An Animal Welfare Platform for Extensive Livestock Production Systems

Vasileios Doulgerakis[1]
v.doulger@uniwa.gr

Dimitrios Kalyvas[1]
d.kalyvas@uniwa.gr

Enkeleda Bocaj[1]
ebocaj@uniwa.gr

Christos Giannousis[1]
giannousis@uniwa.gr

Michalis Feidakis[1]
m.feidakis@uniwa.gr

George P. Laliotis[2]
glaliotis@aua.gr

Charalampos Patrikakis[1]
bpatr@uniwa.gr

Iosif Bizelis[2]
jmpiz@aua.gr

[1]University of West Attica, Department of Electrical & Electronics Engineering
250 Thivon & P. Ralli, 12241, Athens, Greece
[2]Agricultural University of Athens, Department of Animal Breeding & Husbandry
75 Iera Odos, 11855, Athens, Greece

Abstract

Recent EU agricultural policy reforms along with EU investment focus dictate a livestock production showing respect to animal welfare. In line, the recent technological advancements in animal activity recognition offer unique insights towards accurate tracking of animal behaviour, reflecting health, status and well-being issues at farm level. Current study presents ongoing progress of the development of an automated system with a single type of wireless sensor able to record indicators of animal's well-being (i.e. movement, speed and geolocation information of the animal) with low implementation cost, based on Deep Neural Network pattern recognition algorithms. The solution also provides end-users (farmers) with usable and effective information visualisations, so that they take proper actions.

1 Introduction

During the past century, agricultural production was focused mainly on human needs coverage, price and competition. However, in recent decades, consumers expect their food to be produced and processed with greater respect towards animals welfare [MW14], as consumer health has been closely linked to the welfare of animals. Thus, animal welfare is a matter of increasing concern globally [MCL$^+$17, KLH$^+$19], rendering consumers to demand more stringent animal welfare standards. This, is clearly mirrored in recent reforms of Common Agricultural Policy payments of the EU, where emphasis is given on farmers to reach improved levels of animal welfare in order to receive the payments. Moreover, welfare together with food and nutrition security, livelihoods and growth, as well as climate and natural resource use, form the four important and interrelated aspects for

In: A. Editor, B. Coeditor (eds.): Proceedings of the XYZ Workshop, Location, Country, DD-MMM-YYYY, published at http://ceur-ws.org

a sustainable perspective of the livestock sector [Foo18]. Additionally, the EU invests large sums of money on welfare projects (e.g. Welfare Quality® project) also in-line with the recommendation of the Federation of Veterinarians of Europe (FVE) for the use of animal-based indicators as a tool for assessing the welfare conditions of farmed animals [Ber14, Fed18].

Monitoring behavioural changes in livestock animals offers novel insights into the study of animal status and well-being. The causes of such changes may be found in health and welfare challenges, or even threats and changes in their environment. Recent technological advancements offer monitoring of (a) vital indicators such as blood pressure, heart rate, hormonal levels; (b) animal activity tracking (e.g. inability to stand, unresponsiveness to stimuli, movement acceleration); (c) gross change in 24-hour feed consumption; (d) changes to the breeding environment (e.g. cage size or feeder space); (e) other parameters like geolocation information that can be recorded and further analysed. These indicators—especially those designed for animals—may further allow for early identification of animal health, status and well-being issues at farm level, as well as timely intervention and implementation of corrective or mitigation measures.

Techniques for assessing animal welfare have mainly been developed for use under intensive conditions, mostly ignoring animals reared in extensive agricultural systems. Animals kept in such conditions (extensive) face a unique set of challenges as the degrees of freedom and the possibility to develop a normal behaviour are higher. On the other hand, not all measures implemented in intensive systems for behavioural monitoring are applicable. Although technological advances allow the development of state-of-the-art devices for recording animal behaviour and related indicators both in intensive and extensive systems, their use in a large extent, especially in free range agricultural systems, is quite costly for the producer. Current study presents an automated system with a single type of wireless sensor able to record indicators of animal's well-being importance (i.e. movement, speed of movements, geolocation of the animal) with a low implementation cost in extensive sheep production systems. The hardware was implemented in compliance with Deep Learning and Neural Network-based pattern recognition algorithms. A software application was also developed for the end-users (farmers) to provide with both offline and real-time geolocation data of their herd. Any behaviour considered abnormal, according to the historical data registered in the database, may alert them to intervene appropriately.

2 Related Scientific/Lab Work

Last decade's technological advancements in areas of telecommunications, cloud computing, machine learning and smart sensing, have led to a broad range of applications, especially in protected agriculture and livestock production systems.

Monitoring behavioural characteristics, heart and respiratory rate, digestion, temperature, and other vitals of farm animals can reveal valuable information about their health and level of activity, protect them from known illnesses and provide useful details and metrics in terms of farm management. While literature brings new proposals and different architectural approaches, the IoT components for such scenarios, respective Machine Learning Models and a robust Wireless Sensor Network, still remain subject for further investigation and discussion.

Though few, there is a number of publications on particular subjects of animal monitoring with a variety of wearable sensors for livestock farming. In [IV15] authors are pointing out how Heat Stress (HS) level is inversely proportional to dairy production while keeping nutritional input at the same levels, something that increases farmer's production cost. TI's SensorTag (embedded: IR temperature, Humidity and Pressure Sensors, Accelerometer, Gyroscope, Magnetometer) was used in order to collect sensor data characteristics via Bluetooth Low Energy (BLE). Edge processing is deployed, to filter, aggregate, enrich, and analyse a high throughput of data and visualize results in real time. Desktop and mobile applications provide information to end users, related with dairy cattle's health metrics, possible emergency situation detection, and give access on automating immediate actions. Case study results are not available, but authors mention that such deployments can be useful for forecasting insights in dairy operational management and argue that when good control effects in animal breeding is expected, applying IoT on the field, should overcome harsh environmental factors.

An intelligent animal production management system is proposed in [WYC+18], utilizing environmental sensors to monitor some basic parameters of livestock growing environment and control relative conditions like ventilation, temperature, dust presence and lack of required drug quantity, until the feeding environment meets pre-set standards. As a result, an intelligent feed system delivers fixed amount of feed, liquid and appropriate drugs while also detecting poisonous and unwanted substances in nutrition.Individual animals are monitored both via RFID tags (when close to feeding system) and multi-directional video cameras. A "Master Control Computer" gathers and stores locally all data (including videos) transmitted by individual modules, and sends appropriate parameters to a specific Support Vector Machine (SVM) properly configured, according to the needs of proposed system.

Nóbrega et al. [NTCG18] proposed an IoT based, animal behavior monitoring platform purposed to autonomously shepherd ovine within vineyard areas. These specific collars, have embedded processing abilities and are capable of applying a corrective stimuli via electrostatic and auditory cues, through, a posture control algorithm. Raw sensor data is preprocessed on edge devices and relative results are then transmitted to the cloud, to the advantage of the systems overall speed. Furthermore, an infrastructure network built upon a number of devices, relative to the area of interest, is responsible for collecting data and emitting a beaconing signal. This technique, allows for RSSI-based localization techniques, used to determine each animals location. A Gateway device is used to interconnect local network to the Internet, while acting as a network manager and a local alarm generator for critical situations.

In [wM17], cheap equipment like 3-axis accelerometers (ADXL345), Raspberry Pi and a 3.7 V Lithium polymer battery, were used to create a custom collar, to monitor the activity of dairy cattle, in order to detect and inform farmers about illness and signs of heat information in a herd. A comparison between already known and applied Machine Learning methods for human activity recognition (e.g. K nearest neighbour classifier) is presented in this paper, regarding sample recordings of human actions in contrast with recordings of cow actions, each obtained in 30 seconds intervals. Some recordings of cow actions could not be assigned to a single activity class, due to multiple actions; as a result, only 28 recordings of cow actions were used in latter experiments. Data collected by the RPi were manually retrieved because a gateway was not available at the time of the publication. Collected sensor data were processed to evaluate efficiency of cows in four different actions: eating at a trough (A), eating grass in a paddock (B), standing (C) and walking (D). The performance was reduced due to the fact that cows rarely perform actions in isolation and this requires exploration of appropriate machine learning algorithms capable of handling this complexity.

3 Proposed Architecture

The architecture proposed through this experiment utilizes sensors placed on the animals, the data from which are primed and processed locally on an Edge Device acting as a central node. The results are then pushed to the cloud, from where they can be accessed through a companion mobile application.

3.1 Collar Device

For the purpose of data collection, a prototype custom device has been implemented, which would be carried by the animal at all times. The device is designed to fit on the neck of a ruminant animal, like a normal collar, as this is both easy to handle and would not introduce any constrains unfamiliar to the animal. The device should be able to collect data from an accelerometer and a gyroscope for activity recognition, holding also the capacity to geolocate the animal in real time.

3.1.1 Design limitations

From the early stages of development, it became clear that a certain compromise had to be made between battery lifetime and overall size. Although accelerometer and gyroscope data need not be real-time, the immediacy of geolocation data is essential. This dictates a wireless communication method, which should be able to transmit real-time data in a sufficient range, while keeping the power consumption minimal. Consequently, the update frequency of the location of the animal has been set accordingly, both to reduce battery consumption and to locate the animal adequately.

As the first phase of the project requires the collection and characterisation of data, before training any Machine Learning models, all data had to be recorded before any subsequent processing. That meant that no processing or preprocessing can be done on the collar device, at least not at this stage of the project. As a result, a very large amount of data has to be transferred from the animal collar to the edge device every day.

The higher effective range in combination with the need for lower power consumption made prominent that the bulk of the data cannot be transmitted through the same radio, resulting in a 2-separate communication channels between the animal collar and the edge device. The first one offers a small communication range with high data rates while being energy intensive, in contrast to the second one, which offers a much wider range with low power consumption and low data rates. The collar device is therefore communicating with the Edge Device mostly through the second channel, sending samples of its geolocation in high intervals of 6 to 30 seconds (or

Figure 1: The collar device.

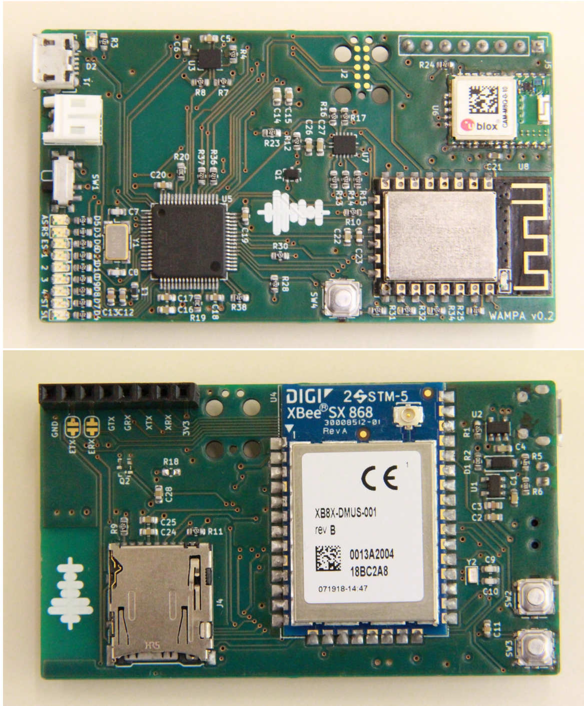

Figure 2: Top and bottom sides of the developped hardware for the collar device.

more), while all detailed activity information is stored locally to the device. Once the device is within range of the first communication method, a bulk transfer of the latest data collected is initiated. This process does not occur more than once daily, unless specifically required.

3.1.2 The hardware components

Having considered all of the aforementioned limitations, we decided on Bosch's BMI160 Inertial Measurement Unit. U-blox's CAM-M8 was selected as a convenient GNSS solution offering an embedded omnidirectional antenna, and a standard microSD card has been employed for storage space. The two selected communication radios are a Wi-Fi module (using the IEEE 802.11b/g/n protocol) for short range needs, chosen for its ability to transmit big chunks of data in quick bursts, and the XBee868 for long range communication, chosen due to its simple and straightforward setup approach which requires no third-party involvement, unlike other popular solutions. The selected orchestrator between all the components is the STM32L162 ARM-Cortex-M3 low-power micro-controller, with the plan to assume, in the future, some of the computational stress from the Edge Device, or even to possibly run a trained Artificial Neural Network Model. All the components were selected to comply with the power requirements set, as well as the dimension restrictions. The final dimensions of the collar device, including a 1800mAh rechargable battery, are 70x40x18mm, without the case.

3.2 Edge Device

Edge devices are used mainly to provide an entry point into the service provider core network [CLF$^+$19]. In this approach this functionality is combined with the local data processing feature. The Edge Device has computational capabilities aiming to ensure both processing of large amounts of data and performing workloads. Such workloads aim to speed up the data processing procedure while it operates reliably in extended offline periods or in real-time processing. The device is located close to the data producing machines (collar devices) and has direct access on the generated information, independently of its type. This component is responsible to manage, process, validate and provide feature analysis on animal data, contributing to the improvement of the livestock production systems. Such features are extracted by utilizing machine learning and deep learning analysis tools capable to identify patterns, relationships and anomalies in animal data. As depicted in Fig. 3, the Edge Device component comprises the following modules:

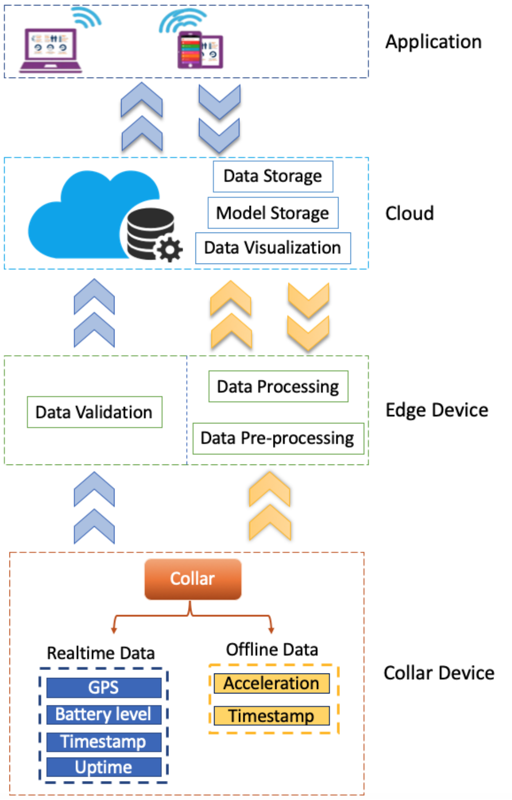

Figure 3: The project architecture.

3.2.1 Data Validation

This module is intended to provide certain well-defined guarantees associated with the accuracy and quality of real-time data before using it. In this sense, different types of validations (e.g. removal or interpolation of missing values) could be performed on the real-time data (such as GNSS data) for integrity and validity inspection. Furthermore, data validation could be a form of data cleansing on the real-time data which are stored in the Cloud or entered via the user application.

3.2.2 Data Preprocessing

The data preprocessing module is responsible for preparing the raw data for processing. In this sense, several machine learning preprocessing techniques are applied including filtering (e.g. noise elimination or correction of false measurements), data integration and aggregation procedures (e.g. data integration or aggregation based on timestamp for redundant sampling) and normalization (e.g. scaling the values of all the attributes in order to have the same weight in the data processing). Data preprocessing has an essential role in the application since it comprises all the heterogeneous sensors.

3.2.3 Data Processing

In this module, machine learning and deep learning tools are utilized to build, evaluate and improve the data model. A Convolutional Neural Network (CNN) architecture is designed to process the raw data of animals and build the model. CNNs take advantage of the large amount of data generated by different sensors to build the model. Moreover, intermediate data fusion processing tools are implemented to combine the data from several different sensors (e.g. accelerometer, gyroscope) producing new raw data expected to be more informative and synthetic for the model than the original input. Additionally, the continuous data generation entails a dynamically evolving model, through continuous evaluation and improvement. The built model is temporarily stored in the Cloud and retrained in the Edge Device when new raw data are available.

3.3 Cloud

The cloud architecture is composed of Java Spring Boot with Hibernate Object-Relational Mapping (ORM) and a PostgreSQL database to store the data. Java Spring Boot is an extension of Spring Framework that provides an easy way to create stand-alone, production-grade Spring based Applications. It is used to create the REST API service which connects the Edge Device and the mobile application with the Cloud.

The REST API is using data models build on data received from the collar devices. Each model is used to filter an API endpoint of the REST service. We deploy two types of data: "real-time" and "offline". The real-time data are sent by the edge device to the cloud, without any data processing, since they deliver crucial GNSS and battery information from the collar devices to the mobile application. The offline data must first be processed by the edge device before being sent to the cloud through the REST API. When the server receives any information from an endpoint, it uses the Hibernate ORM to map the models to PostgreSQL database for storing the received data.

3.4 Mobile Application

The mobile application informs accordingly the user about the animals' location and their well-being. This information is gathered by the edge device and then stored in the Cloud server.

3.4.1 Animal Tracking

The mobile application displays the animals'/herds' locations to a map screen. The animals' locations are refreshed every few seconds with the exact interval being still a subject to research. With this service the stock-farmers have the ability to learn about the movements of their animals and be informed about sudden speed changes, possibly indicating that an animal is being hunted by a predator.

3.4.2 Data Visualization

The mobile application provides useful data visualizations of the animal habits, e.g. feeding state, distance covered per day, time an animal spends standing still or running per day, etc. These visualizations provide stock-farmers with valuable information about the well-being of their animals and help them do adjustments to their growing. All data are processed in the Cloud.

4 Use Cases

4.1 1st scenario: *Monitoring major welfare indicators of sheep in a semi extensive productive system.*

The proposed architecture and prototypes will be applied on sheep reared under semi-extensive conditions. Records will be acquired during the grazing time at a distance up to 1km from the main husbandry, as well as during the housing of animals. A database will be informed with records underpinning normal and abnormal behaviour, which the will be used as threshold for further warning alerts to the farmer.

4.2 2nd scenario: *Assessment of cattles welfare measures in an extensive reared system in Greece.*

The prototypes will be also validated in an autochthonous Greek breed cattle to assess firstly the normal behaviour and well being indicators for the certain breed and secondly to correlate the degree (percentage) of movements with injuries and meat quality characteristics.

5 Conclusion

The current study presents a solution for tracking and monitoring of animal activity and behaviour in livestock farms, obtaining indicators that sustain animal well-being.The solution exploits (i) a single type of wireless sensor (collar device) to record animal activity (i.e. movement, speed, geolocation information) with low implementation cost, (ii) edge computing devices with computational capabilities, able to perform offline and real-time data processing for pattern recognition through Deep Neural Network algorithms, (iii) cloud computing for both data and Deep Learning model storage, and (iv) usable and effective visualisations in mobile devices that provide end-users (farmers) with valuable information. The system has been developed for the management of extensively farmed sheep in Epirus Prefecture and will be validated in two use cases: (i) monitoring major welfare indicators of sheep in a semi extensive productive system, and (ii) assessment of cattle welfare measures in an extensive reared system.

5.1 Future Work

Future steps include further work in data preprocessing on the wearable device, to minimise the amount of transmitted data, as well as the implementation of smarter power-saving algorithms, for battery lifetime optimisation. The possibility of real-time processing and activity recognition, while maintaining an acceptable power consumption, is also to be investigated.

5.1.1 Acknowledgements

This research has been co-financed by the European Union and Greek national funds through the Operational Program Epirus 2014-2020, Topic: "Support of groups of Small and Medium-sized Enterprises (SME) for Research & Technology Development activities in the fields of agri-food, health and biotechnology".

References

[Ber14] Daniel Berckmans. Precision livestock farming technologies for welfare management in intensive livestock systems. *Revue scientifique et technique (International Office of Epizootics)*, 33:189–196, April 2014.

[CLF+19] Min Chen, Wei Li, Giancarlo Fortino, Yixue Hao, Long Hu, and Iztok Humar. A dynamic service migration mechanism in edge cognitive computing. *ACM Transactions on Internet Technology*, 19(2):30:1–30:15, April 2019.

[Fed18] Federation of Veterinarians of Europe. Monitoring of farm animal welfare using animal indicators, November 2018.

[Foo18] Food and Agriculture Organization, Animal Production and Health Division (AGA). Shaping the future of livestock, January 2018.

[IV15] A. Ilapakurti and C. Vuppalapati. Building an iot framework for connected dairy. In *Proc. IEEE First Int. Conf. Big Data Computing Service and Applications*, pages 275–285. IEEE, March 2015.

[KLH+19] Y. Kaurivi, Richard Laven, Rebecca Hickson, Kevin Stafford, and Tim Parkinson. Identification of suitable animal welfare assessment measures for extensive beef systems in new zealand. *Agriculture*, 9(3):66, March 2019.

[MCL+17] Ariel Marcel Tarazona Morales, Maria Camila Ceballos, Guillermo Correa Londoo, Csar Augusto Cuartas Cardona, Juan Fernando Naranjo Ramrez, and Mateus Jos Rodrigues Paranhos da Costa. Welfare of cattle kept in intensive silvopastoral systems: A case report. *Revista Brasileira de Zootecnia*, 46(6):478–488, June 2017.

[MW14] D. J. Mellor and J. R. Webster. Development of animal welfare understanding drives change in minimum welfare standards. *Revue scientifique et technique (International Office of Epizootics)*, 33:121–130, April 2014.

[NTCG18] Luis Nóbrega, Andre Tavares, Antonio Cardoso, and Pedro Gonçalves. Animal monitoring based on IoT technologies. In *2018 IoT Vertical and Topical Summit on Agriculture - Tuscany (IOT Tuscany)*, pages 1–5. IEEE, May 2018.

[wM17] Ciira wa Maina. IoT at the grassroots — exploring the use of sensors for livestock monitoring. In *2017 IST-Africa Week Conference (IST-Africa)*, pages 1–8. IEEE, May 2017.

[WYC+18] Y. Wang, X. Yong, Z. Chen, H. Zheng, J. Zhuang, and J. Liu. The design of an intelligent livestock production monitoring and management system. In *2018 IEEE 7th Data Driven Control and Learning Systems Conference (DDCLS)*, pages 944–948. IEEE, May 2018.