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Automatic cattle activity recognition on grazing systems*

Reconocimiento automático de la actividad de vacunos en pastoreo

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SUMMARY

The use of collars, pedometers or activity tags for cattle behavior recognition in short periods (e.g. 24 h) is expensive. Under this particular situation, the development of low-cost and easy-to-use technologies is relevant. Similar to smartphone apps for human activity recognition, which analyzes data from embedded triaxial accelerometer sensors, we develop an Android app to record activity in cattle. Four main steps were followed: a) data acquisition for model training, b) model training, c) app deploy, and d) app utilization. For data acquisition, we developed a system in which three components were used: two smartphones and a Google Firebase account for data storage. A dataset with 945415 rows and four columns was made. Each row corresponds to the three-axis accelerometer values and the cattle activities (Eating, Resting, or Rumination). For model training, the generated database was used to train a recurrent neural network. The performance of the training was assessed by a confusion matrix. For all actual activities, the trained model provided a high prediction (> 96 %). The trained model was used to deploy an Android app by using the TensorFlow API. Finally, three cell phones (LG gm730) were used to test the app and record the activity of six Holstein cows (3 lactating and 3 non-lactating). Direct and non-systematic observations of the animals were made to evaluate the performance of the app. After training, the model's accuracy was 100, 99, and 96 % for Eating, Rumination, and Resting, respectively. Our results show consistency between the direct observations and the activity recorded by our Android app. In conclusion, this work shows that it is possible to develop low-cost technologies to record the daily activity of grazing cows using the smartphone acceleration data analysis.

KEYWORDS: Android App; Accelerometers; Tensorflow; Animal Behavior; Precision Livestock Farming.

PALABRAS CLAVE: Aplicaciones Android; Acelerómetros; Tensorflow; Comportamiento Animal; Ganadería de Precisión.

RESUMEN

El uso de collares o podómetros para el reconocimiento del comportamiento del ganado en períodos cortos (24 h) es costoso. En esta situación particular, el desarrollo de tecnologías de bajo costo y fáciles de usar es relevante. Al igual que las aplicaciones de celulares para el reconocimiento de la actividad humana, desarrollamos una aplicación de Android para registrar la actividad en el ganado. Se siguieron cuatro pasos: a) adquisición de datos para el entrenamiento del modelo, b) entrenamiento del modelo, c) implementación de aplicaciones y, d) utilización de la aplicación. Para la adquisición de datos, desarrollamos un sistema con tres componentes: dos teléfonos y una cuenta de Google Firebase para el almacenamiento de datos. Se creó un conjunto de datos con 945415 filas y cuatro columnas. Cada fila corresponde a los valores del acelerómetro y las actividades del ganado (comer, descansar o rumiar). La base de datos generada se utilizó para entrenar una red neuronal recurrente. El entrenamiento se evaluó mediante una matriz de confusión. Para todas las actividades, el modelo tuvo una precisión alta (> 96 %). El modelo entrenado se utilizó para desarrollar una aplicación de Android con la API de TensorFlow. Finalmente, se utilizaron tres celulares (LG gm 730) para probar la aplicación y registrar la actividad de seis vacas Holstein (3 lactantes y 3 no lactantes). Se realizaron observaciones directas y no sistemáticas de los animales para evaluar el desempeño de la aplicación. Después del entrenamiento, la precisión del modelo fue del 100, 99 y 96 % para comer, rumiar y descansar, respectivamente. Nuestros resultados muestran coherencia entre las observaciones directas y la actividad registrada por nuestra aplicación de Android. En conclusión, este trabajo muestra que es posible desarrollar tecnologías de bajo costo para registrar la actividad diaria de las vacas en pastoreo utilizando el análisis de datos de aceleración de teléfonos inteligentes.

INTRODUCTION

Monitoring livestock behavior can be a useful tool to improve farm animal management and to detect individual health events (Riaboff *et al*., 2019). The use of automated systems that predict daily behaviors from accelerometer data is widely used in cattle. Feeding time (Reynolds *et al*., 2019), rumination (Benaissa *et al*., 2019a; Rodrigues *et al*., 2019), lying time, predict calving (Krieger *et al*., 2019), welfare assessment traits (e.g. body condition score, udder/ leg hygiene score) temperament traits (e.g. aggressiveness) (Jaeger *et al*., 2019, Chapa *et al*., 2020) or lameness detection (O'Leary *et al*., 2020) can be recorded with accelerometers in collars, pedometers o ear tags.

Commercial accelerometer-based systems, used to record cattle activity, has three main components: the first is a device containing the accelerometer (Werner *et al*., 2019; Giovanetti *et al*., 2020). This device is mounted on the cow's leg, in a collar around the neck, or a tag on the ear. These devices use radiofrequency technology for wirelessly transfer data (Landaluce *et al*., 2020). The second part is an antenna that reads information transmitted from the activity device. The third part is a computer or other device that interprets the data and presents reports to the farmer. In simple terms, this monitoring framework is based on the interpretation of the accelerometer values as animal activity (e.g. eating, resting, or rumination). Although these systems are very useful tools in large-scale livestock management, their use on small farms or for educational or research purposes is unsustainable.

As an alternative, a similar approach with electronic devices containing accelerometers (e.g. Smartphones) can be used for cattle activity recognition (Andriamandroso *et al*., 2017). This alternative is based on the Human Activities Recognition (HAR) approach (Meng *et al*., 2021; Tarafdar *et al*., 2021). Although there are many types of sensors that can be used for the HAR (i.e. Gyroscope, Magnetometer, Electromyography, Electrocardiography), accelerometers are most widely used. An accelerometer is a device used to measure acceleration, on one or various parts of a body. Acceleration is the rate of change of the velocity of an object. The measuring unit is meters per second squared (m/s^2) (Chen *et al*., 2021). To analyze accelerometer data Machine Learning (ML) techniques like decision trees, K-nearest neighbours, support vector machines, hidden Markov models, and artificial neural networks (ANN) have been used (Jobanputra *et al*., 2019).

One of the most popular methods to interpret accelerometer data as an activity are the ANN (Irvine *et al*., 2020). For instance, Convolutional Neural Networks (CNNs). CNN is a type of deep neural network that was developed for use with image data (e.g. such as handwriting recognition). However, now this kind of model can be considered universal, meaning that it can be used to approximate any continuous function to an arbitrary accuracy when the depth of the neural network is large enough (Zhou 2020). The first important work using CNNs to the HAR was by Ming *et al*. (2014). In the paper, the authors develop a simple CNNs model for accelerometer data, where each axis of the accelerometer data is fed into separate convolutional layers, pooling layers, then concatenated before being interpreted by hidden fully connected layers.

Taking into account the challenges of implementing commercial automated monitoring systems and that the HAR is a technique used with success and can be extrapolated to animals. It is possible to consider that the HAR approach can be used in the analysis of cattle behavior. Hence, the objective of this work was to develop an application for Android devices that allow monitoring of the activity of grazing cattle.

METHODS

Four main steps were followed to develop an Android app for Cattle Activities Recognition: a) data acquisition for model training, b) model training, and c) app deploy, and d) app utilization. Data acquisition and app utilization were made in Universidad de Antioquia (Antioquia, Colombia) dairy farm. This farm is located at an altitude of 2.480 m, with 16 °C average temperature and coordinates 6°27'N, and 75°32'W.

Data acquisition for model training

Traditionally, video analysis or direct observation are used to establish which activity corresponds with the accelerometer's values. In our work, we developed a system in which three components were used: two smartphones with internet access and a Google Firebase account for data storage. In this system, one phone is used by the human observer to record the actual cattle activity (eating, resting, or ruminating) into Firebase. The second phone, placed on the backside of the cattle's head, records the triaxial accelerometer values and the actual activity registered in Firebase for the observer. The phone on the animal records the information into a text file every 100 milliseconds (Figure 1).

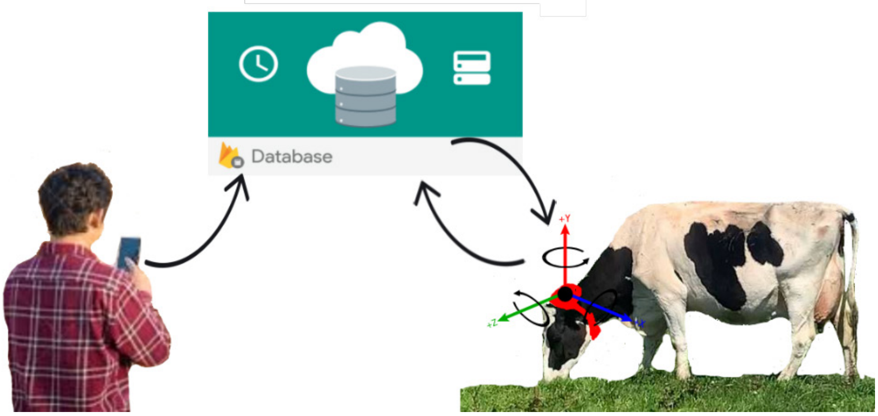

Figure 1. Data acquisition workflow

During 30 days, 20 grazing dairy cows were used for data acquisition. In this process, the observer looks at the cow's activity, then the observer sends the label of current activity to a Real-time Online Database (Firebase), and at the same time, the cell phone on the cow requests the database for the current activity labeling.

Model training

The generated database was used to train a Recurrent Neural Network (RNN) with Long-Short-Term Memory units (LSTM). Training details can be found in the codes shared by Valkov (2017). All the training process was made on Google Colab (Bisong *et al*., 2019) using the Tensorflow Library (Shukla and Fricklas 2018) and Python. 80 % of the total data was randomly selected for model training and the other 20 % was used to test the training. The confusion matrix was used to evaluate the trained model accuracy. Valkov (2017) proposes a RNN containing two fully connected and two LSTM layers (stacked on each other) with 64 units each. The model training was performed with 100 Epoch numbers.

App deploy

During training, the learned parameters (history, predictions, and checkpoint) were stored. The Tensorflow API (version: 1.13.1) and the learned parameters were used to freeze and save the graph weights into a single protobuf file, which is used by the Android app to make predictions. The Android Studio Software (Smyth, 2019) was used to build the final app. Details about the freeze graph process and the Android app template can be found in the codes shared by Valkov (2017). The IntentService Java class, which provides a straightforward structure for running an operation on a single background thread was used to ensure that the application continues to function even if the cell phone screen is turned off (Song *et al*., 2019). Running the app as background services guarantee data collection at least 24 h.

Our Android project has two Java scripts called: Main.java and BackgroundService.java. The Main.java script contains the code necessary to initialize the graphic elements in the app's screen (i.e. buttons, messages and a chart). Figure 2 (right) shows that the app has three buttons called "Start", "Stop" and "Plot". The buttons "Start" and "Stop" initialize and stop the app's Background Service, respectively. The button "Plot" opens a menu to select one of the text files created during the activity monitoring and generates a chart with the activity patterns of grazing, rumination and resting. The "BackgroundService.java" script contains the code necessary to run the app in background, which means that the app can run even if the phone's screen is turned-off. This is a very important feature, because it reduces the battery usage. Each second, the "BackgroundService.java'' script collects the data of the phone's three-axis accelerometer sensor, analyzes this data with the model, and stores the predicted activities in a text file. The app is freely available here: Cattle Activity Recognition.

Figure 2. Cow wearing the device and the app screen. Arrows show the correct position of the smartphone on the cow's head.

App utilization

Three smartphones (LG gm730) were used to record the activity of six Holstein cows (3 lactating and 3 non-lactating). The lactating cows (multiparous) were 170 days in milk (SD = 87 d), had a milk yield of 28 kg (SD = 1,3 kg), and a body weight of 593 kg (SD = 47,8 kg), and the non-lactating (1 primiparous and 2 multiparous) were 268 days of pregnancy (SD = 18 days), and body weight of 561 kg (SD = 75 kg) at the beginning of the experiment. The phones were attached to the back of the cows' heads using a harness (Figure 2) and were removed two days later. Direct and non-systematic observations of the animals were made to contrast the activities recorded by the device. Additionally, the battery life was determined.

RESULTS

Data acquisition

The dataset was 945415 rows and 4 columns. The first three columns in the dataset correspond to the three-axis accelerometer values and the fourth column corresponds to the cattle activities (Eating, Resting, or Rumination). The percentage of each activity in the database was 57, 25, and 18 %, for eating, rumination, and resting, respectively (Figure 3). The size of this database is similar to a famous database called WISDM (Kwapisz *et al*., 2011) which contains 1098207 rows for six human activities controlled under laboratory conditions.

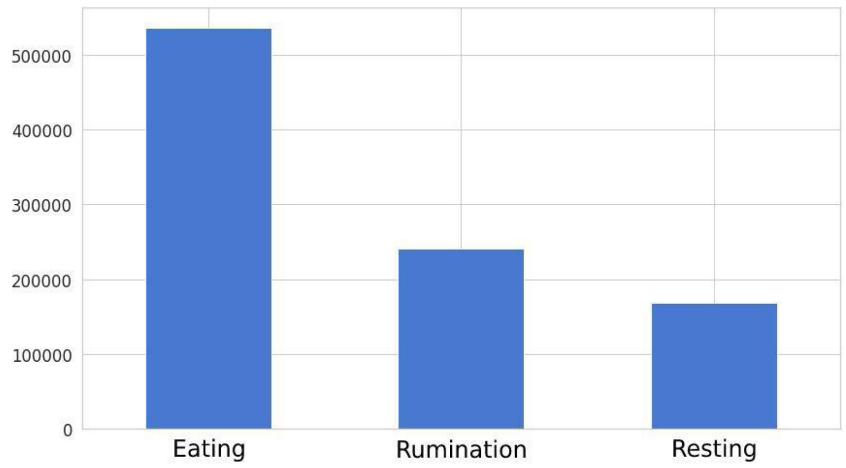

Figure 3. Distribution data acquisition by activity.

For the development of databases that contain information on animal activity and their corresponding acceleration data, direct observation and/or video analysis are used (Benaissa *et al*., 2019b). However, we decided to use an alternative method that allowed us to build the database in an efficient way. Since our system records the animal's activities in real time, it is possible to avoid errors in the concatenation of the acceleration data and the observed activity. And significantly reduces the need to generate laborious information to analyze such as videos.

As shown in Figure 4, There are clear differences in the data behavior among the different cow's activities. Eating is mainly characterized by negative values in the y-axis, resting by low changes in all axes, and rumination by little changes in all axes. To obtain correct prediction results it is necessary that the phone is placed on the animal's head as shown in Figure 2, otherwise the model results will be erroneous, since the model was trained with data obtained in this particular position of the phone.

Figure 4. Time series data recorded by accelerometers mounted on a dairy cow

Model training

The model seems to learn well with accuracy reaching above 99 % and loss hovering at around 0,01 % (Figure 5).

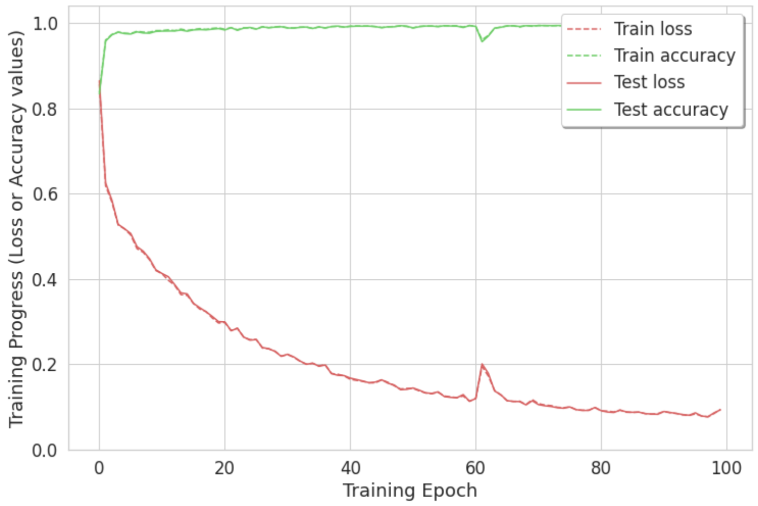

Figure 5. Training session's progress over iterations.

The confusion matrix for the model's predictions (Figure 6) shows that the model's accuracy on the test data was 100, 99, and 96 % for Eating, Rumination, and Resting, respectively.

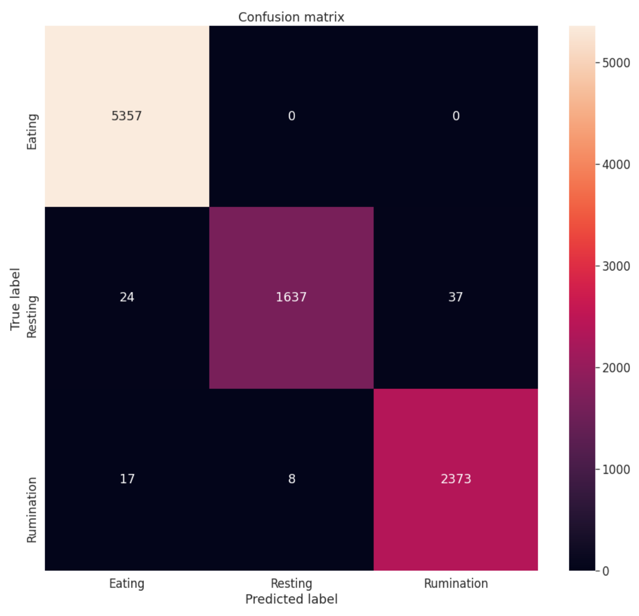

Figure 6. Confusion matrix

App utilization

High consistency was observed between the direct observations and the Eating, Resting, and Rumination activity recorded by the device. In the milking cows, the device was able to identify two peaks of ingestive activity, closely related to the time of milking. In this group, it was observed that ingestive activity decreased at midday and after 18 h. During the night, the milking cows spent equivalent amounts of time for rumination and resting, while the dry cows used the night mainly to rest (Figure 7). The average battery life was higher than 30 h.

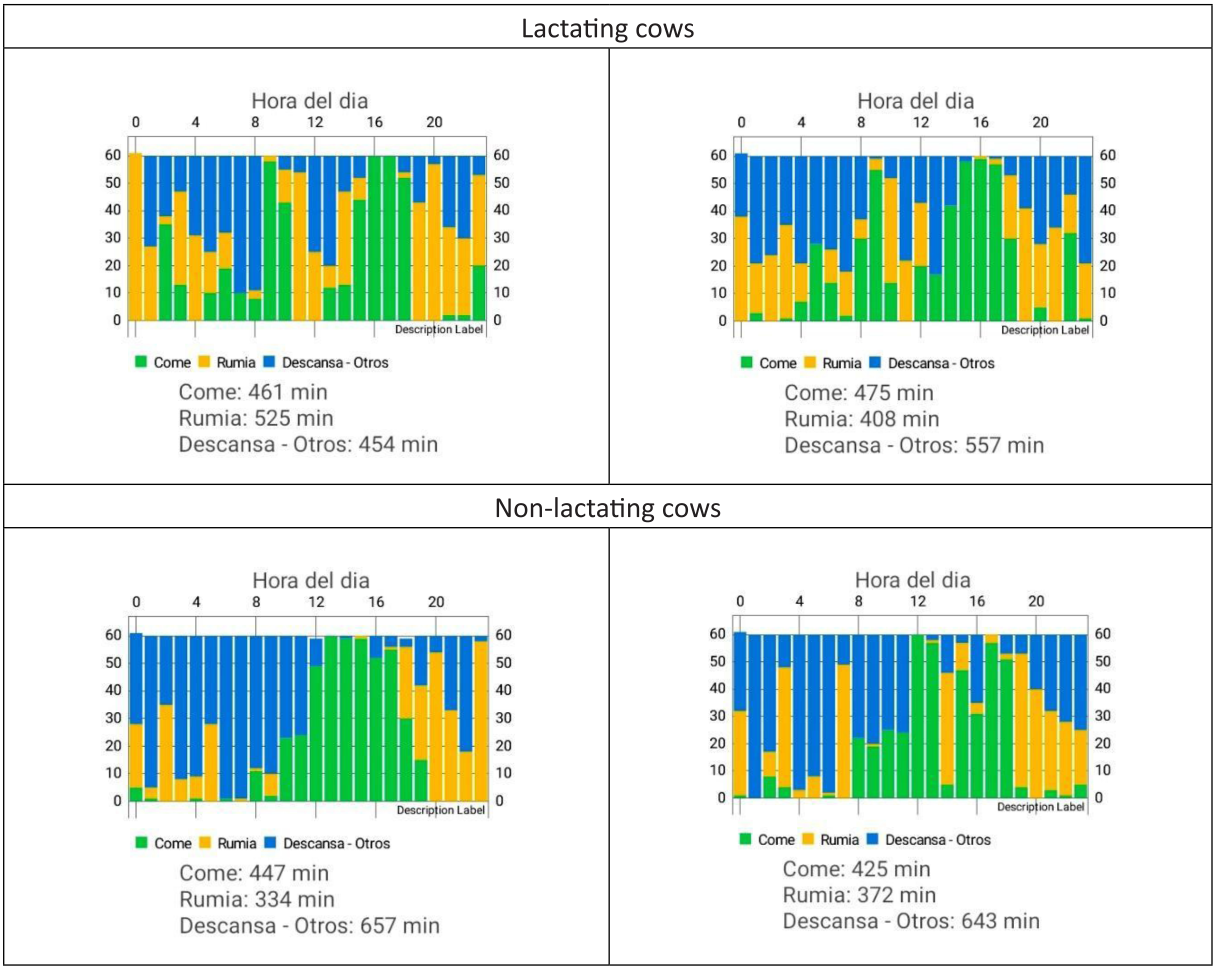

Figure 7. Screen results from the Android app. Green, yellow and blue columns correspond to intake, rumination, and resting activity, respectively.

Human activity recognition (HAR) is a process aimed at the classification of human actions in a given period of time based on discrete measurements (acceleration, rotation speed, geographical coordinates, etc.) made by personal digital devices (Straczkiewicz *et al*., 2021). In recent years, activity recognition with smartphones is a technology widely used in humans, since it allows monitoring elderly people (Voicu *et al*., 2019), healthcare (Ogbuabor and La, 2018), household activities (Della Mea *et al*., 2017), transportation modes (Guvensan *et al*., 2018), and so forth. However, the use of smartphones for activity recognition in animals is very limited.

Traditionally, activity recognition in farm animals is done with complex systems where sensors are placed on the animals' necks or feet. These sensors record data that is processed in a central computer. Although these systems are quite accurate, the high cost represents an obstacle for their implementation on small farms.

We developed this work to generate a low-cost tool that allows farmers, researchers or students to monitor animal activity in short periods of time (24 h). For example, this tool allows us to monitor cows in heat, sick animals or animals in the adaptation period, or simply to better understand the activity patterns of grazing animals on the farm.

CONCLUSION

Our findings indicate that it is possible to record the daily activity of grazing cows based on input variables from smartphone acceleration data. Further studies should test the app under different farming and management systems.

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REFERENCES

ANDRIAMANDROSO, ANDRIAMASINORO-LALAINA-HERINAINA; LEBEAU, FRÉDÉRIC; BECKERS, YVES; FROIDMONT, ERIC; DUFRASNE, ISABELLE; HEINESCH, BERNARD; DUMORTIER, PIERRE; BLANCHY, GUILLAUME; BLAISE, YANNICK; BINDELLE, JÉRÔME. Development of an open-source algorithm based on inertial measurement units (IMU) of a smartphone to detect cattle grass intake and ruminating behaviors. Computers and electronics in agriculture, v. 139, 2017, p. 126-137.
https://doi.org/10.1016/j.compag.2017.05.020

BENAISSA, SAID; TUYTTENS, FRANK A.M.; PLETS, DAVID; CATTRYSSE, HANNES; MARTENS, LUC; VANDAELE, LEEN; WOUT, JOSEPH; SONCK, BART. Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers. Applied Animal Behaviour Science, v. 211, 2019a, p. 9-16.
https://doi.org/10.1016/j.applanim.2018.12.003

BENAISSA, SAID; TUYTTENS, FRANK A.M.; PLETS, DAVID; PESSEMIER, TOONDE; TROGH, JENS; TANGHE, EMMERIC; VANDAELE, LEEN; VAN NUFFEL, ANNELIES; WOUT, JOSEPH; SONCK, BART. On the use of on-cow accelerometers for the classification of behaviours in dairy barns. Research in veterinary science, v. 125, 2019b, p. 425-433.
https://doi.org/10.1016/j.rvsc.2017.10.005

BISONG, EKABA. Google colaboratory. En BISONG, EKABA. Building Machine Learning and Deep Learning Models on Google Cloud Platform. Apress, Berkeley (United States Of America): 2019, p. 59-64.
https://doi.org/10.1007/978-1-4842-4470-8_7

CHAPA, JOSE M.; MASCHAT, KRISTINA; IWERSEN, MICHAEL; BAUMGARTNER, JOHANNES; DRILLICH, MARC. Accelerometer systems as tools for health and welfare assessment in cattle and pigs–a review. Behavioural Processes, 2020, p. 104262.
https://doi.org/10.1016/j.beproc.2020.104262

CHEN, KAIXUAN; DALIN, ZHANG; LINA, YAO; BIN, GUO; ZHIWEN, YU; YUNHAO, LIU. Deep Learning for Sensor-based Human Activity Recognition: Overview, Challenges, and Opportunities. ACM Computing Surveys (CSUR), v. 54, n. 4, p. 1-40.
https://doi.org/10.1145/3447744

DELLA_MEA, VINCENZO; QUATTRIN, OMAR; PARPINEL, MARIA. A feasibility study on smartphone accelerometer-based recognition of household activities and influence of smartphone position. Informatics for Health and Social Care, v. 42, n. 4, 2017, p. 321-334.
https://doi.org/10.1080/17538157.2016.1255214

GIOVANETTI, V.; COSSU, R.; MOLLE, G.; ACCIARO, M.; MAMELI, M.; CABIDDU, A.; SERRA, M.G.; MANCA, C.; RASSU, S.P.G.; DECANDIA, M.; DIMAURO, C. Prediction of bite number and herbage intake by an accelerometer-based system in dairy sheep exposed to different forages during short-term grazing tests. Computers and Electronics in Agriculture, v. 175, 2020. p. 105582.
https://doi.org/10.1016/j.compag.2020.105582

GUVENSAN, M. AMAC; DUSUN, BURAK; CAN, BARIS; TURKMEN, H. IREM. A novel segment-based approach for improving classification performance of transport mode detection. Sensors, v. 18, n. 1, 2018, p. 87.
https://doi.org/10.3390/s18010087

IRVINE, NAOMI; NUGENT, CHRIS; ZHANG, SHUAI; WANG, HUI; WING, W.Y. Neural network ensembles for sensor-based human activity recognition within smart environments. Sensors, v. 20, n. 1, 2020, p. 216.
https://doi.org/10.3390/s20010216

JAEGER, MARIA; BRÜGEMANN, KERSTIN; BRANDT, HORST; KÖNIG, SVEN. Associations between precision sensor data with productivity, health and welfare indicator traits in native black and white dual-purpose cattle under grazing conditions. Applied Animal Behaviour Science, v. 212, 2019, p. 9-18.
https://doi.org/10.1016/j.applanim.2019.01.008

JOBANPUTRA, CHARMI; BAVISHI, JATNA; DOSHI, NISHANT. Human activity recognition: A survey. Procedia Computer Science, v. 155, 2019, p. 698-703.
https://doi.org/10.1016/j.procs.2019.08.100

KRIEGER, STEFANIE; OCZAK, MACIEJ; LIDAUER, LAURA; BERGER, ALEXANDRA; KICKINGER, FLORIAN; ÖHLSCHUSTER, MANFRED; AUER, WOLFGANG; DRILLICH, MARC; IWERSEN, MICHAEL. An ear-attached accelerometer as an on-farm device to predict the onset of calving in dairy cows. Biosystems Engineering, v. 184, 2019, p. 190-199.
https://doi.org/10.1016/j.biosystemseng.2019.06.011

KWAPISZ, JENNIFER R.; WEISS, GARY M.; MOORE, SAMUEL A. Activity recognition using cell phone accelerometers. ACM SigKDD Explorations Newsletter, v. 12, n. 2, 2011. P. 74-82.
https://doi.org/10.1145/1964897.1964918

LANDALUCE, HUGO; ARJONA, LAURA; PERALLOS, ASIER; FALCONE, FRANCISCO; ANGULO, IGNACIO; MURALTER, FLORIAN. A review of iot sensing applications and challenges using RFID and wireless sensor networks. Sensors, v. 20, n. 9, 2020, p. 2495.
https://doi.org/10.3390/s20092495

MENG, LONG; ZHANG, ANJING; CHEN, CHEN; WANG, XINGWEI; JIANG, XINYU; TAO, LINKAI; FAN, JIAHAO; WU, XUEJIAO; DAI, CHENYUN; ZHANG, YIYUAN; VANRUMSTE, BART; TAMURA, TOSHIYO; CHEN, WEI. Exploration of human activity recognition using a single sensor for stroke survivors and able-bodied people. Sensors, v. 21, n. 3, 2021, p. 799.
https://doi.org/10.3390/s21030799

OGBAUBOR, GODWIN; LA, ROBERT. Human activity recognition for healthcare using smartphones. In Proceedings of the 2018 10th international conference on machine learning and computing, 2018, p. 41-46.
https://doi.org/10.1145/3195106.3195157

O'LEARY, N.W.; BYRNE, D.T.; O'CONNOR, A.H.; SHALLOO, L. Invited review: Cattle lameness detection with accelerometers. Journal of dairy science, v. 103, n. 5, 2020, p. 3895-3911.
https://doi.org/10.3168/jds.2019-17123

REYNOLDS, M.A.; BORCHERS, M.R.; DAVIDSON, J.A.; BRADLEY, C.M.; BEWLEY, J.M. An evaluation of technology-recorded rumination and feeding behaviors in dairy heifers. Journal of dairy science, v. 102, n. 7, 2019, p. 6555-6558.
https://doi.org/10.3168/jds.2018-15635

RIABOFF, LUCILE; AUBIN, SEBASTIEN; BEDERE, NICOLAS; COUVREUR, SEBASTIEN; MADOUASSE, AURELIEN; GOUMAND, ETIENNE; CHAUVIN, ALAIN; PLANTIER, GUY. Evaluation of pre-processing methods for the prediction of cattle behaviour from accelerometer data. Computers and Electronics in Agriculture, v. 165, 2019, p. 104961.
https://doi.org/10.1016/j.compag.2019.104961

SHUKLA, NISHANT; KENNETH, FRICKLAS. Machine learning with TensorFlow. 1 ed. Manning Publications Co. 3 Lewis Street Greenwich (United States Of America): 2018, 272 p, ISBN 9781617293870.

SMYTH, NEIL. Android Studio 3.5 Development Essentials-Java Edition: Developing Android 10 (Q) Apps Using Android Studio 3.5, Java and Android Jetpack. Payload Media, 2019, 778 p, ISBN-10 1951442016, ISBN-13 978-1951442019.

SONG, WEI; ZHANG, JING; HUANG, JEFF. ServDroid: detecting service usage inefficiencies in Android applications. En DUMAS, MARLON, PFAHL, DIETMAR; Proceedings of the 2019 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, Association for Computing Machinery. New York (United States Of America): 2019, p. 362-373.
https://doi.org/10.1145/3338906.3338950

STRACZKIEWICZ, MARCIN; JAMES, PETER; ONNELA, JUKKA-PEKKA. A systematic review of smartphone-based human activity recognition methods for health research. NPJ Digital Medicine, v. 4, n. 1, 2021, p. 1-15.
https://doi.org/10.1038/s41746-021-00514-4

TARAFDAR, PRATIK; BOSE, INDRANIL. Recognition of human activities for wellness management using a smartphone and a smartwatch: a boosting approach. Decision Support Systems, v. 140, 2021, p. 113426.
https://doi.org/10.1016/j.dss.2020.113426

VALKOV, VENELIN. Human Activity Recognition using LSTMs on Android — TensorFlow for Hackers (Part VI). 2017. https://medium.com/@curiousily/human-activity-recognition-using-lstms-on-android-tensorflow-for-hackers-part-vi-492da5adef64 [consultado Septiembre 16 de 2021].

VOICU, ROBERT-ANDREI; DOBRE, CIPRIAN; BAJENARU, LIDIA; CIOBANU, RADU-LOAN. Human physical activity recognition using smartphone sensors. Sensors, v. 19, n. 3, 2019, p 458.
https://doi.org/10.3390/s19030458

WERNER, J.; UMSTATTER, C.; LESO, L.; KENNEDY, E.; GEOGHEGAN, A.; SHALLOO, L.; SCHICK, M.; O'BRIEN, B. Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows. animal, v. 13, n. 9, 2019, p. 2070-2079.
https://doi.org/10.1017/S1751731118003658

ZHOU, DING-XUAN. Universality of deep convolutional neural networks. Applied and computational harmonic analysis, v. 48, n. 2, 2020, p. 787-794.
https://doi.org/10.1016/j.acha.2019.06.004