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Ph.D. Thesis

FARMS OF THE FUTURE: INNOVATION THROUGH IOT AND AI IN PRECISION LIVESTOCK FARMING

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This dissertation represents the culmination of a period filled with challenges, growth, and achievements, made all the richer by the exceptional individuals who have been by my side throughout this chapter of my life. As I reach the conclusion of my Ph.D., I find myself reflecting on the many people who have played a crucial role in helping me arrive at this point.

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ABSTRACT

The rapid growth of the global population has significantly increased the demand for food, necessitating improvements in the efficiency and sustainability of livestock farming systems. Traditional intensive farming practices, marked by high stocking densities and poor living conditions, often cause substantial stress to animals, making them more susceptible to diseases. This scenario raises ethical concerns and affects the long-term sustainability of food production systems. Recent societal and regulatory shifts, particularly within the European Union, have emphasized the importance of animal welfare and sustainable agricultural practices. The European Green Deal and Farm to Fork Strategy highlight the need for innovative food systems that reduce resource use, lower greenhouse gas emissions, and protect biodiversity while maintaining high animal welfare standards. In response to these challenges, this dissertation explores the potential of automated monitoring technologies, such as Internet of Things (IoT) devices and Artificial Intelligence (AI), to transform livestock management. Through the deployment of miniaturized IoT devices, advanced camera systems, and sophisticated AI algorithms, it is possible to achieve continuous monitoring of animal health, early disease detection, welfare assessment, behavioral observation, and individual animal identification with minimal human intervention. These technologies not only improve compliance with EU regulations but also address the ethical and environmental issues associated with traditional livestock farming methods. The thesis begins with a thorough overview of sensor-based automatic monitoring systems, focusing on their application in extensive farming environments. It details the current technological landscape, including various device types and data processing techniques. Subsequently, the thesis presents a series of case studies based on experimental trials conducted during the PhD program, offering practical insights into the real-world application of these technologies. This section also examines the ongoing challenges in the field, such as optimizing energy efficiency, ensuring data accuracy, and enhancing network reliability, while suggesting potential avenues for future research. In the final part, the focus shifts to indoor livestock farming, exploring the increasing use of monitoring systems based on computer vision techniques. This part investigates the application of Continual Learning methods to video data for action recognition, proposing innovative adaptations of these methods, traditionally employed in image classification, for video analysis. Overall, this dissertation advances the field of livestock monitoring by integrating cutting-edge technologies with methodological approaches. It provides a solid foundation for developing more effective, reliable, and scalable solutions in the agricultural sector, supporting the transition to more sustainable and welfare-focused farming practices.

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CHAPTER

ONE

MOTIVATIONS AND OBJECTIVES

The escalating global population has precipitated a commensurate surge in food demand, necessitating enhanced efficiency within livestock farming systems. The preponderance of animal-derived products available in mass retail outlets originates from intensive farming environments characterized by overcrowding and sub-optimal conditions, which induce significant animal stress. A wealth of research underscores the heightened susceptibility of stressed livestock to disease, emphasizing the imperative for proactive health monitoring to facilitate early disease detection and welfare improvements. Furthermore, the ethical and environmental implications of livestock farming have come under increasing scrutiny, driving a need for more responsible and sustainable practices. The welfare of animals in farming systems has become a central concern, with society demanding higher standards of care and transparency. At the same time, the environmental impact of livestock production, particularly in terms of resource use, greenhouse gas emissions, and land degradation, has raised significant questions about the long-term viability of current farming practices. In this context The EU has been at the forefront of promoting higher standards for animal welfare and sustainable agricultural practices, reflecting a growing societal concern for the ethical and environmental impacts of livestock production. This commitment is evident in various EU policies and regulations that aim to ensure the humane treatment of animals, reduce environmental degradation, and promote sustainable farming methods.The European Green Deal and the Farm to Fork Strategy, both central to the EU's agenda, emphasize the need for sustainable food systems that minimize resource use, reduce emissions, and protect biodiversity.

Traditionally, monitoring animal health and welfare has relied heavily on direct human observation and manual data collection. While these methods can provide valuable insights, they are often limited by their labor-intensive nature, the potential for human error, and the sporadic nature of observations. To circumvent the limitations of traditional labor-intensive monitoring practices, automated analysis of livestock has emerged as a pivotal technology. Aligned with the European Animal Welfare Quality Project's emphasis on minimizing human-animal interaction to mitigate disease transmission, automated livestock monitoring encompasses a broad spectrum of applications including health assessment, early disease diagnosis, welfare evaluation, behavioral observation, and animal identification. Leveraging advancements in miniaturized IoT devices, Cameras, and Artificial Intelligence, the landscape of livestock monitoring has been revolutionized through the development of innovative systems. The integration of these technologies into livestock farming not only supports compliance with EU regulations but also represents a proactive response to the ethical and environmental challenges facing the industry.

This dissertation is structured into two main parts, reflecting the activities and projects undertaken during this PhD. The first part focuses on automatic monitoring systems based on sensors, with the study and results stemming from two years of work on the PRIN project 'Smart Dairy Farming' coordinated by Prof. Simona M.C. Porto. It begins with an overview of the state-of-the-art monitoring systems for extensive livestock farming, emphasizing the devices and data processing methods employed. Following this, several case studies conducted during the Ph.D. period are presented, featuring experimental field trials. The conclusion of this part addresses the unresolved challenges in the field and discusses potential future trends.

The second part of the dissertation shifts the focus to monitoring systems for indoor livestock farming, with a particular emphasis on systems based on computer vision techniques. In this part, the application of Continual Learning methods on video data is explored for action recognition. Additionally, techniques are proposed to adapt Continual Learning methods, traditionally used for image classification, to video analysis. The studies and results obtained in the application of Continual Learning on videos are the outcome of activities carried out as part of the Rehastart project (Grant identifier: PO FESR 2014-2020, Azione 1.1.5., n. 08ME6201000222- CUP G79J18000610007) coordinated by prof. Concetto Spampinato.

In conclusion, this dissertation not only contributes to the existing body of knowledge in the field of livestock monitoring systems but also opens up new possibilities for future advancements. By addressing both current technologies and emerging techniques, it lays the groundwork for developing more efficient, reliable, and scalable solutions in the agricultural industry.

Part I

Sensor-based cow automatic monitoring systems

Effective animal monitoring is critical for ensuring the health, well-being, and productivity of livestock, as well as for advancing research in wildlife management and conservation. Traditional monitoring methods, often reliant on manual observation, can be labor-intensive and prone to human error. As such, there has been a growing interest in leveraging technology to automate and enhance the monitoring process.

In this chapter, we will focus on the use of sensors for monitoring animal behavior and health. These sensors, including accelerometers and GPS, provide continuous, objective data that can be analyzed to detect changes in movement patterns, health status, and other vital behaviors.

Chapter 2 will introduce the various monitoring systems available, highlighting the motivations behind their adoption, the most commonly used devices, and the specific behaviors that are typically monitored in current research and industry practices. Furthermore, we will delve into the systems proposed in the literature, with a particular focus on the technologies employed, sampling rates, and the methods used for data collection and processing. This analysis will be conducted separately for accelerometers and GPS, exploring how each technology contributes to a more effective and reliable animal monitoring system.

By understanding the strengths and limitations of these technologies, we aim to provide insights into how sensor-based monitoring can be optimized for different animal species and environments.

CHAPTER

TWO

COW BEHAVIOURAL ACTIVITIES IN EXTENSIVE FARMS

Animal welfare has emerged as a paramount global concern in recent years, as highlighted by the 2004 OIE World Conference on Animal Welfare. The international scientific community is persistently working towards developing a unified and shared definition of animal welfare, and is conducting extensive research to improve conditions throughout the production cycle, from breeding to transportation and slaughter. In particular, significant efforts are underway to develop and validate automated systems for monitoring animal welfare during the breeding phase. Recently, Information and Communication Technology (ICT)-based monitoring systems have been introduced to assess animal welfare at the farm level. These systems offer a wide range of applications, including the certification of welfare levels, the evaluation of housing systems, the diagnosis of individual animal welfare problems, and assistance to farmers in identifying, preventing, and resolving herd-level welfare issues. Consumers, increasingly aware of and attentive to ethical food-related issues, place great importance on animal welfare[36, 29, 45]. Studies have shown that the public views allowing dairy cows to express natural behaviors in natural settings as essential. Understanding the relationship between dairy cattle social behavior and their health, productivity, and welfare, alongside farm managers' and consumers' perspectives on dairy cattle welfare and behavior, is crucial. This knowledge is essential for developing relevant indicators for farmers' decision-support systems and for directing communication about "natural" animal behavior towards downstream chain actors, including consumers. Animal behavior is a clear indicator of an animal's physiological and physical state. Major activities for cows, such as feeding, rumination, lying, and walking, require daily monitoring to evaluate welfare conditions. While visual examination by operators can directly assess cows' behavioral activities, this method is time-consuming and labor-intensive, especially on extensive farms[99]. In precision livestock farming (PLF), ICT-based solutions are being developed and validated to enhance the efficiency of livestock monitoring and management [107]. These modern ICT-based solutions are increasingly effective at collecting vast amounts of data, which, when processed using optimized algorithms, can significantly enhance farmers' ability to efficiently and profitably monitor their herds. he Fourth Industrial Revolution has irrevocably transformed industries and economic landscapes by forging interconnected networks of machines, devices, and humans through cutting-edge technologies. This convergence has laid the foundation for intelligent automation, progressively automating repetitive tasks and redefining the role of human labor. Key components of this revolution include the Internet of Things (IoT), big data and analytics, autonomous robots, and cloud computing [122]. The convergence of IoT systems and advanced AI techniques has accelerated significantly in recent times. Sophisticated AI algorithms are increasingly adept at extracting invaluable insights from voluminous sensor data, unlocking knowledge previously unattainable through traditional analysis. [86, 4]. IoT is rapidly advancing in PLF. IoT-based systems connect computing devices, mechanical and digital equipment, items, animals, or humans to a network, facilitating data transfer without needing human-to-human or human-to-computer interaction [1]. The primary components of an IoT-based system include object identification, sensing, communication, computation, service, and semantics, as depicted in 2.1.

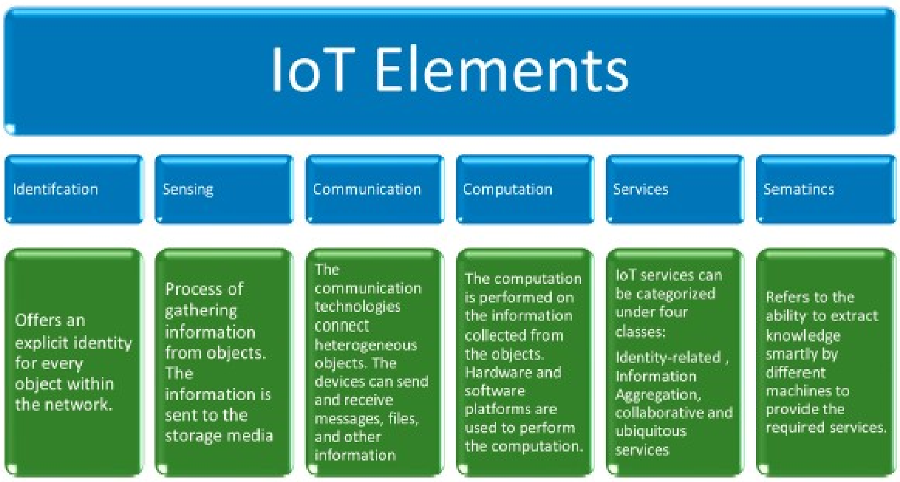

Figure 2.1: *Main elements of an IoT system [1]*

The cattle breeding sector is characterized by high management complexity, attributable to operational protocols that imply a considerable commitment in terms of time, human and economic resources. The assessment of animal welfare and health is traditionally entrusted to visual observation by the staff, although in many production contexts there are high workloads per worker. The three main challenges in efficiently monitoring cow welfare are cost, validity, and timeliness of insights [87]. IoT-based sensors enable the early detection of cow illnesses, allowing farmers to intervene promptly and optimize antibiotic usage, milk production, and veterinary care costs [66]. Consequently, wearable sensors are becoming essential tools for monitoring cows' health and well-being in housed systems. These technologies typically comprise sensor devices that collect data on specific parameters. This data is then processed by software to generate insights, alerts, and recommendations for the livestock producer.[107]. Monitoring changes in cow behavior with IoT-based wearable sensors offers unique insights into the animal's condition and well-being, detecting health and welfare issues, environmental dangers, and changes [42]. Farmers can monitor vital signs, including blood pressure, heart rate, and hormonal levels, along with behaviors like feeding, standing, rumination, and walking [7], and abnormal food and water consumption behaviors [90]. Geo-location data can also be captured and analyzed [28] and by quantifying the duration of specific behaviors, insights into animal health can be derived. During the years, a lots of IoT-based solutions for monitoring cow behavior have been developed, but the focus on intensive housing systems, therefore few research projects have focused on extensive livestock systems. Monitoring grazing animals is challenging due to extensive grazing areas and animals' natural behaviors. The limited human presence in these systems hinders the observation and analysis of atypical behaviors.

This chapter aims to illuminate the technological landscape for monitoring grazing cattle in extensive farming systems. A comprehensive literature review has identified critical challenges, including device battery life, data collection frequency, network coverage, transmission range, and the efficacy of IoT system algorithms in terms of detection accuracy and computational efficiency.[108, 46, 104]. Among the reviewed studies on cattle behavior monitoring, about 80% involved Holsteins, 10% unspecified crosses, Japanese Black Beef Cattle, and Angus, with the remaining 10% unspecified breeds. The average number of animals per study was around 30, though this varied across studies.

2.1 Behavioral Activities Monitoring

Precision Livestock Farming (PLF) offers a potential solution to the challenges inherent in traditional livestock management. PLF, with its focus on ICT-based technologies, provides a means to continuously monitor animals, capturing data on a range of behaviors and physiological parameters. This is particularly advantageous in extensive grazing systems where direct farmer observation is often limited by the vastness of the grazing areas and reduced human-animal interaction. The literature reveals that by leveraging wearable sensors and advanced analytics, various cow behaviors have been monitored, including:

- Locomotion: This is useful for identifying cow fertility, which is indicated by an increase in walking activity [117, 101].

- Feeding: This serves as a good indicator of cow well-being, as unhealthy cows tend to eat less [92]

- Rumination: This is a vital part of the digestive process [43], characterized by continuous rhythmic chewing. This chewing action helps maintain the rumen pH at levels optimal for microbial activity [43].

- Lying: Monitoring the duration of lying can help detect limb abnormalities, as cows that lie down for extended periods without movement may have such issues [6].

Therefore PLF can bridge the gap between traditional management practices and the demands of modern, data-driven agriculture.

2.2 Devices

With the advancement of effective IoT-based technologies, deploying sensor networks in challenging environments, such as barns characterized by dust, lack of power, and internet connectivity, has become feasible. The literature indicates various ICT-based monitoring systems for cows in indoor settings, but their application in extensive grazing farms remains limited. This limitation is likely due to the challenges of using ICT-based monitoring systems in rural areas with typically poor telecommunication network coverage. Moreover, the use of battery-powered wearable sensors can incur significant management and maintenance costs for farmers if the systems are not optimized for energy efficiency [117].

Wearable sensors can collect extensive data, analyze raw data, and alert farmers if cattle behavior deviates from normal ranges [66]. Sensor technologies employed in PLF encompass both invasive and non-invasive approaches[87]. Invasive sensors, often implanted or ingested, capture critical physiological data such as internal temperature. Conversely, non-invasive sensors, attached externally via collars or other devices, monitor animal behavior and environmental conditions including air temperature, humidity, and ventilation.

Invasive sensors provide more accurate data by directly measuring animal health factors but are less commonly used due to their higher cost and potential to stress animals. Non-invasive sensors are more widely used because they are easy to attach, cost-effective, reusable, and cause less stress to animals. Table 2.1 lists major non-invasive sensors used in PLF applications and the aspects of animal behavior they monitor. Cameras and accelerometers are the most common non-invasive sensors for monitoring cow behavior in indoor environments. Video-recording systems offer a low-cost solution to observe the behavior of multiple animals simultaneously with few cameras. However, identifying individual animals remains challenging, even with advanced computer vision methods.

In extensive farms, installing efficient video surveillance systems is impractical due to large grazing areas and unreliable energy sources. Recently, efficient unmanned aerial vehicles (UAVs) equipped with cameras have been proposed for animal monitoring in extensive pastures [76]. However, these UAV-based systems require further development, particularly concerning their short battery life.

GPS and accelerometers are the most prevalent non-invasive sensors employed for monitoring cattle in extensive farming systems. Ex-

Figure 2.2: *Example of pedometer and collar worn by cows [26, 93]*

amples of GPS-based and accelerometer-based monitoring systems are detailed in Table 2. Accelerometer-based systems are highly versatile and affordable. They can be attached to an animal's leg or neck to monitor behavioral activity (2.2). Pedometers, typically attached to the hind leg, quantify step count, while neck-mounted collars measure head movements. GPS sensors are employed to track grazing animals in extensive breeding systems, similar to accelerometers, by using collars. GPS is particularly useful in situations where the vast expanse of grazing grounds makes frequent and precise herd management challenging. For instance, GPS devices can help reduce the risk of theft, prevent animal trespassing, and assist in rescuing injured animals that are unable to move. However, the primary limitation to

Sensor/Device	Aspect of Animal	Disease/Used for
GPRS, GPS,transponders, accelerometers	Cattle's position, inside the barn or outside the barn. Motion changes	Grazing, feeding, lying, behaviour and welfare monitoring Lameness, oestrus
Pressure	-	Feeding and drinking monitoring
Microphone, UHF sensors	Monitor sound levels in barns	Mooing, pain and welfare conditions, rumination, breathing disease
Temperature	Temperature monitor	Fever, ovarian cysts, pneumonia, retained placenta, mastitis
Thermal infrared camera, 2D cameras, 3D cameras	-	Behaviour monitoring, lameness, oestrus
Load sensor	Weight distribution	Lameness
Gas sensor	Breathe ketones, methane emission	Displaced abomasum, ketosis
Radio-frequency identification	Identification	Behaviour and welfare monitoring

Table 2.1: *Non-invasive sensors in PLF applications.*

the broader application of GPS technology is the short battery life of GPS-equipped devices, which currently confines their use mainly to experimental settings.

Device	No. cows	Sampling Rate/ Time Interval	Data Collection and Storage	Aim	Period	Refe.
GPS	10	20 min	Sigfox/On Cloud	Position tracking	45d	[93]
GPS	6	10 min	Sigfox/On Cloud	Position tracking	45d	[33]
GPS	7	30 min	Sigfox/On Cloud	Position tracking	5mth	[57]
GPS	180	5/10/15 min	On Device	Position tracking	1–4mth	[82]
GPS	5	-	GSM	Virtual fencing	4mth	[118]
GPS	50	30 min	Sigfox and Bluetooth/ On Cloud	Position and tracking	5mth	[77]
Accel.	12	25 Hz	On Device	Detect licking behaviour	28d	[113]
Accel.	10	10 Hz	On Device	Detect feeding and rumination	5d	[21]
IMU sensor	3	20 Hz	Bluetooth/ External PC	Classify feeding, rumination, lying, and standing	7d	[92]
Accel.	4	4 Hz	GSM/On Cloud	Classify feeding, rumination, walking, and lying	7d	[94, 32]
Accel.	86	59.5 Hz	On Device	Classify six behaviours	3–4d	[101]
Accel.	24	Acc. 10 Hz	On Device	Monitor cows' behavioural activities	14d	[114]
GPS + Accelerometer	5	Acc. 12 Hz/GPS 1 min	On Device	Monitor cows' behavioural activities and tracking	3mth	[28]
GPS + Accelerometer	26	Acc. 59.5 Hz/GPS 1 Hz	On Device	Understand relation between behaviour and pasture characteristics	5d	[100]
GPS + Accelerometer	24	Acc. 10 Hz/GPS 4 Hz	On Device	Classify animals' behaviours	12d	[44]
GPS + Accelerometer	14	Acc. 10 Hz/GPS 4 Hz	On Device	Monitor cows' location and behavioural activities	12-14d	[56]
GPS + Accelerometer	30	Acc. 10 Hz/GPS 5 min	On Cloud	Monitor tracking movement and tracking location	2-3mth	[56]

Table 2.2: *Example of State-of-the-art IoT systems designed to perform animal monitoring.*

2.3 Accelerometer-based automatic monitoring systems

Recent advancements in precision livestock farming (PLF) have seen the development of automated monitoring systems employing accelerometer technology. As outlined in 2.2 of previous chapter, several studies have explored this approach.

Simanungkalit et al. [113] examined an ear tag accelerometer's ability to detect licking behavior at a block supplement in grazing cattle. They validated the duration of individual licking behavior predicted by the accelerometer and a radio frequency identification (RFID) system. Four Angus steers were equipped with an ear tag containing a three-axis accelerometer.

Riaboff et al. [101] aimed to develop a framework to predict behaviors such as grazing, walking, lying and standing rumination, and lying rest using three-axis accelerometer data. The experimental trial involved 86 cows across four different farms.

An example of an animal monitoring system that used a new decision tree algorithm for real-time classification of feeding and ruminating behaviors in dairy cows was provided by Benaissa et al. [21] . Data for the model were collected using a neck-mounted accelerometer. Each cow wore two devices: a RumiWatch halter, intended for automated ruminant health monitoring, and an accelerometer.

A recurrent neural network (RNN) model to detect and recognize calving-related behaviors was developed by Peng et al. [92]. This model utilizes inertial measurement unit (IMU) sensors, including a three-axis accelerometer, gyroscope, magnetometer, and a wireless Bluetooth connection. Data were collected from three expectant Japanese Black Beef Cattle, paired in two barns, with IMU sensors attached to their collars. The RNN classified behaviors such as feeding, lying and standing rumination, lying, and standing. Additionally, it monitored lying and standing behaviors during the 24 hours before calving, as these behaviors typically change as calving approaches. Monitoring calving is crucial in extensive systems, where the highest calf mortality rates occur due to the lack of immediate assistance during difficult births. Smith et al. [114] used behavior monitoring collars equipped with a 20-channel GPS, a 915 MHz microprocessor and transmitter, a 4 GB micro-SD card for data storage, and a Honeywell compass module HMC6343 with a three-axis MEMS accelerometer and a three-axis magnetoresistive sensor on dairy cows. The inertial measuring unit was the compass module of the behavior monitoring collars (IMU), which measured acceleration in a three-axis system: x-axis (forward-reverse), y-axis (left-right), and z-axis (up-down). The device proposed by Smith et al. [114] performed behavior classification using only accelerometer data.

2.3.1 Sampling Rate and Data Collection

The sampling rate of accelerometers in devices used to monitor animal behavioral activities significantly impacts both battery life and the accuracy of behavior detection. High sampling rates allow for the collection of extensive information, resulting in more samples, but they reduce battery life. Conversely, low sampling rates extend battery life but may not provide data of sufficient quality for accurate behavior classification, as shown by Benaissa et al. [21]. In the literature, accelerometer sampling rates for monitoring animal behavior range from 1 Hz [43] to 100 Hz [5]. Most studies focus on a sampling frequency between 10 Hz and 25 Hz. A common sampling frequency is 20 Hz, as demonstrated by Y. Peng et al. [92]. They used IMU sensors with a wireless Bluetooth connection to a computer, set to collect 9-axis data points and transmit them at 20 Hz. The battery life of the IMU sensors was approximately one week. Riaboff et al. [101] used a sampling frequency of 59.5 Hz, with the observation period lasting around 3-4 days. In Simanungkalit et al. [113], the battery life was slightly longer. They used four 3-dimensional accelerometers with a sampling rate of 25 Hz, embedded in ear tags. These tags were removed at the trial's end, and data were downloaded using proprietary software. The expected battery life was about 28 days. Smith et al. [114] set collars to collect accelerometer data at 10 Hz. The data were stored on an onboard 4 GB micro-SD card and downloaded after the trial. The effective battery life was approximately 14 days.

Recently, studies have reported using frequencies of 4 Hz [93, 32]. These studies will be described in the following chapters, because they are the study case of this thesis.

2.3.2 Data Analysis

The data needed to study animal behavioral activities were collected during experimental trials using the sensors described previous sections and subsequently processed. The main phases of data processing are as follows:

Pre-processing, which typically includes:

- Filtering: To remove noise or minor behaviors.

- Data augmentation: Techniques to artificially increase the amount of data by adding slightly modified copies of the original data.
- Grouping samples in windows: To extract more significant information from groups of samples rather than single samples.
- Feature selection and computation: To select and compute the subset of relevant features used in model building.
- Dataset splitting into subsets: To determine which portion of the dataset to use for training and which for testing the model's performance.
- Recognition: Involves classifying the behaviors of the subjects using the information from the previous steps. This process is performed by a specific model or method. State-of-the-art applications use various methods, including threshold identification, statistical analyses, and more recently, machine and deep learning techniques.

Over time, various techniques have been employed to process the acquired data and extract knowledge. Most studies focus on using accelerometers, which collect time series data representing acceleration values at each instant. Several methods exist for processing time series data, but the most commonly used in PLF research can be categorized into six main groups [102] (Summarized in Table 2.3):

- Statistical Model (SM): Provides a set of statistical assumptions about how sample data are generated, defining a mathematical relationship between random and non-random variables.

- Manual Thresholding (MT): Widely used for its simplicity, crucial for devices with limited computational capabilities and energy-saving requirements. Thresholds are determined using descriptive statistics such as medians, means, maximum, and minimum values from the dataset.

- Machine Learning (ML): A subset of AI focused on creating systems that learn or improve performance based on data. It includes:

  - Supervised Machine Learning (SML): Uses labeled data as input for tasks like classification.
  - Unsupervised Machine Learning (UML): Uses unlabeled data to reclassify and organize inputs based on common features, extracting unknown information.
  - Supervised Ensemble Machine Learning (SEML): Combines predictions from multiple models to improve overall performance.

- Deep Learning (DL): A type of ML based on artificial neural networks (ANN), which use multiple processing layers to extract progressively higher-level features from data. Popular DL algorithms include:

  - Multi-layer perceptron (MLP): A feedforward ANN with an input layer, one or more hidden layers, and an output layer, fully connected between layers.
  - CNN, also known as ConvNet, is a type of feed forward neural network that excels at processing input with a grid-like

architecture, such as images. To summarize the process, neurons in a CNN receive inputs, perform scalar products using weights learned throughout the training, and then apply a non-linearity function to the created result. The CNN's distinctive aspect is the convolution layer, which divides the input into several little parts and then superimposes a filter called the kernel. As a result, each component can be used to extract features, or the main characteristics of the input data.

– Recurrent Neural Network (RNN): this type of artificial neural network (ANN) differs from other networks by incorporating cycles within its architecture. In RNNs, the output from certain layers is fed back as input to the same layer or lower layers, creating feedback loops. This interconnection enables one layer to function as state memory, allowing the network to model dynamic temporal behaviors. By providing a temporal sequence of values as input, RNNs can utilize information from previous time points to influence current processing, effectively capturing dependencies over time.

Technique	**Sub-Type**	**Methods**	**References**
Threshold methods		Logistic Regression (LR), Hidden Markov Models (HMM), Linear Mixed Models	[93, 9]
Statistical models	-	Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Naïve Bayes models (NB), Decision Trees (DT)	[114, 78]
Machine learning	Supervised	Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), k-Nearest Neighbour (k-NN), Naïve Bayes models (NB), Decision Trees (DT)	[112, 119]
	Unsupervised	k-means	[62]
	Ensemble	Random Forest (RF), Extreme Gradient Boosting (XGB), Adaboost (ADA)	[101, 17]
Deep learning		Multilayer Perceptions (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long short-term memory (LSTM)	[22, 89]

Table 2.3: *Methods used for the processing of data acquired through accelerometers to detect cow behaviour.*

2.4 GPS-based automatic monitoring systems

As reported in section 2.1, one of the most used devices to monitor cows on extensive farms are GPS. In the state-of-the, GPS devices have been utilized to prevent cattle theft. For instance, in one study, a GPS collar connected to the Global Mobile Communication System (GSM) was used to monitor animals via a software application. This application notified the farmer when an animal crossed a virtual fence representing its grazing area [104]. Porto et al. [93] introduced a technique for tracking cows in a cow-calf operation using GPS, collecting data at 20-minute intervals.The goal was to identify the animals' locations and determine the agricultural land regions where they spend the most time. The designed system will be described in the next chapter. Monitoring cow positions is vital for understanding the environmental impact of grazing and enhancing routine farm management. Additionally, GPS-based devices can identify a cow's estrus period, marked by increased walking activity, and address the issue of animal theft in real-time. Hassan-Vàsquez et al. [57] examined the environmental impact of livestock production, focusing on the capability of commercial GPS collar data, combined with farm characteristics and meteorological conditions, to map the distribution of cow dung in paddocks. In this study, seven animals were tracked using commercial GPS collars equipped with a GPS unit, a lithium battery pack, and a Sigfox communications module. These collars transmitted the animals' positions to a server in near real-time, with location fixes obtained every 30 minutes when Sigfox coverage was available. Miliward et al. [82] investigated cattle distribution across the landscape using a GPS tracking-based system. The study aimed to evaluate the suitability of guidelines proposed by Holecheck et al. [60], which are designed to assist farmers in managing stocking rates. A critical issue in such applications is the communication network, as many rural areas worldwide still lack efficient and reliable telecommunication infrastructure [93].

2.4.1 Sampling Rate and Data Collection

In GPS-based monitoring systems, the time acquisition interval significantly affects the precision of the distance traveled by cows, the battery life, and the responsiveness of farmers to theft and trespassing incidents [79]. Long intervals between data transmissions increase the risk of data loss, which can undermine the efficiency of the device. Typically, GPS-based devices use sampling intervals ranging from 1 to 60 minutes. The system developed by Porto et al.[93] enabled long-term monitoring of animals by collecting waypoints (latitude and longitude), the date and time of the survey, and the distance traveled by each cow. The data acquisition interval was set at 20 minutes to balance battery life and the ability to conduct further analyses in a Geographical Information Systems (GIS) environment, such as applying Kernel Density Estimation (KDE) algorithms. The device transmitted position information to a cloud server via the Sigfox telecommunication network. Tangorra et al. [118] utilized a GPS/GSM collar prototype with commercial hardware and customized software to track animal movements beyond their grazing area and provide alerts when animals trespassed virtual boundaries. The system featured a standard customizable embedded firmware layer supporting the hardware components, allowing GPS acquisition intervals to be set between 1 second and 1 hour. Maroto-Molina et al. [77] created a low-cost IoT-based system for monitoring herd locations, using GPS collars connected to a Sigfox network and low-cost Bluetooth tags. To conserve battery life, collars transmitted data at 30-minute intervals. In contrast, Millward et al. [82] set GPS sensors to acquire and send animal locations at 5, 10, or 15-minute intervals.

2.4.2 Data Analysis

The data collected by GPS sensors are primarily analyzed using statistical and geospatial tools, such as GIS tools, which facilitated data processing and visualization at the territorial level. Recently, clustering methods from the unsupervised machine learning (UML) category have been applied to process data acquired through GPS sensors. Xu et al. [129] used unsupervised machine learning algorithms to analyze location data to understand the social structure of a small cattle group and individual social behaviors. K-means clustering, based on logical and physical distance, was employed. By comparing clustering results based on logical and physical distances, the study identified leader animals and their influence on individuals within a cattle herd, providing valuable insights into animal herd behavior.

2.5 GPS and Accelerometer Combined Systems

GPS technology alone is inadequate for comprehending the behavioral patterns of grazing livestock. Consequently, researchers have explored the integration of GPS sensors with accelerometers to develop more comprehensive monitoring systems. By incorporating motion sensors into GPS devices, it is possible to effectively assess key behavioral parameters, such as feeding, walking, and lying, in relation to the grazing conditions. As reported by Bailey [16] the combined application of GPS tracking and accelerometer data can facilitate the identification of behavioral alterations associated with animal health issues and welfare concerns. Such integrated systems possess the potential to support farmers in making informed agricultural management decisions, such as feed supplementation. Brennan et al. [28] undertook a study to assess the efficacy of a low-cost, experimentally developed GPS collar equipped with a high-frequency three-axis accelerometer in predicting routine cattle behavior. To understand the correlation between bovine behavior and pasture attributes Riaboff et al. [100] conducted a study by employing a combination of accelerometer and GPS data collected through a collar-mounted RF-Track 3D accelerometer and GPS sensor. Dutta et al [44] employed various machine learning algorithms to classify cattle behavior patterns derived from collar-mounted systems incorporating a three-axis accelerometer, magnetometer, and GPS. Their findings indicate that supervised machine learning methods can accurately categorize bovine behaviors based on these data.

2.5.1 Sampling Rate and Data Collection

As reported several research studies have highlighted the development of integrated systems. For instance, González et al. [56] utilized collars to track the location and behavioral activities of cows. In their study, GPS data were collected at a frequency of 4 Hz (resulting in approximately 345,000 data points per day), while accelerometer data were recorded at 10 Hz (about 862,500 data points per day). These data were stored on a memory card embedded in the devices and were downloaded at the end of the experiment, with the battery life of the device lasting around 12 to 14 days. Continuing in this vein, Dutta et al. [44] used similar collars for tracking both location and behavior, which included a GPS, a 3-axis accelerometer, a 3-axis magneto-resistive sensor, and a 4 GB micro-SD card for data storage. In their study, GPS data were also collected at 4 Hz, while accelerometer data were captured at 10 Hz. Additionally, grazing behavior was monitored using the WhatISee digital application. After the experiment, data were stored on an SD card and later downloaded, with the device's battery life lasting around 12 days. Similarly, Brennan et al. [28] fitted tracking collars with a GPS data logger and a high-frequency accelerometer. In this study, the GPS logger was configured to record a location fix (latitude/longitude) every minute, while the accelerometers captured data at a rate of 12 Hz. The accelerometer data were stored on an onboard 8 GB micro-SD card and were downloaded at the end of the trial. Notably, the battery life of these devices, supported by two independent batteries, extended to around 50 days.

2.5.2 Data Analysis

The studies documented in the literature primarily employed statistical models and machine learning methods to analyze data collected from devices equipped with GPS and accelerometer sensors, as previously mentioned in the sections discussing GPS and accelerometer technologies.

For instance, Gonzàlez L. et al. [56] developed an algorithm to classify data from collars into five distinct behavioral activities, with the objective of determining the proportion of daily time that individual animals spent on each activity. Their approach involved using two different datasets during the experimental trial. Initially, data from accelerometers and GPS were aggregated by calculating the mean and standard deviation (SD) over 10-second intervals. The first dataset, which included a subset of data where behavioral activities were identified based on visual observations, was utilized to identify differences between activities using sensor data, to analyze frequency distributions (histograms) of data across different activities, to select variables appropriate for decision tree models, and to construct conceptual decision trees. The second dataset, encompassing all data related to unknown behavioral activities, was employed to fit probability density functions within mixture models, enabling the determination of threshold values to distinguish between different populations of data points.

Building on this, Cabezas et al. [31] aimed to create a general methodology for recognizing various activities using data from accelerometers and GPS sensors. In their study, accelerometer signals were collected and analyzed for each axis individually, resulting in the extraction of 108 temporal and frequency domain features. They matched a total of 238 activity patterns, such as grazing, ruminating, lying down, and standing still, with raw accelerometer data captured on video. These accelerometer signal features were then used to train a Random Forest (RF) algorithm for categorizing behavioral patterns, while GPS position data were analyzed using an Unsupervised Machine Learning (UML) technique to detect abnormal activity patterns. For this purpose, they opted for the k-medoids clustering method instead of k-means, due to its greater stability in the presence of outliers.

Similarly, Dutta et al. [43] proposed the integration of a temperature sensor, a GPS module, and a 3-axis accelerometer. In their study, datasets from all the animals were utilized daily, and all the acquired data were integrated without applying any filtering. After the data collection phase, the most relevant attributes were selectively extracted to enhance data interpretation. Each dataset included sensor readings for temperature, walking speed, and acceleration along the X, Y, and Z axes. The researchers employed Extreme Gradient Boosting (XGBoost) and Random Forest classifiers to categorize behaviors such as 'standing', 'lying', 'standing and ruminating', 'lying and ruminating', 'walking', and 'walking and grazing'.

In another study, Brennan et al. [28] chose four classification algorithms—Random Forest (RF), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Support Vector Machines (SVM)—to predict livestock behavior. The response variable was livestock behavior, and the predictors were metrics derived from accelerometer and GPS data. The datasets used to build these models comprised data that included observational, GPS, and accelerometer information. The algorithms were employed to classify behavior as either grazing or non-grazing. To validate the accuracy of each model, a validation set technique was used, which involved randomly partitioning each dataset for train and test set.

Lastly, Riaboff et al. [100] focused on exploring the relationship between cows' behaviors and pasture characteristics. Their study was divided into two phases: first, the classification of cows' behaviors, and second, the calculation of time budgets spent in each zone by each cow per day and behavior. Behavior prediction was conducted across six different classes using Extreme Gradient Boosting (XGB), as proposed in a previous study [101]. The classification involved grouping accelerometer data into windows, after which predicted behaviors in successive windows for the same cow were smoothed using the Hidden Markov Model (HMM)-based Viterbi algorithm. These predicted behaviors were then combined with GPS data to calculate time budgets in each zone. To further investigate the relationship between time budgets and pasture characteristics, a Linear Mixed Model (LMM) was applied.

2.6 Conclusions

This chapter reviewed ICT technologies for monitoring cattle welfare in extensive farming systems. IoT-based sensors, such as GPS and accelerometers, enable continuous and automated monitoring of animal behavior, providing valuable data on activities like feeding, rumination, walking, and resting. These data, processed with advanced algorithms, can significantly enhance farm management while reducing the need for manual observations. Despite the advancements, challenges remain in applying these technologies to extensive environments, including battery life, network coverage, and data collection frequency. Further research is needed to optimize these solutions, improve device energy efficiency, and refine behavioral algorithms. In the next chapters, case studies will be described that represent animal monitoring solutions in extensive farming, paying attention to the challenges still present in the field of grazing monitoring. In summary, integrating advanced ICT technologies with precision livestock farming presents a significant opportunity to enhance animal welfare monitoring and farm management in extensive systems.

2.7 Publications

Mancuso D, Castagnolo G, Porto SMC. Cow Behavioural Activities in Extensive Farms: Challenges of Adopting Automatic Monitoring Systems. Sensors. 2023; 23(8):3828. https://doi.org/10.3390/s23083828

CASE STUDIES OF SENSOR-BASED MONITORING SYSTEMS

In the previous chapter, we explored sensor-based automatic cow monitoring systems, as presented over the years in the state of the art.

In this section, we describe case studies focused on cow monitoring, divided into two categories: accelerometer-based and GPS-based systems. Chapters 3, 4, 5, and 6 present accelerometer-based case studies, while chapters 8, 7, and 9 cover GPS-based case studies.

CHAPTER

THREE

COW BEHAVIOURAL ANALYSIS BY DETERMINATION OF STATISTICAL ACCELERATION THRESHOLDS

3.1 Overview

As reported in Chapter 2, in recent years the use of wearable sensors have proven to be valuable tools in livestock farming. Therefore,the use of non-invasive IoT sensors in precision livestock farming has increased, enabling the collection of large data volumes and automation of animal health and welfare monitoring, especially in extensive farms. Accelerometers, popular for monitoring livestock movements, were used in this study to establish acceleration thresholds for automatic detection of cow behaviours, aiming to reduce human intervention and improve livestock management.

3.2 Materials and Method

3.2.1 The herd considered in the research study

The experimental trial was carried out in an existing 180 hectares semi-natural pasture characterized by good availability of meadow and cultivated grazing areas. The breeding system adopted is that of the cow-calf line, that involves keeping calves with mothers during the lactation period until weaning (6/8 months). It can take place entirely outdoors, with cows living in pastures all year. During the summer, from 7:00 to 18:00, cows stayed near the farmer house in a large enclosure of about 2 ha 3.1 where there are several watering tanks while in the rest of the day and night they are moved to the pasture. In this study a 19-month-old cow, which is part of a group of 10 Limousines, was monitored.

3.2.2 Device and data acquisition

A customized device (Fig. 3.2) was built to carry out the experimental activities of this research study and it was equipped with: triaxial MEMS accelerometers, omnidirectional antennas, 32-bit Cortex Microcontroller, GSM/GPRS quad band modules, Li-SOCL2 high-capacity battery and flash memories. This device, protected by a rigid case, was put to the collar of the monitored cow (Fig. 3.2) adopting a leather-reinforced mesh collar. The case containing the electronic device was fixed to the collar by using electrical clamps and duct tape.

Figure 3.1: *Large enclosure near the farmer house where cows stayed during the day*

To limit the rotation of the device around the cow's neck, a weight of 1 kg was attached into the collar. The distance of the device from the weight was chosen to detect the accelerations coming from the jaw oscillations during the rumination phase.The acceleration components along the x, y, and z axes were acquired with a frequency of 4 Hz and recorded in the internal memory of the devices. Through the GSM communication module, the data collected were sent to a cloud, one time an hour, for their processing and display through a Web App, as depicted in Fig. 3.3 developed for the management of the dataset used in the subsequent labeling phase.

3.2.3 Dataset and labeling

The behavioral activities analyzed in the present study were rumination in standing position (R), lying (L), lying with rumination (L-R),

Figure 3.2: *a) Customized device equipped with triaxial accelerometers b) Device attached to the cow collar.*

walking (W), feeding (F), feeding and walking (F-W), feeding to the manger (FM) and drinking (D). These behavioral activities of the monitored cow were observed in two different time intervals: the first in May 2021, for 5 days and the second in June 2021 for 4 days. It was not possible to extend the duration of data acquisition for each time interval because the battery was discharged. The device used in this study is an experimental prototype that use the GSM network, which is highly energy-intensive in the phase of sending accelerometer data to the cloud. The acquired acceleration data were labeled by using video-labeling technique, that is the recognition of the behavioral activities carried out by the cow through the analysis of video recordings acquired during the observation periods. Video recordings of the monitored cow were taken daily in the coolest hours of the day, in the morning from 6:00 to 09:59 and in the afternoon from 18:00 to 21:00. To increase battery life the device entered in sleep mode from 10:00 to 17:59 (Fig. 3.3). A free third-part app was used to apply times-

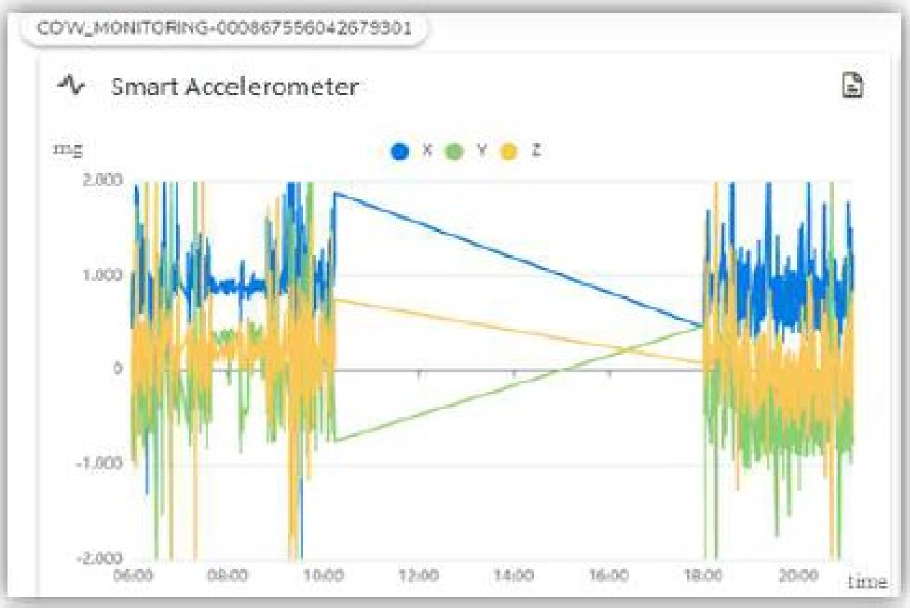

Figure 3.3: *Graph of acquired data. To increase battery life the device entered in sleep mode from 10:00 a.m. to 17:59.*

tamp in each frame. This made it possible to synchronize the video recordings with the accelerometer data that the device periodically sent to the cloud.By carrying out the visual analysis of the acquired video recordings, it was possible to label the accelerometer data by indicating the observed behavioral activities of the cow (Fig. 3.4). During the visual analysis of the video recordings, and the related labeling phase, occurrences of minor behavioral activities were observed such as brusque movements of the ears to ward off flies, brusque movements of the head backwards to scratch or lick itself, sniff the ground before positioning itself in lying. Therefore, to reduce the incidence of outliers in the acceleration dataset, it was necessary to delete the acceleration values related to these minor behavioral activities.

1	Time	X	Y	Z	W	L	R	F
35235	2021/06/27 09:30:27:000	995,52	-312,32	160,064	W			
35236	2021/06/27 09:30:27:250	925,248	-269,376	199,104	W			
35237	2021/06/27 09:30:27:500	1.034,56	-230,336	230,336	W			
35238	2021/06/27 09:30:27:750	1.011,14	-234,24	242,048	W			
35239	2021/06/27 09:30:28:000	1.085,31	-58,56	124,928	W			
35240	2021/06/27 09:30:28:250	1.022,85	-222,528	199,104	W			
35241	2021/06/27 09:30:28:500	1.026,75	-245,952	386,496	W			
35242	2021/06/27 09:30:28:750	1.026,75	-191,296	144,448	W			
35243	2021/06/27 09:30:29:000	999,424	15,616	355,264	W			
35244	2021/06/27 09:30:29:250	1.206,34	-355,264	66,368	W			

Figure 3.4: *Example of the acquired dataset. In the first column there is the timestamp, in the next three columns there are the accelerometer data (mg) measured along the three axes and then the label such as W (Walking), F (Feeding), R (Rumination) etc. The behavior label is associated for each sample.*

3.2.4 Data analysis

Data analysis began with descriptive statistics, such as the mean, maximum, minimum, and standard deviation values of the accelerations detected along the x, y, and z axes, grouped by behavioral activities and observation days. These statistics provided a foundational understanding of the data distribution and variability for each activity and helped identify initial patterns or anomalies in the acceleration data. Subsequently, an Analysis of Variance (ANOVA) test was conducted. The ANOVA test is a statistical method used to compare means across multiple groups to determine if there are any statistically significant differences between them. The goal was to identify statistically significant differences in the accelerations detected along each axis (x, y, z) for different behaviors. By performing the ANOVA test, researchers were able to define the range of accelerations for each axis and ascertain whether the observed variations between the behaviors were greater than what could be expected due to random chance. The ANOVA test compared the medians of accelerations acquired per second (with a sampling frequency of 4 Hz) for each behavior. This approach provided a robust measure, mitigating the impact of outliers and extreme values. The ANOVA test evaluates the null hypothesis that the group medians are equal for each axis, using the F-statistic calculated as follows:

$$\text{Median}(X_{ij}) = \text{median}(\{X_{ij1}, X_{ij2}, X_{ij3}, X_{ij4}\}) \quad \forall i \in \{1, \ldots, 8\},\ j \in \{x, y, z\}$$

$$\text{F} = \frac{\frac{\sum_{i=1}^{8} n_i(\bar{X}_i - \bar{X})^2}{k-1}}{\frac{\sum_{i=1}^{8}\sum_{j=1}^{n_i}(X_{ij} - \bar{X}_i)^2}{N-k}}$$

where:

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{8}\sum_{j=1}^{n_i} X_{ij},$$
$$\bar{X}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} X_{ij},$$
$$N = \sum_{i=1}^{8} n_i, \quad k = 8.$$

After identifying significant differences with the ANOVA test, Tukey's Honest Significant Difference (HSD) test was performed for pairwise comparisons between the behavioral groups. The Tukey test, a post-hoc analysis, determines exactly which group means differ from each other and controls the family-wise error rate, reducing the likelihood of falsely identifying a significant difference. In this study, the Tukey test was applied separately for each axis (x, y, z) to identify any overlaps between the behavioral groups and to determine which axes could effectively discriminate between the different behaviors. This analysis was crucial in understanding which directions of movement were most indicative of specific activities, thereby providing insights into how each behavior could be characterized and differentiated based on the acceleration data. The Tukey HSD test calculates the critical value for significant differences between group means:

$$\text{HSD} = q_{\alpha,k,N-k} \cdot \sqrt{\frac{\text{MSW}}{n}}$$

where:

- $q_{\alpha,k,N-k}$ is the Studentized range distribution critical value for the significance level α, with $k = 8$ groups and $N - k$ degrees of freedom,
- MSW is the Mean Square Within (from ANOVA),
- n is the number of observations per group.

For each pair of groups i, j, if the absolute difference of their means $|\bar{X}_i - \bar{X}_j|$ exceeds the HSD, the difference is considered statistically significant:

$$|\bar{X}_i - \bar{X}_j| > \text{HSD}.$$

These statistical analyses provided insights into which directions of movement were most indicative of specific activities, helping to characterize and differentiate behaviors based on acceleration data effectively.

3.3 Results and discussion

From the analysis conducted it was possible to identify the acceleration components required in order to define thresholds to be able to discriminate cow behavioral activities. Table 3.1 shows, for the x-axis, the results of the ANOVA test conducted for each behavior. Table 3.4 and Fig.3.5 a show the results of Tukey's test for the x axis, and as it can be observed, when considering only the x axis, some behavioral classes overlap, such as: rumination (R) and feeding to manger (FM), lying with rumination (L-R) and walking (W), drinking (D) and lying (L). Acceleration along x-axis made it possible to discriminate only the feeding activity, either in standing or walking position. The ANOVA test results for the y-axis are shown in Table 3.2 while Table 3.4 and Fig. 3.5b show the results of Tukey's test for y-axis. Unlike x-axis component, there are no overlapping areas among the behavioral activities. The same analysis was carried out for the z-axis. Table 3.3 shows the results of to the ANOVA test, while the results of the Tukey test are shown in the Table 3.4 and in the Fig. 3.5c. Similarly, to the case of the x-axis, there are some overlapping values among the behavioral classes when considering only the z-axis and this occurred for lying with rumination (L-R) and rumination (R) and feeding to manger (FM), walking (W) and drinking (D). Acceleration along z-axis made it possible to discriminate lying (L) and the feeding activity, either in standing(F) or walking position (F-W). The Table 3.5 summarize the analysis carried out and it does not show the drinking (D) behavior because the number of samples (N) of these behavioral activities in the whole dataset is strongly unbalanced with respect to the other behaviors. The study showed (Tab.3.5) that the components to be considered in terms of accelerations for the detection of cattle behavior are: x and y axes for rumination(R), y for feeding to manger (FM), y and z (uncertain) for lying with rumination (L-R), y and z for walking (W), all three axes for lying (L), feeding (F) and feeding with walking (F-W). The results of this experimental activity are a first step forward the determination of acceleration thresholds for the automatic detection of the behavioral activities of grazing livestock.

Table 3.1: *Results of the Anova test for x-axis, grouped by behavior*

Median label	N	Mean	StDev	95% CI
L	977	907.10	115.07	(902.05; 912.15)
L-R	1408	934.31	51.01	(930.10; 938.52)
D	94	908.39	43.62	(892.11; 924.66)
F	1504	803.96	103.85	(799.89; 808.03)
FM	1234	952.31	39.77	(947.82; 956.80)
R	2127	956.875	30.309	(953.45; 960.29)
W-F	4073	782.31	93.00	(779.83; 784.78)
W	1540	933.18	87.76	(929.15; 937.20)

Table 3.2: *Results of the Anova test for y-axis, grouped by behavior*

Median label	N	Mean	StDev	95% CI
L	977	-103.06	194.07	(-122.58; -93.55)
L-R	1408	-40.12	174.94	(-48.50; -32.30)
D	94	-322.6	141.0	(-353.30; -291.90)
F	1504	-538.20	163.71	(-545.87; -530.53)
FM	1234	17.32	143.26	(8.85; 25.78)
R	2127	-6.15	112.68	(-12.60; 0.30)
F-W	4073	-585.11	121.33	(-589.77; -580.45)
W	1540	-151.12	203.91	(-158.70; -143.54)

Table 3.3: *Results of the Anova test for z-axis, grouped by behavior*

Median label	N	Mean	StDev	95% CI
L	977	169.91	232.18	(162.41; 177.41)
L-R	1408	196.06	131.22	(189.82; 202.31)
D	94	119.82	93.90	(95.64; 144.00)
F	1504	-72.15	129.37	(-78.19; -66.10)
FM	1234	192.78	77.84	(186.10; 199.45)
R	2127	195.67	66.95	(190.58; 200.75)
F-W	4073	-105.62	98.16	(-109.29; -101.95)
W	1540	152.60	130.39	(146.63; 158.58)

Table 3.4: *Results of the Tukey test for all axes*

Median label	**Grouping X**	**Grouping Y**	**Grouping Z**
R	A	A	A
FM	A	B	A
L-R	B	C	A
W	B	D	B
D	B C	E	C
L	C	F	C
F	D	G	D
F-W	E	H	E

Table 3.5: *Accelerometer axes to be considered for the detection of cattle behavior*

Behavior	**Acceleration component**		
	x	**y**	**z**
R	Required	Required	Not required
L-R	Not required	Required	Uncertain
W	Not required	Required	Required
L	Required	Required	Required
F	Required	Required	Required
F-W	Required	Required	Required
FM	Not required	Required	Not required

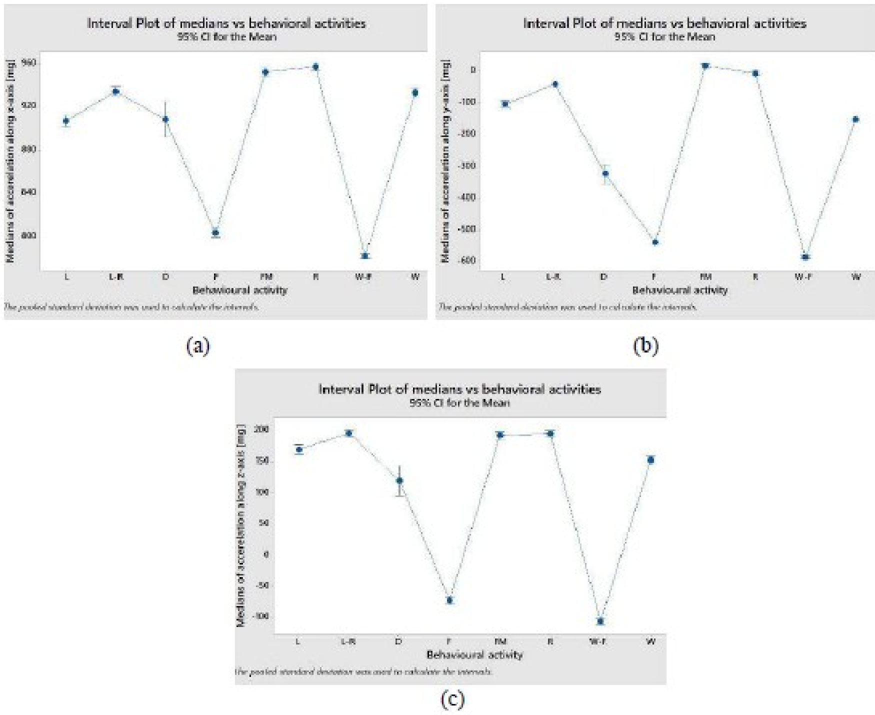

Figure 3.5: *Interval plot of medians for x-axis (a), y-axis (b), z-axis (c), grouped by behavior.*

3.4 Conclusions

Indicators based on cow behavioral activities are relevant to evaluate physiological and physical status of animals, especially in the case of extensive farms where there is an infrequent farmer-to-animal contact. Feeding, rumination, lying and walking are the main daily activities of grazing cattle that should be monitored to ensure the maintenance of animal welfare as well as to improve herd management. The use of motion sensors can provide a valuable method for monitoring animal activities and determining the time budget spent in daily activities, such as for example the evaluation of the feeding and ruminating period, the early detection of abnormalities in walking, the onset of oestrus. Given the promising results of this work, future developments will regard the analyses of multiple data coming from a larger group of animals and the use of machine and deep learning techniques to be able to establish, in a completely automatic process, the thresholds for the discrimination of cow behavioral activities.

3.5 Publications

Porto, S.M.C., Castagnolo, G., Mancino, M., Mancuso, D., Cascone, G. (2022). On the Determination of Acceleration Thresholds for the Automatic Detection of Cow Behavioural Activities in Extensive Livestock Systems. In: Biocca, M., Cavallo, E., Cecchini, M., Failla, S., Romano, E. (eds) Safety, Health and Welfare in Agriculture and Agro-food Systems. SHWA 2020. Lecture Notes in Civil Engineering, vol 252. Springer, Cham.

CHAPTER

FOUR

COW BEHAVIORAL CLASSIFICATION BY CONVOLUTIONAL NEURAL NETWORKS

4.1 Overview

In the previous chapter the topic of determining acceloremetric thresholds was addressed, in order to determine the behavior of cows on pasture, through statistical analysis. In this chapter we will deal with automatic behavior detection using Deep Learning, in particular Convolutional Neural Networks.

4.2 Materials and Method

4.2.1 Data acquisition

The data required to classify grazing cow behaviors were acquired by a customized device equipped with tri-axial MEMS accelerometers, described in Chapter 3. This study monitors two 19-month-old cows, which are part of a group of 10 Limousines replacement heifers. The experimental site and the data acquisition period are the same as the previous case study.

4.2.2 Pre-processing

Collected data are pre-processed to normalize the statistical distribution and to remove samples or sequences of samples that clearly represent outliers. Examples of outlier values, in the acquired dataset, were determined by minor cow behaviors, such as ear movement or chasing flies; they acted as an interruption of the observed behavioral activities and therefore introduced noise into the dataset. Sometimes between the end of one video (used for manual labeling) and the beginning of the next, there were discontinuities in labeling. If such discontinuities are shorter than 2 seconds (8 samples at 4 Hz), they were corrected, and the corresponding labels replaced by the one identified by the operator before and after the discontinuity. Data are provided to the classification model in windows of 20 samples (5 seconds) with consistent labels, so that each window can be assigned a single behavior class. After splitting the dataset into training, validation, and test sets (described in the next section), Z-score normalization is carried out for each axis.

4.2.3 Model and training procedures

The developed model is a Convolutional Neural Network with 1D convolutions. One-dimensional Convolutional Neural Networks (1D CNNs) are a type of neural network architecture particularly suited for processing sequential data. Unlike traditional 2D CNNs, which operate on two-dimensional input data (e.g., images), 1D CNNs apply convolutional operations across one dimension, making them ideal for analyzing time series, audio signals, and other sequential data.

A typical 1D CNN architecture consists of:

- **Convolutional layers**: These layers apply 1D convolutional filters (kernels) to the input data. The output of a 1D convolution operation for an input sequence $x = [x_1, x_2, \ldots, x_n]$ with a filter $w = [w_1, w_2, \ldots, w_k]$ is given by:

$$(x * w)_i = \sum_{j=1}^{k} x_{i+j-1} \cdot w_j$$

  where i ranges over the valid positions in the input sequence, and $*$ denotes the convolution operation.

- **Pooling layers**: Pooling layers, such as max-pooling, are used to reduce the dimensionality of the feature maps while preserving the most important features. For max-pooling with a pool size p, the operation is defined as:

$$y_i = \max(x_{i \cdot p}, x_{i \cdot p+1}, \ldots, x_{i \cdot p+p-1})$$

  where y_i is the pooled output.

- **Fully connected layers**: After several convolutional and pooling layers, the network may include fully connected (dense) layers. These layers flatten the input and connect every neuron to the previous layer's neurons, enabling the network to make final predictions. The output of a fully connected layer can be represented as:

  $$z = W \cdot a + b$$

  where W is the weight matrix, a is the input vector from the previous layer, and b is the bias vector.

1D CNNs are widely used in applications such as time-series forecasting, speech recognition, and biological sequence analysis, where understanding patterns in sequential data is crucial.

The developed model was designed to process input data sequences using several parallel branches, each of which analyzed different combinations of axial measurements (see Fig. 4.1). These branches were organized as input feature channels, allowing the model to simultaneously learn from multiple perspectives of the data. The fundamental idea behind this design is to encourage the model to learn meaningful and distinct features from each axis of measurement (x, y, z) by implementing an inhibition mechanism. This mechanism selectively excludes data from certain subsets of axes during the training process, effectively forcing the model to become robust in recognizing patterns even when information from some axes is missing. This approach was motivated by the findings from preliminary experiments described in Chapter 3. These experiments demonstrated that for certain behavioral activities, the accelerations along all three axes were not necessary for accurate recognition. In some cases, the model was able to achieve high performance using only data from two of the three axes, suggesting that not all axes contribute equally to the recognition of specific behaviors. Based on this insight, the model was designed to ensure that part of the features it extracts are dependent on specific inputs from selected axes only, rather than requiring all three axes. To implement this, the model architecture included multiple branches of 1D convolutional layers, each tailored to process input samples from specific subsets of axes. For all possible combinations that included at least two axes, a separate branch was constructed. For example, one branch might process only the x and y axes, another might handle the y and z axes, and so on. This design allows the model to learn localized patterns from these specific subsets, enhancing its ability to recognize behaviors that might be predominantly characterized by movement along particular axes. Additionally, to account for features that might be associated with individual channels, the model incorporated a branch where the convolutional kernels were shared across all channels. This branch was designed to capture global relationships that span all three axes, thereby enabling the model to learn axis-agnostic features that are invariant to the choice of axes. This is particularly useful for recognizing behaviors that are not specific to any single direction of movement but rather involve a combination of movements across all axes. The model also included a final branch that processed the entire input data, using all three channels (x, y, and z) simultaneously. This branch aimed to learn the most comprehensive feature representations by considering the full spectrum of input data without any exclusions. By integrating this branch, the model can capture complex patterns that require information from all three axes to be accurately understood. After the initial processing in these parallel branches, the features extracted from each branch were concatenated to form a unified feature representation. This combined feature vector was then further processed by a sequence of additional convolutional layers, which were interleaved with max pooling blocks to progressively reduce the dimensionality of the feature space. The max pooling layers help in down-sampling the data, preserving only the most salient features and thereby reducing the computational complexity of the model. Finally, the features were flattened into a one-dimensional vector and fed into a linear classifier for the final prediction. This classifier, typically a fully connected dense layer, takes the high-level features produced by the convolutional layers and maps them to the output classes corresponding to the recognized behavioral activities. The overall architecture of the model, including the structure and connectivity of each convolutional layer, is illustrated in Figure 4.1, which provides a visual representation of how the various components are integrated to work together in processing the input data sequences.

Each convolutional layer was followed by batch normalization and hyperbolic tangent as activation function. As a regularization method, Dropout is employed before the classification layer. The model was trained for 70 epochs with AdamW (Loshchilov and Hutter, 2019) optimizer with a learning rate of 10-5 and 5×10-3 weight decay. As a classification loss function, cross-entropy was employed. In order to deal with class imbalance, weighted random sampling was performed at training time, so that the model received on average the same number of inputs from each class, with repetitions.

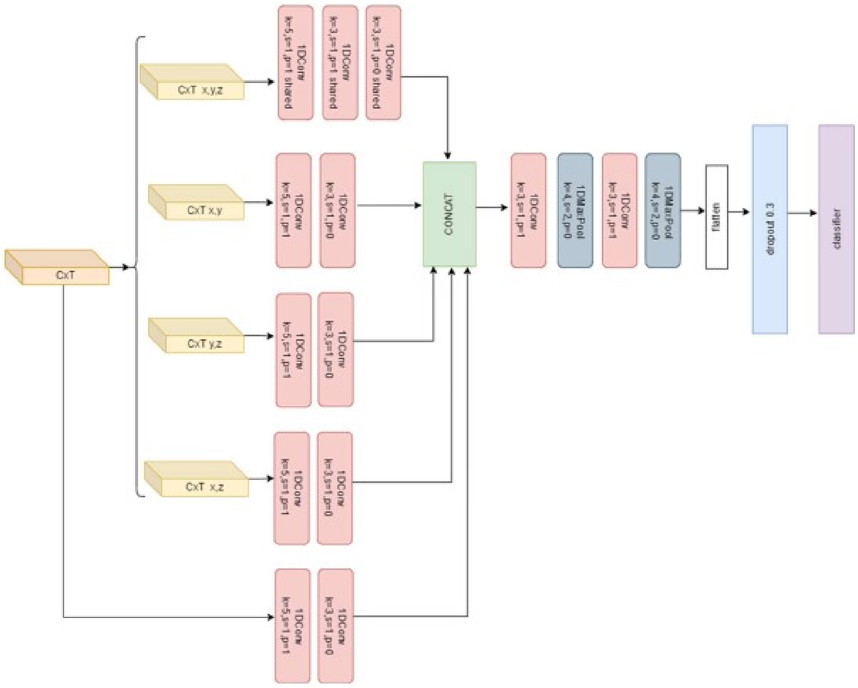

Figure 4.1: *Architecture of the proposed model to classify cow behavioral activities*

4.3 Results and Discussion

Due to the different time spent by cows in each monitored behavioral activity during the time intervals of observation, samples related to the behavioral classes were unbalanced (Tab.4.1). Therefore, we report results in terms of average precision, recall and F1 score over classes, weighted by number of samples in each class, employing 10-fold stratified cross validation. At each cross-validation iteration, 10% of the training data are used as a held-out set to perform model selection among instances at different epochs. Results were reported in terms of mean and standard deviation over the 10 folds.

Table 4.1: *Behavior samples and their percentages*

Behavior	**Samples**	**Percentage (%)**
Feeding in standing position (F-s)	12185	15.17
Walking (W)	15498	19.30
Feeding while walking (F-W)	16222	20.19
Lying (L)	9194	11.45
Rumination in lying (R-L)	27220	33.89
Total	**80319**	**100.00**

Two different experiments were carried out, considering two sets of different classes: in the first, all classes are included (5-class scenario); in the second, activities related to feeding (feeding in standing position and feeding while walking) were merged into a single class (4-class scenario). In this study, the proposed model was compared with two baseline neural network architectures: a 1D CNN model that process data from all axes and consists of a variant of the proposed model when only a single branch is used (the bottom one in Fig. 4.1); a Multi-layer Perceptron (MLP). Results of the experiments of the two scenarios were reported, respectively, in Table 4.2, showing that the proposed architecture significantly outperforms the baselines and is at least on par, if not better, than state-of-the-art approaches (although a direct comparison is not possible, due to the usage of different datasets and the lack of released implementations). It is interesting to note that all models performed better in the 4-class scenario than in 5-class scenario (Tab. 4.2). In particular, the performance of the branched model was lower for the feeding activities in the 5-class scenario (Tab. 4.3). This could be partially attributed to the similarity of the acceleration values recorded for the two behavioral classes. The confusion matrix illustrated in Figure 4.2 confirms that the source of indecision for the model is associated to the feeding while walking and feeding in standing position classes: when the two classes were merged, the accuracy of the model in recognizing the feeding activity was very high (Tab. 4.4).

Table 4.2: *Performance comparison of different models*

Model	Scenario	F_1 Score (%)	Precision (%)	Recall (%)
Branched model	5-class	**81.50 ± 1.29**	**81.00 ± 0.81**	**80.75 ± 0.95**
Simple 1D CNN	5-class	78.96 ± 0.97	79.01 ± 1.02	78.93 ± 1.06
MLP	5-class	74.76 ± 1.26	75.11 ± 1.14	74.42 ± 1.32
Branched model	4-class	**90.01 ± 1.49**	**90.10 ± 1.20**	**89.89 ± 0.91**
Simple 1D CNN	4-class	87.26 ± 0.35	87.21 ± 0.75	87.32 ± 0.62
MLP	4-class	84.79 ± 0.65	85.13 ± 1.10	84.45 ± 1.36

Table 4.3: *Test performance of the branched model in the 5-class scenario*

Behavioural class	F_1 Score (%)	Precision (%)	Recall (%)
F-S	62.00 ± 6.87	65.75 ± 7.08	58.75 ± 7.50
W	84.20 ± 2.38	83.75 ± 2.21	85.75 ± 3.40
F-W	76.75 ± 4.11	73.75 ± 4.01	80.25 ± 3.94
L)	78.50 ± 5.32	74.00 ± 8.60	83.75 ± 1.50
R-L	86.25 ± 3.50	92.50 ± 2.08	88.75 ± 2.50
Weighted average	**81.50 ± 1.29**	**81.00 ± 0.81**	**80.75 ± 0.95**

Table 4.4: *Test performance of branched model in the 4-class scenario.*

Behavioural class	F_1 Score (%)	Precision (%)	Recall (%)
Feeding (F)	95.25 ± 0.50	95.50 ± 0.57	95.00 ± 0.81
W	85.00 ± 3.70	84.75 ± 3.60	85.00 ± 4.01
L	81.25 ± 4.00	79.25 ± 2.50	83.25 ± 4.50
R-L	90.25 ± 2.75	91.50 ± 3.02	90.00 ± 2.16
Weighted average	**90.01 ± 1.49**	**90.10 ± 1.20**	**89.89 ± 0.91**

4.4 Conclusions

The results obtained in this study seem promising and the comparison with other neural network models shows that input processing through

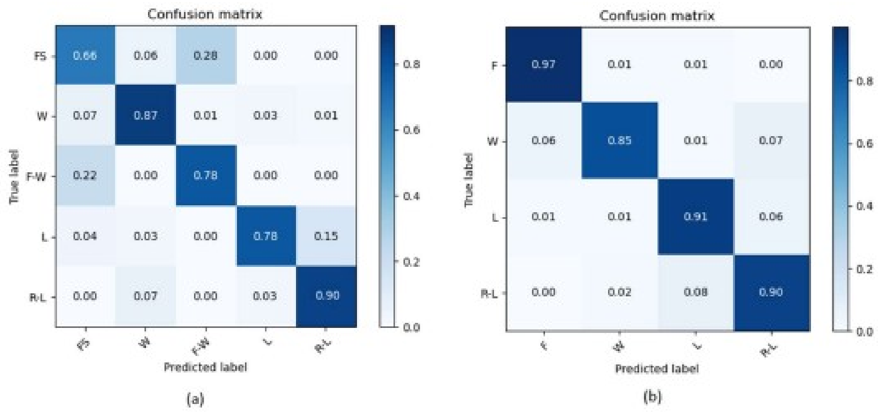

Figure 4.2: *Confusion matrix of branched model for the 5-class scenario (a) and for the 4-class scenario (b). Accuracies are normalized per class*

parallel branches, analyzing different axes combinations, can be a valid approach for the classification of behavioral activity in cows using accelerometer data. The results obtained in this study are preliminary as the dataset used is small. The performance obtained when considering the 5-class scenario can be increased by acquiring more data, in different periods and considering a larger group of animals. However, the merging of the two classes related to feeding activity made it possible to increase the values of F1 score, precision and recall by about 8.51, 9.10 and 9.14 percent points, respectively. Taking into account the relevance for the farmer of the feeding activity, regardless of position assumed by the cows, i.e., standing or while walking, further experiments will regard the optimization in terms of computational cost of the 4-class branched model with the final aim to be implemented in a device to be worn by the cows.

4.5 Publications

Castagnolo, G.; Mancuso, D.; Palazzo, S.; Spampinato, C.; Porto, S.M.C. Cow Behavioural Activities Classification by Convolutional Neural Networks. In Proceedings of the 10th European Conference on Precision Livestock Farming, Vienna, Austria, 29 August–2 September 2022; pp. 48–55.

CHAPTER

FIVE

COMPARATIVE ANALYSIS OF STATISTICAL AND AI-BASED METHODS FOR COW MONITORING

5.1 Overview

The aim of this work is to compare three different data analysis methods for identifying the behavioral activities of grazing cows, ranging from Statistical to Deep Learning-based methods, applied to the same data collection device, highlighting their strengths and weaknesses in relation to the possible application of LPWANs.

5.2 Materials and Method

The device and data collection system used for this analysis are the same reported in Chapters 3 and 4.

5.2.1 Method I

As previously reported the study conducted in Chapter 3, employed descriptive statistics for data analysis, grouped by behavior and observation day. An ANOVA test was then applied to identify significant differences and define acceleration ranges for each axis. Median accelerations per second (sampled at 4Hz) were compared across behavioral classes. The Tukey test further compared behaviors, identifying overlaps in acceleration ranges and useful axes for distinguishing activities. This analysis established thresholds for differentiating cow behaviors based on acceleration data. Therefore the Method I consist in the application of established thresholds, in order to classify the cows' behavior.

5.2.2 Method II

Instead in the study conducted in Chapter 4 a one-dimensional (1D) convolutional neural network (CNN) was used to classify cow behavioral activities using data from triaxial accelerometers installed in collars. The Branched Model, as it is called, processes input data sequences through multiple parallel branches, each analyzing different combinations of axial measurements. This approach enables the model to learn significant features from all axes by selectively excluding data from certain axes, inspired by preliminary experiments showing that not all three axes are necessary for recognizing some behaviors.

5.2.3 Method III

The method III employs Decision Trees to establish accelerometric thresholds for the identification of cow behaviors. Decision Trees, known for their effectiveness in machine learning, use a hierarchical structure to facilitate decision-making. Each node in the Tree poses a question based on a data feature, and each branch represents a possible answer leading to either another question or a final decision at the leaf nodes. In this particular study, the input features for the decision tree are medians calculated from 5-second sample windows acquired at 4Hz. The dataset obtained using the device described earlier was pre-processed. This pre-processing phase involved removing outliers and minor behaviors, grouping samples into 5-second windows, and calculating the median for each axis (x, y, z). Through Grid Search analysis, it was determined that a Decision Tree depth of 10 offered the best compromise between model performance and the number of comparisons needed for implementation in the device firmware. Given the class imbalances in the dataset, the SMOTE technique was utilized to over-sample the less represented classes.

5.3 Results and discussions

5.3.1 Method I

In the study presented in Chapter 3, ANOVA and Tukey tests were conducted to identify which acceleration components could effectively discriminate specific cow behaviors. The ANOVA test provided details on the number of samples, mean value, standard deviation, and

95% confidence interval for each acceleration component. These parameters were determined for each axis and associated with particular behaviors. The accelerometer thresholds for each behavioral class were derived from their respective confidence intervals. Figure 5.1 illustrates the average acceleration values along the three axes for each behavioral group. The ANOVA test revealed some overlap between behavioral classes along the x-axis, such as lying with rumination (L-R) and walking (W). It was found that the x-axis acceleration could only distinguish between feeding activities while standing (F-S) and walking (F-W). The z-axis acceleration, on the other hand, effectively differentiated lying (L) from feeding activities, whether standing or walking. The study determined specific acceleration components for identifying cow behaviors as follows: x and y axes for rumination (R); y and z axes for lying with rumination (R-L); y and z axes for walking (W); and all three axes for lying (L), feeding while standing (F-S), and feeding while walking (F-W) (Tables 5.1 -5.2). This approach has been validated directly in the field on a group of 3 cows. The overall accuracy found is 64%. As reported in Table 5.3 with the thresholds computed in Porto et al. (2021) is possible to recognize Feeding and Rumination in Lying with an accuracy respectively of 74% and 70%. The accuracy for Walking and Lying behaviors is low, respectively 42% and 50%.

5.3.2 Method II

Instead, regarding method II, as reported in the study presented in Chapter 4, two trials were conducted: one involving all classes (5-class scenario) and another combining feeding activities into a single

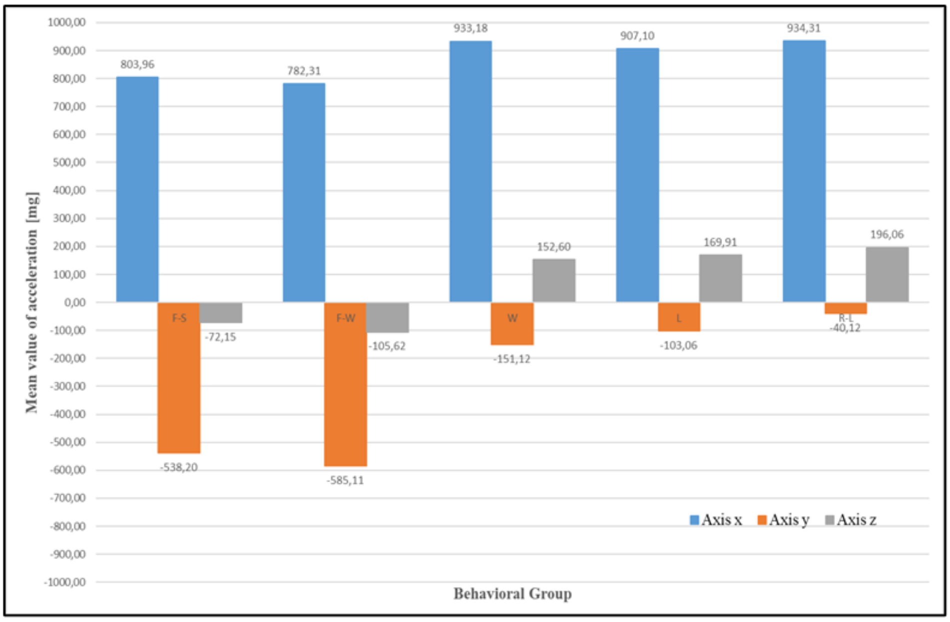

Figure 5.1: *Mean values of acceleration along x, y, z axes as the behavioral group changes from ANOVA test*

Table 5.1: *95% CI for each axis, grouped by behavior group, from ANOVA test (Porto et al., 2021)*

	x-axis	**y-axis**	**z-axis**
$F-S$	799.89 – 808.03	-545.87 – -530.53	-78.19 – -66.10
$F-W$	779.83 – 784.78	-589.77 – -580.45	-109.29 – -101.95
W	929.15 – 937.20	-158.70 – -143.54	146.63 – 158.58
L	902.05 – 912.15	-122.58 – -93.55	162.41 – 177.41
$R-L$	930.10 – 938.52	-48.50 – -32.30	189.82 – 202.31

Table 5.2: *Tukey test outcomes (Porto et al., 2021)*

Acceleration components			
	x-axis	**y-axis**	**z-axis**
F-S	required	required	required
F-W	required	required	required
W	not required	required	required
L	required	required	required
R-L	not required	required	uncertain

Table 5.3: *Results obtained in the field with thresholds computed in (Porto et al., 2021)*

Behavioral Activity	**Accuracy**
F	74.78%
W	42.00%
L	50.00%
R-L	70.00%
Weighted	64.00%

class (4-class scenario). The Branched Model was compared to two basic neural network architectures: a one-dimensional CNN model that processes data from all axes and a multi-layer perceptron (MLP). The results indicated that all models performed better in the 4-class scenario than in the 5-class scenario. The Branched Model performed worse for feeding activities in the 5-class scenario, likely due to the similarity in acceleration values for the two feeding behavior classes (Tables 5.5 and 5.4). The confusion matrix revealed that the model's indecision was primarily between feeding while walking and feeding while standing. The model's accuracy in recognizing feeding activities increased significantly when these two classes were combined (Figure 5.2).

Table 5.4: *Test performance of the branched model in the 5-class scenario*

Behavioural class	**F_1 Score (%)**	**Precision (%)**	**Recall (%)**
F-S	62.00 ± 6.87	65.75 ± 7.08	58.75 ± 7.50
W	84.20 ± 2.38	83.75 ± 2.21	85.75 ± 3.40
F-W	76.75 ± 4.11	73.75 ± 4.01	80.25 ± 3.94
L)	78.50 ± 5.32	74.00 ± 8.60	83.75 ± 1.50
R-L	86.25 ± 3.50	92.50 ± 2.08	88.75 ± 2.50
Weighted average	**81.50 ± 1.29**	**81.00 ± 0.81**	**80.75 ± 0.95**

Table 5.5: *Test performance of branched model in the 4-class scenario.*

Behavioural class	**F_1 Score (%)**	**Precision (%)**	**Recall (%)**
Feeding (F)	95.25 ± 0.50	95.50 ± 0.57	95.00 ± 0.81
W	85.00 ± 3.70	84.75 ± 3.60	85.00 ± 4.01
L	81.25 ± 4.00	79.25 ± 2.50	83.25 ± 4.50
R-L	90.25 ± 2.75	91.50 ± 3.02	90.00 ± 2.16
Weighted average	**90.01 ± 1.49**	**90.10 ± 1.20**	**89.89 ± 0.91**

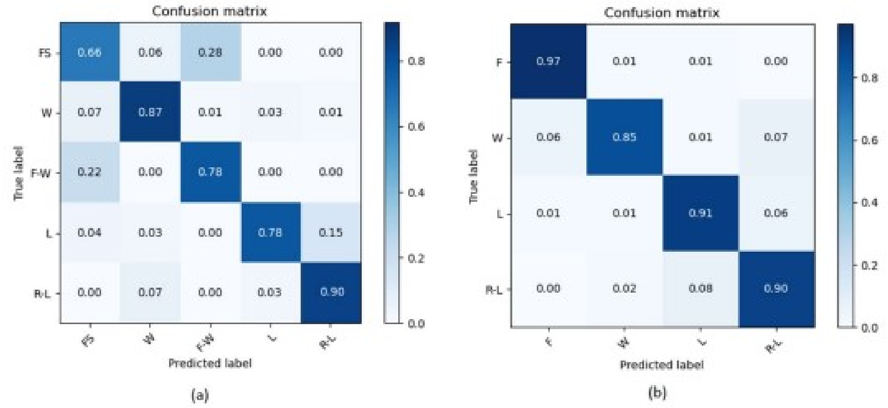

Figure 5.2: *Confusion matrix for Branched Model in 5-class scenario and 4- class scenario (Castagnolo G. et al., 2022)*

5.3.3 Method III

The data processed using the Decision Tree are the same as in the previous section. Similar to the previous analysis, a 10-fold cross-validation was performed. Additionally, two scenarios were considered: a 5-class scenario and a 4-class scenario. The results are shown in Tables 5.6 and 5.7. In the 5-class scenario, the Decision Tree demonstrated high precision for the F-S group, indicating that most predictions for this class were correct. However, the slightly lower recall suggests that some F-S examples were not identified. Overall, high precision balanced by moderate recall reflects an accurate but not exhaustive classification of this group. The precision for the F-W group was significantly low, indicating many false predictions for this class. The higher recall suggests that the model identified a good portion of the F-W examples but at the cost of numerous false positives. The metrics for the W group showed moderate performance, with balanced precision and recall, suggesting reasonable but not outstanding classification ability. The moderate F1 score indicates room for improvement. For the L group, the recall was relatively high, indicating that most examples of this class were identified, but the lower precision pointed to many false positives, reflecting good sensitivity but needing improved specificity. The R-L group showed high precision and good recall, indicating the model was very effective in correctly classifying this class. The high F1 score reflects a positive balance between precision and recall, indicating solid performance for this group. In the 4-class scenario, the Decision Tree achieved better results in discriminating Feeding compared to the previous case, suggesting the model was very effective at recognizing this combined class, reducing errors that occurred when the classes were separated. The metrics for class W slightly decreased compared to the 5-class scenario, with an F1 score of 55.88%, precision of 48.56%, and recall of 65.80%, indicating that the model continued to have moderate difficulty with this class. For the L and R-L groups, the model maintained good performance, with results comparable to the previous scenario. Similar to method II, combining the two Feeding classes led to significant improvements (Figure 5.3).

5.3.4 Discussion

This study examined three distinct methodologies for classifying grazing cattle behaviors: statistical methods, neural networks, and decision trees. Each method presents unique advantages and disadvantages, which must be carefully considered, especially regarding the

Table 5.6: *Test performance, per class, of both scenarios proposed considering 10-fold for Decision Tree*

Behav. groups	**5-class scenario**			**4-class scenario**		
	F1 score (%)	**Precision (%)**	**Recall (%)**	**F1 score (%)**	**Precision (%)**	**Recall (%)**
F-S	79.80±0.02	90.28±0.01	71.02±0.01	93.39±0.06	96.37±0.06	90.61±0.02
F-W	47.53±0.02	36.20±0.02	69.17±0.02	-	-	-
W	57.56±0.02	51.01±0.02	66.15±0.03	55.88±0.04	48.56±0.02	65.80±0.03
L	62.66±0.02	54.76±0.04	73.61±0.05	61.39±0.04	54.05±0.03	71.25±0.04
R-L	78.56±0.01	86.96±0.02	71.71±0.03	78.73±0.02	85.35±0.01	73.08±0.02
Weighted average	**72.83±0.01**	**77.39±0.01**	**71.02±0.01**	**82.47±0.02**	**84.28±0.01**	**81.53±0.01**

Table 5.7: *Test performance of both scenarios proposed considering 10-fold for Decision Tree*

Models	**Scenarios**	**F1 score (%)**	**Precision (%)**	**Recall (%)**
Decision Tree	5-class	72.83±0.01	77.39±0.01	71.02±0.01
Decision Tree	4-class	82.47±0.02	84.28±0.01	81.53±0.01

technological and energy constraints typical of rural environments.

Deep Neural Networks are well-known for their high accuracy in classifying animal behaviors. Their ability to learn complex data representations allows them to effectively distinguish between various activities such as walking, feeding, and lying. However, implementing neural networks on micro-controllers necessitates advanced hardware with higher computational power and memory, significantly increasing costs. Additionally, neural networks require high energy consumption due to the large number of computational operations needed for inference. This is problematic in rural settings where frequent battery

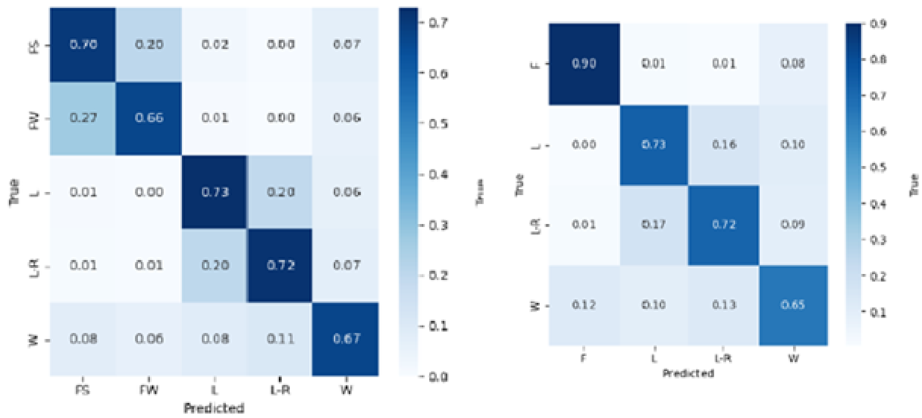

Figure 5.3: *Confusion matrix for Decision Tree in 5-class scenario and 4- class scenario*

recharging is impractical. Therefore, although neural networks could achieve higher accuracy in recognizing different behaviors, the need to transfer a large amount of raw data to a processing unit limits their practical application. Performing edge computing of classification algorithms in wearable devices also increases energy consumption due to the computational costs of neural networks, reducing battery life.

An alternative approach involves transmitting raw accelerometric data to an external server for remote processing. This method leverages cloud computing power to execute complex machine learning algorithms, including deep learning. However, continuous data transmission requires high-bandwidth telecommunications networks, resulting in high energy consumption to maintain connectivity. Furthermore, 4G and 5G network coverage may be insufficient or entirely lacking in grazing areas, limiting this approach's reliability and feasibility. Arcidiacono et al. (2021) found that using Bluetooth Low Energy (BLE) communication to transmit raw data from a triaxial accelerometer resulted in acceptable power consumption. Operating at a 10 Hz sending frequency, the power consumption was about 160 µA, and reducing the frequency to 0.2 Hz lowered the consumption to 10 µA. However, as Mancuso et al. (2023) noted, BLE has a short range, making it unsuitable for large grazing areas typical of extensive livestock systems. While repeaters, gateways, and antennas can extend the range, the feasibility of using BLE depends on the area's size and the availability of a reliable electrical network.

Low-Power Wide-Area Networks (LPWANs) could overcome the limitations of short-range communication systems for monitoring animal behavior in extensive farms, covering large grazing areas (up to 10 km) with a single repeater while preserving battery life. However, due to reduced bandwidth, neural network-based classification models are impractical because of the large data transmission requirements.

In contrast, using accelerometric thresholds, calculable with statistical methods and machine learning algorithms like decision trees, offers a more practical and sustainable solution. These methods can be directly implemented in the firmware of microcontrollers, drastically reducing the need for real-time data transmission and significantly lowering energy consumption, thus extending device battery life. Decision trees, for instance, require fewer computational operations than neural networks, allowing for efficient classification with less powerful, energy-efficient hardware. According to the authors' research, statistical methods with classifiers implemented within wearable devices are compatible with LPWANs. Preliminary tests with a cow behavior monitoring system prototype operating through a LoRa network demonstrated feasibility due to low energy consumption. At a 4 Hz frequency, energy consumption was about 180 µA, and with a high-capacity 6600 mAh Li-SOCL2 battery, this should ensure a battery life of at least two years.

However, accelerometric threshold methods have limitations compared to neural networks. Their behavior classification accuracy can be lower, relying on less complex data features. They may not capture the variability and complexity of animal behaviors as effectively as neural networks, which model nonlinear relationships between data features. Additionally, developing robust accelerometric thresholds requires access to diverse data, which is not always guaranteed, limiting model generalizability across different grazing conditions and behaviors.

In summary, while neural networks offer the highest accuracy for classifying grazing cattle behaviors, technological and energy constraints make their implementation challenging in rural contexts. Methods based on accelerometric thresholds and machine learning, though less accurate, provide a better balance between energy efficiency, cost, and practicality, making them more suitable for analyzing animal behavior in resource-limited environments. Choosing the most appropriate method should consider specific operational conditions, available technological resources, and sufficiently diverse and representative data to train robust models.

5.4 Conclusions

The introduction of IoT into Precision Livestock Farming (PLF) faces challenges like limited battery life and unreliable signals. This study examined three methods for identifying grazing cow behaviors using accelerometer data: Statistical, Deep Learning, and Machine Learning. Neural networks offer high accuracy but require extensive data transfer and high computational power, making them impractical for LPWAN networks. In contrast, the statistical method based on accelerometer thresholds is more suitable for LPWANs, combining moderate energy consumption with a low bit rate, making it ideal for large, connectivity-challenged areas. In summary, while neural networks provide greater accuracy, the statistical method using accelerometer thresholds is more practical for real-time behavior monitoring in extensive grazing systems with LPWANs.

5.5 Publication

Mancuso, D., Bonfanti, M., Castagnolo, G., and Porto, S.M.C. (2024) "Comparative Analysis of Statistical and AI-based methods for Livestock Monitoring in Extensive Systems", Computers and Electronics in Agriculture (submitted)

CHAPTER

SIX

PRELIMINARY OUTCOMES OF A LOW-POWER COW ESTRUS DETECTION SYSTEM IN DAIRY FARMS

6.1 Overview

In livestock management, monitoring the behavior of animals is essential for ensuring their well-being and optimizing production systems. Specifically, in the case of dairy cows, the detection of estrus is of paramount importance. Estrus monitoring not only serves as a critical indicator of the animal's welfare but also represents a significant economic factor for farmers. Timely and accurate detection of estrus allows for better reproductive management, leading to improved conception rates and reduced calving intervals. Consequently, effective estrus detection systems can enhance productivity and profitability in dairy farming. This study focuses on advancing the technology used for estrus detection by integrating a moving mean-based algorithm into a standalone smart pedometer (SASP), designed to provide real-time monitoring through Low-power wide-area networks (LPWAN). The implementation of such a system aims to offer farmers a reliable and efficient tool for managing the reproductive health of their herds, ultimately contributing to both animal welfare and economic gains.

6.2 Introduction

Since the second half of the last century, it was understood that the accurate detection of estrus in dairy cows is an essential step for the improvement of production systems and, therefore, of livestock management. The first automatic systems for the electronic recording of milk production were implemented in the 70s, while for the first attempts to automatically detect estrus it was necessary to wait until the 80s [83]. During estrus, many biological parameters of dairy cows (e.g., skin temperature, milk yield, milk conductivity, and motor activity) [64, 25, 109] can undergo more or less evident alterations and, therefore, the early detection of such modifications allows the timely recognition of estrus. The increase in motor activity during the estrous phase [125] suggested the use of electronic devices to monitor restlessness embedded in collars or pedometers. In a previous study [9], a moving mean-based algorithm for dairy cow's estrus detection from uniaxial-accelerometer data acquired in a free-stall barn was developed. The algorithm was specifically designed to provide farmers with a real-time tool able to detect the 'standing to be mounted' behavior by a specifically oestrus index. In this study that algorithm was implemented in the firmware of a standalone smart pedometer (SASP) which is a customized electronic device designed to use Low-power wide-area networks (LPWAN). After a testing period carried out during the year 2020, six SASPs were installed in a free-stall barn during the summer 2021. The farmer selected six cows among those at thirty days distance on average from calving and six SAPSs were attached to the cow forelegs. Data coming from the SASPs were used to develop a model based on pre-estrus window, technically called pro estrus. The novelty consisted in the possibility of identifying changes in motor activity preceding this physiological event, characterized by the development of follicles and the production of estrogen, which will reach its maximum in the true estrus phase. Moreover, this study makes a new step forward to develop livestock monitoring systems based on LPWAN (e.g., Sigfox, and LoRa).

6.3 Materials and Methods

6.3.1 Stand-alone smart pedometer

The designed SASP was equipped with an accelerometer, which acquired data at 4 Hz, a Sigfox communication module, a micro-controller which calculated the moving-means by using equation 6.1, and a power supply system. The electronic device was sheltered into a customized case and then attached to the cow's leg (Fig. 6.1a). To build the moving mean from uniaxial-accelerometer data (Eq.6.1), an algorithm implemented in the firmware computed the variables reported in Table 6.1. Since there are 96 intervals of 15 minutes in a day, the moving mean over 24 hours (mov_mean_h) was computed by using the following relation:

$$\text{mov\_mean}_h = \frac{\sum_{j=h-95}^{h} \text{sum\_15min}_j}{96} \tag{6.1}$$

The SASP sent the moving means computed by Eq.6.1 to a cloud server at 15 min-intervals. A WebApp was specifically developed to monitor the estrus status by producing a graph of the estrus index (Fig. 6.1b).

6.3.2 The pro-estrus window based model

To develop a model based on pre-estrus window, technically called pro-estrus, during the summer 2021 (period between 17 July – 31 August), the breeder selected six cows among those at thirty days distance on average from calving and one SASP for each cow was attached to cow's foreleg. All cow estrus onsets were detected through a WebApp specifically developed and then validated by the breeder, through the visual and direct identification of all the typical signs of the estrus phase (i.e., frequent bellowing, reflex at the mount, and presence of mucous discharge), and by the veterinarian, through the milk analyses. During the trial, six estrus events occurred. The analysis of the accelerometer curve during estrus (Figure 6.2) allowed the identification of recurring alternation of 'standing' behavior (corresponding to an increase in the accelerometer values) and 'walking' behavior (corresponding to a plateau of the accelerometer curve). During the standing phase, the cow exhibits the willingness to be mounted, as it is ready for insemination. Failure to mount favors the walking phase, since the restless cow tends to move more in search of the bull. The two behaviors alternate until the estrus occurs, and the maximum value (peak) in the accelerometer curve is reached. When the estrus event ends, there is a continuous decrease in the acceleration values detected by the SASP, corresponding to the rest of the animal in the lying posture.

Figure 6.1: *a) SAPS attached to cow's leg. b) Typical trend of the accelerometer curve 96 including the peak due to estrus (testing phase during summer 2020).*

Table 6.1: *Variable definitions*

Variable	**Definition**
acc_x	Acceleration along x axis, acquired at a 4Hz frequency.
$sma_x = \|acc_x\|$	Signal Magnitude Area (sma) along x axis computed at 4Hz frequency.
$\overline{sma}_x$	Mean value of sma_x in one second (1Hz).
$\text{sum\_15min}_j = \sum_{i=1}^{900} sma_{x_i}$	Sum_15min_j is the sum of $\overline{sma}_x$ in each j-th 15-min time interval (900 s).

Data coming from the SASPs were used to develop a model based on a moving window whose duration is equal to pro-estrus time interval. As suggested in the literature [3], the width of the pro-estrus time interval considered in this study was 3 days before estrus event.The analysis of the acceleration curve 6.2 was performed by identifying the following parameters:

- mean value of the acceleration in the three days of the moving window (MV3-days);
- value of the local minimum (MIN) and value of the maximum (MAX) found during estrus event;
- mean value of the slope of each single standing phase (SMS)

From the computation of these parameters, it was possible to define the following estrus indicators:

- width of the estrus window (W) expressed in hours (duration of estrus event)
- mean value of the estrus slope (MS) expressed in mg/h
- increase of the peak compared to the local minimum (I%) expressed in percentage as follows:

$$I\% = \frac{\mathrm{MAX} - \mathrm{MIN}}{\mathrm{MIN}} \cdot 100 \tag{6.2}$$

It has to be noted that the fluctuations in the curve with respect to the average trend in the short term were considered, freeing the analysis from changes in behavior due to seasonality that have nothing

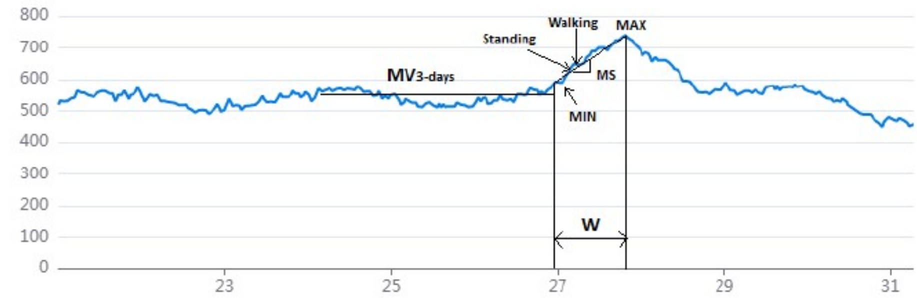

Figure 6.2: *Main parameters in the acceleration curve related to an estrus event detected for one of the six cows.*

to do with estrus event (MV3-days could also differ significantly from the average value in the long term). Based on the previous observations, the proposed model for identifying estrus can establish whether a given increase in the acceleration curve represents an estrus event and, if so, what is the probability related to it. This model included an algorithm developed starting from the mean values and standard deviations calculated for the indicators chosen within the set of the six estruses taken as sample. In detail, for each i-th indicator (W, MS, I%), the error range (E_i), expressing the measure of the uncertainty associated with the quantity, was defined as the difference between the highest and lowest error values computed as follows:

$$E_i = \bar{x}_i \pm \sigma_i \tag{6.3}$$

where x–l is the mean value of the i-th indicator and ”i is the related standard deviation. An increase in the acceleration curve is associated with estrus if, from the analysis of the main parameters of Figure 6.2, at least two of the three indicators fall within the corresponding error ranges. In this case, the algorithm of the pro-estrus detection model generates the following alert: 'Estrus detected'. Conversely, when no indicator falls within the error range, the algorithm does not generate any alert. When only one indicator falls within the error range, the procedure must be repeated by widening the error range by an additional half standard deviation (extended error range Eext):

$$E_{\text{ext},i} = \bar{x}_i \pm 1.5\sigma_i \tag{6.4}$$

In this case, if at least two of the three indicators fall within the extended error range, the algorithm generates the 'Probable Estrus' alert. The algorithm can scan and update the computation about the estrus indicators until the conditions of estrus detection are achieved.

6.4 Results and discussion

To assess the reliability of the proposed method, a statistical analysis of the data from acceleration curves of the sample (Figure 6.3) was carried out. As can be seen, in the observation time interval (from 17th July to 31st August), one estrus event per cow was identified in cows n. 1, 2, 3, 5; in cow n. 4 two estruses occurred; and no estrus was detected in cow n. 6. The acceleration mean values and the maximum values over that period were the following, respectively: 535.8 mg and 745.1 mg (cow n. 1), 534.6 mg and 690.2 mg (cow n. 2), 421.2 mg and 628.9 mg (cow n. 3), 523.4 mg and 615.0 mg (cow n. 4), 521.2 mg and 712.3 mg (cow n. 5). Table 6.2 shows the values of the indicators (W, MS, I%) computed for each estrus event detected by the SASP and successively validated by both the breeder and veterinary. Mean values and standard deviations of the indicators computed for the six estrus events were found to be:

- width of the estrus window: W = 16.8 h; 'w = 2.5 h
- mean value of the estrus slope: M = 9.2 mg/h;"'MS = 2.7 mg/h
- increase of the maximum: = 29.3 %; 'I% = 6.8 %

In accordance with the proposed pro estrus detection model, four estruses could be considered as 'detected' (estruses 1, 3, 4 and 6). Among the remaining two estruses, one could be classified as 'probable' (estrus 2). The event 5 was not recognized as estrus. From this statistical analysis, it can be inferred that the proposed pro-estrus detection model is 67% reliable in recognizing an estrous event (4 events over 6) and 83% reliable in recognizing a probable estrus (5 events over 6). By adding new data input such as milk production and milk conductibility, the model could improve the detection accuracy. The proposed pro-estrus detection model represents an advancement of knowledge compared to the previous studies [7, 8, 9] as it overcomes the limitation due to the analysis of the absolute values of the moving mean over 24 hours.Indeed, these absolute values could be influenced by practices performed by the breeder altering the natural behavior of livestock. As already highlighted in Arcidiacono et al.[9] the breeder, once the first signs of estrus were identified, moves the cow from the barn to a special separate box in order to practice artificial insemination, which can be carried out several hours after such movement. Since the animal is moved from the resting area, once the estrus phase is over, it cannot express the physiological lying behavior, resulting in an increase in the acceleration curve. The pro-estrus detection model, based on the computation of the indicators, ensures the determination of estrus event as independent from the effects of the aforementioned artificial insemination practice.

Table 6.2: *Estrus indicator values for different estrus events*

Estrus indicator	**Symbol**	**Unit**	**1**	**2**	**3**	**4**	**5**	**6**
Duration window	(W)	[h]	17.8	18.8	19.0	16.8	12.3	16.0
Mean slope	(MS)	[mg/h]	8.2	6.4	6.7	10.2	13.6	10.1
Increase percentage	(I%)	[%]	24.2	21.1	26.0	31.4	38.9	34.4

The mean value found for the indicator W fits well with the typical duration of estrus event in dairy cows, that ranges from 3 to 28 h with a higher probability around 16 h [3, 53]. With regard to the assessment of the remaining two indicators, since they were introduced for the first time and constitute the main novelty of this study, a greater number of estrus events (that can be determined using the acceleration curve provided by the SASP) should be analyzed. It could be performed by applying a higher number of devices to monitor the whole herd. This further task will be useful in refining the error ranges and, thus, experimentally validating the model proposed in this work. However, despite the small number of samples tested, a good repeatability of the proposed model was achieved, and it was proved by the low values of the standard deviation compared to the mean values for all the indicators. In addition, in the estrus windows related to each validated estrus event, the indicators (Tab. 6.2) tend to settle on values close to the mean values calculated in the six estruses. This evidence encour-

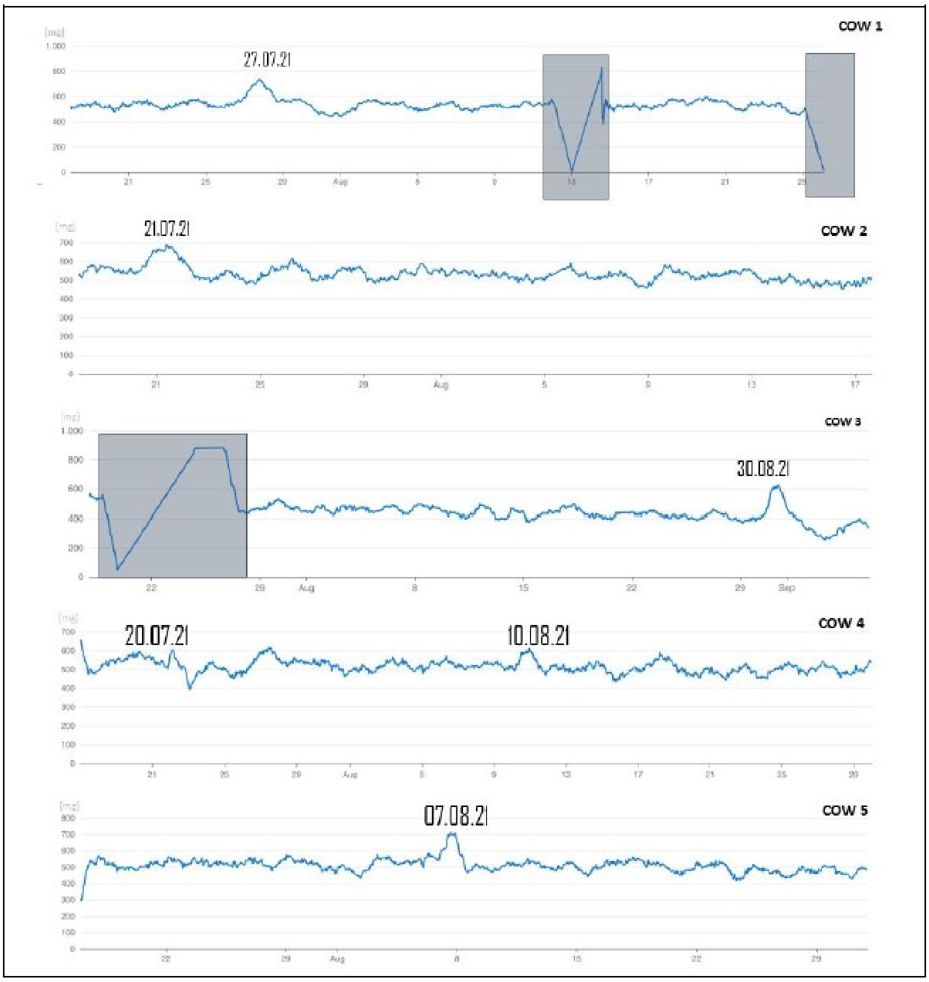

Figure 6.3: *Acceleration curves of tested cows with estrus events. The dates indicate when the estrus was detected. SASP malfunctioning intervals are highlighted in grey.*

ages future experimental validation. All the three indicators (W, MS, I%) can be implemented in the customized WebApp of the SASPs, i.e., in devices not requiring any installation in the barn (as Personal Computers or wired communication and/or power supply networks). Indeed, such devices make use of wireless communication network infrastructures of the LPWAN type to allow long-range communications with a low bit rate between the various connected pedometers. The latter feature is important in rural areas where coverage of GSM/GPRS networks or wired networks (ADSL) is often missing. In this way, besides displaying the acceleration curve, the WebApp will provide the breeder with the early recognition of oestrus events and the relative probability of occurrence.

6.5 Conclusions

In the present study, a new pro-estrus detection model for dairy cows was proposed. This model relies on analyzing the acceleration curve provided by the SASP device, which does not require barn installation. A specially developed algorithm scans the curve and updates the computation of estrus indicators until detection conditions are met, excluding influences unrelated to estrus. The model, considering only motor activity, was 67% reliable in detecting an estrus event and 83% reliable in detecting probable estrus. Incorporating additional data such as milk production and conductibility could enhance detection accuracy.

6.6 Publications

Bonfanti, M.; Castagnolo, G.; Arcidiacono, C. Preliminary Outcomes of a Low-Power Cow Oestrus Detection System in Dairy Farms. In Proceedings of the 10th European Conference on Precision Livestock Farming, Vienna, Austria, 29 August–2 September 2022; pp. 753–760.

CHAPTER

SEVEN

KERNEL DENSITY ESTIMATION ANALYSES BASED ON A LOW POWER GPS FOR CATTLE MONITORING

7.1 Overview

In livestock management, accelerometers are vital tools for monitoring animal behavior, providing detailed insights into activities such as feeding, walking, and resting. However, while accelerometers are excellent for behavior tracking, they do not provide information about the animal's location. This limitation becomes crucial in extensive farming systems, where knowing the precise location of the cattle is essential. In extensive farming, the ability to determine the physical location of each cow is vital not only for managing the herd but also for making informed decisions about grazing patterns and pasture use. Knowing where the cows are allows farmers to assess what they have consumed, monitor the impact on the grazing areas, and make necessary adjustments to prevent overgrazing and soil degradation. The aim of this study was to demonstrate the feasibility of a new automatic system for locating and tracking cows in extensive livestock systems using space-time data from a low-power global positioning system (LP-GPS). This information was utilized to analyze how the herd utilizes the pasture, aiding in the modeling of the environmental impacts of extensive livestock systems through geographical information systems (GIS).

7.2 Materials and Method

7.2.1 Experimental trial

In Sicily, the largest island in the Mediterranean Sea, summer transhumance to highland pastures remains common, particularly in inland areas characterized by a continental climate with moderately cold winters and hot summers. The breed considered in this study typically migrates from the Nebrodi mountains in the province of Messina to the Margilupo district in the municipality of Melilli, within the province of Syracuse, at an altitude of 200 meters above sea level (Figure 7.1).

The experimental activity took place in December 2019. The cows grazed in an area of approximately 100 hectares, enclosed by an electrified fence to prevent trespassing. The herd comprised 90 animals: one Limousine breed bull, 70 suckler cows aged 5 to 10 years, 13 heifers aged 1 to 4 years, and 10 calves under one year old.

The pasture mainly consists of permanent natural fodder typical of the Mediterranean climate, with no cultivation. This vegetation results from the interaction of climatic, soil, and species adaptation factors. Direct surveys and visual inspections revealed that the soil's vegetation cover includes many thorny shrubs and various species of cruciferous and composite grasses, which are not consumed by animals due to their thorny stems. These conditions, combined with the lack of water resources, contribute to the pasture's medium-low production potential.

The main soil characteristics—slope, exposure, and geomorphology—were analyzed using GIS software. Spatial data sets were obtained from the National Geographic Portal via the Download Service. Data related to slope, geomorphology, and exposure were downloaded using a web feature service (WFS) and analyzed in GIS software. Statistical analyses were conducted to extract the mean, maximum, minimum, and standard deviation of basic terrain morphology parameters (altitude, slope, and exposure) to correlate these features with animal locations.

The cattle breeds in this study are rustic and not accustomed to wearing equipment. Therefore, the breeder selected 10 tame animals for the experiment, which were generally accustomed to wearing collars with cowbells. The collars, made from durable plastic material, can be molded to fit the required shape. Each collar is equipped with a bell that sounds when the animal moves, aiding the breeder in tracking the animal (Figure 7.2).

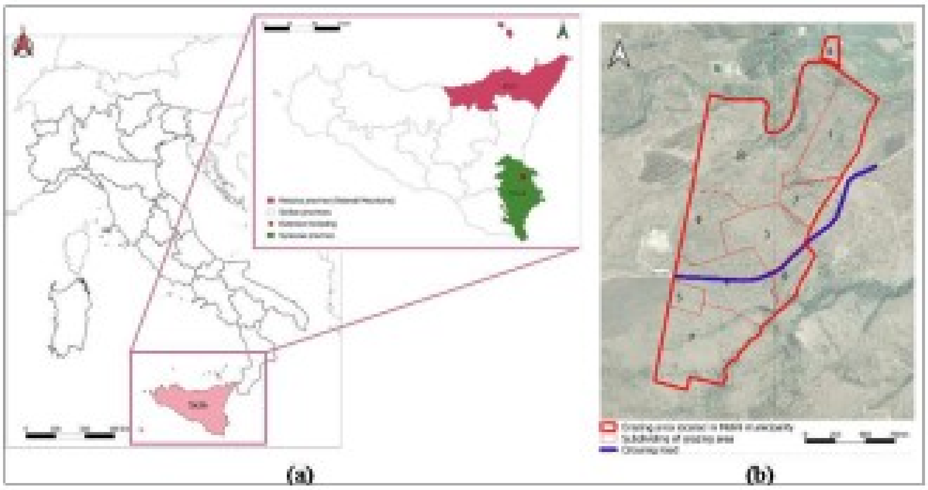

Figure 7.1: *The territorial area by the localisation of the grazing area (red box).*

The bells are specifically shaped and sized to suit animals of different ages and can emit different sounds to help the breeder identify and locate the animals. In the Nebrodi mountains area, this ancient method of tracking animals is still widely used by breeders.

7.2.2 Data collection

The low-power GPS-based system (LP-GPS system) developed in this study comprises wearable devices capable of receiving position information from up to three global navigation satellite systems (NAVSTAR/GPS, Galileo, GLONASS), although only NAVSTAR/GPS was used in this research. After receiving position information, the wearable devices transmit it to a cloud server via the SigFox telecommunication network, as illustrated in Figure 7.3. The SigFox antenna was placed near Monte Lauro in the province of Syracuse, approximately 25 km from the study area.

Figure 7.2: *Low power-global positioning system device attached to the cow's collar.*

This system, designed for long-term animal tracking, collected waypoints (latitude and longitude), detection date and time, and the distance traveled by each cow. The data acquisition interval was set at 20 minutes to ensure long-term data collection suitable for GIS analyses, such as KDE algorithms, while maintaining battery life [65, 116]. According to the literature, both trajectories and behaviors can be estimated accurately with GPS sensors at a high sampling rate of <0.016 Hz [49, 39]. In this study, the LP-GPS collars were equipped solely with GPS sensors, which are energy-consuming, but future phases will integrate additional sensors (e.g., accelerometers at 4 Hz) to study

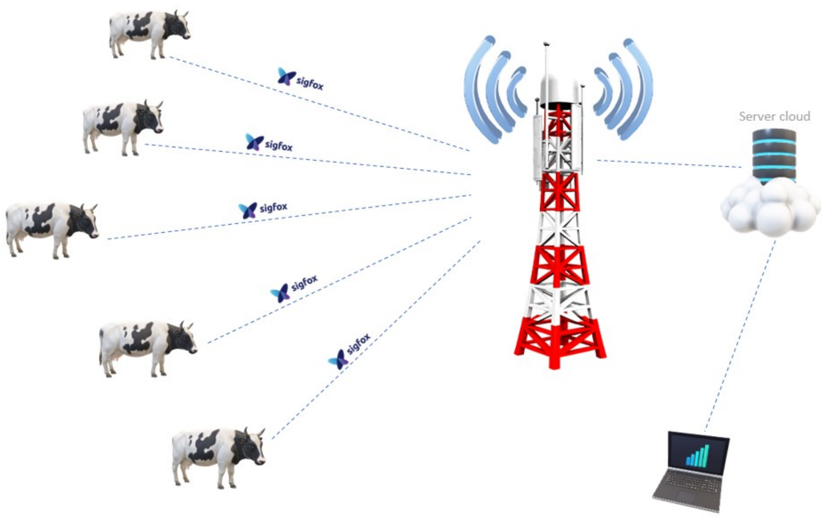

Figure 7.3: *Scheme of the proposed low power GPS-based system (LPGPS).*

cow behavior in extensive systems, following methods used in previous studies [10, 7, 9, 100]. Raizman et al. [97] noted that limited battery life in some studies necessitated hourly or less frequent position detection, reducing the efficiency of grazing animal monitoring. This study prioritized investigating battery life and the suitability of the SigFox communication network, demonstrating that the adopted low sampling rate and LP telecommunication network allowed for longer battery life than those reported in the literature [97, 15, 120]. The device developed in this study featured an omnidirectional GPS antenna and receiver with -167 dBm sensitivity and 72 channels, an ultra-low-power microcontroller, a SigFox radio module (868 MHz, 14 dBm E.R.P.), an omnidirectional SigFox antenna, and was powered

H]

Figure 7.4: *Low-power global positioning system device and the IP case.*

by high-capacity Li-SOCL2 batteries (ExtraCell 3.6 V C ER - 2 × 6500 mA). The device can operate in temperatures ranging from -20 to 50°C and is housed in a small commercial case (119×66×43 mm) with IP68 protection (Figure 6). The LP-GPS devices' location accuracy in a static position was about 4-5 meters, tested by hanging the collars on a perch and recording positions over 24 hours. Ten devices were attached to the collars (Figure 7.4) of ten female cows, differing in age and number of births, selected for their approach ability by the breeder. The device weight (0.3 kg) represented less than 0.1% of the animals' weight, eliminating the need for habituation [48]. Table 7.1 details the selected cows and their associated devices, including specific physiological and pathological events during the trial. The analysis began on December 27, 2019, with collar and device installation. Data recording started on January 1, 2020, due to the Christmas holidays, and continued until January 21, 2020, when the GPS devices were removed from the collars for technical reasons, despite residual battery life. The devices began detaching due to weak anchor points, prompting their removal and reattachment with a safer system. However, due to the lockdown, it was not possible to return to the company before the animals moved to the Nebrodi mountains in June 2020. Despite this, the collected data are deemed sufficient to describe the system's functionality and potential applications for herd management and land use analysis. Data were recorded for 21 days at 20-minute intervals, subdivided into three 7-day periods: January 1-7, January 8-14, and January 15-21. Data from Cow 5 were unavailable due to a collar attachment issue. All information collect was sent to an AppWeb. Data were then imported for further statistical and geospatial analysis.

7.2.3 Data analysis

Geospatial analysis was conducted using Quantum GIS (QGIS) software (v.3.10.11), a free tool provided by the Open-Source Geospatial Foundation (Chicago, USA). QGIS facilitates the organization, analysis, and visualization of spatial data at the territorial level, allowing for a deeper understanding of the relationship between livestock and the environment. By applying the Kernel Density Estimation (KDE) tool in QGIS, land use analyses were performed based on the positional data of each animal equipped with tracking devices.

Kernel Density Estimation (KDE) is a non-parametric method used to estimate the probability density function (PDF) of a random variable. Unlike histograms, which can be discrete and depend on bin width, KDE provides a smooth, continuous estimate of the PDF, making it particularly useful for visualizing the underlying distribution of data.

In biological studies, KDE is commonly employed to calculate the home range of a species, defined as the area of agricultural land or natural habitat where a species lives and conducts its daily activities. KDE analysis offers a density estimation of territory use, highlighting areas frequently occupied by the species.

Given a set of location data points $\{x_1, x_2, \ldots, x_n\}$, the KDE at a point x is defined as:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right),$$

where:

- n is the number of data points (e.g., locations of the species),
- $h > 0$ is the bandwidth parameter, which controls the smoothness of the estimate,
- $K(\cdot)$ is the kernel function, a symmetric, non-negative function that integrates to one.

Common choices for the kernel function K include:

- Gaussian (normal) kernel:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}},$$

- Epanechnikov kernel:

$$K(u) = \frac{3}{4}(1 - u^2) \quad \text{for } |u| \leq 1.$$

The KDE analysis results in maps (either raster or vector images) that represent the most frequently used areas by animals. These maps typically display density levels at 95% (home range, HR) and 50% (core home range, CHR). The home range (HR) represents the area with a 95% probability of finding the monitored species, indicating the broader territory used by the species. The core home range (CHR) represents the area with a 50% probability, highlighting the core areas where the species spends most of its time. Maps were generated for each sample animal and all selected cows to classify preferred areas.

7.3 Results and discussion

7.3.1 Vegetation cover detection and geomorphological analyses of the study area

In the study area, the floristic composition of the field was investigated, revealing a homogeneous pasture with consistent soil characteristics in terms of morphology (slope and exposure), geology, hydrology (geomorphological analysis), and climatic conditions. These analyses took place between late December and the first ten days of January, a period known for medium-low production due to climatic conditions. Following this initial in-field analysis, the pasture was divided into ten distinct areas (1 through 10) (Figure 7.5). The grazing areas 3, 4, 5, and 6, located near the road network, were classified as polyphote pastures. These areas had thin soil coverage with various pabulary species of legumes, cruciferous, and composite grasses, as well as thorny species that animals avoid eating. The sparse vegetation cover in these areas resulted from land exploitation by animals, which inhibited the growth of palatable species and promoted the development of thorny shrubs.

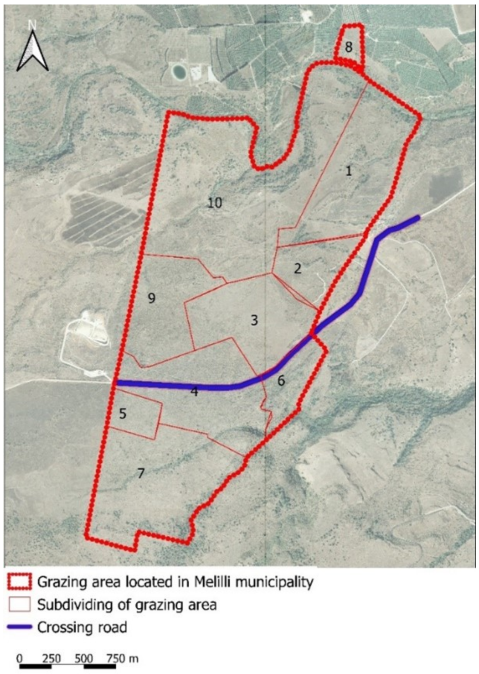

Figure 7.5: *Grazing area subdivided into ten different areas*

Grazing areas 1, 8, 9, and 10, situated far from the road network, were richer in forage due to their proximity to a dam, which served as a water source for the animals. These areas, along with area 7, were relatively homogeneous, characterized by grasses and pabulary legumes, including composites, *asteraceae, umbelliferae,* and *chenopodiaceae*. Dominant grasses included *Bromus sp., Avena sp.*, and *Hordeum sp.* Dominant legumes included *Trifolium subterraneum, Trifolium campestre,* and *Medicago arabica* and *hispida*. The

Table 7.1: *Main characteristics of the ten cows.*

ID cow	Device	Age (year)	Birth	Gender	Calf age	Note
1	0039D0AA	6	3	F	-	-
2	0039D1D9	2	0	F	-	-
3	0039D4B8	10	6	F	30 days	-
4	0039D7AE	6	2	F	-	-
5	0039D35F	4	1	F	-	-
6	0039D56D	2	0	F	-	Estrus
7	0039D883	8	5	F	-	-
8	003911EC	8	5	F	-	Estrus
9	00391A1	4	1	F	-	Lameness
10	0036718F	6	3	F	30 days	-

Mediterranean scrub dominated the vegetation, featuring carob, olive, and citrus trees, along with dwarf shrubs and herbaceous plants such as *Calicotome villosa, Sarcopoterium spinosum*, and *Cynara cardunculus altilis*. The prevalence of these species indicated high land exploitation by animals, leading to the sparsity of palatable species and the takeover of non-palatable species. Using the QGIS software tool, slope and exposure data of the study area were analyzed (Figure 7.6). The slope of the land ranged from 0% to a maximum of 12% across different areas of the extensive breeding grounds. Specifically, areas 1, 2, 3, and 5 had slopes of about 0%, areas 4, 7, and 9 had slopes ranging from 6% to 12%, and area 10 had a slope of about 20% due to an artificial dam on the northern side of the pasture. The entire grazing area had an eastern exposure, providing good solar radiation for the animals, especially during winter (Figure 7.6B). The geomorphological characteristics, as reported in Figure 7.6C, indicated that the area is mostly hilly and crisscrossed by several small waterways, which enhance animal well-being, particularly during occasional hot spring conditions before the animals are moved to the mountains.

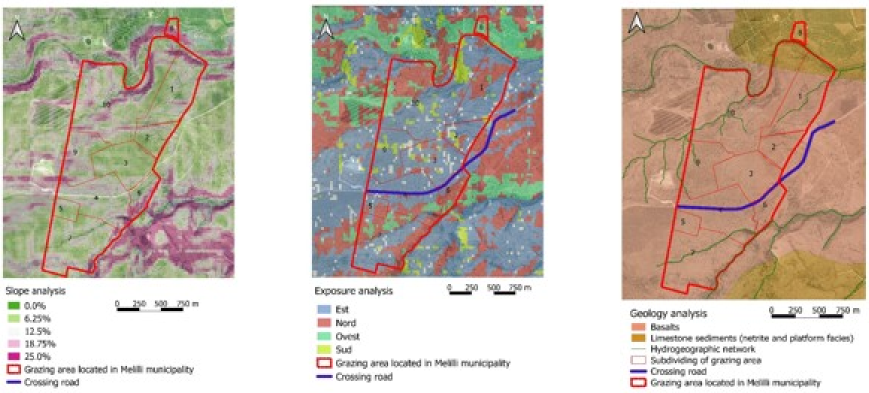

Figure 7.6: *Exposure and slope terrain analyses: A) slope; B) exposure; C) geomorphology.*

7.3.2 Analyses of data acquired

During a 22-day monitoring period, data were collected to locate and track ten cows equipped with LP-GPS collars. The Kernel Density Estimation (KDE) algorithm was applied to the collected data, generating nine thematic maps using QGIS software, each representing one of the monitored cows. These maps show the perimeter of the overall grazing area, a dirt road that divides the area into two parts, and indicate the "home range" (HR) and "core home range" (CHR) areas defined by the KDE algorithm, along with the subdivision of the pasture into ten previously described classes. The resulting heat maps highlighted the grazing areas most frequently used by the animals throughout the data collection period. Table 7.2 reports the results obtained by these analyses for each animal. The cows generally preferred flat areas, with an average slope of 4.7% and a maximum of 6.5%, facing northeast, and located at an average altitude of about 260 meters above sea level. Analysis of the maps (Figure 7.7) revealed that the HR areas (in green) were on average 84% larger than the CHR areas (in red), as reported in Table 7.2 with mean areas of 56.00 hectares and 8.70 hectares, respectively. Specifically, for cows 1, 3, and 10, the HR areas, where the probability of finding the animals is 95%, were similar, averaging around 76.00 hectares, and significantly larger than those of other cows, such as cow 8, which recorded an HR area of 19.95 hectares. Considering the CHR areas, where the probability of finding the animals is 50%, cow 8 had the smallest area (about 3.00 hectares), while cow 3 recorded the largest CHR area (about 14.00 hectares). The processing of data recorded through the developed Web application allowed for the definition of a behavioral profile for each animal. For instance, cow 1 traveled approximately 43 km during the entire observation period (Table 7.3), with an average of 2 km per day, varying between a maximum of 3.5 km and a minimum of 1.3 km. During the first 7-day monitoring interval, the cow traveled about 12 km, registering an increase of 4 km in the second interval due to the need to move in search of better forage, mainly in areas 2, 9, and 10.

Cow 2 traveled about 50 km in total (Table 7.3), with an average of 2.4 km per day and a maximum and minimum distance of 3.6 km and 1.6 km, respectively. In the first 7-day interval, it covered about 18.5 km, but recorded a decrease of 3 km in the second interval.

Table 7.2: *Statistical analyses.*

ID Cow	GPS-altitude	Slope (%)	Exposure (degree)	HR (ha)	CHR (ha)
0039D0AA (ID Cow 1)					
Mean	232.0	5.2	104.9	76.71	11.18
Max	284.0	10.4	348.8	102.6	23.0
Min	171.0	0.9	1.0	30.9	0.5
Dev.	20.9	1.9	102.6	27.1	8.2
0039D1D9 (ID Cow 2)					
Mean	260.7	4.9	121.6	59.69	10.05
Max	318.0	15.4	353.3	107.3	22.9
Min	215.0	0.9	0.9	9.7	0.2
Dev.	22.9	2.7	107.3	26.2	9.0
0039D4B8 (ID Cow 3)					
Mean	239.2	4.4	115.9	74.49	14.34
Max	295.0	13.6	348.8	149.0	36.0
Min	180.0	0.4	0.9	30.6	0.5
Dev.	29.7	2.4	106.4	28.4	10.8
0039D7AE (ID Cow 4)					
Mean	238.3	3.4	101.1	49.32	7.03
Max	390.0	9.5	348.8	85.8	23.0
Min	168.0	0.8	0.9	10.2	0.4
Dev.	28.4	1.6	85.8	21.2	9.2
0039D56D (ID Cow 6)					
Mean	260.4	4.5	104.0	35.77	4.93
Max	348.8	11.6	348.8	95.3	19.6
Min	166.0	1.2	19.9	1.0	0.1
Dev.	25.6	1.8	95.3	28.2	7.8
0039D883 (ID Cow 7)					
Mean	225.2	3.7	114.7	55.41	8.94
Max	288.0	12.9	352.0	95.3	28.2
Min	166.0	0.7	4.8	9.5	0.4
Dev.	27.4	2.0	95.3	23.4	9.3
003911EC (ID Cow 8)					
Mean	194.1	3.9	104.9	19.05	3.27
Max	246.0	13.8	353.2	55.4	16.1
Min	144.0	0.2	1.0	1.2	0.1
Dev.	29.7	2.3	106.4	17.4	5.9
00391A1 (ID Cow 9)					
Mean	200.0	6.5	112.8	61.66	7.43
Max	290.0	21.0	353.3	108.1	22.3
Min	151.0	0.4	1.0	14.5	0.2
Dev.	29.4	3.8	98.4	26.2	8.3
0036718F (ID Cow 10)					
Mean	230.2	5.2	118.6	76.71	11.48
Max	273.0	10.4	352.0	142.7	28.0
Min	188.0	0.9	1.0	30.9	0.5
Dev.	20.9	2.5	100.1	27.1	8.2
ALL Cows					
Mean	231.1	4.7	118.6	-	-
Max	171.4	1.9	15.0	-	-
Min	158.0	2.5	100.1	-	-
Dev.	24.4	2.0	76.8	-	-

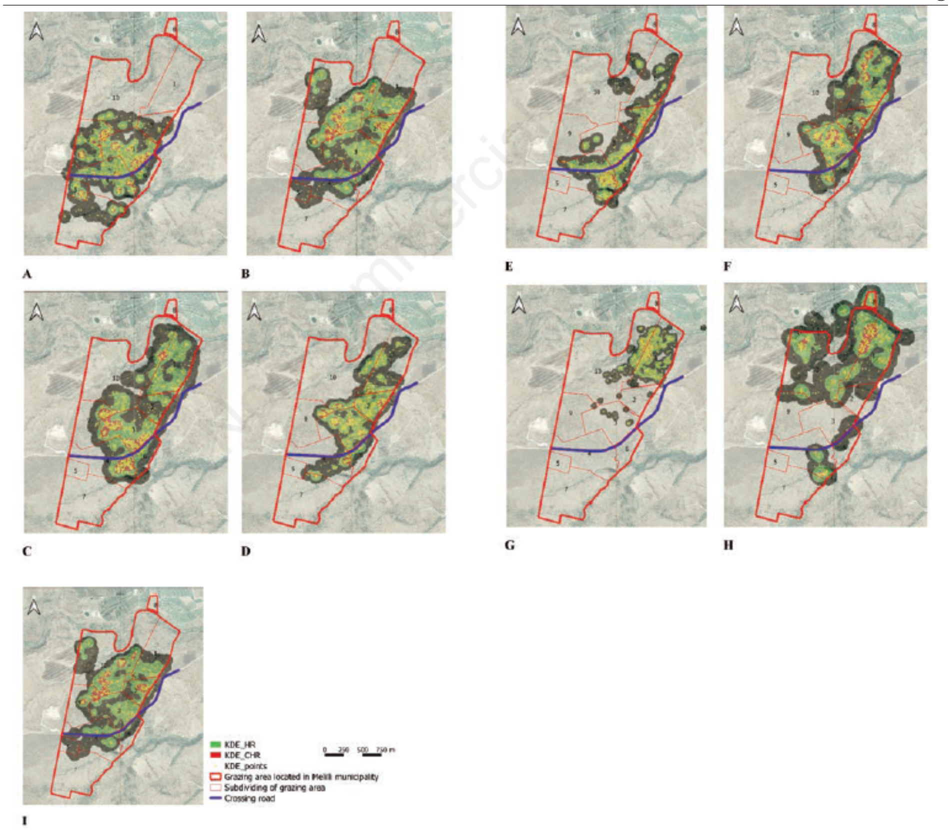

Figure 7.7: *Kernel density estimation (KDE) analyses of the ten cows: A) Cow 1; B) Cow 2; C) Cow 3; D) Cow 4; E) Cow 6; F) Cow 7;G) Cow 8; H) Cow 9; I) Cow 10. HR, home range; CHR, core home range.*

Comparing the heat maps of cows 1 and 2, it emerged that cow 2 frequented areas 1 and 10 more, while cow 1 preferred to stay longer in areas close to the road (i.e., areas 4, 6, 3). This difference is attributed to the fact that cow 2, being younger, preferred group life.

Similarly to cow 2, cow 3 traveled about 50 km, with an average of 2.4 km per day and a maximum and minimum distance of 3.2 km and 1.3 km, respectively. The heat map of cow 3 showed behavior similar to that of cow 2, highlighting an HR area far from the central grazing area, possibly due to the need to move to areas richer in forage and closer to a natural water source (i.e., area 1 and areas 10). This movement occurred mainly in the second observation interval, during which the distance traveled was greater than in the other two periods (18.77 km) (Table 7.3). Cow 4 traveled approximately 48 km, with an average of 2.3 km per day and a maximum and minimum distance of 3.0 km and 1.7 km, respectively (Table 7.3). The heat map showed few HR areas near the road network, with a preference for areas farther from human presence, consistent with its rustic behavior. A similar behavior profile was observed for cow 8, which traveled about 45 km in 21 days. Similar daily travel distances were recorded during the first observation interval, while during the second interval, an increase of about 4 km was recorded on January 10, attributed to the cow's estrus state, as confirmed by the farmer. The heat map shows that the CHR and HR areas are both far from the crossing road, located within the inner part of the grazing area, due to the cow's solitary and rustic nature. Cow 6 traveled approximately 47 km, with an average daily distance of 2.2 km and a maximum and minimum of 4.0 km and 1.1 km, respectively. The heat map shows HR areas along the road, mainly within area 4. As reported by the farmer, the cow entered estrus during the second time interval, with an increase in daily distance traveled on January 12 (4.02 km). Cow 7, compared to the others, showed different travel distances during the three-time intervals considered. It traveled about 54 km, with an average of 2.6

km per day and a maximum and minimum distance of about 4.4 km and 0.86 km (Table 7.3), respectively. An increase of about 2 km in traveled distance was recorded in the third time interval. The CHR and HR areas show that the cow preferred to stay mainly in areas 1, 2, and 3, where most of the HR areas are located, as with cows 1 and 4. Cow 9 traveled the shortest total distance, about 36 km, with a daily average of less than 2 km (1.7 km). In the first observation interval, cow 9 traveled about 14 km, similarly to other cows (i.e., cow 4, cow 8, cow 10); however, both in the second and third intervals, the traveled distance drastically decreased to about 11 km and 10 km, respectively. Observing this sudden reduction in traveled distance, the farmer promptly recognized lameness in cow 9's right front limb, leading to its transfer for medical treatment. The heat map shows that the CHR areas are widely distributed throughout the entire grazing area; instead, the largest HR area indicates that the animal remained there for an extended period, representing the equipped shelter area where the animal was transferred for medical treatment due to lameness (between areas 1 and 10). Cow 10 traveled one of the longest distances, about 52 km, with a daily average of about 2.5 km and a maximum and minimum of 4.7 km and 0.9 km, respectively. Through the heat maps, it was possible to identify the widest HR area, located in area 2, where the cow stayed from January 6 to January 7, 2020, when a drastic decrease in daily traveled distances was registered, similar to what was observed for cow 9. However, during the second and third intervals, the traveled distances increased again due to the need to find new grazing areas richer in forage. Therefore, cow 10 spent more time in area 10, located near the dam. Monitoring the animals' behavioral profiles can be useful for understanding and analyzing the interaction between animals and the environment.

In this regard, through Kernel Density Estimation, it was possible to create heat maps aimed at evaluating the most preferred territorial areas by all the cows considered. The analysis was conducted by closely examining the time intervals within the daytime observation period during which the cows moved from one occupied territorial area to another. Specifically, the analysis was carried out by observing four-time intervals considered most representative of these cows' activities, i.e., from 08:00 a.m. to 10:00 a.m., from 10:00 a.m. to 12:00 p.m., from 12:00 p.m. to 02:00 p.m., from 02:00 p.m. to 04:00 p.m., and from 04:00 p.m. to 06:00 p.m. A heat map was created for each of the selected time intervals, as reported in Figure 7.8.

By analyzing Figures 7.87.8A and 7.8E, obtained by carrying out KDE analyses at 8:00 a.m. and 4:00 p.m., respectively, it is possible to observe similar HR areas (i.e., 96.97 ha and 118.31 ha, respectively), larger than those obtained for Figures 7.8B, 7.8C, and 7.8D (i.e., 68.30 ha, 61.68 ha, 86.28 ha), carried out at 10:00 a.m., 12:00 p.m., and 2:00 p.m., respectively. The similarity between these two HR areas could be explained by the fact that at 8:00 a.m., the animals are still scattered within the grazing area, as they are known to prefer being alone and not grouped during the night hours. Then, after sunrise, the cows began their daily activities (e.g., walking, feeding, ruminating, drinking) before dispersing again throughout the territory to spend the night (4:00 p.m.). As seen from Figures 7.8B, 7.8C, and 7.8D, which show KDE analyses carried out at 10:00 a.m., 12:00 p.m., and 2:00 p.m., respectively, the reported HR areas are smaller than the previously mentioned ones and similar to each other, as the cows grouped together and carried out the same daily activities. To evaluate the territorial areas most visited by all the cows during the entire observation period, the heat map reported in Figure 7.8 was developed. It was built by merging all the HR areas obtained from the previous KDE analyses (Figure 7.7). From Figure 7.9, it is possible to see that, among the six obtained areas (i.e., A, B, C, D, E, F), "area D" was the most frequented by the animals, about 63.00 ha. Furthermore, "area D" registered an HR area more than 80% larger than the others, i.e., 3.90 ha, 0.78 ha, 0.23 ha, 6.90 ha, and 2.40 ha, recorded for "area A", "area B", "area C", "area E", and "area F", respectively. "Area D" was preferred because it was the flattest, near the dam, far from the road network and human presence, and had a great supply of forage, as observed during the visual inspection. The cows' activities influenced the soil cover of this area by removing plants and seeds and returning nutrients through manure. Additionally, animal trampling modifies the natural form of the soil; in fact, it was possible to observe the presence of well-established paths leading to the few watering points. The data obtained from the LP-GPS collars could allow farmers to assess feeding areas and grazing conditions and, if necessary, improve herd management by evaluating possible nutritional supplements or seeking other pastures. The behavioral profiles obtained using data acquired by the LP-GPS collars could represent a crucial aspect of livestock management, as they could enable prompt actions to preserve animal welfare. For instance, by observing the reduction in daily distance traveled by cow 9, the farmer immediately discovered right limb lameness and quickly transferred the cow for medical treatment, preventing further diseases.

Figure 7.8: *Kernel density estimation (KDE) analyses: home range (HR) of all considered cows during the whole observation period: A) time 08:00 a.m.; B) time 10:00 a.m.; C) time 00:00 p.m.; D) time 02:00 p.m.; E) time 04:00 p.m.*

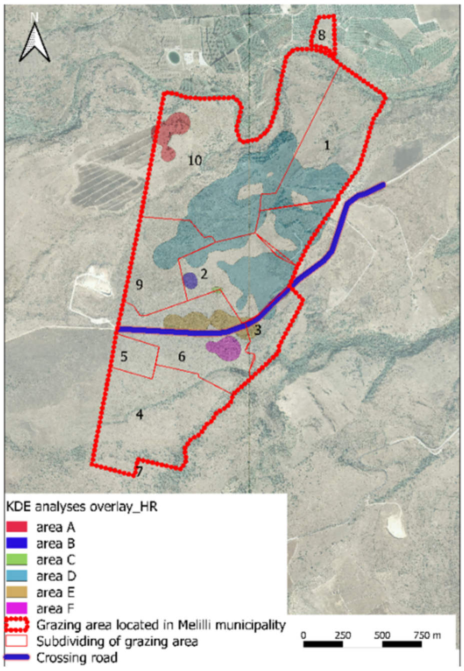

Figure 7.9: *Overlay of home range (HR) areas obtained by Kernel density estimation (KDE) analyses carried out for each herd animal.*

As Frost et al. [49] indicated, since animal behavioral activities are clear indicators of cows' physiological and physical status, particular attention will be paid to further improving the developed automated locating system by implementing additional sensors capable of monitoring the daily activities of grazing cows. In this context, data from LP-GPS collars combined with land use data in a GIS environment could allow the monitoring of significant variations in vegetation structure and the composition and variety of plant species that may arise due to the selection of food essences, trampling, and manure release. Through these actions, the animals modify habitats and populations of invertebrates and other organisms [37].

Changes in grazing intensity or the animal species involved can have significant consequences on biodiversity [19]. Moreover, from a social, economic, and cultural perspective, identifying the most exploited grazing areas can be useful in the context of landscape assessment procedures (relationship between grazing areas and the characteristics of the landscape) [37, 80]. In general, the relationship between animal husbandry and landscape quality can be positively configured, as in the case of rationally managed grazing systems, where maintaining grass in good, clean conditions, along with the presence of grazing animals, contributes to landscape amenities[68]. On the other hand, the presence of marginal areas, which may not be used by animals according to the analyses, could reduce the aesthetic value of the landscape due to the abandonment that might result[104].

This type of automated monitoring system could be significant for transhumance, a practice relevant to breeders as it supplements the normal annual forage and allows access to public economic aids [131]. Moreover, transhumance has significant economic externalities because it increases the cultural values of a territory, improving landscape quality, promoting local products, such as milk and cheese, maintaining local tradition[20], and supporting biodiversity through the conservation of high-value native species[132].

7.4 Conclusions

Real-time monitoring of herds in extensive livestock systems presents a significant challenge in measuring variables that can promptly alert farmers. Quick responses to changes in health, welfare, and production are essential for minimizing management difficulties and enhancing animal welfare. The findings of this study demonstrate the practicality of using GIS analyses combined with LP-GPS devices to locate grazing cattle, as this system can enable long-term tracking of animals. This technology could assist farmers in monitoring cows within grazing areas, allowing them to detect important changes in behavior or to address issues related to animal theft. This research marks an initial step toward further studies that aim to develop a reliable classification of grazing cow behavior based on data from additional sensors, validated through farmer observations. Moreover, the proposed monitoring system could be valuable to local authorities or regional environmental protection agencies. It could assist stakeholders in assessing the impact of extensive dairy cattle and cow-calf operations on soil quality.

7.5 Publications

- S. M. C. Porto, F. Valenti, G. Castagnolo and G. Cascone, "A Low Power GPS-based device to develop KDE analyses for managing herd in extensive livestock systems," 2021 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Trento-Bolzano, Italy, 2021, pp. 243-247
- Porto, S. M., Castagnolo, G., Valenti, F. and Cascone, G. (2022) "Kernel density estimation analyses based on a low power-global positioning system for monitoring environmental issues of grazing cattle", Journal of Agricultural Engineering, 53(2)

Table 7.3: *Daily distance walked by the monitored cows.*

Monitoring (day)	Cow 1 0039D0AA Distance (km)	Cow 2 0039D1D9 Distance (km)	Cow 3 0039D4B8 Distance (km)	Cow 4 0039D7AE Distance (km)	Cow 6 0039D56D Distance (km)	Cow 7 0039D883 Distance (km)	Cow 8 003911EC Distance (km)	Cow 9 00391A1 Distance (km)	Cow 10 0036718F Distance (km)
1	1.94	2.25	2.12	1.66	2.43	2.13	1.55	1.98	2.32
2	1.51	2.83	2.31	2.06	2.34	2.05	2.11	2.32	2.77
3	2.09	1.63	3.21	2.23	2.43	2.81	2.07	2.06	2.83
4	2.07	2.01	2.45	2.11	2.36	3.14	2.21	2.14	2.87
5	1.27	3.01	2.11	1.97	1.92	3.22	1.87	2.44	1.87
6	1.47	2.68	1.77	2.20	2.15	2.62	1.87	2.41	1.05
1st time-interval	**12.22**	**15.61**	**16.59**	**14.41**	**15.38**	**17.49**	**14.00**	**14.46**	**14.93**
7	2.53	2.50	2.43	2.00	2.49	3.42	2.36	1.32	3.37
8	1.89	2.16	2.14	1.94	2.04	2.11	2.11	1.55	2.29
9	3.46	2.56	3.17	2.61	2.04	3.42	4.32	3.01	3.19
10	2.06	2.51	2.60	2.45	2.56	2.59	1.92	2.18	2.14
11	2.48	2.18	2.44	2.53	4.02	3.14	2.45	1.50	2.45
12	2.48	2.10	2.95	2.90	2.19	2.07	1.68	1.03	2.22
13	2.11	2.22	2.71	2.44	2.07	1.27	2.47	1.51	2.13
14	2.16	1.67	2.00	2.43	2.02	2.75	2.66	2.89	1.60
2nd time-interval	**16.04**	**15.35**	**18.77**	**17.07**	**15.88**	**17.36**	**16.94**	**11.60**	**18.40**
15	1.41	2.27	2.66	1.77	2.13	2.36	2.48	1.00	2.16
16	1.67	2.28	2.25	2.00	1.42	2.75	1.54	1.75	2.07
17	1.83	2.46	2.58	2.22	1.82	2.79	1.54	1.75	2.07
18	2.08	2.18	3.13	2.55	3.26	3.96	2.38	0.97	4.67
3rd time-interval	**14.82**	**16.29**	**15.45**	**15.55**	**19.44**	**14.10**	**10.39**	**18.69**	
Total	**43.08**	**50.14**	**50.81**	**47.73**	**46.85**	**54.29**	**45.04**	**36.45**	**52.02**

CHAPTER

EIGHT

IOT TECHNOLOGIES FOR HERD MANAGEMENT

8.1 Overview

As demonstrated in previous studies, GPS provides crucial information that, when processed, can reveal insights into animal habits. In this context, IoT-based solutions are considered valuable for enabling long-distance monitoring of herd positions, thereby aiding in modeling the environmental impacts of extensive livestock systems. The primary objectives of this study were to explore the feasibility of a locating and tracking system in an extensive cow-calf livestock farm situated in southern Italy, an area lacking LPWAN network coverage. This system relied on space-time data provided by a prototype low-power positioning system (LP-GPS) based on the SigFox network. The research also aimed to test the battery life of the LP-GPS devices, with a particular focus on a 10-minute data transmission interval. Additionally, the study sought to evaluate the signal coverage after installing a SigFox repeater in the grazing area. To analyze the activities of the animals around the grazing area, the Kernel Density Estimation and GIS tools were employed.

8.2 Materials and method

8.2.1 Experimental trial

The experimental trial was conducted in an extensive pasture located in central Sicily, Italy, in the town of Aidone in the province of Enna (Fig. 8.1a). This area is situated at an altitude of approximately 800 meters above sea level and features a typical Mediterranean climate, with mild, humid winters and hot, dry summers. The farm spans about 300 hectares and has an irregular topography. The pasture is artificially maintained; farmers sow seeds from various species, including *Trifolium alexandrinum, Vicia sativa, Avena sativa, Triticum aestivum*, and *Hordeum vulgare.*

Through direct surveys and visual inspections of the study area, the floristic composition of the field was examined and found to be homogeneous across the pasture. The area was divided into three distinct sections (Fig. 8.1b): area 1 is characterized by olive trees and spontaneous meadow, area 2 is dominated by *Trifolium alexandrinum*, and area 3 consists of *Triticum stubble, Vicia faba, Vicia sativa*, and various weeds such as *Lolium L, Hedysarum coronarium L, Avena fatua L, Sinapis arvensis and Papaver rhoeas.* For the experiment, the breeder selected 6 female animals from a group of 130 cows in the cow-calf line, as reported in Table 8.1. The grazing area was enclosed with an electrified fence to prevent cattle from trespassing. The experimental activity took place between July and August 2021, with air temperatures ranging from 22°C to 42°C. Area 1 (Fig. 8.1b) was the most comfortable regarding air temperature, as it was equipped with trees providing shade and protection from solar radiation. Consequently, from 6 AM to 5 PM, the herd typically stayed in Area 1, where they had access to a hay-filled manger and a watering tank. During the cooler hours, from 5 PM to 6 AM, the herd was moved to Areas 2 and 3 (Fig. 8.1b), where the cows were free to graze.

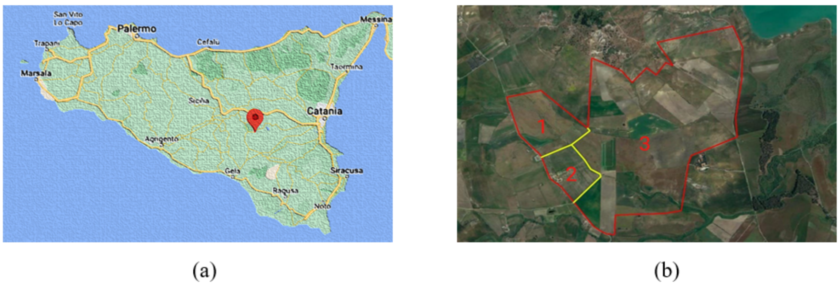

Figure 8.1: *(a) Localisation of the grazing area. (b) Grazing area subdivisions after visual inspection.*

Table 8.1: *Age and breeds of the considered cows*

	Cow 1	Cow 2	Cow 3	Cow 4	Cow 5	Cow 6
Age	6 yr.	6 yr.	9 yr.	2 yr.	3 yr.	2 yr.
Breeds	Italian *"Pezzata Rossa"*	Limousine	Limousine	Limousine *"x Pezzata Rossa"*	Limousine	Limousine

8.2.2 Data collections system

The developed prototype of a low-power positioning system based on the SigFox network (LP-GPS) enables the collection of cows' positions (latitude and longitude) by receiving information from up to three global navigation satellite systems (GPS, Galileo, GLONASS). The proposed system consists of a wearable electronic device, a cloud server for information storage, a WebApp for data management and visualization, and a Sigfox repeater to enhance signal strength and coverage. The wearable electronic device features an omnidirectional GPS antenna and receiver with -167 dBm sensitivity and 72 channels, an ultra-low power microcontroller, a SigFox radio module (868MHz, 14dBm E.R.P.), an omnidirectional SigFox antenna, and is powered by high-capacity Li-SOCL2 batteries. The electronic components are housed in a compact commercial case measuring 119 x 66 x 43 mm, with IP68 protection, making it dust and water-resistant. Each selected cow had a device attached to its collar. These collars, crafted by the breeder from durable plastic material that adapts to the required shape, were designed to minimize stress on the animals. Each collar also included a bell that made a sound when the animal moved, aiding the breeder in tracking the animal. The data acquisition period spanned from July 2021 to August 2021, with KDE analysis referring to 38 days (approximately 6 weeks) of observations taken at 10-minute intervals. For each position detection, along with the longitude and latitude coordinates, the system also stored the date and time of detection and the distance traveled since the previous position detection.

8.2.3 Data analysis

Data collected during the observation period were imported into the QGIS tool for further statistical and geospatial analysis. QGIS enables data elaboration and visualization at the territorial level to better understand the relationship between livestock and the environment. Statistical analysis on the position of each animal in this test was performed using Kernel Density Estimation (KDE), previously explained in Chapter 7. This technique allowed the calculation of the home range of the species, which is the area where a species lives, and provided a density estimation of land use. The results from the KDE analysis produced maps showing the areas of agricultural land most frequently used by each animal, expressed in terms of density (95% density level, or home range - HR). These maps helped identify the areas preferred by the animals. By knowing these areas and the types of forage available in different parts of the land, it was possible to assess the forage most consumed by the animals during the grazing period.

8.3 Results and discussion

By applying KDE algorithm to the dataset acquired through the LP-GPS prototype, 6 thematic maps were obtained by using QGIS software. Each map, one for each cow considered, reports in blue the perimeter of the whole grazing areas, in yellow the position occupied for the longest time and in red all the positions occupied during the observation period. In Table 8.2 the distance travelled per day and per week by each cow during the grazing timeslot are reported. By analysing the maps (Fig. 8.2) emerged that all the cows considered remain for long time into area 2, i.e., the area where the forage is Alexandrine clover, maybe because this kind of forage is considered by cows more palatable than others. Observing the maps, it emerged that, different from the others, cow 2 and cow 6 spent long time not only in area 2 but also in area 3. Comparing the distance traveled per day by each cow (Tab. 2), it emerged that the maximum distance was reached by cow 6 (6.2 km), while the minimum by cow 4 (3.8 km).

Cow	Avg. distance per day	Avg. 1st week	Avg. 2nd week	Average 3rd week	Avg. 4th week	Avg. 5th week	Avg. 6th week
1	4.0	3.8	3.8	5.7	4.3	3.2	3.0
2	4.5	3.5	4.2	5.5	4.8	3.8	3.6
3	4.8	3.5	3.9	5.8	4.7	3.2	3.6
4	3.8	2.8	3.0	4.5	4.7	3.5	3.5
5	4.9	3.6	4.1	5.4	4.9	4.1	4.1
6	6.2	5.3	5.7	7.0	6.5	5.6	5.3

Table 8.2: *Average distance (in km) per day traveled by each cow*

It is notable that cows 5 and 6 traveled greater distances than the others, likely due to their younger age, as detailed in Table 8.1. Although cow 4 is the same age as cow 6, it traveled less due to lameness during the experiment. Analysis of the weekly distance data in Table 8.2 revealed that the cows increased their daily travel by about 1.5-2 km during the third week. This distance gradually decreased during the fifth and sixth weeks, returning to the levels observed in the first and second weeks. The breeder explained this variation as a result of pushing the cows towards zone 3 to diversify their forage intake.

As mentioned in Section 8.2, a SigFox repeater was installed to ensure better signal quality. This installation resulted in more consistent data reception and significantly fewer lost position records compared to previous experiments by Porto et al. [93]. Although the heatmaps

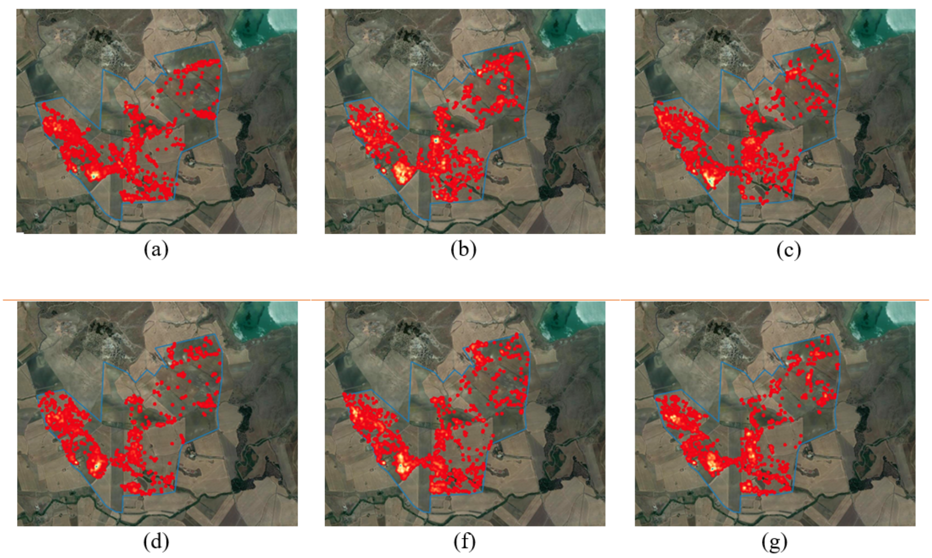

Figure 8.2: *Heatmaps of the six cows. (a) Cow 1. (b) Cow 2. (c) Cow 3. (d) Cow 4. (e) Cow 6*

were computed using six weeks of data, additional data were collected to test battery life, which reached four months in this experiment. This extended battery life was achieved with a 10-minute data monitoring interval. As reported in [97], the limited battery life of some devices in other studies necessitated position detection only once per hour or longer, reducing the effectiveness of monitoring grazing animals. By processing the collected data, it was possible to identify the areas where the cows spent the most time and understand the types of forage they consumed. To gain more insights into cow behavior during grazing and further validate the system, it will be necessary to revise the LP-GPS prototype hardware to integrate an accelerometer and develop software for behavior detection [94, 32]. The heatmaps generated by analyzing the data from the LP-GPS prototype could be crucial for livestock management, providing farmers with feedback on the types of forage consumed and the soil conditions of grazing areas. The potential applications of the proposed LP-GPS prototype may also interest stakeholders, local authorities, and regional environmental protection agencies.

8.4 Publications

Castagnolo, G., Mancuso, D., Valenti, F., Porto, S.M.C., Cascone, G. (2023). IoT Technologies for Herd Management. In: Ferro, V., Giordano, G., Orlando, S., Vallone, M., Cascone, G., Porto, S.M.C. (eds) AIIA 2022: Biosystems Engineering Towards the Green Deal. AIIA 2022. Lecture Notes in Civil Engineering, vol 337. Springer, Cham

CHAPTER

NINE

LOW-POWER NETWORKS AND GIS ANALYSES FOR MONITORING THE SITE USE OF GRAZING CATTLE

9.1 Overview

In Chapter 7 were investigated the effectiveness of an automated system for identifying and monitoring cows in extensive livestock operations using space-time data from a low power global positioning system (LP-GPS). They utilized this data to assess the pasture usage by the herd and estimate the environmental impacts of extensive livestock systems through GIS analysis. Subsequently, in Chapter Y were tested this system in another case study to evaluate its practicality for locating and tracking animals in regions with inadequate LPWAN network coverage. Both studies primarily focused on the viability of the LP-GPS based system for cow monitoring and environmental impact assessment, without addressing battery life, data loss and Sigfox signal strength and coverage. The objective of the current study was to assess the feasibility of the developed LP-GPS based system for tracking and monitoring cows in extensive livestock systems by specifically testing its battery life and the functionality of the low-power network, taking into account its signal strength and coverage in rural areas. The study also compared experimental results presented in Chapters 7 and 8, highlighting improvements in data retention achieved through the installation of a Sigfox repeater.

9.2 Materials and method

9.2.1 Data collection and analysis

The Low Power GPS-Based System (LP-GPS system), described in previous chapters, was applied to two different case studies (i.e., Case I and Case II). The developed system showed that the combination of a low sampling rate and the Low Power communication network provided a longer battery life than other systems investigated in the literature [15]. In detail, the wearable devices, after receiving position information (e.g., latitude and longitude, time of detection, and distance travelled by each animal), send it to a cloud server using the SigFox telecommunication network for processing and visualization through a WebApp. The SigFox antenna located close to Monte Lauro, within the province of Syracuse, was used for both case studies. In detail, the wearable device was equipped with an omnidirectional GPS antenna and receiver with -167 dBm sensitivity and 72 channels, an ultra-low power microcontroller, a SigFox radio module 868 MHz, 14 dBm E.R.P., an omnidirectional SigFox antenna, and was powered by high-capacity Li-SOCL2 batteries.

9.2.2 Case I

In the Case I, described in Chapter 7, the experimental activity was carried out in the territorial area belonging to the municipality of Melilli, in the province of Syracuse, for 21 days (Fig. 9.1). Data were acquired with an acquisition-time interval of 20 min as well as the time interval for sending messages to the cloud server. The 20 min-time interval was chosen to acquire long-time data for both carrying out tailored GIS analyses, such as the application of Kernel Density Estimation (KDE) tool and guaranteeing long lasting battery life. KDE tool, available in QGIS software, was applied by considering the placements of each animal outfitted with the devices.By applying KDE analysis, the maps (i.e., a raster or a vector image), obtained both for each animal of the sample and for all the selected cows to classify the preferred territorial areas, represents the area of the territory most frequently used by animals, in terms of density. In detail, the HR represents the area in which the probability of finding the monitored items is 95 %, while the CHR represents the area in which the probability is 50 % [93]. Ten different animals out of a herd of 90 animals that differed in age and number of births, but all belonging to the same breed (i.e., mix breed), were chosen by the farmer to carry out the experimental activity. Due to a problem with fitting a collar on a cow (i.e., case I_cow 5), the related data could not be analysed therefore, data from only nine wearable devices were collected and elaborated. On acquired data, both spatial and statistical analyses were carried out by using QGIS software for the first ones and KDE for the others through which six thematic maps were obtained, one for each considered cow. Moreover, acquired acquisitions were further analysed to assess possible devices signal losses for each individual cow during the entire observation period.

9.2.3 Case II

The second case study (i.e., Case II),described in Chapter 8, was carried out in an extensive farm located in Aidone municipality, belonging to the province of Enna, for a period of 38 days between (Fig. 9.1). The herd was grazing in an area of about 300 ha, divided into three different territorial areas, bounded by electric fence to prevent livestock trespassing. In this case study, six animals out of a herd of 130 cows, that differed in age and number of births, were chosen by the farmer to carry out the experimental activity. The time interval for data acquisition was set to 10 min with the aim of increasing the battery life, that reached four month-duration. As well as for Case I same spatial and statistical analyses were carried out. Following the results obtained in Case I, a Sigfox repeater was installed in the study area (Fig. 9.1) aimed at increasing the signal power and coverage of the telecommunication network, and consequently reducing the data loss. In order to verify the exact location of the lost data, for each cow all data, detected before and after the lost one, were localized based on their GPS coordinated in QGIS software. Then, the Mean Coordinates plug in available in QGIS, which calculates the mean of the coordinates of a layer starting from a field of the attribute table, was applied, by creating a new points layer containing the simulated lost data for each of the six selected cow. Based on this new layer, in order to better understand the link between data losses, the signal coverage, and the devices, tailored heatmaps, through KDE tool, were carried out.

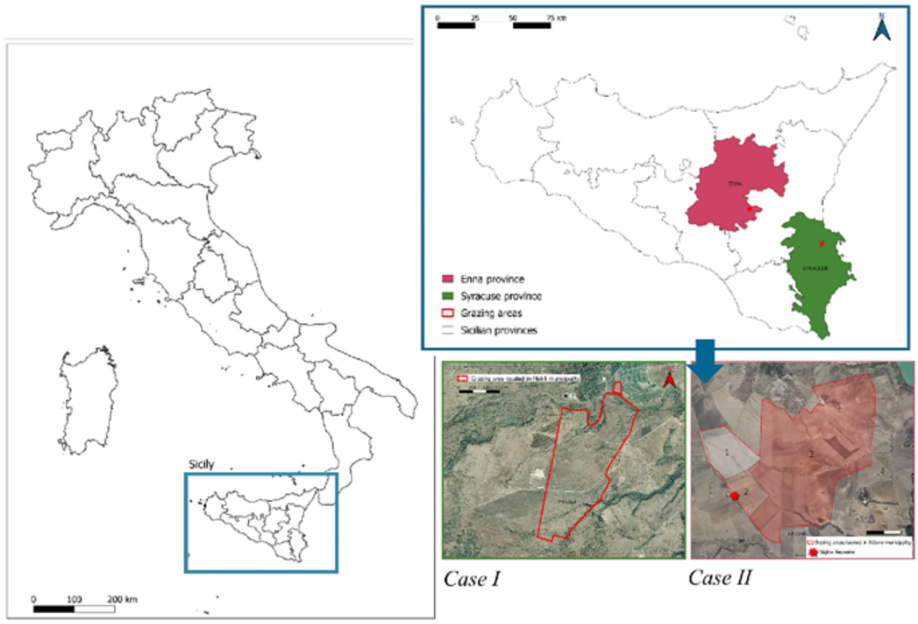

Figure 9.1: *Localization of the grazing areas in the provinces of Syracuse (Case I) and Enna (Case II).*

9.3 Results and discussion

9.3.1 Case I

Collected data from the LP-GPS device and acquired from both direct surveys and visual inspections, were combined, and elaborated for locating and tracking the ten selected cows. By using QGIS, it was possible to highlight those grazing areas most frequently used by animals during the whole data collection period. The area, that resulted as the most preferred by the animals, was that one richest in forage and far from the road. Further analyses and tailored evaluations were carried out on the data acquired through the LP-GPS device as shown in Table 9.1. In detail, it is possible to highlight that, by considering the data collection period (i.e., 21 days) and the data sending time-interval of 20 min (i.e., thus 4 acquisition per hour), the expected acquisitions for each individual device during the entire observation period should have been 2,016 instead of, at least, less than 1,800, as reported in Table 9.1. By analysing the recorded data, it was found that, all devices documented signal losses ranged between 233 and 729 lost samples per cow, with an average of 443 equals to about 22%. Furthermore, as reported in Table 9.1, the devices that have lost the highest percentage of points are those ones referred to the case I_cow 1 and case I_cow 9, with 32.39% (i. e., 653 samples) and 36,16% (i.e., 729 samples) of lost data, respectively. Since the losses were evenly recorded for all the cows it could be due to the low signal power and coverage in the study area. Therefore, by installing a repeater, it could be possible to increase the signal coverage of the telecommunication network and consequently reducing the data loss.

Table 9.1: *Data obtained by the LP-GPS device during the whole observation period.*

Cow ID	Num. lost samples	Num. obtained samples	Num. expected samples	% Num. lost samples
case I_cow 1	653	1363	2016	32.39
case I_cow 2	296	1720	2016	14.68
case I_cow 3	276	1740	2016	13.69
case I_cow 4	233	1783	2016	11.56
case I_cow 6	448	1568	2016	22.22
case I_cow 7	422	1594	2016	20.93
case I_cow 8	445	1571	2016	22.07
case I_cow 9	729	1287	2016	36.16
case I_cow 10	481	1535	2016	23.86
Total	3983	14,161	20,160	19.76

9.3.2 Case II

As well as for Case I, by using KDE tool, available in QGIS software tailored maps for each cow were obtained reporting their most preferred areas among the three considered different ones. It emerged that all the considered cows remain for longer time into area 2 (Fig. 9.1). This latter was most preferred by the animals as it was the richest in forage in particular Trifolium alexandrinum, and because this kind of forage is considered by cows more palatable than others. The heatmaps, representing the territorial area of whole grazing area where the signal coverage most frequently could be lost, were carried out, through KDE tool, for each considered cow (Fig. 9.2). As shown in Fig. 9.2 and reported in Table 9.2, the lost data, considering the increase of the signal coverage by Sigfox repeater installation, were around 6% of the total recorded data, with a minimum of 23 and maximum of 1103 lost samples. Moreover, by observing Fig. 9.2, the heatmaps carried out for case II_cow 4, case II_cow 3, and case II_cow 6, showed the highest concentration of lost data, as confirmed in Table

9.2. By excluding these three selected cows (i.e., case II_cow 3, case II_cow 4, and case II_cow 6), the percentage of lost data was drastically reduced to less than 1%, thanks to the installed Sigfox repeater. These latter demonstrated that the losses data should be attributed to the wearable devices not to the low signal coverage, also because the losses resulted evenly distributed within the whole grazing area, by highlighting the highest number of losses in area 2, exactly where the Sigfox repeater was placed. As reported in Table 9.2, considering the devices embedded to the collars belonging to the case II_cow 3 and case II_cow 4, the recorded losses were 10.63% and 17.27%, respectively. Finally, by comparing the two analysed case studies, i.e., Case I and Case II, it is possible to notice that the installation of the Sigfox repeater contributed to reduce losses of position-related samples. In detail, from a total loss of about 22%, recorded for Case I, a total percentage of lost samples equal to about 5.53% was reached in Case II. In order to improve the performance of the developed system by strongly reducing the number of lost samples, it is important to analyse the behavioural activities of the cows, by combining motion sensors (i.e., accelerometers) and GPS data to reach the most accurate way for measuring animal activity on extensive farm.

In this regard, in literature only few research works that combine GPS data with accelerometers were found, compared to those ones that instead of use single types of data [28]. Among them, most studies focused on the use of GPS collars combined with accelerometers in small pastures and over short time periods [101], therefore, as also demonstrated by the achieved results, checking this technology in bigger pastures and, above all, for longer observation periods is urgently needed. Another important issue highlighted by the achieved results

Table 9.2: *Data obtained by the LP-GPS device during the whole observation period within Case II.*

Cow ID	**Num. lost samples**	**Num. obtained samples**	**Num. expected samples**	**% Num. lost samples**
case II_cow 1	23	6361	6384	0.36
case II_cow 2	41	6343	6384	0.64
case II_cow 3	679	5705	6384	10.63
case II_cow 4	1103	5281	6384	17.27
case II_cow 5	56	6328	6384	0.88
case II_cow 6	217	6167	6384	3.39
Total	2119	36,185	38,304	5.53

and needed of further improvements is how to increase both battery life and network performance in combined GPS and accelerometer systems. In this regard, it is important to highlight that the long battery life reached in both the analysed case studies, especially in Case II (i.e., more than 4 months) was reached by using a 10-minutes data monitoring. Indeed, as stated by [97], due to the limited battery life of the devices, in some research studies, the animal's position was detected only one time per hour, but by reducing the number of detections it is impossible to achieve an efficient monitoring of grazing animals.

9.4 Conclusions

Several studies have shown that knowing the position of animals within a defined area provides key information about their feeding habits, soil consumption, and in some cases, their overall behavior. However, position data alone is not always sufficient; further processing with GIS enables the creation of maps that can be crucial for herd management. Real-time monitoring of herds in extensive livestock systems is challenging for tracking variables that can provide timely alerts to farmers. Additionally, in extensive farms, it is often difficult to monitor animals due to the lack of telecommunications networks or poor signal coverage. In this regard, the results demonstrated that using Low-Power networks (such as Sigfox) allows for continuous herd monitoring while preserving the battery life of the devices, unlike non-low-power networks. Furthermore, the installation of a Sigfox repeater significantly reduced data loss. Specifically, sample loss in a system designed to detect position is a critical issue because most systems proposed in the literature send position data at intervals ranging from minutes to hours. The loss of one or more samples can render the monitoring less useful for both breeders and researchers. Future developments of the proposed system should consider combining GPS and accelerometers with related behavior detection systems, allowing for even more precise monitoring of the herd and minimizing data loss.

9.5 Publications

Mancuso, D., Castagnolo, G., Parlato, M.C.M., Valenti, F. and Porto, S.M.C. (2023) "Low-power networks and GIS analyses for monitoring the site use of grazing cattle", Computers and Electronics in Agriculture, Vol. 210,ISSN 0168-1699

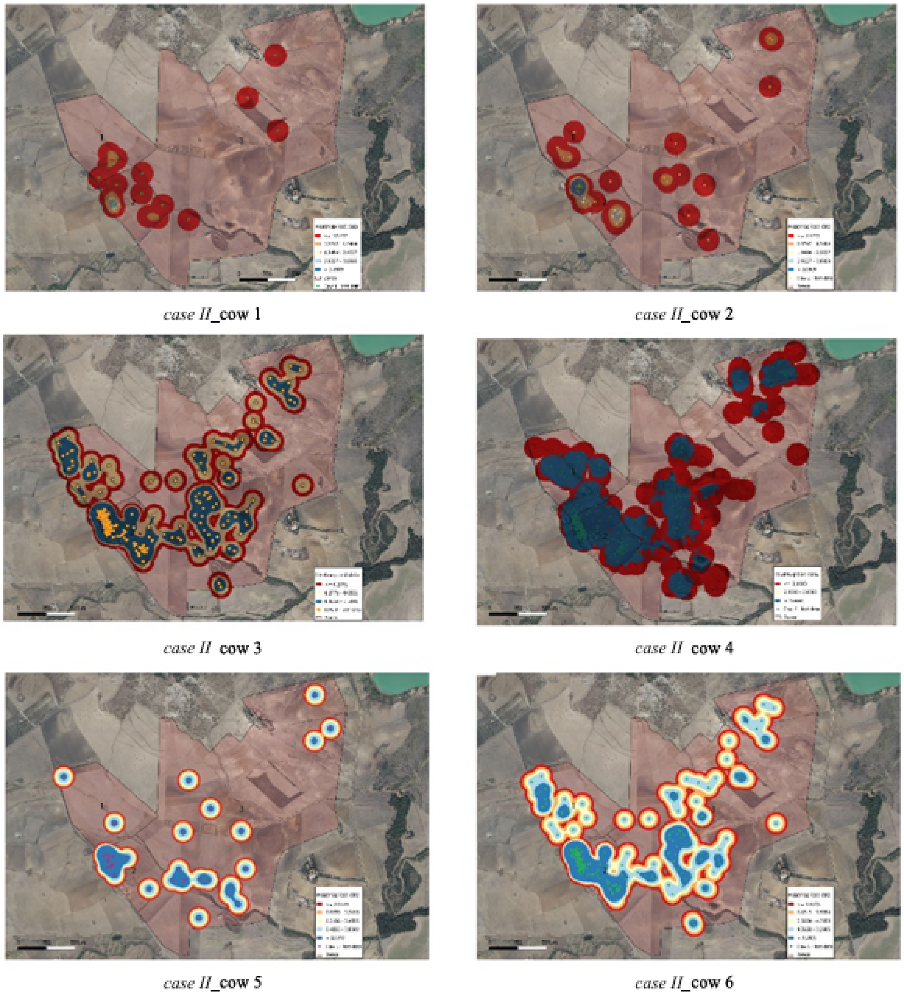

Figure 9.2: *KDE analyses for each cow representing the area of the territory where the signal coverage most frequently could be lost in CASE II.*

CHAPTER

TEN

CHALLENGES AND IMPROVEMENTS

The application of Precision Livestock Farming (PLF) technologies to monitor the behavioral activities of cows in extensive farms has encountered several challenges, which make their use more restrictive compared to indoor environments. Although awareness of the potential benefits of these tools is still limited, the demand from farmers and researchers is on the rise, with expectations of positive outcomes from the spread of PLF in grazing systems, particularly in terms of improving animal welfare and optimizing labor.

As reported in Chapter 2 several studies in the literature have adopted GPS for cattle localization, highlighting common challenges such as miniaturization of sensor technologies and the development of high energy density batteries. As reported by Raizman et al. [97], to extend the battery life of the devices, in some research studies, the position of the animal was detected only once an houre, with the result that in reducing the number of defections, it is impossible to achieve an efficient monitoring of the grazing animals. Another strategy to improve battery life, as reported in the case study presented in the Chapter 3, involves in implementing a standby or sleep modes, where the device is deactivated when sensors are not in use, as well as adjusting the alarm rate based on the activity being performed by the animal. A significant issue with these applications is the reliance on telecommunication networks, which are often inadequate in vast, rural areas where efficient and reliable coverage is lacking [104]. Specifically, mobile tracking systems for livestock require a telecommunications network that does not consume excessive power, as this would further reduce battery life.

To overcome the above problems, different Low-Power Wide-Area Networks (LPWAN) [95] have been proposed, which are types of long-range wireless telecommunication networks characterized by low power consumption and low bit rate. Sigfox and LoRa [55, 81] are two of the most widely used LPWANs in IoT applications in PLF because they offer real-time and low-power monitoring of animals in extensive farms.

For example, in Porto et al.[94] and Castagnolo et al.[32], described in Chapters 7 and 8, the priorities were to study the battery life of the proposed device and to explore the feasibility of a Sigfox-based tracking system in extensive farms. By using the Sigfox network, we achieved a battery life of approximately four months with a 10-minute interval for data collection. The system was also tested in an area with poor telecommunications coverage, where the installation of a repeater allowed continuous monitoring without significant data loss.

The latest advancements, such as LoRaII, offer the potential to determine the position of objects by triangulating the arrival time of packets via highly synchronized base stations. While the position accuracy of LoRaII (10 to 30 meters) may be sufficient for applications involving animals confined to specific areas (e.g., locating sick cows), it may become inadequate when the grazing areas are larger and unfenced. An interesting application of devices embedding GPS sensors are virtual fences. These new technologies are aimed at confining grazing animals without physical fences. Virtual fences operate based on associative learning, using audio signals and a mild electrical discharge to deter animals from crossing predefined boundaries. Since these GPS-equipped devices can also provide animal identification, each animal's position can be tracked during the monitoring period and visualized within the grazing farm using GIS-based software [18]. The data acquired through GPS devices are crucial, as knowing the position of the animal can help reduce the risk of theft or unauthorized movement. Furthermore, by managing GPS data within GIS tools, as explored in Chapters 7,8,9, important aspects such as environmental impact, social factors, and the forage consumed by animals can be analyzed. However, while GPS data can provide insights into the habits of animals, it is not sufficient to fully understand their behavior during grazing. Integrating motion sensors with GPS data offers a more comprehensive method for determining animal activity in extensive farms, providing farmers with immediate alerts in case of abnormal behavior, as reported in [94]. Current research has demonstrated that IoT-based devices with embedded accelerometers can remotely monitor livestock behavior and detect activity changes associated with disease or calving. GPS tracking can also detect calving by monitoring the distance between a cow and the rest of the herd or identifying when cattle gather in sensitive areas. Combining GPS and accelerometer data has proven to be more accurate than using either device alone. One of the major challenges in monitoring livestock behavior with sensors, particularly with combined systems, is managing the large volume of data generated, as noted by [28]. Collecting vast amounts of data poses problems not only in terms of management but also in processing and storage, as higher, and therefore more expensive, computational resources are required. Nowadays, most studies focused on the use of GPS collars or accelerometers, were proved in small pastures over short periods of time. However, the effectiveness of this technology in larger pastures and over extended periods remains to be assessed. For example, Riaboff et al. [100] tested their system for only five days due to battery limitations, which, as the authors noted, is insufficient to explore the relationship between cows and their environment, especially in herding situations where grazing occurs over long periods. An analysis of the existing literature reveals that when a new system or data processing method is proposed, it is often challenging to make direct comparisons, as the software tools and acquired data are not always shared. This lack of transparency hinders a full understanding of the limitations of proposed studies and makes it difficult to replicate results. Ultimately, the studies discussed highlight the need to improve both battery life and the reliability of telecommunications networks. Despite existing technological limitations, solutions to the battery life issue include using low-power telecommunications networks, developing highly optimized firmware focused on energy conservation, employing energy optimization techniques in devices, and reducing the sampling frequency in devices while utilizing high-efficiency batteries. Although higher acquisition frequencies lead to greater energy consumption, they offer more precise behavior detection, such as for rumination or walking. Therefore, it is essential to find a balance between precision and energy consumption [101, 9]. Recently, machine learning (ML) and deep learning (DL) techniques have been proposed for cow activity detection, offering greater generalizability and requiring less human intervention compared to traditional statistical methods or threshold-based approaches. However, the increased computational demands of ML and DL pose a challenge for battery life. To address this, necessary computations are often carried out on cloud platforms, with raw data transmitted from sensors via telecommunications networks. This approach is viable for monitoring cow behavior in intensive indoor systems, where devices that transfer data to the cloud can be powered by an electrical network. However, in extensive grazing systems, this solution is not always feasible, as data transfer via GSM networks, which are highly energy-consuming for wearable devices, is required. Although personal area networks (PAN) or local area networks (LAN) powered by electrical networks could be used for data collection and transfer, their short communication range may not be suitable for large grazing areas. Additionally, while LPWANs can transfer data from sensors, their limited payload capacity may not support the large data volumes required for ML and DL models.

Given these constraints, threshold-based or machine-learning based models could be a practical solution for monitoring grazing cows in rural areas, as they require less computational power and can be implemented in wearable devices, with data transferred via LPWAN. However, to tune effective methods for accurate classification, extensive data collection is necessary. Concerning the reliability of LPWAN telecommunications networks, a potential solution to poor coverage in rural areas could be the installation of network repeaters equipped with energy accumulators powered by renewable sources such as wind or solar energy.

10.1 Publications

Mancuso D, Castagnolo G, Porto SMC. Cow Behavioural Activities in Extensive Farms: Challenges of Adopting Automatic Monitoring Systems. Sensors. 2023; 23(8):3828. https://doi.org/10.3390/s23083828

Part II

Camera-based monitoring systems

CHAPTER

ELEVEN

COW AUTOMATIC MONITORING SYSTEMS IN INDOOR FARMS

The contemporary livestock industry, as reported in previous Chapters, is characterized by a heightened emphasis on animal health, welfare, and productivity. Traditional monitoring practices, reliant on human observation, are labor-intensive, time-consuming, and susceptible to human error. As agricultural operations expand and precision management demands increase, a paradigm shift towards advanced technologies, particularly camera-based systems, has emerged [13]. As reported in Chapter 2 cameras are non-invasive sensors, therefore Camera-based monitoring offers a non-invasive, continuous method [87]. This method is very effective for observing animal behavior, physiological status, and environmental interactions, especially in indoor context. By capturing real-time visual data, is possible to study animal movement, feeding patterns, and social dynamics. In indoor context the camera-based monitoring systems allow multiple advantages, compared to sensor-based. Above all, the use of cameras not involve of physical devices mounted on the animal, and do not create obstacles to the animal movement. Furthermore, a few strategically placed cameras can effectively monitor large groups of animals simultaneously, making this approach not only technologically robust but also economically efficient [127]. This allows farmers to gain comprehensive insights into the behavior and well-being of multiple animals without the need for extensive equipment or frequent manual checks, significantly reducing both labor costs and the need for additional resources. By reducing the need for physical interventions, these systems contribute to a less stressful environment for animals, promoting ethical and humane livestock management practices. The integration of Machine learning and Computer vision algorithms enhances data analysis, enabling the automated identification of behavioral anomalies indicative of potential health issues or discomfort. Early detection of these irregularities is crucial for optimizing animal welfare and preventing disease outbreaks. As the agricultural sector undergoes digital transformation, camera-based monitoring systems are poised to become indispensable tools. This chapter explores the application of these systems across livestock production environments, aiming to revolutionize the understanding, management, and improvement of animal health and well-being.

11.1 Devices

In designing an automatic monitoring system, the fundamental step is obviously the choice of hardware to use. It is strictly related to the type of processing of the acquired data to be used in the future and to the aspects that you want to examine. The selection of an appropriate hardware depends on several factors: characteristics, camera placement, environmental conditions, animal species, intended analysis, and budgetary constraints. In general, in this type of system the following types of devices are used: 2D cameras [52], infrared 2D cameras, 3D cameras[52], Thermal cameras [133] and LiDar[124]. Two-dimensional cameras constitute the predominant imaging technology employed in contemporary livestock monitoring systems, primarily due to their affordability and compatibility with existing stable surveillance infrastructure. In dairy cattle environments, side-view position is commonly used, facilitating simultaneous observation of multiple individuals while enabling assessment of body conformation, particularly in identifying structural anomalies, and behavior monitoring during daily activity. However, 2D cameras exhibit limitations under sub optimal lighting conditions, a frequent challenge in indoor farming settings. Factors such as lens contamination due to dust or insects, lens degradation caused by corrosive atmospheric conditions, and image quality deterioration associated with low light levels can significantly compromise system performance. For this reason, infrared cameras are finding more and more space in this sector, which allow the acquisition of images in low-light conditions and are suitable for environments where the light conditions are not always stable. Obviously with 2D cameras it is not possible to have depth information and this factor precludes accurate assessment of loco motor system pathologies and weight estimation [105]. Additionally, with depth information the segmentation of individual animals from complex background could be more simple and accurate [124]. To address these shortcomings, three-dimensional cameras have emerged as a promising alternative. With 3D cameras is also possible to measure distances and reconstruct 3D models of cows. While offering substantial advantages in terms of data richness and analytical capabilities, the high acquisition and operational costs of 3D imaging systems have restricted their widespread adoption within commercial agricultural settings, relegating their application primarily to research environments. Other devices used in research have been LiDAr, which allow to measure precise distances, penetrate obstacles and allow to perform 3D reconstructions at high resolution. As for thermal cameras, they are used to monitor the health of cows by highlighting increases in body temperature and to study metabolism.

11.2 Animal aspects monitored and tasks

Camera-based monitoring systems have demonstrated significant potential in addressing a wide range of cows husbandry challenges. The core focus areas for these systems can be categorized as follows:

- Behavior and health monitoring [35, 51, 126]
- Locomotor activity and related anomalies: pose and motion estimation [85, 59]
- Reproductions activities: oestrus and mounting [84, 67]

- Weight Estimation [128, 73]

A primary and more investigated application is the continuous observation of animal behavior to identify potential health issues or changes in normal routines. By analyzing visual data, it is possible to detect early indicators of disease, such as lethargy or changes in appetite. Moreover, these systems can be employed to assess overall animal welfare by monitoring social interactions, environmental responses, and resting patterns. The most important behavior monitored are: feeding, lying, rumination and walking. Clearly these types of activities are carried out differently for animals housed in an indoor farm compared to an outdoor one. As regards the precise analysis of animal movement, it is crucial for identifying potential lameness issues, musculoskeletal disorders, and reproductive challenges. Through the application of computer vision techniques, it is feasible to extract detailed information regarding animal posture, gait, and locomotion patterns. These data can be employed to develop early warning systems for detecting abnormalities and to inform targeted intervention strategies. In this context the most investigated task is the lameness identification. Through the camera-based monitoring systems is possible to perform early lameness detection and therefore and apply the correct care to the affected animal. The reproduction monitoring is a critical aspect of livestock management. Camera-based systems can be used to detect behavioral changes associated with estrus, such as increased activity, mounting behavior, and changes in social interactions. Estrus detection, in the case of animals raised indoors that are artificially inseminated, is important, since the early identification of estrus allows the breeder to inseminate the cow at the right time, otherwise this translates into an economic loss for the breeders. By automating this process, farmers can optimize breeding programs and improve reproductive efficiency. “Mounting” in the context of cows refers to mounting or mating behavior. It is a critical aspect of reproductive management in cattle herds, especially dairy cows. Understanding and monitoring this behavior can help breeders determine the optimal time for insemination, thus improving the chances of conception. The use of cameras to monitor ”mounting” in cows represents a significant advancement in the management of bovine reproduction. Thanks to video analysis, farmers can detect mounting even at times when human supervision is limited. This technological approach reduces the margin of error and increases the chances of reproductive success, optimizing the productivity and profitability of the farm. While primarily associated with other sensor technologies, camera-based systems can contribute to weight estimation by analyzing body dimensions and comparing them to established models. Although not as precise as direct weighing methods, this approach can provide valuable estimates for large animal populations, enabling early identification of weight loss or gain, which may indicate underlying health issues. The aforementioned monitoring objectives necessitate the application of a diverse array of computer vision techniques. Core tasks encompass object classification, object segmentation, action recognition, pose estimation, and object tracking, among others. It is evident that the acquisition of video data, as opposed to static images, provides a significantly richer and more informative dataset for the development and deployment of robust computer vision algorithms. The temporal dimension inherent in video sequences enables the capture of dynamic information essential for understanding animal behavior, interactions, and physiological states.

11.3 Cows action recognition from videos

Over the years, various approaches have been developed to classify cow behavior using data captured by cameras, with a particular focus on video action recognition techniques.

Nguyen et al. [88] introduced a notable method for monitoring cattle behavior using a video-based system integrated with deep learning models. This approach involved the use of multiple cameras to record cattle activities, followed by manual annotation to identify individual animals and their behaviors. The method employs Cascade R-CNN for cattle identification and Temporal Segment Networks (TSN) for action recognition, achieving high accuracy in detecting behaviors such as drinking and grazing. By integrating these components into a seamless pipeline, the system offers an automated solution for continuously monitoring cattle welfare on farms, a critical aspect of modern livestock management.

Building on this, Fuentes et al. [50] presented a deep learning framework for hierarchical cattle behavior recognition that leverages spatio-temporal information from video data. Their system combines YOLOv3 for frame-level detection with 3D Convolutional Neural Networks (3D-CNN) to capture temporal context, enabling the identification and localization of 15 distinct cattle behaviors, including both individual and group activities. Designed for real-time operation, this framework serves as an effective tool for monitoring cattle behavior across various farm conditions, offering scalability and adaptability essential for large-scale farming environments.

Similarly, Qiao et al. [96] developed a framework for automated cattle identification using video data. Their approach integrates a Convolutional Neural Network (CNN) for spatial feature extraction with a Bidirectional Long Short-Term Memory (BiLSTM) network to capture spatio-temporal information from video sequences. The inclusion of an attention mechanism further enhances accuracy by focusing on the most relevant features, significantly improving the precision of cattle identification and enabling more personalized management strategies within herds.

Further advancing this field, Wang et al.[123] introduced the E3D (Efficient 3D CNN) network, specifically designed for recognizing basic motion behaviors of dairy cows using video data. E3D combines 3D convolutional layers with the SandGlass-3D module to effectively capture spatio-temporal features, while the Efficient Channel Attention (ECA) mechanism filters out irrelevant background information, enhancing accuracy. The E3D network has been shown to outperform several classical and state-of-the-art models, such as C3D, I3D, and P3D, in terms of both accuracy and efficiency. This makes it a robust and lightweight solution suitable for real-time behavior recognition in natural farm environments, addressing the need for efficient monitoring tools in resource-constrained settings.

In another significant contribution,Li et al. [70] proposed a method for recognizing basic motion behaviors of dairy cows by combining cow skeleton data with hybrid convolutional neural networks (CNN). This approach integrates both 2D and 3D convolutional layers to extract spatio-temporal features from video data, with skeleton information incorporated as an attention mechanism. This method demonstrated superior accuracy and robustness compared to traditional methods, particularly in recognizing behaviors like walking, standing, and lying down. The use of skeleton data also reduces the model's sensitivity to environmental variations, such as changes in brightness and noise, making it a reliable tool for monitoring cow behaviors in real farm settings.

The study by Hua et al.[63] introduces the PoseC3D model, which is specifically designed for recognizing typical motion behaviors of dairy cows based on skeleton features. The method involves two primary steps: skeleton extraction using a modified YOLOX-Pose model, followed by action recognition using the PoseC3D model. YOLOX-Pose efficiently extracts skeletons with high accuracy, while PoseC3D processes the extracted 3D skeleton information to recognize actions such as lying, standing, walking, and lameness. The study not only compares this model against other keypoint extraction and action recognition algorithms, showing superior performance in terms of accuracy and efficiency, but also explores the impact of various factors such as brightness and input modalities on the model's performance. This confirms the model's robustness and suitability for real-time monitoring in dairy farms. Finally Bai et al. [14] proposed the X3DFast model, a lightweight yet effective approach for classifying dairy cow behaviors using video data. The model employs a two-pathway architecture combining X3D and Fast pathways to capture both spatial and temporal features of cow behaviors. The X3D pathway focuses on static spatial features, while the Fast pathway emphasizes dynamic temporal aspects, utilizing R(2+1)D convolutions for enhanced temporal modeling. The model was trained and tested on a dataset reflecting real-world farming conditions, including varying illumination and occlusion. X3DFast achieved a top-1 accuracy of 98.49%, outperforming several existing models, and demonstrated robustness in recognizing behaviors such as walking, standing, lying, and mounting. The study highlights the model's potential for real-time application in dairy farms, contributing to improved animal welfare and farm management.

Collectively, these studies highlight the significant progress made in video-based cattle behavior recognition, particularly through the integration of advanced deep learning models. These advancements promise to enhance the precision, efficiency, and scalability of livestock monitoring systems, which are crucial for improving animal welfare and optimizing farm management practices. As research in this field continues, future developments are expected to focus on refining these models further to handle more complex behaviors and diverse environmental conditions, ensuring their effective deployment in a wide range of agricultural settings.

11.4 Challenges and improvements

The implementation of camera-based monitoring systems in livestock farming, while offering significant advantages, presents several challenges that must be addressed to fully realize their potential. One of the primary challenges is the variability in environmental conditions within indoor farming environments. Furthermore, the vast amounts of data generated by these systems necessitate significant computational resources for real-time processing and storage, which can be cost-prohibitive for many farming operations. The initial investment in high-quality cameras and the required infrastructure can also be a barrier, particularly for smaller farms. These challenges highlight the need for more robust, adaptable, and cost-effective solutions. Looking ahead, one of the key future trends in this domain is the integration of advanced machine learning algorithms with camera-based systems to enhance their robustness and adaptability. Among these, Continual Learning (CL) stands out as a promising approach. CL techniques are designed to enable models to learn from continuous streams of data, adapting to new information without forgetting previously acquired knowledge. This capability is particularly relevant in livestock monitoring, where animal behavior can change rapidly due to environmental factors or health issues. By applying Continual Learning to video data, it becomes possible to develop monitoring systems that not only recognize complex behaviors but also continuously improve their accuracy over time, even as conditions change. This ability to adapt to real-world variability without requiring extensive re-training makes CL a crucial component in the next generation of livestock monitoring technologies. The application of CL to video action recognition is still a relatively unexplored area, but it holds great potential for advancing the precision and reliability of these systems.

CHAPTER

TWELVE

CONTINUAL LEARNING METHODS FOR VIDEO ACTION RECOGNITION

12.1 Overview

In recent years, various state-of-the-art methods for action recognition have been proposed and these approaches have also been applied to recognizing cattle behavior and monitoring their health. However, this field presents several challenges, including the need for neural networks capable of retaining previously learned knowledge. Continual Learning (CL) addresses the problem of learning from an infinite data stream, with the goal of gradually extending and utilizing acquired knowledge for future learning. CL methods aim to train neural networks on non-i.i.d. samples, alleviating catastrophic forgetting while minimizing computational costs and memory footprint.

The need for continual learning techniques is especially crucial in real-world contexts, such as livestock monitoring, where data is neither independent nor identically distributed due to sudden changes in animal behavior. Addressing this variability cannot be achieved through simple fine-tuning, as it would lead to forgetting what models have already learned. This study explores the application of Continual Learning techniques in video analysis, a relatively unexplored area. The objective is to assess whether state-of-the-art continual learning methods can be generalized to high-dimensional spatio-temporal data.

To achieve this, an experimental protocol for continual learning in video action recognition was established, evaluating the performance of state-of-the-art approaches and proposing two methodological modifications. The topic of this chapter was approached using a public human action dataset due to the unavailability of suitable datasets in the cattle domain. However, the conclusions drawn from this work are applicable to other contexts, as the focus here is on action recognition in videos in cL asset.

12.2 Related Work

Video action recognition is a well-known problem in computer vision, given to its wide range of applications, including surveillance [38], behavior understanding [58], content-based retrieval [71]. It is also a complex problem, due to the difficulty to learn spatio-temporal action patterns in a high-dimensional space. Recent advances in deep learning, including attention-based vision transformers [40, 11, 24, 130], have achieved unprecedented results on video action recognition benchmarks, pushing performance of automatic methods closer to humans'. However, current approaches for supervised video action recognition assume a *stationary* data distribution, where all dataset classes and samples are simultaneously available at training time. Recently, this hypothesis has been put under question, giving rise to a line of research on *continual learning* methods, designed to deal with changes in the class distribution (new classes may become available, while others are replaced) and/or in the intra-class data distribution. The relaxation of the stationarity assumption introduces several novel challenges; notably, models trained on sequences of tasks tend to focus on currently-available classes, degrading performance on previously-seen classes — a phenomenon known as "catastrophic forgetting"; similarly, in presence of gradual shifts in the data distribution of a certain class, models become unable to correctly process "older" samples.

While several solutions to continual learning have been proposed, based on architectural priors [106], knowledge distillation [69], regularization [110] or experience replay [103], they have been mostly validated on simple image datasets, such as MNIST, CIFAR10/100 or simplified versions of ImageNet. Hence, it is hard to assess their suitability to more complex use cases, such as video action recognition.

Continual learning aims to cope with catastrophic forgetting in this scenario, using different techniques.

Rehearsal methods keep a *buffer* of samples from previous tasks, to prevent the model from forgetting past knowledge. Methods in this category include DER/DER++ [30], ER [103], GSS [2], FDR [23], HAL [34], GEM [72], AGEM [12] and iCarl [98]. *Knowledge distillation* approaches employ an earlier version of the model (trained on previous tasks) to transfer features or to encourage the current model to emulate past predictions. The pioneering work in this category is LwF [69]; recent approaches have also attempted to integrate auxiliary knowledge from unrelated tasks [27]. *Regularization* methods, e.g., EWC [110], introduce loss terms to counteract modification of backbone features in favor of new tasks. Regularization and knowledge distillation are often employed alongside other techniques: DER/DER++ [30] regularize a cross-entropy loss by enforcing logit similarity of buffered past samples. *Architectural* methods, such as PackNet [74] and HAT [111], progressively extend a model's backbone to cope with new tasks, but require that model capacity must increase with the number of tasks. Pruning methods [54, 75] may help mitigate this issue. Unfortunately, the presence of a buffer and the corresponding memory overhead may become significant, if not prohibitive, when dealing with video sequences, because of the increase introduced by the temporal dimensions. Finally, it should be mentioned that a related problem, i.e., *class-incremental learning*, has already been studied in video action recognition [91]. However, class-incremental learning — i.e., progressively showing new classes to a classification model — only analyzes a portion of the problem (for instance, it does not address *task-incremental* performance) and generally applies a pre-training on a large part (often, half [91, 41, 61]) of the original dataset, which is not a common procedure in the literature for continual learning.

12.2.1 Method

In this work, as in most of continual learning literature, we focus on classification tasks. Hence, let *task* $\mathcal{T}(\mathcal{C}) \sim p(\mathcal{T})$ be a classification problem defined on a set of classes $\mathcal{C} = \{y_1, \ldots, y_c\}$. Given two tasks $\mathcal{T}_i$ and $\mathcal{T}_j$, we assume that the corresponding sets of classes are different, i.e., $\mathcal{C}_i \cap \mathcal{C}_j = \emptyset$: in this context, we define the problem as of either *task-incremental learning* (T-IL) or *class-incremental learning* (C-IL), based on knowledge of the task at inference time.

A *continual learning problem* consists in a sequence of T tasks $(\mathcal{T}_1, \ldots, \mathcal{T}_T)$ sampled from $p(\mathcal{T})$. A model $\mathcal{M}$ is allowed to train on each task $\mathcal{T}_i$, before moving to task $\mathcal{T}_{i+1}$; at a generic task $\mathcal{T}_i$, data from any other tasks cannot be accessed (unless previously store by the model, as in the case of rehearsal methods). Given the task sequence $(\mathcal{T}_1, \ldots, \mathcal{T}_T)$, model $\mathcal{M}$, parameterized by $\boldsymbol{\theta}$, is trained to optimize a classification objective $\mathcal{L}$ (commonly, a cross-entropy loss) on each task at a time, while attempting to prevent performance decreases on previous tasks.

12.2.2 Evaluation procedure

Given a *source dataset* $\mathcal{D}_s$, including videos for a set of class labels $\mathcal{C}_s$, we emulate a sampling of the $p(\mathcal{T})$ distribution by splitting the set of classes into random groups of c classes each. As a result, we obtain a set of tasks $\mathbb{T} = \{\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_N\}$, with $\mathcal{T}_i$ representing a portion of $\mathcal{D}_s$.

We can sample a *continual learning problem* $\{\mathcal{T}_1, \ldots, \mathcal{T}_T\}$ by selecting a random subset of T tasks from $\mathbb{T}$, and train each of the methods under analysis on that problem, to guarantee a fair comparison. This procedure is then repeated for E experiments. For each experiment, a fraction p_{test} of samples from each class is left out as a test set.

Evaluation metrics, averaged over the set of E experiments, include the following:

- Accuracy in task-incremental learning: for each task, we compute test performance using only predictions for the classes included in that task, and average the computed accuracy scores over the set of tasks.
- Accuracy in class-incremental learning: for each task, we compute test performance using predictions for all classes, and average the computed accuracy scores over the set of tasks.
- Buffer size: for rehearsal methods, number of elements stored in the buffer and required memory space.

12.2.3 Memory-efficient variants

Our results (see Sect. 12.3.4) show that, as expected from the literature, rehearsal methods significantly outperform other paradigms. However, buffer memory requirements increase significantly for video sequences. We hereby propose two model-agnostic variants for buffer management, aimed at reducing the number of elements to store while preserving classification accuracy.

Confidence-driven rehearsal. High-dimensionality of videos reflects on a lower generalization power by a set of random buffered samples, due to the curse of dimensionality. Hence, rather than attempting to model the entire distributions of a task's classes, an alternative lies in selecting samples on which the model is *most confidently correct*: while this may hinder the recognition of under-represented class modes, it reinforces knowledge on the most discriminant portion of the distribution, which is also expected to cover the most density mass. In practice, a sample$(\mathbf{x}, y)$ is eligible for buffering if the model's prediction for class y is above a threshold δ.

Information-driven downsampling. Common video classification models require a fixed input size, making it is necessary to downsample longer sequences. Usually, such downsampling is agnostic to frame content; hence, memory efficiency may be achieved through frame selection, so that more informative content is stored in a smaller buffer. We propose to employ the norm of optical flow [47] as a measure of importance, as it quantifies motion and redundancy between consecutive frames. Formally, given a video sequence $\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_p\}$, we compute motion vectors $\{\mathbf{m}_1, \ldots, \mathbf{m}_{p-1}\}$, such that $\mathbf{m}_i = \mathrm{OF}(\mathbf{x}_i, \mathbf{x}_{i+1})$, where OF is the optical flow function. Then, we select the subset of frames with the largest L_2 norm $\|\mathbf{m}_i\|_2$, ordered by their original position in the video.

12.3 Experimental results

12.3.1 Methods

Our benchmark includes state-of-the-art continual learning methods, covering the range of paradigms from the literature: DER [30], DER++ [30], ER [103], FDR [23], HAL [34], GSS [2], GEM [72], AGEM [12], EWC [110] and LwF [69][1]. For a fair comparison, all methods employ the same backbone network, i.e., R(2+1)D [121]: we excluded architectural methods [74, 111] from our analysis, as model capacity extension would lead to an unfair comparison. All methods[2]

[1]We excluded iCarl [98] due to excessive memory requirements, as the reference implementation required a concatenation of all samples of a task with the current buffer.

[2]`https://github.com/aimagelab/mammoth`

included in our experiments are agnostic to data modality, and can be applied to videos without any modifications.

12.3.2 Dataset and task definition

As source dataset $\mathcal{D}_s$, we employ UCF101 [115], a video action recognition dataset featuring 101 categories, with approximately 100-150 videos each; video duration is mostly between 2 and 10 seconds, although longer videos may be present for certain categories. In our experiments, we employ a subset $\mathcal{C}_s$ of 30 classes, by selecting distinguishable actions, removing too similar classes and classes with less than 130 videos. Classes are grouped into pairs (consistently with continual learning procedures on other datasets, e.g., CIFAR10) to create the task set $\mathbb{T}$, including $N = 15$ different tasks. Then, we define a fixed set of 50 continual learning problems, each being a task sequence $\{\mathcal{T}_1, \ldots, \mathcal{T}_T\}$ of $T = 5$ tasks randomly sampled from $\mathbb{T}$. To ensure class balance, for each class we select a subset of 130 videos, with 100 videos used as a training set and the rest as a test set ($p_{\text{test}} = 3/10$).

12.3.3 Training details

We normalize each color channel to zero mean and unitary standard deviation, and resize spatially to 160×160 pixels. Data augmentation includes random cropping at 128×128, random horizontal flipping, and temporal cropping by selecting 16 consecutive frames from a random point. At test time, we apply center-cropping and process all non-overlapping 16-frame windows from an entire video. The R(2+1)D backbone is trained from scratch for 80 epochs per task, using the

RMSProp optimizer (learning rate: 10^{-5}, batch size: 16); in our preliminary experiments, this configuration empirically yielded the most stable results, compared to standard SGD (which showed slow convergence) or Adam (which, for some methods, led to exploding losses). Method-specific hyperparameters were set to default values from the original papers. Training was carried out on a machine with 8-core Intel Xeon Skylake CPU, 64 GB RAM, NVIDIA V100 GPU.

Table 12.1: *Classification accuracy in class-incremental learning (C-IL) and task-incremental learning (T-IL). Rehearsal methods are marked with a ✓.*

Model	**Rehars.**	**C-IL**	**T-IL**
DER++ [30]	✓	47.87 ± 4.31	90.60 ± 2.21
DER [30]	✓	39.80 ± 3.25	88.80 ± 3.64
ER [103]	✓	31.80 ± 6.02	90.21 ± 1.84
FDR [23]	✓	29.33 ± 3.46	80.87 ± 3.12
HAL [34]	✓	25.61 ± 6.35	69.40 ± 8.26
GSS [2]	✓	20.60 ± 2.97	71.86 ± 3.76
AGEM [12]	✓	18.53 ± 2.70	83.40 ± 1.46
LwF [69]		17.13 ± 0.99	57.00 ± 4.14
GEM [72]	✓	16.13 ± 4.36	72.33 ± 9.00
EWC [110]		11.87 ± 1.71	50.33 ± 5.20

12.3.4 Results

We first report the results obtained by state-of-the-art methods under comparison. For rehearsal methods, we employ a buffer size of

200 (a standard value from the literature), corresponding — based on our pre-processing — to an increase in memory requirements by 940 MB. Table 12.1 shows each method's performance in terms of class-incremental and task-incremental classification accuracy; we report mean and standard deviations over the set of continual learning problems defined by our experimental protocol. Methods employing experience replay perform significantly better, as expected from previous literature results on images. It is interesting to note that the top three methods, i.e., DER++, DER and ER achieve very similar task-incremental accuracy, showing effectiveness in learning each individual task, but differ significantly in the capability to retain previous knowledge. In absolute terms, DER++ yields promising accuracy (47.87% in class-incremental learning), considering that its performance on images (CIFAR-10) is about 65% [30], with the same buffer size.

We then assess the impact of the proposed memory-efficient variants on the best-performing methods only, i.e., DER and DER++. Table 12.2 shows the effect of the proposed *confidence-driven rehearsal* (CDR) technique, for different buffer sizes and values of the δ confidence threshold. In the case of DER, enabling CDR with a 100-element buffer pushes class-incremental performance closer to those with buffer size 200; similarly, CDR with a 200-element buffer reaches similar performance as achieved with a 500-element buffer. On the other hand, CDR with DER does not have a significant impact when applied to a 500-element buffer, which may be large enough to compensate for confidence improvements. CDR does not seem to improve task-incremental accuracy, which is reasonable, since it acts on the buffer and mainly addresses forgetting. Applying CDR on DER++ is less effective, though some improvements can be seen, especially with buffer size of 200. However, it is reasonable to assume that the stronger recovery capabilities of DER++ make the contribution of CDR less important. For both DER and DER++, a general trend shows that larger δ values lead to better performance; however, we found that exceeding the $\delta = 0.8$ threshold harms performance: we hypothesize that the distribution of selected samples excessively narrows the data distribution, worsening generalization.

We then evaluate how our *information-driven downsampling* (IDD), based on optical flow, affects model accuracy. Table 12.3 shows that enabling IDD has a positive impact on class-incremental accuracy on DER with small buffers, while it is less effective with larger buffer. On DER++, IDD positively affects only the usage of a 100-element buffer, possibly for similar reasons as discussed in the case of CDR. However, in no case IDD is able to compensate for a smaller buffer size, showing a superiority by CDR in this respect.

12.4 Conclusions

We presented a benchmark of state-of-the-art continual learning methods for video action recognition, showing that methods designed for images are able, to a certain extent, to generalize to videos, achieving promising performance in class-incremental and task-incremental settings. We also propose two memory-efficient variants for buffer sample selection, demonstrating that the CDR variant helps to retain (or even improve) performance even when reducing the buffer size, while the IDD variant is less effective in this regard.

Future improvements of this work will address two main research directions to improve the proposed memory-efficient variants. First, we mean to explore advances to the proposed *confidence-driven rehearsal*, by integrating mechanisms for automatic and adaptive threshold setting. Second, rather than explicitly defining a measure for *information-driven downsampling* (e.g., optical flow norm), we intend to investigate the employment of attention mechanisms to find measures of correlation between input and model representations, thus using the latter as a reference for importance estimation.

12.5 Publications

G. Castagnolo, C. Spampinato, F. Rundo, D. Giordano and S. Palazzo, "A Baseline on Continual Learning Methods for Video Action Recognition," 2023 IEEE International Conference on Image Processing (ICIP), Kuala Lumpur, Malaysia, 2023, pp. 3240-3244, doi: 10.1109/ICIP49359.2023.10222140.

Table 12.2: *Impact of the proposed* confidence-driven rehearsal *(CDR) variant on classification accuracy, for different buffer sizes and values of the δ threshold.*

	Buffer	$\boldsymbol{\delta}$	**C-IL**	**T-IL**
DER++ [30]	500 (2.2 GB)	-	48.20 ± 2.41	91.90 ± 1.74
		0.6	47.22 ± 1.39	91.25 ± 2.21
		0.7	47.00 ± 3.21	92.00 ± 3.09
		0.8	49.22 ± 4.40	90.89 ± 2.11
	200 (0.9 GB)	-	47.87 ± 4.31	90.60 ± 2.21
		0.6	46.47 ± 4.46	89.07 ± 4.39
		0.7	47.80 ± 5.07	90.20 ± 3.54
		0.8	49.40 ± 4.92	88.47 ± 2.19
	100 (0.5 GB)	-	42.00 ± 2.96	88.33 ± 3.90
		0.6	41.00 ± 4.20	86.25 ± 2.87
		0.7	40.11 ± 2.50	87.00 ± 0.58
		0.8	40.00 ± 4.15	88.22 ± 4.70
DER [30]	500 (2.2 GB)	-	44.93 ± 4.88	90.00 ± 1.11
		0.6	43.40 ± 5.15	90.86 ± 3.11
		0.7	43.60 ± 2.60	91.33 ± 1.61
		0.8	43.65 ± 5.21	87.33 ± 3.79
	200 (0.9 GB)	-	39.80 ± 3.25	88.80 ± 3.64
		0.6	40.80 ± 5.31	85.87 ± 3.34
		0.7	44.20 ± 4.65	87.53 ± 3.05
		0.8	44.33 ± 5.10	88.73 ± 2.30
	100 (0.5 GB)	-	33.27 ± 3.80	84.95 ± 6.71
		0.6	35.33 ± 5.25	84.67 ± 5.60
		0.7	36.73 ± 3.47	88.26 ± 6.52
		0.8	37.67 ± 5.17	86.53 ± 3.62

Table 12.3: *Impact of the proposed* information-driven downsampling *(IDD) variant on the performance of DER and DER++, for different buffer sizes.*

	Buffer	IDD	C-IL	T-IL
DER++ [30]	500 (2.2 GB)		48.20 ± 2.41	90.90 ± 1.74
		✓	48.10 ± 1.80	89.66 ± 2.01
	200 (0.9 GB)		47.87 ± 4.31	89.60 ± 2.21
		✓	46.00 ± 1.11	89.93 ± 0.76
	100 (0.5 GB)		42.00 ± 2.96	88.33 ± 3.90
		✓	44.64 ± 3.64	90.13 ± 2.50
DER [30]	500 (2.2 GB)		44.93 ± 4.88	89.00 ± 1.11
		✓	42.50 ± 3.82	88.75 ± 3.11
	200 (0.9 GB)		39.80 ± 3.25	88.80 ± 3.64
		✓	42.20 ± 3.58	87.33 ± 3.81
	100 (0.5 GB)		33.27 ± 3.80	84.95 ± 6.71
		✓	34.93 ± 4.12	84.33 ± 1.66

CHAPTER

THIRTEEN

CONCLUSIONS

This thesis explored and investigated the use of IoT and AI technologies, with a particular focus on sensors and cameras, in animal monitoring, highlighting how these emerging technologies, although already widely used in other contexts, can offer new opportunities for the management and protection of natural resources. In particular, continuous and precise livestock monitoring represents a huge potential to transform the way we manage and protect the environment.

The use of advanced sensors allows for real-time data collection, reducing the need for manual interventions and minimizing the impact on animals. This approach ensures greater precision and timeliness in the detection of anomalous behaviors or conditions, offering significant advantages both in terms of environmental conservation and livestock management. The integration of cameras, enhanced by artificial intelligence, represents a fundamental step towards the automation of video analytics. AI, in fact, not only allows processing large amounts of data in a short time, but also allows identifying and predicting behavior patterns with a precision that would be impossible to achieve through traditional methods.

However, one of the most challenging aspects of this research is related to the lack of specific and accurate data for training AI-based recognition models. Data collection in the context of animal monitoring is time-consuming and requires considerable resources, as data must be acquired in variable and often difficult-to-monitor environments. Furthermore, the need for specialized personnel for data labeling represents a significant challenge, as this process is crucial to ensure the quality and reliability of automated analysis models. Without an adequate amount of labeled data, the effectiveness of AI in recognizing animal behaviors may be limited, reducing the positive impact of these technologies.

Artificial intelligence, in particular through continuous learning techniques, demonstrates a remarkable ability to constantly adapt and improve based on new data, making the system flexible and capable of managing continuously evolving situations. Although in this research this methodology has been applied to human action recognition, given the lack of adequate datasets in the field of cow behavior recognition, the developed framework can easily be extended to video recognition in general, including that related to animals. This represents a promising prospect for future applications in animal monitoring, but also highlights the urgent need to invest in data collection and management specific to these contexts.

Furthermore, another key advantage of using AI is the possibility of developing predictive solutions that can help prevent adverse events, such as diseases in livestock or threats to wildlife, based on proactive analyses of collected data. However, this requires highly specialized algorithms and an advanced technological infrastructure that, although promising, can be costly and energy intensive.

Another key challenge that emerged during the research concerns the need to develop low-cost and energy-efficient solutions. Sustainability is not only about the natural environment, but also about the efficiency of the technologies we use. In animal monitoring contexts, often located in remote or difficult-to-access areas, energy efficiency becomes a determining factor for the viability of operations in the long term. Furthermore, it is essential that these solutions are affordable, to allow their adoption on a large scale, especially in sectors such as agriculture or wildlife conservation, where resources may be limited.

In conclusion, research in this field is complex and challenging, not only because of the lack of data and the need for specialized personnel, but also because of the search for technical solutions that are sustainable, accessible and capable of effectively integrating AI. Despite these difficulties, IoT technologies and artificial intelligence have the potential to profoundly transform animal monitoring, with significant benefits for environmental management and food quality. Addressing these challenges will require continuous and collaborative efforts, but the potential results largely justify the effort, paving the way for a future where technology can truly harmonize with nature.

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