 60 percent of the price of an imported unit.

DairyBot-K3 was selected for the government's 2026 rapid commercialization support program for AI application products and will pursue commercialization and field validation over two years.

Lee Jae-gwang, who runs Doohui Farm, milks 40 of his 100 dairy cows with a robot. Through the government's 2020 livestock Information and Communication Technology support program, he brought in a milking robot along with an automatic calf feeder and a robot that pushes forage toward the cows. He says labor requirements fell by about 70 percent after the robot arrived. When he carried milking units by hand, he often went to the hospital with musculoskeletal disorders; such visits have now fallen markedly. The robot did not solve every problem.

Five cows whose teat arrangements did not suit robot recognition eventually had to be culled, and disposal of wastewater from post-milking cleaning emerged as a new headache. Because he did not initially choose the automatic-cleaning option for the robot's calf feeder, he later paid extra to add it. He says cows suitable for the robot must be selected and raised separately, and there is much to prepare before purchasing the equipment.

Even while milking proceeds, other work is taking place inside the pipes. Inline sensors measure Electrical Conductivity (EC) and Somatic Cell Count (SCC). Mastitis can raise both values, but neither confirms a diagnosis on its own. A milk fat-to-protein ratio above 1.5 is also a screening signal for ketosis just after calving, not a diagnostic threshold. Milk exceeding a standard can be routed by a valve through a separate line rather than to the storage tank, after which the manager checks the cow and raw milk again. In 2026, CowManager unveiled a milk sensor that measures conductivity, flow, vacuum pressure, and temperature for each teat.

The company announced an initial rollout in late 2026 and broader distribution in 2027.

Farms that graze cattle across broad pastures bear the cost of building and repairing wire fences. A Virtual Fence uses GPS collars and boundaries drawn on a phone map to limit cattle movement. As a cow approaches the line, the collar first emits a sound; if she continues, it delivers a brief electric pulse. The pulse uses less energy than an electric fence, but the mode of delivery differs, so intensity cannot be compared directly by number. Nofence communicates between the mobile network and collars and offers products for cattle, sheep, and goats. In April 2026, Halter unveiled a virtual fence connected by satellite.

Its sales regions at the time were the United States and New Zealand, and no data existed for distribution in Korea or validation in mountainous terrain. Whether it would be useful to Korean Hanwoo farms should be judged only after checking domestic radio conditions, regulations, and GPS error under forest cover.

On ranches using virtual fences, rotational grazing can be managed from a phone: cattle are moved into a patch where grass has grown, then transferred to the next once it is eaten down. An app setting can keep animals out of protected streamside areas or habitats of endangered species. In dry regions, the technology is used to direct cattle into stands of dry brush to graze, removing in advance the corridors along which wildfire could spread. Yet discomfort remains over the fact that electric stimulation is applied to livestock.

Animal-welfare groups and some consumers argue that controlling behavior through sound and stimulation causes stress. Companies emphasize that the stimulation is mild and preceded by sound, but they have not completely eliminated the possibility that a malfunctioning collar may repeat it more than necessary. Supporters counter that the pulse is far weaker than the stress of being loaded onto a truck and taken to an unfamiliar ranch, or the pain of a hot-iron brand. Both arguments have grounds of their own, so the dispute is unlikely to subside easily.

In densely wooded mountains, satellite signals have also been reported to drop or bounce, shifting the recorded location of a cow away from her actual position.

Locomotion Scoring technology is expanding its uses. As a cow leaves the parlor through a passage, a 3D camera records the curvature of her back and the spacing of her steps. Across studies, sensitivity ranged from 58 percent to 97 percent and specificity from 42 percent to 99 percent. Some cameras and pressure sensors exceeded 95 percent on both measures, but few systems predict early lameness with the same performance across multiple farms. A back-curvature classification score should not be read directly as an early-diagnosis rate.

The camera score is supporting information used to order the cows whose hooves should be checked; treatment begins only after hoof inspection.

Every one of these technologies carries a price. An imported milking robot costs in the mid-300-million-won range, while a localized model is still around 200 million won. Minor failures are not rare: straw becomes caught in a cleaning brush, or debris jams a robotic-arm joint. One such failure stops milking across the entire barn from that moment. If an arm joint freezes on Friday night, the first challenge is finding a technician who can come over the weekend. Cows cannot postpone milking in the meantime, so people may have to return to doing it by hand.

Farms with robots therefore need both a regular inspection schedule and backup labor for breakdowns. Virtual fences face similar conditions. Satellite signals weaken on wooded pasture, and newly drawn boundaries may reach collars late in remote areas beyond mobile coverage. Dust and manure settling on camera lenses can distort the distance measurements of 3D sensors. When cows crowd into a narrow passage at once, AI may confuse one animal with another.

Even so, the gate opens every dawn. As Lee Jae-gwang of Doohui Farm says, once cows suited to the robot are selected and raised, a person gains time to sleep a little longer or walk through the barn instead of visiting the hospital. While a graph on the screen shows which cow's somatic cell count edged upward last night, another cow is already moving forward on her own at the far end of the barn. Before the manager leaves, he always checks the same line last: whether any name is glowing red today.

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4.2

Pigs: Cameras That Read Posture and Microphones That Count Coughs

The following is a fictional scene reconstructed from swine video research. At 5:00 a.m., pigs in one section of a finishing barn lie in a single mass, backs and bellies piled across one another. Above them, a red light blinks on a ceiling camera. What looks to a person like a mound of flesh must be divided by the computer into individual animals. Pixel by pixel, it must determine where one pig's back ends and whose tail is whose. The burden placed on a single camera and microphone is greater than it first appears.

Earlier computer vision followed rules set by people. It might classify only pixels darker than a prescribed brightness or color as pigs, but a slight shift in lighting could throw the entire rule off. Today's deep-learning models do not have people set these rules. From tens of thousands of photographs, the model finds for itself what is a pig's back and what is a shadow. Yet even this self-taught eye often wavers before a scene where several animals overlap.

Unlike dairy cattle or chickens, pigs rest in groups with their bodies pressed together. The Bounding Box method, which marks each animal with a rectangle, breaks down easily here. If half of a neighboring pig's rump enters the box, the algorithm may count two pigs as one or split one into two. Recent research has therefore moved from rectangles to Segmentation, which labels every pixel. When differences in pixel color and pattern distinguish even the line where two backs touch, animals merged into one by bounding boxes finally separate.

A model trained at pixel level on four behaviors in group-housed pigs, standing, eating, drinking, and resting, achieved a mean Average Precision (mAP) of 96.9 percent and precision of 92.5 percent. By those numbers it was nearly always right, but the researchers noted that accuracy fell visibly in dim light or when mud splashed onto pigs' backs. If the system mistakes two pigs jammed beside the feeder for one, the feed-intake record for that individual is left blank for the entire day.

The next problem begins after individuals have been separated once. When 40 pigs move at the same time inside a pen, the camera must assign a number to each animal and keep following it. This task is called Multi-Object Tracking (MOT). If pig 17 disappears behind a feeder and reappears, the system may register it again under a new number, 42. It loses the animal's identity in the brief moment the body is hidden. Such confusion grows more frequent when pigs butt one another or twist their bodies.

Algorithms such as ORP-Byte mark individuals with oriented, rotating boxes and track the slope and posture of their backs to reduce identity switches. A 2025 model combining improved YOLOv5s and DeepSORT raised precision in detecting pig behavior, including aggressive behavior, from 92.7 percent to 99.3 percent. Individual tracking accuracy also exceeded 94 percent. Even so, identity switches were still reported when eight or nine pigs crowded around a feeder at once. One switch can carry a substantial cost. Repeated ear or tail biting often begins with one animal and spreads through the group.

If the system loses the animal that bit first, its record becomes mixed with another's and the chance for prevention disappears with it.

A pig house is noisy by nature. Large ventilation fans hum and feed-scraper motors grind. In the middle of that noise, a microphone must pick out a single dry cough. When microphone waveforms are transformed into Mel-Frequency Cepstral Coefficients (MFCC), coughs and fan noise leave different patterns. A study locating the source of coughs appeared in 2008. But in a room with hundreds of pigs, identifying the individual that coughed remains difficult.

The Gated Recurrent Unit Autoencoder (GRU-Autoencoder) used by Cowton and colleagues read not cough sounds but time series from environmental sensors for temperature, relative humidity, and carbon dioxide. The researchers reported that environmental changes associated with respiratory symptoms could appear 1 to 7 days earlier. Cough-classification performance from an acoustic model and anomaly detection from an environmental-sensor model are different results.

Commercial systems such as the Pig Cough Monitor and SoundTalks continuously count coughs in a pen. SoundTalks converts recorded audio into a respiratory health score from 0 to 100 and displays it for the farmer. If the score falls, the manager can inspect the pigs in that pen and ask a veterinarian to examine them. More farm-level validation is needed before claiming that this score detects every respiratory disease 4 or 5 days early and thereby reduces antibiotics and mortality. A microphone alert is not a prescription. It is a signpost indicating which pen should be checked first.

Field validation has begun in Korea as well. In June 2026, the National Institute of Animal Science under the Rural Development Administration installed camera- and microphone-based monitoring systems at two pig farms in Gimje and Cheonan and began collecting data. Figures of 91.4 percent for activity, 91.3 percent for coughs and screams, and 90.0 percent for feeding behavior were not field results from those two farms. They were the performance scores of models developed before field deployment.

At the two farms, researchers are matching video and audio data with mortality times and records of stunted pigs to assess real detection performance. Four related studies and patent applications were confirmed, but at the time no answer was yet available on whether the earlier scores would hold in working pig houses.

There is a gap between the numbers in laboratory papers and the numbers a real pig house will produce. Studies reporting mAP or precision of 96 percent or 99 percent must be read together with their filming conditions, lighting, and evaluation data. That gap is precisely why the Gimje and Cheonan trials are needed. Whether earlier model scores will persist in data clouded by dust and noise can be known only after they are matched against farm records.

The method of weighing pigs has changed as well. In the past, workers pushed against their backs with boards and shouted to drive them onto a scale. During those few minutes, pigs could panic, thrash, injure their legs, and set the entire group in motion. A three-dimensional depth camera suspended over a passage scans back length, heart girth, shoulder width, and back area all at once during the seconds a pig walks beneath it. A deep-learning regression model converts these measurements into volume and then body weight, achieving coefficients of determination from 0.96 to 0.98 against actual scale readings.

During those few seconds, the pig does not even know it is being measured. Without stepping on a scale once, a few photographs taken at the same time each day can trace the growth curve of the whole group. Updating Average Daily Gain every day allows the farm to decide daily whether to increase or reduce feed. For a pig farm where moving the shipment date forward or back by only a few days can substantially change feed costs, this seconds-long scan governs a considerable sum of money.

The most dangerous moment in a farrowing house is the few seconds when a sow lies down. Newborn piglets seek her warmth and burrow beneath her belly and back. If she lowers a body weighing around 200 kilograms without knowing they are there, a piglet can be crushed to death at once. The sow is not at fault. As she turns a body dozens of times heavier than her young inside a narrow crate, she cannot always know exactly where each piglet is. This accident, called Crushing, ranks among the leading causes of death before weaning.

Each incident lowers the number of pigs marketed per sow per year, a measure of how many offspring one sow brings safely to shipment. Efforts to prevent it with sound go back decades. In 1989, American researchers tested a device in pig pens that sounded an alarm when it detected a piglet's scream. Long before the internet, when even personal computers were uncommon, someone had already imagined a machine that would respond to the cry of a piglet. The work remained a paper and did not reach commercialization. More than 30 years later, the system is far more sophisticated.

A ceiling camera reads the sow's postural changes in real time and interprets a higher-than-usual frequency of posture changes as a sign of increased crushing risk.

In 2025, researchers used 422 real image instances as training data to detect sow posture. They did not collect 422 crushing incidents. The posture-detection model achieved mAP@50 of 0.976, but this value is not the same as crushing-alert performance. For alerts issued in 60-minute units, sensitivity was 62.5 percent and specificity 60.25 percent. When grouped by day, sensitivity was 71.42 percent and specificity 84.61 percent. The eye that found the sow's posture was sharp; predicting whether that posture would lead to an actual crushing event was far harder.

PigTalk, developed by Taiwanese researchers, listens for piglet screams rather than using a camera. When it detects a sound, it triggers floor vibration or water spraying to encourage the sow to stand. The paper presented 0.05-second processing and a 99.93 percent probability of success from analysis and simulation. These figures should not be read as a piglet-rescue rate on real farms. In July 2026, teams from Chungnam National University and Korea National University of Agriculture and Fisheries began field trials on a Buyeo farm of a separate prototype combining thermal cameras and sound sensors.

The two technologies use different sensors and actuators and cannot be treated as one system.

The eye reading posture, the ear counting coughs, and another eye measuring weight have until now run as separate programs. Recent review papers report that research is shifting toward Multimodal Data Fusion, which places these signals together in one model. If a camera-only system also receives microphone signals, it may catch an early sign that one sense alone would miss, such as a pig whose gait looks normal while its coughs become more frequent first. For now, however, this remains closer to a proposal in papers, and there are few cases of such a system deployed throughout an entire commercial pig house.

Each new camera and microphone requires standards for aligning the data to be set again, so the technology will need more time to take root in the field.

Pig-house air is exceptionally harsh on cameras. Ammonia and hydrogen sulfide rising from manure mix with feed dust and settle as a gray film on the lens. Once a layer of dust covers the lens, a deep-learning model can no longer distinguish a pig's back from a floor shadow and begins producing posture-recognition errors. On humid nights, condensation fogs the lens and repeats the problem; on muggy summer nights, even the inside of the lens may turn cloudy. None of these variables appears in the camera manufacturer's specification sheet. The situation is not much different for sound.

Low-frequency noise from ventilation fans and scraper motors buries the coughs the microphone is meant to hear. As the signal-to-noise ratio falls, the system may detect a cough yet fail to identify the individual pig that made it. This is why people on many farms still wipe lenses by hand once a day. However sophisticated AI becomes, the hand that cleans the lens remains human.

On Jeju, an experiment is confronting this problem directly. In April 2026, the Electronics and Telecommunications Research Institute built a pig-house test space of about 800 square meters on the Jeju National University campus. Alongside sensors measuring temperature, humidity, and ammonia concentration, it installed scrubber equipment that directly filters ammonia odor. CCTV on the same site detects abnormal livestock behavior, while Edge Computing makes decisions inside the pig house and reduces the delay of sending data to a distant server and awaiting a response.

The facility has set a goal of reducing carbon emissions by more than 10 percent from existing levels. However intelligent the cameras and microphones become, they are useless without pipes and filters that keep their eyes and ears clean.

Government agencies or research institutions are involved at the two farms in Gimje and Cheonan, one farm in Buyeo, and the test site on Jeju. The absence of private purchasing cases in public materials does not prove that no such farms exist. Questions remain, however: after research funding ends, who will buy the cameras and microphones, who will clean the lenses, and who will pay for broken equipment?

Before the sun has fully risen, someone still enters the pig house with a dry cloth to wipe a lens. The feed mixer starts rumbling soon afterward. Through its newly clear lens, the camera captures 15 or 16 pigs slowly stirring and standing. In the meantime, the microphone has already recorded the one brief cough that slipped out somewhere among those backs.

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4.3

Chickens: How to See One Bird Among Tens of Thousands

The following scene is reconstructed from poultry-house monitoring research. Open the steel door of a windowless house and a wall of heat and noise covers the body at once. The entire floor moves. Cameras and infrared sensors pass above broilers packed by the hundreds into each section. At the feeder, the tapping of beaks against grains never stops. To the human eye it is a wave of yellow feathers, but the camera divides the posture and movement of each bird in view into pixels.

One manager can walk through a poultry house at most two or three times a day. Expecting that person to find one sick bird among 50,000 during those brief rounds exceeds human ability from the start. By the time outward symptoms appear in a contagious disease such as coccidiosis, caused by parasites spreading through the intestine, it has often already moved across the entire house. The feed conversion ratio soars and deaths follow before the farm learns what happened. As poultry houses grew larger, the individual bird inside them paradoxically became less and less visible.

The rhythms of human patrols and AI monitoring are fundamentally different. In a monitoring system based on Information and Communication Technology (ICT), cameras and microphones do not sleep. They collect signals without touching the birds 24 hours a day, 365 days a year. The terms non-contact and non-invasive mean that a lens does not startle a chicken into thrashing, while something is watching at 3:00 a.m. when no person is there. Across a farm rather than a single house, the number of birds ranges from tens of thousands to hundreds of thousands.

Human rounds cannot increase while bird numbers alone keep rising, so the larger role borne by automated monitoring looks less like a choice than an inevitable consequence. Filling the one- or two-day gaps missed by people is the reason all this equipment entered poultry houses.

The comb and eyes are places where a chicken's health becomes visible. Newcastle disease can cause cyanosis, turning the comb and wattles blue, while coccidiosis and anemia can pale the comb. Infectious laryngotracheitis or bronchitis may bring tearing and swelling around the eyes. A camera can cut out these colors and shapes as a Region of Interest (ROI) and turn them into numbers. Studies have classified comb color in controlled images, but those results are not a record of diagnosing disease several days before mortality in a commercial poultry house.

Once the chicken's head is found in an image, Segmentation cuts out the comb and the area around the eyes. A classification model then calculates redness, swelling, and the proportion of time the eyes are closed. This much can be tested in a laboratory. Continuously following the face of one bird in a house where tens of thousands move on top of one another, separating a color change caused by infection from one caused by lighting, and connecting that judgment to isolation and a veterinary call are separate problems. One pale comb is not a diagnosis of a specific disease.

When a camera marks an abnormal area, a person must also check the birds' breathing, droppings, and mortality records.

A 2026 review from University of Georgia researchers points out that gaps remain in using vision alone to classify welfare automatically under real commercial conditions. Tens of thousands of birds lie overlapping on the floor, lighting is dim or flickers, and feed dust and feathers settle on the lens. Through a dusty lens, even a sick chicken may look healthy. This is why occlusion, lighting, and reproducibility across farms must be written beside a high classification score.

Dust accumulates on lenses and in data alike. What rises from the poultry-house floor is not only feed powder but dried manure dust and loose feathers. Mixed together, they form a thin film across the lens surface. In English, this contamination is called Fouling. Whether the camera is 3D or RGB, as the film thickens the image contours blur. Instead of declining gently, the diagnostic accuracy of a model reading comb color can suddenly collapse. Different housing systems place different obstacles before the camera. In floor-raised broiler houses, overlapping torsos hide combs.

In houses where layers live in tiered cages, the wire partitions themselves stand between camera and face. This obstruction of one body by another, or of a body by wire, is called Occlusion. Both scenes make Individual Identification, separating the birds one by one, difficult. Cage housing therefore appears structurally even less favorable for tracking individuals. A corner beyond the camera's eye ultimately shows the conditions of the space in which that bird lives.

Sound hears what the camera cannot see. A microphone around the feeder captures the waveform created when a bird's beak strikes feed. To pick this tapping out of the noise, signal-processing techniques such as Mel-Frequency Cepstral Coefficients (MFCC) separate the patterns of fan noise from beak impacts. Belgian researchers estimated feed intake this way in 2014. In 2024, teams at the University of Georgia and University of Arkansas created ChickenSense with low-cost equipment. It estimates pecking behavior and feed intake. Feed consumption alone cannot establish Average Daily Gain without a scale.

Chicken calls and pecking sounds are Acoustic Biomarkers that carry the condition of the body. There is a measurable relationship between counting pecks and feed consumption. As pecks per minute increase, the weight of feed disappearing from the trough that day rises with them, in a nearly proportional correlation. Once this relationship is known, no scale is needed. Sound alone can estimate how much the flock ate today, and several days of that pattern can suggest how much it will eat tomorrow. One quiet assumption underlies this arithmetic: the count works only if the microphone hears every peck.

That assumption breaks down in front of the fan. Tunnel ventilation fans that push all the air through a windowless house produce an unending roar. The sound of a beak striking a grain, and the far fainter sound of an early cough, disappear into this noise as signals with a low Signal-to-Noise Ratio (SNR). The more a signal is buried, the more computation the noise-filtering algorithm requires; even then, misdiagnosis may increase rather than decline. The ambition to distinguish the breathing of 30,000 chickens with one microphone often stalls before the fan. There is no quiet poultry house.

As long as the fan runs, the microphone always listens while missing something.

Researchers who know these limits have already set the direction of their next step. The answer for lenses is a dustproof, self-cleaning camera housing that wipes itself even when dust settles. The answer for microphones is an ultralight AI engine that continues running quietly amid fan noise. Such engines are called TinyML: instead of using a server, they finish the calculation inside a small chip beside the sensor. Efforts to combine the two senses in one framework, leaving behind systems that ran cameras and microphones separately, point in the same direction. This is known as Multimodal Data Fusion.

Chickens call when they are sick, startled, or hot. An Artificial Neural Network (ANN) is trained to pair their calls with environmental stressors such as cold, heat, and wind. Recent research has transferred self-supervised models built for human speech, including wav2vec2 and Whisper, to chicken vocalizations. In one study that classified the vocal state of vaccinated laying hens, the F1 score was 0.80. Because F1 is the harmonic mean of precision and recall, this value cannot be converted into the misclassification rate for the full sample.

Temperature and humidity are not the only environmental variables pursued by models that separate one call from another. Harmful gases accumulating in the house and stocking density itself are trained alongside them as variables that change the color of a chicken's voice. The voice can give off an early hint before thermometers and gas sensors catch it.

If calls and comb color are signals from an individual, avian influenza is an event that erases an entire poultry house. In 2025, tens of millions of laying hens in the United States were culled because of highly pathogenic avian influenza, shaking egg prices. In June 2026, virologist Dr. Rong Hai of the University of California, Riverside announced that he had received $1.8 million from the U.S. Department of Agriculture's Animal and Plant Health Inspection Service to develop a monitoring tool combining AI and proteomics. The research looks for protein traces left by infected cells rather than viral genes.

The tool is a development project, not an early-warning product deployed on farms.

Signals once kept apart are now converging. In 2026, a research team collected RGB video, 48-kilohertz audio, thermal images, and temperature and humidity data for 22 weeks in five commercial-style research poultry houses. The dataset reached 10.2 terabytes. The achievement of the paper was not diagnostic accuracy but a data infrastructure that synchronizes and stores readings from different sensors. Gathering several senses has not yet automatically separated sick birds from healthy ones.

The Korean government has joined a similar current. In March 2026, the Ministry of Agriculture, Food and Rural Affairs announced a program supporting rapid commercialization of AI products in the agrifood sector, offering an average of 2 billion won per project across 25 projects that included livestock disease prediction. Government-wide selections were announced on June 19, but the representative livestock example was a slaughter-automation robot. No separate project for chickens or poultry was confirmed.

Whether this technology is truly for the chicken is another question. Cameras reading comb color and microphones listening to calls do not reduce stocking density itself. Finding a sick bird early and changing the crowded space that makes birds sick are different problems. AI can assist with the first. People still set stocking density, choose breeds, and determine the price of eggs and chicken meat.

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CHAPTER 5

Digital Twins and Sustainability

5.1

Digital Twins: Building a Barn Inside a Computer

The following is an imagined scene that brings together several functions still at the research stage. It is five in the morning, and the cattle barn is still dark. A cow rises, lowers her neck, and walks toward the feed bunk. Her breath blooms white in the cold air, and a ventilation fan hums softly above the roof. A blue light blinks on the sensor around her neck, while the lens of an overhead camera quietly tracks her movement. On a monitor in the office, there is another version of the same barn. When the real cow takes a step, her three-dimensional counterpart on the screen bends and extends its legs almost at the same moment.

There is no thick wall or long distance between the two barns. There are only numbers moving back and forth, second by second.

This twin barn built inside a computer is called a Digital Twin, or DT. The barn's temperature and humidity, along with the body temperature and gait of every cow, stream into it by the second and set the barn on the screen in motion in real time. Livestock simulations existed before. But they were closer to posting a table of last year's averages on a wall. They could not tell you whether this cow was developing a fever today or how stale the air was in the corner of a pig house at that moment. A digital twin is different.

It continuously takes in data from sensors and cameras, reflects the present condition of the living animals in the barn, and calculates what may happen an hour or a day later. It is like a living mirror.

The farm manager begins each morning with this screen. Tables and graphs show how much the temperature in each barn rose or fell overnight and how many cows left feed behind. An animal showing a suspicious sign is separated out with a red marker at the top of the display. A check that once required walking from pen to pen can now be narrowed down in seconds. Looking across a week's records also reveals which pens consistently demand more attention.

For this mirror to work, it first needs raw numbers. It begins with the vibrations sent every second by an accelerometer on a cow's neck, footage from an overhead camera, and readings from temperature and humidity gauges on the wall. One level up, those raw numbers become meaningful indicators: how many minutes the cow ruminated that day, how many steps she took, and the temperature deep inside her body. At the next level, the computer uses those indicators to make an assessment. It tries to determine whether the cow is suffering from heat, showing early signs of mastitis, or entering estrus.

If one cow suddenly takes fewer steps and her temperature rises slightly, the computer may read that combination as an early mastitis signal and display a warning on one side of the screen. At the highest level, the digital twin begins to show its real value. It runs a change in the virtual barn first, estimates how the cow would respond, and recommends an action to a person. A paper published in 2026 organized these stacked layers into a single framework.

In 2026, researchers presented an AI system that could distinguish seven cattle behaviors using only video from commercial barn cameras. From the images alone, it identified whether a cow was eating at the feed bunk, drinking, standing, or lying down. The researchers used 4964 human-labeled video clips as training data and augmented the set to 9600 clips. Accuracy was about 85 percent, and the system processed more than 22 frames per second on a single graphics processing unit. Individual behavior records extracted this way could become input data for a digital twin.

The study did not go beyond behavior classification to validate feed calculations and three-dimensional rendering at the same time.

Two computational engines, not one, support these four levels. One is a model that directly solves equations based on the physical laws governing the movement of air and heat. Its backbone is a heat-balance calculation that weighs the heat entering the barn against the heat leaving it. The other is an AI model that finds rules for itself by studying historical data. Physics-based models are accurate but slow; data-driven models are fast but often falter in unfamiliar conditions. Engineers building livestock digital twins layer the two.

Physical equations set the broad frame, Machine Learning (ML) and Deep Learning (DL) fill in the details, and Reinforcement Learning (RL), which refines its own rules through repeated trial and error, searches for the best environmental-control strategy.

Not all of these calculations happen in the same place. A small computer mounted beneath the barn eaves immediately handles time-sensitive work, such as isolating the legs of a cow in a camera image. Calculations that can wait, such as gathering several days of data and reformulating a ration, move to a distant data center. A review published in 2025 concluded that this mix of on-farm and cloud computing is well suited to livestock digital twins.

The two models meet with unusual clarity inside a virtual pig house. In the past, a farmer wondering how many more ventilation fans to install and on which wall had little choice but to put them in place and watch for several days. Computational Fluid Dynamics (CFD) reverses that order by mapping the path of the air first. A virtual pig-house model of this kind was published in an international engineering journal in 2023. When the locations and operating conditions of fans are changed on the screen, color-coded airflow spreads through every corner of the virtual house.

The model reveals where air stagnates and where it circulates, and it can calculate the paths taken by heat and gases inside the building. It is a tool for testing at the design stage how heating, cooling, and ventilation should be operated to maintain the desired temperature. There is not yet evidence that the same model has validated greenhouse-gas changes caused by feed reformulation or the placement of safety rails in farrowing pens.

The digital twin researchers envision for cattle works in a somewhat different direction. It collects each cow's core body temperature, rumination time, feed intake, and milk yield to update the animal's condition, then uses a model to estimate the response to a change in feed or additives. Yet no complete digital twin has been confirmed on a commercial dairy farm that can accurately reproduce rumen pH, milk output, and methane response. The function closest to current field use is decision support: it selects abnormal animals from sensor data and tells veterinarians and managers which pen to inspect first.

A warning on a screen cannot replace a person's hands on an udder or the tests that follow.

Suppose feed prices rise sharply over 10 days. The intended value of this type of calculation becomes clear. It can compare the profit from shipping an animal immediately with the profit from feeding it for another two weeks, using both feed prices and expected weight gain. It can also test different times for turning on ventilation fans and misting systems before a heat wave arrives. But the result depends on the farm's data and the accuracy of the model. A person still has to examine the costs and the animals' condition before making the decision.

The value of a digital twin lies in its ability to examine hazardous conditions in a model before exposing a live animal to them. Before testing a new feed or environment on real cattle or pigs, researchers can narrow the candidate conditions and compare several branches of a biosecurity plan on a screen. A simulation, however, cannot replace experiments that establish safety and effectiveness. A model can run a scenario in which an epidemic such as foot-and-mouth disease spreads to a neighboring farm and help examine when to close the barn and how far to restrict access.

The real biosecurity decision must still follow validated epidemiological evidence and the instructions of the authorities.

This shift has already begun in the real world. In October 2025, Scotland's Rural College (SRUC) described farm-twin as the world's first open-source digital twin for dairy farming. The project was supported by the UK Research and Innovation regional growth program and the Digital Dairy Chain. SRUC explained that the platform brings health records, milk yield, feed intake, and barn-environment data from equipment made by different vendors onto one screen. It can trigger a segregation gate when an animal is suspected of illness and tell the farmer why the action was taken.

“World's first,” however, is SRUC's own description, and it remains to be seen how much open-source software will actually lower adoption costs for small farms.

A similar picture is taking shape in poultry houses. Researchers are trying to reproduce the temperature and ammonia concentration inside houses holding tens of thousands of broilers in a virtual space, then calculate in advance how much mortality might fall if stocking density were reduced. Evidence that the calculations work equally well across dozens or hundreds of real poultry houses remains thin. Species differ in body size and patterns of disease, so a method that works well in cattle cannot simply be transferred to chickens.

The barn on the screen does not always show the same numbers as the real barn. The twin is not perfect. Dust settles thickly on camera lenses. A cow may strike a neck sensor with her horn and knock it out of alignment. Dust and harmful gases in the barn, along with impacts from livestock, often make sensor values jump or disappear altogether. If communications fail briefly on a winter night, the barn on the screen freezes for those few minutes. When the signal returns, it catches up with the backlog all at once.

As calibration drift accumulates and a sensor gradually reads values that are slightly off, the twin begins to move half a beat ahead of or behind the real barn. The screen may say 32 degrees while the thermometer in the barn has already passed 35.

Several academic reviews published in 2026 take a clear-eyed view of this gap. Suresh Neethirajan, a longtime researcher in precision livestock farming, concludes that it is difficult to find an engineering-grade digital twin operating on a commercial dairy or poultry farm. Behind promotional claims of better feed efficiency and earlier disease detection, he argues, there is still little evidence validated over several years on real farms. A separate review of poultry farming likewise found few cases validated under commercial field conditions.

Only one study had tested feed conversion ratio at commercial scale, and evidence on failure rates or the share of systems abandoned after adoption was also scarce. A 2025 review analyzed 122 papers published since 2010. Some prototypes and field trials reported feed-efficiency gains of 15 to 20 percent and reductions in water use of up to 40 percent. The same review warned that robust commercial deployment and external validation were lacking. A gap remains between polished presentations and the floor of a working barn.

Mismatched readings are not the only problem. Even two virtual cows representing the same dairy breed may correspond to real animals that respond quite differently. With different genetic traits and immune states, one cow may gain weight quickly on a given diet while another does not. Capturing these individual differences in full, while also reproducing barn airflow at high resolution, demands considerable cloud-computing resources. A well-capitalized large farm may absorb the expense. For a small farm with 10 or 20 cows, it is a barrier from the start.

Add the cost of renting servers, installing sensors, and employing someone who can interpret the data, and the total can rise beyond what a small farm can bear. Sensor prices are gradually falling, and projects such as SRUC's are beginning to release their software, so the barrier may come down. Yet disputes over who owns the data and how accumulated farm information should be protected from leaks still have no clear answer.

The direction of the technology, then, is less toward automation that removes human hands entirely than toward systems that remain standing when data are interrupted or misaligned and still offer a person the next move. That is why managers look at the screen every morning even though they know it can sometimes be wrong.

Return to the imagined scene at five in the morning. The barn on the screen quietly calculates the temperature and humidity for the next six hours. No one can yet guarantee how closely those numbers will match the real thermometer six hours later. It is still dark outside, and the cows remain lined up at the feed bunk. The manager looks at the numbers once, pulls on a pair of boots, and walks out to the barn.

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5.2

Artificial Intelligence That Understands Language: Generative AI and Large Language Models

The following is an imagined scene showing how barn records might be converted into digital data. At five in the morning, in one corner of a barn, a veterinarian holds a flashlight between his teeth and scrawls something in a clinical notebook. The ink bleeds into the paper. He has been called in because a dairy cow left her feed uneaten and is standing oddly. In winter his fingers stiffen and the writing grows even more crooked, but if he does not write down what he sees today, he may not remember it tomorrow. The page mixes the cow's number and temperature with barely legible drug names and abbreviations only he understands.

After a month, even he may be unsure what one of those abbreviations meant. The notebook does not end with that single day. Similar notebooks have accumulated for years in a barn-office drawer, mixed with hygiene reports from the slaughterhouse and husbandry logs written by the farmer. If the cow falls ill again three months later, a different veterinarian may be the one who has to decipher this scribble.

A machine needs two steps to read such handwriting. First, optical character recognition or a handwriting-recognition system converts the marks on paper into text. Then a natural-language-processing model finds disease names, administered drugs, symptoms, and vaccination dates in the digitized record. BioBERT is a language model trained on biomedical literature, but it does not read handwritten images itself. If the character recognition is wrong, the analysis that follows will be wrong as well.

When records are organized accurately, it becomes easier to see which antibiotic was given to which cow and when, and to check the withdrawal period before shipment. A system can also produce a sentence noting that cough sounds and ammonia-sensor readings changed at the same time. But two values moving together does not establish that ammonia caused the coughing. The farmer must still examine the raw data and the animal after reading a row in the table and a sentence in the report.

Precision livestock software began by presenting sensor data as graphs. When screens filled with dots and lines, the farmer's eyes tired first, and the farmer still had to decide what to do. The following is an imagined use case for the kind of decision-support system that language models are intended to make possible. In the office of a dairy farm, the farmer asks for a combined explanation of Cow 105's temperature, rumination time, and the fat-to-protein ratio in her milk.

The screen reports that rumination has recently fallen while the fat-to-protein ratio has risen, and advises that the cow be checked for metabolic disorders, including ketosis. It does not issue a prescription to change the feed ratio immediately. A veterinarian reviews blood and milk tests, the course of the cow's condition after calving, and feed intake before making a diagnosis and deciding on any dietary adjustment. Researchers are also studying multi-agent architectures in which programs for milk-production curves, reproductive cycles, and feed formulation share data while a language model combines the results into one sentence.

This is not yet a widely validated operating standard on dairy farms. The report handed to the farmer is a note that brings the veterinary examination forward, not a prescription that replaces it.

For an answer like this to be useful, the computer cannot simply invent a plausible sentence. A general conversational AI can hallucinate, presenting false statements as fact. In a barn, even one wrong feed-additive ratio or treatment instruction can affect the health of many cows and the quality of an entire milk supply. To reduce this risk, some studies and prototypes are testing Retrieval-Augmented Generation, or RAG. The system first searches validated papers and the farm's sensor records, then builds its answer from that material.

Attaching references and record locations to the answer makes it easier for a veterinarian to open and inspect the originals. Yet a system can still retrieve a document that does not match the question or misstate what the document says, producing a wrong answer with a citation attached. RAG expands the path to verification; it is not a seal guaranteeing diagnostic accuracy.

Even then, the system will not always give the right answer. Reduced rumination alone could indicate ketosis, temporary indigestion, or the beginning of estrus. Language models tend to favor common patterns in the papers on which they were trained, and may paste the most frequent answer onto this cow as well. Much of the training literature centers on Holstein cattle in the United States or Europe, so recommendations on ration formulation or suitable temperatures may shift slightly out of place when the animal is Hanwoo, the breed commonly raised in Korea.

If a language model misreads a veterinarian's handwritten note at the start, the first wrong character follows every sophisticated search and calculation that comes afterward. A computer's prose sounds equally smooth and confident whether it is right or wrong. There is no hesitation or change of tone to help a farmer judge whether to trust the answer. Training a livestock-specific language model from the ground up would require organizing hundreds of thousands of papers and farm records, and the server costs would be difficult for a small farm to bear alone.

Farmers must also ask whether their own husbandry records are being used as training material by an outside company.

Suppose a cow on a Hanwoo farm suddenly refuses feed and her abdomen swells. Drawing on the common causes that dominate its training literature, an AI may suspect ruminal bloat and recommend a digestive remedy. But if the real cause is mold in rice straw delivered several days earlier, and this cow happens to be unusually sensitive to it, the AI may miss a story that rarely appears in papers. A veterinarian then has to enter the barn, smell the straw, and see the white mold before the real cause comes into view.

No matter how many papers it has read, a machine still loses to a human nose and human eyes when faced with an unfamiliar event found only in this barn. This is why technologies that make the reasoning behind a diagnosis visible are being developed.

An AI system using deep learning may predict disease accurately yet reveal little about why it made the judgment. This is known as the black-box problem. Explainable Artificial Intelligence, or XAI, addresses it through methods such as LIME and SHAP. These methods estimate the direction and degree to which inputs such as rumination time, milk composition, and body temperature moved a particular prediction. The values explain the model's prediction; they are not percentages assigning the causes of disease. In camera images, Grad-CAM can mark the areas a model relied on most heavily with a red heat map.

A veterinarian can inspect the highlighted part of an udder or hoof and check whether the judgment is sound. A red mark alone does not confirm disease. The explanation screen is a guide to where an examination should begin. Treatment and feed changes must follow clinical tests and human judgment.

One line of research aimed at reducing these problems is the Small Language Model, or SLM, which runs on a small computer inside the barn instead of sending data to a corporate server. It can reduce the amount of photographs and voice data sent to the cloud and may continue operating when the internet is down. Processing data on the device, however, does not make the information safe by itself. Access controls, encryption, and update management are still needed.

Multimodal models that read images, sounds, and text together are also under study, but livestock systems combining cough sounds, gait video, and clinical records have not yet reached a stage of broad field validation. Researchers still have to shrink these models without sacrificing performance and train them to understand Korean regional dialects.

Even increasingly sophisticated AI often falls silent before the language of Korean livestock farms. A farmer in his eighties may say, “The cow seems listless,” or “Around here, we feed rice bran when this happens,” using regional dialect and old expressions that a model trained mostly on standard Korean and English-language papers may misread. The same feed may be called sojuk in one region and yeomul in another. If a person fails to understand, they can simply ask again. If an AI misunderstands and sends a command to a feed dispenser or ventilation system, the result can be an accident.

Human confirmation is therefore needed between a voice response and equipment control. In 2025, Korea's Rural Development Administration worked with NAVER Cloud to introduce an agricultural AI agent. It was an early service that supplied farmers with agricultural information and identified pests and diseases from photographs. The source does not show that the system had also been validated to understand livestock dialects or control barn equipment.

AFPRO 2026 presented cases in which AI and robotics were expanding from crop cultivation into livestock and food processing.

A computer that fully understands the dialect and trade slang worn smooth by decades of farm work remains a task for the future.

When the veterinarian leaves the barn in the early morning, the details of the visit are automatically organized on a tablet. The diagnosis, treatment, and date of the next visit are written out clearly. Information that once required a long search through an office filing cabinet is now gathered on one screen, and the time saved lets the veterinarian drive quickly to the next farm. Yet something the farmer muttered moments before in dialect, “That one seems strangely out of sorts today,” has not been transcribed correctly anywhere. The veterinarian understood only about half of it himself.

Even so, he smiles, says that he understands, and decides to return on the next visit to look again with his own eyes. An AI may deftly connect clinical records, papers, and sensor readings. When will a language model fully understand the way a person who has watched cattle in this barn for more than 50 years speaks?

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5.3 Methane, Welfare, and Who Owns the Data

The following is an imagined scene that brings environmental sensors and methane-measurement devices together in a single barn. At five in the morning, before the sound of the feed truck can be heard, only the blades of the ventilation fans turn with a low murmur inside the pig house. Hundreds of pigs live together here, their breathing blending into a low collective mutter. Several electrochemical sensors mounted side by side about 1 meter above the floor simultaneously measure ammonia, carbon dioxide, and hydrogen sulfide, the gas known for its rotten-egg smell. The ammonia display reads 18.5 ppm, and the number changes once a minute.

As the methane-concentration graph in the corner of the screen curves gently upward, an on-site controller known as a gateway increases the speed of the ventilation fans. Even on a winter morning when the thermometer outside falls below freezing, the decision is made without a human hand. It is still dark beyond the windows, and only the instrument-panel lights shine. People are still under their blankets, but the barn is already drawing a steadier breath. In the dairy barn, the scene is different. A cow buries her head in the feed bin beside an automatic milking system, while a box-shaped unit above it draws in her breath.

This device, called GreenFeed, measures the gases rising in her burps during the few minutes she eats and sends the results directly to a server.

There is a name that ties all these scenes together. Precision Livestock Farming (PLF) places sensors and internet-connected devices, the Internet of Things (IoT), throughout a barn to read the condition of each individual animal in real time. Each sensor is made of inexpensive, commonplace components, but the intelligence that gathers and interprets their signals is becoming steadily more sophisticated. Count the sensors attached to livestock and those embedded in barn walls, and the source pouring out data is no longer the person but the cow or the pig. At first, the focus was on producing more milk and meat.

As greenhouse gases and odor complaints have become pressures on the entire livestock industry, the same sensors and the same data have taken on a very different assignment: reduction and verification.

The methane a cow releases in burps and breath is produced as microorganisms ferment grass and feed inside the rumen. On the 100-year time horizon used in the IPCC's Sixth Assessment Report, the global-warming potential of non-fossil methane is about 27 times that of carbon dioxide. The number changes with the time horizon selected. GreenFeed collects a cow's breath while she eats and measures the methane. A handheld Laser Methane Detector (LMD) measures path-integrated methane concentration from a distance. A single reading taken in front of the nostrils is not the animal's daily emissions.

Distance and measurement time must be standardized, and measurements repeated over several days, before animals can be compared. Sealed respiration chambers provide precise reference values, but their cost makes them impractical for thousands of commercial farms. Researchers are therefore testing machine-learning models that combine temperature, humidity, carbon-dioxide and ammonia concentrations, feed intake, and the pH and electrical conductivity of manure to estimate methane concentration. One Korean study compared 8923 observations collected at five-minute intervals over one month in July 2024 in a single pig house.

The HistGB model, based on histogram gradient boosting, achieved a coefficient of determination (R^2) of 0.835 as reported in the text and a root mean square error (RMSE) of 3.899 ppm. The result demonstrates the model's ability to predict methane concentration in that pig house. It did not measure emission volume or emission flux, and methane-sensor readings were needed for training and validation. The model cannot be used directly for monthly emissions reporting or Measurement, Reporting, and Verification until it has been tested again on other farms, in other seasons, and with other species.

Ammonia is an irritant gas released from manure. European Union rules for high-density broiler production require ammonia to be kept at or below 20 ppm at the birds' head height. This is not a universal biological threshold at which inflammation begins at the same moment in pigs and chickens. Harm varies with species, age, concentration, and duration of exposure. When concentrations are high and exposure is prolonged, the eyes and respiratory tract are irritated and the risks of disease and lower productivity rise. Livestock are not the only ones breathing the air.

People who work long hours in barns may also suffer irritation of the eyes and throat and headaches. When doors remain closed and ventilation falls in winter, ammonia can accumulate, making continuous sensor measurement necessary. The human nose adapts to the odor, but an electrochemical sensor continues to record the changing concentration. Hydrogen sulfide surging from a stirred manure pit creates a more immediate danger and, at high concentrations, can quickly cause a person to lose consciousness.

A claim that carbon has been reduced remains only a claim until someone verifies it. That is why Measurement, Reporting, and Verification (MRV) procedures are needed to measure emissions, report them, and verify the results. Precision Nutrition aims to match protein and energy to the needs indicated by an animal's body weight, milk production, and rumination time. It may reduce feed losses, lower the nitrogen excreted in manure, and reduce methane per unit of product. The size of the effect, however, must be established separately in field trials matched to the species, diet, and farm conditions.

Methane can also be estimated from the Mid-Infrared (MIR) spectrum and fatty-acid composition of raw milk. This is not a device that measures methane directly; it is a proxy that passes through an equation calibrated for breed, diet, and parity. Numbers generated by sensors and models do not create carbon credits by themselves. In Korea, trading reductions from an approved offset project requires an approved methodology, a baseline, additionality, project registration, monitoring, verification, and certification.

Livestock-product certification likewise requires compliance with specified reduction criteria and prerequisites, and a certification label does not guarantee that the meat or milk carrying it will command a higher price. Between the numbers in a barn and a market transaction or label on a package lies a long administrative process and the choices of the market.

Who owns all these accumulating numbers? Body weight and gait, feed intake and milk composition, the date of a veterinarian's visit and the drugs used are all stored on a server somewhere. Who owns the data and where they may be reused are often reduced to a few lines on the back of a contract. In a 2022 study of agricultural data, 74 percent of responding farmers said they did not know the terms of their contracts, and 55 percent said they had signed without adequate explanation. Farmers worry that they will be unable to control how their husbandry records are reused or transfer all their data when they change equipment.

Federated Learning (FL) is one technology intended to reduce these concerns. Each farm keeps the original data on its own device while model updates calculated by the devices are gathered to train a shared model. The updates sent outside the farm are not automatically encrypted, and there is a risk that some of the underlying data could be inferred. Safeguards such as secure aggregation, differential privacy, and encryption are needed separately. A Consortium Blockchain allows authorized participants to hold a shared record of transactions, making later changes difficult and leaving a trace when changes occur.

This does not mean that no record can ever be deleted or corrected. Correction procedures are needed to comply with members' rules and privacy laws. Technology may lower the risks of moving data, but the power to change a contract comes from farmers' bargaining position and institutions.

The standard for what it means to care for livestock is changing as well. For many years, animal welfare was explained largely through the Five Freedoms, which seek to free animals from hunger and thirst, pain, and fear. The Five Domains Model was proposed in 1994 and expanded in 2015 to include positive welfare states. It examines nutrition, environment, health, and behavior, then assesses how their effects appear in an animal's mental state. The model reflects the view that animals need not merely be free of suffering; they can experience comfort and pleasure.

The environmental domain considers flooring and space, while the behavioral domain asks whether animals can choose to socialize with others or rest alone. Researchers are using cameras and microphones to distinguish relaxed lying postures, exploratory behavior, and vocalizations in an effort to read positive states as well as early signs of disease. Yet a single behavioral signal does not prove satisfaction or pleasure. A question remains: do these observations serve welfare itself, or do they merely add one more item to a list of productivity indicators?

The technologies that measure welfare with such precision can also increase risks in the opposite direction. Scholars have organized 12 possible threats from precision livestock farming to animal welfare. Among them are the risks that animals will be reduced to numbers on a screen, that people will become numb to frequent alarms, and that devices will harm the body. In a qualitative study visiting 25 farms in France, some farmers said sensors and cameras could reduce the time they spent with animals. Others said the technology aided observation and did not damage the relationship. Neither group's experience can stand in for every farm.

Ear tags and collars, too, can cause pressure, abrasion, and inflammation if they are fitted badly or left unchecked for too long. The fit must be inspected by hand so that a device intended to measure an animal's condition does not make the animal ill instead. Closing the distance between the screen and the barn takes more than better sensors.

Airborne numbers such as methane and ammonia, human respiratory health, and the mental states of livestock are easily placed in separate forms. There is also a name for trying to see all three on one screen. One Welfare holds that the welfare of animals, human life, and the planet's air do not exist separately. A number leaves the barn exhaust, spreads into the atmosphere, returns to a human lung, and enters an animal's lung through the same air. Seen this way, separating the three begins to look stranger than putting them together. Every number on the gateway screen reaches that far.

After night has fully fallen, the barn lights go out one by one, leaving only the gateway screen glowing blue in the darkness. The dry scent of rice straw mingles with feed in the summer evening air. The farmer takes a flashlight and makes one last circuit of the barn. The application has already organized every animal's body temperature, activity, and feed intake for the day, but out of habit the farmer meets each animal's eyes and strokes its back. The dairy cow cannot tell whether the hand has come to check the data or simply to say hello. Under the flashlight, she blinks twice and returns to chewing.

The ammonia reading on the panel by the exhaust continues to change once a minute, while the low sound of the cow's rumination carries on in the dark. Far away, the sound of a truck on the road rises briefly and then disappears beneath the chirring of insects.

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