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Classifying the posture and activity of ewes and lambs using accelerometers and machine learning on a commercial flock

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ABSTRACT

Early decision making in commercial livestock systems is key to maximising animal welfare and production. Detailed information on an animal's phenotype is needed to facilitate this, but can be difficult to obtain in a commercial setting. Research into the use of bio-logging on sheep to continuously monitor individual behaviour and indirectly inform health and production has seen rapid growth in recent years. Much of this research, however, has been conducted on small numbers of animals in an experimental setting and over limited time periods. Previous studies have also focused on ewes and there has been little research on the potential of bio-logging for collecting behavioural data on lambs, despite clear potential relevance for production. The present study aimed to test the feasibility of deploying accelerometers on a commercial sheep flock at a key point in the annual production cycle (lambing), to validate the viability of automated monitoring of sheep behaviour in a commercial setting. Also, we aimed to develop robust machine learning algorithms that can classify both the posture and physical activity of adult sheep and lambs. We used a Random Forest machine learning algorithm to predict: two mutually exclusive postures in ewes and lambs (standing and lying), achieving average accuracies of 83.7% and 85.9% respectively; four mutually exclusive activities in ewes (grazing, ruminating, inactive and walking), achieving an average accuracy of 70.9%; and three mutually exclusive activities in lambs (inactive, suckling, walking), achieving an average accuracy of 80.8%. These performance accuracies on large numbers of individuals afford the opportunity to provide a detailed understanding of the daily activity budget of ewes and lambs. Monitoring changes in daily patterns across the annual production cycle while capturing changes in environmental conditions such as weather, day length, terrain and management could reveal key indicator metrics that may inform production and health and provide early warning systems for key issues in commercial flocks.

1. Introduction

Farmers across the globe face the interlinked challenges of increasing animal production to maintain global demand while preserving animal health and welfare (Waterhouse, 1996). To achieve this, the assessment of both animal health and production is needed; however, this is dependent on the ability to collect phenotypic data on individuals. In a commercial setting, monitoring individual animals is challenging as extensively reared animals are housed and handled infrequently, so changes in health, for example, may not be observed until cases are sufficiently severe (Edwards, 2007). Early detection of changes in health- or production-related traits is needed to reduce both economic and welfare impacts. An individual's behaviour can be used as an early indicator of its physiological state (Dawkins, 2003, 2006). This has key implications for production and welfare as behavioural changes or tendencies can act as an early indicator of production traits or ill-health through changes in posture or physical activity (Biro and Stamps, 2008; Weary et al., 2009; Gougoulis et al., 2010). Here, we aimed to deploy accelerometers on a commercial sheep flock to capture the behaviour of individual animals.

Despite its use, currently, individual behaviour is not monitored in extensive systems as it would be difficult to manually collect objective, high-resolution behavioural data across large spatial and temporal scales on an individual-animal level as large numbers of

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indistinguishable free-ranging animals often need to be checked quickly and infrequently, often by a single observer (Edwards, 2007). Doing so would be a very inefficient, labour-intensive undertaking and not economically viable for a commercial system. However, automated monitoring of animal behaviour (termed 'bio-logging') may offer a solution and is becoming increasingly widespread, with accelerometers currently being a popular tool (Kooyman, 2004; Brown et al., 2013). Tri-axial accelerometers measure both gravitational and inertial acceleration across 3 axes (x,y,z) (Whitford and Klimley, 2019). Bio-logging is increasingly being applied to the farming industry (King, 2017) and accelerometers have been trialled on all commonly farmed ungulate species in a research setting (Moreau et al., 2009; Chapa et al., 2020). The majority of studies deploying accelerometers on livestock make use of machine learning techniques to predict behaviour from accelerometer data (García et al., 2020), with supervised machine learning techniques (where the algorithm is trained on labelled data only) being favoured when classifying sheep behaviour (Kleanthous et al., 2019). To date, however, only the cattle industry has seen the emergence of commercially available products (e.g. MooMonitor+ (Dairymaster, Co. Kerry, Ireland), IceTag (IceRobotics Ltd., Edinburgh, Scotland)).

Although not yet commercially available in the agricultural industry, the use of accelerometers on sheep in experimental settings has increased in recent years (Fogarty et al., 2018) and has been used to detect behavioural states in ewes including grazing, resting, lying, standing, walking and ruminating (Alvarenga et al., 2016; Giovanetti et al., 2017; le Roux et al., 2017; Barwick et al., 2018b; Mansbridge et al., 2018; Walton et al., 2018 and many more). More specific applications have included the identification of urination events (Lush et al., 2018; Marsden et al., 2021), detection of parturition (Fogarty et al., 2020b, 2021), posture discrimination (Radeski and Ilieski, 2017; Fogarty et al., 2020a) and lameness prediction (Al-Rubaye et al., 2018; Barwick et al., 2018a; Kaler et al., 2020).

Accelerometers have also been used to a much lesser extent on rams and lambs to detect specific behaviours such as mounting events (in rams) (Mozo et al., 2019), suckling events (Kuźnicka and Gburzyński, 2017), posture (Högberg et al., 2020) and activity levels (Rurak et al., 2008; Ikurior et al., 2020) in lambs. Monitoring a range of lamb behaviours, for instance suckling behaviour, will allow us to improve our understanding of related key lamb production traits such as growth (Burris and Baugus, 1955).

Despite the large body of literature on the use of accelerometers on sheep in a research setting, there is a need to better contextualise research methods with those required in a commercial setting. In a research setting, studies have trialed various objectives and methodologies with differences in sample size, deployment duration, sampling rate, window size, analysis method, sensor type, sensor position and ethogram yet few have translated their methods to a commercial system (but see Williams et al., 2021). To be feasible on a commercial scale, accelerometers need to be attached quickly with minimal handling to entire flocks, often consisting of large number of animals. Moreover, accelerometers would need to capture a range of behaviours and monitor many animals over long timescales to meet commercial needs. Recent work has trialed sensor deployments on large numbers of animals (Williams et al., 2021), but to date, no study has deployed sensors on an entire flock of animals at varying life stages.

Here we aimed to (i) test the feasibility of deploying accelerometers on an entire commercial sheep flock (100 + animals) at a key point in the annual production cycle (lambing) when ewes and lambs are present, to validate the viability of automated monitoring of sheep behaviour in a commercial setting; and (ii) develop robust machine learning algorithms that can classify both the posture and physical activity of adult sheep and lambs. Though many classifiers for predicting sheep behaviour currently exist, most are trained on few animals over short durations or in an experimental setting and few exist for lambs (Fogarty et al., 2018). Although the use of multiple ethograms has been trialled in Fogarty et al. (2020a), none completely differentiate between posture and activity.

2. Materials and Methods

2.1. Study site and animals

All data collection was approved by the University of Exeter's ethical board (eCLESPsy000541). Data were collected on a commercial sheep farm located in Devon, UK, that houses approximately 120 Poll Dorset ewes that are managed at pasture throughout the year. Rams are introduced for mating in April (following an initial period with a teaser in March) and July (to cover ewes that did not conceive during the first mating season). Ewes lamb in September-October with a later lamb crop in December. During lambing, ewes are moved to indoor pens for 24 hr. Ewes and lambs are then put out to pasture and lambs are finished at grass. Approximately 30–60 ewes and 40–70 lambs are present in a single flock at lambing. Poll Dorsets are well-known for their long breeding season resulting in increased reproductive output outside of the typical UK sheep breeding season. These Autumn-born lambs raise a premium price at sale (Hall et al., 1986).

Routine farm management continued as normal throughout the period of study, and every effort was made to minimise disruption. In line with this, the flock were rotated between fields (sizes ranging from 0.5 to 1 ha) throughout the study and were given unrestricted access to pasture and water year-round. The flock was only handled when brought in for treatment or other farm management. Sequential numbers were sprayed on the left side of each ewe (and their offspring) with coloured livestock spray in line with normal farm management to enable the identification of individuals and ewe-lamb groups.

2.2. Sensor deployment

When considering commercial relevance, device location is key. Sensor placement has varied among previous studies in the literature (Fig. 1a). Sensor positioning determines several things, including (1) the direction of the measurement axes, (2) the activity that can be detected (including key activities relevant to production (e.g. ruminating/jaw movements could not be detected from an accelerometer deployed on the leg) and (3) deployment feasibility on a commercial scale. For example, collar attachment is likely superior over leg/harness attachment as it can be fitted to animals quickly as they are passed through a race without extensive manipulation of the animal and can accurately capture a range of behaviours (Decandia et al., 2021). Additionally, multiple sensors can be attached to collars where this would be more difficult with ear/leg attachment methods and would likely require multiple instrumentation locations.

Here, GENEActiv (Activinsights Ltd., Kimbolton, Cambridgeshire, UK) accelerometer-based sensors (Fig. 1b) were attached to 196 different animals (76 ewes (Fig. 1c) and 120 lambs (Fig. 1d)) for consecutive day periods averaging 10.09 ± 3.35 days across two lambing seasons (September/ October 2019 and December 2020). GENEActiv accelerometers are wrist-worn devices designed to measure activity in humans (Esliger et al., 2011; Rowlands et al., 2014). Devices were set to sample at a rate of 50 Hz (+/−8 g range at 3.9 mg resolution) to maximise data recorded while preserving battery life. Previous studies have used various sampling rates from 5 to 200 Hz. Devices could hold up to 0.5 Gb of raw data and were housed in a water-resistant case along with a rechargeable lithium polymer battery, making them ideal to withstand the array of weather conditions experienced by a free-ranging sheep flock. This work formed part of a larger study in which, along with accelerometers, proximity tags designed by the SocioPatterns collaboration consortium (http://www.sociopatterns.org) and the OpenBeacon project (http://www.openbeacon.org) were also attached to animals; the proximity data, however, were not used in the current study (for more details see Ozella et al., 2020, 2022).

GENEActiv accelerometers were attached to ewes via freely rotating

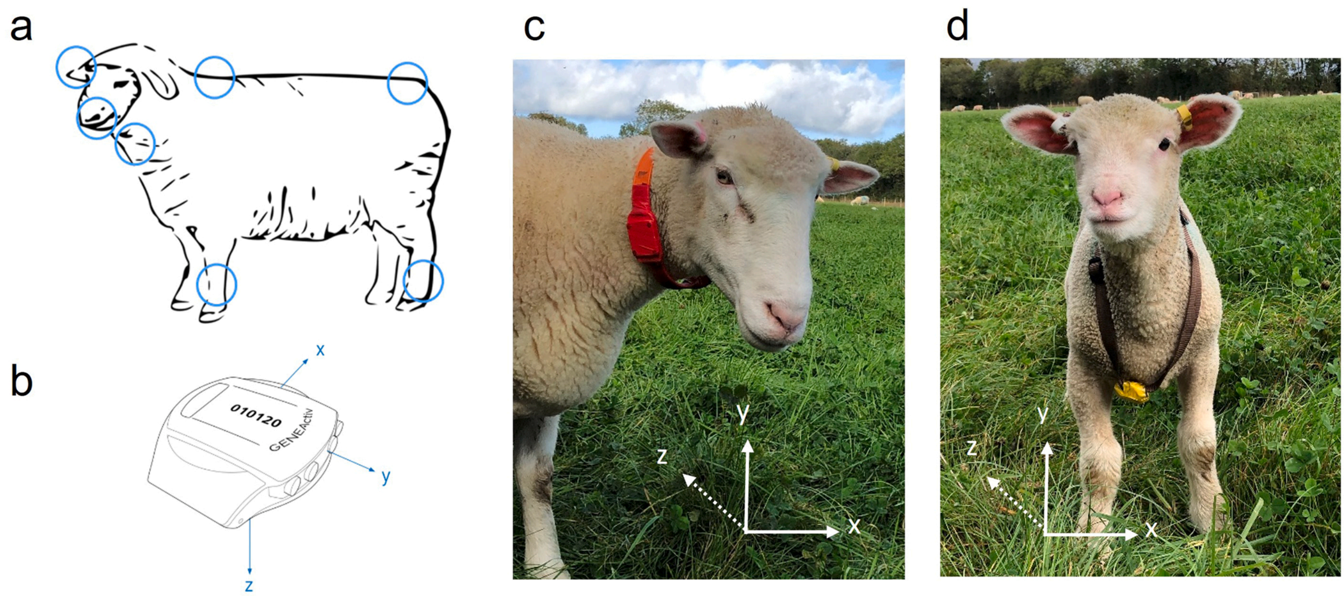

Fig. 1. (a) Common sensor placement locations reported in the literature (reviewed in Fogarty et al., 2018) including the ear, jaw, neck, legs, upper back, and the rear. (b) GENEActiv accelerometer with axis directions. (c) Collar attachment method used on ewes with axis directions. (d) Harness attachment method used on lambs with axis directions.

collars with the orientation of the Y, X and Z axis along the dorso-ventral, lateral and anterior-posterior axes, respectively (Fig. 1c). Neck placement allows for the detection of the majority of primary behaviours sheep perform daily and is the most practical commercially as collars are secure to avoid equipment loss and are quick and easy to deploy with minimal manipulation of the animal required. Due to their smaller body size, sensors were deployed on the chests of lambs via a fixed harness with the orientation of the Y, X and Z axis along the dorso-ventral, lateral and anterior-posterior axes, respectively (Fig. 1d). Harnesses were fitted with an elasticated girth to allow room for growth. Both are common attachment methods (Fig. 1a) and the attachment of devices to sheep has been shown to cause no ill-welfare (Hobbs-Chell et al., 2012). Collars and harnesses both weighed 100 g, well below the recommended threshold of 5% of the animal's body weight for both ewes and lambs (Portugal and White, 2018). Animals were observed for short periods directly following deployments and regularly thereafter to ensure no adverse impacts on welfare, such as lamb rejections or impaired locomotion.

For the present study, data were collected 3 times on an entire flock (196 different animals) during 2 lambing periods (summarised in Table 1). GENEActiv accelerometers collect data continuously, so animals were monitored 24hrs a day for a total of 2432 days.

Table 1
Summary of the 3 deployment periods referred to in this study. Deployments occurred during lambing periods, so ewes and lambs were housed as a single large flock, with no rams present. Collars were deployed on ewes and harnesses on lambs. Some animals were recorded across multiple deployments. On observation days, the flock was observed between ~09:00 h and 17:00 h.

Activity	Posture	Animal	Description
Grazing	Standing	Ewes	Animals grazing with their head down - can be stationary or moving $\leq$ 3 consecutive steps (ranging).
Ruminating	Standing/ Lying	Ewes	Animals ruminating with head up.
Inactive	Standing/ Lying	Ewes/ Lambs	Animals' stationary with minimal head movements - head may be up or level.
Suckling	Standing	Lambs	Lambs feeding from udder of ewe with head up.
Walking	Standing	Ewes/ Lambs	Animals purposely travelling with > 3 consecutive steps - head may be up or level.

2.3. Observations

During each of the three deployments, the entire instrumented flock was also observed by an observer (EP) for a total of 39 days (Table 1). Observations were made using ad hoc sampling on any easily identifiable member of the flock from the boundary of the field the flock occupied at the time. Animals were observed at variable distances depending on flock location with an initial starting distance of at least 10 m to minimise flock disturbance. In total, visual observations were made on a subset (116 animals) of the objectively measured individuals. Observer and accelerometer clocks were synchronized and accelerometer clock drift was measured when data was extracted so the direct observations could be accurately aligned with the tri-axial accelerometer data once compensated for clock drift.

Here we apply the mutually exclusive and collectively exhaustive (MECE) principle (Minto, 2009) when creating ethograms to classify posture and physical activity (Table 2). This ensures classifier performance will not be impacted by difficulties classifying intertwined behaviours as information is arranged into exclusive categories; for example, when categories for standing and grazing exist, this may create confusion for classifiers, as while grazing the animal is also standing. In total, 4 different ethograms were used: detection of (i) posture (standing, lying) and (ii) physical activity (grazing, ruminating, inactive, walking) using collar-mounted accelerometers on adult sheep and detection of (iii) posture (standing, lying) (iv) and activity (suckling, inactive, walking/running) using harness-mounted accelerometers on lambs. See supplementary material for full ethograms (Table 2). Postural and activity states were recorded using ad hoc sampling either for their duration (if <6–10 s) or for a minimum of 10 s as they were exhibited by any easily identifiable member of the flock. Any other activity lasting < 6 s was defined as a behavioural event and excluded from subsequent analysis.

2.4. Feature selection

Here, we extracted statistical and frequency features from the dataset

Table 2
Descriptions of mutually exclusive activities and postures. Standing was defined as animals upright while lying was defined as animals' recumbent. For lambs only, running observations were included within the walking category due to the low number of observations collected for this behaviour.

Deployment	Start date	End date	Visual observation days	Animal	Number of animals	Mean duration (days)	SD duration (days)	Total full days
1	13/09/2019	21/09/2019	8	Ewe	6	7	0	42
				Lamb	9	7	0	63
2	01/10/2019	15/10/2019	13	Ewe	49	13	0	637
				Lamb	65	13	0	845
3	01/12/2020	01/01/2021	18	Ewe	35	14.23	3.14	498
				Lamb	55	6.31	1.46	347

using 6 s windows or epochs with a 50% overlap to maximise the volume of available training data. We chose 6 s windows as we believe this is most relevant to a commercial system to be able to predict key behavioural states. Various window sizes have been trialed in the literature (Decandia et al., 2018), but other authors have had success predicting a range of behaviours in sheep and lambs with similar window sizes 5–7 s (Alvarenga et al., 2016; le Roux et al., 2017, 2019; Mansbridge et al., 2018; Walton et al., 2018; Kaler et al., 2020; Ikurior et al., 2020). While longer windows would contain more information and are less affected by noise or erroneous points, they may miss shorter-lived behaviours such as walking events that may be key indicators of ill-health (Decandia et al., 2018). Also, using longer windows increases the probability of behaviour transitions happening in a window, which makes it more difficult for the algorithm to identify which behavioural state the animal is in as there are two different states in the same window. Shorter windows would add noise or erroneous points.

For each window, the following statistical features were extracted using the R packages GENEAread 2.0.9 (Fang et al., 2020) and GENEAclassify 1.5.2 (Campbell et al., 2021): the mean acceleration (Mean Absolute Gravity-Subtracted Acceleration, MAGSA) and the mean, variance, skewness and MAD (median absolute deviation) of the y axis to measure head position. The x and z axes were combined to calculate collar rotation (for ewes only; see the R package GENEAclassify 1.5.2 (Campbell et al., 2021) for a full description). The mean, variance, skewness and kurtosis of rotation were then calculated (Fisher, 1995). The following frequency domain features were also extracted using reassigned Short-Time Fourier Transformation (Bracewell, 1986): the mean, variance and MAD of the principal frequency (see Table S1 for more detail).

Statistical and frequency features have been used almost exclusively to classify sheep behaviour in similar studies. However, our use of information on collar rotation is novel. All previous studies have either used features that are independent of collar rotation (Kamminga et al., 2017, 2018) or have ensured the sensor is fixed and cannot rotate (Barwick et al., 2018b; Walton et al., 2018). Attachment of a fixed collar is time-consuming and the exact location may vary for each animal, and therefore may not be practical when deploying on a large commercial scale. We included the rotation of the accelerometer to determine it's use as a feature to assist performance (i.e. the accelerometer would rotate more during active behaviours such as walking than when the animal is inactive.

For highly correlated features ($r \geq 0.8$) only 1 feature was included. The importance of features was assessed using the mean decrease in Gini score calculated using the R package randomForest v4.6–14 (Liaw & Wiener, 2002). The 3 most important features were then included in each model to minimise the possibility of overfitting the model (Barwick et al., 2018b, 2020; Fogarty, 2020a).

2.5. Training and test data

In total, using 6 s overlapping windows, 27,039 and 15,896 training data points were available on 49 ewes with collar-mounted accelerometers and 67 lambs with harness-mounted accelerometers respectively. Activity classes showed significant imbalances, for collar-mounted accelerometer data, activity records included 8656 (32.8%) ruminating, 8524 (32.3%) grazing, 8421 (31.9%) inactive and 799 (3.0%) walking observations. For harness-mounted accelerometer data, activity records included 11,004 (76.1%) inactive, 2765 (19.1%) suckling and 684 (4.7%) walking/running observations. Imbalanced data produces suboptimal classification with inflated accuracy for the majority classes and reduced performance for the minority classes (Weiss and Provost, 2003; Sakai et al., 2019).

To achieve optimum classifier performance, the majority classes were down-sampled by randomly selecting a maximum of 100 observations per animal per class for the majority classes. This method was adapted from previous work (Smith et al., 2016; Abell et al., 2017; Fogarty et al., 2020a) and resulted in a more balanced dataset while maintaining data on the same number of individuals. After down-sampling, activity records included 1056 (29.5%) ruminating, 910 (25.5%) grazing, 850 (23.8%) inactive, and 760 (21.3%) walking observations for collar-mounted accelerometers and 1541 (41.1%) suckling, 1521 (40.6%) inactive and 684 (18.3%) walking/running observations for harness-mounted accelerometers. Data for posture ethograms were left in their original, unbalanced state as the classes were relatively balanced with 15,489 (57.3%) lying and 11,550 (42.7%) standing observations for collar-mounted accelerometer data and 11, 046 (69.5%) lying and 4850 (30.5%) standing observations for harness-mounted accelerometer data.

2.6. Classification models

Random forest classification models were developed for each ethogram using the R package caret v6.0–86 (Kuhn et al., 2021). The random forest algorithm is an ensemble learning method that creates multiple decision trees for classification and regression (Breiman, 2001). Each decision tree makes an independent class prediction and the most common class prediction is chosen. Random forest was chosen as it is relatively easy to inspect feature importance, is fairly robust to data imbalances, and has previously been used to classify behaviour in sheep with a high degree of success (e.g. Kleanthous et al., 2018, 2019, 2020; Lush et al., 2018; Mansbridge et al., 2018; Walton et al., 2018; Kaler et al., 2020). When training the classifier, we specified an *mtry* (the number of variables tried at each split) equal to the square root of the number of variables used for classification (approximately 1.7) and *ntree* (the number of trees grown) of 500 (Barwick et al., 2018b; Fogarty et al., 2020a). The classifier was trained and tested using leave-one-out cross-validation (LOOCV) (Smith et al., 2016; Barwick et al., 2018b; Fogarty et al., 2020a). This involves training the algorithm on all of the dataset bar one animal (N-1). Algorithm performance is then tested on the remaining animal. This is iterated through all individuals so the number of observations (N) is equal to the number of instances (Wong, 2015). Average performance metrics are then calculated. K-fold validation using 10 folds was also tested for comparison (Wong, 2015).

2.7. Model validation

All performance metrics were calculate using the R package caret v6.0–86 (Kuhn et al., 2021). To evaluate model performance, the average accuracy was calculated for each classifier.

$$Accuracy = \frac{(True \quad Positives + True \quad Negatives)}{(True \quad Positives + True \quad Negatives + False \quad Positives + False \quad Negatives)}$$

A confusion matrix was then used to calculate the following commonly used metrics for each class (Barwick et al., 2018b; Fogarty et al., 2020a; Alvarenga et al., 2016):

$$Sensitivity \Big/ \quad Recall = \frac{True \quad Positives}{(True \quad Positives + False \quad Negatives)}$$

$$Specificity = \frac{True \quad Negatives}{(True \quad Negatives + False \quad Negatives)}$$

$$Precision = \frac{True \quad Positives}{(True \quad Positives + False \quad Positives)}$$

$$F\text{-}score = \frac{(1 + \quad \beta^2) \times \quad Precision \quad \times Recall}{((\beta^2 \quad \times Precision) + Recall)}$$

3. Results

3.1. Deployment

Deployment times varied; a single collar was able to be fitted in under 30 s as sheep passed through a race with minimal handling of animals required, while a single harness took closer to 1–2 min and extensive manipulation of lambs was needed. Collars required no further intervention until removal ~14 later, whereas some harnesses needed to be adjusted multiple times during the deployment due to the rapid growth of lambs, and therefore some individuals needed to be repeatedly recaptured. Three collars and two harnesses were removed early when animals were removed from the flock due to lamb rejections or health issues, but the majority remained attached for the entire deployment period. We retrieved a total of 90 collars and 129 harnesses (100% return rate). From these, 219 accelerometers returned a total of 2432 sheep days of data (1177 ewe days and 1255 lamb days).

3.2. Collar-mounted accelerometers

For collar-mounted accelerometers, classifiers were trained on a total of 27,039 data points on 49 animals (Table 1). For both posture and activity prediction, the best predictive features were the mean acceleration and the mean and variance of the neck elevation (Fig. 2a, b). The performance metrics for posture and activity prediction from collar-mounted accelerometers are presented in Table 3. The classifier for detecting posture achieved superior performance over the classifier for activity prediction with a mean (± SD) accuracy score (across all iterations of the model) of 83.74% ± 13.42% compared to 70.90% ± 14.06%. Lower performance for activity detection resulted from low Sensitivity's (true positive rate) across all classes (Table 3). This was particularly true for walking (64.34%).

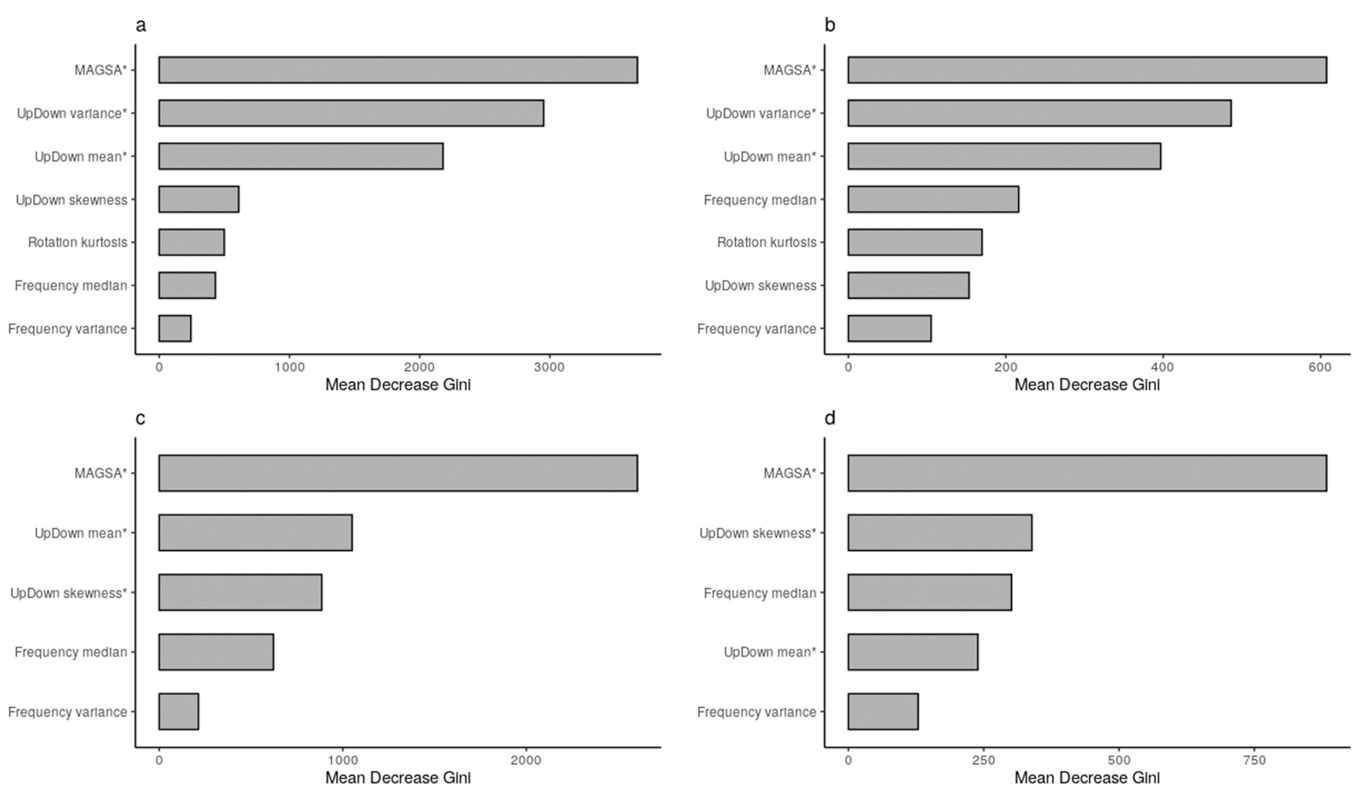

Fig. 2. Features in descending order of importance according to the mean Gini index (Barwick et al., 2018b) for (a) posture and (b) activity detection from collar-mounted accelerometers and for (c) posture and (d) activity detection from harness-mounted accelerometers. The top 3 features were used with the exception of the activity prediction algorithm trained using harness-mounted accelerometer data where the mean of the neck elevation was used in place of the frequency median as there was very little difference in importance ranking and the frequency is computationally expensive to calculate to develop the final algorithms). The 3 features used to develop the final algorithms are indicated (*).

Table 3
Average performance statistics calculated from the confusion matrix (for all iterations of the model trained using LOOCV) to indicate model performance when predicting posture and activity from collar-mounted accelerometers (ewes) and harness-mounted accelerometers (lambs).

Attachment method	Ethogram	Class	Sensitivity/ Recall (%)	Specificity (%)	Precision (%)	F-Score (%)
Collar	Posture	Standing	85.19	93.25	90.39	87.72
		Lying	93.25	85.19	89.41	91.29
	Activity	Grazing	72.75	90.81	72.99	72.87
		inactive	71.65	93.73	78.08	74.72
		Ruminating	77.18	89.25	75.05	76.10
		Walking	64.34	88.85	60.90	62.57
Harness	Posture	Standing	87.40	89.45	78.44	82.68
		Lying	89.45	87.40	94.18	91.75
	Activity	Inactive	83.89	91.51	87.10	85.47
		Walking/running	76.75	94.55	75.87	76.31
		Suckling	81.64	84.99	79.17	80.38

3.3. Harness-mounted accelerometers

For harness-mounted accelerometers, classifiers were trained on a total of 15, 896 data points on 67 animals (Table 1).

For posture prediction, the mean acceleration, the mean of the neck elevation and the skewness of the neck elevation were the best predictive features (Fig. 2c). For activity prediction, the mean acceleration, the frequency median and the skewness of the neck elevation were highlighted as the most important features. However, the mean of the neck elevation was used in place of the frequency median as there was very little difference in importance ranking and the frequency is computationally expensive to calculate (Fig. 2d).

The performance metrics for posture and activity prediction from harness-mounted accelerometers are presented in Table 3. The classifier for detecting posture achieved superior performance over the classifier for activity prediction with a mean (± SD) accuracy score (across all iterations of the model) of 85.91 ± 15.02% compared to 80.81 ± 15.20%. Lower performance for activity detection resulted from the low sensitivity (true positive rate) compared to other classes for walking/running detection (76.75%).

3.4. Validation

All classifiers trained using LOOCV achieved good performance on the majority of individuals (Table S2). Performance was not improved by excluding individuals with very low accuracy scores. Poor predictive performance on individuals for 1 classifier was no associated with poor performance on the other (Table S2). For both attachment locations, posture and activity classifiers trained using LOOCV achieved lower mean performance metrics and higher standard deviations than classifiers trained using K-fold validation (Table 4) but, confusion matrices were similar (Tables S3 and S4 vs S5 and S6), indicating overall classification performance was similar. These differences liekely reflect the between-animal variation that k-fold validation fails to capture.

Table 4
Mean (± SD) accuracy calculated from all iterations of the model trained using either LOOCV (resamples; n = 49 ewes or n = 67 lambs) or k-fold cross validation (resamples; n = 10) to indicate model performance when predicting posture and activity from collar-mounted accelerometers (ewes) and harness-mounted accelerometers (lambs).

		LOOCV		K-Fold	
Attachment method	Ethogram	Accuracy (%)	SD (%)	Accuracy (%)	SD (%)
Collar	Posture	83.74	13.42	90.97	0.69
	Activity	70.90	14.06	78.33	1.69
Harness	Posture	85.91	15.02	94.59	0.49
	Activity	80.81	15.20	86.73	1.40

4. Discussion

In this study we successfully predicted postures and physical activity of ewes using collar-mounted accelerometers and lambs using harness-mounted accelerometers, validating these methods in a commercial context with a large number of animals of varying sizes and ages. Posture classifiers achieved superior performance over activity classifiers. This is also true for other studies that use separate posture classifiers for ewes (Fogarty et al., 2020a) and lambs (Högberg et al., 2020). This is likely due to the exclusivity of classes as lying and standing are distinct postures that cannot be performed simultaneously. Including posture such as standing and activities such as walking and grazing in a single ethogram often leads to reduced performance, for example low sensitivities (54–62.9%) for standing (Barwick et al., 2018b; Fogarty et al., 2020a), as animals are able to stand and graze or stand and walk simultaneously.

Our results indicate walking was the most difficult behaviour to detect with misclassifications of walking events often labelled as grazing (Tables S3 & S4). Despite efforts in the present study to develop a mutually exclusive ethogram for physical activity in sheep, walking and grazing naturally occur simultaneously as, while grazing, free-ranging animals need to locomote a few steps to move to new pasture and feed continuously, described here as 'ranging'. While this is still grazing by our definition (Table 2), this may have been confused with walking due to similar feature characteristics. Misclassification of grazing with walking has also been reported in sheep (Umstätter et al., 2008) and cattle (González et al., 2015).

In the present study, walking for lamb activity classifiers also had a low sensitivity. Other studies have also encountered similar challenges associated with predicting walking behaviours. Fogarty et al. (2020a) achieved low sensitivity and specificity (65.6% and 45.2% respectively) for walking. Walton et al. (2018) tested a range of device placements, sampling rates and epoch sizes and found that walking demonstrated the greatest range of performance. Others have found opposing results and are able to classify walking with low misclassification; Barwick et al. (2018b), for example, achieved sensitives and specificities > 90% for walking using a collar attachment method, although different methods of determining overall accuracies and small sample sizes (Barwick et al., 2018b used 5 sheep) may help explain the differences.

Sample size may be important for predicting walking, as it is a highly variable behaviour influenced by differences in gait, morphology and changes in health or environmental conditions (e.g. lameness, ground firmness) (Blomburg, 2011). Larger sample sizes, similar to that used in this study, may capture more of this variation to create models with better ability to generalise, while making classification more difficult (Riaboff et al., 2022). Our ability to detect walking behaviour could also be impacted by epoch length. In the field, walking bouts were observed to be much shorter than all other activity bouts and Walton et al. (2018) showed walking could be predicted best using higher sampling rates so shorter epochs may potentially improve performance. To mitigate this, future studies could utilise methods such as multiple length windows or auto segmentation approaches affording the potential to include segment length as a feature (Reeves et al., 2007; Hu et al., 2020).

The primary aim of the present study was to classify the behaviour of an entire flock of commercial sheep. While both device attachment locations were successful, there were limitations with harness attachment. For example, this method would miss key behaviours associated with head or jaw motion, such as grazing and ruminating. From a commercial perspective, extensive handling/manipulation of an animal is impractical e.g. as required for a leg or harness attachment (Kleanthous et al., 2019; Radeski and Ilieski, 2017; Barwick et al., 2018b). We suggest a collar attachment method is a more practical in a commercial setting, as it its secure, takes seconds to attach with minimal handling of the animal needed and can be loosely fitted to allow for growth so that it does not need to be adjusted for long periods of time, suiting existing management practices on commercial farms. Also, multiple sensors can be attached to capture a range of behaviours. In comparison, we found using a harness attachment method on lambs took longer, required extensive manipulation of the animal, and required multiple recaptures of the animal to adjust the harness, making it impractical to be used on commercial farms without significant adjustment to on-farm management practices. We suggest focus should be placed on identifying ewe traits that can predict lamb production outcomes.

Other locations that have been suggested for a commercial setting such as the leg or ear (Barwick et al., 2018b, 2018b; Fogarty et al., 2020a; Kaler et al., 2020) may miss key behaviours associated with jaw movement such as ruminating. Also, ear placement is less secure, and devices may fall off (identification ear tags often do), resulting in loss of data and expensive devices and making long-term deployment unfeasible. Moreover, ear placement may lead to reduced performance compared to collar placement, as ear position may be independent of body position, creating similarities in acceleration signatures. Therefore, ear placement may not be able to discriminate between postures such as lying and standing or grazing and standing behaviours (Barwick et al., 2018b).

A secondary goal of this study was to validate the use of an accelerometer to capture a range of lamb behaviours. Despite extensive validation work in ewes, only a small number of studies have attempted to validate the detection of behaviours in lambs (Rurak et al., 2008; Kuźnicka and Gburzyński, 2017; Högberg et al., 2020). Although not feasible to apply on a commercial scale without significant changes to on-farm management, understanding lamb behaviour with a higher degree of resolution than time active vs inactive (although links between activity levels and health outcomes have been reported; Ikurior et al., 2020) is directly relevant to production. For example, the detection of suckling behaviour in lambs is key to understanding growth rates (Burris and Baugus, 1955) and may enable the identification of health issues in ewes such as mastitis (Gougoulis et al., 2010). The present study has been able to accurately predict a range of lamb postures (standing/lying) and activities (suckling, walking/running and inactivity), providing huge potential for future studies to investigate the potential links with production traits. There is also further opportunity to expand this work and include grazing and ruminating behaviours in lambs, which may offer insights into variability associated with weaning age and subsequent growth rate for example (Brown, 1964). This study did not classify these behaviours as the majority of our sample was made up of lambs $<$ 20 days old that were not yet weaned, so these behaviours were rarely seen.

Our findings suggest that, for all classifiers, the mean acceleration and mean neck elevation were key features. This was expected as postures and activity classes have distinct head positions and intensities associated with them; for example, grazing is performed with the head down and with higher levels of movement compared to ruminating, which is performed with the head up and requires less movement. For collar-mounted accelerometers, the variance of neck elevation was also evaluated as important for both posture and activity classifiers. This is likely as more variance in neck positions is associated with certain postures such as standing, as a larger range of activities are performed in this posture. Also, more variance in neck position may be associated with certain activity classes such as walking.

Rotation features calculated for collar-mounted accelerometers, although useful, were highly correlated with the mean acceleration as more movement resulted in more sensor rotation. For harness-mounted accelerometers, the mean acceleration was the most important feature by far for distinguishing classes, most likely because all lamb behaviours described had distinct intensities associated with them, and therefore other features may have contributed little additional information. Future studies on sheep should allow rotation of the accelerometer and include sensor rotation as a feature. Further work should also trial structure-based features or automatically derived features that have proven useful for human activity recognition (Xiao et al., 2016).

Our findings also revealed classifier performance varied by individual. This has been described previously on sheep (Barwick et al., 2020) and is likely due to the variability associated with individual animals; for example, different morphology may cause differences in collar/harness fit and subsequent sensor placement (Blomburg, 2011). We used LOOCV to capture these differences despite the slight improvement in the performance of classifiers trained using k-fold validation. To ensure classifiers are useful on a commercial scale, care should be taken to train the classifier on a sufficient number of animals in an unrestricted environment in order to capture sufficient variation in animals e.g. size, age, and morphology, and in various environmental conditions. In human physical activity measurement, classifiers trained on lab-based data generally perform poorly on free-living data (Ellis et al., 2016; Pavey et al., 2017). Classifiers trained to predict sheep behaviour have also shown reduced performance when tested on new data or different environmental conditions such as different sward heights (Guo et al., 2018; Vázquez-Diosdado et al., 2019). Here we collected training data on a large number of animals (196) housed on a working commercial farm over three 2 week periods across 2 lambing seasons to minimise these potential biases and ensure the generality of our algorithm.

5. Conclusions

The current study successfully developed robust random forest classifiers that we believe can reasonably classify the behaviour of adult sheep and lambs in multiple dimensions. Classifiers were able to predict posture with $>$ 80% accuracy and physical activity with $>$ 70% accuracy on a commercial flock, bridging the gap between research and commercial systems. These methods open up the potential to automate the monitoring of individual-level changes in daily patterns in commercial sheep flocks which could help identify key indicator metrics to inform production and health. This is an important first step in developing early warning systems for key issues in commercial flocks, including lameness and senescence or for identifying selection metrics such as resilience to environmental conditions to enable early decision making on-farm. Future work may consider using a semi-supervised machine learning approach (where the algorithm is trained on both labelled and unlabelled data) to make use of the large datasets collected by sensors. Future work should also focus on the development of devices with longer battery life, real-time classification algorithms and wireless data transfer to allow longer deployments and make commercial application more feasible. Also, the feasibility of using algorithms to detect ram-specific behaviours such as mounting could be explored to predict ewe oestrous and lambing date with better accuracy than current methods (e.g. raddles) provide. This would give a complete picture of the production cycle including an entire flock of varying sexes and ages.

Data Availability

A censored version of the data is available upon request.

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Declaration of Competing Interest

The authors declare no conflicts of interest.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.applanim.2022.105630.

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