

Artificial Intelligence Applications in Smart Feedlot and Livestock Management: A Comprehensive Review with Perspectives for Malaysia

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ABSTRACT

The livestock sector faces increasing pressure to improve productivity, animal welfare, resource efficiency, and decision-making under labor and sustainability constraints. This review evaluates Artificial Intelligence (AI)-enabled smart feedlot and livestock management, with emphasis on model suitability, deployment limitations, and relevance to Malaysia. A PRISMA-guided structured literature review was conducted with a main search period from January 2018 to September 2026. Seventy-two unique publications were assessed; seven were excluded and 65 records were retained, comprising 23 primary empirical studies selected for detailed comparative synthesis and 42 records classified as supporting or background material. The evidence indicates that no single AI technique is universally superior. Classical machine-learning methods remain suitable for structured and sensor-derived data, whereas deep learning and computer vision are advantageous for image, video, and temporal data when sufficient representative data and computational resources are available. Across studies, generalizability is frequently constrained by small numbers of independent animals, single-farm validation, class imbalance, controlled acquisition conditions, and limited external testing. IoT communication technologies, including LoRaWAN, BLE, NB-IoT, LTE-M, WiFi 6, and 5G, provide complementary capabilities for livestock monitoring rather than a single optimal network solution. Emerging Malaysian studies demonstrate potential in cattle phenotyping, rural connectivity, environmental modelling, and traceability, although large-scale commercial AI validation remains limited. Based on the synthesis, this review presents a literature-informed Smart Feedlot Framework integrating animal identification, sensing, edge/cloud analytics, AI, decision support, and management feedback across eight operational domains. Future research should prioritize cross-farm validation, biologically representative datasets, interoperability, computational efficiency, and measurable operational and economic outcomes.

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1. INTRODUCTION

Livestock production contributes substantially to global food security, nutrition, employment, and rural livelihoods, while simultaneously facing increasing pressure to improve productivity, resource efficiency, animal welfare, and environmental sustainability. These pressures are particularly relevant to intensive cattle and feedlot systems, where management decisions must account for individual-animal health, feed intake, growth performance, reproduction, environmental conditions, and operational cost. Conventional management

commonly relies on periodic observation and manual measurements, which may provide insufficient temporal resolution for detecting subtle changes in animal behavior or production performance [1].

Precision Livestock Farming (PLF) has emerged as a technology-enabled approach to addressing these limitations through continuous or high-frequency monitoring of individual animals and their production environment. Internet of Things (IoT) devices, wearable sensors, automated feeding systems, cameras, depth sensors, environmental monitors, and farm-management platforms can generate large volumes of longitudinal data. When appropriately integrated, these technologies can provide information on feeding behavior, activity, health status, growth, reproduction, environmental exposure, and animal location, enabling more timely and data-driven management [2].

Artificial Intelligence (AI), including classical Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), and time-series analytics, provides methods for extracting actionable information from these heterogeneous data streams. Reported livestock applications include animal detection and identification, body-weight estimation, behavior recognition, disease-risk screening, reproductive monitoring, feed-intake prediction, and decision support. However, strong performance within individual experimental datasets does not necessarily imply equivalent performance under commercial conditions. Existing studies differ substantially in species, sample size, sensing modality, prediction target, class balance, validation strategy, and computing requirements. Small numbers of biologically independent animals, single-farm evaluation, controlled data-acquisition conditions, and limited external validation remain recurring challenges in the transition from experimental models to operational livestock systems [3].

The deployment challenge extends beyond prediction algorithms. Practical smart-livestock systems require reliable animal identification, communication networks, edge or cloud computing, interoperable data streams, and Decision Support Systems (DSS) capable of translating model outputs into management actions. Communication technologies such as LoRaWAN, Bluetooth Low Energy (BLE), NB-IoT, LTE-M, WiFi, and 5G provide different trade-offs in transmission range, bandwidth, energy consumption, infrastructure requirements, and cost. Similarly, the appropriate AI technique depends on whether the application involves structured farm records, wearable-sensor time series, images, video, or multimodal data. Evaluation of livestock AI should therefore consider task suitability and deployment constraints in addition to reported predictive performance [4].

These issues are especially relevant to Malaysia. Official livestock statistics indicate that the national beef self-sufficiency ratio was 15.9% in 2023, highlighting the continuing gap between domestic production and demand [5]. National policy under the National Agrofood Policy 2021–2030 promotes modernization, smart agriculture, innovation, and improvement of domestic ruminant production [6]. At the same time, Malaysian livestock systems operate under tropical environmental conditions and include diverse farm scales and production arrangements. Recent Malaysian studies and national digital initiatives demonstrate emerging activity in cattle phenotyping, livestock-related environmental modelling, rural communication infrastructure, and animal traceability [7], [8], [9], but evidence of large-scale commercial AI deployment remains limited.

Against this background, this review examines AI-enabled livestock management from both technological and operational perspectives. Rather than comparing algorithms solely according to reported accuracy, the review considers model suitability in relation to data modality, biological sample size, generalizability, interpretability, computational requirements, sensing infrastructure, and deployment environment. Primary empirical studies are distinguished from supporting methodological, technical, review, and policy literature. The synthesis is used to develop a literature-informed Smart Feedlot Framework that integrates eight operational domains through sensing, AI analytics, edge/cloud processing, decision support, and management feedback. Particular attention is given to the applicability and current maturity of these technologies in the Malaysian livestock context.

This review addresses the following research questions:

- RQ1: What AI techniques have been applied in feedlot and livestock management, and what performance outcomes and limitations have been reported?
- RQ2: How do IoT and sensor networks enable intelligent livestock monitoring, and what communication and computing architectures are suitable for different operational requirements?
- RQ3: What is the current state of AI and digital-technology adoption in the Malaysian livestock industry, and what barriers and opportunities influence further adoption?
- RQ4: What research priorities and technological frameworks can support the development of reliable and operationally useful intelligent livestock-management systems?

The remainder of this paper is organized as follows. Section 2 describes the review methodology and evidence-classification process. Section 3 presents the Smart Feedlot Ecosystem and its operational integration. Section 4 critically compares AI techniques used in livestock management. Section 5 examines IoT, sensing, and

communication architecture. Section 6 synthesizes major AI applications and their deployment considerations in livestock operations. Section 7 discusses the Malaysian livestock sector, development programmes, and emerging local evidence, while Section 8 summarizes the principal findings and research priorities.

2. METHODOLOGY OF LITERATURE REVIEW

2.1. Review Design and Scope

This study adopted a structured literature review approach guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles [10]. The review was designed to identify, evaluate, and comparatively synthesize evidence on artificial intelligence and digital technologies used in livestock and feedlot management. Rather than limiting the synthesis to model performance, the review also considered the type of input data, livestock application, study setting, dataset characteristics, practical limitations, and potential for field deployment.

The review was organized around the four research questions stated in Section 1. Two categories of literature were distinguished during the synthesis. Primary empirical studies were used for comparative analysis of AI techniques, datasets, applications, and reported performance. Supporting references, including review articles, methodological papers, communication-technology studies, foundational AI publications, and Malaysian policy documents, were used to provide technical, conceptual, and contextual background but were not treated as primary empirical evidence.

2.2. Information Sources and Search Strategy

The literature base was developed from the academic sources used in the original manuscript and was subsequently updated during manuscript revision to address evidence gaps identified by the reviewers. The principal sources considered included Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and publisher databases, while targeted supplementary searches were conducted using Google Scholar to identify recent studies relevant to specific evidence gaps.

The main publication window was January 2018 to September 2026. Earlier publications were retained only when they provided foundational methodological or technological background and were not counted as primary studies in the comparative evidence synthesis.

Search terms combined technology-related and livestock-related concepts. Representative search combinations included:

- (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“livestock” OR “cattle” OR “feedlot” OR “beef cattle”);
- (“computer vision” OR “object detection” OR “image recognition”) AND (“cattle” OR “livestock monitoring” OR “animal behavior”);
- (“IoT” OR “sensor network” OR “LoRaWAN” OR “NB-IoT”) AND (“livestock” OR “precision livestock farming”);
- (“disease prediction” OR “bovine respiratory disease” OR “heat stress”) AND (“machine learning” OR “artificial intelligence”) AND cattle; and
- (“livestock” OR “cattle” OR “smart farming”) AND (“Malaysia” OR “Malaysian”).

Additional targeted searches were conducted for feed-intake and feed-efficiency prediction, reproductive monitoring, explainable AI, edge computing, digital twins, livestock communication technologies, and Malaysian implementation examples. Reference lists of relevant review and empirical articles were also examined to identify additional studies directly related to the review questions.

2.3. Eligibility Criteria and Study Classification

Studies were considered eligible for the primary evidence synthesis when they: (1) investigated livestock or closely related farm-animal management applications; (2) applied AI, machine learning, deep learning, computer vision, sensor analytics, or closely related digital technologies; (3) reported an empirical evaluation using animal, sensor, image, behavioral, environmental, or production data; (4) provided sufficient methodological and outcome information to support interpretation; and (5) were published within the main review period from 2018 to September 2026. Studies involving cattle were prioritized because of the feedlot focus of this review, while studies involving other livestock species were retained when the technological approach was transferable to cattle or feedlot management.

Records were excluded from the primary evidence synthesis when they were unrelated to livestock management, lacked an empirical evaluation, provided insufficient methodological information, or addressed technological applications with no meaningful relevance to the review questions. Publications outside the

primary date range, general AI methodology papers, review articles, policy documents, and conceptual studies were not automatically discarded; where relevant, they were classified as supporting references rather than primary empirical studies.

This distinction was introduced to avoid conflating direct experimental evidence with background literature. For example, foundational publications describing Random Forest, XGBoost, explainable AI, or Digital Twin concepts were used to explain the respective technologies but were not counted as evidence of livestock-specific model performance.

2.4. Screening and Evidence Synthesis

During the revision process, the literature base was consolidated and audited to improve traceability between the cited literature and the claims presented in the review. A total of 72 unique publications were assessed. Seven records were excluded because they were unrelated to the review scope or did not provide suitable evidence. Of the remaining 65 records, 23 primary empirical studies met the criteria for detailed comparative evidence synthesis. The remaining 42 records were classified as supporting or background material considered during methodological, technical, review, and policy assessment. Only supporting sources directly cited in the manuscript are included in the reference list.

For each primary study, information was extracted on livestock species, application domain, AI or analytical technique, input data, dataset or sample characteristics, reported performance metrics, principal findings, and study limitations. The studies were subsequently grouped into major application areas, including animal detection and identification, behavior monitoring, body-weight and body-condition estimation, disease and health prediction, feed-intake and feed-efficiency modelling, reproductive monitoring, heat-stress assessment, and supporting smart-farming infrastructure.

Because performance metrics differed substantially across applications and datasets, model results were not ranked solely according to numerical accuracy. Instead, the synthesis considered task characteristics, data modality, sample size, model complexity, validation design, deployment requirements, and reported limitations. This comparative approach was used to assess the practical suitability of different AI techniques for specific livestock-management applications.

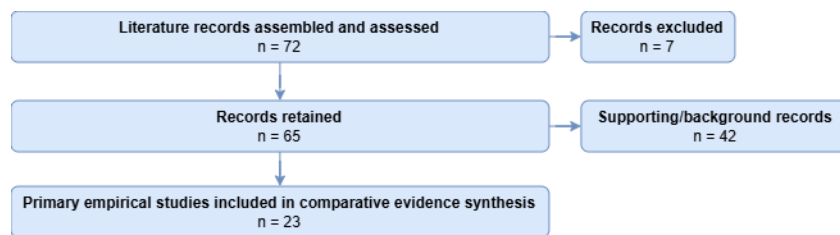


Figure 1. PRISMA-guided literature screening and classification workflow used in the revised review

Table 1. Summary of primary empirical studies included in the comparative evidence synthesis

Study	Species	Application	AI / Technology	Dataset / Sample	Main findings and limitation
Bello et al. (2024) [11]	Cattle	Detection and identification	YOLO, Mask R-CNN, Faster R-CNN	Cattle image dataset	Enhanced Mask R-CNN achieved 97% mAP with reported inference time of 0.2 s; external generalizability and dataset composition require consideration.
Chen et al. (2020) [12]	Pig	Feeding-behavior monitoring	CNN, LSTM	Two pig pens monitored for 3 days	Test accuracy 98.4%, sensitivity 98.8%, and specificity 98.3%; separate-pen testing strengthens validation, although transferability to cattle remains indirect.
Fuentes et al. (2020) [13]	Cattle	Behavior recognition	Deep learning / computer vision	RGB livestock videos collected under day and night conditions; 15 behavior categories	Demonstrated multi-category cattle behavior recognition under varying illumination; detailed performance depends on behavior class and recording conditions.

Gjergji et al. (2020) [14]	Beef cattle	Body-weight estimation	CNN, SHAP	Beef-cattle image dataset	Best CNN reported MAE of 23.19 kg; demonstrates non-contact weight estimation but performance depends on image quality and population characteristics.
Hao et al. (2023)[15]	Cattle	Detection and body-part recognition	YOLOv5-EMA, Grad-CAM	Cattle images annotated for body, individual, leg and head	mAP@0.5 approximately 95% across body-part targets; promising detection performance but field generalization requires broader validation.
Hou et al. (2023) [16]	Beef cattle	Body-weight estimation	LiDAR, PointNet++	100 beef cattle	Segmentation accuracy 95.1%; body-weight prediction MAPE 3.2% and RMSE 10.2 kg; requires specialized 3D sensing infrastructure.
Neupane et al. (2024) [17]	Dairy cattle	Lameness detection	Random Forest, accelerometer/time-series analysis	310 Holstein cows from one herd	Several models achieved >90% classification accuracy for specific behavioral variables; single-herd design limits external generalizability.
Qiao et al. (2019) [18]	Beef cattle	Individual identification	CNN-LSTM	516 rear-view videos from 41 cattle	CNN-LSTM achieved 88–91% identification accuracy depending on sequence length; biological sample remained relatively small.
Xiong et al. (2023) [19]	Beef cattle	Weight and body-condition estimation	Depth imaging	58 mature crossbred beef cows	Test performance supported non-contact BW estimation, but small sample size and imbalanced BCS classes reduced robustness.
Zhang et al. (2019) [20]	Pig	Detection and tracking	Computer vision / tracking algorithm	Commercial-farm video under daylight and infrared conditions	Demonstrated multi-animal tracking under challenging farm conditions; evidence is transferable to cattle only at the technology level.
Bushby et al. (2024) [3]	Dairy calves	BRD prediction	Gradient boosting, automatic feeder, UWB sensing	172 calves; 229 behavioral features	Gradient boosting achieved accuracy 0.773, sensitivity 0.625 and specificity 0.872; moderate sensitivity limits standalone clinical use.
Bowen et al. (2021) [21]	Dairy calves	BRD prediction	Random Forest, moving average, accelerometer, feeder data	~100 calves	RF showed high specificity (0.95) but low sensitivity (0.35); combining approaches improved balanced accuracy, showing disease prediction remains sensitivity-limited.
Sikka et al. (2020) [22]	Buffalo	Feed efficiency / RFI	Isotonic regression and other ML models	42 Murrah buffalo heifers; 96-day feeding trial	Isotonic regression performed favorably for feed-efficiency prediction; cross-species evidence and RFI should not be interpreted as direct cattle FCR prediction.
Martin et al. (2021) [23]	Dairy cattle	DMI and RFI prediction	MLR, PLS, ANN, stacked ensemble	124 Holstein cows	Simple MLR remained competitive with complex ML for DMI, while RFI prediction was weak across models; complexity did not guarantee superiority.
Davison et al.	Beef cattle	Feed intake and FCR estimation	SVR, Random Forest	80 finishing steers monitored for 56 days	Predicted feed intake combined with weight gain produced strong agreement with measured

(2023) [24]					FCR; FCR was derived rather than directly predicted.
Hossain et al. (2025) [25]	Cattle	Weight estimation and XAI	CNN, EfficientNetB3, LIME	2,052 original images from 513 cattle	Best CNN achieved MAE 18.02 kg and RMSE 19.85 kg; LIME highlighted biologically relevant body regions, although animal-level split independence should be verified.
Becker et al. (2021) [26]	Dairy cattle	Heat-stress classification	Logistic regression, Gaussian NB, Random Forest	Cows subjected to different heat-abatement treatments	Best-performing algorithm varied according to treatment and target, indicating model suitability depends strongly on feature composition and context.
Silva et al. (2026) [27]	Nelore cattle	Tropical heat-stress classification	Neural network / deep learning	30 cattle; 676 observations	Accuracy around 72% and AUC around 0.67, with low specificity; shows that tropical heat-stress classification remains difficult despite DL.
Wang et al. (2020) [28]	Dairy cattle	Estrus detection	KNN, BPNN, LDA, CART, PCA, UWB and accelerometer	12 cows; 25,684 sensor records	Best configurations achieved high sensitivity and accuracy, but only 12 independent animals were studied, limiting generalization.
Yang et al. (2024) [29]	Dairy cattle	Calving prediction	CNN, LSTM, CNN-LSTM, CNN-BiLSTM-attention, TimeGAN	25 cows for development + 11 additional test cows	Best model achieved precision 0.9147, recall 0.9459 and F1 0.9300; performance depended strongly on synthetic-data augmentation.
Alonso et al. (2020) [30]	Dairy cattle	Edge-IoT platform and DSS	IoT, edge computing, AI, blockchain	Real mixed farm with 180 dairy cows and 302 ha associated crops	Real deployment showed reduced cloud traffic and improved IoT-edge communication reliability; dairy setting differs from beef feedlots.
Ma et al. (2020) [31]	Dairy cattle	Estrus detection / NB-IoT	NB-IoT, LSTM, CNN	40 cows; 6 estrus-positive cows	LSTM reported sensitivity 94%, specificity 98% and PPV 95%; very small number of positive animals limits confidence in generalization.
Shahrai et al. (2026) [7]	Crossbred Brahman cattle, Malaysia	Carcass-trait prediction	Real-time ultrasound, RGB imaging, regression	74 cattle at a commercial Malaysian cattle farm; 15 matched slaughter samples for model development	REA prediction achieved R^2 0.921 and strong RTU-RGB correlation; only 15 carcass samples were available, creating overfitting risk.

Table 1 highlights the heterogeneity of current AI applications in livestock management. Direct numerical comparison across studies should be interpreted cautiously because the studies differ substantially in species, sample size, sensing modality, prediction target, validation strategy and performance metric. High performance on a constrained image-classification task, for example, does not necessarily imply superior suitability for longitudinal disease prediction or commercial feedlot deployment. Consequently, the following sections evaluate AI techniques not only according to reported predictive performance, but also according to data requirements, generalizability, computational complexity and operational suitability.

3. SMART FEEDLOT ECOSYSTEM

A modern feedlot system encompasses a complex set of inter-related operational processes spanning animal intake and identification, nutrition management, health surveillance, environmental control, growth monitoring, waste management, and logistics. Effective integration of these processes is fundamental to achieving optimal feed conversion ratios (FCR), minimizing mortality, ensuring animal welfare compliance, and maintaining farm profitability. Smart feedlot systems leverage digital technologies to automate, optimize, and intelligently manage each of these operational dimensions.

The emergence of Artificial Intelligence (AI), Internet of Things (IoT), Computer Vision, and data analytics has accelerated the adoption of Precision Livestock Farming (PLF), enabling real-time monitoring

and data-driven decision-making at both individual animal and farm levels. Through continuous collection and analysis of operational data, smart feedlot systems can provide actionable insights into animal health, feeding behavior, growth performance, environmental conditions, and resource utilization. Such capabilities support early disease detection, improved productivity, reduced operational costs, and enhanced sustainability.

For Malaysia, the adoption of smart feedlot and precision livestock farming technologies is increasingly important to strengthen food security, improve national livestock self-sufficiency, and enhance the competitiveness of the local livestock industry. As demand for animal protein continues to increase, the transition from conventional management practices toward intelligent and automated livestock systems is essential. Accelerating the deployment of AI-driven feedlot technologies can help Malaysia modernize its livestock sector, increase production efficiency, and support the nation's broader Industry 4.0 and digital agriculture initiatives.

3.1. Feedlot Process Architecture and Operational Integration

Figure 2 presents the conceptual architecture of a smart feedlot ecosystem, illustrating the data flows between physical operations, sensor networks, AI processing layers, and farm management decision support.

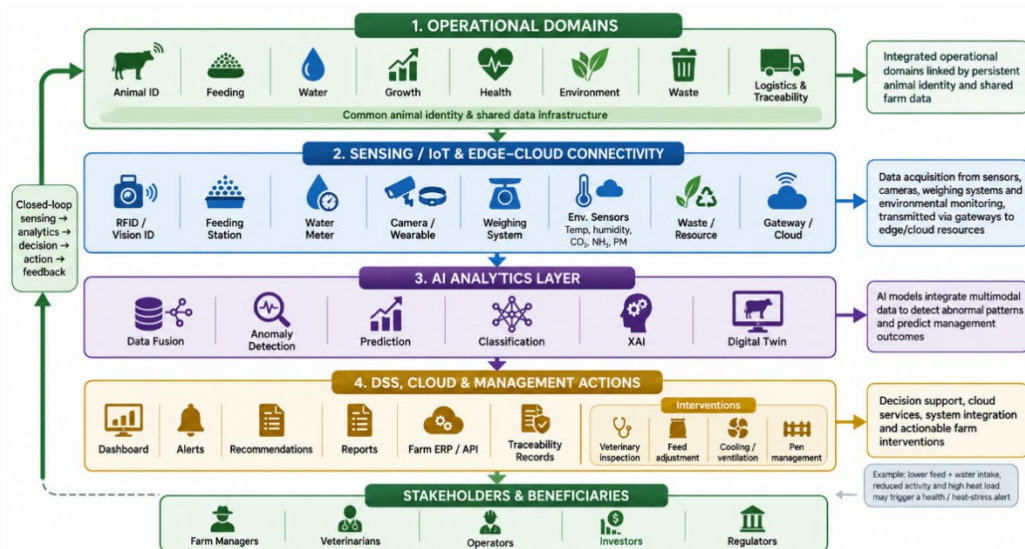


Figure 2. Conceptual architecture of a Smart Feedlot Ecosystem with layered IoT, AI and decision-support integration

The proposed smart feedlot ecosystem comprises eight interdependent operational domains: animal identification, feeding management, water monitoring, growth monitoring, health monitoring, environmental monitoring, waste management, and logistics and traceability. Rather than functioning as isolated modules, these domains are linked through a common animal identity and shared data infrastructure. RFID or vision-based identification provides a persistent identifier that connects feeding events, water intake, body-weight measurements, behavioral observations, health records, and location information to each individual animal. Environmental measurements, including temperature, humidity and air-quality indicators, provide additional context for interpreting changes in feeding behavior, activity, growth and health. Waste and resource-use data are aggregated at farm level, while logistics and traceability modules preserve animal and production records as animals move through the production cycle.

Operationally, the framework follows a closed-loop sensing–analytics–decision–action process. Data generated by animal-mounted sensors, feeding stations, cameras, weighing systems and environmental sensors are transmitted through local gateways to edge or cloud computing resources. AI models then integrate these heterogeneous data streams to identify abnormal patterns or predict management outcomes. The resulting information is presented through a Decision Support System (DSS), which may generate alerts or recommendations for veterinary inspection, feed adjustment, cooling or ventilation, pen management, or other farm interventions. Subsequent sensor measurements provide feedback on the animal or farm response, allowing management decisions and predictive models to be updated over time. Consequently, a change detected in one domain can influence decisions in another; for example, reduced feed and water intake combined with decreased activity and elevated environmental heat load may trigger a health or heat-stress alert rather than being interpreted as an isolated feeding anomaly.

The feasibility of such layered integration is supported by practical implementations reported in the literature. Alonso et al. deployed the SmartDairyTracer platform in a real mixed dairy farm in Spain containing approximately 180 dairy cows and 302 ha of associated feed crops. The platform integrated heterogeneous IoT networks for cattle, barn environmental conditions and crop monitoring with an edge-computing layer for data preprocessing and a cloud-based business layer for analytics, alert management and decision support. Machine-learning functionality could also be executed at the edge using lightweight frameworks, while traceability information was incorporated through distributed-ledger technologies. The deployment demonstrated the practical feasibility of linking sensing, edge processing, cloud analytics and management applications within a livestock production environment. Although the system was developed for dairy rather than beef-feedlot production, its layered architecture provides an operational precedent for the sensor–edge/cloud–DSS integration proposed in the present Smart Feedlot Framework [30].

As an illustrative beef-feedlot scenario, an animal entering the facility could first be assigned an RFID-linked digital record. Feeding and water systems would continuously record intake, while cameras or wearable sensors monitor activity and growth and environmental sensors measure heat-load conditions. If the system detects a simultaneous decline in feed intake and activity during a period of elevated heat load, the analytics layer could prioritize the animal for inspection and recommend cooling or management intervention through the DSS. Subsequent changes in intake, behavior and weight gain would then provide feedback on the effectiveness of the intervention. The same animal identity and production history could subsequently be retained for movement, treatment and traceability records. This scenario illustrates how the individual operational domains in Figure 2 can function as an integrated management cycle rather than as independent monitoring systems.

The proposed framework therefore represents a literature-informed conceptual architecture rather than a field-validated system. Feedlot-scale implementation and prospective validation remain necessary to quantify its technical performance, economic feasibility, interoperability, and robustness under commercial operating conditions.

4. ARTIFICIAL INTELLIGENCE TECHNIQUES IN LIVESTOCK MANAGEMENT

4.1. Classical Machine Learning for Structured and Sensor Data

Classical machine-learning techniques remain relevant in livestock management because many farm datasets are structured, relatively small, and heterogeneous rather than extremely large. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), gradient boosting, logistic regression, and related ensemble methods can operate effectively on features derived from feeding systems, accelerometers, environmental sensors, production records, and health observations. Their comparatively modest computational requirements also make them attractive for farm-level applications where extensive GPU infrastructure or large annotated datasets are unavailable.

However, the suitability of these algorithms varies substantially according to the prediction task and input representation. SVMs have demonstrated good performance for accelerometer-based behavior recognition, particularly when behavioral classes can be separated using carefully engineered movement features. Their performance nevertheless depends strongly on feature design, kernel selection, and parameter tuning, which reduces their flexibility as the dimensionality and heterogeneity of sensor data increases. RF and gradient-boosting models are generally better suited to mixed tabular variables and can capture nonlinear interactions while also providing feature-importance information that supports model interpretation.

Recent disease-prediction studies illustrate these trade-offs. Bowen et al. [21] used feeding and activity information to predict respiratory disease in pre-weaned calves. RF achieved high specificity but considerably lower sensitivity, indicating that the model was more reliable for identifying healthy animals than for detecting all diseased animals. Bushby et al. [3], using a larger set of feeding, movement and social-behavioral features, reported that gradient boosting provided the strongest overall discrimination among the evaluated models, although sensitivity remained moderate. These findings suggest that model performance in livestock health monitoring depends not only on algorithm selection but also on the richness and clinical relevance of the available behavioral features.

A similar pattern is evident in feed-intake and feed-efficiency modelling. Martin et al. [23] compared multiple linear regression, partial least squares, artificial neural networks and stacked ensembles for dry-matter-intake and residual-feed-intake prediction. More complex learning methods did not consistently outperform simpler statistical approaches, particularly for residual feed intake. Davison et al. [24] used machine-learning-based feed-intake estimates to derive individual feed conversion ratios in finishing beef cattle, demonstrating the operational value of predictive modelling for identifying high- and low-performing animals. Together, these studies show that increasing model complexity does not automatically improve decision usefulness; prediction target, feature quality, biological variability and validation design remain equally important.

From a deployment perspective, classical machine-learning models are therefore particularly suitable when data are predominantly structured, sample sizes are moderate, computational resources are constrained, and some degree of feature-level interpretability is required. Their principal limitation is that they generally depend on engineered features and may be less effective than deep-learning approaches when raw video, images, or long multivariate time-series must be modelled directly.

4.2. Deep Learning for Temporal and High-Dimensional Data

Deep-learning approaches are particularly useful when livestock applications involve high-dimensional or sequential data such as images, video, accelerometer signals, and multivariate time series. In contrast to classical machine-learning methods that often require manually engineered features, deep neural networks can learn task-relevant representations directly from raw or minimally processed data. This advantage is particularly important for computer vision and longitudinal behavioral monitoring, although it is accompanied by greater computational requirements, larger data needs, and a higher risk of overfitting when the number of independent animals is limited.

Convolutional Neural Networks (CNNs) have been widely applied to spatial information contained in livestock images. Gjergji et al. [14] demonstrated the feasibility of CNN-based body-weight estimation in beef cattle, reporting a mean absolute error of 23.19 kg. Although such non-contact approaches can reduce the labor and animal handling associated with conventional weighing, their performance remains sensitive to image acquisition conditions, animal population characteristics, and the representativeness of the training dataset. Similar considerations apply to image-based detection and behavioral applications, where high performance on a controlled dataset does not necessarily guarantee robustness under changes in illumination, camera position, animal density, or farm environment.

Recurrent and hybrid neural architectures are more suitable when temporal dependencies are important. Qiao et al. [18] combined CNN-based visual feature extraction with LSTM sequence modelling for individual cattle identification from rear-view videos, achieving approximately 88–91% identification accuracy depending on sequence length. The approach illustrates how temporal information can improve interpretation of video sequences, but the study involved only 41 cattle, limiting conclusions regarding generalization to substantially larger herds. In another livestock application, Chen et al. [12] combined CNN and LSTM components for video-based feeding-behavior recognition in pigs and reported high classification performance. Testing on a separate pen strengthened the evaluation design, although direct transfer of the reported performance to cattle or feedlot settings cannot be assumed.

Temporal deep learning has also shown value for reproductive monitoring. Yang et al. [29] compared CNN, LSTM, CNN-LSTM, and CNN-BiLSTM-attention architectures for calving prediction using tail-mounted triaxial accelerometer data. The best model achieved precision of 0.9147, recall of 0.9459, and an F1-score of 0.9300, and generated alerts within 12 h before calving for all 11 cows in the independent alert test. However, performance improved substantially after TimeGAN-based synthetic-data augmentation, indicating that the reported accuracy was strongly influenced by the strategy used to address class imbalance. The relatively small number of independent animals also remains an important limitation for commercial-scale generalization.

Ma et al. [31] similarly applied an LSTM model to NB-IoT-based estrus monitoring in dairy cattle and reported sensitivity of 94%, specificity of 98%, and positive predictive value of 95%. Nevertheless, only six of the 40 monitored cows were estrus-positive, illustrating a recurrent issue in livestock deep-learning studies: very large numbers of sensor observations can be generated from relatively few independent animals. Evaluation based primarily on observation counts may therefore overstate the diversity of the biological population represented in the dataset.

Transformer and Vision Transformer architectures are increasingly discussed for agricultural image and time-series analysis, but livestock-specific empirical evidence in the present review corpus remains less mature than that available for CNN- and LSTM-based approaches. Their attention mechanisms offer potential advantages for modelling long-range relationships and multimodal sensor streams, but they generally require larger datasets and greater computational resources. Consequently, Transformer-based models are better regarded at present as an emerging direction for livestock monitoring rather than an established replacement for CNN, recurrent, or classical machine-learning approaches [32].

Overall, deep learning is most appropriate when the input data contains complex spatial or temporal structure that cannot be represented efficiently through manual feature engineering. CNNs are naturally suited to visual information, while recurrent and hybrid architectures can exploit sequential patterns in video and wearable-sensor data. Their practical advantage, however, depends on whether improvements in predictive performance justify the additional requirements for labelled data, computation, model validation, and deployment infrastructure. For many livestock applications, biological sample size and cross-farm validation remain more important constraints than network architecture alone.

4.3. Computer Vision for Detection, Identification, Tracking, and Phenotyping

Computer vision is among the most extensively investigated AI approaches in livestock monitoring because cameras can collect information continuously and non-invasively without requiring physical contact with every animal. Current applications include animal detection, individual identification, behavioral recognition, body measurement, weight estimation, body-condition assessment, and tracking. However, these tasks impose different technical requirements. Detection primarily determines whether and where an animal is present, segmentation delineates animal boundaries more precisely, identification associates observations with individual animals, while tracking maintains those identities across successive video frames.

Object-detection studies demonstrate that high predictive performance is achievable under well-defined image conditions. Hao et al. [15] applied a YOLOv5-EMA architecture to cattle body and body-part detection and reported mAP@0.5 values of approximately 95% across several detection targets. The one-stage YOLO architecture is attractive for real-time livestock monitoring because detection and localization are performed within a single inference pipeline. In contrast, Bello et al. [11] compared YOLO, Faster R-CNN, and Mask R-CNN-based approaches and reported an enhanced Mask R-CNN model with approximately 97% mAP and an inference time of about 0.2 s. These results illustrate an important deployment trade-off: lightweight one-stage detectors are well suited to continuous monitoring, whereas instance-segmentation architectures can provide more detailed animal boundaries when precise morphological information is required.

The value of segmentation becomes particularly evident in automated phenotyping and body-weight estimation. Hou et al. [16] used LiDAR-derived three-dimensional cattle data with PointNet++ and reported segmentation accuracy of 95.1%, together with body-weight prediction MAPE of 3.2% and RMSE of 10.2 kg in 100 beef cattle. Compared with conventional RGB imaging, three-dimensional sensing can provide richer geometric information and reduce dependence on visual texture. Its practical limitation is the requirement for specialized depth or LiDAR hardware, calibration, installation infrastructure, and controlled animal positioning. Xiong et al. [19] similarly demonstrated the feasibility of depth-image-based body-weight and body-condition estimation in mature beef cows, but their sample of 58 animals and imbalanced body-condition categories illustrate how apparently promising image-based systems can remain constrained by biological sample diversity.

Individual identification and tracking introduce additional challenges because models must preserve animal identity despite changes in posture, orientation, occlusion, illumination, and interaction with other animals. Qiao et al. [18] used a CNN-LSTM framework for individual cattle identification from rear-view video and achieved approximately 88–91% accuracy depending on sequence length. Temporal modelling therefore provided useful information beyond individual image frames, although the study included only 41 cattle. Zhang et al. [20] demonstrated multi-animal detection and tracking under commercial pig-farm conditions using both daylight and infrared video. Although the species differs from cattle, the study highlights the general technical challenge of maintaining identity in group-housed animals under variable illumination and frequent occlusion.

Computer vision can also extend from animal localization to behavioral interpretation. Fuentes et al. [13] applied spatio-temporal deep learning to recognize multiple cattle behaviors from video collected under different illumination conditions, including both daytime and nighttime recordings. Such systems demonstrate the potential for continuous, non-contact behavioral monitoring, but behavioral classification is generally more demanding than simple detection because visually similar actions may differ only in motion pattern, duration, or social context. Performance therefore depends not only on the visual model but also on camera placement, temporal resolution, class balance, and the consistency of behavioral annotation.

Across these applications, direct comparison of reported accuracy or mAP values should be made cautiously. A detector evaluated on static images, a segmentation model applied to three-dimensional point clouds, an identification model evaluated on a limited herd, and a behavioral classifier operating on video sequences solve fundamentally different tasks. High performance in one setting therefore does not imply equivalent robustness in another. For commercial feedlot deployment, model selection should consider the required output, camera or sensor cost, inference speed, animal density, robustness to occlusion and lighting variation, and whether the system has been validated across farms, breeds, seasons, and management conditions.

From an operational perspective, real-time object detectors are most suitable for continuous animal localization and counting; segmentation and depth-based approaches are advantageous when accurate body geometry is required; temporal identification and tracking models are necessary when observations must be linked to individual animals over time; and spatio-temporal models are preferable when behavior rather than appearance is the principal target. The main remaining challenge is therefore not simply improving benchmark accuracy, but demonstrating robust cross-environment performance under realistic commercial conditions.

4.4. Explainable AI and Model Transparency

Explainable Artificial Intelligence (XAI) is increasingly important in livestock decision-support systems because high predictive performance alone may be insufficient when model outputs influence veterinary inspection, feeding intervention, reproductive management, or other operational decisions. In this context, explanation methods can help users understand which features or image regions contribute most strongly to a prediction, but they should not be interpreted as proof that a model has learned biologically causal relationships.

The suitability of an explanation method depends strongly on the underlying data and model type. SHAP provides feature-level attribution and is particularly useful for structured or tabular models such as tree ensembles, where farm managers or researchers may wish to identify which behavioral, environmental, or production variables contribute most strongly to a prediction. Its principal advantage is that local explanations for individual predictions can also be aggregated to examine broader feature-importance patterns. However, interpretation becomes more difficult when predictors are highly correlated, and feature attribution should not be equated with biological causality [33].

Model-agnostic approaches such as LIME are useful when explanations are required for complex models without modifying the original architecture. A livestock-specific example is provided by Hossain et al. [25], who applied LIME to a CNN-based cattle body-weight estimation framework. The best model reported an MAE of 18.02 kg and RMSE of 19.85 kg, while the explanation maps highlighted body regions such as the rib cage, abdomen, and hindquarters as influential for prediction. This provides a useful example of XAI being used not only to report predictive performance but also to examine whether the model is focusing on visually plausible anatomical regions. Nevertheless, such local explanations remain sensitive to the perturbation and approximation procedure, and the interpretability result does not by itself establish external generalizability.

Visual explanation methods such as Grad-CAM are particularly suitable for convolutional models because they produce saliency maps indicating which image regions contribute most strongly to a prediction or detection. Hao et al. [15], for example, incorporated visual explanation into a YOLO-based cattle detection framework to inspect model attention across cattle and body-part targets. Such methods are comparatively intuitive for farm operators and researchers because the explanation can be overlaid directly on the source image. Their limitation is that saliency maps are generally coarse and descriptive; they show where the network attended but do not demonstrate why a biological outcome occurred.

These approaches therefore address different interpretability needs. SHAP is more appropriate when the primary question is which structured variables influence a prediction, whereas LIME and Grad-CAM are more useful for examining individual predictions from image-based models. In practical livestock systems, the choice of XAI method should consequently follow the data modality and decision context rather than being treated as an additional visualization step applied after model development.

Current livestock-specific evidence for XAI remains relatively limited compared with the wider use of machine learning and computer vision. Many studies still report accuracy, AUC, RMSE, or mAP without systematically evaluating whether explanations are stable, biologically meaningful, understandable to farm users, or useful for management decisions. XAI should therefore be considered a supporting component of model validation and decision support rather than a substitute for external validation, representative datasets, or prospective field evaluation.

4.5. Comparative Suitability of AI Techniques for Livestock Applications

The reviewed evidence indicates that no single AI technique is consistently superior across livestock-management applications. Model suitability depends primarily on the prediction task, data modality, biological sample size, interpretability requirements, computational resources, and intended deployment environment. Consequently, performance metrics reported in individual studies should be interpreted within their experimental context rather than used to establish a universal ranking of algorithms.

Classical machine-learning approaches remain particularly suitable for structured farm records and engineered sensor features. Random Forest, Support Vector Machine, gradient boosting, logistic regression, and related methods can perform effectively with moderate sample sizes and relatively limited computational resources. They are therefore attractive for feed-intake modelling, health-risk classification, and sensor-derived behavioral analysis. Their main limitations are dependence on feature engineering and reduced flexibility when raw image, video, or long multivariate time-series data must be processed directly. The studies of Bushby et al. [3], Bowen et al. [21], Martin et al. [23], and Davison et al. [24] further demonstrate that strong predictive performance depends as much on feature quality, target definition, and validation design as on algorithm complexity.

Deep-learning approaches provide greater flexibility for high-dimensional and sequential data. CNNs are naturally suited to image-based applications, while recurrent and hybrid architectures can capture temporal relationships in video and wearable-sensor streams. However, their practical advantage is most apparent when sufficient representative data are available. Several studies in the reviewed corpus achieved high performance

despite relatively small numbers of independent animals, including cattle-identification, estrus-detection, and calving-prediction studies. This distinction between the number of sensor observations and the number of biologically independent animals is important because a large volume of repeated measurements does not necessarily guarantee population-level generalizability.

Computer-vision systems are especially promising for continuous, non-contact monitoring, but the appropriate architecture depends on the required output. One-stage object detectors are well suited to real-time localization and counting, whereas segmentation and three-dimensional approaches provide richer geometric information for phenotyping and body-weight estimation. Temporal identification and tracking models are required when observations must remain associated with individual animals over time. These more advanced visual systems generally impose greater requirements for camera placement, annotation, hardware, calibration, and robustness to occlusion and illumination changes. The strong performance reported by Bello et al. [11], Hao et al. [15], Hou et al. [16], and Xiong et al. [19] should therefore be considered together with the infrastructure and validation conditions under which those results were obtained.

Explainability introduces a different dimension of suitability. XAI methods such as SHAP, LIME, and Grad-CAM do not replace the predictive model but can improve transparency by showing which variables or image regions influence a prediction. They are most useful when model outputs support management or veterinary decisions that require human interpretation. Nevertheless, explanation quality does not compensate for poor external validation, biased training data, or weak biological sample representation. In livestock applications, XAI should therefore be viewed as a complementary requirement for trustworthy decision support rather than as an independent indicator of model quality.

From a deployment perspective, the choice of model should also reflect where inference is expected to occur. Classical models and lightweight neural networks are more compatible with edge devices and resource-constrained farm infrastructure, while larger deep-learning and multimodal models may require GPU-enabled edge servers or cloud processing. Cloud-based computation can support more complex analytics but introduces dependence on reliable connectivity, whereas edge processing reduces latency and network traffic but imposes tighter memory, energy, and maintenance constraints. These trade-offs are particularly relevant in rural and developing-country livestock environments, where communication infrastructure may be inconsistent.

Overall, the evidence suggests that model selection in smart livestock systems should follow a task-driven rather than algorithm-driven strategy. Structured production and sensor data generally favor classical machine-learning methods; raw visual data favor CNN-based and computer-vision architectures; sequential behavioral or reproductive signals favor temporal models; and XAI techniques are most valuable when predictions must be interpreted by farm managers or veterinarians. Future work should therefore prioritize robust cross-farm validation, biologically representative datasets, computational efficiency, and integration with operational decision-making rather than pursuing marginal improvements in benchmark accuracy alone.

5. IoT AND SENSOR-BASED LIVESTOCK MONITORING

5.1. Sensing Modalities

The deployment of heterogeneous sensor networks is foundational to intelligent livestock monitoring, generating the real-time, multi-dimensional data streams that AI models require for accurate inference [34]. In modern Precision Livestock Farming (PLF), sensors serve as the primary interface between animals, farm environments, and digital management systems. Continuous monitoring enables the collection of physiological, behavioral, environmental, and production-related information that can be analyzed to support data-driven decision-making.

Recent advances in sensor technologies have enabled continuous and non-invasive monitoring of livestock health, welfare, productivity, and environmental conditions. Wearable devices, RFID tags, GPS trackers, accelerometers, thermal cameras, and environmental sensors can capture detailed information regarding animal movement, feeding behavior, rumination patterns, body temperature, location, and surrounding environmental conditions. These data streams provide valuable insights into animal performance and facilitate the early detection of disease, stress, reproductive events, and abnormal behavior.

The integration of multiple sensing modalities further enhances monitoring accuracy by enabling sensor fusion approaches. For example, combining accelerometer data with thermal imaging and environmental measurements can provide a more comprehensive assessment of animal health than relying on a single sensor source. Such multi-sensor systems form the foundation of AI-driven smart feedlot platforms, where machine learning and deep learning algorithms transform raw sensor data into actionable recommendations for farm managers and veterinarians.

Table 2 summarizes representative sensor categories used in livestock monitoring, including their measurement parameters, mounting configurations, and principal applications.

Table 2. Sensor categories, measurement parameters, mounting configurations, and applications in smart livestock monitoring systems

Sensor Type	Measurement Parameter	Mounting	Key Applications
RFID (UHF)	Animal identity, location	Ear tag, leg band	Traceability, pen assignment, feeding events
GPS/GNSS	Position, movement range	Collar, ear tag	Grazing mapping, activity, geofencing
3-axis Accelerometer	Activity, posture, steps	Collar, leg band, ear tag	Behavior classification, lameness detection, oestrus
Rumen Bolus	pH, temperature, activity	Oral/rumen implant	Acidosis, ketosis, fever detection
Thermal Camera (LWIR)	Surface temperature	Fixed overhead/pan-tilt	Heat stress, mastitis, fever screening
RGB Camera	Visual scene	Fixed, PTZ, UAV-mounted	BCS, weight estimation, behavior, counting
Weighbridge/Scale	Live body weight	Walk-over, pen floor	ADG calculation, FCR monitoring
Temperature/Humidity (DHT)	Ambient THI	Fixed in-pen/barn	Heat stress index, ventilation control
Gas Sensor (MQ/NDIR)	NH ₃ , CO ₂ , CH ₄ , H ₂ S	Fixed in-pen	Air quality, stress, GHG emission tracking
Water Flow Meter	Water intake volume	Inline plumbing	Dehydration detection, health proxy
Smart Ear Tag (BLE/LoRa)	Temperature, activity, GPS	Ear tag	Individual health & location monitoring

5.2. IoT Communication Architectures

Communication technology in livestock monitoring should be selected according to sensing modality, transmission range, power availability, required data rate, farm topology, and access to network infrastructure. Consequently, no single wireless technology is optimal for all smart-feedlot applications. Low-power wide-area technologies are more appropriate for small sensor payloads transmitted over large distances, whereas short-range or broadband networks are better suited to high-frequency wearable data or image and video transmission.

LoRaWAN is particularly suitable for low-power, wide-area monitoring in extensive grazing areas, large feedlots, and remote farms where sensors periodically transmit relatively small packets of information such as location, activity, temperature, or environmental measurements. Its principal advantages are long communication range, low energy consumption, and the possibility of deploying a private gateway without relying continuously on public cellular infrastructure. These characteristics make LoRaWAN attractive for battery-powered animal and environmental sensors. However, its relatively low data rate makes it unsuitable for continuous image or video transmission, and network performance can be affected by terrain, physical obstruction, gateway placement, and increasing device density [4].

Bluetooth Low Energy (BLE) is better suited to short-range communication between wearable devices and nearby gateways located within barns, pens, handling facilities, or feeding stations. Compared with long-range technologies, BLE supports more frequent data exchange while maintaining relatively low power consumption, making it useful for accelerometers, proximity sensing, and smart ear tags. Its principal limitation is communication range: reliable farm-scale coverage generally requires multiple gateways or relay points. BLE performance may also vary with animal position, physical obstructions, device placement, and radio propagation within livestock facilities [4].

Cellular low-power wide-area technologies provide an alternative when operator infrastructure is available. NB-IoT offers low-power connectivity with broad cellular coverage and is appropriate for small, intermittent sensor transmissions where mobility and very high data rates are not primary requirements. Ma et al. [31] demonstrated its livestock applicability by integrating NB-IoT communication with neck-mounted sensing and LSTM-based estrus detection in dairy cattle. The approach reported high sensitivity and specificity, although only six of the 40 monitored cows were estrus-positive, limiting the strength of conclusions regarding generalization. LTE-M provides a related cellular option with greater support for mobility and higher data throughput than NB-IoT, making it potentially more appropriate for moving assets or applications requiring more frequent data exchange. Both approaches, however, depend on operator coverage, service availability, subscription cost, and network conditions at the farm location.

WiFi 6 is most appropriate for local, infrastructure-rich livestock environments that require substantially higher data throughput, including barns or intensive feedlots equipped with multiple cameras, edge servers, or high-frequency sensor gateways. Its high capacity and comparatively low latency make it attractive for local transfer of images and video to nearby computing infrastructure. In contrast to low-power wide-area networks,

however, WiFi requires greater power availability and relatively dense access-point deployment, and its coverage can deteriorate across large outdoor production areas.

5G provides the greatest potential bandwidth and lowest communication latency among the technologies considered, making it relevant to applications involving multiple video streams, edge-AI inference, autonomous equipment, or other near-real-time services. It can therefore complement local edge computing in intensive smart-farm environments. Nevertheless, livestock-specific deployment evidence remains comparatively limited, and practical adoption depends strongly on rural coverage, infrastructure investment, device cost, and network availability. These constraints are particularly important in developing-country and remote-farm settings, where the theoretical capabilities of 5G may not correspond to actual field connectivity [8].

The six communication technologies should therefore be considered complementary rather than competing alternatives. A practical smart-feedlot architecture may combine BLE for communication between animal-mounted devices and nearby gateways, LoRaWAN for low-power farm-wide sensor coverage, NB-IoT or LTE-M for direct cellular telemetry where operator coverage is available, and WiFi 6 or 5G for high-bandwidth communication between cameras, edge-computing nodes, and cloud services. Hybrid architectures provide greater flexibility because each data stream can be assigned to a communication technology according to its bandwidth, latency, range, and energy requirements [4], [8], [31].

Table 3. Comparative suitability of wireless communication technologies for livestock monitoring

Technology	Suitable livestock scenario	Main advantage	Main limitation
LoRaWAN	Remote/extensive farms; location, activity and environmental sensors	Long range, low power, private gateway possible	Low bandwidth; unsuitable for video
BLE	Ear tags/collars communicating with nearby barn or pen gateways	Low power, frequent short-range transmission	Short range; multiple gateways may be required
NB-IoT	Low-volume animal/environmental telemetry where cellular coverage exists	Wide-area cellular connectivity, low power	Operator dependence, low data rate, limited mobility compared with LTE-M
LTE-M	Mobile livestock devices and moderate-rate cellular telemetry	Better mobility and data rate than NB-IoT	Operator coverage, subscription and energy requirements
WiFi 6	Cameras, edge servers and dense sensors in intensive barns/feedlots	High throughput and local capacity	Shorter coverage and higher infrastructure/power requirements
5G	Video analytics, edge AI, autonomous/high-bandwidth applications	High bandwidth and low latency	Rural coverage, infrastructure cost, and limited livestock-specific validation

Note: Comparative characteristics were synthesized from communication-technology literature and livestock implementation studies [4], [8], [31].

Figure 3 illustrates how this complementary communication technologies can be incorporated within a layered smart-feedlot network. Animal-mounted and pen-level devices communicate with local gateways using technologies selected according to their range and power requirements. Edge or fog nodes can then perform local preprocessing and AI inference before selected data are transmitted to cloud-based applications for longer-term storage, analytics, and management decision support.

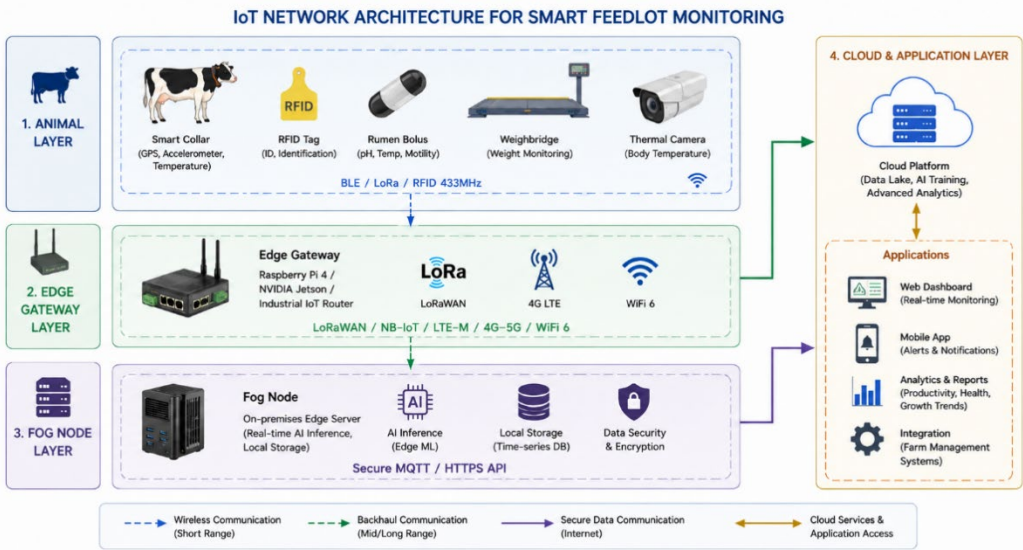


Figure 3. IoT Network Architecture for Smart Feedlot Monitoring

6. AI APPLICATIONS IN FEEDLOT OPERATIONS

6.1. Precision Feeding and Growth Performance Monitoring

Precision feeding and growth monitoring are central to smart-feedlot management because feed intake, weight gain, and feed efficiency directly influence production cost and market readiness. AI-based approaches can support these functions by estimating feed intake from behavioral and production variables, identifying animals with atypical performance, and enabling non-contact assessment of body weight and body condition. However, the reviewed evidence indicates that predictive performance depends strongly on the target variable, data quality, and measurement infrastructure, and that more complex models do not consistently outperform simpler approaches.

For feed-intake and feed-efficiency prediction, Martin et al. [23] compared multiple linear regression, partial least squares, artificial neural networks, and stacked ensemble models using performance, behavioral, and metabolite variables in dairy cattle. Simple multiple linear regression remained competitive for dry-matter-intake prediction, while residual-feed-intake prediction was comparatively weak across approaches. This finding is important for smart-feedlot deployment because it shows that increasing model complexity does not necessarily improve practical prediction when the biological target is inherently variable or weakly represented by the available predictors.

Davison et al. [24] evaluated machine-learning approaches for estimating individual feed intake in finishing beef cattle and subsequently used predicted intake together with measured weight gain to derive feed conversion ratio. The resulting estimates showed strong agreement with measured FCR, demonstrating that indirect prediction of feed intake can support animal-level performance classification when individual intake measurements are difficult to obtain continuously. Nevertheless, FCR in this study was derived rather than directly predicted, and model performance differed according to feeding treatment. This distinction is important because performance obtained under controlled diet groups may not transfer directly to commercial feedlots with different rations, breeds, or management conditions.

Growth monitoring has increasingly shifted toward non-contact computer-vision and three-dimensional sensing approaches. Gjergji et al. [14] demonstrated CNN-based body-weight estimation from cattle images, reporting a mean absolute error of 23.19 kg. The approach illustrates the potential for reducing repeated manual weighing, but image-based prediction remains sensitive to camera configuration, animal posture, image quality, and population characteristics. Hou et al. [16] used LiDAR-derived three-dimensional data and a PointNet++ model in 100 beef cattle, reporting a body-weight prediction MAPE of 3.2% and RMSE of 10.2 kg. Compared with two-dimensional imaging, 3D sensing provides richer geometric information, but requires more specialized hardware, calibration, and installation infrastructure.

Xiong et al. [19] similarly used depth imaging for body-weight and body-condition estimation in mature beef cows. The study supports the feasibility of non-contact phenotyping, while also illustrating a common limitation in livestock AI research: relatively small biological sample sizes and imbalanced body-condition classes can constrain model robustness. Consequently, apparently high performance under a particular herd or imaging configuration should not be interpreted as evidence of equivalent accuracy across breeds, ages, farms, or production systems.

Taken together, the reviewed evidence suggests that precision feeding and growth monitoring should be implemented as complementary rather than isolated functions. Feed-intake models provide information about consumption and efficiency, while vision- or depth-based systems provide repeated estimates of body weight and condition. Linking these streams at the individual-animal level can support earlier identification of animals whose intake and growth trajectories diverge from expected performance. The operational value of such systems therefore depends not only on predictive accuracy but also on measurement cost, frequency, robustness, and the ability to associate longitudinal observations with a persistent animal identity.

For commercial feedlot deployment, simpler statistical or machine-learning models may remain appropriate when reliable structured feeding and production data are already available, whereas computer-vision and 3D sensing approaches become more attractive when continuous or low-contact weight monitoring is required. Future studies should prioritize external validation across farms and diets, repeated measurements over complete feeding periods, and direct evaluation of whether prediction-driven interventions improve feed efficiency or economic performance rather than reporting prediction error alone.

6.2 Animal Health, Welfare, and Reproductive Monitoring

Animal health and reproductive monitoring differ from many visual livestock applications because the operational objective is often early detection of relatively infrequent events rather than classification of continuously observable states. For disease, heat stress, lameness, estrus, and calving prediction, overall accuracy alone can therefore be misleading. Sensitivity, specificity, class balance, lead time, and the number

of biologically independent animals are particularly important when evaluating whether a model is suitable for practical intervention.

Bovine Respiratory Disease (BRD) provides a clear example of this challenge. Bushby et al. [3] analyzed feeding, movement, and social-behavioral information from 172 pre-weaned calves using 229 derived behavioral features. Gradient boosting achieved an accuracy of 0.773, sensitivity of 0.625, and specificity of 0.872. Although the model showed useful discriminatory capability, the moderate sensitivity indicates that a substantial proportion of affected animals could still be missed if the system were used as a standalone diagnostic tool. Bowen et al. [21] similarly evaluated feeding and activity behavior for early respiratory-disease prediction and reported that Random Forest achieved high specificity of 0.95 but substantially lower sensitivity of 0.35. Combining behavioral indicators improved the balance between detection and false-positive control, but disease identification remained sensitivity-limited.

These BRD studies illustrate why apparently strong classification results need to be interpreted according to the management objective. In screening applications, high specificity reduces unnecessary inspections, but insufficient sensitivity may allow diseased animals to remain undetected. Sensor-based AI is therefore better viewed as an early-warning mechanism that prioritizes animals for inspection rather than as a replacement for veterinary diagnosis. The contrast between the two studies also indicates that richer behavioral information can improve discrimination, although differences in feature construction, population, and evaluation design prevent direct numerical ranking of the models.

Welfare-related monitoring presents similar generalization challenges. Neupane et al. [17] evaluated machine-learning approaches for predicting lameness using accelerometer-derived behavioral information from 310 Holstein cows. Several models achieved classification accuracy above 90% for specific behavioral variables, demonstrating the potential of wearable sensing for automated welfare monitoring. However, all animals originated from a single herd, meaning that performance may be influenced by farm-specific management, flooring, housing, sensor placement, and behavioral patterns. Cross-herd validation is therefore necessary before such performance can be assumed to be transferred to other production environments.

Heat-stress classification is particularly relevant to tropical livestock systems because environmental exposure interacts with animal physiology and behavior. Becker et al. [26] compared logistic regression, Gaussian Naive Bayes, and Random Forest approaches and found that the most suitable algorithm varied according to the treatment condition and prediction target. This suggests that heat-stress modelling is strongly dependent on the available physiological and environmental features rather than on a universally superior classifier. Silva et al. [27] reached a similar conclusion under tropical conditions using Nelore cattle in the Brazilian Amazon. Despite using a neural-network approach, the study reported approximately 72% accuracy and an AUC of about 0.67, with comparatively low specificity. The result demonstrates that increasing model complexity does not necessarily overcome limited biological sample size, class imbalance, or incomplete representation of heat-stress physiology.

Reproductive monitoring provides a contrasting application in which temporal changes in movement and behavior can contain strong predictive signals. Wang et al. [28] combined UWB location and accelerometer data with several machine-learning classifiers for estrus detection. Although the dataset contained 25,684 sensor records and several configurations achieved high sensitivity and accuracy, the measurements originated from only 12 cows. This distinction is important because repeated observations from a small number of animals do not provide the same evidence of generalizability as validation across a large independent herd.

Ma et al. [31] demonstrated another approach by combining neck-mounted sensing, NB-IoT communication, and LSTM-based estrus classification. The model reported sensitivity of 94%, specificity of 98%, and positive predictive value of 95%. However, only six of the 40 monitored cows were estrus-positive, so the strong numerical performance should be interpreted in the context of the small number of positive biological cases. In practical reproductive management, prospective validation across larger numbers of estrus events is necessary before such performance can be assumed to remain stable under different animals, farms, and management conditions.

Calving prediction further illustrates both the potential and the limitations of temporal deep learning. Yang et al. [29] compared CNN, LSTM, CNN-LSTM, and CNN-BiLSTM-attention models using tail-mounted triaxial accelerometer data. Their best-performing model achieved precision of 0.9147, recall of 0.9459, and an F1-score of 0.9300, and the independent alert test successfully generated advance alerts for the additional test cows. However, the study involved a relatively small number of independent animals, and model performance improved substantially after TimeGAN-based synthetic-data augmentation. Synthetic augmentation can be valuable for rare-event prediction, but strong dependence on generated samples also indicates that performance should be confirmed using larger naturally observed datasets.

Across health, welfare, and reproductive applications, the reviewed evidence therefore suggests that model suitability is determined as much by event prevalence, sensor modality, biological sample size, and intervention requirements as by algorithm choice. For disease screening, sensitivity and clinically useful lead time are especially important; for welfare monitoring, robustness across herds and housing systems is critical; and for

reproductive events, longitudinal sequence modelling can be advantageous but requires validation across sufficient numbers of independent events. These systems are therefore most appropriately deployed as decision-support tools that identify animals requiring attention, while final clinical or reproductive management decisions remain integrated with animal observation and professional judgement.

6.3 Predictive Analytics and Decision Support Systems

Predictive analytics becomes operationally valuable in livestock management when model outputs are translated into timely management decisions rather than reported only as prediction scores. In a smart-feedlot context, data from feeding systems, wearable sensors, environmental monitors, cameras, and production records can be integrated to identify deviations from expected animal or herd-level patterns. The resulting predictions can then be presented through a Decision Support System (DSS) as alerts, risk scores, or prioritized recommendations for further inspection or intervention.

The reviewed evidence illustrates that the usefulness of such systems depends strongly on how prediction outputs are interpreted. For example, BRD models reported by Bushby et al. and Bowen et al. were able to identify behavioral patterns associated with disease risk, but neither approach achieved sufficiently high sensitivity to justify treating the model as an autonomous diagnostic system. Their more realistic role is therefore to prioritize animals for veterinary inspection, allowing farm staff to focus attention on individuals showing combinations of abnormal feeding, movement, or social behavior.

A similar principle applies to production-oriented decision support. Davison et al. [24] used predicted feed intake together with measured weight gain to estimate individual FCR, allowing animals to be classified according to production performance. Such information could support ration review, pen management, or identification of animals whose performance deviates from expectation. However, the value of these predictions depends on whether the resulting intervention improves production efficiency; prediction accuracy alone does not establish economic or managerial benefit.

Practical implementation also requires appropriate computing and communication architecture. Alonso et al. [30] demonstrated a deployed livestock IoT platform in which heterogeneous sensor data were processed through edge and cloud layers before being delivered to business and decision-support applications. Edge processing reduced the need to transmit all raw data continuously and allowed part of the analytical workload to be performed close to the farm. This architecture is particularly relevant to livestock environments where connectivity may be intermittent or where real-time alerts are required.

Effective livestock DSS should therefore operate as a human-in-the-loop system. AI models can continuously screen large volumes of sensor and production data, while farm managers or veterinarians interpret alerts in combination with animal history, visual inspection, and operational context. This arrangement is especially important when false negatives may delay treatment or false positives may create unnecessary labor and intervention.

Future development should consequently evaluate decision-support systems using operational outcomes in addition to conventional machine-learning metrics. Relevant measures include alert lead time, false-alarm rate, intervention frequency, labor savings, treatment outcomes, feed-efficiency improvement, and economic return. Such evaluation would provide stronger evidence of commercial value than demonstrating high accuracy, AUC, or RMSE in isolation.

6.4 Feed Conversion Ratio and Feed-Efficiency Prediction

Feed Conversion Ratio (FCR), commonly expressed as feed intake relative to body-weight gain, is an important indicator of production efficiency in feedlot systems. From an AI perspective, however, direct prediction of FCR remains less extensively validated than prediction of its constituent variables, particularly feed intake and weight gain. This distinction is important because a model that accurately predicts feed intake does not necessarily constitute a directly validated FCR-prediction model.

Davison et al. [24] provide a relevant beef-cattle example. Machine-learning models were used to estimate individual feed intake in 80 finishing steers over a 56-day period, after which predicted intake was combined with measured weight gain to derive individual FCR. The study demonstrated that machine-learning-based intake estimates could support identification of animals with comparatively high or low feed-conversion performance. However, FCR was calculated from the predicted intake rather than predicted directly as an independent model target, and prediction performance varied according to feeding treatment. These findings indicate that diet composition and management conditions may affect the transferability of feed-efficiency models between production systems. Related evidence from residual feed intake (RFI) studies further demonstrates that feed efficiency is a biologically complex prediction target. Martin et al. [23] compared multiple linear regression, partial least squares, artificial neural networks, and stacked models for dry-matter-intake and RFI prediction in 124 Holstein cows. While several approaches provided useful estimates of dry-

matter intake, RFI was substantially more difficult to predict, and complex neural or ensemble models did not consistently outperform simpler regression approaches. This suggests that algorithmic complexity alone cannot compensate for limited explanatory information in the available production and behavioral variables.

Sikka et al. [22] examined feed-conversion efficiency in 42 Murrah buffalo heifers during a 96-day feeding experiment using machine-learning approaches applied to blood metabolic variables and average daily gain. The study identified relationships between metabolic indicators and feed-efficiency characteristics and demonstrated the potential of machine learning for identifying biologically informative predictors. Nevertheless, the study involved buffalo rather than beef cattle and a relatively small experimental population. Its findings should therefore be regarded as transferable evidence for feed-efficiency modelling rather than direct validation of an FCR-prediction system for commercial cattle feedlots.

Collectively, these studies show that feed-efficiency prediction can be approached through several related targets, including feed intake, RFI, average daily gain, and derived FCR. These measures should not be treated as interchangeable because they represent different biological and management concepts. Feed intake models primarily estimate consumption, RFI represents feed intake relative to expected requirements, whereas FCR directly relates feed consumed to weight gained. The most appropriate prediction target therefore depends on whether the management objective is monitoring consumption, identifying biologically efficient animals, or evaluating production efficiency over a feeding period.

For smart-feedlot applications, a more practical strategy may be to integrate repeated estimates of feed intake and body weight rather than relying on a single standalone FCR model. Automated feeding systems can provide longitudinal intake information, while walk-over weighing, depth imaging, or computer vision can provide repeated estimates of growth. Combining these measurements at the individual-animal level would allow FCR trajectories to be updated throughout the production cycle and could enable earlier identification of animals deviating from expected performance. However, the commercial value of such systems still requires validation across different diets, breeds, growth stages, and feedlot environments. Therefore, current evidence supports AI as a promising tool for feed-efficiency assessment, but does not yet establish a universally applicable model for direct FCR prediction. Future studies should clearly distinguish between measured and predicted feed intake, directly predicted and derived FCR, and animal-level versus observation-level validation. External testing across independent feedlots is also necessary before reported prediction performance can be translated into routine nutritional or economic decision-making.

Table 4. Comparative synthesis of representative AI applications and deployment considerations

Application domain	Representative evidence	Data / AI approach	Main practical strength	Key limitation / deployment consideration
Body weight and growth monitoring	Gjergji et al. [14]; Hou et al. [16]; Xiong et al. [19]	RGB/depth/LiDAR; CNN and PointNet++	Enables repeated, non-contact estimation of weight and body characteristics	Performance depends on imaging conditions and population; 3D systems require specialised hardware and calibration
BRD early warning	Bushby et al. [3]; Bowen et al. [21]	Feeding, movement and social-behavior data; gradient boosting and RF	Can prioritize animals showing behavioral patterns associated with disease	Sensitivity remained moderate or low; should support rather than replace clinical inspection
Behavior and individual monitoring	Fuentes et al. [13]; Qiao et al. [18]	Video; spatio-temporal DL and CNN-LSTM	Enables continuous, non-contact behavior and identity monitoring	Occlusion, illumination, camera position and limited herd diversity constrain generalization
Heat-stress and welfare monitoring	Becker et al. [26]; Silva et al. [27]; Neupane et al. [17]	Environmental, physiological and accelerometer data; classical ML and neural networks	Supports continuous screening of welfare-related changes	Performance varies across targets and management conditions; cross-herd validation remains limited
Reproductive monitoring	Wang et al. [28]; Ma et al. [31]; Yang et al. [29]	Accelerometer/UWB/NB-IoT time-series; ML, LSTM and hybrid DL	Temporal data can provide early indication of estrus and calving events	Independent animal/event numbers are often small; class imbalance and synthetic augmentation can influence results
Feed intake and feed efficiency	Martin et al. [23]; Davison et al. [24]; Sikka et al. [22]	Production, behavioral and metabolic variables; regression, RF/SVR, ANN and related ML	Supports estimation of intake and identification of animals differing in feed efficiency	Direct FCR prediction evidence remains limited; RFI, intake and FCR are not interchangeable targets
Decision support and system integration	Alonso et al. [30]	Heterogeneous IoT data; edge-cloud analytics and DSS	Converts sensor streams into farm-level alerts and management information	Requires reliable integration, connectivity and validation of whether alerts improve operational outcomes

Table 4 demonstrates that the practical value of AI in livestock management depends on the correspondence between the biological task, data source, modelling approach and deployment environment. High predictive performance within a specific experimental dataset does not necessarily translate into equivalent commercial value. Disease and welfare applications require particular attention to sensitivity and false alarms, visual monitoring systems require robustness to environmental variation, reproductive models require sufficient independent biological events, and feed-efficiency applications require clear distinction between intake, RFI and FCR. Across domains, external validation and integration with operational decision-making remain more important than selecting an algorithm solely on the basis of benchmark performance.

7. MALAYSIAN LIVESTOCK INDUSTRY AND AI ADOPTION

7.1 Industry Overview and National Statistics

Malaysia's livestock sector shows substantial differences in domestic production capacity across commodity groups. According to official Department of Veterinary Services (DVS) statistics, national beef and buffalo-meat production reached approximately 38,667 metric tonnes in 2023, while the self-sufficiency ratio (SSR) was only 15.9% [5]. This indicates a substantial gap between domestic production and national demand and highlights the continued importance of improving productivity and production efficiency in the ruminant sector.

The structure of the livestock industry also varies considerably between beef, dairy, and poultry production. In Peninsular Malaysia, DVS recorded approximately 636,214 beef cattle and 30,306 dairy cattle in 2023 [5]. These figures should be interpreted as Peninsular Malaysian livestock populations rather than national totals because the corresponding tables do not include Sabah and Sarawak. At the national commodity level, fresh-milk self-sufficiency reached 66.8% in 2023 [5], which is substantially higher than the beef self-sufficiency level but still below full domestic self-sufficiency.

Poultry production provides a contrasting example of a livestock subsector with considerably higher domestic supply capacity. In 2023, the self-sufficiency ratio was approximately 90.2% for poultry meat and 106.5% for chicken and duck eggs [5]. The contrast between poultry and ruminant production illustrates that livestock modernization in Malaysia cannot be considered uniformly across species and production systems. Beef-cattle production faces different constraints relating to reproduction, growth period, feed resources, land availability, animal monitoring, and production scale.

These structural conditions provide an important context for the adoption of Precision Livestock Farming and AI-based management systems. In the beef sector, technologies that improve individual-animal monitoring, feed-efficiency assessment, reproductive management, disease detection, and growth measurement may contribute to improved production efficiency. However, technological adoption should not be assumed to increase national self-sufficiency automatically; benefits ultimately depend on whether digital systems produce measurable improvements in farm-level productivity, cost, animal health, and management decision-making.

National policy also provides a broader motivation for livestock modernization. The National Agrofood Policy 2021–2030 identifies livestock as one of its priority subsectors and includes smart agriculture, research and innovation, value-chain strengthening, and sustainable production among its strategic directions. The policy sets a 2030 self-sufficiency target of 50% for beef and 100% for fresh milk [6]. These targets indicate a substantial intended expansion in domestic ruminant production capacity and create a relevant policy context for evaluating technologies that can support more efficient and data-driven livestock management.

7.2 Ruminant Development and Traceability Programmes

Malaysia has implemented several programmes aimed at strengthening domestic beef-cattle production. An earlier initiative was the National Feedlot Centre (NFC), developed under the Ninth Malaysia Plan beginning in 2006. The programme was designed around a central feedlot in Gemas, Negeri Sembilan, together with a network of contract and satellite farms. Parliamentary records describe the Gemas facility as having a planned capacity of 20,000 cattle per production cycle, while the associated National Satellite Farm component was intended to involve 310 farms. National Feedlot Corporation Sdn. Bhd. was appointed as the private-sector integrator responsible for coordinating production across the value chain [35].

More recently, the Department of Veterinary Services introduced the Program Pengganda30 (P30) for the 2026–2030 period under the Thirteenth Malaysia Plan. The programme is intended to support progress toward a 50% beef self-sufficiency target by 2030 through expansion of breeding capacity and farm production. DVS states that the programme is planned around 310 livestock packages involving approximately 31,000 breeding

cows and 3,100 breeding bulls, implemented through a public–private partnership approach. Eligible production settings include integrated farms, breedlots, permanent ruminant-production areas, satellite farms, grazing areas, and cattle–oil-palm integration systems across Malaysia, including Sabah and Sarawak [36].

In parallel with production-development programmes, animal identification and traceability provide an important digital foundation for livestock management. DVS operates the Malaysian Animal Traceability System (MATs) to support animal identification and traceability activities. The official DVS Animal Passport portal identifies the Animal Passport as a government document implemented under the MATs project [37]. Such traceability infrastructure can provide a foundation for linking animal identity with longitudinal production, health, and management records.

These programmes provide infrastructure that could support future precision-livestock applications, but production-development and traceability systems should be distinguished from AI deployment itself. Breeding programmes, animal identification databases, and digital movement records can provide structured information that may later be integrated with sensor, feeding, health, and growth data. Realizing this potential would require interoperable data standards, reliable individual-animal identification, appropriate data access, and farm-level systems capable of linking operational sensor measurements with longitudinal animal records.

7.3 Future Opportunities and Emerging Malaysian Evidence

Although AI adoption in the Malaysian livestock sector remains at an early stage, recent local studies provide concrete examples of how digital technologies could be adapted to tropical cattle production. These studies represent different components of a future smart-livestock ecosystem, including animal phenotyping, communication infrastructure, environmental analytics, and farm-level data integration. However, the available Malaysian evidence remains limited in scale, and most applications should currently be interpreted as proof-of-concept or enabling technologies rather than mature commercial AI deployments.

A recent Malaysian example is provided by Shahrai et al. [7], who investigated real-time ultrasound (RTU) and RGB imaging for non-invasive prediction of ribeye traits in tropical Crossbred Brahman cattle. The study involved 74 cattle and was conducted with participation from a commercial cattle farm and slaughterhouse in Selangor. The regression model for ribeye area achieved an R^2 of 0.921, demonstrating the potential of image-based and non-invasive technologies for carcass-quality assessment under Malaysian production conditions. Nevertheless, only 15 matched ribeye samples were available for model development and comparison, and the authors acknowledged the potential for overfitting. Larger independent datasets are therefore required before the approach can be adopted as a routine commercial decision-support tool.

Communication infrastructure represents another important enabling factor. Leong [8] evaluated a 5G-enabled smart-farming architecture using rural Malaysian testbeds in Sabah and Perak, integrating IoT sensing, edge computing, and applications that included livestock monitoring. The study demonstrated the technical potential of 5G and edge processing for lower-latency agricultural data transmission compared with conventional mobile connectivity. Such infrastructure could support high-frequency sensor streams, image transmission, and real-time livestock alerts. However, the study addresses broader smart-farming communication rather than a full commercial cattle-feedlot implementation, and rural coverage, infrastructure cost, and digital capability remain important constraints for practical adoption.

Malaysian research has also explored AI-related methods for environmental aspects of livestock production. Peng Eng Kiat et al. [9] developed a Particle Swarm Optimization model to project methane emissions from livestock populations in Sarawak using livestock population data and IPCC-based emission estimates. This study demonstrates the potential of computational intelligence for supporting environmental planning and sustainability assessment within the Malaysian livestock sector. Nevertheless, it represents population-level modelling rather than real-time farm sensing or individual-animal management, highlighting the gap between analytical research and operational Precision Livestock Farming deployment.

Collectively, these examples indicate that Malaysia already has several components required for more integrated intelligent-livestock systems, but they remain fragmented across individual research projects and infrastructure initiatives. A practical next step would be to connect reliable individual-animal identification and traceability with farm-level feeding, growth, health, environmental, and behavioral data. Existing traceability infrastructure such as the Malaysian Animal Traceability System, together with livestock-development programmes discussed in Section 7.2, could provide an institutional basis for pilot deployments, although interoperability and access to longitudinal farm data would need to be established before large-scale AI analytics become feasible.

Future Malaysian research should therefore prioritize field validation rather than algorithm development alone. Multi-farm studies involving locally relevant cattle breeds, tropical environmental conditions, different feeding systems, and sufficiently large independent animal populations are needed to determine whether

models developed under controlled conditions remain reliable in commercial settings. Particular opportunities include non-contact growth and carcass assessment, feed-efficiency monitoring, heat-stress detection, reproductive monitoring, and edge-based health alerts. Economic evaluation should also accompany technical validation because the commercial viability of smart-feedlot technologies will depend on whether improvements in productivity, labor efficiency, animal health, or feed utilization justify sensor, connectivity, and maintenance costs.

8. CONCLUSIONS

This review examined the application of Artificial Intelligence, IoT, sensor technologies, computer vision, and decision-support systems in smart feedlot and livestock management, with particular consideration of their relevance to the Malaysian livestock sector. The revised screening corpus comprised 65 retained records, including 23 primary empirical studies used for detailed comparative evidence synthesis, while the remaining records were classified as supporting or background material. Rather than identifying a universally superior algorithm, the reviewed evidence indicates that model suitability depends on the biological task, data modality, independent animal sample size, validation design, computational requirements, and intended deployment environment.

Classical machine-learning approaches remain appropriate for structured production records and engineered sensor features, particularly where datasets and computational resources are moderate. Deep-learning and computer-vision approaches provide greater flexibility for image, video, and temporal sensor data, enabling applications such as animal detection, identification, behavior recognition, growth estimation, reproductive monitoring, and non-contact phenotyping. However, strong performance reported within individual studies should be interpreted cautiously because many datasets involve limited numbers of independent animals, single farms, controlled acquisition conditions, or substantial class imbalance. Across health and welfare applications in particular, sensitivity, false-alarm rates, lead time, and cross-farm generalizability may be more operationally important than overall accuracy alone.

The evidence also demonstrates that AI should be considered as part of an integrated livestock-management system rather than as an isolated prediction model. Combining animal identification, feeding, growth, health, environmental, and behavioral data through IoT connectivity, edge or cloud processing, and Decision Support Systems can support continuous monitoring and prioritization of management actions. Communication technologies such as LoRaWAN, BLE, NB-IoT, LTE-M, WiFi 6, and 5G offer complementary capabilities rather than a single optimal network solution, with selection depending on transmission range, bandwidth, energy consumption, infrastructure availability, and application requirements. Similarly, explainability methods such as SHAP, LIME, and Grad-CAM can improve transparency but do not substitute for representative datasets, external validation, or field evaluation.

For feeding and production management, the reviewed studies show potential for estimating feed intake, body weight, growth, and feed-efficiency indicators. Nevertheless, feed intake, residual feed intake, and feed conversion ratio represent different prediction targets and should not be treated interchangeably. Evidence for direct FCR prediction remains more limited than evidence for predicting its constituent or related variables. Future studies should therefore clearly define prediction targets, distinguish independent animals from repeated sensor observations, and evaluate whether model-assisted interventions produce measurable improvements in productivity, animal health, labor efficiency, or economic return.

In Malaysia, the relatively low beef self-sufficiency level and ongoing livestock-development and digitalization programmes provide a relevant context for Precision Livestock Farming. Emerging Malaysian studies demonstrate local activity in cattle phenotyping, communication infrastructure, environmental modelling, and animal traceability, but evidence of large-scale commercial AI deployment remains limited. Future Malaysian research should prioritize multi-farm validation using locally relevant breeds, tropical production conditions, and sufficiently large independent animal populations. Integration between animal identification, farm sensor systems, longitudinal production records, and decision-support platforms also requires greater attention to data interoperability and practical implementation costs.

Overall, the transition from experimental livestock AI to operational smart-feedlot systems will depend less on incremental improvements in benchmark accuracy and more on robust field validation, reliable sensor and communication infrastructure, biologically representative datasets, computational efficiency, interoperability, and demonstrated management value. The conceptual Smart Feedlot Framework presented in this review provides a literature-informed architecture for integrating sensing, AI analytics, edge and cloud computing, and human decision support. Its practical value, however, should be established through prospective implementation and validation in commercial feedlot environments.

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