***Application***This study introduces a depth-only deep learning system for bovine identification, enabling breed-agnostic monitoring, critical for precision livestock farming. We show that depth, as a biometric, can potentially broaden the real-world applicability of our coat-pattern based method to the majority of UK cattle breeds that lack distinctive coat patterns.  
  
***Introduction***In the dairy industry, monitoring individual cows is essential for improving farm productivity and managing disease outbreaks through contact tracing and social interactions. Individual identification allows tailored care and boosts production by enabling body condition scoring and yield monitoring. However, as herd sizes increase, the skewed cow-to-human ratio complicates manual monitoring tasks, therefore automated systems are in demand.

Traditional approaches to cattle identification, such as RFID tags, face financial and welfare challenges (Awad, 2016). Additionally, reliance on coat patterns limits the application our previous approach to certain cattle breeds, such as Holstein-Friesians (Andrew et al., 2023).

This study introduces a depth-only biometric identification system that uses commercial 3D depth cameras to address these limitations. This method uses body morphology as a biometric measure, overcoming the constraints of coat-pattern biometric. Deep learning architectures, including ResNet and PointNet, are employed to differentiate individuals using depth data, offering a scalable solution for real-world farm environments.

***Materials and Methods***The CowDepth2023 dataset consists of 21,490 synchronised dorsal view colour-depth image pairs from 99 Holstein-Friesian cows monitored over 14 days (Sharma et al., 2024). We used a Kinect V2 depth camera placed 4 meters above the ground. The camera recorded depth and RGB streams at 30 Hz. Depth maps were pre-processed to isolate individual cows through thresholding (2–3.4 meters range) and background subtraction. Images were manually annotated with identification labels through visual comparison with coat patterns. Depth maps were converted to 3D point clouds using camera, ensuring consistent mapping from pixel coordinates (u, v, z) to physical units (x, y, z). Point clouds were uniformly resampled to 2048 points using the farthest point sampling algorithm (Eldar et al., 1994).The ResNet-50 architecture was employed with a Spatial Context Module (SCM) to prioritise regions in depth maps. The model generated 128-dimensional embeddings representing individual identity. PointNet was used to process point clouds directly. The architecture employed Multi-Layer Perceptrons to create embeddings invariant to the order of input points.Metric learning was employed to train the models and differentiate between depth maps/point clouds of the different animals. The metric learning framework ensures that embedding formed clusters of examples belonging to the same individual while maintaining separation between other individuals. The CowDepth2023 dataset was split into training (70%), and testing (30%) sets for evaluation. Open-set validation removed temporal neighbours to simulate real-world variability. The k-Nearest Neighbours (kNN) algorithm was used to classify the embeddings to cow labels.

***Results***Model performance was quantified with classification accuracy and evaluated across five randomised splits. According to Table 1, the baseline ResNet model achieves a kNN mean accuracy of 99.88% with colour images of coat patterns. In comparison, our ResNet model with depth map as input performs similarly well on the test data, with only 0.05% less accuracy. Furthermore, including the SCM layer does not yield any significant improvement; in the case of colour images, the accuracy slightly increases by 0.03%, and decreases by 0.01% in the case of depth maps. The performance of PointNet model is sensitive to the number of input 3D points. Overall, both ResNet and PointNet models can generalise well on depth maps and point clouds, respectively, and exhibit performance that is comparable to models that use colour images of coat patterns.

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| **Table 1** kNN test accuracies for various models. For all the models arranged in rows, the third column reports the difference in accuracy from the best-performing baseline model – ResNet with SCM (colour). | | |
| **Model** | **Mean and range** | **Diff. from baseline** |
| ResNet-50 (Colour) | 99.88\%, (-0.13, +0.08) | -0.04 |
| ResNet-50-SCM (Colour) | **99.91\%, (-0.13, +0.06)** | 0.00 |
| ResNet-50 (Depth) | **99.83\%, (-0.17, +0.07)** | -0.08 |
| ResNet-50-SCM (Depth) | 99.82\%, (-0.19, +0.09) | -0.09 |
| PointNet (2048 points) | **99.09\%, (-0.70, +0.19)** | -0.82 |
| PointNet (64 points) | 87.58\%, (-1.64, +0.62) | -12.33 |

***Conclusions***

Utilizing depth data captured by 3D cameras, ResNet and PointNet architectures demonstrated high accuracy for individual identification. The proposed methodology leverages dorsal-view body morphology as a biometric measure, enabling identification for breeds lacking distinct coat patterns, which constitute a significant portion of cattle populations in the UK. This depth-only approach demonstrates practical potential for enhancing precision livestock farming and personalised animal welfare.

Future work will explore longitudinal studies to test the system's reliability over time, paving the way for more comprehensive applications in welfare monitoring.

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