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Research Paper

Automated 24-h cattle feeding behaviour analysis using Raspberry Pi, infrared imaging, and deep learning-based head position and ID classification

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ABSTRACT

Monitoring cattle feeding behaviour is essential for assessing animal wellbeing. While recent vision-based systems advance behavioural analysis, many cannot link behaviour to feed intake, operate day and night, or detect interactions like muzzle-to-feed contact. They also rely on small, unrepresentative datasets and complex architectures that hinder collaboration. This study presents a low-cost, scalable framework using infrared imaging and motion-triggered video capture to identify cattle feeding behaviours and presence at the feed bunk. Using a Raspberry Pi with an infrared camera and open-source motion detection software, 503 video recordings were collected across varied light conditions. From these, two supervised models were trained: a convolutional neural network (CNN) for head-position classification, including muzzle-to-feed contact (test accuracy: 94.86%, loss = 0.17) and another for individual identification. Trained on 10,103 frames, the animal identification model distinguished feeder occupancy and specific individuals with high test-set accuracy (98.52%, loss = 0.05), dropping to 89.5% when evaluated on an external dataset of 25,453 manually annotated frames. This discrepancy highlights challenges in generalising to real-world conditions. Together, the models link feeding events to individual animals and feed bin weights to estimate intake. Future work will refine ingestion behaviour detection, while modularity allows potential deployment on edge or server-based farm management platforms. Findings show simple systems enable robust behavioural monitoring and interdisciplinary collaboration by lowering technical barriers for animal scientists. The framework supports scalable, data-driven livestock management and integration with precision farming systems.

Science4Impact statement

This research underscores the necessity of comprehensive, high-quality training datasets that capture real-world variability, for both day and nighttime monitoring of cattle feeding behaviours. By distinguishing between "up" and "down" head positions—not merely detecting presence at the feeder—this approach provides critical insights for more accurate, 24-h behavioural analysis. Such granular observations facilitate earlier disease detection, refined feed intake estimation, and enhanced welfare monitoring. In validating a low-cost, infrared-equipped system, we highlight the importance of data collection protocols, robust annotation, and continuous model refinement. This science-driven solution promises to democratise access to actionable insights, bridging the gap between ethological research and on-farm deployment of Precision Livestock Farming technologies.

Nomenclature Table

Abbreviation	*Definition*
ABA	Automated Behavioural Analysis — the use of computer vision or sensors to automatically identify and quantify animal behaviours.
PLF	Precision Livestock Farming — technology-driven livestock management systems aimed at improving productivity, welfare, and sustainability.
RFID	*Radio-Frequency Identification* — a wireless system using tags and readers for tracking and identification of animals.
TMR	*Total Mixed Ration* — a feeding strategy where all dietary components are blended to ensure consistent intake of nutrients

(*continued on next page*)

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(*continued*)

Abbreviation	Definition
VGG16	A convolutional neural network (CNN) architecture with 16 layers, commonly used for image classification tasks and transfer learning.
VNC	Virtual Network Computing — a remote desktop sharing system enabling access to graphical interfaces over a network.

1. Introduction

Precision livestock technologies aim to improve animal health, welfare, and efficiency through early detection of behavioural irregularities. These systems support continuous monitoring for lameness (Maselyne et al., 2017), oestrus (Knight, 2020), and early disease (Dittrich et al., 2019), though most track few variables (Van Erp-van der Kooij & Rutter, 2020). For example, camera systems typically detect only feeder presence (Bresolin et al., 2023), while commercial platforms, such as GrowSafe (GrowSafe Systems Ltd., Airdrie, AB, Canada) provide visit frequency and head-down duration. Given feeding behaviour correlates with intake (Schwartzkopf-Genswein et al., 1999), vision-based systems may offer predictive potential. However, current camera and intake monitoring systems overlook behavioural complexity. To address this gap, this research proposes a 24-h vision-based Automated Behavioural Analysis (ABA) system to enrich PLF feeding assessments.

Animal behaviour has been studied using data from wearable sensors, such as accelerometers to measure jaw movements (Van Erp-Van der Kooij, 2021), and through direct observation, either in person or via video recordings (Tolkamp et al., 2000). While direct observation captures a wide range of behaviours, it is labour-intensive, subjective, and limited by time, restricting long-term analysis (Sowell et al., 1998). In contrast, approaches such as jaw movement tracking and other automated systems offer more consistent, large-scale data. Integrating appropriate video technology with deep learning to develop Automated Behavioural Analysis (ABA) systems provides a detailed, computerised, and less invasive alternative to traditional wearable methods (Dawkins, 2004).

Feeding behaviour has been monitored using both computerised feeding systems and camera-based approaches. Computerised systems measure parameters such as individual feeding events, total bunk visit duration and the daily time spent at the feeder (Schwartzkopf-Genswein et al., 1999). These systems typically rely on physical identification methods, such as RFID tagging, to link data to individual animals (Rushen et al., 2012). Camera-based systems instead require identification algorithms to distinguish individuals, as shown by Achour et al. (2020), who developed a system using a top-down view to detect head position at the feeder during daylight hours. Feeding was classified when the animal's head was down in the feeder. However, most existing systems only detect feeder presence, not specific feeding states (Porto et al., 2015; Yang et al., 2018). Early changes in feeding patterns can signal disease onset, allowing timely intervention that shortens illness duration, improves treatment response, and enhances welfare, thereby reducing economic losses (Urton et al., 2005; González et al., 2008). Feeding behaviour also reflects social dynamics, as dominant animals access feed first. Analysing these patterns helps evaluate how group housing or feeding protocols affect competition (DeVries et al., 2004). Additionally, feeding behaviour can indicate dietary deficiencies that may impact fertility and offspring health (Dunn and Moss, 1992). Feeding patterns also correlate with feed efficiency (Schwartzkopf-Genswein et al., 1999; Haskell et al., 2019; Tolkamp et al., 2000), suggesting behavioural monitoring could serve as a cost-effective proxy for estimating intake and selecting more efficient animals (Seymour et al., 2019).

Recent vision-based approaches have demonstrated the feasibility of identifying individual cows and estimating feeding time using facial region analysis and geometric criteria at the feed bunk (e.g. Kawagoe et al., 2023). Such systems provide valuable information on feeding duration but typically treat feeding as a binary state and do not explicitly link observed behaviour with measured feed intake. These limitations highlight the need for approaches that capture greater behavioural detail and support integration with intake-related data streams.

Recent advances in computer vision and deep learning have substantially expanded the scope of automated livestock monitoring systems, enabling real-time behaviour recognition, individual identification, and multi-camera tracking under commercial farm conditions. State-of-the-art platforms increasingly integrate multi-modal sensors, multi-camera fusion, and complex inference pipelines to support continuous, high-resolution monitoring across entire barns (e.g. Moe et al., 2025; Nasir et al., 2025). While these systems demonstrate impressive capability, they often rely on extensive infrastructure, specialised hardware, and high computational resources, which can limit accessibility and scalability. In parallel, more focused vision-based approaches have demonstrated efficient identification and feeding time estimation using facial or head-region analysis, albeit with simplified behavioural representations and limited linkage to intake-related outcomes (Kawagoe et al., 2023; Yu et al., 2024). Recent reviews highlight that balancing model complexity, robustness, cost, and interpretability remains a central challenge for practical deployment of AI-driven livestock monitoring systems (Mahato and Neethirajan, 2025). Within this context, there is a continued need for low-cost, modular frameworks that leverage modern computer vision while remaining suitable for research-driven development and future on-farm integration.

Developing an Automated Behavioural Analysis (ABA) system requires accounting for environmental factors such as temperature, dust, moisture, light, and potential physical damage from livestock, machinery, or rodents. These factors affect system reliability, longevity, and safety as exposed components may endanger animals or workers. Consistent image quality and physical durability are essential for accurate data collection, scalability, and safe deployment. Designing for robustness also improves scientific integrity by supporting reproducibility across diverse farming conditions, making ABA systems both durable and adaptable (Nasirahmadi et al., 2017). Proper equipment placement is equally important to ensure visibility of target behaviours while maintaining accessibility for maintenance and calibration (Neethirajan, 2020). Decisions around data storage—local vs. cloud—also impact system performance and flexibility. A key challenge in ABA implementation is managing and analysing large video datasets, which demand high computational power and analytical effort (Siegford et al., 2023). System effectiveness further depends on high-quality training data that accurately captures individual behaviours. However, complex architectures can hinder collaboration between engineers and ethologists, limiting the integration of behavioural knowledge into technical design. Addressing these issues helps ensure ABA systems generate reliable, actionable insights. ABA systems serve two primary roles: as standalone monitoring tools or as validation frameworks for emerging Precision Livestock Farming (PLF) technologies. In the latter, they offer a benchmark to evaluate sensor accuracy and performance, improving the reliability of automated data streams and supporting enhanced livestock management. The primary aim of this study is to develop an affordable Automated Behavioural Analysis (ABA) system that could (1) link feeding behaviours to feed intake, (2) provide continuous 24-h behaviour monitoring, and (3) detect muzzle-to-feed contact as an indicator of ingestion. While the system operates continuously to capture feeding behaviour across day and night, the primary aim of this study was to develop and validate a research-grade Automated Behavioural Analysis (ABA) framework rather than a fully deployed real-time decision-support product. The hypothesis is that low-cost imaging, behavioural classification, and intake-linked analysis can be combined within a modular pipeline suitable for interdisciplinary research and future on-farm automation. The framework addresses limitations in existing systems, including poor linkage between behaviour and intake, lack of round-the-clock monitoring, and challenges in detecting ingestion events.

2. Materials and methods

2.1. Data acquisition

An automatic recording system (Fig. 1) was developed to monitor feeding behaviours in five pen-fed British Blue heifers (368.6 ± 27.1 kg) offered a total mixed ration (TMR) through an automated feeder (GrowSafe Systems Ltd., Airdrie, AB, Canada). Positioned ~0.6 m from the feeder rim, the camera captured clear lateral footage of muzzle–feed contact during both day and night (Fig. 2), offering visibility not possible from top-down views. Recordings were made at 640 × 480 resolution at 20 fps. The system included a Raspberry Pi 4 Model B (1 GB), Raspberry Pi NoIR Camera Module V2.1 (Raspberry Pi Ltd., Cambridge, UK), infrared light, casing, and connectors. Motion-triggered video capture was enabled using the Linux package Motion (Heenan, 2020), which saved 5 s before and after detected movement at the feed bunk, reducing storage demands. The Raspberry Pi functioned as a virtual network computing (VNC) server and stored footage on a connected USB drive. Remote access and live viewing were enabled via Remote.It (remot3.It, Inc., Petaluma, CA, USA). Recordings were collected on April 19–21, 2023, yielding 117 videos (8.58 GB), 230 videos (21.1 GB), and 156 videos (11.6 GB), respectively. The Raspberry Pi served as a low-cost, edge-based data acquisition unit responsible for continuous 24-h video capture under infrared illumination and motion-triggered recording. In the present study, deep learning model training and inference were performed offline to prioritise model development, validation, and interpretability. However, the modular system design allows inference to be deployed either locally on more powerful edge devices (e.g. NVIDIA Jetson platforms) or remotely on a server, depending on farm infrastructure and use case. In a practical deployment scenario, only derived behavioural metrics and alerts, rather than raw video, would be transmitted to farm management systems, reducing data bandwidth and computational demands.

2.2. Head position model training and evaluation

A total of 503 videos were recorded to capture cattle feeding behaviour and processed into individual frames at 1 fps. From each day, 40% of frames were randomly sampled and manually annotated, resulting in 20,727 labelled frames. This sampling rate was selected to balance manual annotation effort with sufficient temporal coverage to capture behavioural variability and transitions between feeding-related head-position states. The annotated dataset was split 80/20 for training and testing a head position classification model. The remaining 60% of frames (n = 40,159) were pseudo-labelled using the trained model, of which 24,044 frames were manually reviewed to evaluate model generalisation without contaminating the original test set.

All video frames used for model training and evaluation were manually annotated by a trained researcher with experience in cattle feeding behaviour. Annotation was based on visual inspection of each frame, with particular emphasis on head position relative to the feed bunk and visible muzzle–feed contact. Frames were classified into six head-position and context classes: *up*, *up_full*, *down*, *down_full*, *no_animal*, and *weighted*. The *down* and *down_full* classes were assigned only when the animal's muzzle was visibly in contact with the feed, and feeding was inferred based on direct visual evidence of ingestion-related posture. In contrast, *up* and *up_full* indicated head elevation above the feed surface without visible muzzle contact, and were not considered feeding events. This distinction was made to avoid the ambiguity present in systems where feeding is inferred solely from head-down position without confirmation of feed contact. *No_animal* denoted absence of cattle, allowing feed weight to be treated as reliable. Weighted captured interference by other objects such as birds. Although these classes are

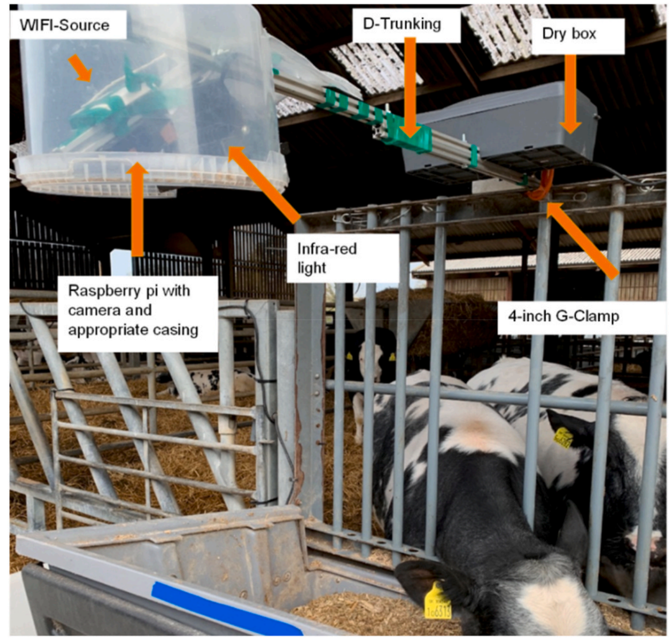

Fig. 1. Setup of the automated camera monitoring rig showing a cow feeding from a GrowSafe bin. In some cases, the animal's ID was verified through its visible ear tag in the images.

referred to as feeding-related states for modelling purposes, they represent visually defined head-position and environmental conditions rather than distinct biological behaviours.

The deep learning model was built in TensorFlow/Keras using VGG16 for feature extraction. Frames were resized to 224 × 224 pixels. VGG16's original fully connected layers were replaced with Flatten, Dense (512 and 256 neurons, ReLU), Dropout, and a final SoftMax layer for six-class output. The model used the Adam optimiser (learning rate: 0.00001) and categorical cross-entropy loss, with accuracy as the evaluation metric. Early stopping based on validation loss was implemented to reduce overfitting. VGG16 was selected for its strong performance in image classification and relatively low computational cost due to its straightforward, sequential architecture. Furthermore VGG16 is easier to fine-tune on modest behavioural datasets than deeper and more complex architectures such as Inception, which require more extensive optimisation and larger datasets to achieve stable performance (Alruily et al., 2025). Despite this, future work may explore these alternative CNN architectures (e.g. Inception) to benchmark performance and validate architectural suitability for behavioural classification in farm environments.

2.3. Animal identification model training and evaluation

Following the development of the head position model, a separate supervised model was trained to identify individual animals. A total of 13,469 frames were manually annotated with Animal IDs and split 75/25 for training and testing. The model architecture mirrored that of the head position classifier, using a VGG16-based CNN. To assess performance under more varied conditions, predictions were generated on a larger set of previously unseen frames. Of these, 25,453 previously unseen frames were manually reviewed against the predicted label to evaluate accuracy and generalisation, while preserving test set integrity and enabling robust post-inference assessment on real-world data. Animal identification labels were assigned manually based on visual confirmation of individual ear tags and distinctive coat markings visible within the video frames. Frames where animal identity could not be confidently confirmed due to occlusion, motion blur, or partial visibility were excluded from the labelled training and test datasets. This

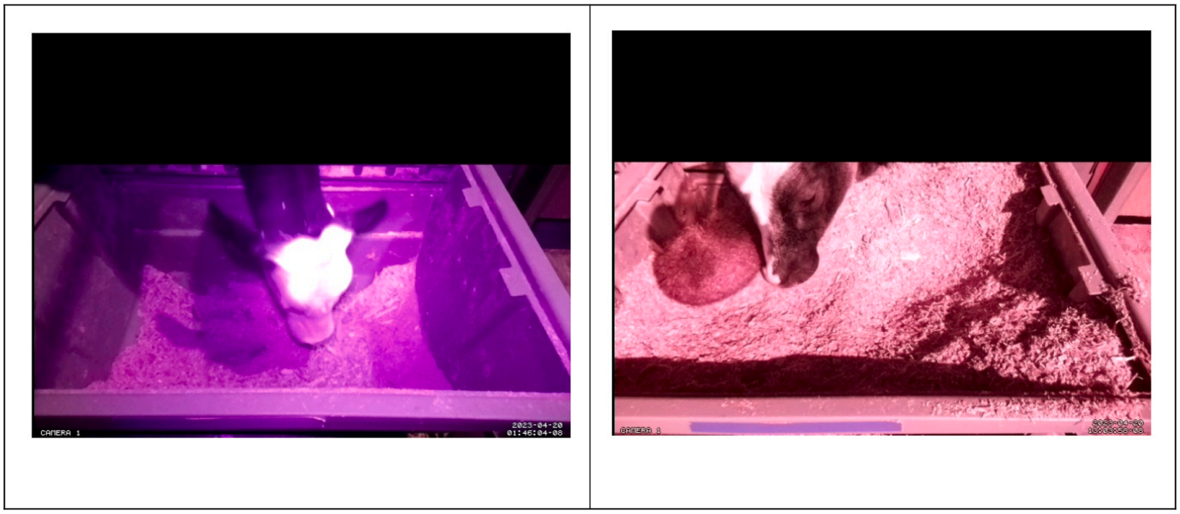

Fig. 2. Example of the 640 x 480 px images obtained from the automated camera monitoring rig during the day (left) and at night (right).

conservative annotation method ensured high-confidence ground truth labels for supervised learning and evaluation.

2.4. Preprocessing for behavioural analysis

To align behavioural data with feed intake, video timestamps were synchronised with feed bin weight measurements using a unified time format (YYYY-MM-DD HH:MM:SS). This enabled precise matching of behaviour and intake data from the GrowSafe system. Consecutive frames sharing the same behaviour class and animal ID were grouped into behavioural events, with durations calculated in seconds. Feed intake for each *down* event (i.e. muzzle-to-feed contact) was estimated by comparing average feed bin weight before and after the event, linking observed ingestion behaviour with measured feed consumption. Behavioural metrics were then calculated on a per-animal basis. Bunk visits were counted each time an individual appeared at the feed bin, regardless of muzzle contact. *Down* events were recorded when the muzzle contacted the feed, and their durations were summed. *Up* events, when the head was raised during a feeding session, were also counted and timed.

Feeding deliveries were manually labelled to exclude periods when feed was physically added into the feeding bins, preventing skewed intake data. The three feed deliveries occurred on: April 19 (16:04:47–16:06:36, +18.9 kg), April 20 (10:22:48–10:24:03, +179.4 kg), and April 21 (09:30:11–09:32:16, +75.24 kg). Metrics were generated only for feed deliveries one and two. Feed delivery three was excluded because animal identification outputs for this feed delivery were not subjected to manual post-inference validation, which was applied to feed delivery one and two; inclusion without verification risked introducing identity-related error into the behavioural metrics. Future implementations of this pipeline should incorporate automated data quality assurance procedures. These may include outlier detection for biologically implausible feeding durations or intake estimates, as well as routine verification of animal identity consistency across sequential frames and visits. Such checks would improve robustness when behavioural outputs are integrated with external data streams.

3. Results and discussion

3.1. System performance

The recording system reliably captured cattle feeding behaviours across three feed deliveries, using motion-triggered infrared video to focus on periods of activity at the feed bunk. This approach substantially reduced unnecessary data collection, resulting in a more manageable dataset while maintaining behavioural coverage. Across the 72-h monitoring period, motion-triggered recording generated 503 short video clips (approximately 41.3 GB), capturing only feeding activity amounting to approximately 17 h. In contrast, continuous recording at the same resolution and frame rate would have produced uninterrupted footage over the full monitoring period, equating to an estimated 140 GB of video, substantially increasing storage and processing demands.

No significant changes in feed weight were observed during non-recorded intervals, indicating the system successfully captured relevant feeding events. The portable design allowed consistent operation under real farm conditions and demonstrated suitability for behavioural monitoring in varied research settings. This simple modular structure allowed animal scientists to install, adapt, and maintain the system themselves, minimising the need for engineering support and enabling more flexible, collaborative refinement of research protocols. The camera monitoring system was constructed from commercially available components with a design that prioritised affordability (total cost £124.53+VAT, see Table 1 for full break down) and adaptability to enable deployment in typical farm environments, without reliance on proprietary technologies. It is important to distinguish between

Table 1
Cost breakdown and detailed list of items for the camera monitoring device.

Component	Cost (GBP/£) (excluding VAT)
CCTV Security Camera - Splenssy 96 LEDS IR Illuminator 850 nm Array Infrared Lamps With Sensor 12v Night Vision Outdoor Waterproof	16.66
Adapter for Infra-Red Light	7.49
Raspberry Pi 4 Model B (1 GB)	28.00
Raspberry Pi NoIR Camera Module V2.1	23.75
PiShell Black & White Case: A Multi-Colored Protective Case for the Raspberry Pi 3 B+ and Camera, Raspberry Pi Case Cover	4.99
1 RS PRO Silver Aluminium, Anodized Profile Strut, 20 × 20 mm, 5 mm Groove, 1m Length	11.42
Fixtures and Fittings (screws/tape)	5.00
D-Line Weatherproof Electrical Box, Outdoor Extension Socket Box, IP54, 2x Entry and Exit Sections for Ease of Use	12.46
4 Inch G-clamp	4.99
SanDisk 64 GB Ultra Fit USB 3.2 Flash Drive Up to 130 MB/s Read (small to fit in the back of the pi)	6.92
Bucket to provide shelter from wind and rain	2.85
Total Cost	**£124.53**

continuous monitoring and real-time inference within the context of this study.

The system operated continuously over 24 h to capture feeding behaviour, while behavioural classification and intake analysis were conducted post hoc. This design choice reflects the study's research objective: to evaluate behavioural definitions, model robustness, and intake linkage under real farm conditions. While real-time inference was not implemented here, the computational requirements of the trained models are compatible with edge-based deployment on modern embedded platforms, enabling future real-time or near-real-time operation as part of an integrated farm management workflow.

3.2. Head position model performance

A convolutional neural network (CNN) based on the pre-trained VGG16 architecture was fine-tuned to classify head positions during feeding. The model was trained using 20,727 manually annotated video frames, categorised into six head-position and context classes (*up*, *down*, *down_full*, *up_full*, *no_animal*, and *weighted)*. On a held-out test set (n = 4145), the model achieved a classification accuracy of 94.89% and a categorical cross-entropy loss of 0.17, with 213 misclassified frames.

Model training dynamics are presented in Fig. 3 (accuracy) and Fig. 4 (loss). In both figures, the blue line denotes training performance, while the orange line represents validation performance. The close correspondence between training and validation curves across epochs suggests strong generalisability and minimal overfitting. To assess robustness on unseen data, the trained model was applied to an additional pseudo-labelled dataset (n = 24,044), with all predictions subsequently reviewed manually. The model achieved an accuracy of 93.20% on this set, misclassifying 1675 frames. While not a formal test set, this post hoc validation served as a practical quality assurance step, confirming model reliability across variable conditions typical of farm environments. Relative to prior work by Achour et al. (2020), who reported 92.61% classification accuracy using top-down daytime imagery, the present approach incorporates both diurnal and nocturnal data and employs a classification framework (rather than object detection or segmentation), enabling reduced annotation burden and expanded sample size. Although the CNN architecture is pre-existing, the application to a behaviourally diverse dataset spanning diurnal and nocturnal conditions represents a substantive methodological contribution.

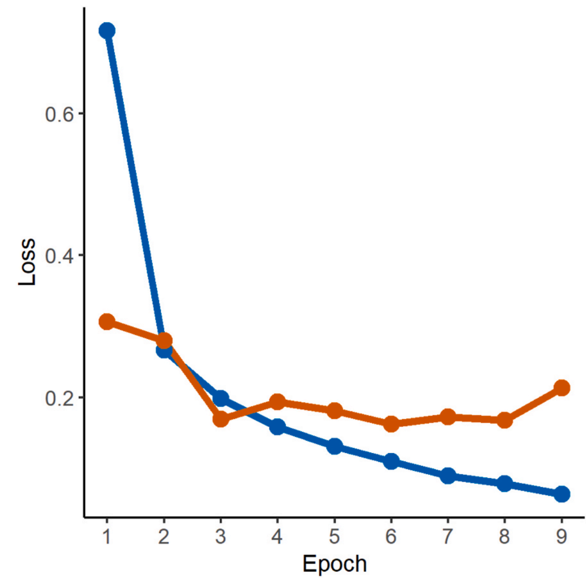

Fig. 4. Training and validation loss for the head position classification model across epochs. The blue line indicates training loss; the orange line indicates validation loss. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

3.3. Animal identification model performance

A convolutional neural network based on the VGG16 architecture was fine-tuned to identify individual heifers at the feed bunk. Accurate animal identification is critical for linking observed feeding behaviours to corresponding feed intake events. The model was trained on 10,103 manually annotated video frames and achieved a classification accuracy of 98.52% on the test set, with a categorical cross-entropy loss of 0.05.

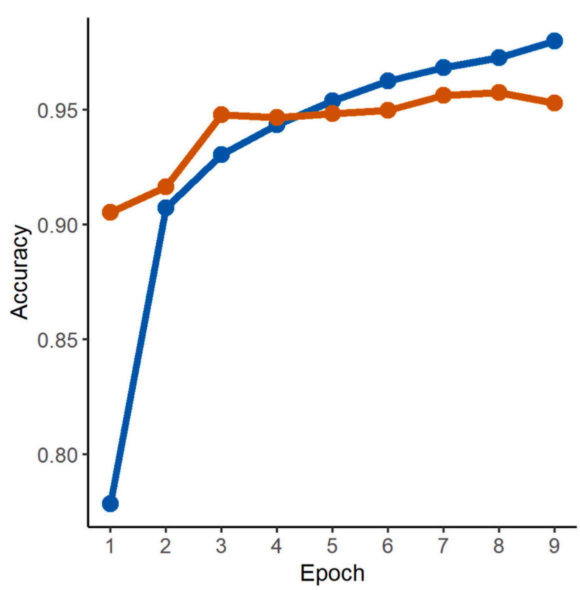

Fig. 3. Training and validation accuracy of the head position classification model over nine epochs. The blue line indicates training accuracy; the orange line indicates validation accuracy. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

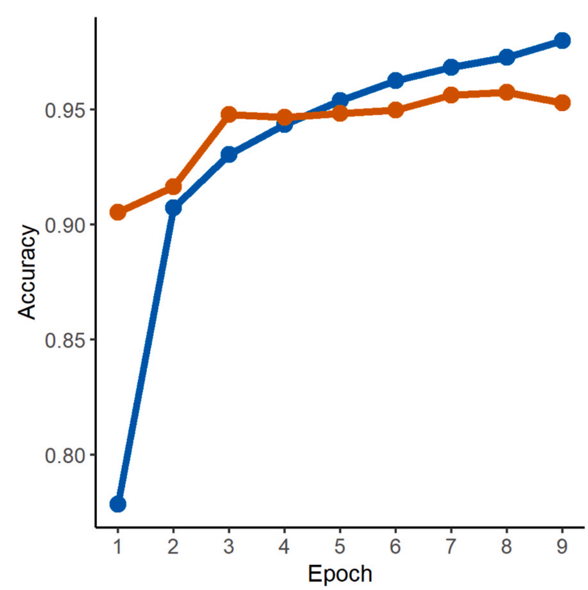

Fig. 5. Training and validation accuracy of the animal identification model across epochs. The blue line represents training accuracy; the orange line represents validation accuracy. Accuracy plateaued after epoch 6, indicating model convergence. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Training dynamics, including accuracy and loss, are presented in Figs. 5 and 6, respectively. In both figures, training performance is indicated in blue, and validation performance is indicated in orange.

To assess generalisability under practical conditions, the model was applied to an independent set of 25,453 video frames drawn from previously unseen recordings of the same animals within the same housing environment and manually validated. Accuracy on this real-world dataset was reduced to 89.5%. A total of 118 frames were excluded prior to evaluation because no match decision was produced due to insufficient identity confidence. This reduction in performance relative to internal testing represents a key finding of the study.

Analysis of misclassified external frames revealed a shift in behavioural context and head-pose distribution (Table 2). Misclassified samples were disproportionately associated with raised head positions ('up'), which reduce the visibility of discriminative facial features within the region of interest, which was optimised for feeding detection rather than full-face recognition. Importantly, this performance gap does not arise from classical domain-shift factors, such as differences in animal identity, housing conditions, or camera infrastructure, as the external dataset comprised the same animals recorded within the same environment. Instead, behavioural pose variability, particularly when the head is posed as up, was the dominant factor limiting generalisation.

Although the underlying CNN architecture was pre-existing, its application to a behaviourally diverse, farm-based dataset spanning diurnal and nocturnal conditions, combined with large-scale post-inference validation, represents a substantive methodological contribution. In contrast to prior work using smaller datasets and more constrained posture ranges (e.g. Achour et al., 2020), the present study evaluated the context of the feeding event and differing postures.

Future improvements aimed at reducing misclassification may include the integration of pose-estimation models to ensure that optimally informative facial views are provided for animal identification, alongside continuous model retraining and targeted manual spot-checking of pseudo-labelled data. Additional improvements may be achieved through the use of multiple camera angles and enhanced illumination to improve facial visibility under variable postures and lighting conditions. For practical integration with external production datasets, robust animal identification is essential. Therefore, future work should focus on strengthening identity verification across consecutive frames and feeding visits, particularly when behavioural outputs are linked with longitudinal performance or health records. Incorporating temporal consistency checks and confidence-based filtering would help minimise identity-related error when combining vision-based outputs with third-party farm management systems.

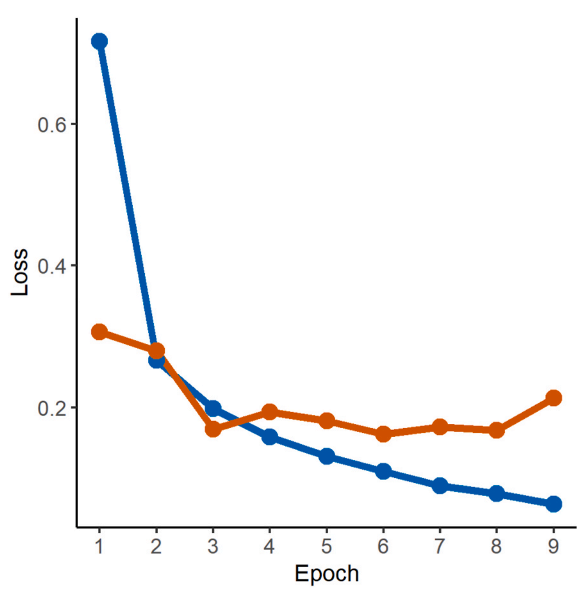

Fig. 6. Training and validation loss for the animal identification model across epochs. The blue line indicates training loss; the orange line indicates validation loss. Loss values decreased consistently, suggesting stable learning with limited overfitting. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

A known limitation of vision-based animal identification systems is sensitivity to changes in appearance over time (Nasirahmadi et al., 2017), including growth, seasonal coat changes, contamination (e.g. mud or feed), and variations in illumination. The observed reduction in performance on large volumes of unseen data highlights the impact of such real-world variability and reflects a broader challenge for long-term deployment of purely vision-based identification systems. In group-housed and dynamic populations, maintaining reliable individual identification using vision alone remains challenging. Therefore, practical deployment is likely to benefit from hybrid approaches that combine vision-based behavioural monitoring with low-frequency identification methods, such as RFID, providing periodic identity confirmation without continuous reliance on wearable sensors. Such multimodal strategies may support long-term identity persistence while allowing vision models to focus on behavioural classification, consistent with challenges noted in prior work (Nasirahmadi et al., 2017; Siegford et al., 2023).

3.4. Feeding behaviour metrics

The system developed in this study enabled detailed, continuous quantification of feeding behaviours at the individual animal level (Table 3). Across two feed deliveries, bunk visit frequency ranged from 22 to 67 visits per animal, while "down" events, indicating muzzle contact with feed, ranged from 103 to 218 events per animal. The duration of these down events varied from 886 to 3661 s, demonstrating individual variation in feeding engagement. When synchronised with feed bin weight data, these behavioural metrics allow estimation of feed intake on a per-event basis by linking time-stamped muzzle-to-feed contact events with corresponding changes in feed weight. This represents a substantial management advantage: producers can identify underperforming or at-risk animals based on reduced feeding frequency or duration, detect changes in intake patterns that may signal emerging health or welfare issues, and monitor feeding competitiveness or access in group housing systems. Unlike traditional methods such as direct observation or RFID-based intake systems, this vision-based approach captures high-resolution temporal data without requiring wearable devices or specialised infrastructure, reducing costs, handling stress, and barriers to scalability. Additionally, the ability to distinguish between feeding related states (e.g., head down vs. head up) provides behavioural nuance that is not captured by systems that record feeder presence alone. Kawagoe et al. (2023) demonstrated that facial region detection combined with reference line analysis can be used to estimate feeding time and identify individual cows under controlled feeding conditions. In contrast, the present study adopts a behaviour-classification approach that distinguishes between multiple feeding-related states, including head-up and muzzle-to-feed contact events. Rather than focusing solely on feeding duration, these behavioural classifications are synchronised with feed bin weight measurements, enabling estimation of intake-related metrics. The use of infrared imaging supports continuous monitoring across both daylight and nocturnal conditions, extending applicability to 24-h observation periods. Beyond short-term intake estimation, the behavioural metrics generated by this system have potential value for longer-term health, welfare, and performance monitoring. Because outputs are time-stamped and resolved at the individual-animal level, they could be integrated with existing farm management software and routinely collected production records, such as milk yield or liveweight gain. This would enable trend-based monitoring of feeding behaviour over time, supporting earlier identification of animals deviating from expected behavioural or performance

Table 2
Distribution of head-position classes across training, testing, and external datasets for the animal identification model. Misclassified external samples show an increased prevalence of raised head positions ('up'), indicating reduced facial visibility as a key contributor to generalisation error.

Dataset	No. of images (n)	Event (%)				
		Down	Down_full	Up	Up_full	No_animal
Train	10,103	33.0	22.9	29.3	9.5	5.3
Test	3366	32.8	22.0	29.4	9.7	6.0
External – correctly matched	22,782	37.3	13.1	28.4	5.3	15.5
External – misclassified	2671	46.7	2.9	40.6	2.6	5.2

Table 3
Summary of feeding behaviour metrics across feed deliveries.

Metric	Feed Deliveries	Animal ID				
		6271	6278	6282	6303	6313
Number of bunk visits	1	67	33	30	22	35
	2	56	53	40	30	34
Number of "down" events	1	175	103	176	149	141
	2	124	218	197	108	137
Duration of "down" events (s)	1	1304	886	1863	2967	1585
	2	1129	1869	3661	3590	1535
Number of "up" events	1	241	136	211	171	181
	2	165	245	221	124	142
Duration of "up" events (s)	1	1668	1137	2574	1771	1895
	2	627	1538	1639	358	934

trajectories. In this context, the system may function as a decision-support tool within broader precision livestock farming workflows rather than as a standalone monitoring solution.

Importantly, both models enabled the generation of detailed individual level behavioural metrics, such as bunk visit frequency, up/down event duration, and number of feeding events, which were synchronised with feed bin weight measurements to estimate feed intake without reliance on RFID-based tagging. Compared to conventional approaches, based on feeder presence alone or manual observation, this framework offers higher temporal resolution, richer behavioural characterisation, and continuous monitoring across both daylight and nocturnal periods.

Future research should build on this framework by refining feeding behaviour relationships, evaluating which behavioural metrics are most informative for predicting intake, and assessing how these relationships vary across animals, production stages, and management systems. Additional work is also required to enhance model generalisation and validate performance across different breeds and housing environments.

4. Conclusions

This study implemented and validated a low-cost Automated Behavioural Analysis (ABA) framework capable of continuous, day-and-night monitoring of cattle feeding behaviour under real farm conditions. By integrating infrared camera with deep learning based behavioural classification and animal identification, the system provides a scalable, accessible, non-invasive alternative to wearable tracking devices. It's modular, low-complexity design supports interdisciplinary collaboration, allowing research teams across engineering and animal science to adapt, deploy, and extend the framework without reliance on specialised hardware or advanced coding expertise. The head position classification model demonstrated strong performance in detecting muzzle-to-feed contact and supporting the quantification of feeding behaviours, while post-inference evaluation on large volumes of unseen data provided valuable insight into model generalisability. The animal identification model achieved a high internal accuracy but exhibited reduced performance on unseen data, particularly in "up" positions where facial visibility was reduced. These findings highlight the importance of expanded training dataset, optimised camera placement, and posture-aware approaches to improve robustness across variable behavioural and lighting conditions. Overall, this study contributes a practical, low-barrier research framework for precision livestock monitoring. While the system demonstrates the feasibility of low-cost, continuous feeding behaviour analysis, it is presented as a research and development platform rather than a fully deployed commercial solution and requires further validation prior to large-scale on-farm adoption.

CRediT authorship contribution statement

G. Wager-Jones: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **M. Butler:** Software, Resources, Methodology, Data curation, Conceptualization. **W.E. Harris:** Supervision. **M. Rutter:** Supervision, Conceptualization. **E. Bleach:** Writing – review & editing, Supervision. **K. Behrendt:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization.

Declaration of generative AI and AI assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to check sentences were clear and concise. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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