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Predictive analytics of cattle behavior using machine learning techniques: A case study

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Abstract:
Livestock management is a critical aspect of agricultural sustainability and food security. Today, there is a pressing need for advanced tools in cattle behavior analysis to improve livestock welfare and productivity. We aimed to enhance cattle behavior classification by using accelerometers fitted in wearable collars. Deep learning techniques were employed to classify behavioral patterns in cattle such as feeding, moving, and lying. Ultimately, our study sought to improve livestock management practices, including the monitoring of health and overall well-being.
The study was conducted in a local barn, where cattle were outfitted with specially designed collars with accelerometer sensors. These sensors recorded intricate movements, facilitating the collection of comprehensive behavioral data. Deep learning algorithms were used to process and analyze the accelerometer data, enabling precise classification of various behaviors exhibited by the cattle.
Our results showed the effectiveness of AI-driven classification techniques in distinguishing cattle behaviors with a high degree of accuracy. Our findings underscore the potential of deep learning techniques in optimizing livestock management practices.
This research significantly advances livestock management by offering a simple continuous monitoring solution for cattle behavior. Deep learning techniques not only enhance our understanding of cattle behavior but also pave the way for intelligent systems that empower farmers to make informed decisions. By promoting healthier and more productive livestock, this research contributes to the broader goal of enhancing global food security and sustainability in the livestock industry.

Keywords: Precision agriculture, food security, livestock farming, cattle veterinary, accelerometer data, behavior classification, Convolutional Neural Networks

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INTRODUCTION

Monitoring livestock behavior is a critical aspect of modern livestock management [1], offering a valuable means to detect health issues and ensure the overall well-being of the animals [2]. Cattle, like other domesticated livestock, exhibit distinct behavior patterns that can serve as early indicators of health problems [3]. Changes in behavior, such as reduced activity, changed feeding habits, or abnormal movements, can often signal underlying health issues [4], including illness, stress, or discomfort [5]. Recognizing these deviations in real-time is crucial, as it allows for timely intervention and veterinary care [6], potentially preventing the spread of diseases and reducing treatment costs [7]. By leveraging technology, such as accelerometer sensors, and employing artificial intelligence techniques, we can gain a deeper understanding of cattle behavior [8] and develop predictive models to promptly identify deviations from normal behavior [9].

Studies have successfully collected and analyzed data from cattle to identify and differentiate various behaviors such as standing, lying, walking, grazing, and ruminating [10]. This data provides valuable insights into animal activity patterns, time budgets, and potential health issues [11].

Machine learning algorithms have been employed to classify cattle behaviors [12] with high accuracy. These algorithms learn from labeled datasets, where video scene data is associated with specific behaviors based on visual observations or video recordings [13].

Integrating accelerometer data or other sensors, such as GPS, gyroscopes, and magnetometers, can further enhance the accuracy and range of behavior classifications [14]. This allows for monitoring finer movements, tracking location, and identifying specific behaviors such as eating, drinking, and social interactions [15].

Accurate behavior monitoring helps optimize feeding, milking schedules, and environmental conditions, thus ultimately improving animal welfare, productivity, and profitability [16]. However, there are a number of challenges such as long-term sensor durability, data processing limitations, and ethical considerations [17].

Research on deep learning architectures and multimodal data fusion can improve accuracy and provide deeper insights [18]. The development of low-cost, lightweight, and long-lasting sensors will facilitate wider adoption [19]. Integrating behavior monitoring with precision livestock farming systems can further optimize resource allocation and improve overall farm management [20].

The emergence of deep learning has further revolutionized the field of cattle behavior recognition. Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in extracting complex patterns from sensor data [21], leading to significant improvements in accuracy and performance. Notably, CNN models achieved 98% accuracy in classifying animal behaviors, highlighting the power of deep learning for analyzing more diverse activity patterns [22]. Additionally, using Long Short-Term Memory (LSTM) networks for analyzing time-series data proved highly accurate in identifying specific feeding behaviors [23], showcasing the potential of deep learning for exploring nuanced behavioral patterns.

Researchers have already explored the integration of video recordings, vocalizations, and physiological signals, to gain a comprehensive understanding of animal behavior and health [24]. This multimodal approach offers opportunities to analyze intricate aspects of well-being beyond simple activity levels. For instance, a study combined accelerometer and video data to identify lameness in dairy cows with 95% accuracy, which demonstrated the potential of this combined approach for detecting specific health issues [25]. Similarly, other researchers used acoustic signals and machine learning to detect respiratory diseases in cattle with 97% accuracy [26], highlighting the potential of analyzing vocalizations for early disease identification.

Several commercial solutions are now available that leverage the power of AI-driven behavior analysis to improve livestock management practices. These systems, such as Mootral, SmaXtec, and Calibrate, offer farmers real-time insights into animal activity, enabling them to optimize feeding schedules, monitor health, and improve overall well-being. This commercialization of AI technology signifies its growing impact on the livestock industry and its potential to revolutionize farming practices.

In this study, we used accelerometer sensors instead of video scenes for cattle behavior monitoring. Accelerometer sensors offer distinct advantages over video cameras. They provide non-intrusive, continuous monitoring of cattle behavior in real-time, capturing subtle changes and patterns without the need for extensive data storage. With lower power consumption, easy deployment, and reduced sensitivity to environmental conditions, accelerometer sensors are particularly suitable for outdoor settings. Focused data collection and the absence of visual images mitigate privacy concerns, making accelerometer sensors well-suited for agricultural and research applications. Additionally, they can be easily attached to cattle, allowing for efficient and cost-effective monitoring, especially in remote areas. Unlike monitoring through video scenes, accelerometer sensors do not require a lot of equipment and processing power. While accelerometer sensors excel in certain aspects, the choice between them and video cameras ultimately depends on the specific goals and requirements of the monitoring system.

Transforming raw data generated by accelerometer sensors into accurate predictions of actual behaviors in cattle involves several key steps. Initially, data is collected through wearable accelerometers which record motion and activity patterns. This raw sensor data is then preprocessed, which includes cleaning and filtering, to remove noise and ensure data quality [27]. The second step is extraction, where relevant characteristics of the data are identified and quantified, such as acceleration patterns during different activities [28]. Once the feature set is prepared, machine learning models, which often include supervised learning algorithms, are trained on labeled data by associating sensor readings with known cattle behaviors. The trained models are then applied to unlabeled data to predict behaviors in real-time. Regular model evaluation and refinement are crucial to enhance predictive accuracy and adapt to changing cattle behaviors or environmental conditions [29]. Finally, the predictions are translated into actionable insights for livestock managers, helping them make informed decisions for better cattle care and management practices [30].

We aimed to investigate the feasibility of using accelerometer data to automatically classify cattle behavior using the power of AI. Accelerometers are relatively inexpensive and non-invasive sensors that can be easily attached to cattle collars. This makes them a promising tool for continuous monitoring of cattle behavior [31]. By analyzing the acceleration patterns in cattle, we can identify distinct behavioral patterns associated with different activities, including feeding, ruminating, moving, and lying [32]. This information can be used to improve animal welfare, productivity, and health [33]. For example, by monitoring feeding patterns, we can identify cows that may be underfed or have feed of poor quality [34]. Additionally, by monitoring rumination time, we can identify cows that may be suffering from digestive problems [35]. Finally, by monitoring moving and lying patterns, we can identify cows that may be lame or stressed [36].

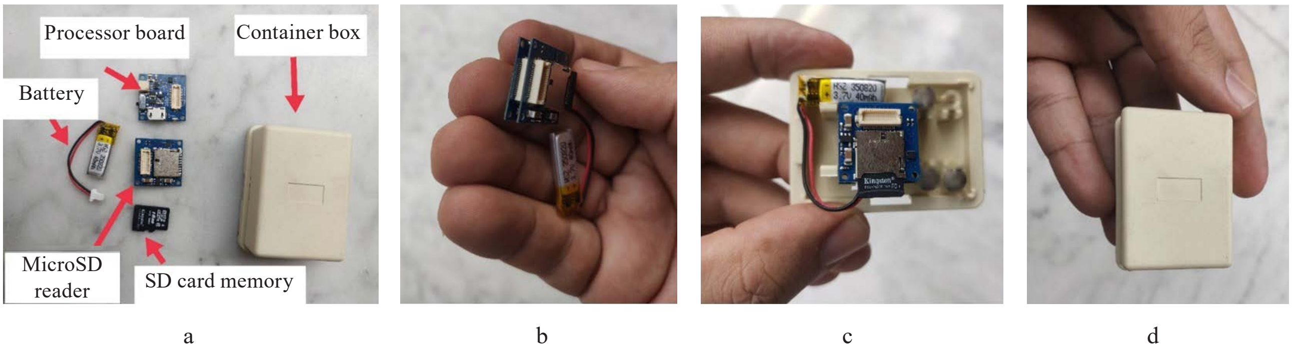


Figure 1 Data collection device components (a), the processor board and the MicroSD reader (b), the setup in the container box (c), and the closed container box (d)

Accelerometer-based monitoring systems have extensive potential applications [37]. They can significantly improve cattle welfare, productivity, and health [38], contributing to enhancing global food security [39].

STUDY OBJECTS AND METHODS

Data collection. We collected data in a local barn in the suburbs of Marrakesh city (Morocco) from 03 to 08 October 2023. There, six cows of multiple breeds were equipped with collars containing accelerometer sensors. These sensors recorded the acceleration and movement patterns of the cattle for five days. The cows moved freely while being filmed and the data was collected over this specific period to capture various behaviors such as moving, feeding, and other essential activities.

A small accelerometer and a data logger were employed for gathering cattle movement data. Specifically, we used a Tiny Zero processor board equipped with an Arduino-compatible microcontroller featuring a SAMD21 processor. The board included a Bosch BMA250 3-axis accelerometer. A Tiny Circuits MicroSD shield was used as a data logger. It stored data on a 16 GB MicroSD card, streamlining data collection. As a power source, we used a 290-mAh Tiny Circuits lithium polymer battery with compatible connectors.

The Tiny Zero processor board, which is central to the device's operation, offers a USB connectivity port, power management, and a battery charging capability in a compact 20×20-mm form. Also, the device features an accelerometer that integrates the low-power Bosch BMA250 3-axis accelerometer into the board without increasing its size. All 20 IO pins are readily available for use, making it a versatile platform for data collection.

This ultra-compact, lightweight, low-power, and cost-effective accelerometer is specifically tailored for our cattle behavior research. Its key features include a weight of less than 3 grams (excluding the battery and the box), a battery life ranging from 2 weeks to 1 month, and a total cost of under 60 United States dollars (USD). The device is constructed from easily attainable components and offers room for customization within the Arduino ecosystem. Figure 1 shows the components of this data collection device.

Figure 2 The data collection device attached to an adjustable neck-mounted collar (a) and its length (b)

Assembling the device is a straightforward process: the MicroSD shield is attached to the Tiny Zero processor board through the white connectors, the battery is connected to the designated battery connector on the processor board, and the MicroSD card is inserted into the SD slot on the MicroSD shield. When assembled, all the components are securely fixed inside the container plastic box.

The data collection devices with accelerometer sensors were attached to neck-mounted collars (Fig. 2).

Barn layout. The layout of the barn used for this study played a crucial role in the data collection process and in the interpretation of the observed cattle behaviors. The study took place in a rectangular barn with a total area of 600 square meters. The interior was divided into three sections: a freestall area housing 6 cows in individual stalls, a 200-square-meter runway for additional movement and interaction, and a dedicated feeding and watering area. Artificial lighting provided consistent brightness throughout the day. A ventilation system maintained the air quality and prevented overheating, which was particularly important during hot weather. Non-slip rubber matting covered the freestall area and runway for comfort and traction, while the feeding and watering area had a concrete floor for easy cleaning.

The layout encouraged linear movements between the stalls and the feeding area, facilitating data collection.

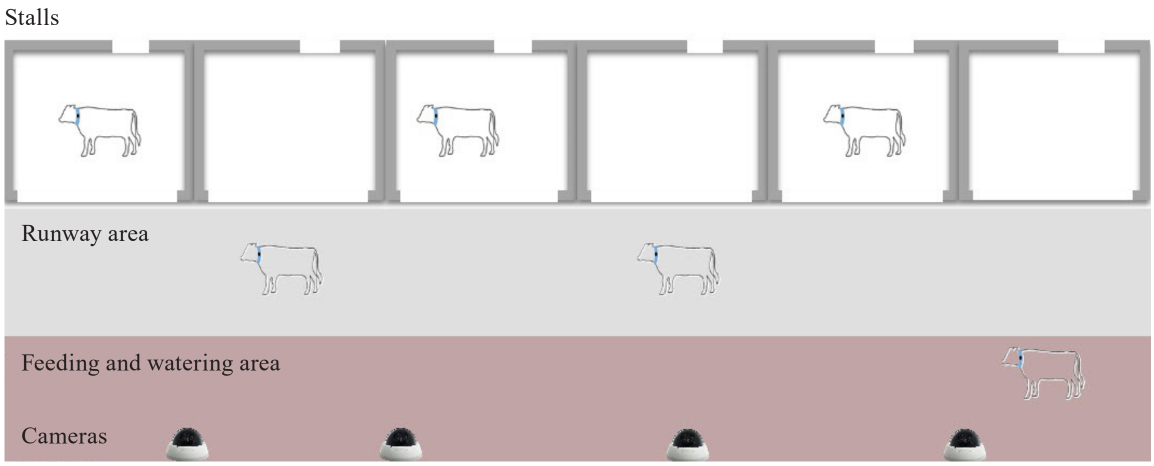
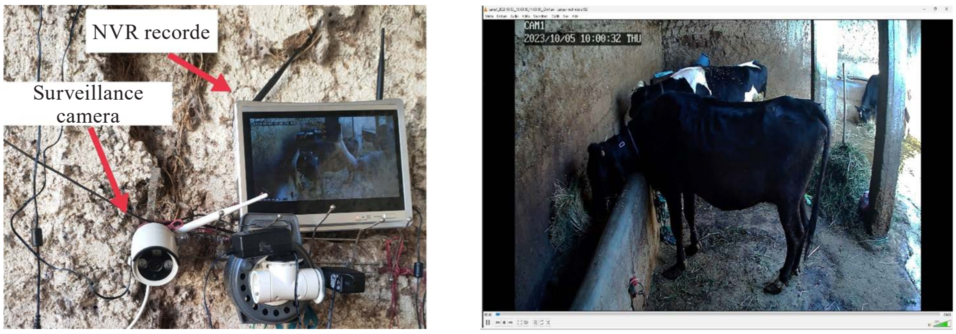


Figure 3 The overall layout of the barn



a　　b

Figure 4 Surveillance camera system components (a) and a screenshot from a recorded video file (b)

Figure 5 The three-axis neck-mounted accelerometer-based collar

The runway and the feeding area provided opportunities for social interactions important for mental health and natural behaviors. The comfortable stalls with mattresses encouraged lying down, providing ample data for identifying lying behavior patterns. The feeding area offered easy access to both hay and grain, allowing for efficient data collection on feeding duration and frequency.

While the barn size may have limited the range of observed movements and interactions, the controlled environment and carefully designed layout facilitated accurate and efficient data collection. Figure 3 shows the overall layout of the barn.

Surveillance system. For cattle surveillance, we used a HeimVision HM243 camera system kit consisting of four wireless cameras recording at 1080pixeis resolution, with a 110° angle of field and a night vision range of 50 ft. The Network Video Recorder (NVR) had a 12-inch monitor with a 500 GB hard drive for recording video scenes (Fig. 4). The cameras were set up to capture cattle behavior from different angles and record it 24 hours a day. Every camera generated a video file each hour and the NVR device saved it in the imbedded hard drive.

Accelerometer sensors. The data collection devices attached to the collars were mounted very tightly to the necks of the cows to ensure proper functioning of the accelerometers. Additionally, a counterweight was incorporated to guarantee the stability of the accelerometer. The data collection devices with three-axis accelerometers were fixed to the left side of the neck (Fig. 5). The X-axis sensed vertical (down-up) movement, the Y-axis detected horizontal (left-right) motion, and the Z-axis perceived forward-backward motion. The collars were worn by six cows for five days, with the tri-axial accelerometer set recording data at 10 Hz, 10 data points per second.

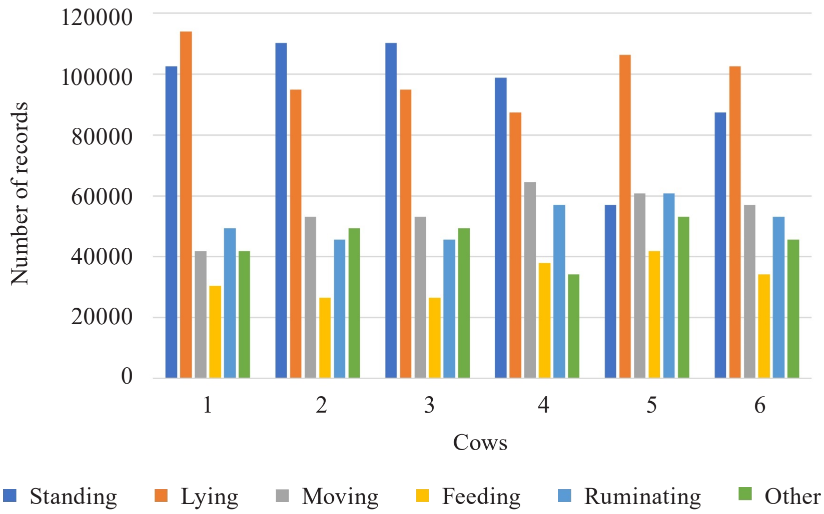


Figure 6 The frequency of recorded behaviors for each cow

Data labeling. The data was collected from the accelerometer sensors for five days (120 h per animal). Then, we selected 10 hours per each animal from 9 a.m. to 7 p.m. on those days when the cows displayed high activity and multiple behaviors. Our observations were meticulously recorded for each individual animal using the surveillance camera system. After retrieving the collars and uploading the data at the end of the trial, we used these recorded observations to label the corresponding accelerometer data.

For annotating the data, six observers were responsible for documenting the behaviors of the cows. Each observer was assigned to monitor one cow throughout the specified period, and the cows were observed sequentially. Five distinct behaviors were recorded: feeding, lying, standing, moving, and ruminating. Any behaviors not falling within these predefined categories (such as drinking, grooming, scratching, defecating, and urinating) were categorized as "other".

The labeling process presented certain challenges and was a labor-intensive task. Particularly, identifying rare behaviors could prove challenging, as they occurred infrequently and might easily be overlooked even by experienced observers. Additionally, distinguishing between periods of resting and rumination was often difficult, as there were instances of short resting episodes occurring during rumination, and vice versa, which were not always distinctly discernible. Furthermore, during periods of resting or rumination, whether standing or lying, cattle would occasionally exhibit subtle movements, such as head motions, ear flicks, or muscle twitches, which we meticulously observed and categorized as "other" behavior.

Dataset. We created a labeled dataset to classify cattle behavior by using the labeled accelerometer data. Particularly, we recorded the acceleration data from the 3-axis MEMS accelerometer at 10 Hz, with 10 data points per second. Each labeled segment represented a continuous period during which the cattle displayed a specific behavior.

Table 1 The total number and percentage of records for each behavior class

Behavior	Records	Percentage, %
Standing	524334	23
Lying	615522	27
Moving	341958	15
Feeding	205176	9
Ruminating	319158	14
Other	273564	12

Table 2 Dataset CSV file columns

Column Name	Description
Timestamp	The recorded date and time of the data are provided in ISO 8601 format
X	The acceleration measured in the x-direction
Y	The acceleration measured in the y-direction
Z	The acceleration measured in the z-direction
Classification	Behavior classification as labeled based on video scenes

Our choice of a window size of 10 data points per second was primarily guided by existing literature and our experimentation with various window sizes. This particular window size appears adequate for highlighting subtle distinctions between the considered behavior classes. Figure 6 shows the frequency of recorded behaviors for each cow. The total number and percentage of records for each behavior class is shown Table 1.

Every animal was given a distinct identifier XX ranging from 01 to 06. The generated accelerometer data was stored in CSV format in separate files named data-XX.csv, where XX represented the specific animal identifier. Each file consisted of four columns organized as shown in Table 2.

Data preprocessing. Raw data can be noisy and contain artifacts that can interfere with the performance of the Convolutional Neural Networks (CNNs). Therefore, the raw accelerometer data was preprocessed to eliminate noise, filter out outliers, and convert it into a format suitable for deep learning. The preprocessing steps included filtering, segmentation, normalization, data augmentation, and feature extraction.

Filtering is used to remove noise and other unwanted signals from the data. For example, a high-pass filter is used to remove low-frequency signals such as drift, while a low-pass filter is used to remove high-frequency noise. For this purpose, we chose a median filter. This type of filter is effective in removing noise while preserving the overall shape of the signal.

Segmentation is used to divide the data into smaller, more manageable chunks. It is helpful for CNN models, which are typically trained on batches of data. We applied sliding window segmentation that divides the data into overlapping windows of a fixed length. This is a common approach for time series data, as it allows the CNN model to learn from both the current data point and the previous data points.

Normalization is used to scale the data so that all the features have a similar range of values. This can help the CNN model to learn more effectively. For this reason, we chose standard score normalization. This type of normalization subtracts the mean from each data point and then divides it by the standard deviation.

We used a data augmentation technique called temporal jittering. This technique involves randomly shifting the data in time. It helps improve the robustness of the CNN model to noise and variations in the data.

Feature extraction is used to extract meaningful features from the data. This helps the CNN model to learn more complex patterns in the data. For that, we extracted both time domain and frequency domain features. Time domain features are calculated directly from the accelerometer data, such as the mean, standard deviation, as well as maximum and minimum values. Frequency domain features are calculated from the Fourier transform of the accelerometer data, such as the power spectral density and the dominant frequency.

Once the data was preprocessed, we fed it to the CNN model for classification purposes. The details on the data collection, labeling, preprocessing, and behavior classification phases are shown in Fig. 7.

Behavior classification. We developed an advanced Convolutional Neural Network (CNN) model architecture to classify cattle behavior (Table 3). The choice of an architecture for a particular application depends on the specific dataset and requirements. The kernel sizes and stride lengths can be adjusted to extract different levels of features from the accelerometer data. The number

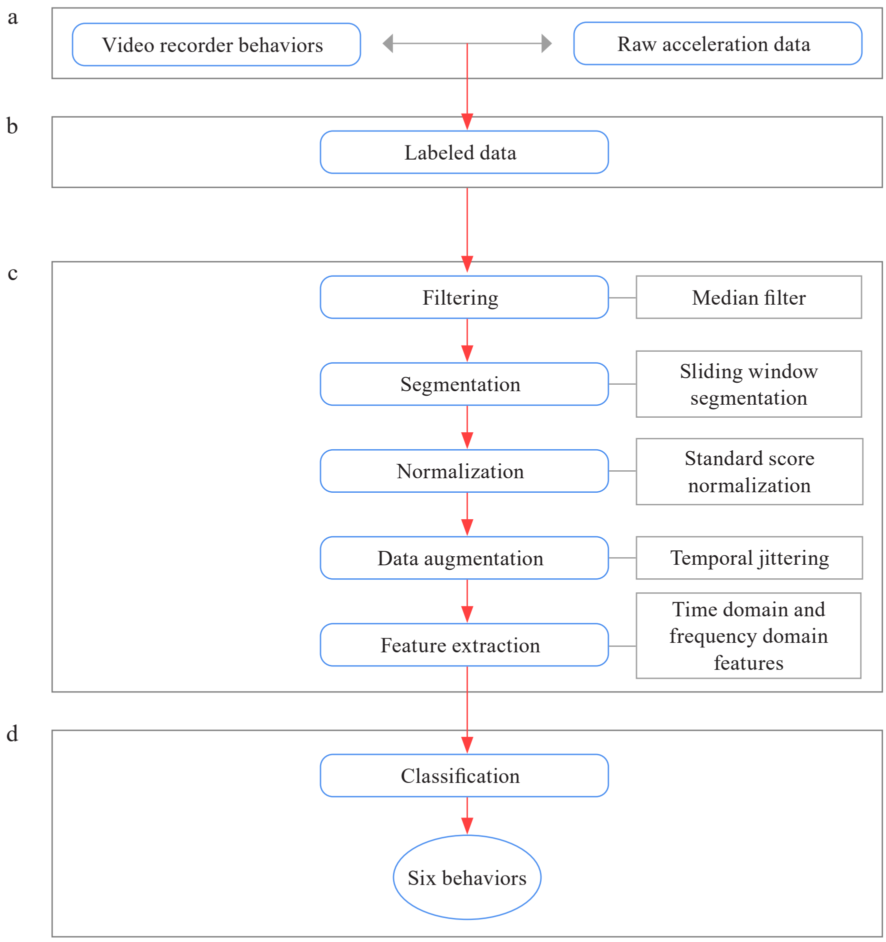


Figure 7 Data collection phase (a), data labeling phase (b), data preprocessing phase (c), and behavior classification phase (d) Segmentation

Table 3 CNN model architecture

Layer	Configuration	Output Shape
Input	(36000, 3)	(36000, 3)
Conv1D_1	filters: 320	(36000, 320)
BatchNorm_1		(36000, 320)
Activation_1	ReLU	(36000, 320)
MaxPooling1D_1	pool_size: 2	(18000, 320)
Conv1D_2	filters: 205, 120	(18000, 205, 120)
BatchNorm_2		(18000, 205, 120)
Activation_2	ReLU	(18000, 205, 120)
MaxPooling1D_2	pool_size: 2	(9000, 205, 120)
Flatten		(1846, 400)
Dense_1	units: 1024	1024
BatchNorm_3		1024
Activation_3	ReLU	1024
Dropout_1	dropout: 0.5	1024
Dense_2	units: 512	(512)
BatchNorm_4		(512)
Activation_4	ReLU	(512)
Dropout_2	dropout: 0.5	(512)
Output	units: 6	(6)

of convolutional layers and dense layers can also be adjusted to achieve the desired trade-off between accuracy and complexity. The dropout layers can be used to reduce overfitting. The Softmax activation function is used in the output layer to produce a probability distribution for each of the target classes.

Input represents the input layer with a shape (sequence_length, num_channels), where sequence length is the length of the time series data, and num channels is the number of channels in the input data. Conv1D is the convolutional layer with a specified number of filters. BatchNorm is a batch normalization layer to normalize the activations of the previous layer. Activation is the activation function, typically ReLU (Rectified Linear Unit). MaxPooling1D is the max pooling layer to down-sample the spatial dimensions. Flatten is used to flatten the input to a one-dimensional tensor. Dense is a fully connected layer with a specified number of units. Dropout is a dropout layer to prevent overfitting by randomly setting a fraction of input units to zero during training. Output is the output layer with the number of units equal to the number of classes for classification.

Performance evaluation. To evaluate the Convolutional Neural Network (CNN) model for cattle behavior classification, we used the Accuracy, Precision, Recall, and F1-score metrics, as defined in Table 4.

TP is the true positive, TN is the true negative, FP is the false positive, and FN is the false negative values.

In addition to the above metrics, we also tested our model using a confusion matrix. The confusion matrix shows the number of correct and incorrect predictions for each class. It can be used to identify any classes that the model is struggling to classify correctly.

RESULTS AND DISCUSSION

Our experiments demonstrated that deep neural networks, particularly Convolutional Neural Networks (CNNs), outperformed other algorithms in classifying cattle behavior [40]. Our CNN-based model achieved an overall accuracy of 97.99% in distinguishing different behaviors. Figure 8 shows the model performance during training and validation for 30 epochs.

Our results proved that the current model can be used as a real-time monitoring system that can process accelerometer data and provide instantaneous feedback on cattle behavior. This system can be integrated into the farm's infrastructure, enabling farmers to make informed decisions promptly. Table 5 shows the results of the evaluation metrics for each class.

According to the confusion matrix (Fig. 9), the model was good at classifying the cattle that were lying, moving, or standing. However, it was more likely to misclassify the cattle that were ruminating or feeding. This might be because these behaviors are more similar to each other than they are to the other behaviors.

The use of AI-driven approaches, specifically CNNs, to classify cattle behaviors based on accelerometer data presents a significant advancement in the field of precision livestock farming. Our results indicate a high level of accuracy indistinguishing between distinct behaviors such as standing, lying, moving, feeding, ruminating, and others, showcasing the potential of this technology for real-time monitoring of cattle activities in a barn environment.

The success of our CNN-based model in accurately classifying cattle behaviors is a testament to the robustness of deep learning algorithms in capturing complex patterns inherent in accelerometer data. The model's ability to differentiate these fundamental behaviors is crucial for understanding the daily activities and well-being of cattle, providing valuable insights for herd management and animal welfare.

However, a notable challenge emerged in the classification of feeding and ruminating behaviors. The model demonstrated a higher likelihood of misclassifying these behaviors, which can be attributed to the inherent similarities between them. Feeding and ruminating share common movement patterns and postures, making it more challenging for the algorithm to distinguish between

Table 4 Evaluation metrics

Evaluation metric	**Definition**	Equation
Accuracy	The percentage of predictions that are correct.	(TP + TN) / (TP + TN + FP + FN)
Precision	The percentage of positive predictions that are correct.	TP / (TP + FP)
Recall	The percentage of all positive cases that are correctly identified.	TP / (TP + FN)
F1 score	A harmonic mean of precision and recall.	2* (Precision * Recall) / (Precision + Recall)

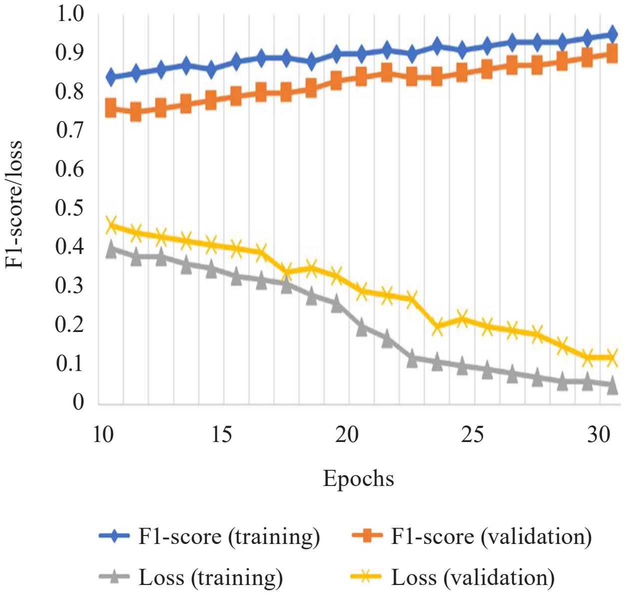


Figure 8 Model performance during training and validation

Table 5 Model performance indicators

Class	Accuracy, %	Precision, %	Recall, %	F1 score, %
Standing	99.20	99.50	99.00	99.91
Lying	99.30	99.80	99.91	96.98
Moving	99.00	99.10	96.14	99.86
Feeding	94.03	94.10	94.30	94.36
Ruminating	97.05	97.30	97.42	97.53
Other	99.35	96.55	99.22	99.83

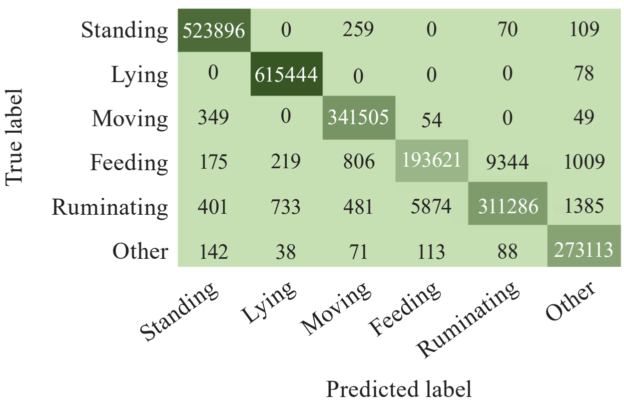


Figure 9 Confusion matrix

them accurately. This suggests that further refinement of the model may be necessary, potentially incorporating additional features or fine-tuning the network architecture to enhance the discrimination between these closely related behaviors.

One potential avenue for improvement could involve incorporating temporal information into the model. By considering the sequential nature of cattle behaviors, the model may gain a better understanding of the transitions between feeding and ruminating, improving its ability to discern subtle differences. Additionally, a larger and more diverse dataset, including variations in feeding and ruminating behaviors, could contribute to a more comprehensive training of the model, potentially addressing the observed misclassification.

Despite the challenges encountered in specific behavior classifications, our study highlights the overall efficiency of AI-powered approaches in cattle behavior monitoring. The implementation of wearable accelerometer devices offers a non-invasive and continuous monitoring solution, providing farmers and researchers with valuable insights into the daily activities and health status of individual animals within a herd. These devices are much better than video cameras, which require continuous monitoring, use a large bandwidth, and need a lot of processing power.

Deep learning models enable continuous monitoring of animal behavior, providing a comprehensive understanding of activity patterns and potential changes. This eliminates the need for manual observation and reduces subjectivity in data collection.

AI-based solutions can be easily scaled to monitor large herds of cattle, which makes them ideal for commercial farms and large-scale operations.

By continuously tracking behavior patterns, AI models can identify subtle changes indicative of health problems or stress. This enables early intervention and treatment, potentially improving animal welfare and preventing significant losses.

Insights gained from behavior analysis can be used to optimize feeding schedules, housing conditions, and other management practices. This can ultimately improve production efficiency and food security in addition to animal well-being.

Overall, our findings underscore the potential of AI-powered classification using wearable accelerometer devices in enhancing the understanding of cattle behaviors. While the model excels in distinguishing between certain activities, addressing the challenges associated with subtle behavioral nuances, such as feeding and ruminating, remains an area for future research and refinement. As technology continues to evolve, the integration of advanced machine learning techniques holds promise for revolutionizing precision livestock farming and promoting the welfare of cattle in agricultural settings. The ability to monitor cattle behavior in real-time not only enhances animal welfare but also increases the farm's efficiency. This technology can aid in detecting health issues, optimizing feeding schedules, and reducing labor costs.

CONCLUSION

In this study, we presented an innovative approach to classifying cattle behavior based on accelerometer data collected from the collars equipped with specialized sensors. Machine learning techniques, particularly deep neural networks, proved to be highly effective in accurately classifying different behaviors. These techniques have significant potential for real-time monitoring and decision support in cattle farming. As we continue to refine and expand this technology, it promises to revolutionize the way cattle farming is conducted, benefitting both animals and farmers.

CONTRIBUTION

The authors were equally involved in writing the manuscript and are equally responsible for plagiarism.

CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this article.

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This study is an integral part of an ongoing research on digital agriculture conducted collaboratively by a team of experts affiliated with the LIMATI Laboratory at Sultan Moulay Slimane University in Morocco.

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