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# 1 Automated detection of sow posture changes with 2 millimeter-wave radars and deep learning

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## 17 **Highlights**

- 18
- 19 • Automated behavioural analysis is a major challenge for precision farming.
  - 20 • We developed automated detection of lactating sow postures with radars and deep  
21 learning.
  - 22 • We identified five postures, including transitions risky for the piglets.
  - 23 • Our method is accurate, fast and requires less memory than computer vision.
  - 24 • Radars thus hold considerable promises for high through-put recording of livestock  
25 activity.
- 26  
27

28 **Abstract**

29

30 Automated behavioural monitoring is increasingly required for animal welfare and precision  
31 agriculture. In pig farming, detailed analyses of sow activity are essential to identify and reduce  
32 the risks of piglets being crushed during postural changes of their mothers. Here we introduce a  
33 new, non-invasive, fast and accurate method for monitoring sow behaviour based on millimeter-  
34 wave radars and deep learning analysis. We used our method to predict postural changes in  
35 crated sows and distinguish the dangerous one that lie down abruptly from those that lie down  
36 carefully using transient postures. Two radars were placed on a metal backing above the head  
37 and the upper part of the back of each of ten sows to monitor their activity during 5 hours. We  
38 analysed the radar data with a convolutional neural network and identified five postures. The  
39 average sensitivity was 96.9% for standing, 90.8% for lying, 91.4% for nursing, 87.6% for  
40 sitting, but only 11.9% for kneeling. However, the average specificity and accuracy were greater  
41 than 92% for the five postures. Interestingly, two of the ten sows occasionally moved directly  
42 from standing to lying, without using the transient postures sitting and kneeling, thereby  
43 displaying risky behaviours for their piglets. Our radar-based classifier is more accurate, faster  
44 and require less memory than current computer vision approaches. Using more sows will  
45 improve the algorithm performance and facilitate future applications for large scale deployment  
46 in animal farming.

47

48 **Key-words:** animal welfare, lactating sow, radar sensor, convolutional neural network,  
49 behavioural classification

50

51

## 52 **Introduction**

53  
54 An animal's behaviour can inform about its stress level (von Borel et al. 2007) and personality  
55 (O'Malley et al., 2019). In the case of livestock, detailed behavioural are increasingly used to  
56 address key economic, ethical and societal issues related to animal health and welfare. In pig  
57 farming, for instance, sows are often confined in crates during the lactation period in order to  
58 limit their movements and slow down postural changes that can be dangerous for the piglets  
59 (Edwards and Fraser, 1997; Edwards et al. 2002). However, these rearing conditions are not  
60 ethically acceptable anymore. Long-term detailed behavioural monitoring of sow activity has  
61 thus become essential to move towards freer housing conditions during the lactation period (e.g.  
62 Chidgey et al., 2015; see Baxter et al. 2012 for a review). Ultimately, selecting sows that are  
63 calm, careful towards their piglets, and do not suffer from leg problems as future breeders would  
64 promote the use of more welfare-friendly systems.

65 The study of sow behaviour over extended periods of time is a fairly recent approach and  
66 technological solutions combining sensors and signal analyses for automated monitoring are  
67 being developed at a tremendous speed (Fernandes et al., 2020). Two broad categories of  
68 approaches have been used. Invasive technologies include sensors attached to the animals, such  
69 as accelerometers that record the acceleration and orientation of the sow across time. These  
70 sensors are typically embedded in an ear tag (Traulsen et al. 2018, Oczak et al 2020), a collar  
71 (Cornou et al., 2011), a harness (Canario et al., 2018), or fastened to one leg (Ringenberg et al  
72 2010). However, as piglets grow, they increasingly explore their environment and are likely to  
73 chew the device insistently, which may lead the sow to change posture and activity if the  
74 discomfort is significant.

75 Non-invasive technologies include remote sensors, such as infrared cells or video  
76 cameras. When positioned above a sow, infrared sensors enable the discrimination of lying,  
77 sitting and standing postures (Mainau et al. 2009). Cameras have been used to identify different  
78 postures when combined with machine or deep learning for data analysis (Zheng et al. 2018).  
79 Several image processing methods have proved effective in estimating the posture of sows kept  
80 in a crate (Bonneau et al. 2021, Nasirahmadi et al. 2019, Okinda et al. 2018). For instance,  
81 convolutional neural networks have been used to estimate the posture of a sow with its litter in

82 an individual pen (Nasirahmadi et al. 2019). The rate of good classification for these methods is  
83 close to or above 90% for several classes of postures (e.g. sitting, standing, lying down). This  
84 suggest further development of algorithms for these non-invasive technologies can lead to the  
85 automatic monitoring of livestock behaviour at large scale in a near future. Pigs are good models  
86 to develop and crash test these approaches since sows are isolated from conspecifics during the  
87 lactation period. However, this seems out of reach with current computer vision approaches as  
88 the require large memories and computational power to be functional.

89 Here we introduce a non-invasive method for the automated detection of sow posture  
90 based on Frequency-Modulated Continuous-Wave (FMCW) millimeter-wave radars and  
91 illustrate its efficiency to identify postural changes of the sow that are risky for the piglets, when  
92 sows are maintained in crates. The ability of FMCW radars to monitor animal behaviour was  
93 recently demonstrated in insects (e.g. bees: Dore et al. 2020) and mammals (e.g. sheep: Henry et  
94 al. 2019; Dore et al. 2021). The main advantage of radars is that data collection and processing is  
95 fast and requires less memory than computer vision (the memory used for each measure is 1Mb  
96 and 5Gb for one image without compression). Manteuffel (2019) used Doppler radars to analyse  
97 sow activity, but limited their investigation to the detection of movements, since this kind of  
98 radars only gives the speed of the sow across time. In our study, we first compared the efficiency  
99 of the radar tracking system to state of art video tracking. We then applied a Convolutional  
100 Neural Network (CNN) to the data in order to classify the postures and measure the quality of  
101 posture prediction.

102

## 103 **Materials and Methods**

104

### 105 *Sows and ground-truth measurements*

106 Measurements were made on ten lactating sows from the Large White breed, on the GenESI  
107 INRAE experimental farm of Le Magneraud (France; doi: 10.15454/1.5572415481185847E12).  
108 Sows were studied up to two weeks after farrowing. Their behaviour was monitored with FMCW  
109 radars for a minimum of five hours. Video recordings were made in parallel to assess the  
110 reliability of the radar measurements. Postures were annotated manually from these recordings  
111 frame by frame every 100ms. The synchronisation between the radar and the video

112 measurements was performed *a posteriori* by detecting manually the kneeling posture. This  
113 posture was chosen as reference because it was easily distinguished on the radar signal and was  
114 observed on all sows. We used five hours of annotated data per sow and considered five postures  
115 (Figure 1): standing; sitting; lying (i.e. ventrally); nursing (i.e. lying laterally with udder  
116 exposed), and kneeling.

117

### 118 ***Experimental Setup***

119 Two millimeter-wave FMCW radars (EasyRadar) manufactured by Silicon Radar (Frankfurt,  
120 Germany) were used. The radars were attached on a metal structure in the middle axis of the  
121 crate (Figure 1). One radar was placed above the sow's head (i.e. 1.40m above ground). The other  
122 radar was located at the same height in the upper part of the sow's back, at a distance of 55cm  
123 from the first radar. Each radar transmitted a frequency-modulated electromagnetic signal (*chirp*)  
124 every 5ms with the carrier frequency of 122GHz, a modulation bandwidth  $B$  of 6.9GHz, and a  
125 transmitted power of 4mW. The radars were used as altimeters with the theoretical depth  
126 resolution  $d=c/(2B)$ , where  $c=3e8$ m/s is the speed of light in vacuum. A resolution of 2.1cm was  
127 sufficient to estimate the posture of the sow. Radars were small enough ( $100 \times 70$ mm<sup>2</sup>) to be  
128 easily mounted above the crate without affecting the behaviour of the sows. A dielectric lens was  
129 mounted in front of each radar antenna to obtain a half-power beam width of 8°. In this way, the  
130 radars illuminated the sow, but not the top metallic bars of the crate.

131

### 132 ***Radar signal analysis and electromagnetic clutter mitigation***

133 The raw data (radar signal) are available upon request to the corresponding author. To estimate  
134 the posture of the sows, we analysed the signal delivered by the two radars over time. We  
135 computed the *beat frequency spectrum* (i.e., echo level magnitude as a function of the distance)  
136 by applying a Fourier transform (Stove et al. 1992) on the time signal. The result was a 2D raw  
137 data image of echo levels from which the posture of the sow could be estimated (Figure 2A).  
138 However, potential electromagnetic clutter, for instance due to the electromagnetic  
139 backscattering from the crate or from the piglets close to the sow, may alter the estimation  
140 accuracy of the posture. In order to mitigate this clutter, we used time-gating and spatial filtering.  
141 First, we applied a mean filter on the data across the slow time axis (Figure 2B). The mean was

142 estimated over 1s, which corresponds to 20 consecutive radar measurements. Next, we applied  
143 Gabor filters to reduce the impact of uncorrelated data over time (Feichtinger and Strohmer  
144 2012; see Figure 2C). Finally, we used an average filter (Figure 2D). The main advantage of  
145 using these filters is that they are simple to implement and suitable to real-time applications. In  
146 the final filtered 2D radar image (Figure 2D), some distinguishable behaviours of the sow could  
147 be detected at the distance of 1m, such as the transition to the standing posture around 1300s,  
148 2700s and 3400s. These images obtained from two radars were used as input data for the posture  
149 classifier (see below).

150

### 151 *Classification of sow postures using a Convolutional Neural Network analysis*

152 To extract the postures of the sows, we used a CNN-based classifier. This approach has  
153 previously proved efficient for optical image classification (Simonyan and Zisserman 2015).  
154 Here the number of convolution layers as well as the number of filters per layer were chosen to  
155 speed up the training step of the model. A total of 16 filters were used for the first convolutional  
156 layers and the number of filters was doubled after each reduction phase (as proposed in  
157 Simonyan and Zisserman 2015). An illustration of the different layers of the network, including  
158 phases of convolution, activation, batch normalisation, pooling, dense, and dropout, is given in  
159 Figure 3.

160 CNN models were applied individually on each sow, since radar to ground distances were  
161 adjusted to the body size of each sow. To build a model, data from each sow was separated into  
162 two subsets containing respectively the first 60% and the last 40% of each posture data. The first  
163 subset was used for the training of the CNN. The second subset was used to estimate the quality  
164 of the predictions by checking that the results on the training dataset were not due to overfitting.  
165 During the training phase, we used 32 annotated data between two adaptations of the neural  
166 network weights. The CNN weights were adjusted following the method described by (Kingma  
167 and Ba 2014) which used a stochastic gradient descent and momentum estimation to optimise the  
168 neural network weights. The cost function was the standard function used by Murphy (2012) for  
169 multi-class classification. This function computes the minimal cross entropy for each output  
170 class. During the initial training, the five postures of interest were considered (Figure 1). After  
171 the training phase, each CNN was tested on the validation dataset.

172 The performance of the classifier in terms of the number of sow posture images that were  
173 correctly classified as well as the misclassified cases for each class was assessed with the  
174 confusion matrices. In the multi-class classification task, the evaluation metrics are computed  
175 based on these confusion matrices. We used three evaluation metrics to estimate the quality of  
176 the classifier: the specificity, the sensitivity and the accuracy (Fawcett 2006). The specificity ( $sp$ )  
177 indicates if the classifier gives negative results when the considered posture is not seen. The  
178 sensitivity ( $sb$ ) indicates if the classifier gives positive results when the considered posture is  
179 seen. The accuracy ( $acc$ ) indicates how often the classifier gives the true posture. Specificity,  
180 sensitivity and accuracy were calculated as follows:

181

$$sp = \frac{TN}{TN + FP}, \quad sb = \frac{TP}{TP + FN}, \quad acc = \frac{TN + TP}{TN + TP + FP + FN}$$

182

183 Where  $TP$  is the number of times that the estimated class corresponds to the true class,  $TN$  is the  
184 number of times the class is not predicted and corresponds to another class,  $FP$  is the number of  
185 times that the class is predicted, but does not correspond to the true class, and  $FN$  is the number  
186 of times that the class is not predicted and does correspond to the considered class.

187

## 188 **Results**

189

190 For a detailed analysis of the quantitative results, the ten individual classification architectures  
191 were compared in the form of confusion matrices (global matrix for the ten sows, and individual  
192 matrices for each sow) shown in Figure 4. All occurrences of true/predicted postures are reported  
193 in the matrices for the 5 detected postures. The probability of false detection for each posture is  
194 derived from these first results. The specificity and sensitivity values of postures computed from  
195 the confusion matrices are reported in Table 1. Highest specificity values were obtained for  
196 sitting (99.3%) and standing (99.8%). On average, all postures had an accuracy and a specificity  
197 higher than 92%. Sensitivity was higher than 90% for all postures except kneeling that was  
198 detected in less than 10% of the time. Nursing and lying were confused by 10% on average.  
199 Kneeling had the lowest sensitivity (9.1%), but a high specificity (99.5%) and a high accuracy

200 (99.4%). Our method can thus detect four out of five postures with a high specificity, a high  
201 sensibility and a high accuracy.

202 The pie charts of the ground-truth measurements and estimated measurements of sow  
203 postures obtained from the validation datasets are shown in Figure 5. The relative time spent by  
204 each sow in each posture over a 2-hours period (corresponding to the validation dataset) was  
205 correctly estimated, with an error of less than 10% for all postures except kneeling. The  
206 difficulty in correctly estimating kneeling is likely due to the lack of sufficient radar data to  
207 analyse this posture with a convolutional neural network. Kneeling lasted only a few seconds  
208 (mean: 16s, standard deviation: 7s), which is considerably less than the other postures that lasted  
209 several minutes or hours (Table 2). In addition, the kneeling posture was much more sensitive  
210 than other postures to the measurement errors induced by the observer's annotation delay (i.e.  
211 time needed to press a computer key to record the change in posture). Graphs of the probability  
212 of posture transitions indicate that the different sows lie down differently (Figure 7). In  
213 particular, two of them occasionally moved directly from standing to lying, without using the  
214 transient postures sitting and kneeling.

215

## 216 **Discussion**

217

218 Automated monitoring of behaviour in farm animals is a major challenge to improve animal  
219 welfare and breeding programs for genetic selection. In the case of pig farming, sow postural  
220 activity can be used as an indicator of health problems linked to increased piglet mortality. Here  
221 we introduced a new method for automated monitoring of postures and posture changes of sows  
222 kept in crate using the FMCW radars and a CNN classification. This solution is accurate, faster  
223 and requires little memory to store the data. It is thus applicable in real time. It also provides the  
224 advantages of not being affected by lightening condition (i.e. day and night analysis is never  
225 altered by the light at the level of the crate where the sow is measured) and non-invasive (i.e. do  
226 not alter sow behaviour in any way).

227

### 228 ***Comparison with existing methods***

229 Our radar-based tracking system provides several advantages over other existing methods. For  
230 instance, the radars are more accurate and less invasive than accelerometers (Ringgenberg et al.  
231 2010; Canario et al., 2018). Although the detection sensitivity with the two approaches were  
232 similar for the three postures lying, nursing and standing, the radar data gave an estimation of the  
233 sitting posture with a much higher sensitivity than accelerometers (90% with radars, 37% with  
234 accelerometers). In addition, detecting other postures such as the sitting is meaningful for the  
235 analysis of sow behaviour related to piglet crushing, because it is included in the calculation of  
236 sow postural changes that are risky for the piglets (Melisová et al., 2014). Presumably, lying  
237 down through the transient postures sitting and kneeling indicates that sows are cautious towards  
238 their piglets when lying down.

239 We also found that the radar data processing is much faster and requires less memory  
240 than video processing for comparable results (Leonard et al., 2019; Bonneau et al. 2021). For  
241 example, Zheng et al. (2018) obtained similar results on the same five postures with a Kinect  
242 camera and a deep learning analysis on sows kept in individual pen, i.e., with more possibility to  
243 move. Using the same experimental design as ours, Bonneau et al (2021) achieved 98%  
244 sensitivity for four postures with a conventional 2D camera. Therefore, the main advantage of  
245 our approach lies in the processing of radar signal which is faster and requires less memory than  
246 that of video signal. Indeed, the processing by successive filtering is fast enough for a real-time  
247 application and this procedure is easily parallelisable. Using an Intel Core i7 processor with 4  
248 threads makes it possible to process 12000 radar measurements per second. For a single  
249 measurement with two radars, only 800 bits are required, compared with several millions  
250 (3Mbits) for a standard definition camera. In our study the total data size of the five hours of  
251 measurements on ten sows presented was 2Go, which is compatible with the use of radars at  
252 large scale for farming applications. Additionally, by default and contrary to video image  
253 analysis, our analysis is independent of light conditions. This may be particularly relevant for  
254 future applications such as monitoring farrowing, which preferably takes place outside the  
255 working hours of the care takers, and therefore when the rooms are not lit (Canario et al., 2014).

256

### 257 *New possible analyses*

258 Beyond being non-invasive, accurate and fast, the radar approach could be used to monitor sow

259 carefulness when lying down (Pokorná et al., 2008). In the past, posture changes were rarely  
260 characterised by considering the passage through transient postures, i.e., kneeling and sitting (but  
261 see Pokorná et al., 2008; Wischner et al., 2010) and if so, have involved small groups of animals.  
262 Automated monitoring with radars in a farrowing crate enables such accurate recording of  
263 whether the sow lies down carefully. This feature can be linked to piglet crushing events.

264 Our data also indicate it is possible to detect piglets with radars. Prior to this study,  
265 preliminary measurements were performed in which the sow's postures were estimated and the  
266 standard deviation was calculated over 20min, while the sow remained in a given posture. The  
267 standard deviation obtained was of 2.5cm for the nursing posture which is slightly higher than  
268 the theoretical depth resolution. However, the electromagnetic clutter may alter the measurement  
269 accuracy in some situations. For example, part of the metal bars of the crate that are visible to the  
270 radar may generate undesirable electromagnetic backscattering and result in false detections in  
271 the CNN analyses. This negative effect can be limited by precise positioning of the radars, so  
272 that the radar main beam does not intercept the metallic bars. False detections may also occur  
273 when piglets are close to the sow, or when they ride on its back. Figure 6 illustrates this  
274 phenomenon with two 2D radar images recorded simultaneously above (a) the head and (b) the  
275 back of a sow. The posture estimated from the radar processing (indicated as red cross)  
276 sometimes varies abruptly, due to the presence of piglets in the area of interest, i.e., on the back  
277 of the sow (e.g. around 600s, 800s and 1100s). Detection of the piglets at the udder is therefore  
278 presumably possible. The radars can be effective in monitoring additional behavioural aspects of  
279 the sow-piglets relationship that are of importance for piglet survival.

280

### 281 *Conclusions and perspectives*

282 Our study demonstrates the applicability and efficiency of FMCW radars to monitor postures and  
283 postural changes of crated sows. This approach holds considerable promises for future  
284 applications since minor developments are possible to improve the system. For instance, adding  
285 radars will enable to detect new postures and consolidate the estimation of the current ones. Our  
286 method was applied to detect the postural activity of the sow from the estimation of the height of  
287 its head and its back. Consequently, it could not detect lateral movements of the sow and if the  
288 sow was lying on the right or left side. This estimation would be possible by adding a third radar

289 on the side of the sow for detecting lateral movements and consequently, for estimating the  
290 orientation of the sow in the crate and whether she is nursing the piglets or not. Moreover, the  
291 kneeling posture was not correctly estimated for any sow. This posture is interesting to capture,  
292 as it reflects a cautious approach of the sow to lie down, compared with sows that slide along the  
293 bars from the standing posture (Pokorná et al., 2008). Sliding is a less suitable way to lie down  
294 for sows as it induces some piglet crushing (Fraser 1990, Damm et al. 2005). The kneeling  
295 posture lasts only a few seconds, and its estimation is sensitive to potential annotation errors due  
296 to human delay between observation and pressing a computer key. However, from the  
297 monitoring of more sows and fixing the radar on the crate rather than a metallic structure above,  
298 it should be possible to improve the reliability of the measurement and the accuracy of the  
299 posture estimator.

300 Using different types of radars can also improve piglet detection. With our method, the  
301 detection of piglets on the floor is difficult because they rarely enter the radars field of view and  
302 are small compared to the sow. The radar beam width was too small to allow detecting piglets.  
303 One solution to this problem would be to use two 2D radars instead of the current device, and  
304 position one on each side of the sow. In this way, the detection should work even if the sow  
305 hides the piglets from one of the radars beam. Access to such data on the presence of piglets  
306 around the sow would benefit the characterisation of sow carefulness to lie down (Pokorná et al.,  
307 2008; Wischner et al., 2010). Adjusting radar characteristics can also increase detection  
308 distances. Until now, results were obtained in indoor environment where the sow cannot move.  
309 The radar detects the back of the sow at all times. The use of radar with sows free of movements  
310 can be more challenging. Then, it should be possible to detect the sow by using a single 3D radar  
311 with a larger beam width, including position and posture simultaneously. To do so, the radar  
312 should be placed centrally on the ceiling above the pen to cover the entire pen with the radar  
313 beam.

314 Finally, adding data would also make it possible to define a single classifier to estimate  
315 the posture for all sows and develop more detailed behavioural analyses (Bonneau et al., 2021).  
316 So far, the relevance of radars to detect sows that are injured (e.g. excessive time spent lying) or  
317 that are not careful towards their piglets (e.g. fast transition from standing to lying) has not been  
318 studied. Data recorded for longer periods on animals contrasted on these aspects could be

319 collected with the radar technology. All these improvements are easily reachable, which strongly  
320 suggests that automated fine recording with radars will help to analyse the relationship between  
321 sow postural changes and risk of piglet crushing. Importantly, radar tracking has limited  
322 constraints on the size and shape of animals (Henry et al. 2018; Dore et al. 2020; Dore et al.  
323 2021), thus offering ample possibilities for tracking a wide range of animals in various  
324 environments in applied and fundamental ethology research.

325

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327

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338

## 339 **Competing interest**

340

341 The authors have no competing interest.

342

## 343 **References**

344

345 Baxter, E. M., Lawrence, A. B., & Edwards, S. A. (2012). Alternative farrowing  
346 accommodation: Welfare and economic aspects of existing farrowing and lactation systems  
347 for pigs. *Animal*, 6, 96–117.

- 348 Bonneau, M., Benet, B., Labrune, Y., Bailly, J., Ricard, E., & Canario, L. (2021). Predicting sow  
349 postures from video images: Comparison of convolutional neural networks and  
350 segmentation combined with support vector machines under various training and testing  
351 setups. *Biosystems Engineering*, *212*, 19–29.
- 352 Canario, L., Bidanel, J.P., & Rydhmer, L. (2014). Genetic trends in maternal and neonatal  
353 behaviors and their association with perinatal survival in French Large White swine.  
354 *Frontiers in Genetics*, *5*, 1-16.
- 355 Canario, L., Labrune, Y., Bompa, J.-F., Billon, Y., Ravon, L., Reignier, S., Bailly, J., & Ricard,  
356 E. (2018). Development and validation of an embedded tool to measure postural activity of  
357 lactating sows. *Swine Days' Research*, *50*, 329-330.
- 358 Cornou C., Lundbye-Christensen S., & Kristensen A.R. (2011). Modelling and monitoring sows'  
359 activity types in farrowing house using acceleration data. *Computer and Electronics in*  
360 *Agriculture*, *76(2)*, 316-324.
- 361 Chidgey, K. L., Morel, P. C., Stafford, K. J., & Barugh, I. W. (2015). Sow and piglet  
362 productivity and sow reproductive performance in farrowing pens with temporary crating or  
363 farrowing crates on a commercial New Zealand pig farm. *Livestock Science*, *173*, 87–94.
- 364 Damm, B. I., Forkman, B., & Pedersen, L. J. (2005). Lying down and rolling behaviour in sows  
365 in relation to piglet crushing. *Applied Animal Behaviour Science*, *90*, 3–20.
- 366 Dore, A., Henry, D., Lihoreau, M., & Aubert, H. (2020). 3D trajectories of multiple untagged  
367 flying insects from millimetre-wave beamscanning radar. *2020 IEEE International*  
368 *Symposium on Antennas and Propagation and North American Radio Science Meeting*,  
369 1209–1210.
- 370 Dore, A., Pasquaretta, C., Henry, D., Ricard, E., Bompard, J. F., Bonneau, M., Hazard D., Aubert  
371 H. & Lihoreau, M. (2021). A Non-Invasive Millimetre-Wave Radar Sensor for Automated  
372 Behavioural Tracking in Precision Farming—Application to Sheep Husbandry. *Sensors*, *21*,  
373 8140.
- 374 Edwards, S. A. (2002). Perinatal mortality in the pig: Environmental or physiological solutions?  
375 *Livestock Production Science*, *78*, 3–12.
- 376 Edwards, S. A., & Fraser, D. (1997). Housing systems for farrowing and lactation. *Pig Journal*,  
377 *39*, 77–89.

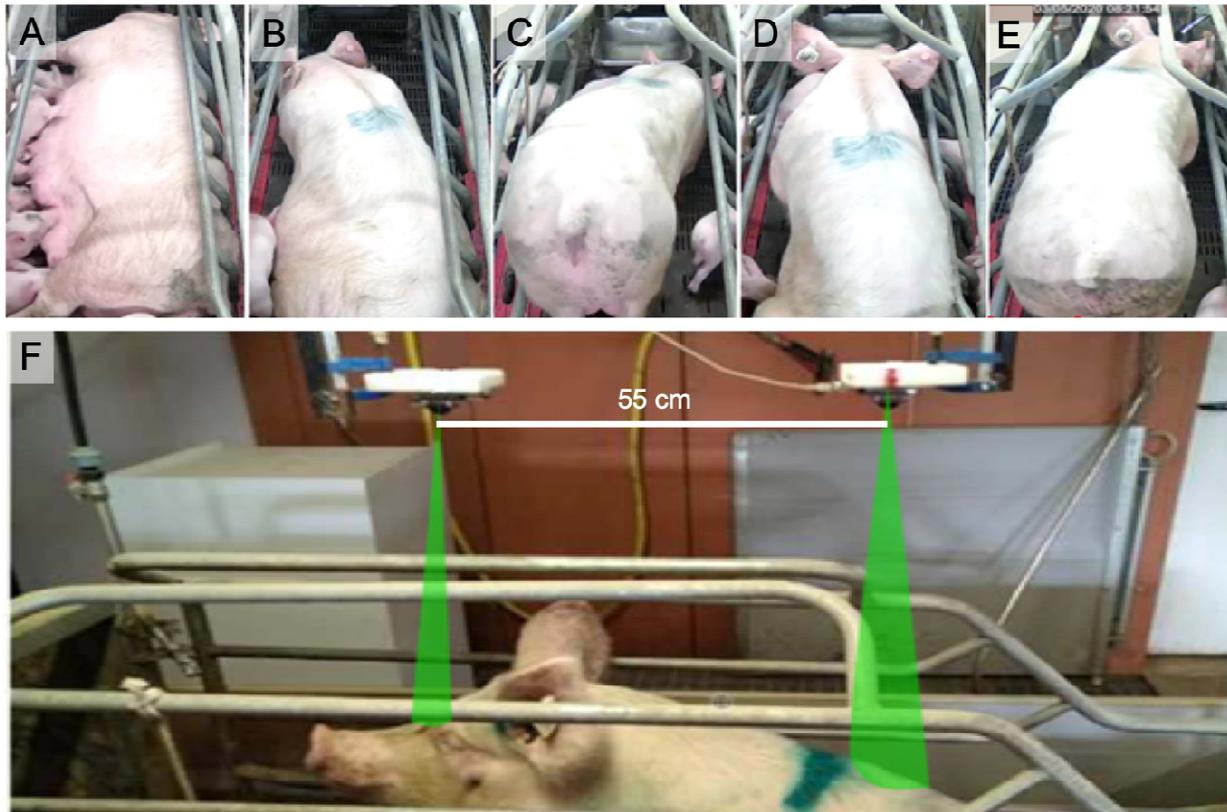
- 378 Feichtinger, H. G., & Strohmer, T. (2012). *Gabor analysis and algorithms: Theory and*  
379 *applications*. Springer Science & Business Media.
- 380 Fernandes, A. F. A., Dórea, J. R. R. & Rosa, G. J. M. (2020). Image Analysis and Computer  
381 Vision Applications in Animal Sciences: An Overview. *Frontiers in Veterinary Science*  
382 7:551269. doi: 10.3389/fvets.2020.551269.
- 383 Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, 27, 861–874
- 384 Fraser, D. (1990). Behavioural perspectives on piglet survival. *Journal of reproduction and*  
385 *Fertility*. 40, 355–370.
- 386 Henry, D., Aubert, H., Ricard, E., Hazard, D., & Lihoreau, M. (2018). Automated monitoring of  
387 livestock behavior using frequency-modulated continuous-wave radars. *Progress in*  
388 *Electromagnetics Research*. 69, 573 151–160.
- 389 Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *ArXiv Preprint*  
390 *ArXiv:1412.6980*.
- 391 Leonard, S. M., Xin, H., Brown-Brandl, T. M., & Ramirez, B. C. (2019). Development and  
392 application of an image acquisition system for characterizing sow behaviors in farrowing  
393 stalls. *Computers and Electronics in Agriculture*, 163, 104866.
- 394 Mainau, E., Dalmau, A., Ruiz-de-la-Torre, J. L., & Manteca, X. (2009). Validation of an  
395 automatic system to detect position changes in puerperal sows. *Applied Animal Behaviour*  
396 *Science*, 121, 96–102.
- 397 Manteuffel, C. (2019). Parturition detection in sows as test case for measuring activity behaviour  
398 in farm animals by means of radar sensors. *Biosystems Engineering*, 184, 200–206.
- 399 Melisová, M., Illmann, G., Chaloupková, H., & Bozdechová, B. (2014). Sow postural changes,  
400 responsiveness to piglet screams, and their impact on piglet mortality in pens and crates.  
401 *Journal of Animal Science*, 92, 3064–3072.
- 402 Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT press.
- 403 Nasirahmadi, A., Sturm, B., Edwards, S., Jeppsson, K.-H., Olsson, A.-C., Müller, S., & Hensel,  
404 O. (2019). Deep learning and machine vision approaches for posture detection of individual  
405 pigs. *Sensors*, 19, 3738.
- 406 O'Malley, C.I., Turner, S.P., D'Eath, R.B., Steibel, J.P., Bates, R.O., Ernst, C.W., & Siegford,  
407 J.M. (2019). Animal personality in the management and welfare of pigs. *Applied Animal*

- 408 *Behaviour Science*, 218, 104821.
- 409 Oczak, M., Maschat, K., & Baumgartner, J. (2020). Dynamics of sows' activity housed in  
410 farrowing pens with possibility of temporary crating might indicate the time when sows  
411 should be confined in a crate before the onset of farrowing. *Animals*, 10, 6.
- 412 Okinda, C., Lu, M., Nyalala, I., Li, J., & Shen, M. (2018). Asphyxia occurrence detection in  
413 sows during the farrowing phase by inter-birth interval evaluation. *Computers and*  
414 *Electronics in Agriculture*, 152, 221–232.
- 415 Pokorná, Z., Illmann, G., Simecková, M., Chaloupková, H., & Kratinová, P. (2008). Carefulness  
416 and flexibility of lying down behaviour in sows during 24h post-partum in relation to piglet  
417 position. *Applied Animal Behaviour Science*, 114, 346-358.
- 418 Ringgenberg, N., Bergeron, R., & Devillers, N. (2010). Validation of accelerometers to  
419 automatically record sow postures and stepping behaviour. *Applied Animal Behaviour*  
420 *Science*, 128,37–44.
- 421 Simonyan, K., & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale  
422 Image Recognition. *ArXiv:1409.1556*
- 423 Stove, A. G. (1992). Linear FMCW radar techniques. *IEE Proceedings F (Radar and Signal*  
424 *Processing)*, 139, 343–350.
- 425 Traulsen, I., Scheel, C., Auer, W., Burfeind, O., & Krieter, J. (2018). Using acceleration data to  
426 automatically detect the onset of farrowing in sows. *Sensors*, 18, 170.
- 427 Von Borell, E., Dobson, H., & Prunier, A. (2007). Stress, behaviour and reproductive  
428 performance in female cattle and pigs. *Hormones and Behavior*, 52, 130–138.
- 429 Wischner, D., Kemper, N., Stamer, E., Hellbrügge, B., Presuhn, U., & Krieter, J. (2010). Pre-  
430 lying behaviour patterns in confined sows and their effects on crushing of piglets. *Applied*  
431 *Animal Behaviour Science*, 122, 21-27.
- 432 Zheng, C., Zhu, X., Yang, X., Wang, L., Tu, S., & Xue, Y. (2018). Automatic recognition of  
433 lactating sow postures from depth images by deep learning detector. *Computers and*  
434 *Electronics in Agriculture*, 147, 51–63.

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438 **Figures**

439

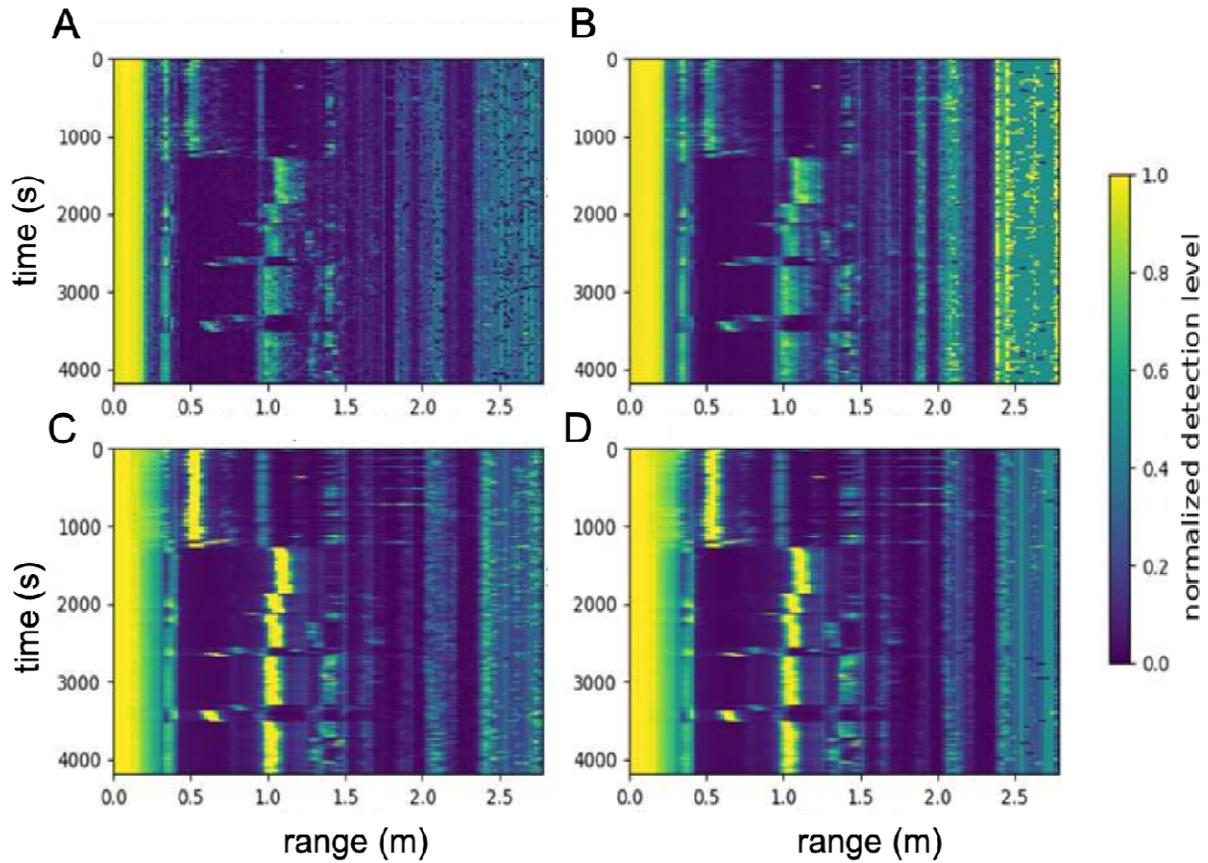


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441 Figure 1 – Images of sow postures as recorded by the video camera: A) nursing (lying laterally  
442 with udder exposed), B) lying (ventrally), C) kneeling, D) sitting, E) standing. F) Two FMCW  
443 radars were positioned above the sow to monitor head and back elevation. Radar beams are  
444 highlighted in green.

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447  
448 Figure 2 – Outputs from the successive filters applied to the radar signal. A) Raw data; B)  
449 Temporal average filter; C) Gabor filter; D) Gabor filter plus average filter. Blue to yellow  
450 colours show low to high echo levels.

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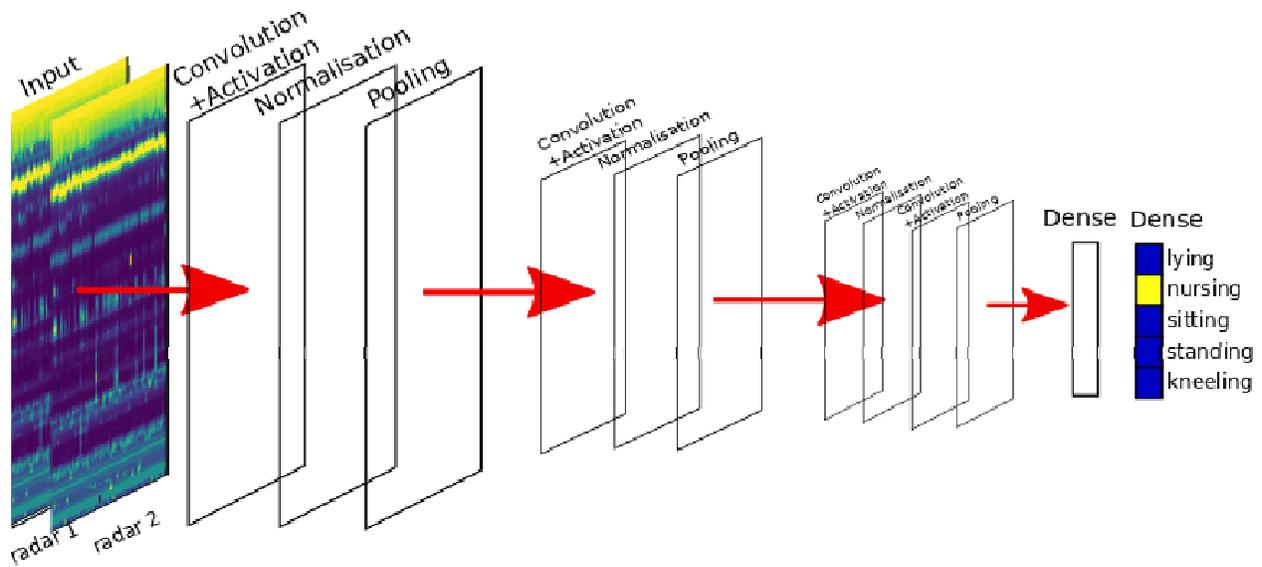
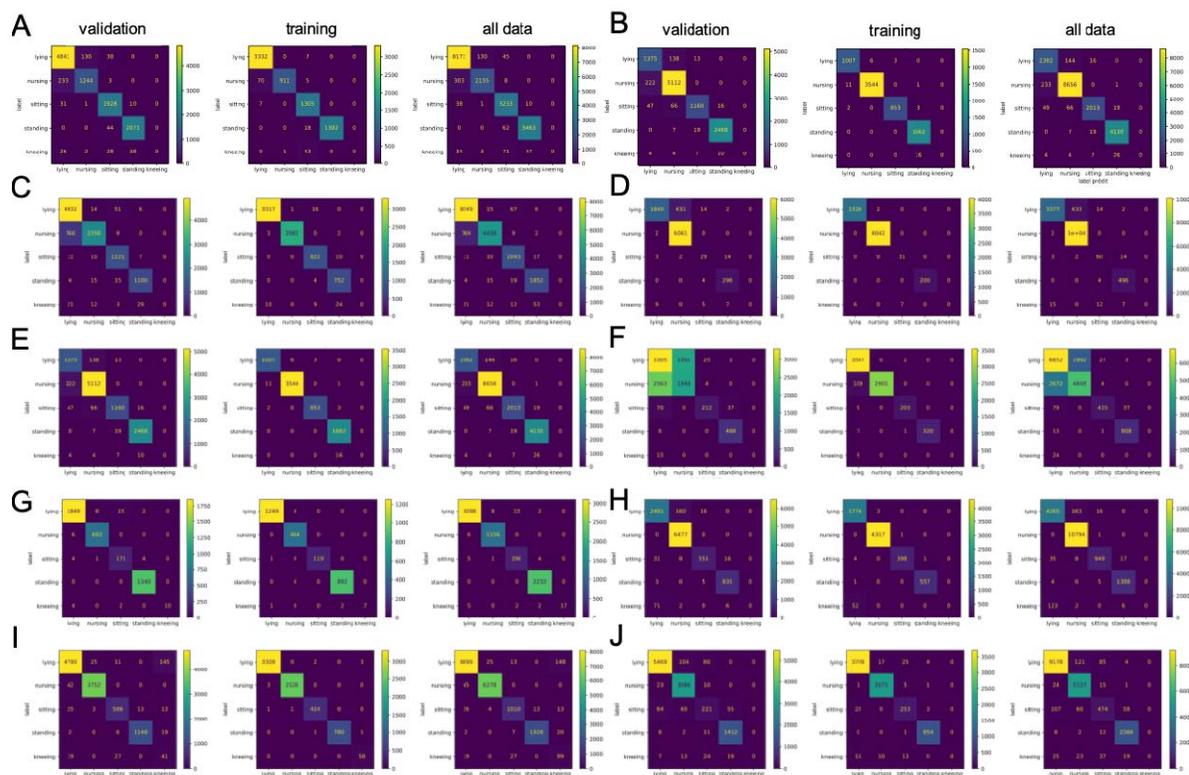


Figure 3 – Illustration of the CNN model applied to radar images for estimating sow postures. Each convolution layer consists of a convolution filter of size 3x3. The pooling layer reduces the size of the data and dense layers are fully connected neurons.

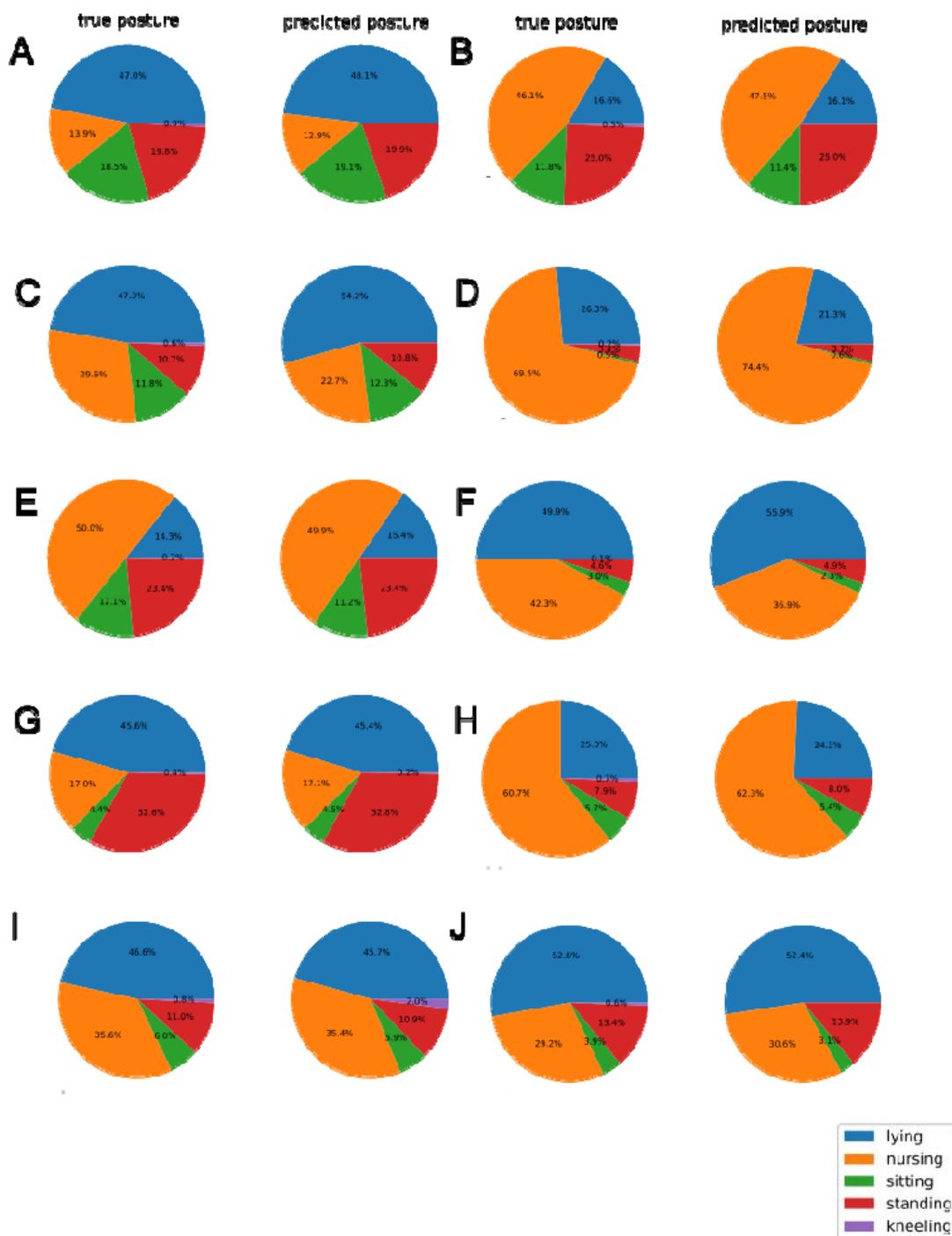
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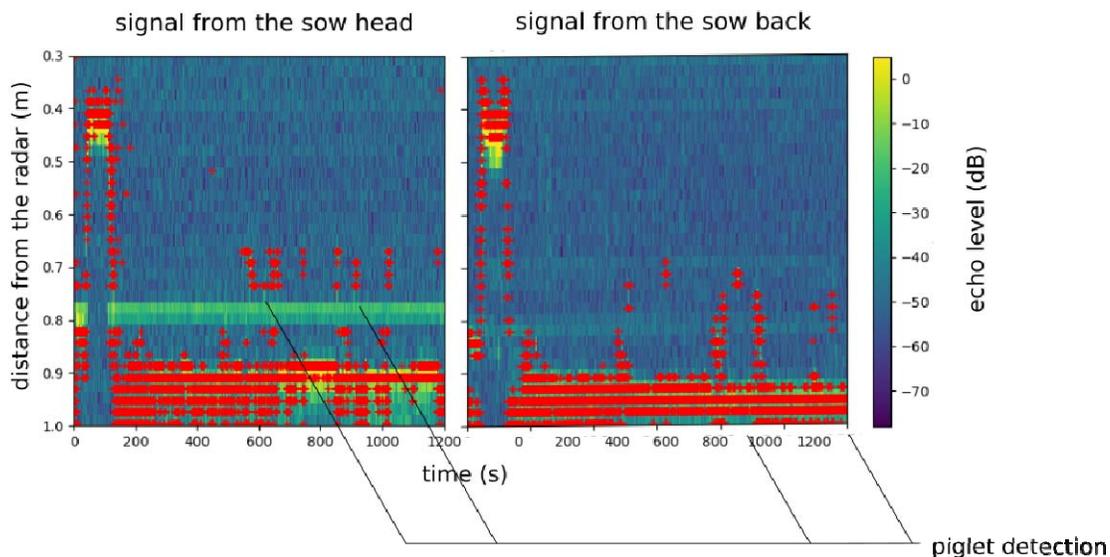
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456 Figure 4 - Confusion matrices for the 10 sows (A-J) and postures obtained from the individual  
 457 CNN analyses. Vertical and horizontal axes indicate ground-truth measurement of the sow's  
 458 posture and the estimated posture, respectively.



459  
 460 Figure 5 – Percentage of time spent in the different postures by each sow (A-J) according to  
 461 truth-ground measurement and estimated postures in the validation datasets. The higher the  
 462 similarity between the true pie chart and the estimated pie chart of a sow, the better the

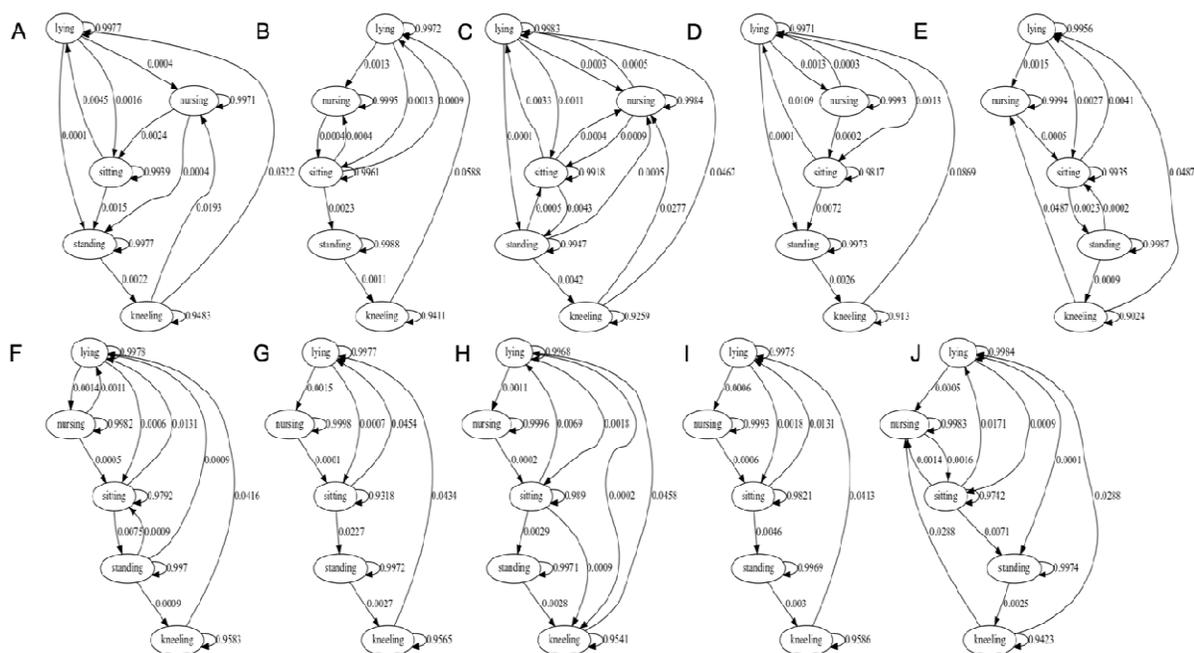
463 prediction for that sow.



464 Figure 6 - Two-dimensional images of the two radars illuminating (a) the head and (b) the back  
465 of a sow when piglets are riding on its back. Red crosses represent the computed first local  
466 maxima for each slow time bin. The presence of piglets on the sow back can be observed at  
467 various times. A threshold for the distance estimation can be used (around 0.6m for the two  
468 radars) to determine if the sow is lying or standing.

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472 Figure 7 - Graphs of the probability of posture transitions, i.e., the probability of switching  
 473 between the 5 postures for the 10 sows (A-J) over a 5 hours period. Labels A-J correspond to the  
 474 same sows as in Table 1.

475 **Tables**

476 Table 1 - Specificity, sensitivity and accuracy of each of the 5 postures for the 10 sows obtained from individual CNNs. Labels

477 A-J correspond to the same sows as in Figure 7.

	sensitivity					Specificity				
posture	lying	nursing	sitting	standing	kneeling	lying	nursing	sitting	standing	kneeling
sow A	96.7	84.1	97.9	97.9	0.0	94.9	98.6	98.7	99.4	100.0
sow B	95.0	100.0	95.2	98.6	0.0	99.6	97.4	99.8	99.5	100.0
sow C	98.6	75.3	97.8	97.0	0.0	85.6	99.3	99.2	99.6	100.0
sow D	80.5	100.0	60.4	98.7	0.0	99.8	83.8	99.7	99.7	100.0
sow E	90.1	95.8	90.0	99.0	0.0	97.0	96.0	99.6	99.7	100.0
sow F	62.1	43.2	66.5	98.8	0.0	50.3	67.6	99.7	99.6	100.0
sow G	98.7	99.1	95.0	100.0	62.5	99.4	99.7	99.6	99.8	100.0
sow H	93.4	100.0	90.9	99.1	0.0	98.7	95.9	99.8	99.8	100.0
sow I	96.4	98.9	91.6	97.7	47.1	98.5	99.6	99.6	99.9	98.3
sow J	97.1	98.9	52.6	98.5	0.0	97.6	97.6	99.0	99.2	100.0
Mean	90.3	90.2	91.2	98.5	9.9	92.9	94.3	99.5	99.6	99.8
Std	10.9	17.4	16.3	0.8	22.2	14.5	9.8	0.4	0.2	0.5

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479

480 Table 2 – Time spent in each of the 5 postures by the 10 sows over the 5 hours period.

Posture	total time spent (h)	rate of time spent (%)	mean of duration (min)	std of duration (min)
lying	16.66	33.56	7.19	5.99
nursing	22.67	45.67	20.31	30.51
sitting	3.76	7.57	1.72	2.23
standing	6.32	12.72	7.02	10.36
kneeling	0.24	0.48	0.29	0.14

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