Deep Learning-Based Classification of Stress in Sows Using Facial Images

Syed U. Yunas[1], Ajmal Shahbaz[1], Emma M. Baxter[2], Marianne Farish[2], Kenneth M. D. Rutherford[2], Mark F. Hansen[1], Melvyn L. Smith[1] and Lyndon N. Smith[1]

[1]*Centre for Machine Vision, University of the West of England (UWE), Bristol, U.K.*

[2]*Scotland's Rural College (SRUC), Edinburgh, U.K.*

{*syed.yunas, ajmal.shahbaz*}*@uwe.ac.uk*, {*emma.baxter, marianne.farish, kenny.rutherford*}*@sruc.ac.uk,*

Keywords: Sow Stress Classification, YOLO Model, Convolutional Neural Network (CNN), Deep Learning in Agriculture, Animal Welfare Monitoring, Stress Detection from Facial Images.

Abstract: Stress in pigs is a significant factor contributing to poor health, increased antimicrobial usage, and the subsequent risk of antimicrobial resistance (AMR), which poses a major challenge for the global pig farming industry. In this paper, we propose using deep learning (DL) methods to classify stress levels in sows based on facial features captured from images. Early identification of stress can enable targeted interventions, potentially reducing health risks and mitigating AMR concerns. Our approach utilizes convolutional neural network (CNN) models, specifically YOLO8l-cls, to classify the stress levels of sows (pregnant pigs) into low-stressed and high-stressed categories. Experimental results demonstrate that YOLO8l-cls outperforms other classification methods, with an overall F1-score of 0.74, Cohen's Kappa of 0.63, and MCC of 0.60. This highlights the model's effectiveness in accurately identifying stress levels and its potential as a practical tool for stress management in pig farming, with benefits for animal welfare, the farming industry, and broader efforts to minimize AMR risk.

1 INTRODUCTION

Modern livestock production demands a keen focus on animal well-being, driven not only by ethical considerations but also by its significant impact on factors such as animal health, productivity, and product quality (Manteca and Alonso, 2000). Stress in pigs is a major concern as chronic stress weakens their immune system, making them more susceptible to infections (Bartolomé et al., 2004). This, in turn, fuels the overuse of antibiotics for treatment and prevention, a significant contributor to the global threat of Antimicrobial Resistance (AMR) (Arjun et al., 2020). There is also potential for transgenerational harm when mothers experience stress during pregnancy that can affect perinatal programming via epigenetic mechanisms, thus having significant implications for offspring development (Weinstock, 2008; Ruijven and Oliehoek, 2017).

Early detection of stress in pigs is therefore paramount for effective intervention. Traditional methods, such as manual behavioural observation or invasive physiological sampling, offer limited solutions. They are time-consuming, expensive, and, in the case of invasive physiological sampling, could cause further distress to the animals (Wechsler, 2000), (Broom, 2011). The development of a non-invasive automated approach for objectively identifying animals susceptible to stress might ultimately allow selection of pigs better equipped to cope with health and environmental challenges.

Advancements in image and video analysis powered by deep learning, particularly the use of Convolutional Neural Networks (CNNs) for extracting robust visual features, have revolutionized the study of animal behaviour (Alpaydin et al., 2020). CNNs have shown promising results in detecting stress among different livestock species, including pigs, cows, poultry, and fish, through the identification of facial expressions or body language cues exhibited by these animals (Wang et al., 2020b; Yang et al., 2020; Liu et al., 2020; Arriaga et al., 2021).

Our study builds upon the prior work by researchers (Hansen et al., 2021), which developed a CNN-based model to detect stress in young female pigs (gilts) within a controlled social defeat experimental setup, achieving over 90% accuracy in classifying gilts as stressed or not stressed. In contrast, the

Yunas, S. U., Shahbaz, A., Baxter, E. M., Farish, M., Rutherford, K. M. D., Hansen, M. F., Smith, M. L. and Smith, L. N.
Deep Learning-Based Classification of Stress in Sows Using Facial Images.
DOI: 10.5220/0013327900003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 1*, pages 390-396
ISBN: 978-989-758-731-3; ISSN: 2184-4305

(a) Recording sows: Four of the six pregnant sows.
(b) Image cropping to exclude occlusions from metal pen bars.
(c) Sow segmentation performed using Mask-RCNN.
Figure 1: Experimental setup and data pre-processing of sow images.

current study extends this application to real-world, routine farming conditions, specifically within dry sow houses where pregnant sows are monitored under standard farming practices. Unlike the model developed by Hansen et al., which performed a binary classification of stressed versus non-stressed animals, our study offers a more nuanced approach by categorizing stress levels into Low-Stressed (LS) and High-Stressed (HS) groups. This distinction provides a deeper understanding of stress levels in sows, enabling a more detailed assessment of their well-being in typical farming environments. We employed and evaluated two advanced deep learning models—a fine-tuned (FT) version of the original model used by Hansen et al. and the YOLO8l-cls model (Ultralytics, 2024)—to enhance classification performance and ensure robustness across diverse stress indicators and scenarios encountered in routine farming. These modifications aim to not only demonstrate the scalability of deep learning-based stress detection but also adapt the methodology to better align with the practical needs of commercial pig farming, thereby advancing the utility and applicability of automated stress monitoring systems in real-world settings.

The structure of this paper is as follows: Section II discusses the experimental setup, including the hardware, dataset, and training process. Section III provides an overview of the original, FT, and YOLO8 models, including performance metrics used to evaluate these models. Section IV presents the results and discusses their implications. Finally, Section V concludes the paper.

2 EXPERIMENTAL

2.1 Hardware

Video footage was captured on-farm at SRUC's Pig Research Centre, with all experiments reviewed and approved by SRUC's Ethical Review Board (AE14-2022). The setup placed cameras within the dry sow house, where sows are housed in individual straw pens with feed stalls. To optimize video recording efficiency, each camera employed motion detection, automatically activating to capture high-resolution images (1920x1080 pixels) at 30 frames per second when sows entered the feeding areas. Preventative measures, such as mounting camera brackets outside pen stalls, minimized the risk of animal interference with equipment, ensuring both safety and ideal conditions for the subjects.

Stress indicators in sows are often visible through subtle changes in facial cues—such as the ears, eyes, cheeks, and snout (Wang et al., 2020a). To reliably capture these features, the cameras were positioned at the end of each feed stall as shown in figure 1a, ensuring the complete face, including eyes and nose, were visible in each image. During pre-processing, images were refined to focus primarily on the face, although sometimes the sow's body or legs were also captured due to their proximity to the camera. This approach was intended to enhance consistency in analyzing facial stress markers while minimizing interference from other body parts.

2.2 Dataset

A dataset of 900 images was captured from six sows on day 70 of their gestation. Modifications and fine-tuning were applied to this dataset as described below. Stress susceptibility, provided by SRUC as ground truth data, was determined based on each sow's social rank and vulnerability to stress during food competition, following the methodology outlined by (Dwyer et al., 2000). This was further validated through behavioral observations (Janssens et al., 1995) and cortisol measurements from saliva samples (Jong et al., 1998), which classified the animals into low-stress (LS) and high-stress (HS) groups.

Figure 2: Architecture of the Fine-tuned (FT) model.

To ensure consistency in stress susceptibility categories, the ground truth data was verified through multiple behavioral observations and controlled measurements. This expert-labeled data served as the foundation for training and validating our model, ensuring that its classifications accurately reflected genuine stress markers rather than individual differences between animals.

Prior to model testing and training, all images were cropped to exclude any occlusions from metal pen bars, and a Mask-RCNN (He et al., 2017) was employed for background segmentation, as shown in figure 1b and 1c respectively. This approach ensured that each image contained only the essential facial features for analysis, improving the model's focus on relevant stress indicators.

2.3 Training Process

The dataset images were trained against ground truth labels using a Windows 11 PC with a Core i9 processor running at 3 GHz, 32 GB of RAM, and an Nvidia RTX 4090 GPU with 24 GB of memory. The DL models were implemented using the PyTorch library, version 2.1.1 (Paszke et al., 2019). The training process involved 1,000 epochs with a batch size of 32, a learning rate of 0.0001, and utilizing the Adam optimizer.

3 MODEL OVERVIEW

In this section, we outline the architectures of the models employed in this study:

3.1 Original and Fine-Tuned (FT) Models

The original model (Hansen et al., 2021) consists of six ReLU-activated convolutional layers, five dropout layers, three max-pooling layers, and two fully connected layers. A sigmoid function is applied to determine the probability of a sow being stressed, with a threshold (typically above 0.8) used to classify stress presence.

In our study, the original model was fine-tuned on the new dataset to better represent stress features as observed on the farm as either low-stressed (LS) or high-stressed (HS). While the original model was designed to classify stressed (positive class) vs. non-stressed (negative class), this study focuses on quantifying stress levels into LS and HS categories. To accommodate this, the final layer of the network was modified to produce two output values, as illustrated in figure 2. This adjustment removes the need for thresholding the output, enabling direct classification of stress levels.

3.2 YOLO8 Model

YOLO (You Only Look Once) is a versatile deep learning framework widely used for various computer vision tasks such as detection, segmentation, classification, and pose estimation. Its architecture processes an image by dividing it into a grid, predicting bounding boxes, object confidence scores, and class probabilities simultaneously. By applying Non-Maximum Suppression (NMS) to eliminate overlapping detections, YOLO efficiently delivers accurate predictions in real-time.

In this study, we utilize YOLO8l-cls (Ultralytics, 2024), a classification-specific variant of YOLO8, to predict stress levels in sows from facial images. This model was chosen for its strong performance in image classification, making it well-suited for use as a stress classifier. It was also selected to compare its stress classification capabilities against both the original and fine-tuned (FT) models.

3.3 Performance Metrics

Precision, Recall, and F1-Score are essential metrics in classification tasks, crucial for assessing DL models' performance. Precision, representing the ratio of true positive predictions to the total positive predic-

Table 1: Cross-validation Results for Sow Stress Classification with Original, Fine-tuned (FT), and YOLO8l-cls Models.

Class	Original Model (Train: 0 fold, Test: 3-fold)					FT Model (Train: 2-fold, Test: 1-fold)					YOLO8l-cls Model (Train: 2-fold, Test: 1-fold)				
	Precision	**Recall**	**F1-Score**	**MCC**	**Kappa**	**Precision**	**Recall**	**F1-Score**	**MCC**	**Kappa**	**Precision**	**Recall**	**F1-Score**	**MCC**	**Kappa**
All	0.36	0.44	0.40	-0.12	-0.05	0.71	0.70	0.71	0.50	0.52	0.74	0.74	0.74	0.60	0.63
Low-Stressed (LS)	0.26	0.07	0.11	-0.20	-0.10	0.66	0.83	0.74	0.52	0.54	0.73	0.78	0.75	0.63	0.65
High-Stressed (HS)	0.46	0.81	0.59	0.02	0.00	0.77	0.57	0.66	0.48	0.50	0.76	0.51	0.61	0.55	0.56

tions made by the model, is expressed mathematically as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (1)$$

It indicates the proportion of correctly predicted positive instances out of all instances predicted as positive. Higher precision values suggest fewer false positive predictions, reflecting the model's ability to avoid misclassification. Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances correctly identified by the model, calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (2)$$

Higher recall values indicate the model's effectiveness in capturing most positive instances while minimizing false negative predictions. The F1-score, which is the harmonic mean of precision and recall, provides a single metric that balances both concerns, calculated as:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

A higher F1-score indicates a good balance between precision and recall, offering a more comprehensive measure of the model's performance.

In addition to precision, recall, and F1-score, we also calculate the Matthews Correlation Coefficient (MCC) and Cohen's Kappa to provide a more comprehensive evaluation of the models' performance. These metrics help account for class imbalance and offer insights into the models' classification reliability.

The **Matthews Correlation Coefficient (MCC)** is a robust metric for binary classification, especially with imbalanced datasets. It is defined as:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (4)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. MCC values range from -1 (total disagreement) to +1 (perfect prediction), with 0 indicating no better performance than random chance.

The **Cohen's Kappa (κ)** statistic measures the agreement between predicted and actual classifications, adjusting for chance agreement:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (5)$$

where p_o is the observed agreement, and p_e is the expected agreement by chance. Cohen's Kappa ranges from -1 (no agreement) to +1 (perfect agreement).

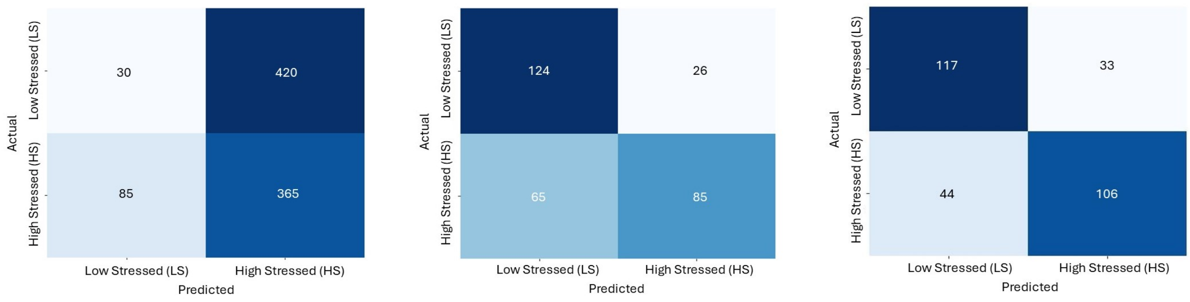
These metrics are computed for each model—Original, Fine-Tuned (FT), and YOLO8l-cls—on both Low-Stressed (LS) and High-Stressed (HS) classes. Results are detailed in Table 1 for comparative evaluation.

4 RESULTS AND DISCUSSION

Table 1 provides an overview of the performance metrics obtained from the cross-validation experiments for sow stress classification. It details these metrics for each model—Original, Fine-tuned (FT), and YOLO8l-cls—across the stress classes: Low-Stressed (LS) and High-Stressed (HS). The table includes additional metrics such as Matthews Correlation Coefficient (MCC) and Cohen's Kappa, providing a more comprehensive evaluation of model performance.

Our dataset consists of 900 images from six sows (three LS and three HS). These images are divided into three folds, with 150 carefully selected images from each sow, ensuring that each fold contains data from one LS and one HS sow. The original model, pretrained on the dataset used in (Hansen et al., 2021), was tested on all three folds to evaluate its generalization capabilities across the entire dataset. In contrast, the fine-tuned (FT) and YOLO8l models were fine-tuned on two folds and tested on the remaining fold to assess their performance after transfer learning on a subset of the data. This approach allows for a more targeted evaluation of the models' ability to adapt and improve performance on specific stress indicators in the dry sow house environment.

Figure 3 presents the confusion matrices for the three models. The original model, shown in Figure 3a, struggles to classify LS sows accurately, misclassifying 420 out of 450 LS sows as HS. This poor per-



(a) Original model. (b) FT model. (c) YOLO8l-cls model.

Figure 3: Results for Sow Stress Classification with Original, Fine-tuned (FT), and YOLO8l-cls Models.

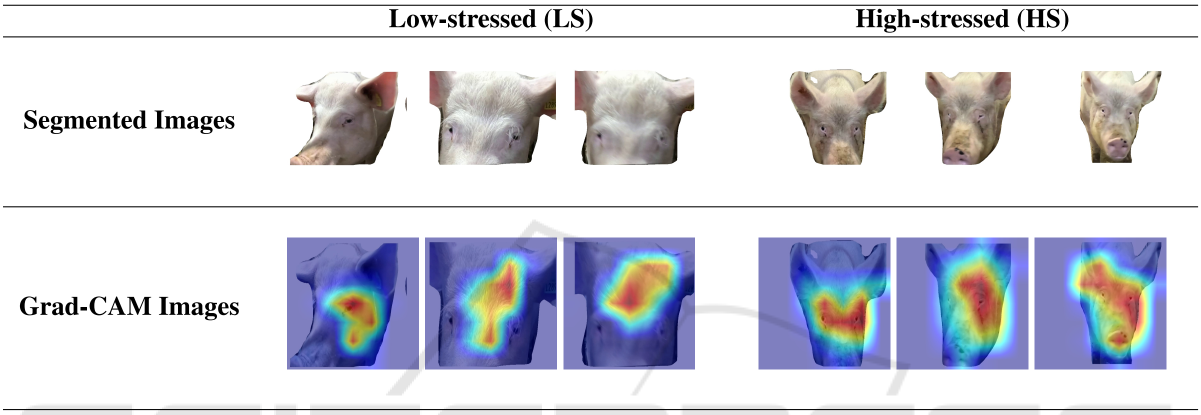


Figure 4: Grad-CAM visualizations of Low-Stressed (LS) and High-Stressed (HS) category sows using YOLO8l-cls model with segmented input images.

formance is reflected in Table 1, where LS class metrics are low (Precision: 0.26, Recall: 0.07, F1-Score: 0.11). The Cohen's Kappa of -0.10 and MCC of -0.20 further indicate weak agreement between predictions and ground truth, suggesting a significant bias toward the HS class.

The FT model, shown in Figure 3b, improves significantly, classifying 124 out of 150 LS sows correctly. This improvement is reflected in the increased precision (0.66), recall (0.83), and F1-Score (0.74) for the LS class. The MCC and Kappa values of 0.52 and 0.54, respectively, also indicate a more balanced classification performance.

The YOLO8l-cls model, shown in Figure 3c, demonstrates the best overall performance, achieving a balanced classification across stress classes. It correctly identifies 117 out of 150 LS sows and 106 out of 150 HS sows. The performance metrics are the highest among the models tested, with LS precision, recall, and F1-score of 0.73, 0.78, and 0.75, respectively, and HS values of 0.76, 0.51, and 0.61. MCC and Kappa values of 0.60 and 0.63 further support the model's reliability in predicting both stress categories more accurately.

The inclusion of MCC and Cohen's Kappa provides deeper insights into the models' abilities to balance precision and recall across classes. MCC values near zero or negative indicate poor agreement with ground truth, as seen in the original model's performance. The FT and YOLO8l-cls models, however, show positive MCC and Kappa values, reflecting better agreement and a reduced bias between stress classes.

Overall, the YOLO8l-cls model outperforms both the original and FT models, achieving the highest F1-Score (0.74) and the strongest Kappa (0.63). The Grad-CAM visualizations in Figure 4 further confirm the model's effectiveness in identifying stress-related regions in sow faces, highlighting key regions around the eyes and forehead. This comprehensive analysis emphasizes the importance of incorporating metrics like MCC and Cohen's Kappa in model evaluations for more accurate and balanced performance assessments.

5 CONCLUSIONS

This study investigated the use of deep learning (DL) models, particularly the YOLO8l-cls model, to classify stress levels in sows based on facial features in a realistic farming environment, aiming to improve animal welfare and reduce antimicrobial resistance (AMR) risks in pig farming. The results showed that the original pretrained model struggled to identify low-stressed (LS) sows in a real-world scenario due to its inability to capture subtle stress indicators, while fine-tuning improved performance. The YOLO8l-cls model exhibited the highest overall performance, with an F1-score of 0.74, Cohen's Kappa of 0.63, and MCC of 0.60, indicating stronger agreement and better generalization across both LS and high-stressed (HS) categories. Its ability to balance precision and recall and accurately identify subtle stress markers in the facial regions underscores its potential.

These findings highlight YOLO8l-cls as a practical tool for real-time monitoring of sow stress, enabling early intervention and improving health management in farming environments. The model's ability to detect stress markers, particularly in facial regions, demonstrates its relevance for enhancing animal welfare and addressing AMR concerns. However, the relatively small number of sows in this study limits the model's generalizability. Future work will focus on expanding the dataset, incorporating more diverse stress conditions, and testing the model on cross-generational data, including both parents and offspring, to explore the potential heritability of stress markers. Further research will also assess the model's scalability in larger farming environments to validate its reliability and applicability across different setups.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the financial support provided by the Joint Programming Initiative on Antimi-crobial Resistance (JPIAMR) for the FARM-CARE project, 'FARM interventions to Control Antimicrobial ResistancE - Full Stage' (ID: 7429446), and the Medical Research Council (MRC) for funding the UK part of the project (MRC research grant number: MR/W031264/1). This project is part of a collaboration between the University of the West of England, Scotland's Rural College, University of Copenhagen, Teagasc, University Hospital Bonn, Statens Serum Institut (SSI), and Porkcolombia Association.

REFERENCES

Alpaydin, K., Ucar, Y. S., and Devrim, M. E. (2020). Deep learning-based approaches for animal behavior analysis: A review. *Computers and Electronics in Agriculture*, 170.

Arjun, G. S. R. D. D., Mary, S. A., and Daniel, M. K. S. A. (2020). Antibiotic use in agriculture and its impact on antimicrobial resistance. *Environmental Science and Pollution Research*, 27(6):6021–6031.

Arriaga, S. D. R. M., Doe, J., and Smith, A. (2021). Machine learning techniques for fish behavior analysis. *Aquaculture Reports*, 20.

Bartolomé, E., Puigdueta, I., Guàrdia, M., Estevez, M., and Gomis, J. (2004). Effect of chronic transportation stress on welfare and meat quality of weaned piglets. *Meat Science*, 67(2):337–342.

Broom, D. (2011). Assessing welfare based on biological principles. *Journal of Agricultural and Environmental Ethics*, 24(1):215–227.

Dwyer, D. M. M., Ison, S. C., and Lawrence, S. A. (2000). The use of a food competition test to assess social rank in pigs. *Applied Animal Behaviour Science*, 66(4):297–308.

Hansen, M. F., Baxter, E. M., Rutherford, K. M. D., Futro, A., Smith, M. L., and Smith, L. N. (2021). Towards facial expression recognition for on-farm welfare assessment in pigs. *Agriculture*, 11(9):847.

He, K., Gkioxari, G., Dollár, P., and Girshick, R. (2017). Mask r-cnn. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 2961–2969. IEEE.

Janssens, C. J., Helmond, F. A., and Wiegant, V. M. (1995). The effect of chronic stress on plasma cortisol concentrations in cyclic female pigs depends on the time of day. *Domest. Anim. Endocrinol.*, 12(2):167–177.

Jong, I. C. D., Ekkel, E. D., Burgwal, J. A. V. D., Lambooij, E., Korte, S. M., Ruis, M. A., Koolhaas, J. M., and Blokhuis, H. J. (1998). Effects of strawbedding on physiological responses to stressors and behavior in growing pigs. *Physiol. Behav.*, 64(3):303–310.

Liu, X., Wu, H., Chen, S., and Li, H. (2020). Automatic recognition of stress in broiler chickens based on deep learning. *Sensors*, 20(15):4251.

Manteca, X. and Alonso, D. (2000). Stress and meat quality of pigs. *Livestock Production Science*, 65(2-3):239–248.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köp, A., Yang, E. Z., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S. (2019). Pytorch: An imperative style, high-performance deep learning library. *CoRR*, abs/1912.01703. [Online]. Available: http://arxiv.org/abs/1912.01703.

Ruijven, T. and Oliehoek, K. (2017). Prenatal stress and (neuro)epigenetic programming: Consequences for behavior and social development. *Neuroscience & Biobehavioral Reviews*, 80:604–616.

Ultralytics (2024). *YOLOv8 Classification*. [Online]. Available: https://docs.ultralytics.com/tasks/classify/.

Wang, H., Wu, S., and Zhang, Y. (2020a). Facial expression recognition for pig welfare assessment: A deep learning approach. *Animals*, 10(12):2261.

Wang, H., Zhang, S., and Li, T. (2020b). Facial expression recognition for pig welfare assessment: A deep learning approach. *Animals*, 10(12):2261.

Wechsler, B. (2000). The use of physiological measurements in the assessment of animal welfare. *Animal Welfare*, 9(2):203–210.

Weinstock, M. (2008). The long-term effects of prenatal stress on offspring. *Current Directions in Psychological Science*, 17(5):308–313.

Yang, J., Chen, X., and Zhao, F. (2020). Deep learning for identifying cattle behavior in dairy farms. *Computers and Electronics in Agriculture*, 173:105453.