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Short Communication

Development and validation of a deep learning–based system for nighttime behavioral monitoring in captive Asian elephants: A preliminary study

Kittichai Wantanajittikul[1], Siriphan Kongsawasdi[2,3], Wattanapong Suttapak[4], Natdanai Hirata[1], Pawinee Kulnanan[5], Chatchote Thitaram[3,5,6], Pakkanut Bansiddhi[3,5,6], Janine L. Brown[3,5,7] and Siripat Khammesri[2,*]

[1] *Department of Radiologic Technology, Faculty of Associated Medical Sciences, Chiang Mai University, Chiang Mai 50200, Thailand*
[2] *Department of Physical Therapy, Faculty of Associated Medical Sciences, Chiang Mai University, Chiang Mai 50200, Thailand*
[3] *Center of Elephant, Wildlife and Companion Animals Research, Chiang Mai University, Chiang Mai 50100, Thailand*
[4] *Division of Computer Engineering, School of Information and Communication Technology, University of Phayao, Phayao 56000, Thailand*
[5] *Center of Elephant and Wildlife Health, Chiang Mai University Animal Hospital, Chiang Mai, 50100, Thailand*
[6] *Faculty of Veterinary Medicine, Chiang Mai University, Chiang Mai 50100, Thailand*
[7] *Center for Species Survival, Smithsonian National Zoo and Conservation Biology Institute, 1500 Remount Rd., Front Royal, VA 22630, USA*

Abstract

Concerns over the welfare of captive elephants in tourism highlight the importance of objective and non-invasive behavioral monitoring. This study developed and validated a method for automated classification of key elephant behaviors using nighttime CCTV footage. An experienced veterinarian categorized video recordings of two adult male elephants in Thailand into four categories: walking, standing, eating, and sleeping. Two convolutional neural network models, ResNet-18 and ResNet-50, were trained and tested using four-fold cross-validation. Both models achieved a high overall accuracy of more than 90 percent, and sleep was detected with the most reliability, with a sensitivity of 99 percent. These findings suggest that automated behavior recognition may be useful for continuous welfare monitoring in captive elephants. The approach provides a cost-effective and practical monitoring system that may help identify behavioral changes associated with discomfort or disease.

Keywords: Behavior classification, Captive elephants, CCTV monitoring, Deep learning, Welfare assessment.

* **Corresponding author**: Siripat Khammesri, Department of Physical Therapy, Faculty of Associated Medical Sciences, Chiang Mai University, Chiang Mai 50200, Thailand E-mail: siripat_khammesri@cmu.ac.th, Tel: +66-61-164-9292.

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INTRODUCTION

In Thailand, elephant camp tourism is frequently considered a "must-do" experience for tourists. However, the public, international travel agencies, and animal rights activists continue to raise concerns about the welfare of the elephants involved. Emotions frequently override scientific data when drawing the conclusion that the majority of captive elephants are mistreated. Therefore, when determining whether specific practices are good or bad for elephant welfare, it can be difficult to separate feelings, beliefs, and facts (Bansiddhi et al., 2020).

Food shortages, nutritionally inadequate diets, living in limited space and no opportunity for free exploration, abuse, inappropriate training methods, and limited access to adequate veterinary care are some of the major welfare issues for captive elephants that have been reported in many countries. Numerous health problems, including obesity, wound, foot disease, and stressful situations, which result from these factors (Bansiddhi et al., 2018; Bansiddhi et al., 2020; Brown et al., 2020), all of these have an adverse effect on quality of life. The two most common approaches for evaluating and improving the welfare of captive elephants are the Five Freedoms and the Five Domains framework. The Five Domains framework evaluates welfare across Nutrition, Environment, Health, Behavioral interactions, and Mental state (Mellor and Beausoleil, 2015; Ghimire et al., 2024a; Ghimire et al., 2024b).

The environment domain encompasses various elements that contribute to the comfort and well-being of individuals, including designated rest areas. According to Meehan et al. (Meehan et al., 2016), housing and habitat are essential management aspects for promoting the welfare of captive elephants. According to Bansiddhi et al. (Bansiddhi et al., 2018), one-third of elephant camps in northern Thailand offer shaded tethering areas during the day using either built shelters or tree cover, which protect elephants from the sun and rain during working hours (Phuangkum et al., 2005). Due to limited space, most elephants are chained at night with chains ranging from three to six meters long (Bansiddhi et al., 2018). Research is needed to investigate how rest areas and restraint management within those spaces impact elephant behavior, both positively and negatively.

Sleep monitoring has become an increasingly popular non-invasive behavioral method for assessing the welfare of captive elephants (Williams et al., 2015; Schiffmann et al., 2018; Kalirathinam et al., 2019). This makes it simpler to make assessments, collect information, and compare things throughout period of time. The duration and quality of an animal's sleep also affects its mental and physical health (Siegel, 2009; Villafuerte et al., 2015; Walsh, 2017). Stress levels are related to how long and how well it sleeps. Animals that lack adequate sleep are more stressed than animals that do (Abou-Ismail et al., 2007; Villafuerte et al., 2015; Pires et al., 2016). Keeping track of elephants' sleep patterns could be an indicator of underlying issues like drowsiness, lethargy, insomnia, or stomach problems, which could help find diseases earlier (Walsh, 2017). Sleep is a valuable welfare indicator that can support welfare enhancement and may also serve as a diagnostic tool for abnormal conditions, given the correlation between stress and sleep quantity and quality.

Deep learning has substantially advanced animal recognition by supporting automated detection, classification, and behavioral assessment from large-scale visual datasets collected through cameras and sensor systems (Rajagukguk et al., 2025). In particular, convolutional neural networks provide high levels of accuracy in identifying species and discerning specific behaviors, even under variable and complex environmental conditions (Binta Islam et al., 2023). These approaches have become integral to wildlife monitoring, ecological studies, and livestock management, where they enable efficient processing and interpretation of extensive image and video data (Bevan et al., 2024; Rohan et al., 2024).

Recent studies have applied artificial intelligence to behavioral monitoring in captive wildlife. A DeepLabCut-based pose estimation framework has been used

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to classify postural and locomotor behaviors in captive African elephants (Lund et al., 2024). A temporal deep learning model incorporating sequential motion information has also been developed to detect stereotypical behaviors in captive wild animals (Yin et al., 2024).

While these approaches highlight the potential of pose-based and video-based modeling, they often require extensive annotation or computational resources. In contrast, simplified image-based classification using standard CCTV systems may offer a more practical solution for routine welfare monitoring in field settings.

There is no study on automatic recognition of sleep behavior by using deep learning in Asian elephants. The aim of this study was to develop an algorithm for identifying key behaviors of captive elephants, such as walking, standing, eating, and sleeping, that are associated with healthy status, as determined by a veterinarian. The dataset is intended to serve as a reference for implementing deep learning techniques in automated behavioral monitoring, thereby enhancing welfare evaluations and facilitating the early detection of abnormal signs in captive elephants.

MATERIALS AND METHODS

Study Animals and Setting

The study protocol was approved by the Institutional Animal Care and Use Committee, Faculty of Veterinary Medicine, Chiang Mai University, Chiang Mai, Thailand (FVM-ACUC; R17/2567). Two male captive adult elephants 20 and 35 years respectively housed at a privately-operated elephant camp were included. These elephants work in the bareback riding program for less than 4 hours per day. Both elephants were routinely tethered during non-working hours (18:00–06:00) for at least 8 hours per day and lived in shelters equipped with closed-circuit television (CCTV) for behavioral monitoring. The resting area consisted of a simple shed positioned under a large tree, providing natural shade and protection. Each elephant was secured with a chain of up to 10 meters in length, allowing moderate freedom of movement within the designated area. Water was supplied through a mountain tap-water system and river, ensuring continuous access to drinking water. Social opportunities were available during daytime activities. Recordings were obtained one elephant at a time to generate a labeled dataset for training deep learning models.

Data Collection

Video data were recorded daily during the overnight tethering period (18:00–06:00) from December 2024 to March 2025 using a CCTV system (PTZ 4G ZQS-099, GLINK) with a resolution of 2304 × 1296 pixels and a frame rate of 15 fps. The duration of each video ranged from 10 seconds to 2 minutes, depending on motion-triggered activity detection. The camera was positioned to capture the entire resting area. Elephants were typically tethered individually within designated spaces, with tether chains measuring at least 3 meters in length during the night.

Activity classification

The video data were annotated by an experienced veterinarian to identify four behavioral categories: walking, standing, eating, and sleeping. Behavioral categories were operationally defined as rational as follows: walking was defined as forward locomotion with ≥2 consecutive steps; standing as an upright posture without forward locomotion for ≥10 s; eating as continuous feeding-related trunk-to-food movements for ≥10 s; and sleeping as lateral recumbency with minimal movement for ≥10 s. Unclear video segments were excluded. Image frames corresponding to each category were then extracted automatically, resulting in 663, 1,607, 90, and 877 images, respectively. Examples of these categories are

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presented in Figure 1. To ensure clarity, accuracy, and consistency, each elephant was recorded individually, and video segments representing the target behaviors were carefully selected to construct the dataset.

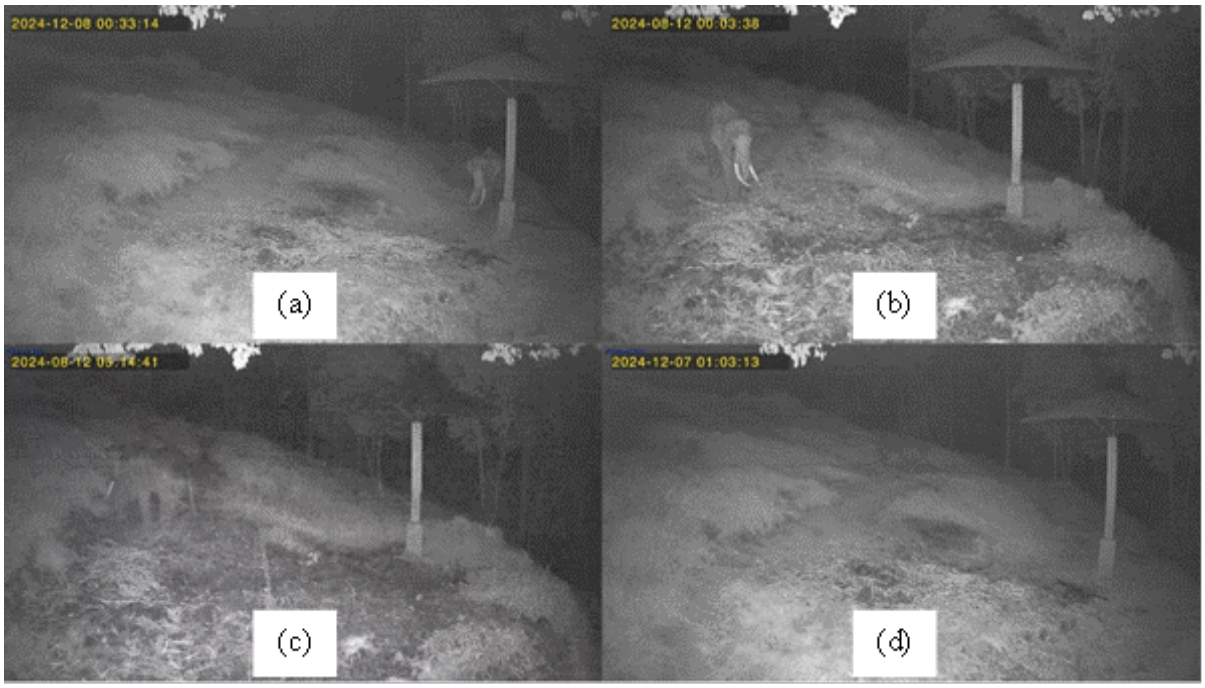


Figure 1 Examples of night-time behavioral video recordings in the elephants' resting area, captured via closed-circuit television (CCTV). Frames illustrate (a) standing, (b) eating, (c) walking, and (d) sleeping. These recordings were used for behavioral annotation by an experienced veterinarian to develop the dataset.

Model training

The training was conducted using four-fold cross-validation. Each fold was trained with a batch size of 32 images, where each image was augmented by resizing to 448 × 448 pixels, applying a 50% random horizontal flip, and performing a random rotation of up to 10 degrees. The learning rate was fixed at 0.0001, and the Adam optimizer was used with cross-entropy loss and class weights of 1.00, 0.41, 4.70, and 0.75 for the walking, standing, eating, and sleeping classes, respectively. Each model was trained for up to 400 epochs, with early stopping applied if no improvement was observed for 50 epochs. Both ResNet-18 and ResNet-50 architectures (He et al., 2016) (22) were utilized for feature extraction and classification across the four classes using a fully connected network.

Evaluation metrics

Confusion matrices were employed to visualize the classification performance across all behavioral categories. For each fold, evaluation metrics were computed and then averaged to obtain overall performance scores for both ResNet-18 and ResNet-50 models. Model performance was assessed using several commonly adopted metrics in deep learning–based classification tasks, including accuracy, sensitivity (recall), specificity, precision, and F1-score, which are particularly relevant for animal activity recognition and health monitoring (Sokolova and Lapalme, 2009).

Accuracy (Acc) (Eq.1) was defined as the proportion of correctly classified samples among all observations:

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$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad \text{(Eq.1)}$$

Sensitivity (Sens) (Eq.2) or recall measured the model's ability to correctly identify positive samples (true behavior instances):

$$\mathrm{Sens} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad \text{(Eq.2)}$$

Specificity (Spec) (Eq.3) reflected the ability to correctly reject other classes:

$$\mathrm{Spec} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \quad \text{(Eq.3)}$$

Precision (Prec) (Eq.4) indicated the proportion of correctly predicted samples within each predicted class:

$$\mathrm{Prec} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \quad \text{(Eq.4)}$$

Finally, the F1-score (Eq.5) represented a harmonic mean between precision and sensitivity, balancing false positives and false negatives.

$$\mathrm{F1} = 2 \times \frac{\mathrm{Prec} \times \mathrm{Sens}}{\mathrm{Prec} + \mathrm{Sens}} \quad \text{(Eq.5)}$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

The overall process of this study is illustrated in Figure 2.

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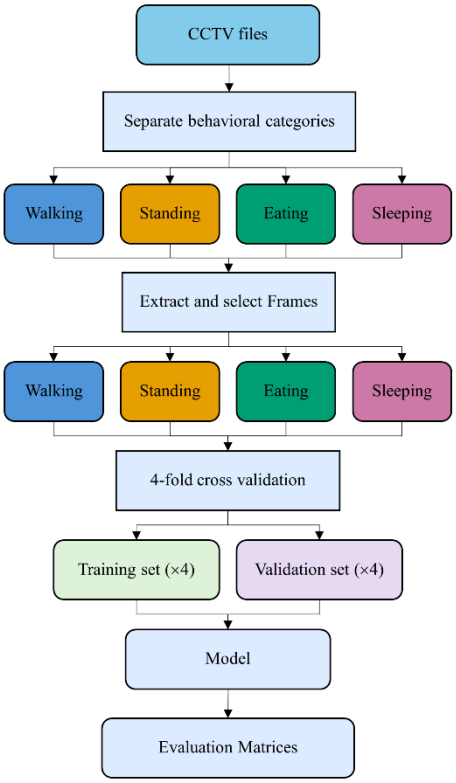


Figure 2 The workflow of the study.

RESULTS

The model performances for each fold are listed in Tables 1. Classification of the folds of both models are demonstrated in the confusion matrices provided in Figures 3-4.

Both ResNet-18 and ResNet-50 architectures demonstrated strong and stable performance across all four folds in classifying elephant behaviors (walking, standing, eating, and sleeping) from nighttime CCTV footage.

The ResNet-18 model achieved an overall average accuracy of 90.67%, with a macro-average sensitivity of 88.35% and specificity of 96.38%. Class-wise performance showed high reliability across all behaviors: walking (Sensitivity 81.48%, Specificity 95.42%), standing (90.10%, 91.60%), eating (82.26%, 98.51%), and sleeping (99.54%, 100%). The ResNet-50 model achieved a slightly higher overall accuracy of 90.80%, with a macro-average sensitivity of 88.28% and specificity of 96.36%. Class-wise sensitivity and specificity were: walking (80.42%, 95.65%), standing (90.73%, 91.11%), eating (82.31%, 98.70%), and sleeping (99.66%, 100%).

To provide a more comprehensive performance evaluation, precision and F1-scores were also computed from the confusion matrices. For ResNet-18, the macro-average precision, recall, and F1-score were 83.73%, 88.35%, and 85.57%, respectively. For ResNet-50, these values were 84.69%, 88.28%, and 86.08%, respectively.

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Table 1 Detailed performance metrics (%) for each fold of both ResNet-18 and ResNet-50 models

Fold	Activity	ResNet-18					ResNet-50				
		Sens	Spec	Prec	F1	Acc	Sens	Spec	Prec	F1	Acc
1	Walking	78.92	95.96	83.44	81.11	90.62	80.12	95.34	81.60	80.85	90.62
	Standing	91.54	90.20	90.20	90.86		91.29	90.20	90.17	90.73	
	Eating	78.26	98.73	64.29	70.59		69.57	99.24	72.73	71.11	
	Sleeping	99.09	100.00	100.00	99.54		99.54	100.00	100.00	99.77	
2	Walking	80.12	96.12	84.18	82.10	90.74	76.51	96.74	85.81	80.89	90.74
	Standing	91.04	90.69	90.59	90.82		91.54	89.95	89.98	90.75	
	Eating	72.73	98.48	57.14	64.00		90.91	98.35	60.61	72.73	
	Sleeping	100.00	100.00	100.00	100.00		100.00	100.00	100.00	100.00	
3	Walking	80.72	95.65	82.72	81.71	90.73	81.93	94.40	79.07	80.47	89.99
	Standing	90.05	92.14	91.88	90.95		88.81	91.89	91.54	90.15	
	Eating	95.45	98.09	58.33	72.41		81.82	98.48	60.00	69.23	
	Sleeping	99.09	100.00	100.00	99.54		99.09	100.00	100.00	99.54	
4	Walking	86.14	93.93	78.57	82.18	90.61	83.13	96.11	84.66	83.89	91.84
	Standing	87.78	93.38	92.88	90.26		91.27	92.40	92.19	91.73	
	Eating	82.61	98.73	65.52	73.08		86.96	98.73	66.67	75.47	
	Sleeping	100.00	100.00	100.00	100.00		100.00	100.00	100.00	100.00	
Avg	Walking	81.48	95.42	82.23	81.78	90.67	80.42	95.65	82.78	81.53	90.80
	Standing	90.10	91.60	91.39	90.72		90.73	91.11	90.97	90.84	
	Eating	82.26	98.51	61.32	70.02		82.31	98.70	65.00	72.14	
	Sleeping	99.54	100.00	100.00	99.77		99.66	100.00	100.00	99.83	
Macro Avg		88.35	96.38	83.73	85.57		88.28	96.36	84.69	86.08	

Abbreviations: Accuracy (Acc); Sensitivity (Sens); Specificity (Spec); Precision (Prec); F1-score (F1)

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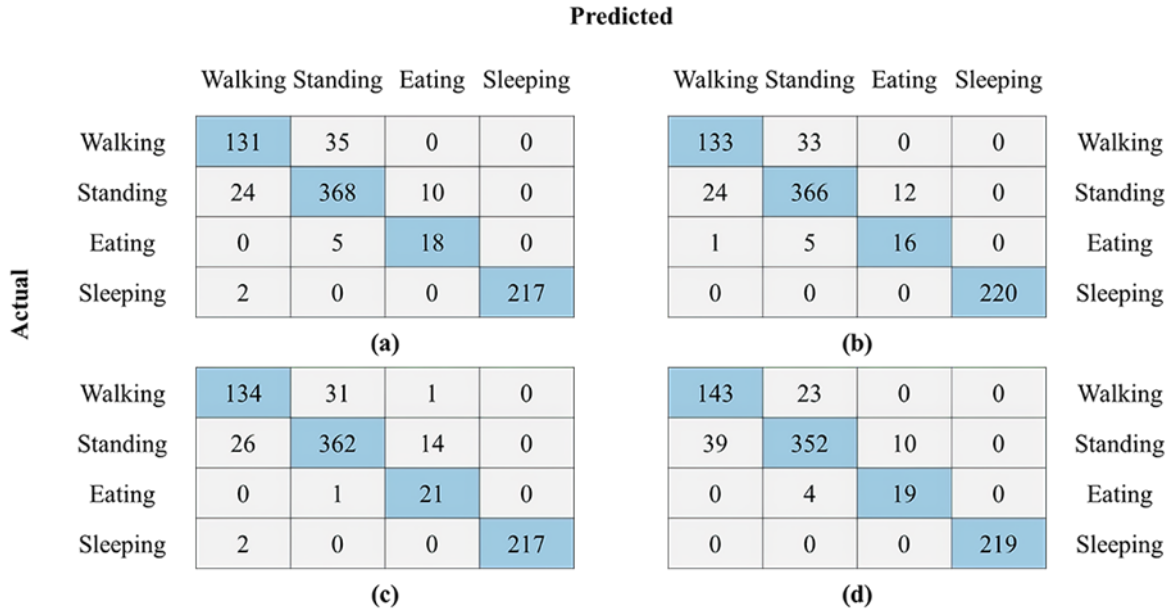


Figure 3 Confusion matrices of the ResNet-18 model. The figure listed (a) fold 1, (b) fold 2, (c) fold 3, and (d) fold 4.

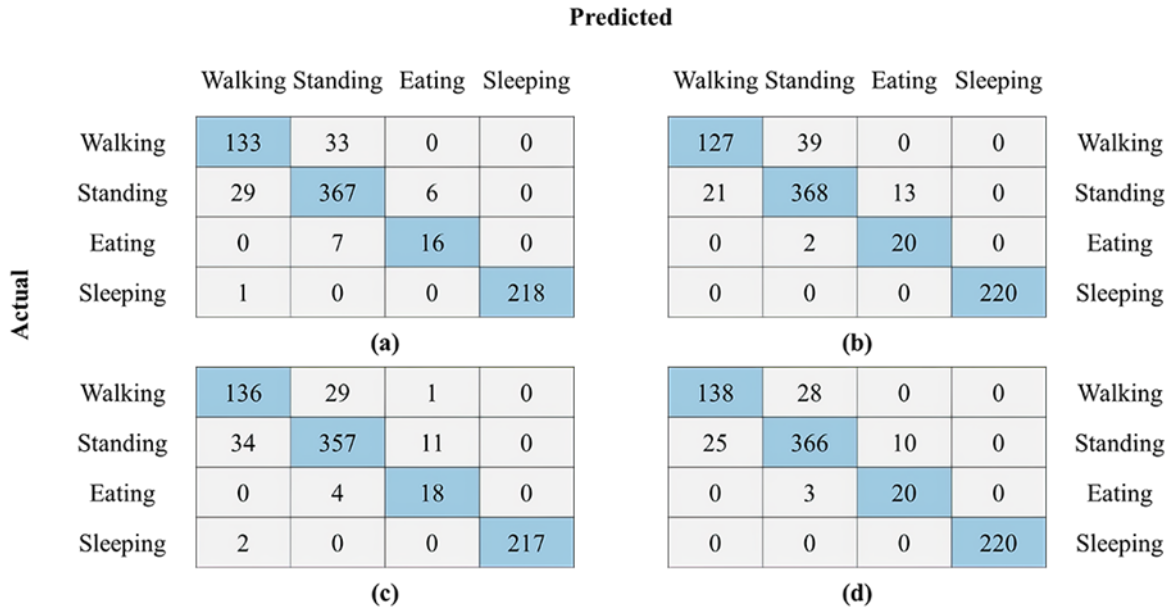


Figure 4 Confusion matrices of the ResNet-50 model. The figure listed (a) fold 1, (b) fold 2, (c) fold 3, and (d) fold 4.

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DISCUSSION

This study demonstrated that deep learning models, specifically ResNet-18 and ResNet-50, can accurately and automatically classify key behaviors of captive elephants from nighttime CCTV footage, achieving overall accuracies of approximately 90–91%. Both models performed exceptionally well in identifying sleeping behavior, achieving approximately ≥99% sensitivity, near-perfect precision (≈100%), and F1-scores of about 99–100%, reflecting the distinct and static posture characteristic of a sleeping elephant. In contrast, behaviors such as walking and eating exhibited slightly lower, though still robust, sensitivities (≈80–82%) and moderate F1-scores (≈70–82%). This reduction may be attributed to greater variability in posture, class imbalance, or occasional visual obstructions within the enclosure.

From the confusion matrices presented in Figures 3–4, misclassification was primarily observed between walking and standing. This occurs because still frames extracted from walking sequences often resemble standing postures. The most distinctive feature separating these two behaviors, motion, is inherently lost when dynamic video sequences are decomposed into static frames. Consequently, the model becomes prone to confusion between these two classes.

Both ResNet-18 and ResNet-50 exhibited consistent cross-fold performance, with macro-average precision, recall, and F1-scores generally falling within approximately 83–85% (precision), 88% (recall), and 85–86% (F1) for both models. The slightly better results obtained with ResNet-50 indicate a marginal gain from deeper architecture, though the improvement is minimal. This suggests that the simpler ResNet-18 could serve as a computationally efficient alternative without substantial performance loss, which is advantageous for real-world deployment in field conditions where processing resources may be limited.

The findings of this study align with a growing body of research supporting non-invasive AI-based monitoring as a valuable tool for animal welfare assessment (Siegel 2009; Walsh 2017). While prior studies have highlighted the importance of sleep duration and quality as welfare indicators, the present work contributes an automated, scalable approach that minimizes the limitations of manual observation. The proposed system, integrating computer vision and deep learning, could enable continuous 24-hour behavioral surveillance, providing objective, data-driven insights into elephant welfare and supporting the early detection of potential health or stress-related issues.

When considered alongside recent AI-based behavioral monitoring studies, the present results highlight key methodological trade-offs. Pose-based approaches preserve anatomical structure through keypoint extraction and may improve discrimination of locomotor states, particularly when camera placement reliably captures full-body posture (Lund et al., 2024). In contrast, the current image-level CNN framework was intentionally designed to operate using a single standard CCTV camera, prioritizing simplicity and field deployability over more complex pose-estimation or multi-camera infrastructure. Although this streamlined setup does not explicitly encode motion information and may reduce sensitivity for distinguishing closely related locomotor states, it demonstrates that reliable classification of welfare-relevant behaviors, particularly sleep, can be achieved under practical management conditions. Likewise, temporally structured models offer advantages for detecting dynamic or repetitive patterns (Yin et al., 2024). Future integration of temporal modeling may further enhance behavioral resolution while maintaining operational feasibility.

The integration of CCTV with automated behavioral recognition provides a non-invasive method for continuous documentation of behavioral patterns without requiring direct human observation. In many facilities within range countries, tethering remains standard husbandry practice and, while it constrains locomotor freedom, reflects current management conditions for captive elephants. Within this context, the monitoring approach applied in this study provides a practical method

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for objectively recording daily behaviors over extended periods. With further refinement and validation, similar systems could be considered for use in tourist camps and zoological settings where continuous behavioral information can support management and welfare assessment.

Several limitations should be acknowledged when interpreting these findings. The dataset contained only two adult male elephants from a single facility, which restricts the generalizability of the models to other age classes, sexes, and management systems. A formal a priori sample size calculation was not performed, as the primary objective of this study was to establish technical feasibility and methodological validation rather than to estimate population-level behavioral prevalence. In addition, the eating class contained relatively few annotated samples and consequently produced the lowest performance metrics, underscoring the influence of class imbalance on supervised model training. This imbalance was partly attributable to the recording context. Elephants were typically provided their final meal before the overnight tethering period (18:00–06:00). During tethering, "eating" behavior was mainly based on foraging on available grass within the nighttime area, which limited the number of clear eating segments available for frame extraction and contributed to class imbalance. External validation across multiple facilities, age groups, and management systems will be essential to confirm model robustness under varied environmental and lighting conditions. Future studies should therefore expand data collection to elephants from multiple camps and diverse management contexts in order to strengthen external validity.

As previously mentioned, the primary misclassification in identifying the difference between walking and standing could be reduced by using temporal modeling that preserves motion information across frames. Future research could also extend the framework to detect more subtle welfare-related indicators, such as stereotypic behaviors (e.g., swaying) or social interactions, thereby advancing the application of AI in animal welfare monitoring and behavioral science.

CONCLUSIONS

This study developed and validated deep learning algorithms based on ResNet-18 and ResNet-50 architectures for automated classification of four key behaviors, walking, standing, eating, and sleeping, in captive elephants using nighttime CCTV footage. Both models achieved high overall accuracies and excellent macro-average performance, with precision, recall, and F1-scores. Sleeping was the most accurately identified behavior, whereas eating showed lower performance, likely influenced by class imbalance and its visual similarity to standing. These findings support the feasibility of using AI-based systems for continuous, non-invasive monitoring of elephant behavior. The proposed framework offers a practical basis for welfare management, enabling veterinarians and caretakers to use behavioral insights for early identification of distress or illness during routine welfare assessments. The continuous development, including expansion of the dataset, temporal modeling integration, and evaluation across various management contexts, may provide a data-driven welfare assessment and decision support system for elephant care and management.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

Kittichai Wantanajittikul: Conceptualization, Methodology, Software, Writing – Original Draft Preparation.
Siriphan Kongsawasdi: Conceptualization, Funding acquisition, Project administration, Writing – Review & Editing.
Wattanapong Suttapak: Formal analysis, Methodology, Software, Validation, Visualization.
Natdanai Hirata: Data Curation, Software.
Pawinee Kulnanan: Data Curation.
Chatchote Thitaram: Writing – Review & Editing.
Pakkanut Bansiddhi: Methodology, Writing – Review & Editing.
Janine L. Brown: Conceptualization, Supervision.
Siripat Khammesri: Data curation, Investigation, Project administration, Resources, Writing – Original Draft Preparation.

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