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Optimizing the Accuracy and Efficiency of Camera Trap Image Analysis: Evaluating AI Model Performance and a Semi-Automated Workflow

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Highlights

What are the main findings?

- Initial Conservation AI UK Mammals model outputs demonstrated high precision (>0.80) for foxes (*Vulpes vulpes*) and hedgehogs (*Erinaceus europaeus*) but low recall (<0.50) for hedgehogs.
- Following retraining, AI model performance improved substantially. However, discrepancies between AI and human classifications remained statistically significant, indicating that human accuracy still outperformed that of the AI model. Recall scores for hedgehogs also remained low despite these improvements.

What are the implications of the main findings?

- We present a semi-automated, three-step workflow incorporating an AI generalist object detector, an AI species-specific classifier, and manual validation as an alternative image classification method that accelerates camera trap data analysis whilst maintaining classification accuracy.
- The findings provide baseline performance estimates of Conservation AI's UK Mammals model and highlight the importance of continuous AI model training, the value of citizen science in expanding training datasets, and the need for adaptable workflows in camera trap studies.

Check for updates

Academic Editor: Prasad S. Thenkabail

Received: 5 December 2025
Revised: 23 January 2026
Accepted: 1 February 2026
Published: 4 February 2026

Abstract

The widespread adoption of camera trap surveys for wildlife monitoring has generated a substantial volume of ecological data, yet processing constraints persist due to the time-consuming process of manual image classification and the reliability of automated systems. This study assesses the performance of Conservation AI's UK Mammals model in classifying three species—Western European hedgehogs (*Erinaceus europaeus*), red foxes (*Vulpes vulpes*), and European badgers (*Meles meles*)—from a subsample of 234 records from camera trap images collected through a citizen science initiative across residential gardens. This analysis was repeated after retraining the model to assess improvement in model performance. Initial model outputs demonstrated high precision (>0.80) for foxes and hedgehogs but low recall (<0.50) for hedgehogs, with the lowest recall probability of 0.12 at the 95% confidence threshold (CT). Following retraining, model performance improved substantially across all metrics, with average F1-scores (weighted average of precision and recall across the three species tested) improving at all CTs, though discrepancies with human classifications remained statistically significant. Based on performance results from this study, we present a semi-automated, three-step workflow incorporating an artificially intelligent (AI) generalist object detector (MegaDetector), an AI species-specific classifier (Conservation AI), and manual validation. Where privacy concerns restrict citizen science contributions, our pipeline offers an alternative that accelerates camera trap data analysis whilst maintaining classification accuracy. The findings provide baseline performance estimates of Conservation AI's UK Mammals model and present an approach that offers a practical solution to improve the efficiency of using camera traps in ecological research and conservation planning. We also highlight the importance of continuous AI model training, the value of citizen science in expanding training datasets, and the need for adaptable workflows in camera trap studies.

Keywords: camera trap data; image data processing; wildlife monitoring; AI-assisted image classification; citizen science; machine learning; semi-automated workflow

1. Introduction

Over the last decade, camera traps have become an essential tool for wildlife monitoring, providing valuable data for understanding species ecology, behaviour, and conservation [1–3]. Beyond monitoring species distributions and abundance [4,5], camera trap surveys can facilitate the study of activity patterns, species interactions, and social dynamics [6–8]. This survey method offers a non-invasive and automated approach that enables data collection across large spatiotemporal scales [9,10], with minimal human interference, facilitating the study of elusive species and natural behaviour [11]. Additionally, camera traps record all species within their field of view, enabling the detection of non-target species and potentially contributing to broader biodiversity assessments [12].

Large-scale camera trap studies can generate a substantial volume of image data, presenting significant challenges for data storage, management, and analysis [13,14]. Image classification is particularly time-consuming and can delay the delivery of results critical for conservation and management decisions [15,16]. The growing demand for efficient data processing has driven the development of Artificial Intelligence (AI), particularly Deep Learning (DL), a subset of machine learning, to automate camera trap image analysis [14]. DL methods learn complex patterns directly from large datasets using versatile learning algorithms without manually designed parameters [17]. AI-driven approaches, such as Convolutional Neural Networks (CNNs), consist of multiple layers that learn distinct data representations at varying levels of abstraction to refine its understanding of complex features and improve accuracy [17].

Several AI platforms have been developed to improve the efficiency of camera trap data processing. These platforms can filter "blank" images; distinguish animals from humans or vehicles [18]; classify species [19]; identify individuals [20]; and count the number of individuals of a single species [14]. However, despite their advantages in processing speed and efficiency, AI-based image classification still faces practical and methodological challenges. Many AI models are based on transfer learning, involving fine-tuning pre-trained foundation models such as a Faster Regional-based Convolutional Neural Network (R-CNN) or a You Only Look Once (YOLO) model [21,22], which typically require thousands of labelled images per species to achieve optimal performance [23].

The accuracy of AI classifications remain variables across studies, with some reporting lower accuracy than human classification [18,24,25], while others have demonstrated strong performance [26]. For example, Vélez et al. [27] reported low to moderate recall (<0.70) across several platforms including Conservation AI [28], MLWIC2 (Machine Learning for Wildlife Image Classification [29], and Wildlife Insights [30], although precision was high for certain species and taxonomic groups. In contrast, MegaDetector [31] achieved high accuracy when distinguishing "blank" images from those containing an animal, a finding also reported by Leorna and Brinkman [32]. Other platforms [33] have shown comparable performance to human observers in terms of speed, cost, carbon efficiency, and accuracy, with a 98% species-level accuracy reported in the United States [15] using a trained deep convolutional neural network [32] and a F1-score of 96.2% reported using a two-stage deep learning pipeline that integrates a global model and a species-specific model [34].

Many researchers have recognized the limitations of fully automated and fully manual approaches to camera trap image analysis [14,35] and employ a hybrid workflow that combines AI and human classifications. Platforms such as eMammal [10] and MammalWeb [36] enable citizen scientists to contribute to image classification efforts, though classification accuracy can vary depending on participants' identification expertise [35,37].

To gain a quantitative understanding of the effectiveness of AI and model retraining, an aspect that has received limited attention, we evaluate the performance of Conservation AI's UK Mammals model (one of the most developed UK Mammal detection algorithms available) using a subsample of camera trap images, before and after model retraining [15,27,38]. Conservation AI [28] is a cloud-based platform developed at Liverpool John Moores University (UK) that classifies camera trap images containing wildlife species from the UK, North America, and Africa. The online platform applies region-specific models to uploaded images and assigns species labels alongside confidence scores, providing a user-friendly interface for camera trap image classification [28]. We also introduce a novel semi-automated, three-step workflow that integrates a generalist AI model (MegaDetector) to remove blank images, a species-specific classifier (Conservation AI), and manual verification (Figure 1). This proposed workflow aims to balance efficiency and accuracy when processing large-scale camera trap datasets [32] and offers an alternative to fully automated [39] or fully manual [13] classification approaches.

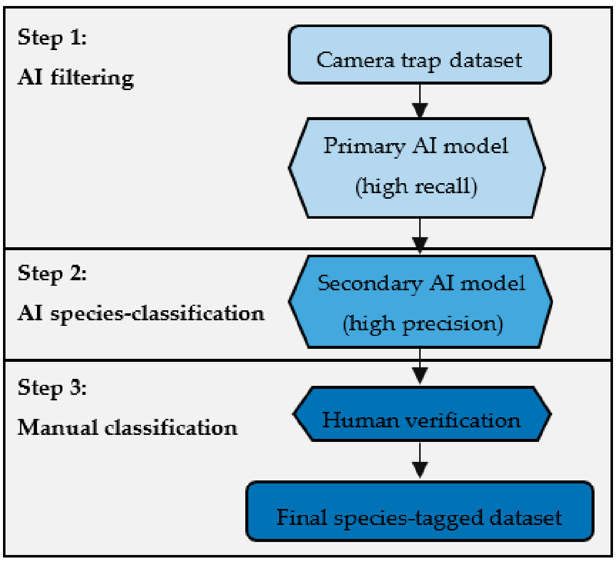

Figure 1. Conceptual overview of the semi-automated, three-step workflow designed to create a pipeline for camera trap image analysis by combining two AI image classification stages and manual verification.

2. Materials and Methods

2.1. Data Collection

Camera trap data were collected as part of a Chester Zoo citizen science project (Hedgehog Watch) in 2021. West European hedgehogs (*Erinaceus europaeus*, hereafter hedgehogs) were used as a flagship species to encourage public participation in an extensive garden wildlife camera trap survey. The project involved volunteers from the public within a 116 km^2 catchment area, pre-determined by Chester Zoo, signing up to participate and deploy camera traps in their gardens between March and October from 2021 to 2023 [40]. Additionally, a further 79 rural locations were surveyed to ensure spatial coverage across the sample area. Therefore, the full dataset contained 494 camera trap sites and produced a total of 850,870 images. This study used a randomly selected subsample of 234 records from 170 camera trap surveys conducted between April and October in 2021 and 2022 to evaluate Conservation AI's UK Mammals model performance. This subsample was derived from a wide range of surveys to ensure it is representative of the full image dataset. Images represented independent snapshots from different gardens at different times to avoid pseudo-replication in consecutive frames and annotation drift. While it is possible that the same individual could appear in multiple images—for example, if the same individual visited more than one garden or the same garden at different times—such occurrences are unavoidable in most camera trap studies and are negligible for this analysis.

Browning trail cameras (model BTC-7A, Browning, Birmingham, AL, USA) were deployed by volunteers, set to the Trail Cam operation mode, with high (12 MP) photo quality, a 1 min photograph delay, a three-shot standard multi-shot mode, and a fast trigger speed (0.4–0.7 s). Cameras were fixed to a stable structure (tree, fence post, etc.) around three metres away from an open area with an unobstructed field of view. They were placed 20–30 cm above the ground and angled slightly downwards or parallel to the flat surface [41,42].

2.2. Classification Methods

Model accuracy was estimated using classification performance for three species: hedgehogs, red foxes (*Vulpes vulpes*, hereafter foxes), and European badgers (*Meles meles*, hereafter badgers) (Figure 2). These three mammals had at least eight records (hedgehogs = 177 detections, foxes = 49 detections, badgers = 8 detections) in the dataset and were visually distinctive compared to other species (e.g., rodents).

The subsample was submitted to Conservation AI's online platform, and the UK Mammals model was used to assign species classifications using a set of pre-defined species labels. The model assigned a level of confidence to each detection, with higher values reflecting a more certain classification. The subsample was also manually analyzed by the first author and a research assistant [43,44] by inspecting images and assigning species classifications using Timelapse software (v2.3.2.8; [45,46]). Timelapse is an image analyzer that reads and displays images and allows the user to build a custom interface to examine images efficiently. To standardize the species classification process for both the AI and the manual approach, species labels were created in Timelapse prior to classifying images using the Quick Paste tool to match those pre-determined labels used by Conservation AI. The tool allows species details, such as the name and number of animals in the image, to be pre-set to minimize the time required to process each image.

Estimates of precision, recall, and F1-scores (weighted average of precision and recall) [47] were calculated using True Positives (TP), the number of observations where the species was correctly identified as being present in the image; False Positives (FP), the number of observations where the species was absent but was classified as being present; and False Negatives (FN), the number of observations where the species was present but was classified as being absent (Table 1). Mean F1-scores were also calculated using the total F1-score across all three species, divided by the number of species.

Figure 2. Sample camera trap images showing the focal species (**A**) European badger (*Meles meles*), (**B**) red fox (*Vulpes vulpes*), and (**C**) Western European hedgehog (*Erinaceus europaeus*).

Table 1. Metrics and equations used to measure Conservation AI's UK Mammals model performance (TP: True positives, FP: False positives, FN: False negatives) [47].

Metric	Equation	Interpretation
Precision	TP/(TP + FP)	Probability the species is correctly classified as present given that the AI system classified it as present.
Recall	TP/(TP + FN)	Probability the species is correctly classified as present given that the species truly is present.
F1-score	2 × precision × recall/(precision + recall)	Weighted average of precision and recall.

Performance estimates were calculated across a range of confidence thresholds (0.65, 0.75, 0.85, 0.95), a common practice in machine learning to demonstrate how increasing certainty affects classification performance through trade-offs between precision and recall [15,27]. Adjusting confidence thresholds has been shown to influence accuracy and consequently, ecological inference; for example, excluding low-confidence predictions can improve the reliability of species-level classifications [14,48]. More specifically, higher confidence thresholds reduce false positives by prioritizing precision, whereas lower thresholds increase recall by reducing false negatives. Evaluating model performance across multiple confidence thresholds therefore supports informed threshold selection based on study objectives and the relative importance of precision, recall, or a balance of both.

Outputs from both Conservation AI and Timelapse containing species classifications and image filenames were exported. Additionally, classification confidence levels were extracted from the AI output. The two sets of species classifications from two different human viewers were cross-checked and then combined into a single dataset along with AI-assigned species classifications from the pre- and post-trained models. Therefore, the combined dataset consisted of image filenames, species classifications from both human and AI vision, and confidence levels. In this case, human vision was assumed to be accurate as both observers were wildlife researchers with existing UK mammal identification skills and classifications between them both aligned; therefore, confidence levels were set at a value of 1 [13,25].

2.3. Data Analysis

All analyses were performed using R Statistical Software (v4.2.2; [49]). The performance of Conservation AI's UK Mammals model was assessed using the purrr package (v1.0.1; [50]). AI and human vision classifications were joined to estimate model performance metrics (precision, recall, and F1-scores) for each species, compared to human vision [50]. Performance metrics were classified as low (<0.50), moderate (0.50–0.79), and high (>0.80) [24] and were estimated for each species at confidence thresholds (CT) of 0.65, 0.75, 0.85, and 0.95. The pre-trained assessment calculated baseline model performance estimates. Following this, the model was re-trained by manually classifying an additional 2341 images. The same metrics (precision, recall, and F1-scores) were then re-calculated for the original subsample in a post-trained assessment.

Confusion matrices were constructed to visualize the patterns of AI classifications among the three focal species using the pre- and post-trained AI models. Proportions of images were categorized as "Correct" if the AI-assigned and human-assigned classification matched, "Misclassified" if the AI model identified a different species, or "Blank" if the AI model did not detect an animal. A confidence threshold of 0.85 was selected for the confusion matrices as a pragmatic trade-off between precision and recall estimates [51].

Results from the pre- and post-trained models were compared using the McNemar's chi-squared statistic [52] to assess whether the proportion of accurate species classifications differed significantly between models. Classifications generated by each AI model were categorized as Matched or Unmatched relative to human-assigned classifications, and comparisons were summarized in a two-dimensional contingency table. The assumptions of the McNemar's test were met, as paired nominal data were used, observations were independent, and discordant pairs were sufficient for reliable inference [53].

The Cohen's Kappa test [54] was used to estimate an unweighted kappa statistic from the irr package (v0.84.1; [55]) that provided an index of interrater agreement between (1) human vision and the pre-trained AI model, and (2) human vision and the post-trained AI model. The strength of interrater agreement was categorized based on the Cohen's Kappa value (κ) [56] (Table 2). A bootstrap estimate (1000 replicates) was used to estimate the change in Kappa between models, and the associated 95% confidence interval was calculated. Cohen's Kappa can be sensitive to class imbalance and prevalence effects, which can result in low Kappa values despite high overall agreement. Therefore, Kappa estimates were interpreted alongside accuracy-based metrics to provide a more complete assessment of model performance [57,58].

Table 2. Interpretation of the strength of interrater agreement indicated by the Cohen's Kappa value (κ) [54,56].

Cohen's Kappa Value (κ)	Strength of Agreement
<0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Excellent

2.4. Measuring Efficiency

The time taken for both human and AI vision to classify the subsample was measured to provide an estimate of efficiency for both methods. For AI vision, the Conservation AI team measured the length of time the model took to finish processing the subsample of images. For human vision, two separate individuals measured the length of time it took to manually classify the subsample. An average of the two time periods from both individuals was calculated.

To provide a realistic estimate of the amount of time it would take to process the full dataset using both approaches, the time durations using AI and human vision were extrapolated. Estimates for both approaches were calculated by multiplying the average number of seconds taken to classify an image (based on the total time taken to classify the subsample (N = 187 images)), by the total number of images in the full dataset (N = 850,870). The total number of seconds was then divided by 60 to produce the number of minutes and by 60 again to provide the number of hours. Finally, the total number of hours was divided by 24 to provide an estimated number of days required to process the dataset. For human vision, the total number of hours was also divided by 8 to represent the typical length of a working day in the UK [59].

3. Results

3.1. Species-Level Estimates

The pre-training assessment provided baseline performance estimates for Conservation AI's UK Mammals model compared to human vision (Table 3; Figure 3). The model had high precision values (>0.80) at all CTs for hedgehogs and foxes, meaning these species were correctly classified as present given that the AI model classified them as present. However, precision values for badgers were low (<0.50), except at 95% CT, where it increased to 0.86.

Inversely, recall estimates were moderate (0.50–0.79) for badgers at all CTs. This shows that the AI model had the same moderate level of confidence that badgers were correctly classified as present given that they truly were present. Foxes had moderate recall estimates at all CTs, except at 95%, which was low. Hedgehogs had low recall estimates (<0.50), with the lowest recall probability of 0.12 at the 95% CT. The F1-scores corroborate these estimates, showing that badgers had a low F1-score at 65% and 75% CTs, moderate at 85%, and high at 95%. Foxes and hedgehogs had a moderate and low F1-score, respectively, at all CTs (Figure 3).

Table 3. Conservation AI's UK Mammals model performance metrics from a pre- and post-trained assessment, using two sets of classifications shared by AI and human vision (precision: probability the species is correctly classified as present given that the AI system classified it as present, recall: probability the species is correctly classified as present given that the species truly is present, F1-score: weighted average of precision and recall). Confidence thresholds of 0.65, 0.75, 0.85, and 0.95 were used for determining classifications of each species.

		Pre-Trained Model			Post-Trained Model		
		Performance Metrics					
Confidence Threshold (CT)	**Species**	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
0.65	Fox	1.00	0.61	0.76	1.00	0.63	0.78
	Hedgehog	1.00	0.20	0.34	1.00	0.44	0.61
	Badger	0.33	0.75	0.46	0.78	0.88	0.82
0.75	Fox	1.00	0.57	0.73	1.00	0.61	0.76
	Hedgehog	1.00	0.17	0.29	1.00	0.40	0.57
	Badger	0.38	0.75	0.50	0.78	0.88	0.82
0.85	Fox	1.00	0.51	0.68	1.00	0.55	0.71
	Hedgehog	1.00	0.15	0.26	1.00	0.38	0.56
	Badger	0.43	0.75	0.55	0.88	0.88	0.88
0.95	Fox	1.00	0.47	0.64	1.00	0.51	0.68
	Hedgehog	1.00	0.12	0.21	1.00	0.30	0.46
	Badger	0.86	0.75	0.80	1.00	0.62	0.77

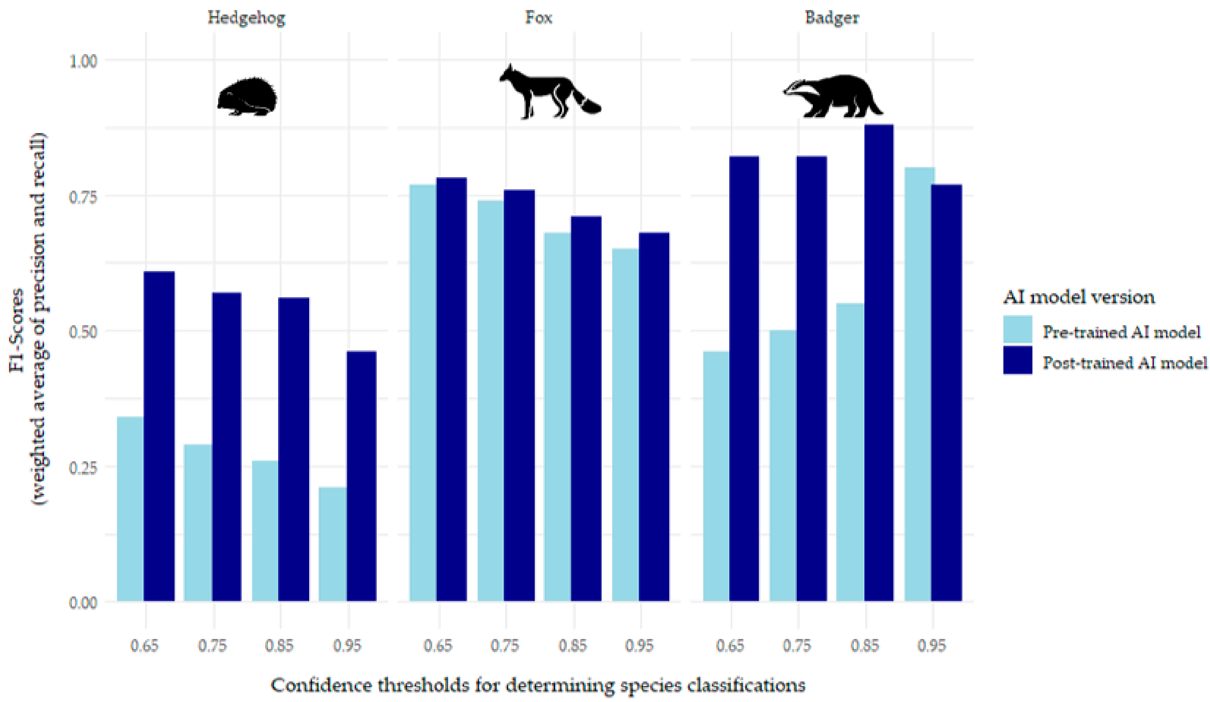

Figure 3. Conservation AI's UK Mammals Model F1-scores (weighted average of precision and recall) from two sets of classifications shared by AI and human vision from a pre-trained and post-trained model. Confidence thresholds of 0.65, 0.75, 0.85, and 0.95 were used for determining classifications of three different species.

The post-training assessment provided model performance estimates after the algorithm had undergone additional training (Table 3; Figure 3). Precision probability remained at 1.00 for foxes and hedgehogs but increased for badgers by 136% (0.65 CT), 105% (0.75 and 0.85 CT), and 16% (0.95 CT) to reach a probability value of 1.00. Recall estimates improved for all species. Although badger estimates increased by 17% at all CTs, improving from moderate to high, recall decreased by 17% and remained moderate at 95% CT. Fox recall estimates increased by 2% (0.65 CT), 5% (0.75 CT), 6% (0.85 CT), and 6% (0.95 CT), improving to be moderate at all CTs. Hedgehog recall estimates increased the most out of all three species (120% (0.65 CT), 150% (0.75 CT), 171% (0.85 CT), and 173% (0.95 CT)) but remained low at all CTs. F1-scores improved for all species, with badgers improving to be high at all CTs, except at 95% CT, where they were moderate. They were followed by foxes, which improved but remained moderate. Hedgehog F1-scores improved to be moderate at all CTs, except at 95%, where they remained low (Figure 3). Overall, the post-training assessment shows that the model was able to precisely classify all three species, most accurately recall badgers, and least accurately recall hedgehogs from a subsample of camera trap images.

The confusion matrices demonstrate the patterns of AI-assigned classifications, supporting the observed overall high precision, lower recall results and the improvements in the post-trained AI model (Figure 4). Hedgehogs were the most frequently misclassified and undetected species. Although a higher proportion of hedgehog classifications were correct using the post-trained AI model, more than half (60%) of hedgehogs remained undetected. Foxes were correctly classified by AI around half of the time, with the remaining half going undetected. Badgers were rarely misclassified as other species; the main issue was missing detections, which were relatively low in the post-trained model (12%).

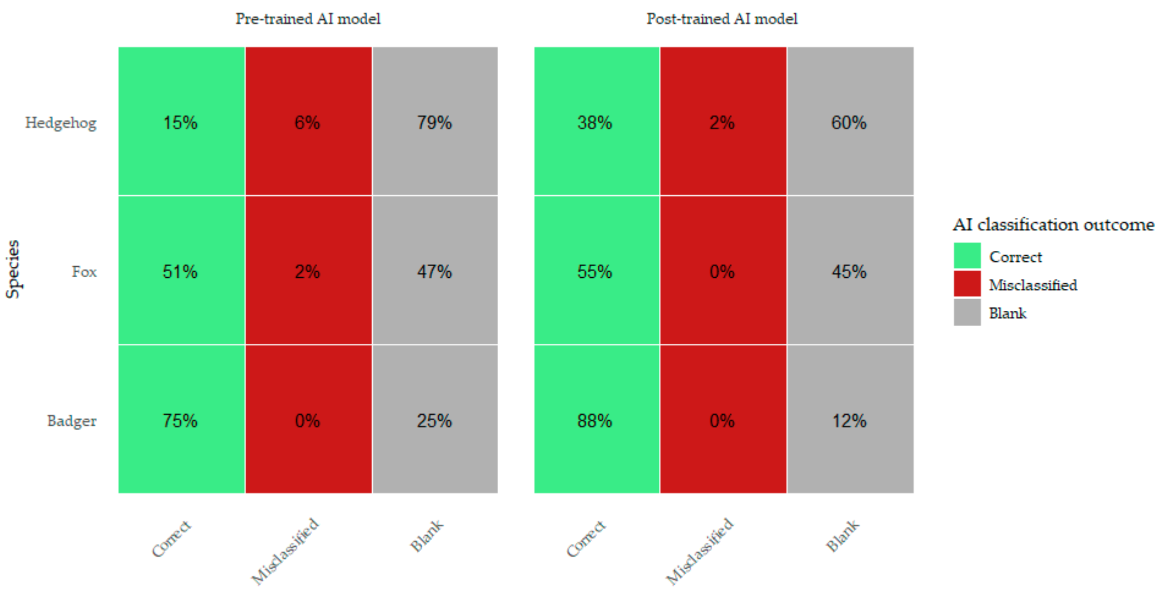

Figure 4. The proportion of AI-assigned classifications recorded as "Correct" (matched the human-assigned classification), "Misclassified" (as a different species), or "Blank" (undetected), for three focal species: European hedgehogs (*E. europaeus*), red foxes (*V. vulpes*), and European badgers (*M. meles*), using the pre- and post-trained Conservation AI UK Mammals model and a 85% confidence threshold.

3.2. Overall Estimates

In the pre-trained evaluation, average F1-scores were moderate at 65%, 75% and 95% CTs and low at 85% CTs (Table 4). The Cohen's Kappa test indicated fair agreement (κ = 0.21), but a significant difference between human- and AI-assigned classifications from the pre-trained model (z = 10.9, p <0.001). In the post-trained evaluation, average F1-scores improved at all CTs but remained moderate, increasing by 42% (0.65 CT), 41% (0.75 CT), 47% (0.85 CT), and 16% (0.95 CT) (Table 4; Figure 5). AI-assigned classifications showed a significant improvement (κ = 0.11 difference, 95% CI: 0.07–0.15) in agreement with human-assigned classifications, with post-trained estimates indicating a fair agreement (κ = 0.31) but a significant difference between human and AI assigned classifications remained

($z = 12.1$, $p < 0.001$). The McNemar's test indicated significantly more accurate species classifications assigned by the post-trained AI model, compared to the pre-trained model (χ^2 (1) = 30.2, $p < 0.001$).

Table 4. Conservation AI's UK Mammals Model performance using two sets of classifications shared by AI and human vision, from a pre- and post-trained model (average F1-scores: mean weighted average of precision and recall from three species F1-scores). Confidence thresholds of 0.65, 0.75, 0.85, and 0.95 were used for determining classifications of each species.

Confidence Threshold (CT)	Pre-Trained Model	Post-Trained Model
0.65	0.52	0.74
0.75	0.51	0.72
0.85	0.49	0.72
0.95	0.55	0.64

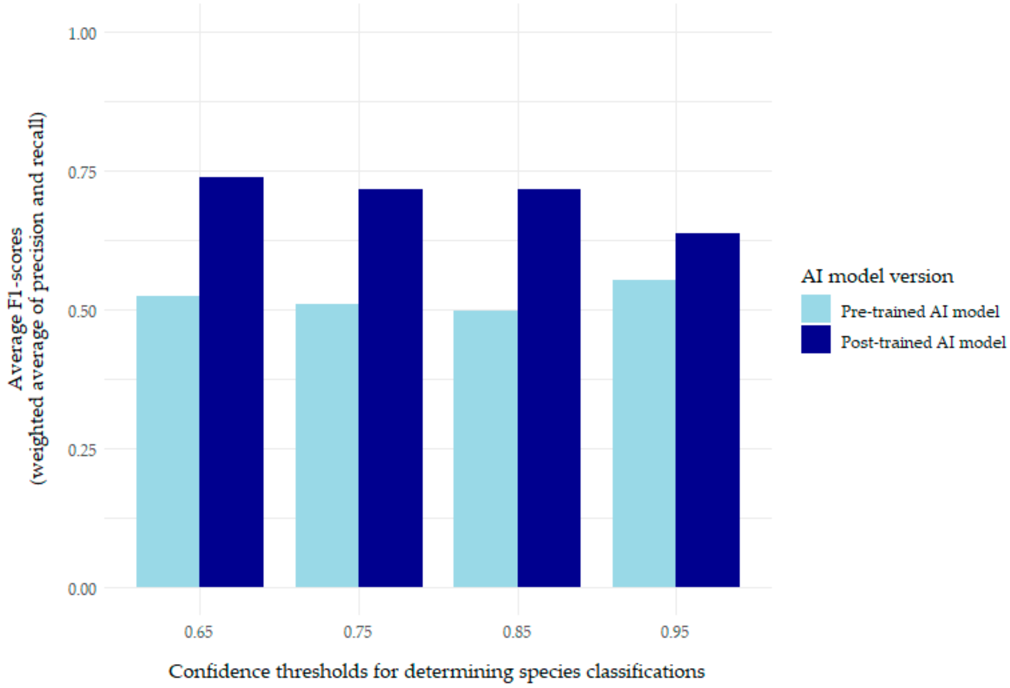

Figure 5. Conservation AI's UK Mammals Model average F1-scores (mean weighted average of precision and recall from three species F1-scores) from two sets of classifications shared by AI and human vision from a pre-trained and post-trained model. Confidence thresholds of 0.65, 0.75, 0.85, and 0.95 were used for determining species classifications.

3.3. *Efficiency*

The AI model processed the subsample of images in 30 s and a single image in an average of 0.16 s, while human vision processed the sample in an average of 10 min and an image in an average of 3.2 s (Table 5). Extrapolated values suggest that 37.8 h or 1.6 days would be required for AI vision to process the full dataset of 850,870 images, whereas 756.3 h or 31.5 days would be required for human vision to process the same dataset. However, as previously mentioned, unlike AI, a human would be unable to consistently work over a 24 h period. Therefore, 94.5 days, working 8 h per day, would be a more realistic estimate of the length of time required for a human to process the full dataset [59].

Table 5. Extrapolated values, from a subsample of camera trap image classifications, which provide an estimate of the time required to process the full dataset of 850,870 images using human and AI vision.

Classification Method	Estimated Length of Time Required to Classify Camera Trap Dataset (850,870 Images)				
	Seconds	Minutes	Hours	Days (24 h)	Days (8 h)
Human vision	2,722,784	45,379.7	756.3	31.5	94.5
AI vision	136,139.2	2269.0	37.8	1.6	-

4. Discussion

4.1. AI Model Performance and Retraining Effects

Our findings provide baseline performance estimates of Conservation AI's pre-trained UK Mammals model and demonstrate the potential for improved model performance following algorithm retraining. Although average F1-scores in the post-trained model improved from baseline estimates in the pre-trained model, AI model classifications remained significantly different from human-assigned classifications. The F1-scores achieved by the post-trained AI model were notably higher than those of the pre-trained model at all CTs, with improved precision and recall, but scores remained moderate. These findings align with wider research demonstrating that AI models often achieve high precision [24], but their performance can vary considerably by species and is often limited by challenges in achieving high accuracy [15,48].

4.2. Species-Specific Detection Differences

The model could detect foxes and badgers reasonably well, but a high rate of false negatives indicates that the AI frequently failed to detect hedgehogs, despite being able to accurately classify all three species once detected. The differences in identification accuracy among the three species are likely driven by a combination of biological traits, environmental context, and model design [34,60]. Hedgehogs are small and round-bodied and lack prominent features, meaning they could be easily obscured by the environmental heterogeneity of residential gardens containing features such as furniture, dense vegetation, or long grass. In contrast, foxes and badgers are larger-bodied with more distinctive silhouettes and often occupy a greater proportion of the image frame compared to small species [61]. These species also differ in movement patterns, which can influence whether individuals are captured clear in single frames [62,63]. Hedgehogs' tendency to remain partially concealed could have contributed to fewer high-quality detection opportunities [34,64], whereas foxes and badgers are more likely to be exposed [65,66]. However, these are hypothesized explanations that require additional testing. Consistent with our findings, a previous evaluation of Conservation AI's model reported high precision for some species but low to moderate recall (<0.70), particularly for small mammals such as rodents and squirrels [27]. This suggests that the challenges faced by AI in detecting smaller species that are easily obstructed may be attributed to the insignificant features of such species in the training data [27,34,67].

4.3. Environmental Context, Sampling Conditions, and Model Transferability

It is also possible that artificial garden characteristics included in the images were potentially not included or underrepresented in the models' training data. The lack of transferability to new environments whilst maintaining accuracy [68] remains a challenge for AI and highlights an ongoing limitation in AI-based ecological monitoring [35]. This is of particular concern in the UK, where a large proportion (18–27%) of urban landscapes are comprised of private gardens [69], highlighting the need for more adaptable and contextaware AI models within large-scale automated biodiversity monitoring [35]. However, our findings highlight the value of citizen science in facilitating camera trap deployment in private gardens and urban green spaces, enabling the collection of data on UK mammals that are often restricted to these otherwise inaccessible areas [70]. This can potentially enhance AI recognition of urban species and various garden features, thereby expanding the diversity of training datasets and improving the transferability of AI models.

Additionally, images in our study were mostly captured at nighttime, which could have affected detection rates [71]. Despite this, the significant improvement in the post-trained model performance highlights the importance and effectiveness of continuous algorithm training to improve species detection and classification accuracy [33]. However, badgers, a primarily rural species [72,73], were detected in a relatively small number of garden camera trap surveys, compared to the two urban-adapted species [74,75]. This disparity may suggest that the true AI detection rates for badgers were potentially underestimated due to the small sample potentially not capturing a realistic representation of background and subject variation [76]. However, our findings indicate that Conservation AI's UK Mammals model demonstrated accurate recall and identification of badgers, suggesting that the limited sample size likely had a minimal effect on the overall results.

4.4. AI Efficiency and Operational Trade-Offs

Despite the lower accuracy of AI classifications compared to human classifications, AI models can process images notably faster than humans [25], highlighting the efficiency of AI-based systems in handling large image datasets [14,33,77]. However, the specifications of hardware used for image processing can influence processing speed and efficiency [78], while the hardware configuration required for AI operations, cloud service costs, or local deployment barriers are crucial factors affecting adoption by conservation agencies [27,79].

However, AI maintains an operational advantage over human vision in terms of continuous and consistent image processing [35]. Unlike humans, who are realistically limited to an average 8 h workday [59], an AI model could operate 24 h a day without fatigue. Furthermore, human concentration levels can fluctuate over time and vary between individuals [80,81], potentially affecting the accuracy and consistency of species detections. Although human vision was assumed to be accurate in our study, it remains possible that some animals could have been missed. To mitigate this, two independent observers were employed, and AI accuracy was calculated relative to human observations [34,43,44]. Nevertheless, variability in human consistency may introduce observer bias, a constraint not encountered by AI-based detection. One potential strategy to address this is to involve multiple individuals in processing subsamples of image datasets. However, if trained individuals are required, this approach may incur additional costs that must be considered.

When evaluating automated versus manual approaches to camera trap image classification, there is an inherent trade-off between the costs and benefits of each method. While challenges remain in applying AI to camera trap image analysis, its efficiency-related advantages are clear, though often come at the expense of reduced accuracy compared to human observation. Although Schneider et al. [23] suggest that over ~95% recall is a practical benchmark for reliable species classifications, the level of AI performance considered acceptable by conservationists will vary depending on the relative importance of efficiency versus accuracy, driven by specific research objectives and associated time constraints.

4.5. Hybrid Approaches: AI, Human Verification, and Citizen Science

Alternatively, there is potential in applying a combination of AI and citizen science classifications [82]. Citizen science platforms such as eMammal [10], MammalWeb [36], eBird [83], and Zooniverse [84] engage public volunteers in camera trap projects to improve image analysis efficiency. However, species identification skills can vary depending on individual knowledge and experience, which can impact accuracy [35]. Additionally, some image datasets that include images captured in private residential gardens, such as the one used in our study, pose privacy concerns that restrict sharing to publicly accessible databases, meaning citizen scientists cannot contribute to classifications. When citizen science participation is an option, it is frequently reported that, although involving humans in image processing increases the time taken to obtain classifications, it reduces errors considerably and improves the accuracy of the results [25,35]. Furthermore, involving citizen scientists supports conservation by promoting public awareness and engagement [85].

Using human analysis of camera trap images can also provide more intuitive insights beyond species identification, such as behaviours or interactions that AI may not capture [24,86]. Humans can also analyze sequences of images to detect animals by recognizing movement across frames, whereas many AI models typically analyze images individually [32]. For example, when an animal is not clearly visible in a single image, a human observer may still infer its presence by tracking its movement across a series of consecutive images. A potential constraint associated with using human vision is the process of learning to use image analysis software such as Timelapse [45,46] or digiKam [87], which is typically required when processing large image datasets. While some AI platforms require proficiency in coding to process images, others, such as Conservation AI, offer user-friendly interfaces that allow direct image uploads, thereby eliminating the need for users to acquire new technical skills. Conversely, AI classification models require continuous retraining to enhance performance, a process that depends on large datasets and substantial human effort to manually verify images and guide the training [33].

Our study involved human observers who worked in the wildlife conservation field and thus had prior knowledge, which may have led to more accurate identifications than would be expected from untrained members of the public [37,88,89]. This could have introduced potential observer bias [33], with reported human vision accuracy not representing broader, non-expert populations.

4.6. Implications for Workflow Design and Ecological Monitoring

Based on the AI model performance results from this study, a semi-automated workflow with a three-stage classification method was designed to overcome challenges associated with accuracy and efficiency for future camera trap studies, when citizen science classification was not an option due to privacy restrictions (Figure 6). This method aimed to create a pipeline for camera trap data analysis as an alternative to a fully automated or manual approach to processing the full dataset [40]. To balance classification accuracy and efficiency, the workflow combines two AI models (MegaDetector and Conservation AI) with manual classification [34].

The first step uses a primary AI model with high recall estimates (MegaDetector) [18,32] as an initial filter to identify blank images and those containing an animal. Selecting a lower confidence threshold for accepting classifications at this stage will increase recall and reduce the number of false negatives, minimizing the risk of excluding images containing an animal [27]. However, this is at the expense of reducing precision and potentially including more false positives that may require additional manual validation. The second step involves a secondary AI model with high precision estimates to classify images containing an animal at the species level (Conservation AI) [28]. Selecting a high confidence threshold at this stage will increase precision and reduce the number of false positives, minimizing the risk of misclassification [27], but at the expense of reducing recall and potentially resulting in more false negatives that may require additional manual validation. The final step involves manually reviewing images that meet the following

https://doi.org/10.3390/rs18030502

criteria: images classified by the primary AI filter as (i) containing an animal with a confidence level below the confidence threshold or (ii) blank with a confidence level below the threshold. Additionally, images processed by the secondary AI filter that are classified as (iii) containing a species with a confidence level below the threshold and (iv) all images classified as blank will require manual classification (Figure 6).

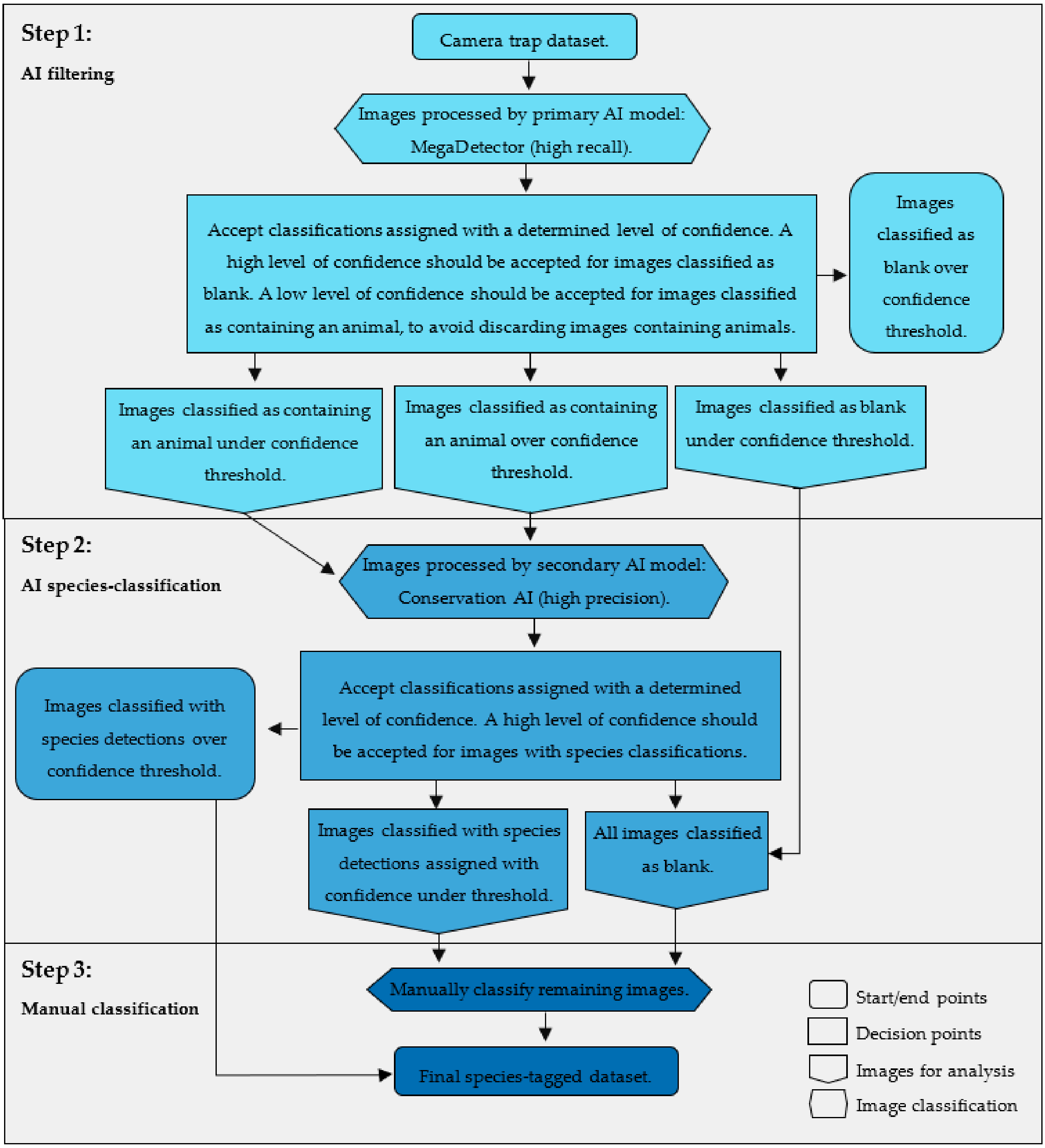

Figure 6. A semi-automated three-step workflow that combines two AI image classification platforms (MegaDetector and Conservation AI) and manual verification to improve the efficiency and accuracy of camera trap image analysis.

Accuracy is enhanced through the manual validation of images with classification probabilities below a predefined confidence threshold. This method streamlines image processing whilst maintaining accuracy by harnessing the strengths of two AI platforms and incorporating manual validation, providing a balanced alternative to using a single-platform automated system and fully manual classification, when citizen science classifications are not possible. This workflow suggests using MegaDetector, reported to detect animals with approximately 95% accuracy [32], as the primary AI step to filter blank images and Conservation AI as the secondary AI step to classify species. However, this workflow is adaptable and can incorporate different AI models suited for other camera trap image analysis. By narrowing the gap between data collection and analysis, this workflow can potentially provide more timely insights to inform decision-making [38,90]. One current limitation is the time required to reformat AI-exported data, which often varies in structure and must be standardized prior to manual review [27].

4.7. Further Research Recommendations

Therefore, we recommend that future research carefully considers the design of image analysis workflows, balancing trade-offs between accuracy and efficiency based on study objectives. Key factors to consider include data volume, processing limitations, time constraints, target species, and the type of ecological information needed to achieve research objectives [14,23,24,45,91–93]. Gaining an insight into the baseline error levels considered acceptable by conservationists, when using AI to help reduce the time gap between data collection and research output, could help to guide future investment in AI model training. Furthermore, evaluating AI model performance across a broader range of species, particularly small-bodied and visually cryptic mammals, as well as across different geographic regions, habitat types, and conditions such as lighting, camera angles, and degrees of occlusion, would provide a more comprehensive understanding of model reliability and generalizability [15,61,94]. By further assessing how AI performs under different conditions and for other species, researchers could better quantify uncertainty in automated classifications, improve training datasets, and refine model algorithms. Finally, further research into how distance metrics from the camera to the animal, based on animal size, affect AI classification and how this methodology could be implemented practically for mammals is needed to potentially improve the identification of smaller species [39,67].

4.8. Key Points and Applications

Overall, our study demonstrates that retraining AI models improves the accuracy of AI classifications of camera trap images. Although, the moderate F1-scores achieved by Conservation AI's post-trained UK Mammals model highlight the ongoing limitations of fully automated workflows [15,48], they emphasize that AI performance is species- and context-dependent, with reduced reliability of smaller, more camouflaged species [27]. Nevertheless, AI substantially improves the efficiency of processing large camera trap datasets [14,77]. Our findings support the use of a semi-automated three-step workflow that combines high-recall detection, high-precision species classification, and targeted manual validation. This integrated approach provides a practical balance between accuracy and efficiency for ecological monitoring, particularly where citizen science contributions are not feasible, enabling the more timely delivery of findings for conservation decision-making. The proposed workflow is readily applicable to solve real-world challenges in camera trap image analysis.

5. Conclusions

Our study provides baseline estimates of camera trap image classifications using Conservation AI's UK Mammals model. The importance of ongoing algorithm training to enhance species identification accuracy is demonstrated by improvements observed in the post-trained assessment. Although accuracy remained moderate following training, the AI model notably outperformed human vision in processing efficiency. These findings align with wider research indicating that AI provides a more efficient but generally less accurate approach to image analysis. This trade-off between accuracy and efficiency presents challenges when choosing between automated or manual methods for image classification. Existing projects have incorporated citizen science to overcome these challenges; however, the reliability of results can vary, and certain datasets pose privacy concerns that restrict sharing to publicly accessible databases for citizen scientist classification. To overcome this, we developed a semi-automated workflow that combines two AI models with manual classification to balance these competing priorities. We anticipate that our findings will inform key considerations in applying AI and manual review techniques for camera trap data processing and assist in guiding future workflow development.

Author Contributions: All authors contributed to the study conception and design. Data processing and analysis were performed by K.H. (Kelly Hitchcock). The first draft of the manuscript was written by K.H. (Kelly Hitchcock), and all authors provided comments. All authors have read and agreed to the published version of the manuscript.

Funding: This study was match funded under a studentship agreement between Nottingham Trent University, UK and Chester Zoo, UK.

Data Availability Statement: The original data presented in the study are openly available in Zenodo at https://doi.org/10.5281/zenodo.17779383.

Acknowledgments: We are grateful to all who supported Chester Zoo's Hedgehog Watch, in particular Hannah Khwaja, Olivia Maidment, Natasha Murwill, Andrew Moss, the Chester Zoo Conservation Education & Engagement and Field Programmes Teams, the Chester Zoo volunteers who supported the project, and all the citizen scientists who participated. We are also grateful for the contributions to image analysis made by Katie Vertigen.

Conflicts of Interest: The authors declare no conflicts of interest.

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