

## Role of Artificial Intelligence in Modern Livestock Production

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### Abstract

Artificial intelligence is increasingly used in livestock production to convert large volumes of sensor, image and production data into practical information. Machine-learning systems can support detection of lameness, heat, calving, abnormal feeding, respiratory problems and changes in milk production. Computer vision can analyse posture, movement, body condition or animal counts without physical contact, while predictive models can combine historical production, weather and health data to identify animals at greater risk. AI can also assist feeding, breeding, environmental control and farm logistics. Its main advantage is the ability to recognise patterns that are difficult to monitor continuously by human observation in large herds or flocks. However, AI outputs are only as reliable as the data used to train and operate the system. Differences in breed, housing, camera angle, farm routine or disease prevalence can reduce performance when a model is transferred to a new setting. Farmers also need understandable alerts rather than complex scores. Responsible use therefore requires validation, data quality, privacy, maintenance and human oversight. AI should strengthen stockmanship and veterinary judgement, not replace them. When integrated carefully with good farm management, it can improve early detection, labour efficiency, resource use and animal welfare.

**Keywords:** Artificial Intelligence, Precision Livestock, Machine Learning, Computer Vision, Animal Monitoring, Decision Support

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### Introduction

Modern livestock farms can generate data from milk meters, feeders, activity sensors, cameras, weighing systems and environmental monitors. Artificial intelligence refers to computational methods that learn patterns from such data and use them for classification, prediction or decision support. Practical implementation of introduction should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to turning sensor, image and production data into specific management questions rather than collecting data without purpose. A practical plan is to define a practical use case such as health screening, feeding, reproduction or welfare and establish how AI output will be checked by

farm staff. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include data completeness, alert usefulness, response time, confirmed cases, production trends and labour saved. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that AI can create false confidence when model output is accepted without checking data quality, farm context or animal condition. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

AI is attractive because it can monitor many animals continuously. The technology is most useful when it answers a clear management question, such as which cows need health examination today or which pen is showing abnormal feed intake, rather than simply producing more data. The value of introduction also depends on integration with the wider production system. Management should connect turning sensor, image and production data into specific management questions rather than collecting data without purpose with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for data completeness, alert usefulness, response time, confirmed cases, production trends and labour saved. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because AI can create false confidence when model output is accepted without checking data quality, farm context or animal condition, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

### **Machine Learning for Health Detection**

Machine-learning models can combine changes in activity, rumination, milk yield and Practical implementation of machine learning for health detection should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to recognising deviations in activity, rumination, milk, temperature or intake that may precede visible illness. A practical plan is to train or validate models on representative animals, compare alerts with veterinary findings and revise thresholds as herd conditions change. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention.

Monitoring can include sensitivity, specificity, false alarms, missed cases, time to detection and clinical outcome after intervention. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that a model developed in another breed, housing system or disease environment may perform differently after transfer. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

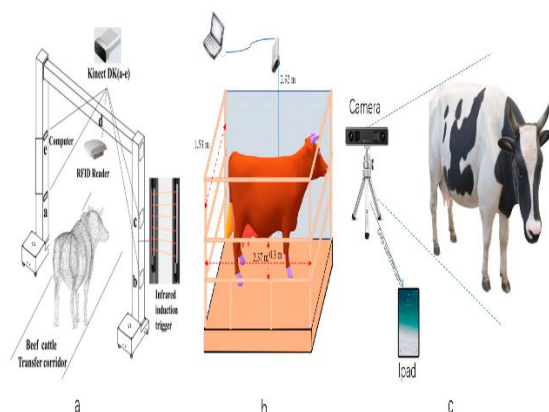
temperature to identify animals that differ from their normal pattern. These systems may flag disease before severe clinical signs develop, allowing workers to examine a smaller number of high-risk animals. The value of machine learning for health detection also depends on integration with the wider production system. Management should connect recognising deviations in activity, rumination, milk, temperature or intake that may precede visible illness with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for sensitivity, specificity, false alarms, missed cases, time to detection and clinical outcome after intervention. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because a model developed in another breed, housing system or disease environment may perform differently after transfer, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

Performance depends on the quality of labelled training data. A model developed in one breed or housing system may not perform equally well elsewhere. Farms should therefore

compare alerts with veterinary diagnosis and review false positive and false negative results.

## Computer Vision and Contact-Free Monitoring

Cameras can be used for body condition scoring, lameness assessment, behaviour recognition and animal counting. Computer vision is attractive because it does not require every animal to wear a sensor, and a single camera can monitor a group continuously. Practical implementation of computer vision and contact-free monitoring should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to using cameras to assess posture, body condition, locomotion, behaviour, counts and spatial use without attaching a device to every animal. A practical plan is to standardise camera position, lighting and background, keep lenses clean and test algorithms under crowding and real farm movement.



Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include classification accuracy, unusable images, occlusion rate, repeated identification and agreement with trained human scoring. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that dust, shadows, animal overlap, changing coat colour or body size can reduce accuracy and should be considered during deployment. Therefore records should be reviewed regularly and important deviations checked by the

relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Lighting, dust, crowding and camera position can reduce accuracy. Animals may also obscure one another. Robust systems must be validated under real farm conditions rather than only on carefully selected images. The value of computer vision and contact-free monitoring also depends on integration with the wider production system. Management should connect using cameras to assess posture, body condition, locomotion, behaviour, counts and spatial use without attaching a device to every animal with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for classification accuracy, unusable images, occlusion rate, repeated identification and agreement with trained human scoring. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because dust, shadows, animal overlap, changing coat colour or body size can reduce accuracy and should be considered during deployment, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

**Table 1. Selected AI applications in livestock production.**

| Application              | Typical data and output                                                               |
|--------------------------|---------------------------------------------------------------------------------------|
| Health-risk detection    | Activity, rumination, milk and temperature data used to flag animals for examination. |
| Computer-vision lameness | Video-based gait or posture features used to identify mobility problems.              |
| Estrus prediction        | Activity and behavioural patterns used to support insemination timing.                |
| Precision feeding        | Feed intake, body weight and production used to refine nutrient allocation.           |
| Heat-stress control      | Weather and animal-response data used to guide cooling or ventilation.                |
| Flock/herd monitoring    | Images or sound used to detect distribution, crowding or abnormal behaviour.          |

## **Feeding and Production Optimisation**

AI can analyse feed intake, milk yield, live weight and ration composition to support precision feeding. Predictive models may identify groups that are over- or under-supplied with nutrients and can help forecast feed demand or production. Practical implementation of feeding and production optimisation should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to using production history and current performance to support ration allocation, feed forecasting and identification of inefficient groups. A practical plan is to combine AI suggestions with measured feed composition, body condition, stage of production and nutritionist review before changing rations. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include feed intake, refusals, milk or growth, feed efficiency, body condition, rumination and cost per unit of output. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that an algorithm may optimise a short-term production target while overlooking rumen health, fertility, welfare or longer-term resilience. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Decisions should remain biologically sensible. A model that maximises short-term output without considering rumen health, body condition or fertility could be harmful. Nutritionists and farmers should define constraints before automated recommendations are implemented. The value of feeding and production optimisation also depends on integration with the wider production system. Management should connect using production history and current performance to support ration allocation, feed forecasting and

identification of inefficient groups with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for feed intake, refusals, milk or growth, feed efficiency, body condition, rumination and cost per unit of output. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because an algorithm may optimise a short-term production target while overlooking rumen health, fertility, welfare or longer-term resilience, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

## **Reproduction, Calving and Young Stock**

Activity patterns are widely used for estrus detection, and AI can refine predictions by incorporating previous cycles, production and environmental conditions. Changes in movement, lying and feeding may also support calving prediction. Practical implementation of reproduction, calving and young stock should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to supporting heat detection, calving alerts, pregnancy-risk assessment and early recognition of abnormal calf feeding or behaviour. A practical plan is to link activity and camera alerts with breeding dates, parity, expected calving and individual calf identification, then confirm events through observation. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include heat alerts, confirmed oestrus, conception, calving accuracy, calf meal patterns, growth and disease events. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is

that reproductive and neonatal events have biological variability, so a prediction should trigger checking rather than automatic treatment. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

In calves and young stock, image and feeding data can help identify growth differences or reduced milk intake. Early alerts can improve attention, but they should trigger observation and examination rather than automatic treatment. The value of reproduction, calving and young stock also depends on integration with the wider production system. Management should connect supporting heat detection, calving alerts, pregnancy-risk assessment and early recognition of abnormal calf feeding or behaviour with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for heat alerts, confirmed oestrus, conception, calving accuracy, calf meal patterns, growth and disease events. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because reproductive and neonatal events have biological variability, so a prediction should trigger checking rather than automatic treatment, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

### **Environmental Control and Farm Operations**

AI can support ventilation and cooling by integrating temperature, humidity and animal behaviour. Forecasting models can also help plan feed inventory, labour and manure handling. In poultry, image and sound analysis are being explored for flock distribution and respiratory abnormalities. Practical

implementation of environmental control and farm operations should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to predicting heat load, ventilation needs, water demand, labour priorities and equipment use from environmental and animal data. A practical plan is to integrate weather and barn sensors with clear control ranges, manual override and backup plans for power or network failure. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include temperature-humidity index, fan runtime, water use, animal respiration, heat-related production loss, equipment alarms and recovery time. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that closed-loop control can create rapid problems if faulty sensors command the wrong response and staff do not notice. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Automated control should have safe limits and manual override. Sensor failure or a poor prediction should not be allowed to create dangerous heat or ventilation conditions. The value of environmental control and farm operations also depends on integration with the wider production system. Management should connect predicting heat load, ventilation needs, water demand, labour priorities and equipment use from environmental and animal data with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for temperature-humidity index, fan runtime, water use, animal respiration, heat-related production loss, equipment alarms and recovery time. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics.

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**Table 2. Checklist for responsible use of livestock AI.**

| Question                         | Why it matters                                                                |
|----------------------------------|-------------------------------------------------------------------------------|
| Was the model validated locally? | Performance can change with breed, housing, equipment and disease prevalence. |
| Are sensors calibrated?          | Poor input data leads to unreliable predictions.                              |
| Is the alert understandable?     | Workers need to know what action to take.                                     |
| Is there human review?           | Clinical and welfare decisions require professional judgement.                |
| Are data protected?              | Farm and animal records may be commercially sensitive.                        |
| Is performance audited?          | False alerts and missed cases should be measured over time.                   |

## Animal Welfare Applications

Welfare assessment often depends on behaviour that changes over time. AI can provide repeated measurements of lying, walking, social interaction or use of resources. This can complement periodic human audits and make it easier to identify pens or animals that need attention. Practical implementation of animal welfare applications should start with a clear baseline and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to identifying lameness, abnormal posture, reduced lying, social isolation and other welfare changes that deserve inspection. A practical plan is to use AI as a screening layer and combine results with locomotion scoring, body condition, lesion checks and stockperson observations. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include confirmed welfare cases, severity, treatment timing, recurrence, lying time, locomotion score and culling outcome. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that welfare cannot be reduced to a single

algorithmic score because pain, fear, disease and resource competition require contextual interpretation. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Welfare cannot be reduced to a single score. Pain, fear, health, comfort and social needs require interpretation. Automated monitoring should be used as one component of a broader welfare programme. The value of animal welfare applications also depends on integration with the wider production system. Management should connect identifying lameness, abnormal posture, reduced lying, social isolation and other welfare changes that deserve inspection with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for confirmed welfare cases, severity, treatment timing, recurrence, lying time, locomotion score and culling outcome. Evaluation should consider productivity together with health or soil function, labour, input use, risk and economics. Because welfare cannot be reduced to a single algorithmic score because pain, fear, disease and resource competition require contextual interpretation, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

## Data Quality, Ethics and Farmer Trust

Livestock AI systems may collect commercially sensitive farm information. Users should understand who owns the data, where they are stored and whether they are used to train commercial models. Cybersecurity and access control become more important as equipment is connected to the internet. Practical implementation of data quality, ethics and farmer trust should start with a clear baseline

and a defined management objective. For responsible use of artificial intelligence in modern livestock production, priority should be given to ensuring that data ownership, privacy, bias, explainability and responsibility are addressed before AI becomes routine. A practical plan is to document where data are stored, who can access them, how models are updated and how users can challenge or override recommendations. Changes should be introduced consistently so their effects can be interpreted. Workers should know the normal range and the signs that require attention. Monitoring can include missing data, model drift, user acceptance, alert explanations, cybersecurity incidents and agreement between predictions and real outcomes. Trends are more useful than isolated readings because season, production stage and local conditions alter expected performance. One limitation is that poor transparency and unexplained recommendations can reduce farmer trust and make accountability difficult when an error affects animals or production. Therefore records should be reviewed regularly and important deviations checked by the relevant farm, veterinary, technical or crop specialist. Measures that fit available labour, infrastructure and budget are more likely to be maintained and to produce reliable long-term benefit.

Explainable alerts improve trust. Farmers are more likely to act when the system shows the reason for an alert, such as a combined decline in rumination and milk, rather than an unexplained risk score. Human oversight remains essential for clinical and welfare decisions. The value of data quality, ethics and farmer trust also depends on integration with the wider production system. Management should connect ensuring that data ownership, privacy, bias, explainability and responsibility are addressed before AI becomes routine with routine records, clear responsibilities and a response plan. Where equipment, biological processes or field operations are involved, timing, maintenance and quality control matter as much as the initial choice. Records should show what was done and the response observed, particularly for missing data, model drift, user acceptance, alert explanations, cybersecurity incidents and agreement between predictions and real outcomes. Evaluation should consider

productivity together with health or soil function, labour, input use, risk and economics. Because poor transparency and unexplained recommendations can reduce farmer trust and make accountability difficult when an error affects animals or production, weak results should first prompt a review of implementation and local constraints. Comparison with a previous season, baseline or similar group helps separate real improvement from normal variation. This adaptive process allows timing, thresholds and resource use to be refined as experience accumulates.

## Conclusion

Artificial intelligence can help modern livestock farms convert continuous data into timely action. Health detection, computer vision, feeding, reproduction and environmental control are among the most promising applications.

The technology should be judged by farm outcomes rather than novelty. Validation, clear alerts, data governance and professional oversight are necessary so that AI improves productivity and welfare without replacing observation or veterinary responsibility.

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