Axel MONTOUT1,2: Year One Progress Report

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Contents

Abbreviations

FAMACHA: (FAffa MAlan CHArt) is a method whereby only certain sheep or goats in a flock are selected for treatment against wireworm (also known as barbers pole worm, Haemonchus contortus). Sheep are selected for treatment based on the degree of anaemia they are displaying in their mucous membranes. In turn, the degree of anaemia is assessed through a colour guided chart.

Thesis plan

Section	Progress
Part A: Application of state of the art supervised machine learning technique for early detection of helminths infection in goats using accelerometer data	Used dataset of goat activity level and report of FAMACHA score evaluation to train an SVM classifier. Results shows high accuracy in the prediction In the process of writing a paper for publication
Part B: Study and application of unsupervised machine learning techniques to improve the scalability of the system.	In progress
Part C: Try the system on dataset from different type of livestock (sheep, cattle, …)	NA

Prediction of helminths infection in small ruminant with cost effective device using accelerometers

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Prevention of disease in livestock farming is key to the economic development of resource poor communities. The FAMACHA© scoring system has been used successfully to detect the level of helminth infection of small ruminant. The method is an effective way to fight against anthelmintic resistance in countries such as South Africa. In recent years accelerometer has become widely available devices of multiple use. In an attempt to answer the question "Can the activity level of an animal be used as a predictor of its well-being ?" we used machine learning and dimentionality reduction techniques namely the Support vector algorithm (SVM) and Linear discriminant analysis (LDA) to detect the decrease in the health of the animals. In this paper, we describe how we trained a classifier to achieve a highly accurate prediction of the increase of the FAMACHA© score for a given animal.

FAMACHA | Machine learning | Data normalization | preprocessing | Dimentionality reduction | Accelerometer | Activity level | Linear discriminant analysis | Radio frequency identification

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1. Introduction.

Livestock farming in resources poor communities presents multiple challenges. The main issue being effective health diagnosis of every animals. Which is usually performed manually across the herd. Although multiple worm control strategies for small scale farms exist [1], including technologies such as Chemical dewormers, grazing management, specific diet, ethnoveterinary remedies, vaccination, and anthelmintic. They all require extensive manual labor and expenses. In addition poor practice give rise to anthelmintic resitance which is prevalent in countries such as South Africa [2] due to farmers relying on conventional anthelmintic drugs as sole method of control against worm infection. Furthermore sheep and goat farming in tropical region suffer from tremendous economic loss [3] because of helminths infection and their difficult management.

In the hope to reduce cost and labour a novel automated approach to worm control was tested in this paper. We developed an automated system which could predict the level of worm infection based on the increase of the FAMACHA© score(Bath et al. 1996) of an animal which is a strong indicator of the general health of the individual and the herd.

Accelerometer data has successfully been used to classify goat grazing behaviour [4] [5] which could potentially be used for assessment of animal welfare. In this case study a transponder containing an accelerometer and mounted on a collar was used to collect the activity level of 30 goats. For a period of 1 year and 2 months the FAMACHA© score of every animal was assessed every 2 weeks. Different supervised machine learning techniques was explored in order to find the most accurate model at detecting the increase of FAMACHA© score form 1 to 2. The activity level of the individual in a time period before testing is used as input as well as other features such as the humidity and temperature as it is known that worm infection increases in wet seasons [6], [3].

As of the time of writing this paper no previous studies presented FAMACHA© score prediction based on the activity level of small ruminant. Challenges in this approach mainly involves data normalization and limited amount of FAMACHA© score records.

2. Methods.

2.1. sites and materiel. The study focuses on the data collected in the Delmas farm in the small town of Hilton, South Africa. 35 female native South African goats, with an age range of 3 to 7 years old were equipped with an RFID transponder mounted on a collar. Each ewe was periodically tested for FAMACHA© score evaluation and treated if necessary. A single solar panel powered base station operating at the frequency of 868 Mhz is mounted above ground at the top of a five meter wooden pole is installed on the farm. The transponder contains an active RFID transceiver operating at 868Mhz as well as a battery and a A1 type accelerometer for activity level measurement.

The accelerometer have a set acceleration threshold of 2g. The sensor output a decimal value which is calculated by increment of a counter every time the sensed acceleration reach a value above the threshold at an interval of 1 minute. Data transmission cannot be performed if the signal to noise ratio is below 10dB. In order to extend the battery life the tag only transmit data to the base station at specific times. The data

transmitted include: the identifier of the transponder, the battery level, the signal strength, a timestamp, and the activity level. Although sensor overflow has been observed, on average activity level output values range between 0 and 124 without re-sampling.
The base station relays the collected data via the general packet radio services (GPRS) technology to a web server which provide access and the possibility to export the data.
To reduce the occurrence of tag to tag transmission collisions and increase tag read rates the carrier sense multiple access (CSMA) was adopted [7].

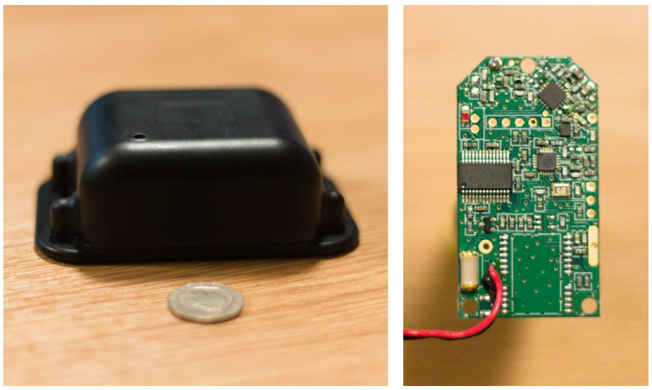

Fig. 1. Transponder (including, accelerometer, RFID antenna, Microcontroller.)

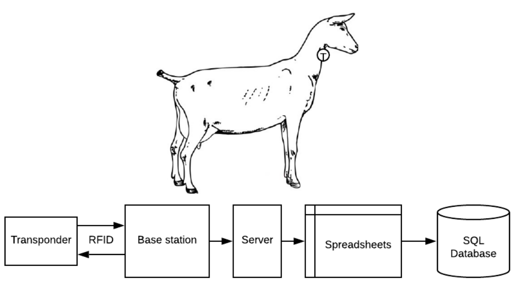

Fig. 2. illustration of the data collection pathway for one transponder.

2.2. Data management. Due to storage limitation regular export of the recorded data was carried out. The exports take the form of excel spreadsheets containing the sensor outputs in the desired time frame. The raw data is then parsed into an SQL database. The data is strategical re-sampled in multiple time resolution for efficient interactive visualization purposes. Indeed loading the entire data-set multiple times is computationally expensive and ineffective. The table storing the raw data recorded at the minute resolution contains 40659086 records.

2.3. Visualization. Visualising the data is an important step before analysis. For that purpose an interactive visualisation tool was developed in order to reveal the herd activity as well as every individual activity over the recorded period. Furthermore the tool allowed us to monitor faulty transponder and failed transmission. And provided validation of expected behaviours such as decrease activity at night. However it were not possible to detect obvious change in activity which might indicate decrease in the health of an animal.

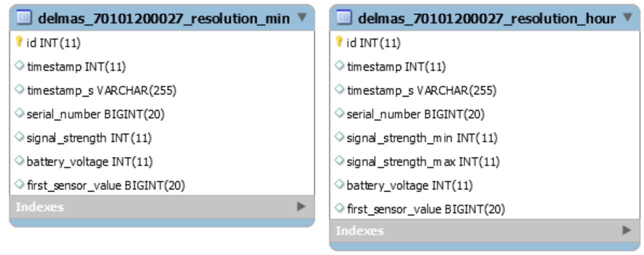

Fig. 3. Schematic representation of the SQL tables containing the data at the minute and hour resolution.

This research is based on the belief that there are intrinsic patterns in the activity level over time of an animal which can indicate the heal status of the individual. Such patterns could be detected with the use of machine learning techniques. The visualisation also revealed the need for data pre-processing. Non normalized data would introduce bias in the analysis. Important change in the activity signal average amplitude across the herd was observed. Calibration of the sensors is believed to be the cause.

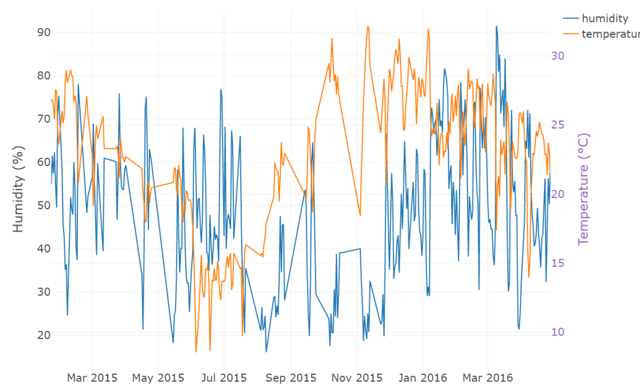

Fig. 4. Graph of the air humidity percentage and temperature in the use case farm Delmas.

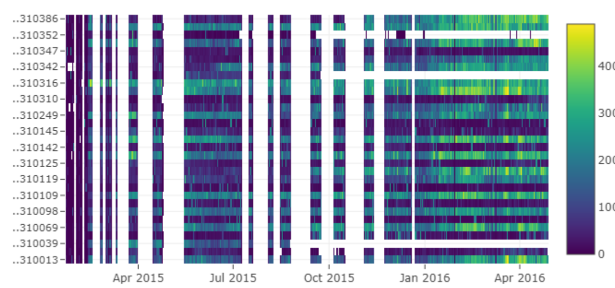

Fig. 5. Illustration of the activity level over time of the herd without normalisation. Each row displays the activity level of an individual in the farm. This graph reveals the extend of missing data as well as the difference in amplitude scale across the herd. This graph is generated with the data re-sampled at the day resolution. The y axis shows the different transponder id.

2.4. Pre-processing. Normalisation of the data is an important step before analysis. The following describe the different steps of the normalisation applied. Considering the activity level of a goat g over time t as a signal defined as:

$$a_g(t) = [a_g t_0, \dots, a_g t_n]$$

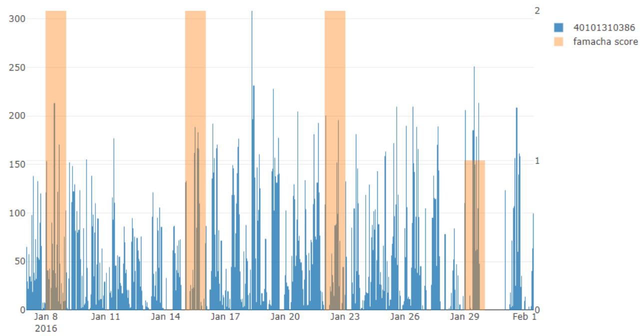

Fig. 6. Illustration of the activity level over time of one goat. This graph is generated with the data re-sampled at the 10 minutes resolution. The left y axis shows the activity level value. The right y axis shows the value of the FAMACHA© score.

And the activity of the herd of n individuals over time t define as being the mean activity for every animal:

$$h(t) = \left[\frac{\sum_{i=0}^{n} a_{gi}(t_0)}{n}, \ldots, \frac{\sum_{i=0}^{n} a_{gi}(t_n)}{n}\right]$$

If a signal $a_g(t)$ of length l contains a high percentage of missing or irrational data the signal is dismissed. Two thresholds are defined for the number of zero and missing values to determine the validity of the signal.

$$threshold_1 = \frac{l}{number\, of\, missing\, values}$$

$$threshold_2 = \frac{l}{number\, of\, zero\, values}$$

- Firstly the Anscombe transform [8] is applied to the signal.

$$anscombe(x) = 2 \times \sqrt{x + \frac{3}{8}}$$

$$A_g(t) = [anscombe(a_g t_0), \ldots, anscombe(a_g t_n)]$$

- Secondly the median of the fraction at every point in time between the herd activity and every individual is calculated.

$$\alpha_g = median\left(\left[\frac{h(t_0)}{A_g(t_0)}, \ldots, \frac{h(t_n)}{A_g(t_n)}\right]\right)$$

- Finally the obtained coefficient is multiplied to the signal.

$$activity_g(t) = [A_g t_0 \times \alpha_g, \ldots, A_g t_n \times \alpha_g] = A_g(t) \times \alpha_g$$

2.5. Machine learning. This paper focuses its study on supervised machine learning techniques. Different classifiers including Support Vector machine [9], linear regression and multiple layer perceptron [10] was trained in order to evaluate the accuracy in the prediction of the increase of the FAMACHA© score from 1 to 2.

Given the data acquired by direct observation and testing of the herd provided by the farm and the activity data collected by the sensors. Training data-set was constructed. A training set is composed of input data and a classification label.

The classification label is a binary value which describes two status:

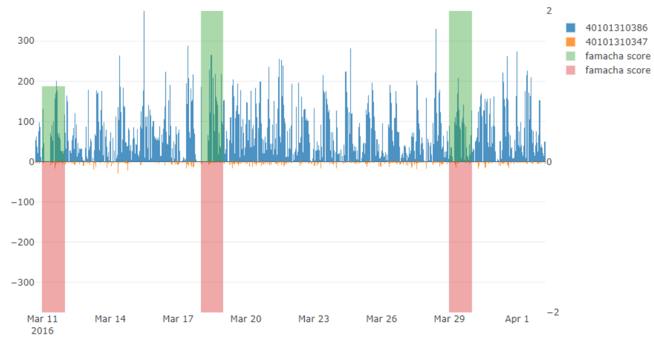

Fig. 7. Illustration of the mirrored activity level over time of two goats before normalisation. This graph is generated with the data re-sampled at the 10 minutes re sampling resolution. The left y axis shows the activity level value. The right y axis shows the value of the FAMACHA© score.

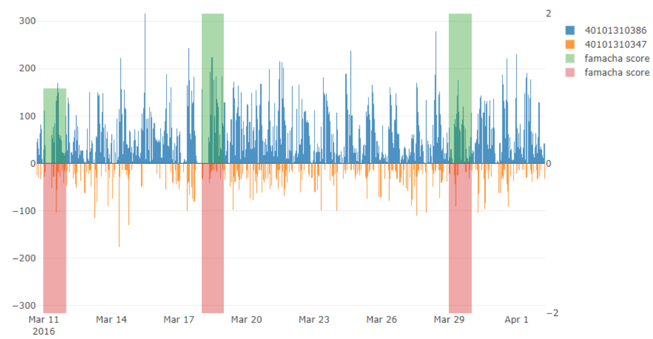

Fig. 8. Illustration of the mirrored activity level over time of two goats after normalisation. This graph is generated with the data re-sampled at the 10 minutes re sampling resolution. The left y axis shows the activity level value. The right y axis shows the value of the FAMACHA© score.

- "FAMACHA© score increased form 1 to 2".
- "FAMACHA© score did not increase".

Multiple configurations were used for the input data. A configuration contains one or several sources of data. The tested configurations use the following data sources:

- activity level of a goat over a variable number of days before the last FAMACHA© test at different sampling resolution.
- humidity and temperature of the city provided by historical weather forecast online services.
- timestamp of every activity point measurement.

Additionally the activity data is used either in it's raw format of activity measurement per period of time or transformed to the frequency domain with the continuous wavelet transform (Grossmann and Morlet 1984).

The input is formatted as an array of features which contains the value of the data source. When multiple sources are used the arrays are appended together. the resulting array is then scaled individually to unit norm (vector length). Lastly the dimension of the array is reduced via linear discriminant analysis(LDA) which is a widely used technique for feature analysis in supervised classification [11] where high dimensional data is challenging to process due to the volume and the often redundant nature of such data. LDA permit to keep the most informative features in the input array increasing

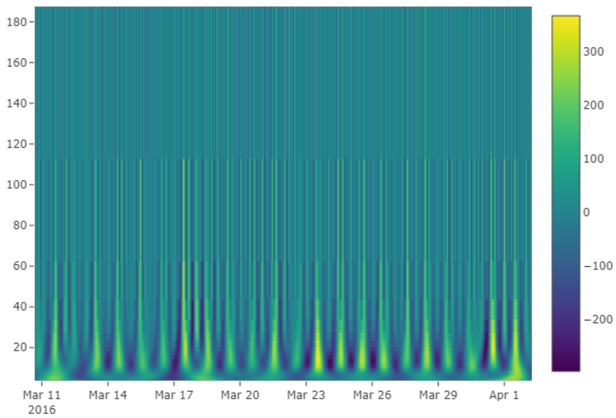

Fig. 9. Graph of the transformed activity level over time of a goat using the continuous wavelet transform. A Gaussian wavelet is used. This graph is generated with the data re-sampled at the 10 minutes re sampling resolution. The left y axis shows the frequency value in Hertz.

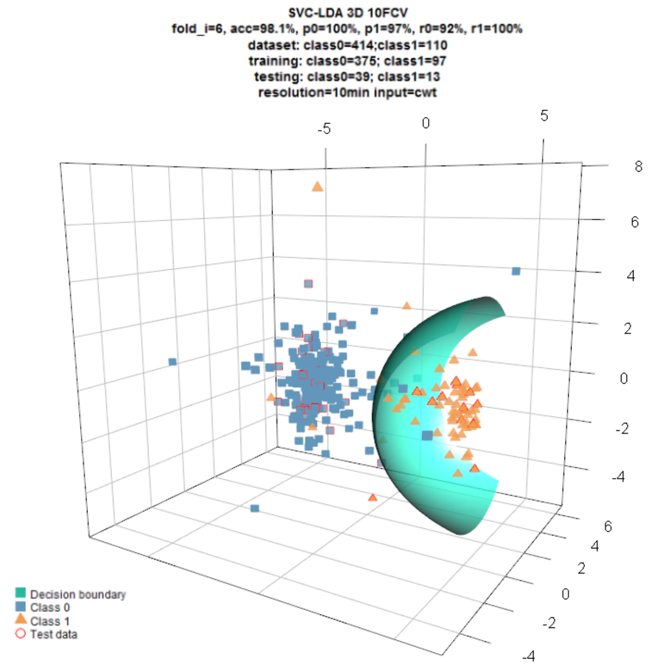

Fig. 11. 3D Illustration of the data classification using a SVM classifier for the following input: cwt, lda reduced to 3 features, resolution 10 minutes, 6 days before FAMACHA© test. Clear cluster can be observed, the squared points represent the data for no increase in the FAMACHA© score while the triangles correspond to the data for the increase of the FAMACHA© score.

class separation, in conjunction with allowing 2D and 3D visualization of the data set.
the constructed training sets are then fed to different classifiers including, SVM, linear regression, and MPL. Nested cross validation is used to first find the best classifier parameters and prevent over-fitting. Once the hyper-parameters are found 10 fold stratified cross validation is used for testing of the model.

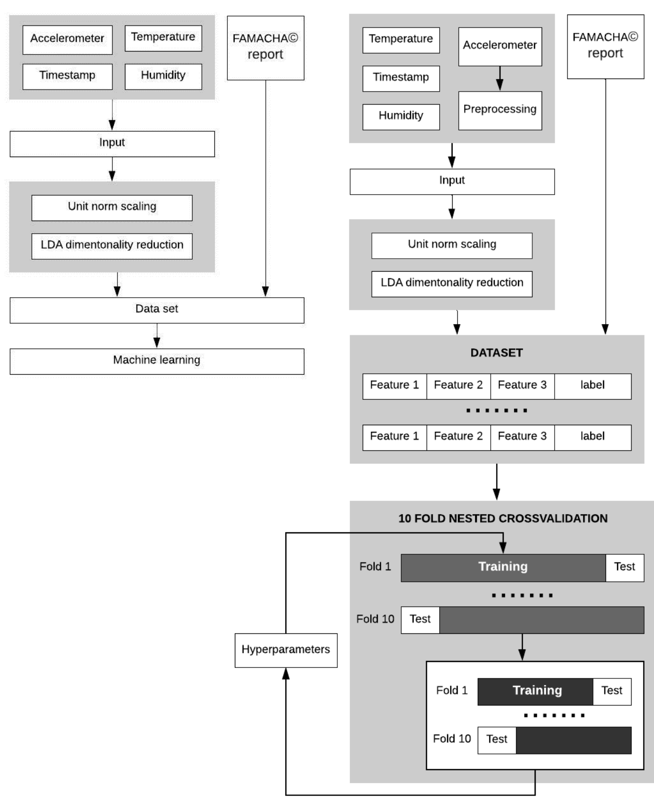

Fig. 10. Simplified and detailed illustration of the machine learning pipeline.

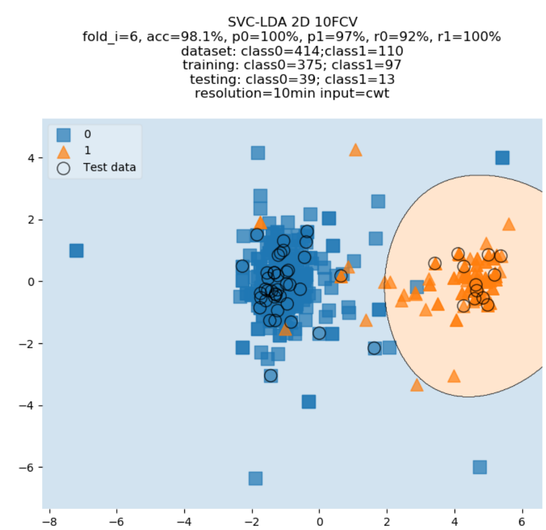

Fig. 12. 2D Illustration of the data classification using a SVM classifier for the following input: cwt, lda reduced to 2 features, resolution 10 minutes, 6 days before FAMACHA© test. Clear cluster can be observed, the squared points represent the data for no increase in the FAMACHA© score while the triangles correspond to the data for the increase of the FAMACHA© score.

3. Results.

3.1. Classifier accuracy. The following table shows the prediction result of different classifier sorted by accuracy with different input configurations.

Classifier	Accuracy	Specificity	Recall	Precision	F-score	d*	R**	input***
svm-2d	97.53	91.57	97.53	97.57	97.48	6	10min	cwt
svm-2d	97.53	91.57	97.53	97.57	97.48	6	10min	cwt+h
svm-2d	97.53	91.57	97.53	97.57	97.48	6	10min	cwt+t
svm-2d	97.53	91.57	97.53	97.57	97.48	6	10min	cwt+h+t
svm-3d	97.12	88.24	97.12	97.34	96.9	6	10min	cwt
svm-3d	97.12	89.9	97.12	97.12	97.02	6	10min	cwt+t
svm-3d	96.72	87.9	96.72	96.74	96.6	6	10min	cwt+h
svm-3d	96.3	89.9	96.3	96.46	96.25	6	10min	cwt+h+t
svm-2d	89.22	49.4	89.22	90.26	87.63	6	10min	a+h
svm-2d	87.17	42.42	87.17	88.78	85.09	6	10min	a+h+t
svm-3d	86.81	39.25	86.81	87.22	84.33	6	10min	a+h
svm-3d	82.22	19.83	82.22	79.78	76.81	6	10min	a+h+t
svm-2d	79.35	6.44	79.35	72.57	71.59	6	10min	a
svm-3d	78.52	5	78.52	65.17	69.79	6	10min	a
svm-2d	78.15	3.33	78.15	66.51	69.71	6	10min	a+i+h+t
svm-2d	78.1	3.67	78.1	64.8	69.51	6	10min	a+t
svm-3d	78.1	2	78.1	63.2	68.97	6	10min	a+t
svm-2d	77.68	0	77.68	60.84	68.1	6	10min	t
svm-2d	77.68	0	77.68	60.84	68.1	6	10min	h
svm-2d	77.68	0	77.68	60.84	68.1	6	10min	h+t
svm-3d	77.68	0	77.68	60.84	68.1	6	10min	t
svm-3d	77.68	0	77.68	60.84	68.1	6	10min	h
svm-3d	77.68	0	77.68	60.84	68.1	6	10min	h+t
svm-3d	77.28	0	77.28	60.8	67.9	6	10min	a+i+h+t

Table 1. * Number of days of activity data before FAMACHA© test.
** Activity data re-sampling resolution.
*** t: Temperature, h: Humidity, cwt: Continuous wavelet transform, a: activity in time domain, i: time indexes

3.2. Most important features. In order to find which part of the input data describes best the two classes an analysis of the linear SVM classifier output coefficients is performed. Each feature in the input signal is given a weight after classification. In the case where the features array contains the coefficients of the continuous wavelet transform of the re-sampled activity signal, we will firstly use the attributed weight of each feature to construct a weight map of the cwt input for each class. And secondly compute the inverse continuous wavelet transform of the obtained weight map. The resulting time domain signal gives insight on how the classifier perceives the activity level of the goats with a stable FAMACHA© score of 1 and the goats for which the FAMACHA© score increased form 1 to 2. The results of this experiment revealed a frequency differences in the activity of the goats for the 2 classes. High frequency motions can be observed in the output signal of the classifier for the healthy goat compared to lower frequency motions for the goats presenting an increase of the FAMACHA© score from 1 to 2.

3.3. Concept drift. The notion of "concept drift" describes the decrease of performance of a given classifier due to changing environmental or sensing conditions on long period of time. In other words over time, training data collected at the start of a given period becomes less representative of future data. This is a common issue in long duration supervised classification problems which use real life data which is in most scenario intrinsically changing [5].
The following experiment was devise to display how much concept drift affect the data collected in our use case. The

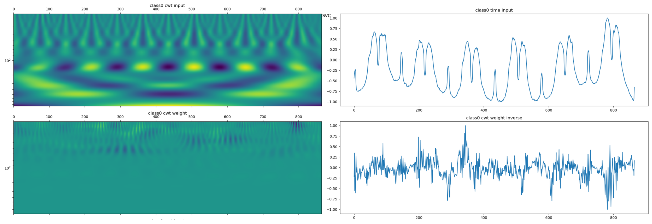

Fig. 13. The top left graph shows the cwt of the mean activity of the healthy goats which will be use as input for a linear SVM classifier. The top right graph shows the signal used to compute the cwt on the top left. This signal contains the mean activity of the healthy goats 6 days before FAMACHA© evaluation. The bottom left graph shows the weight map of all the coefficients in the cwt input on the top left after attribution by the SVM classifier. On the bottom right the inverse cwt of the weight map is displayed

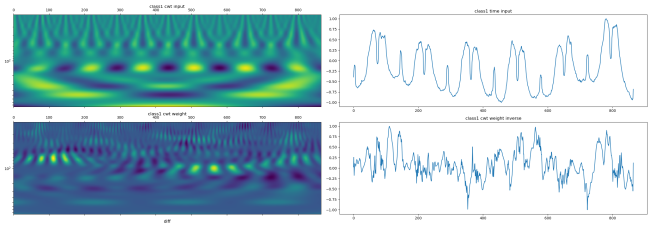

Fig. 14. The top left graph shows the cwt of the mean activity of the unhealthy goats which will be use as input for a linear SVM classifier. The top right graph shows the signal used to compute the cwt on the top left. This signal contains the mean activity of the unhealthy goats 6 days before FAMACHA© evaluation. The bottom left graph shows the weight map of all the coefficients in the cwt input on the top left after attribution by the SVM classifier. On the bottom right the inverse cwt of the weight map is displayed

entire data set was split in two periods of equal time, the first 6 months period starting the 30/03/2015 and finishing the 11/03/2016 and the second 6 months period beginning the 11/03/2016 and ending the 29/04/2016. The first period was used as training set for a linear SVM classifier and the second period was used as testing data. Similarly the second period was used as training data and the first as testing data for another SVM classifier. For both case the features arrays in the training and testing sets was reduced to 2D arrays with the LDA dimensionality reduction algorithm. The table bellow presents the obtained results.

Classifier	Precision	Recall	F1score	d*	R**	input***
SVM1(linear)	98.0	98.0	98.0	6	10	cwt
SVM2(linear)	94.0	94.0	94.0	6	10	cwt

Table 2. SVM1 trained on the first period, tested on the second period. SVM2 trained on the second period, tested on the first period.* Number of days of activity data before FAMACHA© test.
** Activity data re-sampling resolution.
*** cwt: Continuous wavelet transform

The experiment did not reveal a decrease in the accuracy of the prediction. However the time 1 year time period used for this experiment is till relatively short. Repeating the same experiment on a longer time frame need to be done to reveal the concept drift impact on our system.

4. Conclusion and Future Perspectives. The analysis revealed high accuracy in the prediction of the increase of the FAMACHA© score form 1 to 2. Provided that the activity data is collected for a 5 to 6 days period. Furthermore transforming the time domain activity data to the frequency

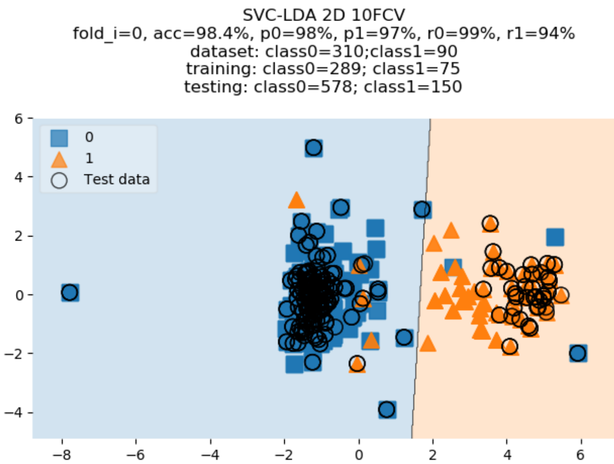

Fig. 15. 2D Illustration of the data classification using a linear SVM classifier. Training with the first period data and testing with the second period data. Squared points represent the data for FAMACHA© score 1 with no increase while the triangles correspond to the data for the increase of the FAMACHA© score.

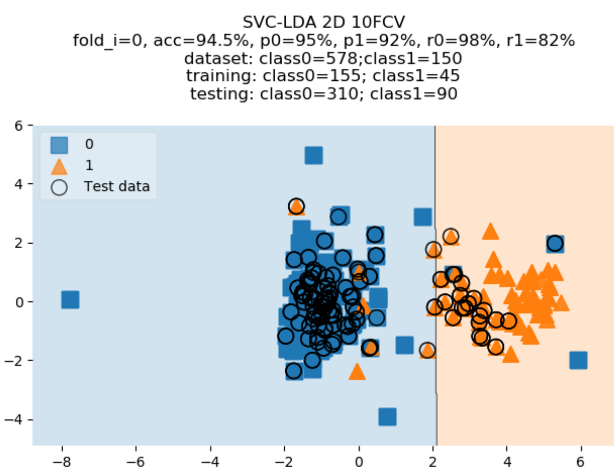

Fig. 16. 2D Illustration of the data classification using a linear SVM classifier. Training with the second period data and training with the second period data. Squared points represent the data for FAMACHA© score 1 with no increase while the triangles correspond to the data for the increase of the FAMACHA© score.

domain with the use of the continuous wavelet transform improved substantially the accuracy rate. Temperature and humidity data did not substantially improved the prediction accuracy.
However multiple limitation are to be considered. Indeed the amount of training data available is limited, only 560 pairs could be computed from the data sources. Due to the difficulty to acquire the ground truth data which require heavy manual labour. In addition class imbalances might induce bias in the results, as the ratio of class "FAMACHA© score is increasing from 1 to 2" is equal to 21.42% (120 sets) whereas the class "FAMACHA© score did not increase" amount for 78.57% (440 sets) of the data-set. It is also very likely that the training data obtained is highly dependent on the topology of the farm location together with sensor calibration variability the classifier trained are unlikely to perform as well in other farms without a prior period of activity data collection and FAMACHA© score monitoring.
For those reason the use of unsupervised learning techniques is appealing. Such techniques would possibly reduce even further manual labour and cost by using activity data as sole input, analysis would ideally allow to detect outliers in the data points.

5. Software and Hardware Availability. Source code is open source:

- https://github.com/orgs/biospi/teams/lab

Acknowledgments

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