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Research Paper

CKSP: Cross-species knowledge sharing and preserving for universal animal activity recognition

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ABSTRACT

Deep learning techniques are dominating automated animal activity recognition (AAR) tasks with wearable sensors due to their high performance on large-scale labelled data. However, current deep learning-based AAR models are trained solely on datasets of individual animal species, constraining their applicability in practice and performing poorly when training data are limited. In this study, a one-for-many framework is proposed, dubbed Cross-species Knowledge Sharing and Preserving (CKSP), based on sensor data from diverse animal species. Given the coexistence of generic and species-specific behavioural patterns among different species, a Shared-Preserved Convolution (SPConv) module is designed. This module assigns an individual low-rank convolutional layer to each species for extracting species-specific features and employs a shared full-rank convolutional layer to learn generic features. This enables the CKSP framework to learn inter-species complementarity and alleviates data limitations via increasing data diversity. Considering the training conflict arising from discrepancies in data distributions among species, a Species-specific Batch Normalisation (SBN) module is devised that involves multiple BN layers to separately fit the distributions of different species. To validate CKSP's effectiveness, experiments are performed on three public datasets from horses, sheep, and cattle, respectively. The results show that this approach remarkably boosts the classification performance compared to the baseline method (one-for-one framework) solely trained on individual-species data, with increments of 6.04 %, 2.06 %, and 3.66 % in accuracy, and 10.33 %, 3.67 %, and 7.90 % in F1-score for the horse, sheep, and cattle datasets, respectively. This proves the promising capabilities of the method in leveraging multi-species data to augment classification performance.

Science4Impact statement

Our research focuses on applying wearable sensors and deep learning techniques to monitor animal behaviour and welfare. Given the limitation of current deep learning-based AAR models, which are species-specific and struggle with scarce training data, this paper introduces a novel one-for-many framework. This framework is applicable for classifying behaviours across multiple animal species while mitigating data scarcity issues by leveraging cross-species information. Experimental results confirm its superior classification performance compared to species-specific models (one-for-one framework), particularly in scenarios with limited data for individual species. To our knowledge, we are the first to develop a universal AAR framework, along with solutions for learning shared and species-specific patterns among species, enhancing its practicality and ease of deployment. It also opens up a new perspective in addressing data limitation challenges by leveraging data diversity across multiple species. In summary, the

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proposed method offers benefits to animal welfare monitoring research, technology transfer endeavours, and directly aids farmers, consultants, and animal inspectors.

Nomenclature

Symbols	
A	A matrix that is initialised with random Gaussian values $\mathcal{N}(0, \sigma^2)$
B	A matrix that is initialised as zero
s	Animal species
W_{LR}	The original parameter tensor in the low-rank convolution layer
x^s	Feature maps of species s at a given layer
x_b^s	Feature map of the b-th sample within a batch of species s
x_o^s	The output of x^s fed into a low-rank convolution layer of species s
y_b^s	The output of x_b^s fed into a batch normalisation layer of species s
Greek symbols	
β^s	A moving variance in the batch normalisation layer of species s
γ^s	A moving mean in the batch normalisation layer of species s
$\mathcal{L}$	Overall loss function
$\mathcal{L}^s$	Class-balanced focal loss of species s
Abbreviations	
AAR	Animal Activity Recognition
BN	Batch Normalisation
CKSP	Cross-species Knowledge Sharing and Preserving
CNN	Convolutional Neural Network
FRConv	Full-Rank Convolution
LoRA	Low-Rank Adaptation
LRConv	Low-Rank Convolution
MLP	Multi-Layer Perceptron
RNN	Recurrent Neural Network
SBN	Species-specific Batch Normalisation
SPConv	Shared-Preserved Convolution

1. Introduction

Automated animal activity recognition (AAR) with wearable sensors empowers caretakers to continuously and remotely monitor behavioural variations in animals, considerably decreasing workloads and expenses in veterinary practices while enhancing the efficiency and sustainability of livestock management (Mao, Huang, et al., 2023). Wearable sensors are often incorporated into both research-oriented and commercial devices for specific applications, like the Whistle Fit (Chambers et al., 2021) and Ceres Tags (Wang et al., 2023). These devices are attached to various animal body parts, including necks, ears, and legs, to capture motion data like acceleration and angular velocity. These data are then processed and analysed using smart computing techniques to achieve accurate classification of animal behaviours, such as cattle grazing and walking (Arablouei, Wang, Currie, et al., 2023), Arablouei, Wang, Bishop-hurley, & Liu, 2023nd sheep scratching and resting (Kleanthous, Hussain, Khan, Sneddon, & Liatsis, 2022).

Currently, deep learning is dominating wearable sensor-aided AAR tasks owing to its exceptional feature extraction abilities, showcasing favourable performance in discriminating animal behaviours across a wide range of scenarios (Kleanthous, Hussain, Khan, Sneddon, Al-Shamma'a, et al., 2022; Riaboff et al., 2022). Arablouei et al. (2021) examined the application of a multilayer perceptron (MLP) in cattle behaviour recognition, achieving a higher accuracy of 93.4 % than several machine learning methods, such as support vector machines. Their developed MLP model was subsequently utilised in further research, consistently exhibiting promising results (Arablouei, Wang, Currie, et al., 2023, Arablouei, Wang, Bishop-hurley, & Liu, 2023). Convolutional neural networks (CNNs), as the most commonly applied method in AAR tasks, have achieved high accuracies, often exceeding 90 %, attributed primarily to their capabilities to capture local temporal dependencies and exhibit scale invariance (Mao et al., 2023). Furthermore, recent studies have explored combining CNNs with recurrent neural networks (RNNs) for classifying animal behaviours using sensor data, with the hybrid models tending to exhibit desirable performance than pure CNN- and RNN-based models (Liseune et al., 2021; Wang et al., 2023).

Despite the satisfactory performance, current deep learning-based AAR methods (Arablouei, Wang, Currie, et al., 2023; Riaboff et al., 2022; Wang et al., 2023) still have the following issues. (1) These approaches are generally trained on datasets of individual animal species. This greatly constrains their applicability in real-world scenarios, as they cannot be directly applied to different species due to data discrepancy (e.g., different sampling rates over identical time spans or distinct movement patterns). Meanwhile, designing and training unique models for each species is time-consuming and also leads to inconvenience for deployment. (2) The exceptional performance of deep learning-based methods normally hinges on the availability of large-scale, labelled training data. However, the availability of datasets for some species is sometimes constrained by some inevitable factors, such as the laborious and time-consuming labelling process, insufficient animal objects and collection difficulty, among others. Insufficient training data results in weak feature representation ability, inferior generalisation performance, or even optimisation failure (Li, Tokgoz, et al., 2021). Therefore, existing one-for-one models are not promising solutions for the AAR task.

An intuitive idea to avoid the above issues is developing a universal AAR framework that is applicable to various animal species. However, to guarantee that this one-for-many framework can outperform existing one-for-one models, two goals need to be achieved: seeking common ground and reserving differences between behaviours of different species. Firstly, some behaviours of different species demonstrate similarities in motion patterns, e.g., grazing for sheep and cattle and standing for all species (Arnold, 1984; Patkowski et al., 2019; Pluta et al., 2013). When the training samples of one class for a species are limited or the diversity of training data for a species is poor, the hypothesis is that constructing multi-species training datasets can improve data quality by sharing similar behaviour patterns (common ground) among various species, thereby boosting the performance of a universal AAR framework. Secondly, inherent differences in behaviours between different species, primarily manifested in distinct movement patterns and divergent feature distributions, inevitably pose challenges to the stable training of a universal framework. Inter-species variation in motion patterns affects a universal AAR framework in capturing invariant features across different species while hindering model convergence. Distinct distributions among species also make it challenging to learn universal global statistical measures, which contradicts the assertion that neural networks' high performance typically depends on a well-normalised data distribution (Wang et al., 2019). Hence, exploring a practical solution that simultaneously exploits cross-species behavioural similarities and preserves their unique characteristics becomes imperative.

In this study, a universal AAR framework is proposed, dubbed Cross-species Knowledge Sharing and Preserving (CKSP), based on sensor data across diverse animal species. Essentially, the CKSP is versatile, being applicable to different species with distinct interested behaviours. It primarily aims to capture common behavioural patterns across species while preserving species-specific characteristics, enabling effective recognition of diverse behaviours without retraining. The proposed CKSP is designed to be versatile and generalisable, providing a foundational approach that mitigates the limitations of single-species models.

2. Theory and method formulation

The proposed Cross-species Knowledge Sharing and Preserving (CKSP) method aims to develop a universal AAR framework based on multi-species sensor datasets, and such a framework is broadly applicable to different species while tackling the data limitation challenge typically encountered when relying solely on individual species data. Fig. 1 illustrates the overall workflow of the CKSP framework, mainly encompassing three parts, i.e., data preprocessing, feature extraction,

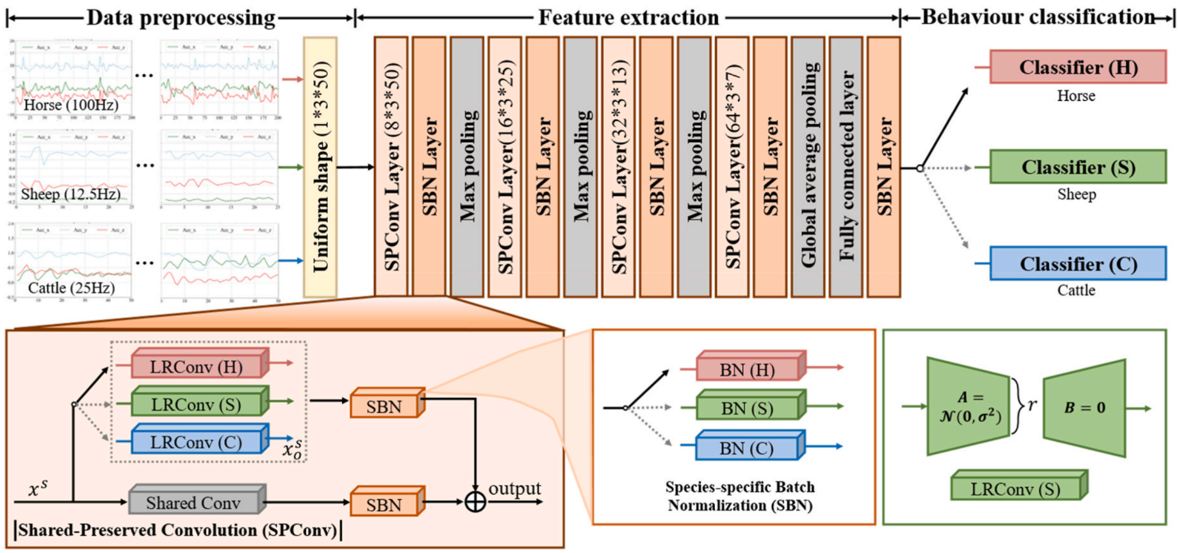


Fig. 1. The overall workflow of the Cross-species Knowledge Sharing and Preserving (CKSP) framework, which consists of data preprocessing, feature extraction, and behavioural classification. Herein, "H", "S", and "C" denote horse, sheep, and cattle, respectively.

and behavioural classification.

2.1. Data preprocessing

Data from diverse species will initially undergo preprocessing prior to being input into the network for feature extraction. In addition, the data dimensions of different farms or institutions are normally inconsistent due to various settings (e.g., different sampling rates over identical time spans). This directly affects the feature learning capability and generalisation of classification models, particularly those based on CNN-based models with fixed kernel sizes. To tackle this issue, the input dimensions across species are adjusted to equal sizes. Herein, an example of a multi-species dataset is taken with 2-s signal samples, sampled at 12.5 Hz for sheep, 25 Hz for cattle, and 100 Hz for horses. This results in input sizes of $1 \times 3 \times 25$, $1 \times 3 \times 50$, and $1 \times 3 \times 200$, respectively. Given the balance between performance and resource consumption, a 25 Hz sampling rate is commonly adopted, as supported by recent research (Eerdekens et al., 2021;Kleanthous, Hussain, Khan, Sneddon, Al-Shamma'a, et al., 2022; Riaboff et al., 2022). Therefore, these 2-s inputs are standardised to a size of $1 \times 3 \times 50$, akin to 25 Hz sampled data, by exploiting the bilinear-neighbour interpolation technique (Thévenaz et al., 2000). Afterwards, these unified data are imported into the network for further feature extraction.

2.2. Shared and preserved feature extraction

The feature extraction phase within the proposed CKSP framework comprises convolutional layers, batch normalisation layers, max-pooling layers, global average-pooling layers, and fully connected layers, as shown in Fig. 1. Typically, different species exhibit common characteristics yet possess distinct movement patterns and divergent feature distributions. Inter-species discrepancies in movement patterns hinder conventional networks' efficiency in discerning invariant features across species, accompanied by slow convergence. Additionally, inconsistent feature distributions challenge the derivation of universal statistical measures applicable to multiple species. To tackle these challenges, a novel feature learning methodology, comprised of a Shared-Preserved Convolution (SPConv) module and a Species-specific Batch Normalisation (SBN) module, is introduced, as presented in Fig. 1. In the SPConv module, individual convolutional layers are dedicated to each species to extract species-specific features, complemented by a shared full-rank convolutional layer that learns generic movement patterns. Following the convolutional operation, the SBN module is strategically integrated to separately fit the distributions of different species, thereby augmenting the model's adaptability to inter-species variation. The SPConv module and SBN module are detailed as follows.

2.2.1. Shared-Preserved Convolution (SPConv) module

In recent years, the practice of fine-tuning large language models has garnered growing attention due to their remarkable capability of extracting task-specific features from individual task datasets while preserving the general knowledge acquired from extensive pre-training on large data corpora (Malladi et al., 2023). Considering the substantial computational burden associated with directly fine-tuning large parameter sets, Low-Rank Adaptation (LoRA) has been proposed to mitigate this issue by incorporating a low-rank parameter matrix branch, significantly reducing parameter size while effectively acquiring task-specific features (Hu et al., 2022). It enables the acquisition of domain-specific knowledge through a trainable low-rank parameter matrix, while the pre-trained full-rank parameter matrix remains fixed to preserve general knowledge.

The LoRA technique in large language model fine-tuning aligns closely with the objectives of this study in two aspects: the pre-trained model's function parallels this network's shared feature extraction, and the branch of low-rank parameter matrix during fine-tuning aligns with capturing species-specific information in the proposed architecture (Sun et al., 2024). Inspired by this insight, a Shared-Preserved Convolution (SPConv) module is proposed with dual branches: one employs a shared full-rank convolutional layer to distil shared generic features, while the other assigns individual low-rank convolutional layers to each species for the extraction of species-specific features, as shown in Fig. 1.

Let $x^s \in R^{c \times h \times w}$ represents the feature representation of species s at a given layer, where c, h, and w denote the channel number and spatial dimensions, respectively. x^s is input into a shared full-rank convolutional layer with a 1×3 kernel to learn shared general features. Meanwhile, x^s is fed into a Low-Rank Convolution (LRConv) layer to obtain personalised features of species s, yielding $x_o^s \in R^{c' \times h' \times w'}$. Different to a traditional 1×3 convolution operation, LRConv decomposes the original parameter tensor W_{LR} of size $c' \times 3 \times 1 \times c$ into two parameter matrices: $B \in R^{(c' \times 3) \times r}$ and $A \in R^{r \times (1 \times c)}$, where r denotes the low-rank value. Therefore, the LRConv operation can be formulated as:

$$x_o^s = W_{LR} x^s = R(BA) x^s, \tag{1}$$

where BA denotes a matrix of dimensions $(c' \times 3) \times (1 \times c)$, and $R(BA)$ refers to reshaping matrix BA into the form of $c' \times 3 \times 1 \times c$. Matrix A is initialised with random Gaussian values $\mathscr{N}(0, \sigma^2)$ and B is initialised as zero, implying $W_{LR} = R(BA)$ is initially set to zero during training.

Notably, unlike the LoRA technique of starting with pre-trained general knowledge, this proposed method concurrently trains both shared and species-specific convolutional parameters from scratch.

2.2.2. Species-specific Batch Normalisation (SBN) module

Batch Normalisation (BN) has been used for mitigating internal covariate shifts and enhancing feature discriminability while accelerating the learning process (Ioffe & Szegedy, 2015). It typically operates within a batch, normalising the values across each channel by adjusting them to have zero mean and unit variance across the entire batch. Following this normalisation, an affine transformation, parameterised by trainable parameters $[\gamma,\beta]$, is imposed on the normalised feature maps. During the training process, the BN layer is able to capture global statistics measures – a moving mean and a moving variance – which are later fixed and utilised to normalise features in the testing phase, ensuring stable performance.

The efficacy of BN operations in prevailing studies largely relies on the assumption that training data originates from the same species and follows a uniform distribution. However, the data collected from diverse animal species in this study exhibits distinct movement patterns, thereby posing a challenge to acquiring universal global statistical measures that are viable across various species. As illustrated in Fig. 2, species-specific global statistics obtained from the BN layers of networks separately trained on data from each species (e.g., horse, sheep, and cattle) are visualised. It can be observed that these statistics display notable discrepancies between different species, particularly in the deeper layers that contain more discriminative and semantically rich features. Directly aggregating these data with inherent statistical variations for joint training inevitably imposes difficulties on the network to learn generic features and impedes model convergence. In addition, the shared statistical parameters, as learned, inadequately mirror the feature distribution of individual species, thereby undermining the classification performance of models during the testing phase across diverse species.

To address the aforementioned issue, motivated by the efficacy of employing separate BN layers in handling data heterogeneity from diverse origins (Li, Jiang, et al., 2021; Liu et al., 2020), a Species-specific Batch Normalisation (SBN) module is designed. The SBN module assigns an individual BN layer for each species and is incorporated subsequent to each convolutional or fully connected layer. Specifically, the SBN module sets each animal species s with respective trainable variables $[\gamma^s, \beta^s]$. Let $x_b^s \in [x_1^s, \ldots, x_B^s]$ represent the feature map of the b-th sample within a batch of species s for a certain channel at a given layer, such that the corresponding output y_b^s can be formulated as:

$$y_b^s = \gamma^s \cdot \widetilde{x}_b^s + \beta^s, \text{with } \widetilde{x}_b^s = \frac{x_b^s - E[x_b^s]}{\sqrt{Var[x_b^s] + \epsilon}}. \tag{2}$$

The learned global statistics $[\gamma^s,\beta^s]$, i.e., the moving mean and moving variance, are then utilised to normalise features extracted from the test data pertaining to species s. Through individual feature normalisation, the model is capable of learning precise statistics tailored to each species, which in turn accelerates convergence and boosts the model's classification capabilities. Herein, the standard shared convolutional layer and BN layer is substituted with the proposed SPConv and SBN modules in all layers except the initial one. This is based on the findings that shallower layers typically concentrate on generic feature extraction (Lang et al., 2022), and the initial layer exhibits less pronounced differences in feature distributions among species (Fig. 2).

2.3. Behavioural classification

Considering the behavioural disparities among different animal species, to enhance the applicability of models across various species, species-specific classifiers are appended following the feature extraction stage. As presented in Fig. 1, for each animal species, a separate classifier comprised of a single fully connected layer is adopted. Class-balanced focal loss is applied as the loss function, which has been validated in addressing class imbalance problems (Cui et al., 2019; Mao et al., 2021). To guarantee the model remains unbiased towards any one species and can concurrently learn knowledge from distinct species, data are evenly distributed from various species within each batch during the training process. Hence, the overall loss function can be formulated as the average of losses across all S species:

$$\mathscr{L} = \frac{\sum_{s=1}^{S} \mathscr{L}^s}{S}, \tag{3}$$

where $\mathscr{L}^s$ denotes the class-balanced focal loss of species s.

Utilising the loss in Eq. (3), the proposed CKSP framework can enhance the classification performance for individual species and flexibly accommodate diverse behavioural categories across different species.

3. Materials and methods

3.1. Datasets

The proposed CKSP is evaluated by utilising three publicly available datasets collected from horses (Kamminga, Janßen, et al., 2019), sheep (Kleanthous, Hussain, Khan, Sneddon, & Liatsis, 2022) and cattle (Li, Tokgoz, et al., 2021), respectively. The specifics are summarised in Table 1.

Horse dataset. The horse dataset encompasses 87,621 2-s samples, acquired from six horses using neck-attached inertial measurement units

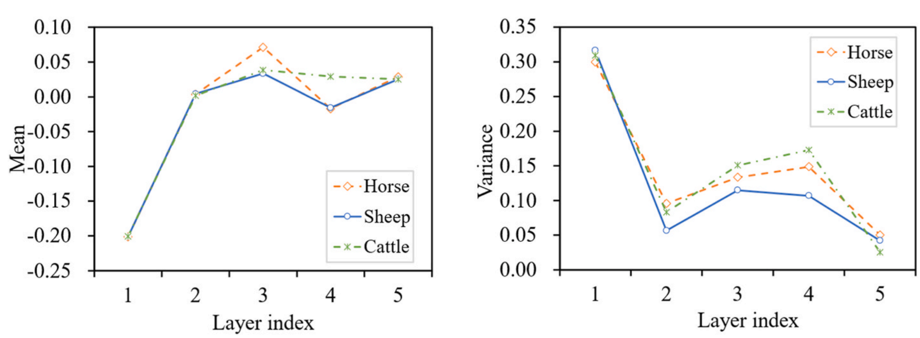


Fig. 2. The moving mean and variance derived from the classification model trained exclusively on single-species data. These values represent the layer-wise averages of the batch normalisation statistics.

Table 1
Illustration of datasets collected from cattle, horses, and sheep.

Dataset	Animal count	Sampling rate	Activity	Number of 2-s samples	Reference
Horse	6	100	Grazing, galloping, standing, trotting, and walking	87,621	(Kamminga et al., 2019)
Sheep	9	12.5	Grazing, active (walking and scratching), and inactive (standing and resting)	149,725	(Kleanthous et al., 2022)
Cattle	6	25	Grazing, moving, resting, ruminating, and salting	10,429	(Li, Tokgoz, et al., 2021)

with a sampling rate of 100 Hz. Based on existing studies on horse behaviour recognition (Kamminga et al., 2019; Mao, Zhu, et al., 2023), five extensively labelled activities are considered, including grazing, galloping, standing, trotting, and walking, with percentages of 18.31 %, 4.50 %, 5.84 %, 28.62 %, and 42.73 %, respectively. Triaxial accelerometer measurements are employed, resulting in a tensor shape of $1 \times 3 \times 200$ for each 2-s sample.

Sheep dataset. The sheep dataset consists of 149,725 2-s motion data collected from nine sheep using neck-attached accelerometers with a sampling rate of 12.5 Hz. Five activities, including grazing, walking, scratching, standing, and resting, are contained and merged into three main unified behaviours, i.e., grazing, active (including walking and scratching), and inactive (including standing and resting), with percentages of 19.74 %, 15.53 %, and 64.73 %, respectively. The triaxial accelerometer data constructs a tensor of dimensions $1 \times 3 \times 25$ for each sample.

Cattle dataset. The cattle dataset is collected from six different Japanese black beef cows using neck-attached accelerometers with a sampling rate of 25 Hz. Based on existing studies on cattle behaviour recognition (Arablouei, Wang, Currie, et al., 2023; C. Li, Jiang, et al., 2021; Minati et al., 2023), five frequent cattle behaviours are considered, including grazing, ruminating, resting, moving, and salting, with percentages of 6.10 %, 19.32 %, 54.25 %, 16.29 %, and 4.04 %, respectively. The dataset contains a total of 10,429 2-s data samples, with each sample comprising triaxial accelerometer data structured as a tensor of $1 \times 3 \times 50$.

3.2. Experimental setup

To evaluate the proposed CKSP, it was contrasted directly with a baseline model (Single-Net), which is trained exclusively on data from individual species. The architecture of the Single-Net follows the single-modality network proposed in a previous study (Mao et al., 2021), which has been validated for recognising the activities of horses and goats (Mao et al., 2021, 2023b). To assess the contributions of the SPConv and SBN modules, the CKSP with and without each module was tested and compared. Within SPConv, the LRConv operation employs low-rank decomposition to adapt species-specific convolution while reducing parameters. To examine its advantage, we compared the CKSP using LRConv layers against a variant with full-rank convolution (FRConv) layers. Furthermore, by leveraging multi-species datasets, CKSP aims to establish a universal AAR framework capable of capturing broader movement patterns across species, thereby mitigating performance degradation due to limited single-species samples. To validate its effectiveness under data scarcity, we compared the Single-Net and CKSP across reduced dataset sizes (75 %, 50 %, 25 %, and 10 % of the original data).

Precision, recall, F1-score, and accuracy were used as evaluation metrics to gauge the overall performance of the classification network. Generalisation capability was evaluated through a stratified 5-fold cross-validation strategy, where samples were divided into three, one, and one fold for training, validation, and testing datasets, respectively. To ensure that the model remains unbiased towards any individual species and demonstrates the approach's effectiveness under limited data scenarios, the training data for each species was downsampled to match the size of the smallest dataset. These balanced data were subsequently combined to train the model, ensuring that each training batch contained a uniform number of samples from every species.

To further assess the generalisation capability of the CKSP across individual animals, we conducted comparative tests between CKSP and the Single-Net using a subject-independent evaluation protocol. For horses and cattle, data from one individual was reserved for testing, data from another for validation, and the remaining four individuals were used for training, ensuring no overlap between training and inference stages. This procedure was repeated three times, each time with a different individual assigned to the test set. Since the sheep dataset lacks individual identification, it was randomly partitioned into training (70 %), validation (10 %), and test (20 %) sets. The experiments were also repeated three times, and results from all trials were averaged to ensure robustness. Notably, the training data for each species were also downsampled to match the size of the smallest species dataset, thereby mitigating potential model bias.

During the training, L_2 regularisation with a weight decay of 0.06 was applied to the loss function to mitigate overfitting. An Adam optimiser was used with an initial learning rate of 1×10^{-4} and a reduction factor of 0.1 every 20 epochs. The training ran for 100 epochs with a batch size of 256. The model achieving the highest validation accuracy was saved and evaluated on the test set for verification. All tests were performed utilising the PyTorch platform on an NVIDIA GeForce RTX 2080 graphics processing unit. The source code is available at https://github.com/Max-1234-hub/CKSP.

4. Results and discussion

4.1. Performance comparisons with the baseline method

The comparative performance between the Single-Net and CKSP method are presented in Fig. 3. It revealed that the proposed CKSP exhibited promising performance, achieving accuracies of 96.44 %, 92.89 %, 90.01 % on the horse, sheep, and cattle datasets respectively, accompanied by F1-scores of 96.02 %, 86.79 %, and 88.40 %, precision values of 95.07 %, 87.39 %, and 85.76 %, and recall values of 97.03 %, 86.59 %, and 91.60 % on the respective datasets. The CKSP outperformed the Single-Net in terms of all evaluation metrics, with increments of 6.04 %, 2.06 %, and 3.66 % in accuracy, 10.33 %, 3.67 %, and 7.90 % in F1-score, 12.46 %, 3.87 %, and 8.96 % in precision, and 6.24 %, 3.66 %, and 4.03 % in recall for the horse, sheep, and cattle datasets, respectively. This demonstrated the promising capabilities of the proposed method in leveraging multi-species data to augment classification performance.

Fig. 4 illustrates the recall confusion matrices for the Single-Net and CKSP method, revealing the latter's notable potential to improve classification accuracy across diverse activity categories. Specifically, recall represents the percentage of correctly classified samples. Compared to the Single-Net (Fig. 4a), the proposed CKSP method (Fig. 4b) significantly elevated recall values for nearly all activities, demonstrating varying degrees of increment. In particular, the CKSP method elevated the recognition accuracy for various horse behaviours above 95 %, and for cattle, around 90 % or even higher. Even though the classification accuracy for sheep activities, including grazing and active, was less than desirable, the CKSP method managed to enhance the classification of these activities by 6.68 % and 4.18 %, respectively. It can be observed

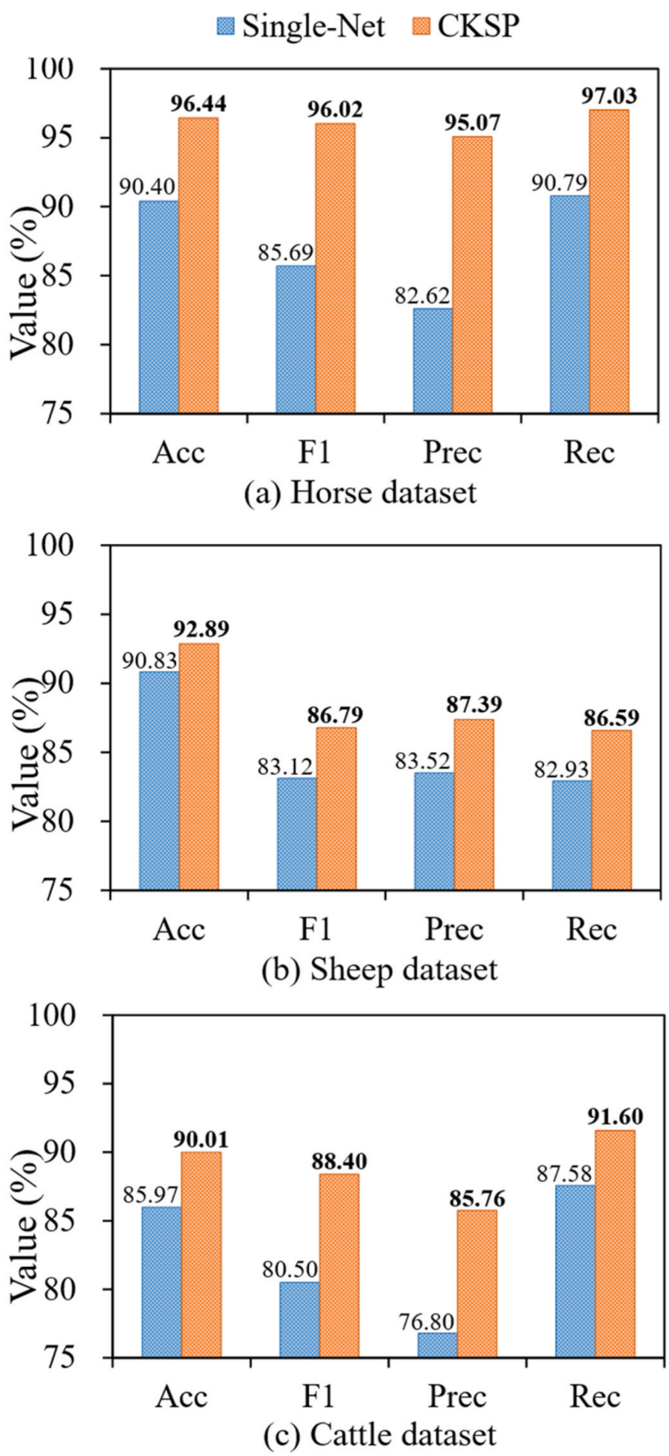


Fig. 3. Comparison results of the proposed CKSP with the Single-Net on the horse (a), sheep (b), and cattle (c) datasets. Herein, "Acc", "F1", "Prec", and "Rec" denote accuracy, F1-score, precision, and recall, respectively.

that grazing and active behaviours in sheep were prone to misclassification with one another, aligning with the findings on sheep activity recognition reported in Kleanthous, Hussain, Khan, Sneddon, and Liatsis (2022). This might be accounted for by the similarity in movements exhibited during grazing and active behaviours in sheep in some cases. Thus, exploring potential solutions to alleviate the impact of activity similarities on classification performance deserves attention in forthcoming studies.

4.2. Ablation studies

4.2.1. Evaluation of SPConv and SBN modules

Table 2 summarises the performance of CKSP with and without SPConv and/or SBN modules across the three datasets. We can see that the CKSP without both modules, i.e., directly sharing feature extraction parameters across distinct animal species, yielded inferior results. Conversely, the integration of the SBN module enabled the CKSP method to obtain premium performance with different degrees of improvement, implying the critical importance of fitting species-specific feature distributions for different species. Notably, including the SPConv module alongside the SBN module yielded additional enhancements to classification performance, evidenced by accuracy increments of 8.67 %, 2.02 %, 11.64 %; F1-score gains of 13.69 %, 3.66 %, 19.79 %; precision boosts of 15.84 %, 3.93 %, 17.26 %; and recall increases of 7.13 %, 3.74 %, 11.93 % for the horse, sheep, and cattle datasets, respectively. This confirms the earlier assertion that a combination of shared and personalised learning parameters is necessary, given the coexistence of both generic and species-specific behavioural patterns across different species. However, the exclusive use of the SPConv module without the SBN module resulted in diminished performance, potentially due to the conflicting nature of learning species-specific parameters while still assuming a shared feature distribution.

Fig. 5 displays the training and validation accuracy curves across three distinct species for models configured without and with the combined utilisation of SPConv and SBN modules. The CKSP method, when equipped with both SPConv and SBN modules, converged faster and exhibited a smoother training trajectory compared to the configuration lacking these modules. This reflects that CKSP could effectively mitigate data heterogeneity and expedite convergence by extracting robust representations from multi-species data.

4.2.2. Analysis of the SPConv module

The performance of the CKSP framework when equipped with LRConv versus FRConv layers is illustrated in Table 3. It was obvious that the CKSP employing LRConv layers demonstrated superior performance compared to the version utilising FRConv layers, regardless of the varied values of r (2–16). This evidenced the efficacy of the implemented LRConv layers in enhancing performance. Moreover, the total parameter count within the species-specific branches adopting LRConv layers was smaller than those using FRConv layers, highlighting the additional advantage of employing LRConv layers in terms of efficiency. Table 3 also presents the performance of the CKSP method with varying r values (i.e., 2, 4, 8, 12, and 16). When r is set to 12, the CKSP attained the highest values across all evaluation metrics for horse and cattle behaviour classification and demonstrated favourable performance in classifying sheep behaviours. This underscores the potential advantage of judiciously selecting the value of r for enhancing the overall classification performance.

4.3. Robustness against variations in dataset size

To validate the classification ability of the CKSP approach under the context of data limitation, Fig. 6 presents the comparative classification performance between the Single-Net and CKSP over varying percentages (i.e., 75 %, 50 %, 25 %, and 10 %) of the original dataset. The CKSP exhibited remarkable stability in classifying horse and sheep behaviours, and the improvement margin it gained over the Single-Net increased as the dataset size decreased. The findings indicate the robustness of the CKSP method, and it effectively benefited from the diversity of multi-species datasets, particularly in scenarios characterised by data scarcity. The CKSP method's performance in cattle classification consistently echoed the trends observed in the preceding species (horse and sheep) as the dataset shrank from 100 % to 25 %. Despite a conspicuous drop in data percentage to 10 %, it persistently surpassed the Single-Net's performance. This phenomenon might be

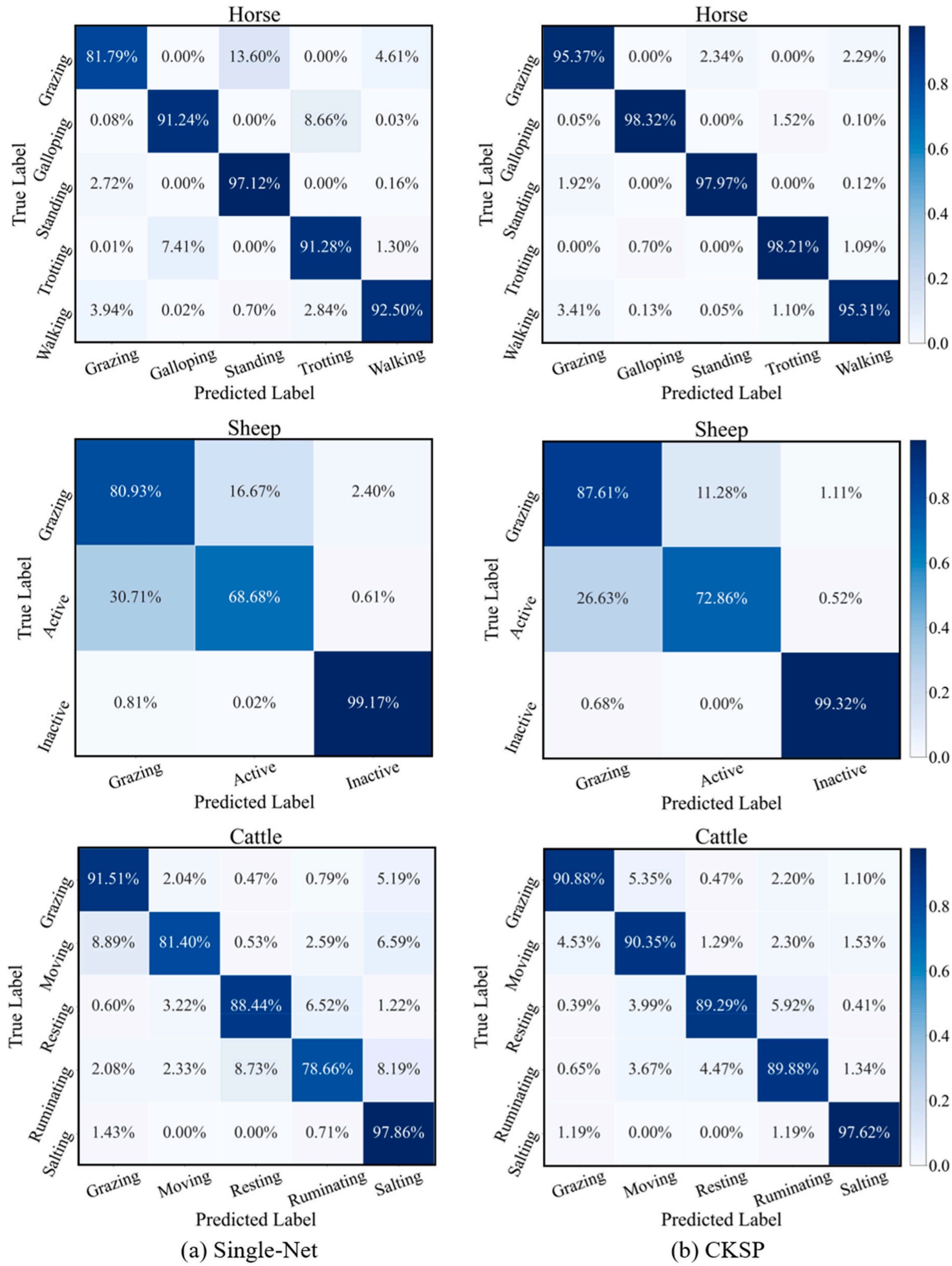


Fig. 4. Confusion matrices of the Single-Net (a) and CKSP (b) on the horse, sheep, and cattle dataset.

attributed to certain behaviours unique to cattle, i.e., ruminating and salting. When the sample size decreased to a certain threshold, even aggregating data from diverse species did not sufficiently augment the diversity of these specific behaviours, thereby imposing limitations on performance improvement.

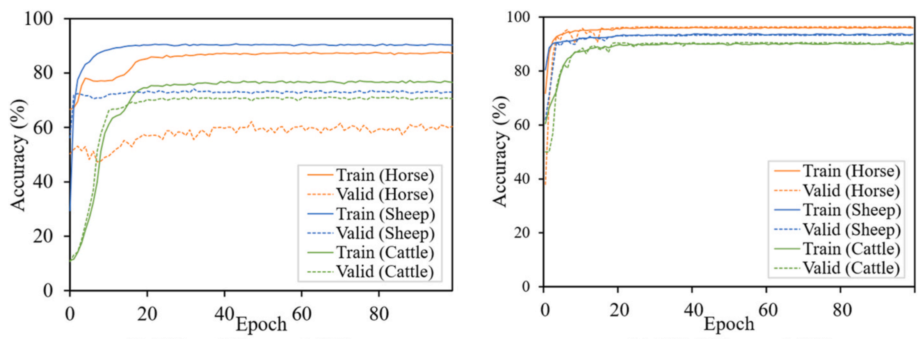
4.4. *Visualisation*

To bolster the interpretability of the CKSP framework and to gain insights into which parts of the input data contributed most to the model's predictions, saliency maps for various behaviours across three animal species are presented in Fig. 7. These saliency maps underscore

Table 2
Ablation results of the proposed CSKP framework, assessing its performance with and without SPConv and/or SBN modules.

Configurations		Horse				Sheep				Cattle			
SPConv	SBN	Acc (%)	F1 (%)	Prec (%)	Rec (%)	Acc (%)	F1 (%)	Prec (%)	Rec (%)	Acc (%)	F1 (%)	Prec (%)	Rec (%)
		61.16	67.59	75.91	70.44	73.51	52.92	70.10	50.15	71.52	60.53	68.88	69.79
√		76.97	62.32	63.92	67.85	60.60	49.23	61.68	56.51	63.77	41.19	48.15	46.53
	√	87.77	82.33	79.23	89.90	90.87	83.13	83.46	82.85	78.37	68.61	68.50	79.67
√	√	**96.44***	**96.02**	**95.07**	**97.03**	**92.89**	**86.79**	**87.39**	**86.59**	**90.01**	**88.40**	**85.76**	**91.60**

Acc: accuracy; F1: F1-score; Prec: precision; Rec: recall. * The best result for each metric is highlighted in bold.



(a) Without SPConv and SBN (b) With SPConv and SBN

Fig. 5. The training and validation accuracy over three different animal species under the CKSP without (a) and with (b) both the SPConv and SBN modules.

Table 3
Experimental results comparing CKSP integrated with full-rank convolution (FRConv) layer and low-rank convolution (LRConv) layers across different *r* values.

SPConv		Horse				Sheep				Cattle			
		Acc[#] (%)	F1 (%)	Prec (%)	Rec (%)	Acc (%)	F1 (%)	Prec (%)	Rec (%)	Acc (%)	F1 (%)	Prec (%)	Rec (%)
FRConv		93.07	89.92	87.16	94.03	90.72	82.71	83.07	82.61	84.76	78.40	75.17	85.48
LRConv	$r = 2$	94.26	92.35	90.09	95.23	91.79	84.73	85.22	84.55	87.70	84.46	80.94	89.38
	$r = 4$	95.40	94.16	92.41	96.21	92.44	86.05	86.40	85.96	88.91	86.28	82.92	90.61
	$r = 8$	95.79	95.20	93.83	96.71	92.80	86.61	87.24	86.40	89.26	87.87	85.05	91.43
	$r = 12$	**96.44***	**96.02**	**95.07**	**97.03**	92.89	86.79	87.39	86.59	**90.01**	**88.40**	**85.76**	**91.60**
	$r = 16$	95.23	95.08	93.77	96.59	**92.96**	**86.90**	**87.45**	**86.68**	89.04	87.41	84.38	91.22

Acc: accuracy; F1: F1-score; Prec: precision; Rec: recall. * The best result for each metric is highlighted in bold.

the critical regions within the input data along both temporal and axis dimensions, which were pivotal for behavioural classification. As observed in the left column of Fig. 7, the overall trend of contribution aligned with the periodicity of dynamic behaviours (e.g., trotting and active) along the temporal dimension. Conversely, the right column of Fig. 7 reveals that the contribution typically resided along two principal axes among static behaviours (e.g., grazing and resting). Specifically, the contributions from grazing behaviours of both horses and sheep exhibited a similar trend, that is, predominantly relying on the information from the “x” and “z” axes. These observations further substantiate the effectiveness of the proposed CKSP framework in distinguishing behaviours.

4.5. Generalisation capability

The generalisation performance of the Single-Net and CKSP across different individual animals was reported in Table 4. Notably, the CKSP framework achieved superior generalisation performance compared to Single-Net when evaluated on unseen individuals across all three animal species. These results further validate the effectiveness of the CKSP approach in enhancing classification performance through cross-species knowledge transfer.

4.6. Limitations and implications

The proposed CKSP approach can be applied to diverse species while mitigating the challenge of data limitation by learning cross-species features. Nevertheless, the efficacy of enhancing diversity through aggregating multi-species datasets typically hinges on the prerequisite that two or more species have comparable behavioural categories. To this point, a universal and standardised dictionary of behaviours still needs to be established through extensive research and field studies, with each behaviour being linked to animal health and well-being. This dictionary will serve as a reference for future researchers, who are encouraged to collect data based on their areas of interest within this dictionary and, where possible, strive for data openness. This collaborative endeavour paves the way for developing a large AAR model grounded in a universal database, laying a robust foundation for upcoming advancements.

The current challenge resides in discerning inter-activity similarity, where distinct animal behaviours exhibit similar characteristics or movement patterns (Mao, Huang, et al., 2023). This hinders deep learning models from extracting discriminative features that uniquely identify activities, leading to confusion in classifying them (Chen et al., 2021), as evidenced by the challenge of differentiating sheep grazing from active behaviour in this study. Hence, the next step to refine classification accuracy for similar activities involves exploring viable approaches, such as fine-grained activity recognition (De et al., 2015),

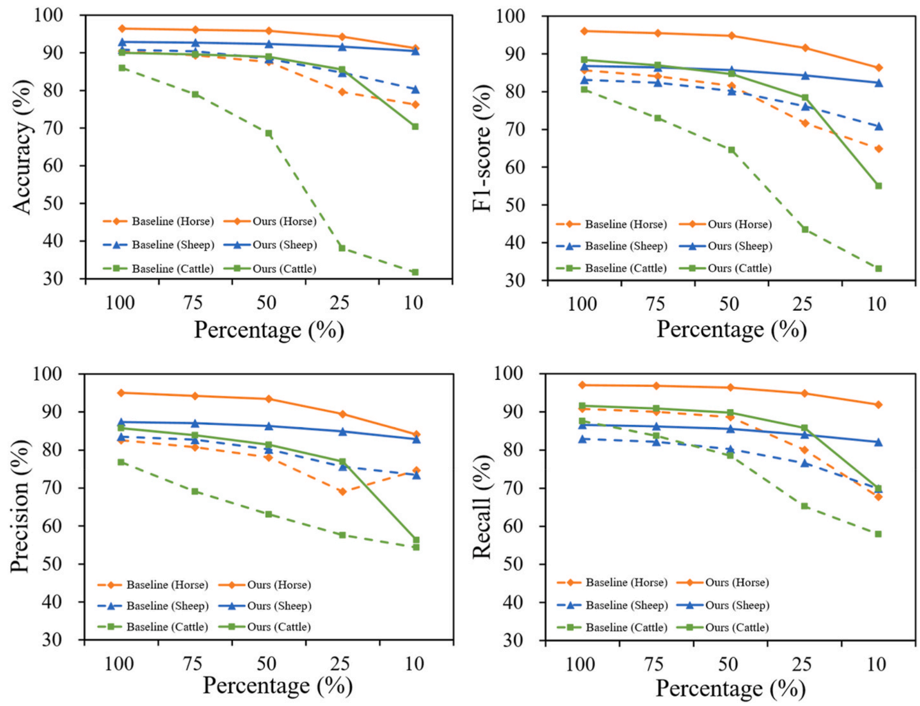


Fig. 6. Classification performance of the Single-Net and our CKSP approach over varying data sizes.

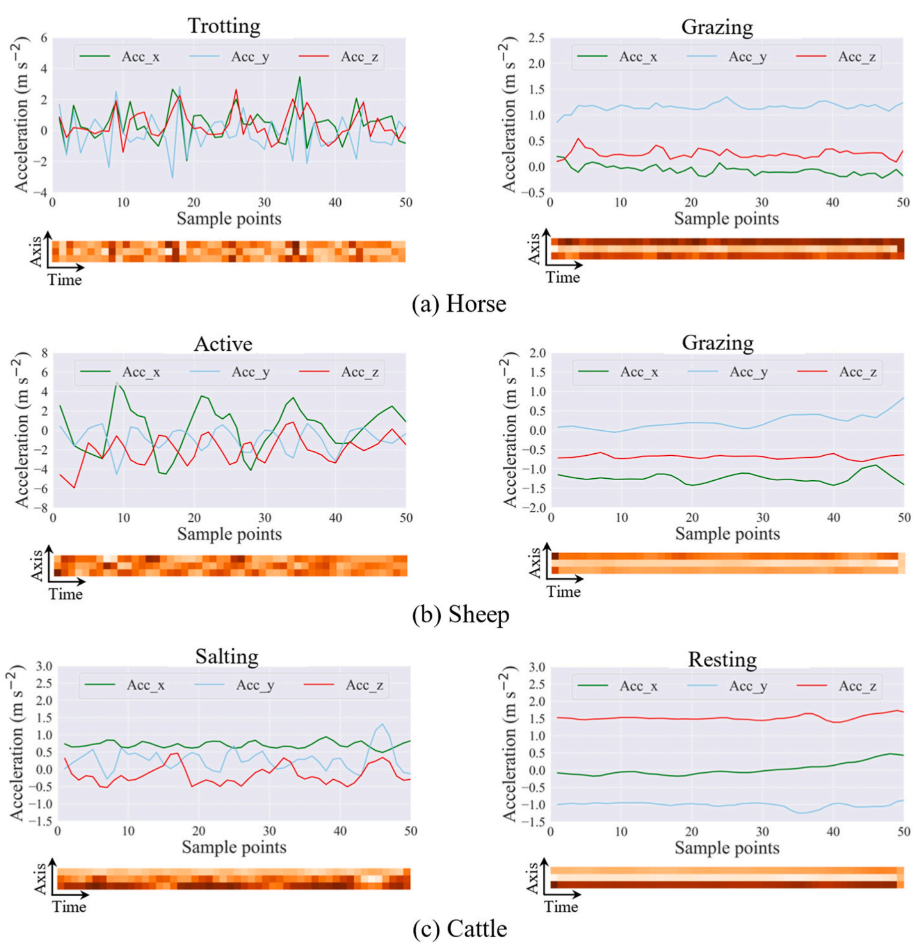


Fig. 7. Visualisation of saliency maps for input data across different behavioural categories in three species, including “trotting” and “grazing” of horse (a), “active” and “grazing” of sheep (b), and “salting” and “resting” of cattle (c).

Table 4
Comparison of the proposed CKSP framework with the Single-Net in generalisation ability across various animal individuals.

Animal species	Method	Accuracy (%)	F1-score (%)	Precision (%)	Recall (%)
Horse	Single-Net	86.30	78.56	75.61	86.19
	Our CKSP	**94.05**	**93.21**	**91.82**	**94.83**
Sheep	Single-Net	90.61	82.74	83.21	82.49
	Our CKSP	**92.74**	**86.44**	**87.21**	**86.17**
Cattle	Single-Net	68.18	50.35	49.17	61.55
	Our CKSP	**85.38**	**77.75**	**72.94**	**85.81**

context-aware modelling (Yurur et al., 2014), and integrating multiple wearable sensor types (Halachmi et al., 2019).

This study focused primarily on the core challenge of establishing a unified animal behaviour framework, rather than on advancing preprocessing methodologies, such as outlier detection and missing value handling, although these are critical for maintaining data integrity. In practice, outlier detection and missing value handling remain open challenges in data science, and thus are regarded as a valuable direction for future research. The systematic exploration of adaptive outlier detection methods, such as regression-based and machine learning-based techniques for multivariate time series, as suggested by recent studies (Alimohammadi & Chen, 2022; Blázquez-garcía et al., 2021), will be needed in subsequent work.

This framework is designed with computational efficiency in mind, enabling near real-time behaviour classification suitable for deployment in advanced animal monitoring systems. With only 29k parameters and an average inference time of 0.3 ms sample^{-1}, the model met the low-latency requirements of IoT-enabled livestock farming (Zhang et al., 2021). This efficiency allows seamless integration with wearable sensor-based monitoring systems for the timely detection of critical behaviours and early disease warning. Furthermore, the ultra-lightweight architecture is ideal for edge-device deployment, ensuring privacy-preserving on-device processing without reliance on cloud infrastructure. Future work will focus on optimising sensor-hardware co-design and exploring distributed machine learning to enhance scalability and adaptability in precision livestock farming.

5. Conclusions

This study developed a universal AAR framework, named the Cross-species Knowledge Sharing and Preserving (CKSP) method, involving an SPConv module and an SBN module and based on sensor data collected across diverse animal species. The CKSP is applicable to diverse species with distinct interested behaviours while mitigating the challenges of data limitation by learning cross-species features. Specifically, the SPConv module adequately considered the coexistence of both similarities and differences in behaviours among different species by deploying a shared full-rank convolutional layer to learn generic features and assigning individual low-rank convolutional layers to each species for extracting species-specific features. Given that different species exhibited distinct data distributions, the SBN module allocated a separate BN layer to each species, independently adapting to the unique distribution characteristics of each, thereby enhancing normalisation efficacy across diverse species. The experimental outcomes revealed that the CKSP method surpassed Single-Net, which was trained exclusively on species-specific data. Ablation studies underscored the efficacy and importance of each component in the CKSP approach, emphasising their contribution to overcoming challenges posed by limited sample sizes of individual species. In short, this work opens up a potential pathway for developing a large-scale AAR model, thereby advancing the field of precision livestock farming.

CRediT authorship contribution statement

Axiu Mao: Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Meilu Zhu:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **Zhaojin Guo:** Data curation. **Zheng He:** Visualization. **Tomas Norton:** Writing – review & editing. **Kai Liu:** Writing – review & editing, Conceptualization.

Data availability statement

The data used in the current study are open-source data, which can be accessed at: https://data.4tu.nl/articles/_/12687551/1 (Horse), https://zenodo.org/record/5849025#.ZE-y_3ZByHu (Cattle), https://github.com/nkleanthous2015/Sheep_activity_Data (Sheep). The CKSP source code is available at https://github.com/Max-1234-hub/CKSP.

Statement on the Use of Generative AI and AI assisted technologies in the writing process

No generative AI or AI-assisted technologies were used during the preparation of this work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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