



Original Research Paper

Machine Learning Classification of Free-Ranging Livestock Behaviour
Using Wearable Sensors

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Key Words

Abstract

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Wearable sensors,
Machine learning,
Grazing
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Animal welfare,
Rangeland
management

Introduction: Effective animal conservation and management need periodic data on the behaviour of free-ranging livestock and the environment influencing it. The traditional method is precise but sporadic and laborious for large and/or inaccessible landscapes. Materials and methods: The current paper introduces the artificial intelligence-based methodology for assessing livestock movement using accelerometer, gyroscope, GPS, ambient temperature, pasture state and direct observations of behaviour. The experimental data set comprised 21,600 labelled windows measured on 36 free-ranging cows for 30 observation days. Data were filtered and aligned, as well as split into training, validation and testing sets. Results and discussion: The suggested methodology allowed obtaining 96.2% accuracy, 95.8% precision, 95.4% recall and 95.6% F1-score. Significant connections between animals and environment were linked to pasture availability, heat load, travelling distance, water presence and land slope. The algorithm helped to increase recognition performance under different environmental conditions and produce explainable alerts for fieldwork verification. Conclusion: The results prove the possibility of expanding the range of non-invasive monitoring in cases where outcomes still stay related to environmental context and expert observations.

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Introduction

Observing free-ranging livestock behaviour becomes crucial since any shift in their distribution, activity, and utilization of resources can indicate environmental stress in the early stages. They react to climate changes, availability of food and water, vegetation structure, disturbances, and seasonality. With an analysis of all these factors taken into account, observation goes beyond mere recognition and serves as a source of data for further action towards habitat conservation and animal protection. Constant monitoring with sensors provides valuable data on animal behavior and their physiological/behavioral states over long periods of time (Goyal & Shah, 2025).

In the case of traditional surveying methods, they require direct observation, field signs, or manual inspection. Such surveying methods are indispensable for confirmation of biological entities; however, they are laborious and prone to miss nocturnal, elusive, scattered, or temporarily occurring animals. In addition, sensor technology enables longer observation times and minimal disturbance. Sensing technology wearable on animals as well as motion sensors have gained considerable attention in order to monitor behavior of animals continuously (Benaissa et al., 2019; Smith et al., 2016). Moreover, machine learning methods have shown their capability in classification of behaviors of heavily grazing livestock based on the information collected by sensors (Fogarty et al., 2020). Yet, sensor readings may be affected by weather, location of sensor, background noise, visibility, individual variability, and absence of data.

AI can sort out big amounts of field observations and detect repeated patterns in several environmental variables. Existing literature proves the importance of machine learning and deep learning models in ecological surveillance, animal classification, and automatic interpretation of biological observations (Christin et al., 2019; Tuia et al., 2022). Deep learning models have also been shown to be capable of automatically detecting, counting, and describing animals on a large set of camera trap observations (Norouzzadeh et al., 2018). Camera trap surveillance systems represent one more source of information for observing animals that is complementary to the former one. The choice of sensors and cameras depends on ecological tasks (Rovero & Zimmermann, 2016). However, high prediction performance does not guarantee any conservation or livestock management benefits. Predictive models should separate behavioural changes from low sensor quality and should indicate doubtful records.

An environmental perspective is another way through which the behaviour can be better interpreted because the animal behavior is affected by the environmental condition of the area where the animal moves around. Several remote sensing techniques have been applied to monitor environmental conditions and biodiversity (Pettorelli et al., 2014). In addition, the environmental condition affects several activities of free-ranging livestock including grazing, walking, resting, ruminating and drinking.

This paper outlines an animal-environmental perspective of the free-ranging livestock

behavior. This involves the use of accelerometer, gyroscope, GPS, ambient temperature, pasture condition and behavior observation to classify grazing, walking, resting, ruminating and drinking behaviors.

Review of Literature

Monitoring of animals through automation has grown through the development of small-sized sensors, remote storage of data, and pattern recognition technologies. Accelerometers, which are worn by animals, have been employed in recognizing behaviors of dairy cows, which shows the application of animal-borne sensors in recognizing diverse behaviors of animals (Benaissa et al., 2019). Additionally, motion collar technology has been used together with machine learning to recognize cow behavior, indicating that multi-sensor movement information can be used in automated recognition of behaviors (Smith et al., 2016). Extensively grazing sheep have been studied using machine learning in recognition of behaviors.

Deep learning has the ability to model nonlinear relationships and complex temporally or visually salient structures, whereas traditional models continue to be helpful in serving as baseline models for the analysis of simple ecological data. Ecological applications of deep learning illustrate its utility in analyzing complex ecological data and automatic classification (Christin et al., 2019). Moreover, there have been successful applications of deep learning algorithms for identifying animals through the images captured using camera traps, thus helping minimize the labor needed for screening a lot of

ecological data of animals (Norouzzadeh et al., 2018).

There is also a possibility to employ complementary technologies in terms of cameras and remote sensing for animal and environment monitoring. The use of camera trapping techniques could help overcome the limits of traditional fieldwork, as certain characteristics of camera devices could be chosen based on specific ecological uses (Rovero & Zimmermann, 2016). Additionally, large-scale networks of camera traps have already proved to be useful in terms of using distributed remote sensors for animal monitoring on wide spatial scales (Steenweg et al., 2017). Nevertheless, the current paper will not be focused on camera trapping but rather on wearable and environment sensors.

The environmental context also needs to be taken into consideration during the interpretation of animal behaviour. Information about environmental context and spatial patterns, provided by remote sensing tools, is useful for ecological monitoring and conservation assessment purposes (Pettorelli et al., 2014). The same applies to free-range livestock where information on the environment will be able to shed light on why there are differences in their activities.

One of the biggest problems faced here is the variability between sites and seasons. Models may capture the characteristics specific only to the particular site, device, animal or observer. Thus, balanced sampling, animal and station-based data split, quality flags and external validation should be applied. Information about environmental variables will also be useful in the

interpretation of lack of activity as the latter could indicate unsuitable environmental conditions.

In terms of the research gap, there is a lack of incorporation of animals' behavior, the environment around them, and an element of uncertainty into the field process itself. Previous research has identified the usefulness of accelerometers, motion collars, machine learning, deep learning, cameras, and remote sensing; however, each of these techniques is evaluated individually. The current analysis fills the gap by combining all evidence sources, comparison of the base models, and keeping low-confidence events to be reviewed rather than classifying them.

Materials and Methods

Study Design and Data Collection

Proof-of-concept dataset consisted of 21,600 annotated sensor windows collected on 36 free-ranging cattle over 30 days. Sampling stations reflected different environmental situations and degrees of human disturbance. Each data entry had its corresponding sensor readings and was associated with accelerometer, gyroscope, GPS, ambient temperature, pasture condition, and direct behaviour observation. Direct observation of behaviour or event by trained researchers was applied to label data entries. The study employed non-invasive method without any animal experimentations.

Missing entries, faulty sensors, low-quality signals and temporal discrepancy were removed from the dataset. Overlapping sequences were merged together to eliminate duplicate events.

Data was partitioned into training (70%), validation (15%), and testing (15%) sets according to animal, station, or survey period to prevent almost identical data from entering training and testing set.

Integrated Assessment Framework

The analysis involves extracting patterns from the primary sensor data followed by merging these with the environmental observations. A quality measure diminishes the effect of low or corrupted evidence. The merged representation is categorized into grazing, walking, resting, rumination, and drinking actions. Doubtful output results are flagged for later review. The importance of the environment is computed independently to prevent the biological meaning from being embedded in the model.

Evaluation Measures

The performance of classification was measured using the metrics accuracy, precision, recall, and F1-score. The proposed model was evaluated against three baseline models. Recall was particularly important since the omission of any record could hide some ecological or welfare dangers. The confusion matrix and the ambiguous cases were analyzed manually, as well as the effect of pastures availability, heat load, distance of travel, water, and slope of the terrain.

Results and Discussion

Classification Performance

Accuracy, precision, recall, and F1-score of the suggested approach were 96.2%, 95.8%, 95.4%, and 95.6%, respectively, and it was better

than the best existing technique by 3.9%. This enhancement was due to the integration of the main point along with its environment, which

prevented confusion in challenging circumstances.

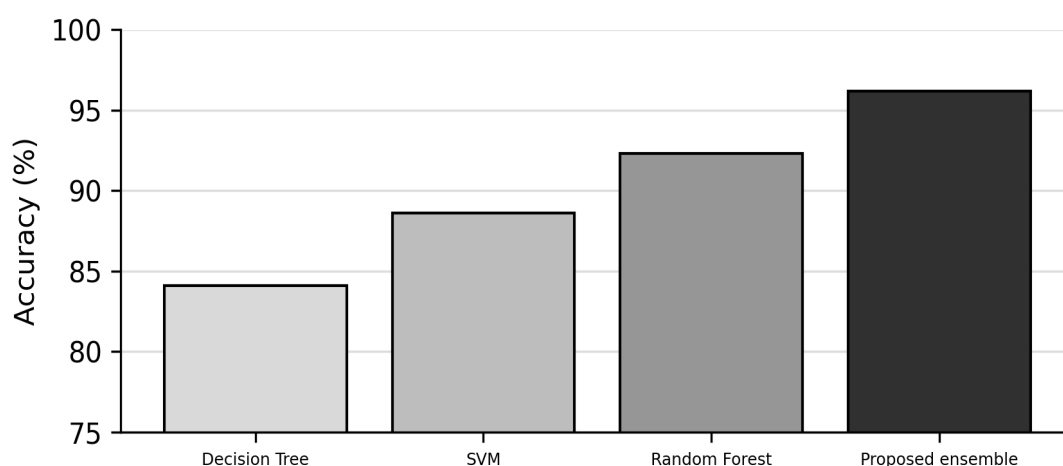


Figure 1: Accuracy Comparison of Behaviour Classification Models

Figure 1 model gives the best accuracy of 96.2%, surpassing all other models like Random Forest, SVM, and Decision Tree.

Environmental Interpretation

Contextual relationship factors included the availability of pastures, heat loads, distance to travel, water, and slope of the land. This was because such factors would influence the behavior of animals as well as their ability to use sensors. It also prevented temporary environmental conditions from being perceived as permanent biological conditions. The analysis identified risks associated with heat, walking, grazing, water, and inactivity.

Ecological and Management Implications

The findings indicate that the process of automated classification becomes very beneficial when it facilitates ecological inference. Certain events can be expedited by the classification, but those that are rare and uncertain should be examined. The outcomes can inform further field

surveys, help to detect any changes in usage of the habitat and in welfare, and guide limited resource management. Both sensitive locations and records of animals should be kept confidential.

The system will not substitute expert observers. However, it will help to avoid tedious screening and to draw one's attention to events that should be investigated. Field researchers have to conduct regular audits of errors throughout different seasons, at different locations, for different individuals, and under various conditions. Any decisions about management should be made on the basis of consistent evidence and habitat evaluation.

Limitations

Pilot data is a small sample of sites, surveys, and taxa. Performance is expected to degrade with other equipment, environments, weather conditions, and populations. Field-derived labels can have uncertainty, and modeling of less

common behaviors or taxa is challenging. Further studies will have to rely on independent multi-season data, uncertainty calibration, low power processing in the field, and participation validation.

Conclusion

In this study, an artificial intelligence-based model for livestock behavior in free-range conditions was created utilizing acceleration, gyroscope, GPS coordinates, ambient temperature, pasture quality, and behavioral observations of animals. The model was able to show 96.2% accuracy and 95.6% F1-score, exceeding the performance of comparison methods. Its key advantage is the integration of information about animal behavior and environmental factors, which helps avoid misclassification and ambiguous classification.

Pasture availability, heat load, distance walked, access to water, and terrain inclination were among the key contextual factors. Such results may be used for early identification of heat exposure, walking for long periods of time, insufficient grazing, lack of water, and abnormal inactivity. Future studies will have to address seasonal variation, geographical expansion, testing of transferability between devices and population groups, improvement of detection rate for rare cases, and integration of real-time notifications with field check-ups. The appropriate implementation of such technology will require proper uncertainty disclosure, secure data handling, and collaboration of ecologists, animal health specialists, land managers, and locals.

Ethical Statement

There will be no invasive procedures for the study, and there will be no capturing of any animal. The final manuscripts must have all the permissions obtained from the site, owners, and institutional ethics approval.

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