Early prediction of declining health in small ruminants with accelerometers and machine learning

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Assessment of the health status of individual animals is a key step in timely and targeted treatment of infections, which is critical in the fight against anthelmintic and antimicrobial resistance. The FAMACHA scoring system has been used successfully to detect anaemia caused by infection with the parasitic nematode *Haemonchus contortus* in small ruminants and is an effective way to identify individuals in need of treatment. However, assessing FAMACHA is labour-intensive and costly as individuals must be manually examined at frequent intervals. Here, we used accelerometers to measure the individual activity of extensively grazing small ruminants (sheep and goats) exposed to natural *Haemonchus contortus* worm infection in southern Africa over long time-scales (13+ months). When combined with machine learning, this activity data can predict poorer health (increases in FAMACHA score), as well as those individuals that respond to treatment, all with precision up to 80%. We demonstrate that these classifiers remain robust over time. Interpretation of trained classifiers reveal that poorer health mainly affects the night-time activity levels, in both sheep and goats. Our study thus reveals common behavioural patterns across two small ruminant species, which low cost biologgers can exploit to detect subtle changes in animal health and enable timely and targeted intervention. This has real potential to improve economic outcomes and animal welfare as well as limit the use of anthelmintic drugs and diminish pressures on anthelmintic resistance in both commercial and resource-poor communal farming.

FAMACHA | *Haemonchus contortus* | Anthelmintic Resistance | Precision Livestock Farming | Accelerometers | Machine Learning

Livestock farming in resource-poor communities presents multiple challenges such as tremendous economic losses from a variety of diseases, including parasitic helminth infections (1) which makes optimal helminth management imperative for a farmer to achieve, but is complex and especially difficult without access to expert help.

The gastro-intestinal nematode *Haemonchus contortus* (H. contortus) has a particularly heavy impact on small ruminants in tropical and subtropical regions, as these regions provide a favourable environment for the parasite's development. Each female *H. contortus* produces up to 10,000 eggs per day (2), and these develop into infective larvae in a few days under warm and moist conditions. Re-infection can result in high parasite burdens and acute disease outbreaks often leading to death, especially among young animals (3). Disease is primarily the result of blood-feeding by adult worms in the gut, leading to anaemia, protein loss, and associated consequences for health, growth and fertility (4). The economic loss due to helminth infection in sheep and goat production is substantial, for example an estimated $40 million per annum in the Kano area of northern Nigeria and $26 million per annum in Kenya (1).

Although multiple worm control strategies for RP farmers exist (5), including chemical dewormers, vaccination, anthelmintic drugs, grazing management, specific diets and ethnoveterinary remedies, they all require high manual labour and other expenses (6, 7). In addition, widespread use of anthelmintic drugs has led to high prevalence of anthelmintic resistance (AR) in countries such as South Africa (8–10). This is due to farmers relying on anthelmintics as the sole method of control against helminth infection, and poor practices such as treating the entire herd when only a few individuals are affected. Although helminth infections are curable, they are common and exact high ongoing costs relative to other diseases due to the complexity and operational difficulties of effective and sustainable management (11). Indeed, farmers in Sub-Saharan Africa rank helminths as the most important disease in small ruminants, in spite of more visible (*e.g.* ectoparasitic)

Significance Statement

Increasing availability make biologgers and machine learning viable solutions to current challenges in global livestock farming. We demonstrate a pipeline that accurately predicts early signs of parasitic disease in small ruminants. With *Haemonchus contortus* nematode infection in sheep and goats as the exemplar, we illustrate that the predictive model generalises across time without retraining. We show that prediction is driven by different activity pattern in animals with poor health during the night. Our findings suggest that health of individual livestock can be monitored remotely, reducing labour costs, improving animal welfare, and allowing for targeted selective treatment under contrasting farming conditions. This will decrease animal loss, maximise economic outcomes, and reduce pressures on drug resistance.

A.W.D and T.B. designed and supervised machine learning research. J.A.V.W designed and supervised field trials and data collection. D.L. and D.Z.N. conducted field trials. J.A.V.W, E.R.M, T.H.T and C.C.I contributed parisitology, agricultural and behavioural science expertise. A.X.M and R.S.B. performed research and analyzed data. A.X.M wrote the paper with contributions from all other authors.

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and ostensibly more damaging (*e.g.* foot and mouth disease virus) pathogens (12).

A path to more sustainable and efficient control of *Haemonchus* infection is the effective clinical evaluation of individual animals, and selective treatment of those unable to cope (13), leaving the rest untreated. This targeted treatment is preferable because helminths are aggregated among their hosts, such that a few individuals in a group tend to carry the majority of the disease burden, and disproportionally drive onward transmission (14). The untreated individuals provide refugia for anthelmintic-susceptible genotypes, slowing the development of AR (13, 15, 16). The FAMACHA clinical system was developed to deliver on this principle in sheep and goats, and consists of a calibrated colour chart against which the colour of the conjunctivae of the eye is compared (17, 18). FAMACHA scores range from 1 to 5, with score 1 being the most healthy, equating to haematocrit $\geq 28\%$, and score 5 the most severely anaemic (haematocrit $\leq 12\%$). The scoring system requires minimal training, provides immediate results, and does not rely on expensive equipment or laboratory analysis. However, training is needed, and there is a shortage of qualified trainers, particularly in resource poor regions. Furthermore, the system relies on frequent close handling and examination of individual animals, which is laborious and costly, given that examination of entire herds is required weekly during high risk periods (17).

A promising alternative could be to use biologgers to remotely monitor behaviour linked to poor health (19–22). Thanks to advancements in on-animal sensor technology, effective tracking and monitoring of terrestrial animals can now give access to large quantities of data on their behaviour and their interactions between each other and with their environment (23). Accelerometry data has been successfully used to classify livestock behaviour, for example Moreau *et al.* (24) identified eating, resting and walking in goat activities by using tri-axial accelerometers together with moving averages and multiple thresholds. This approach is however highly sensitive to the sensor position on the animal. Other studies used machine learning approaches. Vazquez *et al.* (25) used a combination of accelerometry and gyroscopic data with online learning to detect sheep behaviour (walking, standing and lying) with automatic updating of the model for future data classification. Scoley *et al.* (26) studied the effect of milk and forage feeding in dairy calves with the IceQube® automatic activity sensors (IceRobotics Ltd., Edinburgh, Scotland, UK). The study revealed that calves displayed activity linked to hunger if they were fed high level of milk replacement in their early file but was fed reduced levels later. By combining GPS data and 3-axis accelerometry data, González *et al.* (27) were able to accurately detect foraging and travelling behaviour in grazing cattle. Högberg *et al.* (28) measured the accuracy of two commercial sensors (CowScout(GEA Farm Technologies) and the IceTag® (IceRobotics Ltd.) mounted on dairy cows. Both devices use accelerometers to determine lying, standing and walking. The study showed that lying and standing could accurately be detected but walking detection was inaccurate.

Although these studies focus on specific activities and all have the potential to be used for livestock management through the monitoring of behaviour, in all cases they did not consider the potentially rich raw data directly, but instead used summary statistics derived from limited behavioral classes. With the aim of improving animal welfare and reducing drug use, labour and other costs, we have developed a novel automated approach for detecting changes in the FAMACHA score of individual animals based solely on raw accelerometry data (Fig. 1).

Table 1. Characteristics of the study group

	Cedara	Delmas
Data collection period	April 2012 to July 2013	March 2015 to April 2016
Species	Goat	Sheep
Animals tagged	227	64
Tag type	Accitrack v1	Accitrack v2
Age range	2-6 years	2-6 years
Average weight	44.19 kg	72.79 kg
FAMACHA evaluation	fortnightly	weekly
Animals evaluated	32	13
Max n samples	397	496

Our study group consists of a sheep flock in Delmas, Mpumalanga Province, South Africa, and a goat herd at Cedara Government Agricultural Animal Production Research Farm, Howick, KwaZulu-Natal, South Africa (Table 1). A

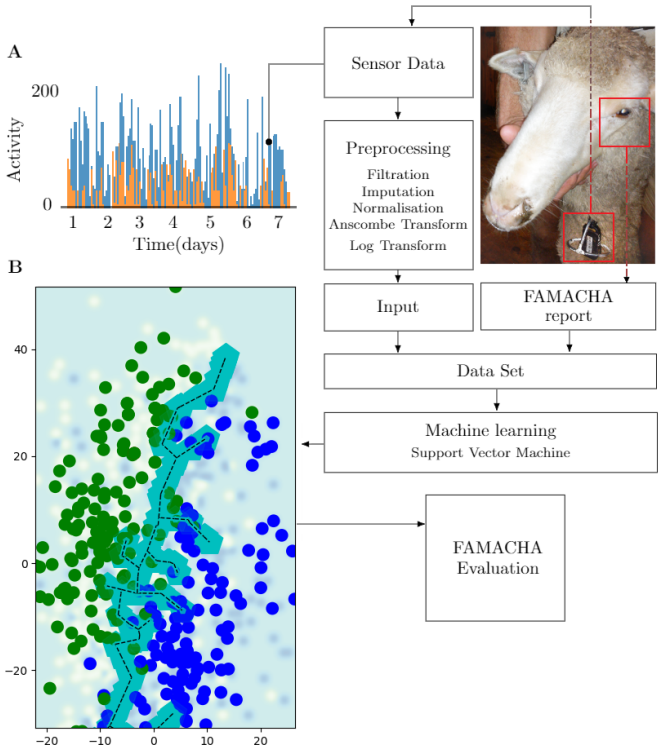

Fig. 1. Schematic of our machine learning pipeline. (A) The biologger outputs accelerometry data as a count of the instances the acceleration exceeded 2g over a short interval. Here we show derived activity time series for two animals (blue/orange) over a 7 day period with a bin size of 1 minute. As can be seen, there are significant differences in signal magnitude which we account for through preprocessing. **(B)** The high-dimensional time series data is then combined with the FAMACHA report for supervised machine learning. The scatter plot shows clustering of the animals samples in this space for training (blue and green points represent healthy and unhealthy animals, respectively;). A Support Vector Machine with 5-fold cross-validation repeated 10 times is then used to derive the classification boundary (turquoise) and to derive predicted probabilities that each sample is healthy or unhealthy.

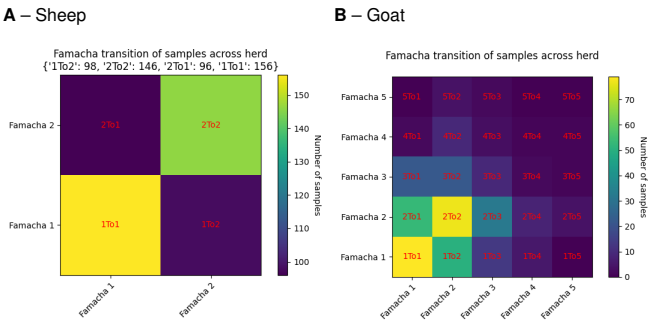

Fig. 2. FAMACHA transitions available. Illustration of the amount of Famacha transitions in the dataset

transponder containing an accelerometer was suspended by a sturdy ribbon around the neck of each animal and used to measure activity levels continuously for more than a year (Table 1). During this time, the FAMACHA score was assessed every week for sheep, and every two weeks for goats. A supervised machine learning pipeline with cross-validation to guard against over-fitting was developed (Fig. 1) to predict an increase in FAMACHA score from 1 ("optimal") to 2 ("acceptable"), as well as from 2 to 1 after individual anthelmintic treatment. Classification drift including robustness to seasonality was assessed through temporal validation. As our model is linear, we were also able to perform inverse transformation of the trained classifiers for visual interpretation of the behavioral cues that distinguish healthy animals from those with a trajectory to poorer health.

Results.

Classifying health status. We first aimed at predicting which individuals would have a FAMACHA score of $2 \rightarrow 2$ based solely on the 5 days of accelerometry data immediately prior to the sate ($2 \rightarrow 2$). For this we had 156 cases of FAMACHA $1 \rightarrow 1$ and 146 examples of FAMACHA $2 \rightarrow 2$ for the sheep at Delmas. With these annotations we trained and tested our supervised machine learning pipeline using 5-fold cross-validation repeated 10 times to provide estimates of model performance with low bias and variance. The machine learning pipeline was able to predict the presence of FAMACHA score $2 \rightarrow 2$ with median precision of 74% (75% and 73% for the healthy class and the unhealthy class, respectively). In a Receiver Operating Characteristic (ROC) analysis, the median area under the curve (AUC) was 81% for the sheep

For the goats at Cedara we created 79 examples of FAMACHA $1 \rightarrow 1$ and 77 FAMACHA $2 \rightarrow 2$. the median precision was 66% (66% and 66% for the healthy class and the unhealthy class respectively) for individual goats declining in health. In the ROC analysis the median AUC was 72%. The observed lower prediction power is likely due to the smaller

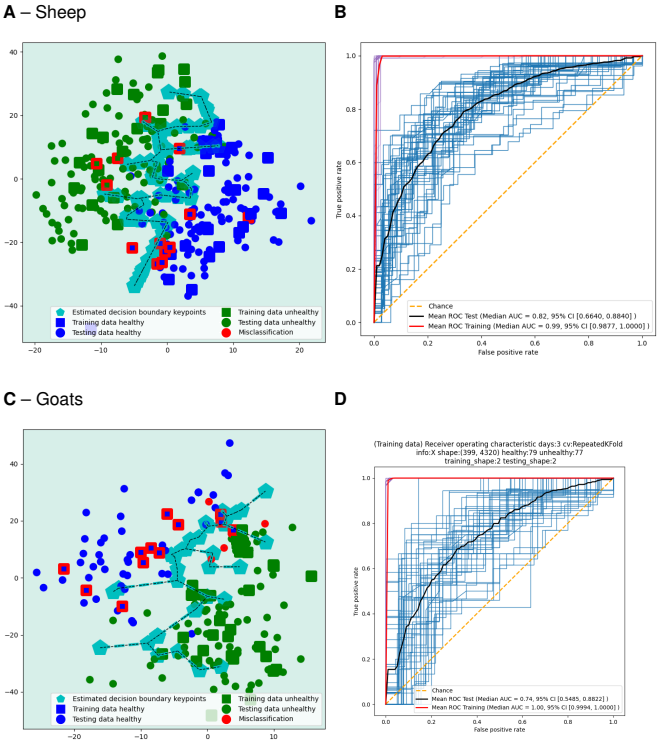

Fig. 3. Classifying health status. On the sheep farm the machine learning was trained to discriminate FAMACHA $1 \rightarrow 1$ against FAMACHA $2 \rightarrow 2$ using 5 days of accelerometry data directly preceding the FAMACHA evaluation. On the goat farm the model was trained to discriminate FAMACHA $1 \rightarrow 1$ against FAMACHA $2 \rightarrow 2$ using 3 days of accelerometry data. (A) Decision boundary plot and (B) Receiver Operating Characteristic (ROC) curve for training and testing on sheep. (C) Decision boundary plot and (D) ROC curve for training and testing on goats.

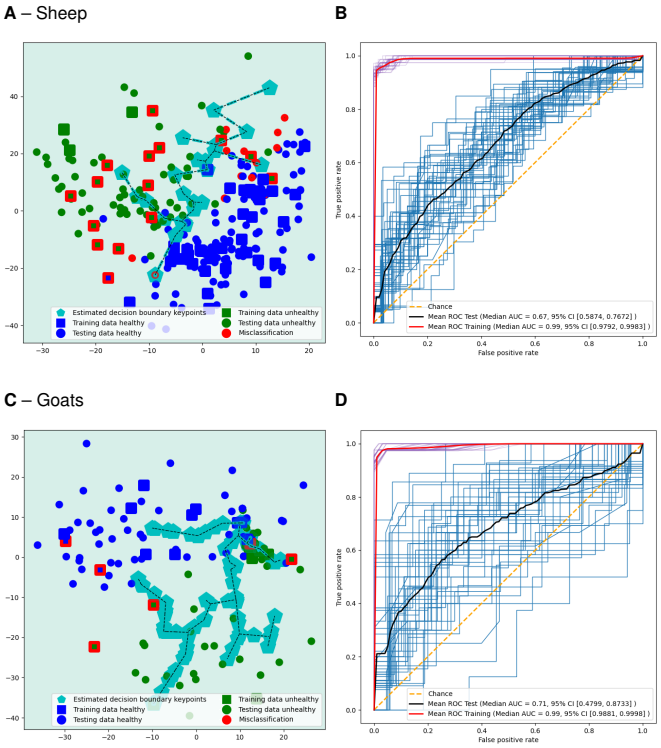

Fig. 4. Classifying the response to treatment. For both farms the machine learning was trained to discriminate FAMACHA $2 \rightarrow 1$ against FAMACHA $1 \rightarrow 1$ using 7 days of accelerometry data directly proceeding anthelmintic treatment for the Sheep farm and 7 days for the Goat farm. (A) Decision boundary plot and (B) Receiver Operating Characteristic (ROC) curve for training and testing on sheep. (C) Decision boundary plot and (D) ROC curve for training and testing on goats.

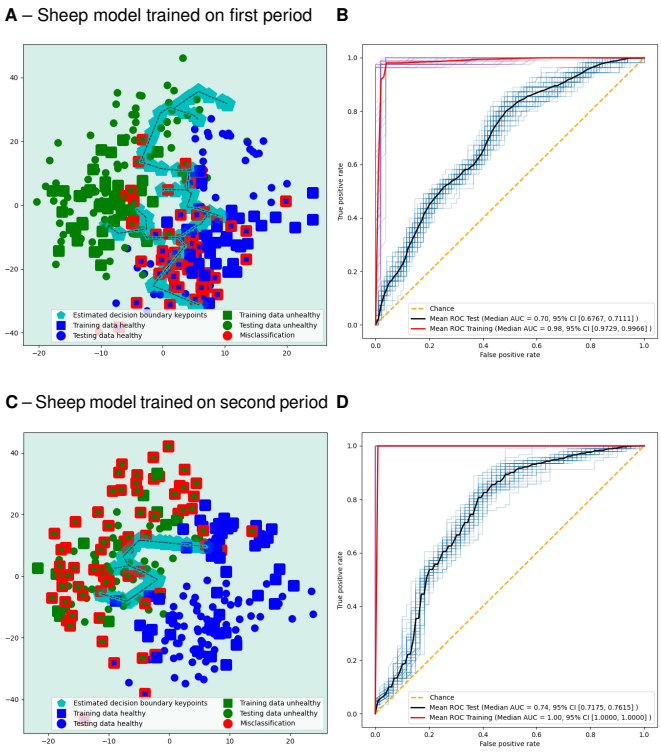

Fig. 5. Temporal validation. On both farm we used 6 days of accelerometry data directly preceding FAMACHA evaluation. On the sheep farm the machine learning was trained to discriminate FAMACHA $1 \rightarrow 1$ against FAMACHA $2 \rightarrow 2$. To assess concept drift the datasets was splits to obtain two equally sized consecutive period, data from the first period was used for training while data from the second period was used for testing. (A) Scatter plot and (B) ROC curve for training on the first period and testing on the second. (C) Scatter plot and (D) ROC curve for training on the second period and testing on the first.

number of examples for the goats.

Classifying the response to treatment. As part of routine husbandry, each animal which scored ≥ 2 during a FAMACHA evaluation was immediately treated with Levamisole (Ripercol-L, Bayer Animal Health) at $7.5\,mg.kg^{-1}$ (29). We created a dataset to examine our ability to predict which animals responded well to treatment, comparing FAMACHA $2 \rightarrow 1$ against FAMACHA $1 \rightarrow 1$. This was based on classifying the 5 days of accelerometer data immediately following treatment for the sheep. For the goat, FAMACHA $2 \rightarrow 1$ against FAMACHA $1 \rightarrow 1$ was compared and 3 days of accelerometer data was used.

For this we had 50 examples of FAMACHA $2 \rightarrow 1$, 67 for FAMACHA $1 \rightarrow 1$ for the sheep, and 53 examples of FAMACHA $2 \rightarrow 1$ and 79 examples of FAMACHA $1 \rightarrow 1$ for the goats.

This resulted in a modest training set size which may diminish the performance of the machine learning (Fig. 2). Nevertheless, the classifier was able to predict a drop in FAMACHA score indicating a response to treatment with median precision of 64% and 55% for the sheep and goats, respectively, and no change in FAMACHA score with median precision of 61% and 66%. As shown in Fig. 4, the median AUC was 65% for the sheep and 70% for the goats.

Temporal validation to assess concept drift. The notion of "concept drift" describes the decrease in performance of a given classifier due to changing environmental or sensing conditions over a period of time. For example, 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 that use real life data which is, in most scenarios, changing intrinsically (25). An analysis was devised to test how much concept drift affects our findings. Two equally-sized periods of data were extracted from the sheep and goat datasets to maximise seasonal differences: (i) the first period from March 2015 to October 2015; (ii) the subsequent period from October 2015 to April 2016 for the Sheep farm. The first period contained 136 (54 healthy and 82 unhealthy) samples using 6 days of activity data and 151 (96 healthy and 55 unhealthy) in the second period. For the Sheep farm, it is clear from observing the resulting scatter plots of the trained classifiers (Fig. 5) that while there is little observable drift in the activity of the healthy animals, the less healthy animals cluster differently depending on time period. Nevertheless, these clusters do not interfere with the decision boundary and hence the overall precision of prediction did not noticeably decrease, yielding a median AUC of 70% for the sheep when training on the first period and testing on the second and 74% when doing the reverse.

For the goat farm, only 46 (26 healthy and 20 unhealthy) samples were built for the first period and 51 (14 healthy and 37 unhealthy) samples for the second one, which yielded a median AUC of 58% when training on the first period and testing on the second, while we obtained a 40% median AUC when doing the reverse. Because of the limited number of samples that was available on the Goat farm, the latter results are inconclusive.

Interpreting the classifier. In order to understand how our model discriminates between animals on healthy and less healthy trajectories, we analysed the output of the classifiers in Fig. 3 by multiplying the derived SVM feature weights (30) which define the classification boundary. As illustrated in Fig. 6, the result shows that the trained model ascribes more importance to activity during the night for the sheep farm. For the goat farm the results were inconclusive.

Discussion. Our analyses reveal that increase in FAMACHA score from 1 ("optimal") to 2 ("acceptable") and remaining at 2 for up 1 week for Sheep and 2 weeks for goats, which is considered sub-clinical disease, can be predicted from behaviour measured using low-cost biologgers. We discovered that the discriminative ability of our classifier increases during the night for the sheep, with inconclusive results for the goats possibly due to the smaller sample size.

While efforts in developed countries have been focused on building high-precision, securely-mounted and precisely fitted sensors, we demonstrate that robust results can be gained from much simpler, low-cost systems with rudimentary maintenance requirements suitable for both commercial and RP farmers in developing countries. It is important to note that due to significant calibration and mounting variation between transponders, including loosening of the transponder over time, it was necessary to perform normalisation of each activity trace to the herd/flock mean. This meant that uniform reductions in activity level from week to week are likely to

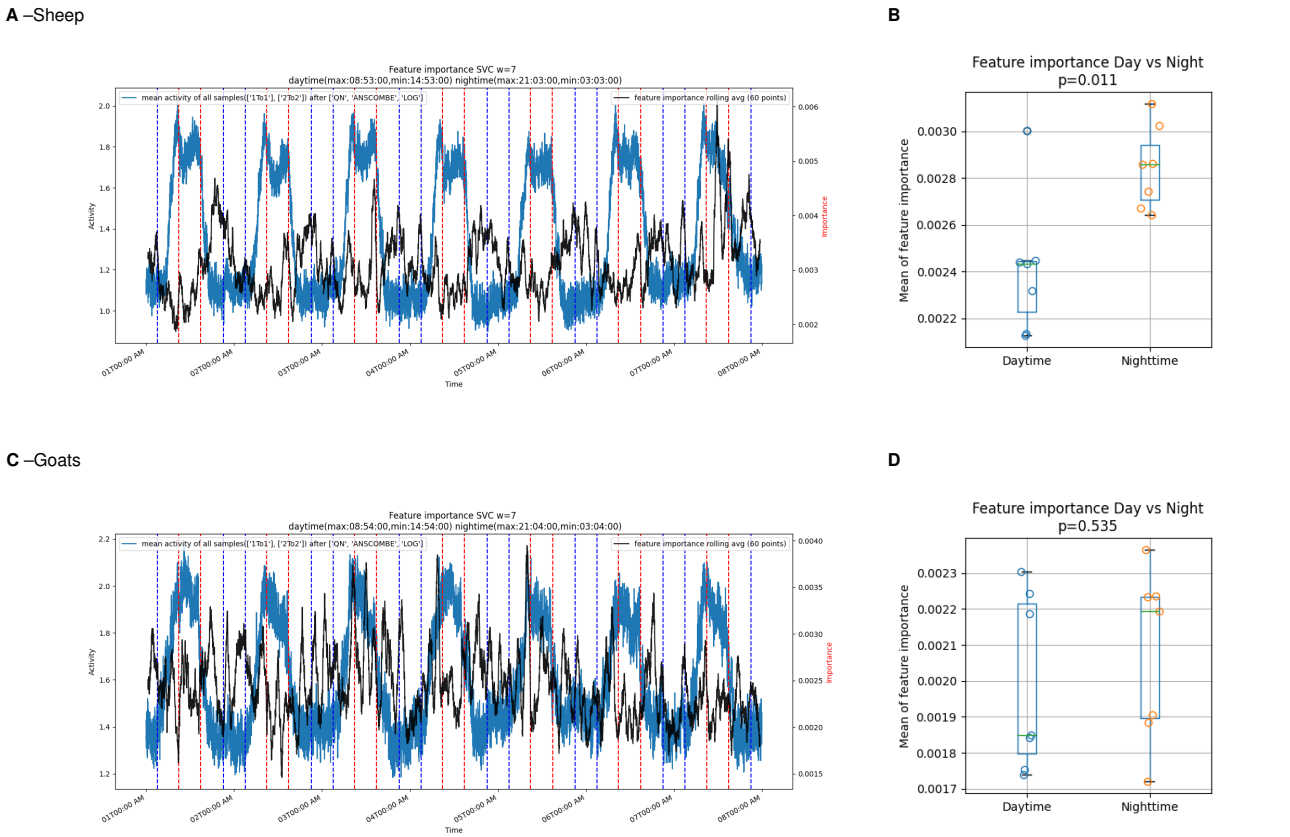

Fig. 6. Interpretation of the classifiers from Fig. 3. After fitting the SVM model (A) (C) with the 5 days activity post-proccessed time series of the Sheep farm, the blue trace shows the mean of all the samples. We can display the average of the feature importance attributed by the classifier, black trace while the red trace shows the raw feature importance. **Statistical analysis** (B)(D) Illustrates the median importance of all 5 daytime periods vs all 5 night time periods, daytime being defined between the latest sunrise and the earliest sunset, 6:53am to 17:21pm, illustrated by the vertical dotted blue and red lines respectively. Similarly (E) (G) shows the feature importance with the 3 days activity time series of the goat farm while (F) (H) shows the median importance of the daytime and the night time.

be normalised out of our data. Nevertheless, a biological reason for a completely uniform reduction in activity level is implausible; instead, intensities of some daily activities are likely to be impacted more than others. We have shown that changes in the variation of activity levels constitute a strong predictor of early changes in health status, as regards haemonchosis and are robust to technical variation.

In this study we have focused on accelerometry data, but exogenous factors such as temperature, rainfall, body weight, and yield farming data could all be beneficial to the prediction, particularly as *H. contortus* is well known to hatch after humid, hot weather, and to require rainfall for movement onto pasture (31, 32). Nevertheless, optimal incorporation of these data types is challenging because of their potential non-linear and/or lagged or cumulative effect on health. Conversely, the fundamental advantage of high-dimensional longitudinal data from accelerometers is that the end effect of these covariates could intrinsically be contained within the data directly, which machine learning approaches have the potential to deconvolute. The ability of machine learning to detect health-relevant changes in behaviour under variable climatic conditions could make it especially useful as climate change drives increasingly unpredictable transmission patterns among helminths (33); and hence to support adaptation to climate change by resource poor farmers (34).

Collecting robust annotated datasets is especially challenging in resource poor farming systems where farming practices are generally less consistent, regulated and well-funded. Because of this and the need for intensive manual labour over a prolonged period, our datasets are highly valuable. Although the training data obtained is dependent on farm topology, location and management, we have shown that a basic machine learning pipeline can discriminate on behavioural cues dominated by fluctuations in activity levels. Some concept drift was found, particularly among animals with increasing parasitic burden. This suggests two broad avenues for future research: (a) Starting from deployments of our pre-trained model, use of online reinforcement learning techniques to create a 'lifelong learning' decision support system which identifies animals for FAMACHA evaluation and feeds back the results to dynamically update the model calibration and improve future predictions; (b) Multivariate time-course statistical modelling to further characterise the nature of sheep and goat behaviour in health and disease.

Notably, in this study we have focused on FAMACHA evaluation of *H. contortus* infection; whether multi-label classification of a range of different disease states and transient events is possible is currently unknown but would require

extensive studies to attain the appropriate predictive power. In addition, as our accelerometry data is based on a simple activity count paradigm, we hypothesise that activity traces could be derived from other sensor types, such as video, for direct input into our prediction model.

Helminths negatively impact livestock productivity worldwide, and in resource poor settings are considered 'neglected cold spot' diseases, in that they are preventable in principle, but farmers continue to struggle to manage their effects (35). Technical improvements in helminth control consequently have especially high potential to positively impact farmer livelihoods, with knock-on benefits for human nutrition and health (36). The FAMACHA system has been successfully adopted by smallholder farmers in Africa, but sustained use is difficult because of high training and labour requirements (37). Our results show that it is feasible to apply machine learning approaches to data streams that are attainable on smallholder farms in Africa to detect early changes in health status and support timely and targeted intervention.

Methods.

Study group. Data were collected from a farm of 108 acres close to Delmas in Mpumalanga Province, South Africa, and at Cedara, a government research farm and agricultural college, the pastures of which comprise of 25 acres adjacent to Hilton, KwaZulu-Natal. As described in Table 1, 31 female adult *Ile de France* sheep ewes at Delmas and 64 goats at Cedara were individually FAMACHA-evaluated (17) at weekly or fortnightly intervals, respectively, and had associated longitudinal accelerometry data recorded within the study period. On both farms there were multiple improved pastures, which were irrigated, that were used alternatively at intervals according to visual assessment of amounts of available water and forage. At both farms, young adult ewes/does were randomly selected for the trials, without attention to reproductive class, but remained with their flocks/herds of origin for the duration of each trial. The animals were kraaled at night and let out at a standard time in the mornings for herding to pasture, where they remained until collected and returned to the kraals in late afternoon. Adjustments were made according to season and special management events such as vaccination and hoof inspection, which were conducted first thing in the morning.

Telemetric monitoring. Telemetric monitoring systems were supplied by Accitrack Ltd., Paarl, South Africa. Tagged animals on both farms were equipped with low cost RFID transponders suspended by a sturdy ribbon around the neck (Fig. 1). A single solar-powered base station was installed on each farm, mounted at the top of a five-meter wooden pole. Each transponder contains an active RFID transceiver operating at 868Mhz as well as a battery and an A1 type accelerometer for measuring activity level. The accelerometers had a set acceleration threshold of 2g so that every time an acceleration $\geq$ 2g is sensed, a stored integer is incremented by +1. Version 2 transponders had an increased range (10km versus 1km) and a larger battery, at the expense of significantly increased weight. In addition, version 2 transponders also output minimum and maximum acceleration for the three orthogonal axes at each time interval, but this data was not utilised. All tags were set to transmit the data every minute to the base station, at which time the accelerometer count was reset to zero. In order to extend battery life, the tag only transmits data to the base station once a minute, with data transmitted including the identifier of the transponder, the battery level, the signal strength, a timestamp, and the activity level. Data transmission is not performed if the signal-to-noise ratio drops below 10dB, which can occur when there are significant occlusions between the animal and base station. In these cases, the data for that time interval is lost. Through mobile connectivity with General Package Radio Services (GPRS), the base station then regularly forwards the received data to the Accitrack cloud repository.

Data management and visualisation. All raw data is stored on the cloud repository for two weeks only due to storage limitations, hence it was manually downloaded regularly by a researcher at the University of Pretoria for archival (29). The exported data took the form of Excel spreadsheets containing the sensor outputs in the desired time frame. In cases where the data was not retrieved from the cloud infrastructure, datasets for that time period were lost. For this work we parsed the raw excel data into an SQL database. The table storing the raw data recorded at the original minute resolution contains 40,659,086 records. The data was re-binned into multiple time resolutions (Δt) for efficient interactive visualisation. This tool was developed for exploratory analysis to allow us to determine whether transponders were faulty and failed to transmit, and provided visual verification of expected behaviours such as decreased activity levels at night. The visualisation also revealed the need for data pre-processing, as changes in average activity signal amplitude across the herd was observed due to varying calibration of the sensors. In addition, the mounted position of the sensor on each animal influences the sensor's measurement of acceleration, *e.g.* a looser collar would allow broader movement of the sensor thus higher activity values. In contrast, however, long wool tended greatly to reduce the numbers of occasions on which activity registered.

Pre-processing. We consider a set of animals $r = 1, 2, \ldots n$ with associated FAMACHA scores $f_{r,d}$ evaluated on days $d = 1, 2, \ldots T$, where T is the total number of consecutive days being sampled. Each FAMACHA evaluation is associated with a trace of activity counts $a_{r,d}(t_i)$ over time intervals t_i where $i = 0, 1, \ldots \tau$, where τ is the total number of samples within a day (d with a temporal resolution of Δt) either preceding or proceeding the evaluation depending on the anaylsis. Only traces containing a low percentage of missing data and zeros (thus indicating the collar was attached to the animal and functioning correctly) were retained. If the traces exhibited either 50% of the values to be zeros or 20% of the values to be nonexistent, then these were dismissed.

To correct for scaling differences due to device calibration and mounting differences between animals, and the mounting loosening over time, we first define a mean "herd-level" activity trace across all animals with FAMACHA evaluations on the same day:

$$h_d(t_i) \quad = \quad \left[\frac{\sum_{r=1}^{n} a_{r,d}(t_i)}{n} \right] \qquad [1]$$

A scaling coefficient for each trace $s_{r,d}$ is then derived as the median of the trace after having divided it by the herd-level

trace:

$$s_{r,d} = median\left(\left[\frac{h(t_0)}{a_r(t_0)}, \ldots, \frac{h(t_\tau)}{a_r(t_\tau)}\right]\right) \quad [2]$$

Normalised activity traces b_r are then derived by multiplying each original trace by its respective scaling coefficient:

$$b_{r,d}(t_i) = s_{r,d} \times a_{r,d}(t_i) \quad [3]$$

Because our activity data are counts and hence more closely follow Poisson statistics than the Gaussian distribution expected by conventional machine learning methodology, after normalisation we perform an Anscombe transform (38) for variance stabilisation to an approximate Gaussian distribution:

$$b'_{r,d}(t_i) = 2 \times \sqrt{b_{r,d}(t_i) + \frac{3}{8}} \quad [4]$$

Imputation. Imputing the data saved by an individual transponder without considering the others is intrinsically limiting the ability of any algorithm to accurately predict the missing data points as only the data from this transponder is used. In our study, we can take advantage of the Multi-Directional Recurrent Neural Networks (MRNN) imputation techniques approach devised by Yoon et al (39) which takes advantage of the temporal component in multiple data streams. In our case, this approach can take advantage of the information contained in all of the transponders in the herd to impute the missing data.

Machine learning with internal validation. Classification analyses utilised a Support Vector Machine (SVM) (40). Training/testing datasets for this supervised machine learning technique were constructed using the FAMACHA scores and the standardized activity traces. Repeated nested k-fold cross validation was used to optimize the hyperparameters and evaluate the model. Kim *et al.* (41) showed that the repeated cross validation estimator outperforms the non-repeated version by reducing the variability of the estimator and providing lower bias. Hence we choose to use 10-times repeated 5-fold cross validation to assess a realistic estimate of the performance of the model predictions while making the most of the dataset available.

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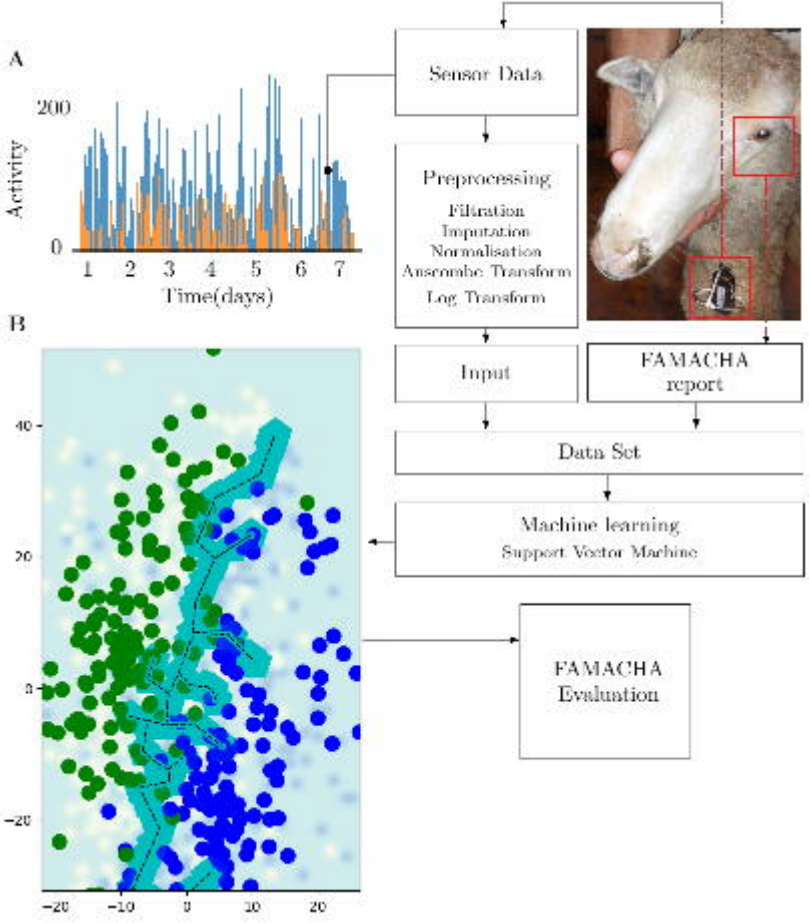
A
200
0
Activity
1
2
3
4
5
6
7
Time(days)
B
40
20
0
−20
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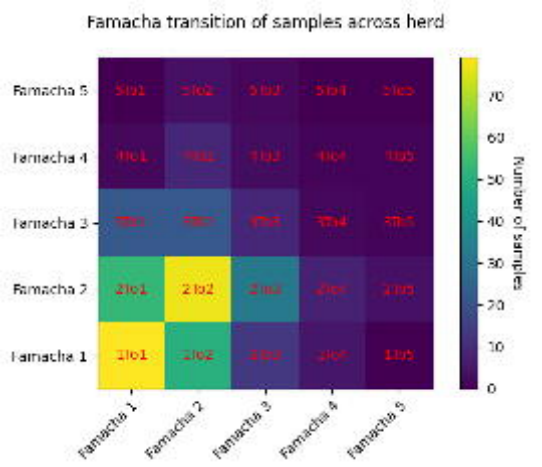
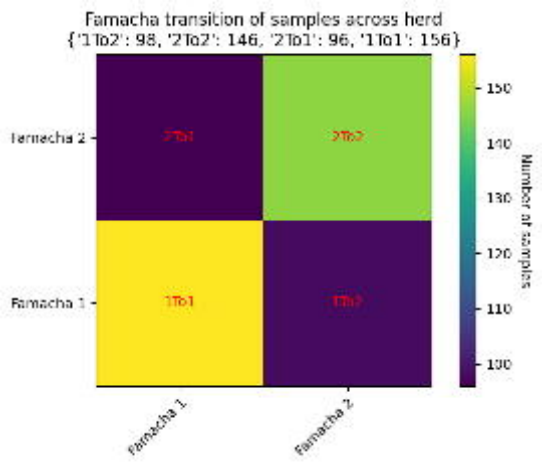
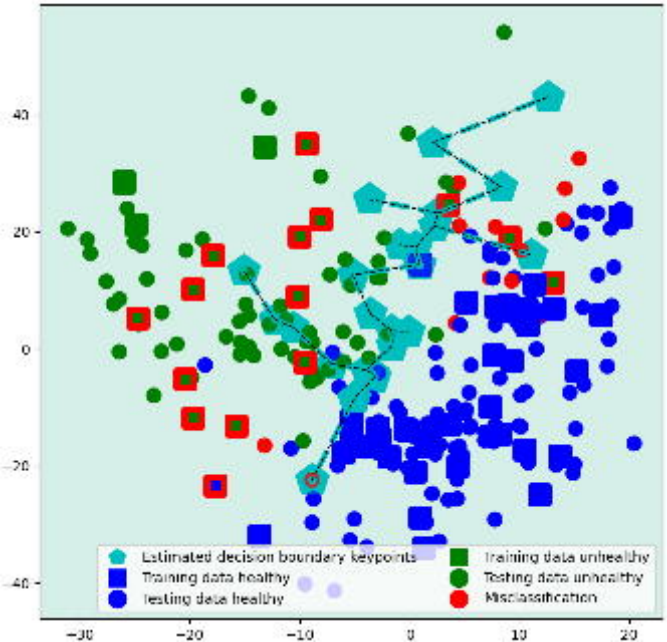
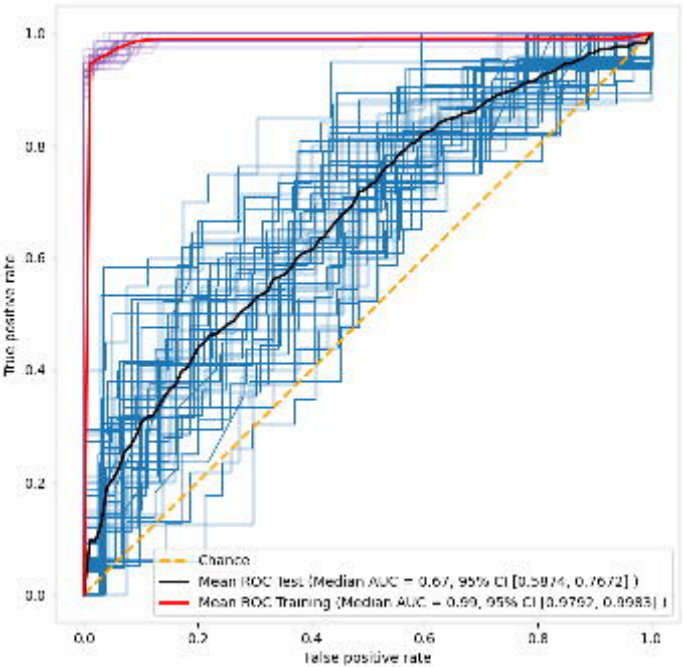
20
Sensor Data
Preprocessing
Filtration
Imputation
Normalisation
Anscombe Transform
Log Transform
Input
FAMACHA report
Data Set
Machine learning
Support Vector Machine
FAMACHA Evaluation


Famacha transition of samples across herd
Famacha 5
Famacha 4
Famacha 3
Famacha 2
Famacha 1
Number of samples
0
10
20
30
40
50
60
70


Famacha transition of samples across herd
{'1To2': 98, '2To2': 146, '2To1': 96, '1To1': 156}
Famacha 2
Famacha 1
2To1
2To2
1To1
1To2
Famacha 1
Famacha 2
150
140
130
120
110
100
Number of samples


Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification
40
20
0
−20
−40
−30
−20
−10
0
10
20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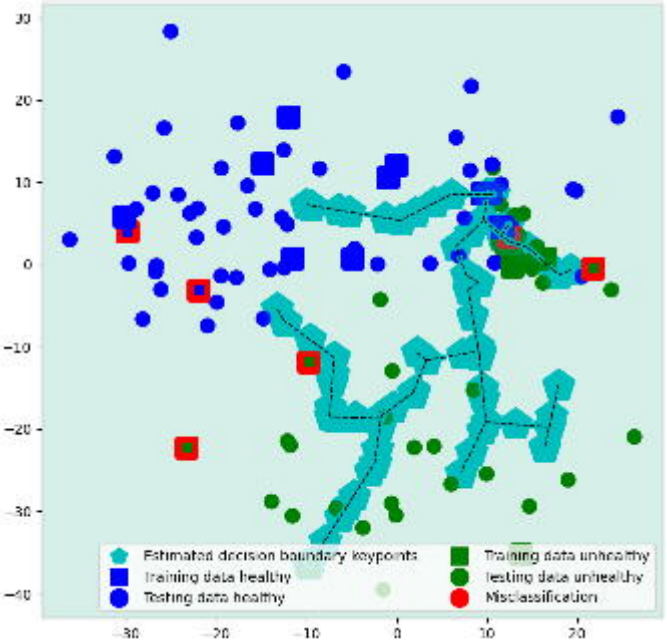
0.8
0.6
0.4
0.2
0.0
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate
Chance
Mean ROC test (Median AUC = 0.67, 95% CI [0.5874, 0.7672])
Mean ROC Training (Median AUC = 0.99, 95% CI [0.9792, 0.9983])


30
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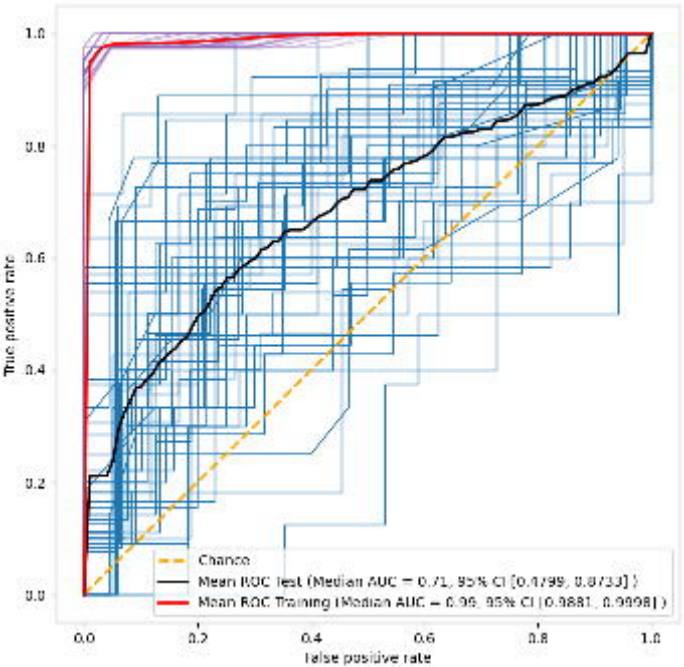
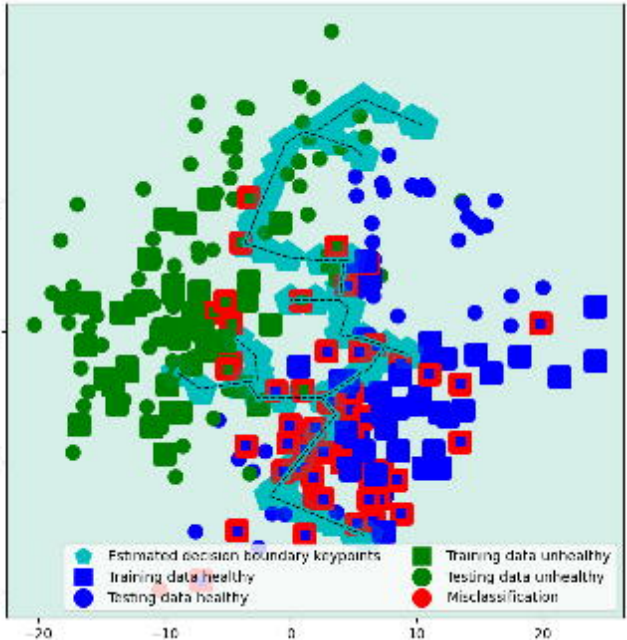
10
20
Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification


1.0
0.8
0.6
0.4
0.2
0.0
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate
Chance
Mean ROC test (Median AUC = 0.71, 95% CI [0.4799, 0.8733])
Mean ROC Training (Median AUC = 0.99, 95% CI [0.9881, 0.9998])


Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification
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10
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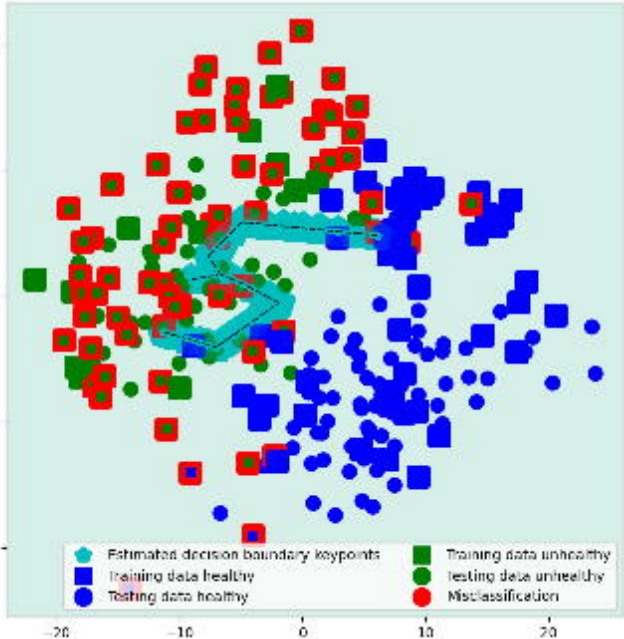
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10
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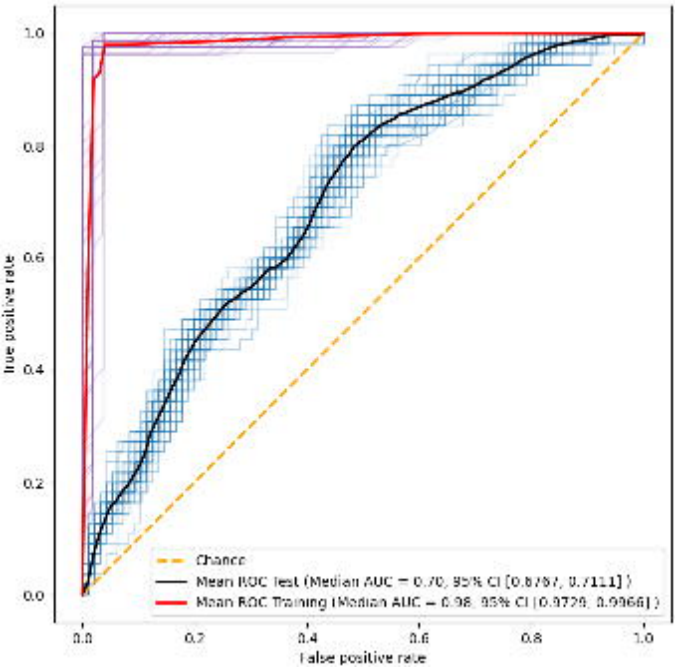
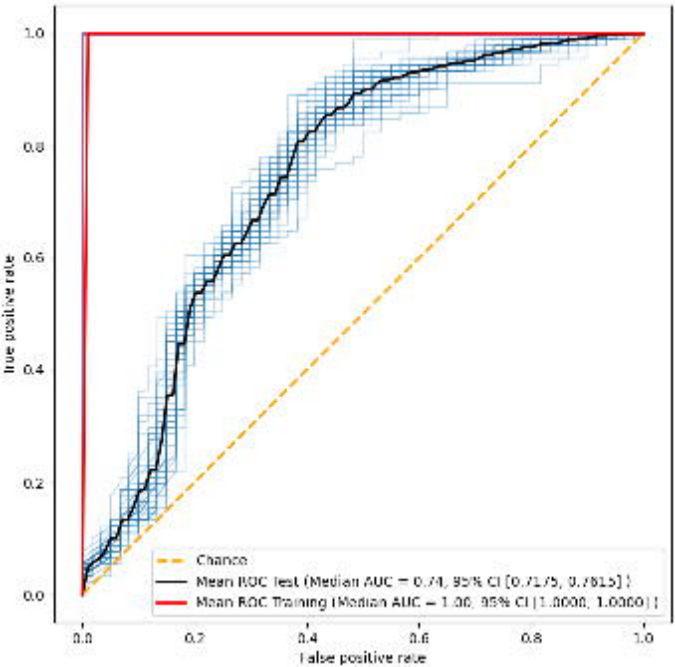
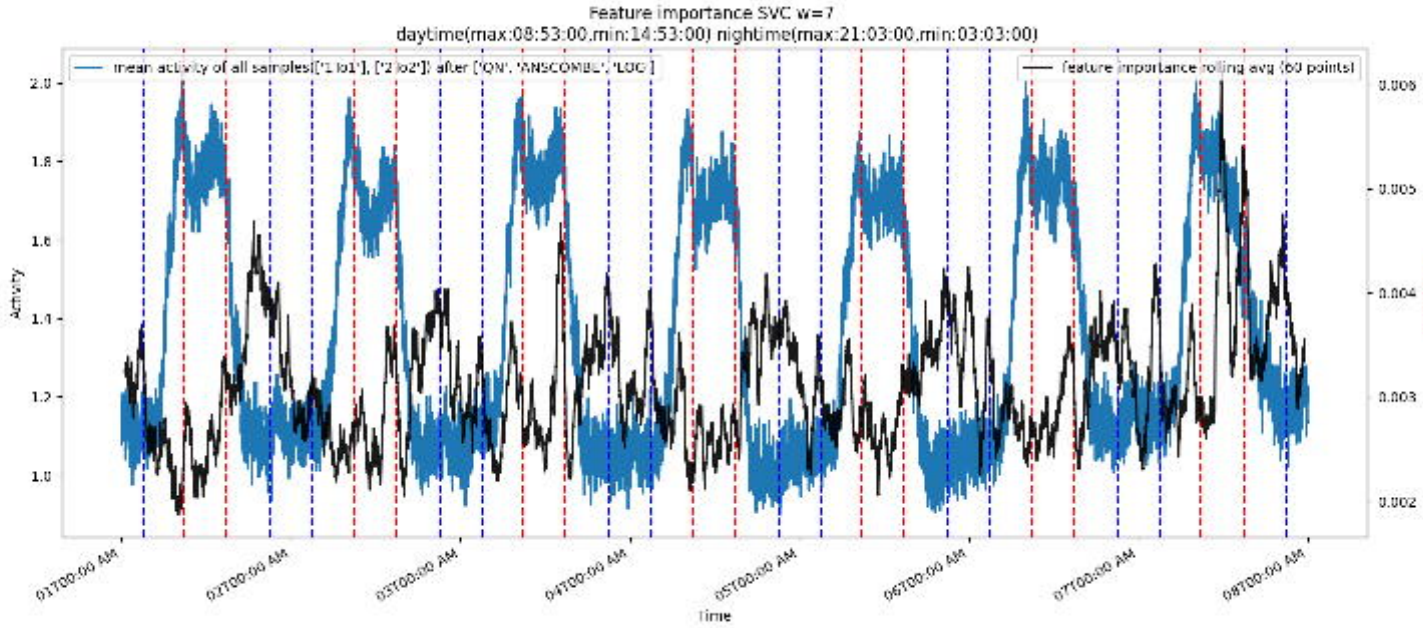
Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification


1.0
0.8
0.6
0.4
0.2
0.0
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate
Chance
Mean ROC Test (Median AUC = 0.70, 95% CI [0.6787, 0.7111])
Mean ROC Training (Median AUC = 0.98, 95% CI [0.9729, 0.9866])


1.0
0.8
0.6
0.4
0.2
0.0
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate
Chance
Mean ROC Test (Median AUC = 0.74, 95% CI [0.7175, 0.7815])
Mean ROC Training (Median AUC = 1.00, 95% CI [1.0000, 1.0000])


Feature importance SVC w=7
daytime(max:08:53:00,min:14:53:00) nightime(max:21:03:00,min:03:03:00)
mean activity of all samples['1 lo1'], ['2 lo2']] after ['ON', 'ANSCOMBE', 'LOG']
feature importance rolling avg (60 points)
Activity
Importance
Time
2.0
1.8
1.6
1.4
1.2
1.0
0.006
0.005
0.004
0.003
0.002
01:00:00 AM
02:00:00 AM
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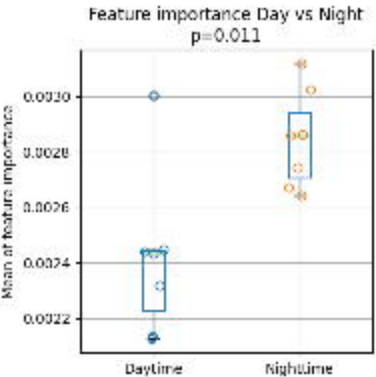
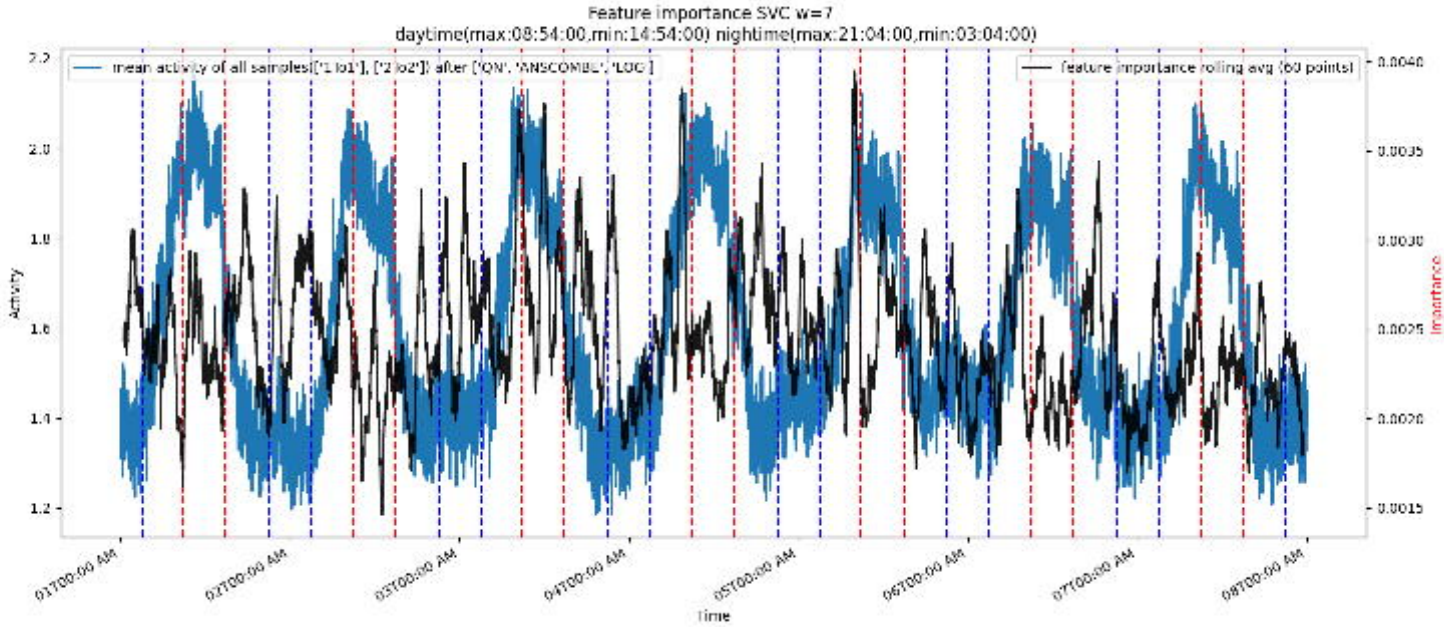

Feature importance Day vs Night
p=0.011
Mean of feature importance
0.0030
0.0028
0.0026
0.0024
0.0022
Daytime
Nighttime


Feature importance SVC w=7
daytime(max:08:54:00,min:14:54:00) nightime(max:21:04:00,min:03:04:00)
mean activity of all samples['1 lo1'], ['2 lo2']] after ['ON', 'ANSCOMBE', 'LOG']
feature importance rolling avg (60 points)
Activity
Importance
Time
2.2
2.0
1.8
1.6
1.4
1.2
0.0040
0.0035
0.0030
0.0025
0.0020
0.0015
01:00:00 AM
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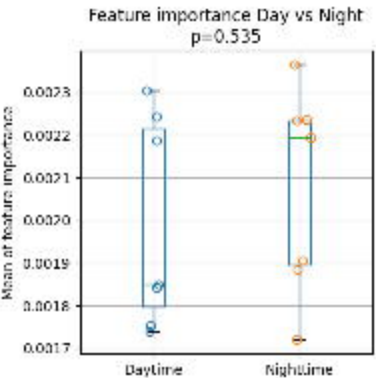
Feature importance Day vs Night
p=0.535
Mean of feature importance
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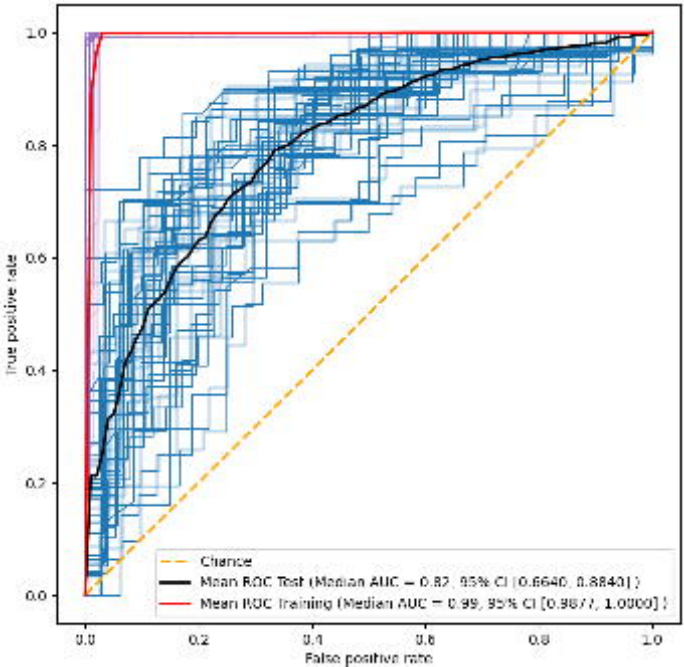
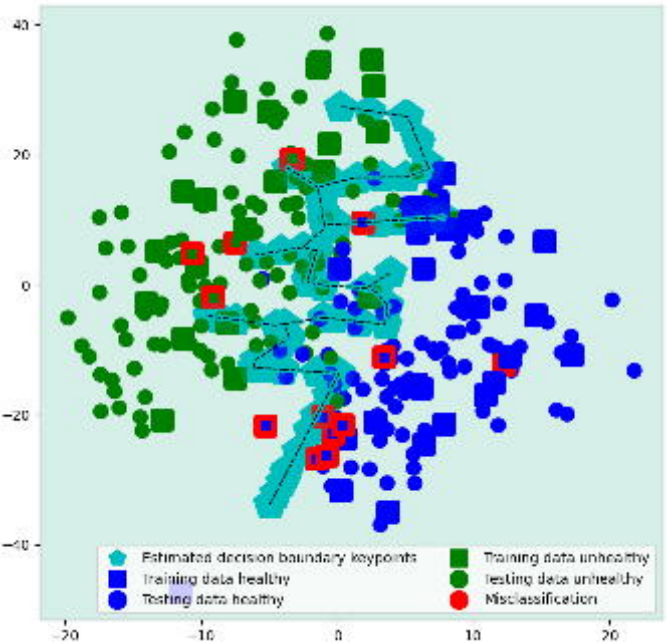
0.0022
0.0021
0.0020
0.0019
0.0018
0.0017
Daytime
Nighttime


1.0
0.8
0.6
0.4
0.2
0.0
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate
Chance
Mean ROC Test (Median AUC = 0.82, 95% CI [0.6640, 0.8840])
Mean ROC Training (Median AUC = 0.99, 95% CI [0.9877, 1.0000])


40
20
0
−20
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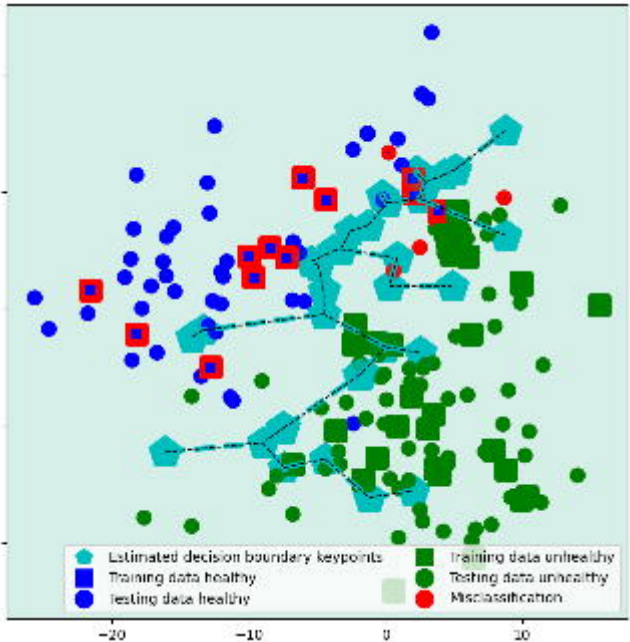
0
10
20
Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification


40
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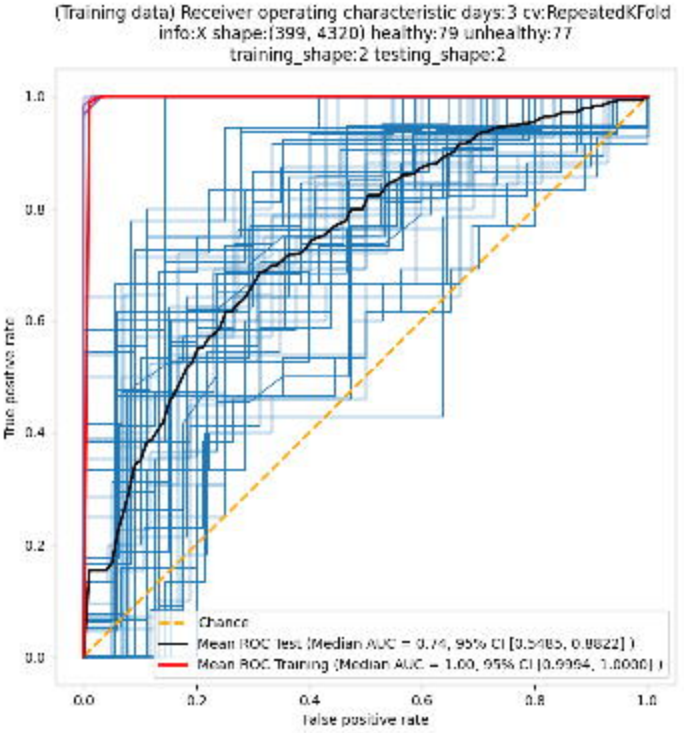
10
Estimated decision boundary keypoints
Training data healthy
Testing data healthy
Training data unhealthy
Testing data unhealthy
Misclassification


(Training data) Receiver operating characteristic days:3 cv:RepeatedKFold
info:X shape:(399, 4320) healthy:79 unhealthy:77
training_shape:2 testing_shape:2
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0
Chance
Mean ROC test (Median AUC = 0.74, 95% CI [0.5485, 0.8822])
Mean ROC Training (Median AUC = 1.00, 95% CI [0.9964, 1.0000])