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Needle in a haystack: towards the use of machine learning to detect Texas tortoises in large datasets

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***Abstract*.—Texas tortoises (*Gopherus berlandieri*) are an elusive reptile native to south-central Texas and northern Mexico. Unlike their congeners in North America, the Texas tortoise does not create a conspicuous burrow that can be monitored. Instead, they create a shallow depression (known as a pallet) often in thick vegetation that obscures the tortoise from a surveyor's view. Camera traps provide an alternative to visual encounter surveys that allows for a greater number of survey hours without disturbing the environment. Because Texas tortoises are ectothermic, time-lapse mode must be used, which generates massive datasets. Machine learning provides an opportunity to streamline the identification of tortoises in these datasets. Our goal was to train machine learning models in the identification of Texas tortoises across key representatives of their habitat types and make the model available for use. We have established grids of camera traps across the range of the Texas tortoise. In Python, we developed a deep-learning model for image segmentation. Given an input image, the trained model detects tortoises and draws a polygon. We used CVAT.ai to annotate the images by drawing bounding polygons around tortoises in each image. The annotated training images were used for transfer learning with a pre-existing computer vision model which can enable skillful detection without requiring a massive set of annotated training examples. We used precision-recall curves to evaluate performance. We then tested the models using a test dataset that had been excluded from the training process. The top performing model had a precision score of 0.93, recall of 0.83, and accuracy of 0.86 on the test dataset. This machine learning model, which has been made available online, could make trail cameras a viable option to detect Texas tortoises. This model provides a valuable resource to streamline post trail camera data-collection which can allow for greater monitoring efforts of the Texas tortoise and support conservation efforts.**

Keywords. Trail camera, instance segmentation, *Gopherus berlandieri*, Testudinidae, image recognition, R-CNN

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Introduction

Accurately and efficiently monitoring reptile and amphibian populations is essential to their conservation and management (Scott and Seigel 1992). Numerous techniques have been used to survey terrestrial turtle populations including transect surveys, intensive plot surveys, and road-cruising surveys (Judd and Rose 2000). The Texas tortoise, a Species of Greatest Conservation Need in Texas (TPWD 2012a), can be difficult to survey due to the dense scrub habitat through their range, lack of conspicuous burrow use (Auffenberg and Weaver 1969), and overall low densities (0.24 – 5.5 tortoises per ha, Kazmaier et al. 2001; Carlson et al. 2018; Elissetche 2024; Moeller 2024). Road-cruising surveys have been a popular technique to detect this species (Rose and Judd 1975; Thode 1999; Kazmaier et al. 2001; Scalise 2011; Parandhaman 2015) both due to the limited public land in Texas (Wagner and Kreuter 2003) and the visibility created by roads. However, recent success rates of road-cruising surveys have returned less than one Texas tortoise detection per 100 survey hours on Texas highways (Parandhaman 2015). Additionally, habitat analysis evidence on Texas tortoises indicates that primary roads (i.e., high-traffic roads) act as a barrier to Texas tortoise movement (Guerra 2020). Several

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properties on which Texas tortoises reside do not have many accessible roads through much of their habitat. As such, constrained ground searches (i.e. defined area searches, transect and grid surveys) are another common method used for Texas tortoise surveys (Thode 1999; Rose et al. 2011; Carlson et al. 2018; Moeller et al. 2024; Elissetche 2024). These methods can allow surveyors to directly encounter Texas tortoises in their habitat that may be missed through road cruising. However, ground searches can be inefficient given the limited daily activity (a few hours daily during the peak of summer; Guerra 2024) and limited movement of this species (Guerra 2024). Surveying for Texas tortoises during periods of movement is often crucial to locate them as the shallow pallets they dig (Auffenberg and Weaver 1969) can leave them undetectable in undergrowth (Figure 1). The frequent inability to recapture tortoises without a radio transmitter (Bury and Smith 1986) and lengths of time that can pass without seeing Texas tortoises in low density sites (i.e. Texas tortoise presence not being documented for 16 years at San Antonio Missions National Historic Park [SAMNHP]; SAMNHP 2023) underscore how easy it is to miss Texas tortoises through active survey methods. The limitations of road-cruising and ground searches highlight the need to explore different options to monitor the Texas tortoise, especially in low density sites.

Camera trapping has grown in popularity as a method to document the presence of elusive species given the non-invasive and passive nature of these devices while still allowing for a robust sample size. Camera traps are especially beneficial for elusive species that have limited activity (Agha et al. 2015) and movement, such as the Texas tortoise. Despite the versatility of camera traps, mammals, birds, and fish have been the primary focus of these studies (Mallet and Pelletier 2014; Meek et al. 2014). Welbourne et al. (2015) argue that using

Fig. 1. A Texas tortoise palleted down in guinea grass at the Oso Bay Wetlands Preserve and Learning Center.

this methodology to monitor herpetofauna is one of the remaining frontiers for camera trapping research. Tortoise camera trap research has largely been limited to monitoring burrows to answer questions about nesting ecology, activity patterns, and burrow visitation (Alexy et al. 2003; Agha et al. 2015; Dziadzio and Smith 2016; Agha et al. 2017) with focus on gopher tortoise (*Gopherus polyphemus*) and Mojave Desert tortoise (*Gopherus agassizii*). Texas tortoises have previously been detected through camera traps (Kutugata et al. 2021). However, this study used passive infrared motion-sensitive cameras, as the focus was on a large ungulate, likely impacting Texas tortoise detection rates.

The time-lapse mode often required to accurately capture reptiles moving on the landscape (Pomezanski and Bennet 2018) can generate massive datasets (Pomezanski and Bennet 2018). Platforms that utilize artificial intelligence (AI), such as Wildlife Insights (Ahumada et al. 2020), are more commonly used as a solution to reduce the labor needed to manually classify images. However, the requirement of data sharing (Ahumada et al. 2020; Vélez et al. 2022) or costs associated with some platforms may be a barrier to use. Additionally, large models may not be accurate at classifying rare species due to unbalanced data classes (Norouzzadeha et al. 2018). Thus, researchers have developed models to recognize specific species (e.g. Bjerge et al. 2022; Hilton et al. 2022; Jeantet et al. 2024; Soria et al. 2024) and communities of species (ex: Chen et al. 2014; Chen et al. 2019; Kutugara et al. 2021; Zualkernan et al. 2022; Baek et al. 2024; Hopkins et al. 2024). Specifically with tortoises, Convolutional Neural Networks (CNNs) which learn to automatically extract image features have been successful in detecting gopher tortoises and cutting time-lapse videos where they are detected (Hilton et al. 2022). Further, a multi-species model of south Texas wildlife successfully identified a handful of Texas tortoises in the dataset (Kutugara et al. 2021). The south Texas model treated the problem as an image classification task, whereas the gopher tortoise model treated the problem as an object detection task. In computer vision, image classification is the task of assigning images to a class based on predefined class labels (Rawat and Wang 2017). The task of object detection often adds to the classification process by marking the location of a class within an image (Tian et al. 2022). These tasks can be limited in their specificity. Object detection uses a bounding box to predict a class (He et al. 2017), which can lead to the inclusion of additional data (i.e. the background environment) not related to the object of interest. This can introduce ambiguity into the machine learning task which relies on labeled data to learn associations between input predictors (e.g. an image) and the annotated target (e.g. an image with bounding boxes). When the objects are represented by a bounding box, larger numbers of training images may be required for the learning process to distinguish between features relevant to the target and background features. On the other hand, segmentation tasks often use a mask to conduct per-pixel classification within an image (He et al. 2017). In sea turtles, where complex habitat is an issue in classification, models trained on segmentation tasks were superior at detecting turtles than those trained on object detection alone (Baek et al. 2024). Segmentation-based trained models are a promising route for Texas tortoises that are often in complex habitats.

The goal of this study is to inform design for camera trap surveys for Texas tortoises and provide a model that can be used by others to search for Texas tortoises in their camera datasets. The specific objectives are to (1) compare overall detection probability between different camera trap survey designs, (2) create a machine learning segmentation model to identify tortoises in images, and (3) compare the performance of this machine learning model to pre-existing models. The creation of more specific guidelines to survey the Texas tortoise and an efficient model to detect these animals can be helpful for determining whether these tortoises are still present at sites historically in their range. Additionally, camera trap surveys could potentially determine the success of translocation efforts by passively monitoring the settlement of tortoises into a new area.

Materials and Methods

Study Sites

We conducted camera trap surveys of Texas tortoises at Chaparral Wildlife Management Area (CWMA), Las Palomas Wildlife Management Area (LPWMA), Cactus Creek Ranch (CCR), and Laguna Atascosa National Wildlife Refuge (LANWR) Longoria Unit (Figure 2). At CWMA (28.31, -99.40), the West Guajalote and West Blocker pastures are comprised of open canopy with herbaceous ground cover and scrub mottes dominated by honey mesquite and acacia (Kazmaier et al. 2001). The Longoria Unit of LPWMA (26.31, -97.82) is primarily characterized by pristine Tamaulipan thornscrub (Kearney et al. 2020) with small agriculture fields. CCR and Unit 8 of LANWR (26.26, -97.36) are characterized by scrub dominated by mesquite (Briggs 2016) mixed with coastal prairie. This work was conducted under specific MOUs with CWMA and LPWMA, special use permit 2022-LA-026 for LANWR, and with landowner permission at CCR.

Camera Deployment

At each location, we placed a grid of camera traps consisting of a total of 40-45 cameras. The cameras were spaced either 250 or 500 m apart based on available spacing at the site. Further, we alternated between paired cameras (cameras facing North-South) and a singular camera (camera facing South) at each station

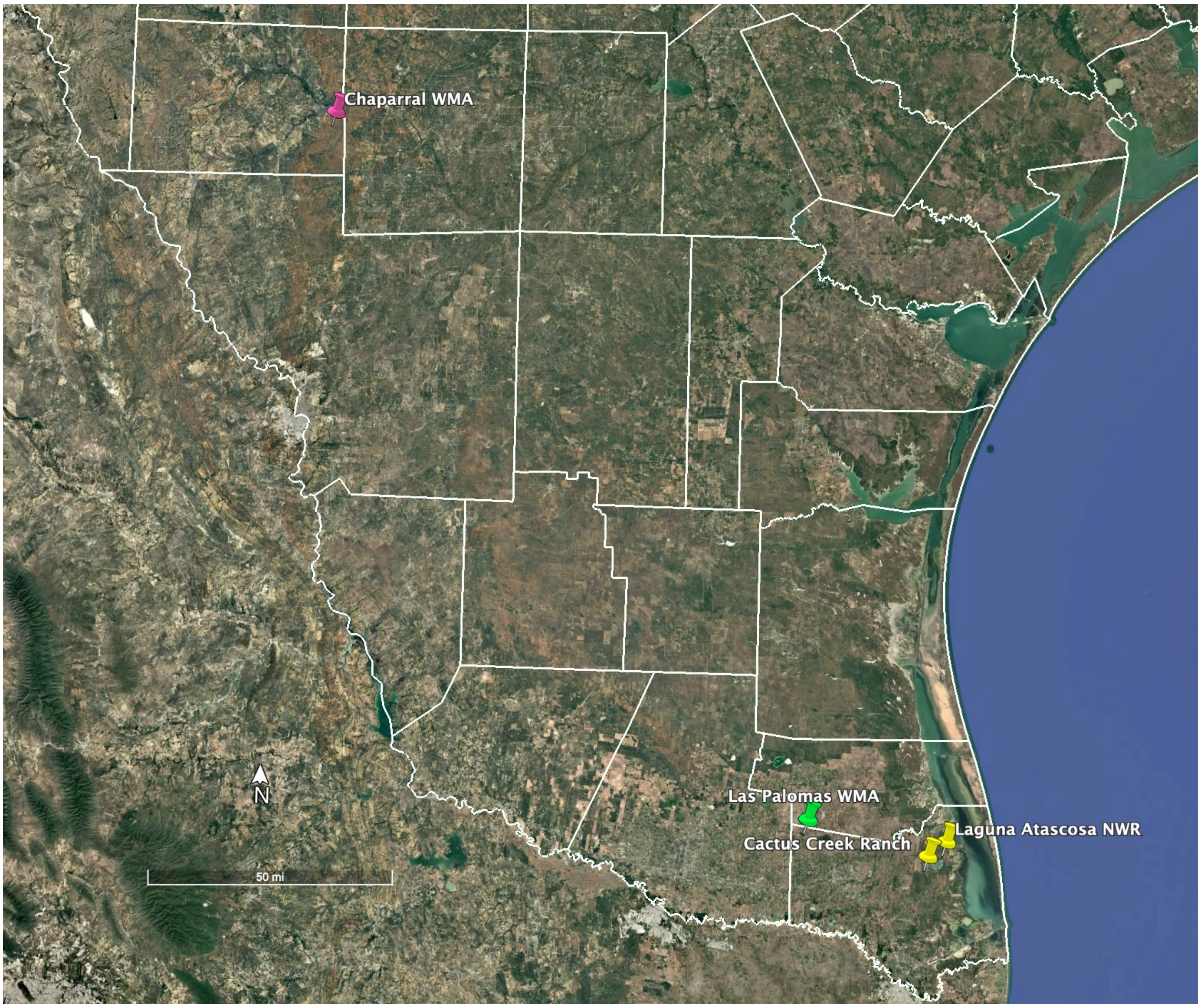

Fig. 2. Location of camera grids indicated by name with pin corresponding to habitat type (pink; brushland, green; Tamaulipan thornscrub/agriculture, yellow; Tamaulipan thornscrub/coastal prairie) created in Google Earth.

to understand whether an additional camera at a station significantly increased detection probability. We used Browning Dark Ops Pro DCL trail cameras set to the Timelapse Plus mode, where IR triggered images could still be collected between timelapse period. We set the camera so that a photograph was taken every two minutes during daylight hours and the motion-trigger mode had a 30 second delay between photos. We selected these settings to ensure tortoises were captured on camera and to assess whether tortoises could be detected via motion-trigger alone. In the field, we mounted cameras horizontally on t-posts ~40 cm off the ground and at a ~45° angle to target tortoises. These grids remained active for ~8 weeks (early May – late June, early July – late August, early September – early November). After this period, we relocated them to the next location. Grids were active between May and November of 2022 and 2023 with two replicates per site to minimize the impact of seasonality on detection. In 2023, LANWR acted as the replicate for CCR to allow for spacing cameras 500 m apart.

Camera grid design

To understand the effects of camera trap array design, we used t-tests to compare the impact of grid design and paired/unpaired status on tortoise detection. Further, we used ANOVAs to compare the impact of habitat type and season on tortoise detection. For these analyses, unique detections were considered based on camera trap day (i.e., if there were multiple detections on a single day, only one detection was counted).

Creating and annotating the training dataset

We confirmed the presence of Texas tortoises in photos using the VLC media player (Version 3.0.17.3; Denis-Courmont et al. 1996). We noted the time that Texas tortoises entered and exited the frame, how long the tortoise was on camera, whether the tortoise triggered the motion detector (determined by the timestamps), and any activity displayed (palleting, feeding, and copulation). We exported all frames with a Texas tortoise present

Table 1. Composition of the test dataset and all training datasets. Model 4 (M4) included every instance of an annotated tortoise.

Data Set	Total Photos	Tortoises	Blanks	Non-Tortoise Animal
Test	**274**	**165**	**65**	**44**
M1	**1291**	**715**	**569**	**0**
M2	**1490**	**715**	**380**	**395**
M3	**1880**	**1086**	**794**	**0**
M4	**2705**	**1332**	**420**	**953**

to be part of the training dataset. We selected random Texas tortoise images from iNaturalist, released under a Creative Commons license, to have a wider breadth of habitat (including photos from their range in Mexico) and camera angle representation. Additional Texas tortoise images were provided from a study on wildlife crossing structures at Texas A&M University-Kingsville (Yamashita et al. 2024), which also allowed the model to train on different camera angles, and another trail camera brand (Reconyx). We included several blank photographs and photographs of non-tortoise animals in the training dataset. Effective machine learning requires a variety of inputs to be present in the training dataset. Without examples of non-tortoise animals, the learning task can be highly ambiguous. The model may learn to treat non-background features as the target class (tortoise), especially if they share visual characteristics with the tortoises. For the non-tortoise animals, we placed special emphasis on including several armadillo photos as we anticipated it would be the animal the model could confuse with tortoises. We used a uniform random number generator to randomly withhold ~10% of the images from the training dataset to comprise the test set (Table 1). Given that this number generation operated on an image-level basis, images from within a sequence of tortoise photos were occasionally split between the training and test dataset leading to mild data leakage. The test set included images from all sites, datasets, and across all seasons.

Finally, we augmented the training dataset by rotating and inverting images, cropping the image, and changing the contrast, exposure, brightness, and saturation values. Augmenting image datasets with synthetic, modified inputs is a common technique for training machine learning models. Presenting the model with perturbations of the real images has been shown to improve detection skill for numerous applications (Dosovitskiy et al. 2014; Ronneberger et al. 2015; Minaee et al. 2022), especially when the size of the training dataset is relatively small. This is done to limit overfitting; by presenting the same image feature from multiple angles, colors, and noise, the model can better distinguish between the truly relevant features (e.g. target object edges and textures) and artifacts from the data collection process (e.g. camera orientation and color calibration).

With Computer Vision Analysis Tool (CVAT.ai, Version 2.14; Sekachev et al. 2019), we drew polygons over the outline of each Texas tortoise in every uploaded frame to create instance segmentation annotations. If vegetation obscured part of the tortoise, we adjusted the outline of the polygon to exclude as much plant material as possible. We also loaded the blank and non-tortoise images into CVAT.ai to create the annotation files, however, no objects were annotated. We downloaded each of these annotation files in .json format which contains segmentation annotation data and is compatible with the Microsoft Common Objects in Context dataset (MSCOCO, Lin et al. 2014).

Ethical note

ChatGPT-3.5 was used to help generate and modify the machine learning pipeline. This pipeline is composed of four stages: data preprocessing, specification of the machine learning architecture, model training, and evaluation of the trained model. The pipeline was developed iteratively. Generated code was tested manually, and modifications were made to the ChatGPT-produced code when issues were encountered. No generative AI was used in any other aspect of this research.

Data preprocessing

Prior to training the models, the annotation files were processed to extract all the relevant data (labels, bounding boxes, image IDs, and segmentation data) to be bundled in a format appropriate for the machine learning architecture. Prior to use in the model training process, the segmentations were converted to binary masks. Tools from the NumPy library (Harris et al. 2020) were used to convert the pixels within the segmentation mask to one value, while pixels outside were converted to another value. Once these pixels were converted, tools from the OpenCV library (Bradski 2000) were used to fill the polygon outline and create the mask. These masks were then transformed to an 8-bit integer that was compatible with PyTorch (Ansel et al. 2024), a popular framework used to design and train machine learning models.

Transfer learning

We opted to use the transfer learning technique to train the models in identification of Texas tortoises from segmentation annotations. Transfer learning is a machine learning method where a new model is initialized based on strategies learned by an existing, similar model

(Joachims 1999; Pan and Yang 2010). Intuitively, the learned strategies for the existing model provide a starting point for the new model despite being trained for a different task. In addition to potentially improving training efficiency, it may enable achieving skillful models even with a severely limited datasets (Joachims 1999; Pan and Yang 2010) as in this research. Transfer learning has been rapidly adopted across many fields to enable development of skillful models despite severely limited training data sizes (Weiss et al. 2016). Deep learning practitioners have found that a model trained for one task can learn information that can be beneficial for another task. For example, models trained using the MSCOCO dataset are capable of skillful detection of 80 different classes such as dog, car, and person. The MSCOCO dataset is a large collection of labelled images curated to enable research in computer vision (Lin et al. 2014). Even though such models have not been trained for domain-specific tasks like prediction of a Texas tortoise in complex habitats, they already have extensive knowledge of generic visual patterns (textures, edges, etc.) and how they can be composed into higher-level visual concepts. Typically, the machine learning process starts by initializing the model with random weights that are iteratively refined through the training process based on error minimization. With transfer learning, a new model can be created that inherits some of this knowledge and adapts to a new task. This is achieved by creating a new model whose weights are pre-initialized using the weights learned from the pre-trained model. The final layers of the architecture are modified to suit the new model task. With the new model and weights transferred from another skillful segmentation model, the training process adjusts those weights for the new task (here, tortoise detection) using the annotated dataset. By leveraging the pattern-recognition skills of the model trained with 164,000 cases, new task-specific models can be trained with a fraction of the data that would be required to train from scratch.

For the models, Faster R-CNN (Ren et al. 2016) and Mask R-CNN (He et al. 2017) were used for this purpose. Both models use Region Proposal Networks (RPNs) and are pre-trained on the MSCOCO dataset (Lin et al. 2014). We used Mask R-CNN with the ResNet50 backbone that is 50 layers deep (He et al. 2017). Faster R-CNN was used to predict the bounding boxes, whereas Mask R-CNN predicted the weights, classes, and masks. Both use CNNs as their main learning backbone. CNNs are a type of artificial neural network designed to extract image features (O'Shea and Nash 2015). Using a sequence of convolutional layers, the networks learn increasingly complex image concepts (O'Shea and Nash 2015). Initial layers learn extremely granular features like "vertical edge" or "speckled texture". Subsequent network layers combine these to learn abstract features like eyes, grasses, and shells. CNNs are the main tool in machine learning for learning image features and are used within a variety of machine learning architectures such as region-based CNNs (R-CNN). With R-CNNs, features are extracted from an input image and processed by the backbone network to generate a feature map (Ren et al. 2016). This feature map is then used by the RPN to predict multiple regions where the object may be and uses bounding boxes and classification scores to refine these proposals (Ren et al. 2016).

Tools from the PyTorch library (Ansel et al. 2024) were used to define the deep learning architecture and train the models. We ran models with a batch size of 12 and maximum epoch size of 150. We used a learning rate of 0.0005 and a weight decay of 0.001. We calculated average total loss (which included classifier loss, bounding box regression loss, bounding box RPN regression loss, mask loss, and object score loss, Ren et al. 2016; He et al. 2017) per epoch to determine when to stop model training. When the average total loss had not improved by 0.002 for 5 epochs, the model stopped training.

Model evaluation

To evaluate model performance, we calculated precision and recall at different confidence thresholds and plotted a Precision-Recall Curve with MatPlotLib (Hunter 2007). Precision is a measure of how often the model correctly predicts the object of interest out of all predictions the model makes and is calculated using the following equation:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Meanwhile, recall is a measure of how many of the objects of interest were predicted and is calculated using the following equation:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

These values were calculated at different confidence threshold values ranging from 0.35 to 0.90 with a step value of 0.05. To determine whether a value was a true positive (TP) or false positive (FP), we used an Intersection over Union (IoU) threshold of 0.5. The IoU is a comparison of the overlap between the ground truth bounding box and the predicted bounding box and the overall area these bounding boxes cover:

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union}$$

This means, 50% or more of the predicted bounding box would have to overlap the ground truth bounding box to be counted as a TP, otherwise it would be counted as a FP. Only one TP was counted per image unless multiple tortoises were present in the image. If none of the predictions on a tortoise image were a TP or no predictions were made, then a false negative (FN) was counted. For blank images, any predictions that exceeded the confidence threshold were counted as a FP. If no predictions exceeded the confidence threshold, then a true negative (TN) was counted. With all the TP, TN, FP, and FN a confusion matrix was made set at the 0.5 confidence threshold and plotted with the matrix using the seaborn library (Waskom 2021).

All the calculated precision and recall scores were collected by the confidence threshold value. Then, the average precision and average recall were calculated at each confidence threshold value. With these averages, we calculated the F1 score which is a harmonic mean of the precision and recall. The F1 score was calculated at each threshold value with the following equation:

$$F1 = 2 * \frac{precision * recall}{precision + recall}$$

Accuracy is a measure of how many times the image is correctly sorted out of all predictions made. It was calculated at each threshold using the following equation:

$$Accuracy = \frac{true\ positives + true\ negatives}{true\ positives + true\ negatives + false\ positives + false\ negatives}$$

Finally, the false positive rate (FPR) is a measure of how many FP are predicted out of the total negative cases (both true and predicted):

$$False\ Positive\ Rate = \frac{false\ positives}{false\ positives + true\ negatives}$$

We compared four main models: model with blank landscape photos (M1), model with blank landscape photos and non-tortoise animals (M2), model with augmented photos and blank landscapes (M3), and a model with augmented photos, blank landscape photos, and non-tortoise animals (M4) (Table 1). We examined the precision, accuracy, recall, FPR, and F1 score to determine which model performed best. We prioritized higher recall and accuracy as the inclusion of more tortoises was deemed more important than fewer false positives. We assessed top model performance by calculating the area under the curve of a true positive rate and false positive rate comparison across all thresholds.

Final model evaluation

Using the test dataset, we compared the top performing model to the Wildlife Insights model (WI; Ahumada et al. 2020) and the South Texas wildlife model (ST; Kutugara et al. 2021) based on Precision, Recall, Accuracy, and F1 scores. For each image, we marked a TP if the predicted box overlapped the tortoise (or 2 if two tortoises were present and marked) and had a confidence score of > 0.5. A FN was marked if no predicted boxes overlapped the tortoise(s), or the predictions had a confidence score of < 0.5. A TN was marked when the image was blank and no predictions exceeding the threshold were made. For these comparisons, we did not include non-tortoise animals as this model is solely meant to classify tortoises and would complicate determining FP, TP, etc. Given that the WI model is not well trained on Texas tortoises, we compared the performance of the model at two levels: when it identified a Texas tortoise as an animal (TP whenever a tortoise was identified at a confidence greater than 0.5), and when it identified a Texas tortoise as a tortoise (family Testudinidae). The same was done for the ST model, however TP were not marked at a 0.5 value since this model works as a classifier (sorts it into folders) rather than an object detector. Finally, false positives were marked when a prediction with a confidence score of > 0.5 was made that did not overlap a tortoise.

Results

Across the six survey periods, there were a total of 111 unique Texas tortoise detections. There was an average of 18.5 Texas tortoise detections per survey period across 5.5 camera stations (18% of stations). Camera spacing ($n_{250m} = 112$, $n_{500m} = 60$) did not have a significant effect on tortoise detections (t = -0.02, p-value = 0.98, lower 95% CI = -0.61, upper 95% CI = 0.59). Paired (n = 81) vs. un-paired (n = 91) camera status did not have a significant effect on tortoise detections (t = 0.02, p-value = 0.98, lower 95% CI = -0.60, upper 95% CI = 0.61). There was no significant impact of seasonality ($n_{fall} = 55$, $n_{summer} = 57$, $n_{spring} = 60$) on tortoise detections (F-value = 0.09, p-value = 0.91, df = 2). Further, habitat type ($n_{brush} = 60$, $n_{coast} = 58$, $n_{thorn} = 54$) did not have an impact on tortoise detections (F-value = 0.26, p-value = 0.77, df = 2).

Training results

Based on the rate of training loss, we compared M1 at 58 epochs, M2 at 58 epochs, M3 at 71 epochs, and M4 at 67 epochs. The training diagnostics indicated that both M3 and M4 performed marginally better than M1 and

Table 2. Model diagnostics based on training dataset. Precision, recall, F1 score (harmonic mean), accuracy, and false positive rate (FPR) are calculated at the 50% confidence threshold (0.5) and the average of each measure across several thresholds (30% - 90%) are reported here.

	Precision		Recall		F1 Score		Accuracy		FPR	
Model	Avg	0.5	Avg	0.5	Avg	0.5	Avg	0.5	Avg	0.5
M1	0.90	0.89	0.98	0.99	0.94	0.94	0.93	0.93	0.13	0.14
M2	0.89	0.87	0.98	0.99	0.93	0.93	0.94	0.93	0.10	0.12
M3	0.95	0.94	0.99	0.99	0.97	0.97	0.97	0.96	0.07	0.07
M4	0.93	0.93	0.99	0.99	0.96	0.96	0.96	0.96	0.07	0.07

Table 3. Performance of all four models with the test dataset. The true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are used to calculate the precision, recall, accuracy, and false positive rate (FPR) at a 0.5 confidence score. Bolded values indicate the best performance for each metric.

Model	TP	TN	FP	FN	Precision	Recall	Accuracy	FPR	F1 Score
M1	122	70	45	45	0.73	0.73	0.68	0.39	0.73
M2	118	100	15	49	0.89	0.71	0.77	0.13	0.79
M3	137	67	52	30	0.72	0.82	0.71	0.44	0.77
M4	139	102	10	28	**0.93**	**0.83**	**0.86**	**0.09**	**0.88**

M2 across all metrics (Table 2). However, the difference across metrics was only ~3% following training. When comparing model performance with the test dataset, M4 performed best across all metrics (Table 3). On recall, M3 was most comparable to M4 with the M4 recall only slightly higher (~1%), however the precision and FPR were notably different for M4 (21% higher precision and 35% lower FPR; Table 3). The precision of M2 was comparable to M4, with M4 precision being 9% higher, however the recall was 12% higher in M4. Given the accuracy and F1 score of M4 were 9% and 0.1 higher than the next closest model, we used M4 to compare to pre-existing models.

Performance of top model

Model 4 predicted the correct label >96% of the time at a confidence of 50% (Figure 3). The recall score starts to drop at a confidence score of 85%, whereas precision continues to rise (Figure 4). Based on the F1 score, the model recall and precision are best at 85-90% confidence score (Figure 5). The FPR rate change slows at 45% confidence threshold (Figure 6). Finally, the AUC was 0.995 (Figure 7).

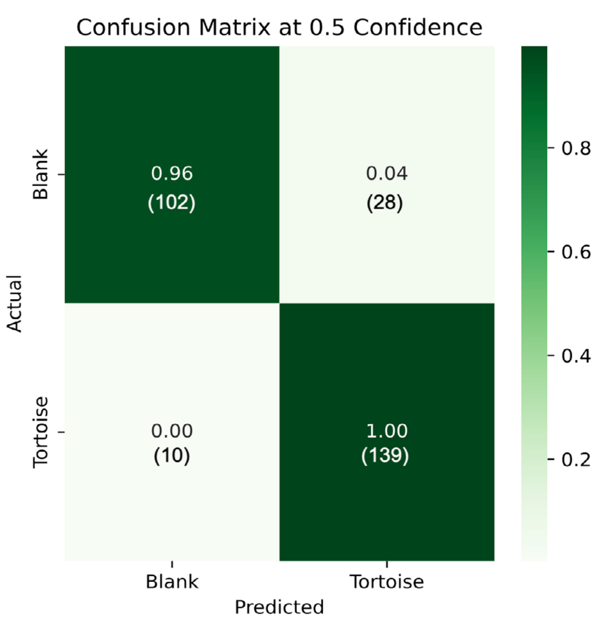

Fig. 3. Heat map of the confusion matrix of the top performing model (M4) at the 50% confidence threshold on the test dataset. Darker greens indicate a greater proportion of predictions fell into those categories.

Comparison to pre-existing models

The best model from this study (hereafter, TT model) had the highest recall, accuracy, and F1 score of the compared models (Table 4). The WI model had the highest precision (100%) when the model was required to correctly classify to the family level Testudinidae. However, the TT model had a 66% higher recall than the WI model at the family level specificity. Additionally, the only other metric where the TT model was outperformed was the FPR; for both the WI and ST model, no images were incorrectly classified as a tortoise, so their FPR was 0% compared to the 6% of the TT model.

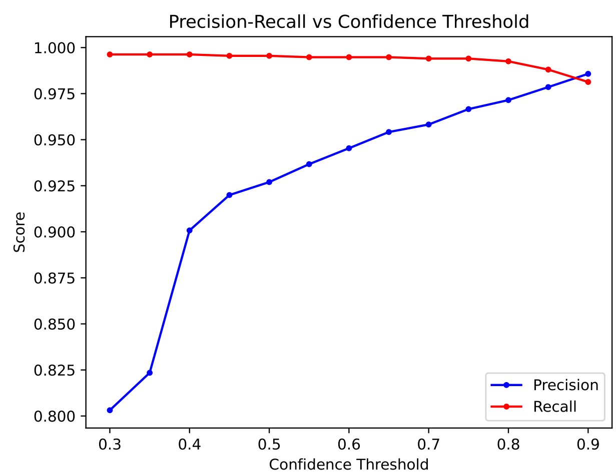

Fig. 4. Precision and recall plotted per confidence threshold value for model 4.

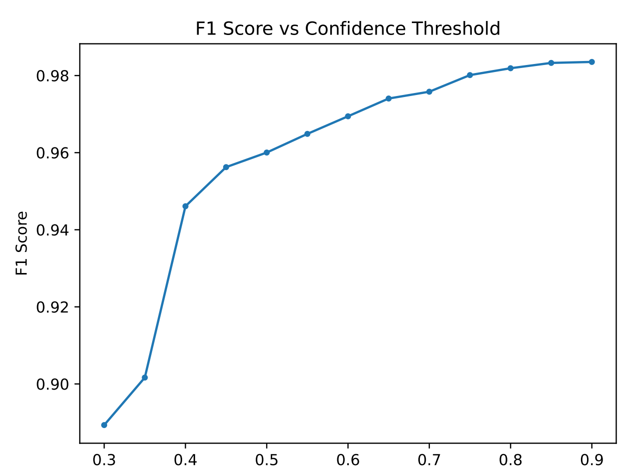

Fig. 5. The calculated F1 Score for Model 4 per confidence threshold value.

Table 4. Performance of Wildlife Insights (WI: including animal label for tortoises, strictly tortoise as the positive label), the South Texas multi-species model (ST: including animal label for tortoises, strictly tortoise as the positive label), and the best Texas tortoise model from this study (TT) with the test dataset. The true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) are used to calculate the precision, recall, accuracy, and false positive rate (FPR) at a 0.5 confidence score. Bolded values indicate the best performance for each metric.

Model	TP	FP	TN	FN	Precision	Recall	F1 Score	Accuracy	FPR
WI animal	116	6	64	52	0.95	0.69	0.80	0.76	0.09
WI tortoise	27	0	64	147	**1.00**	0.16	0.27	0.38	0.00
ST animal	99	30	34	64	0.77	0.61	0.68	0.59	0.47
ST tortoise	0	0	64	163	0.00	0.00	0.00	0.28	0.00
TT model	139	4	64	28	0.97	**0.83**	**0.90**	**0.86**	**0.06**

Table 5. Composition of dataset based on the habitat type.

Habitat Type	Tamaulipan Thornscrub	Brush	Grassland/Prairie	Bare Ground
Photos	678	210	465	137

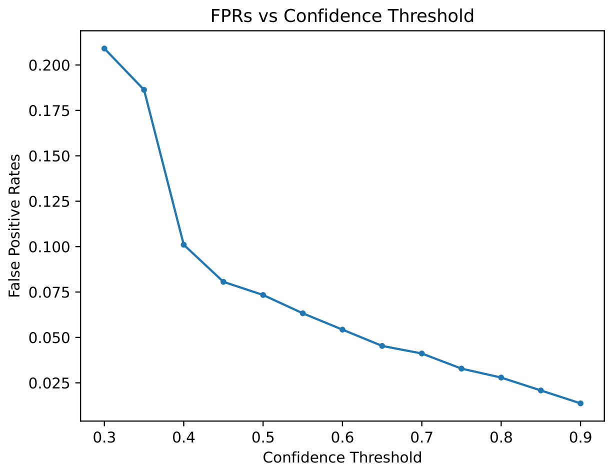

Fig. 6. The false positive rate calculated for model 4 per confidence threshold value.

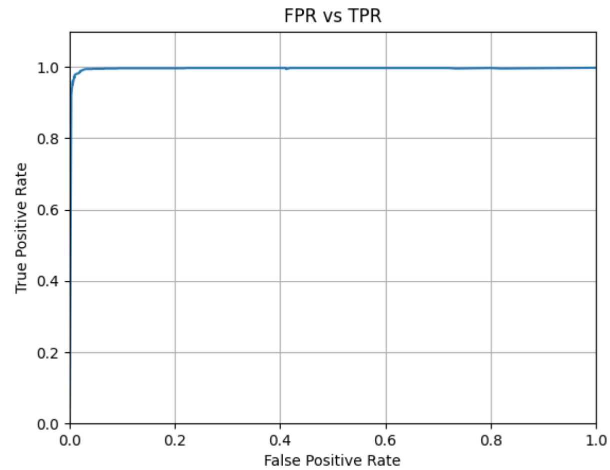

Fig. 7: False Positive Rate vs True Positive Rate for model 4 evaluation.

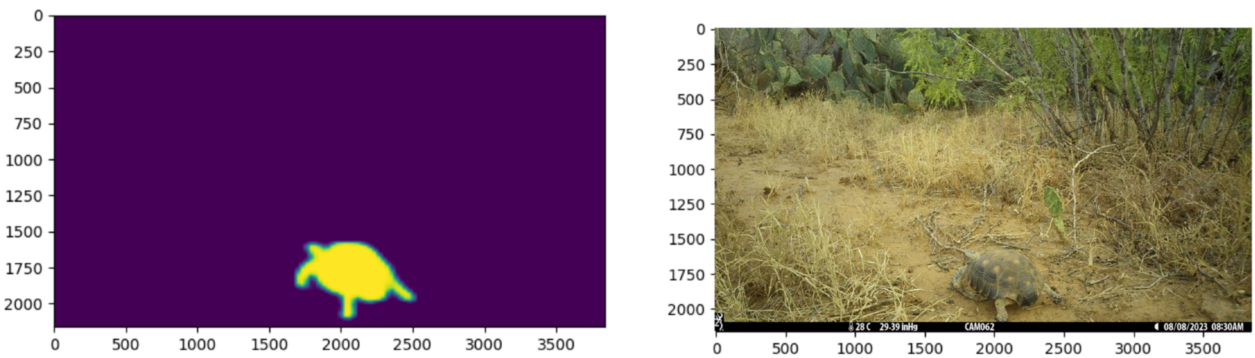
Fig. 8: Demonstration of predictive mask output from the final model (left) beside the image displaying the tortoise (right).

Discussion

This study is the first to use systematically deployed camera traps to target tortoises. Previously, studies using camera traps focused on a species of tortoise have targeted inhabited areas (e.g. burrows or rock crevices; Agha et al. 2015; Agha et al. 2017; Knapp et al. 2017; Hilton et al. 2022; Dirr et al. 2024; Ngwava et al. 2024) or structures (e.g. feed stations, road culverts, railroad crossings, or artificial ponds; Ballouard et al. 2016; Nafus et al. 2017; Rautsaw et al. 2018; Harju 2022) as a focal point. Although none of the camera grid design variables had a significant impact on tortoise detection, camera traps appear to be a promising method to detect Texas tortoises. The use of artificial ponds, regardless of whether water was currently present, increased detection rate in Hermann's tortoises (Ballouard et al. 2016) and could be explored in Texas tortoises. For sites where Texas tortoises are readily detected (e.g. Chaparral WMA), camera traps may not be as effective as active surveys. For sites where tortoises are rarely detected, camera traps could be a great tool to assess

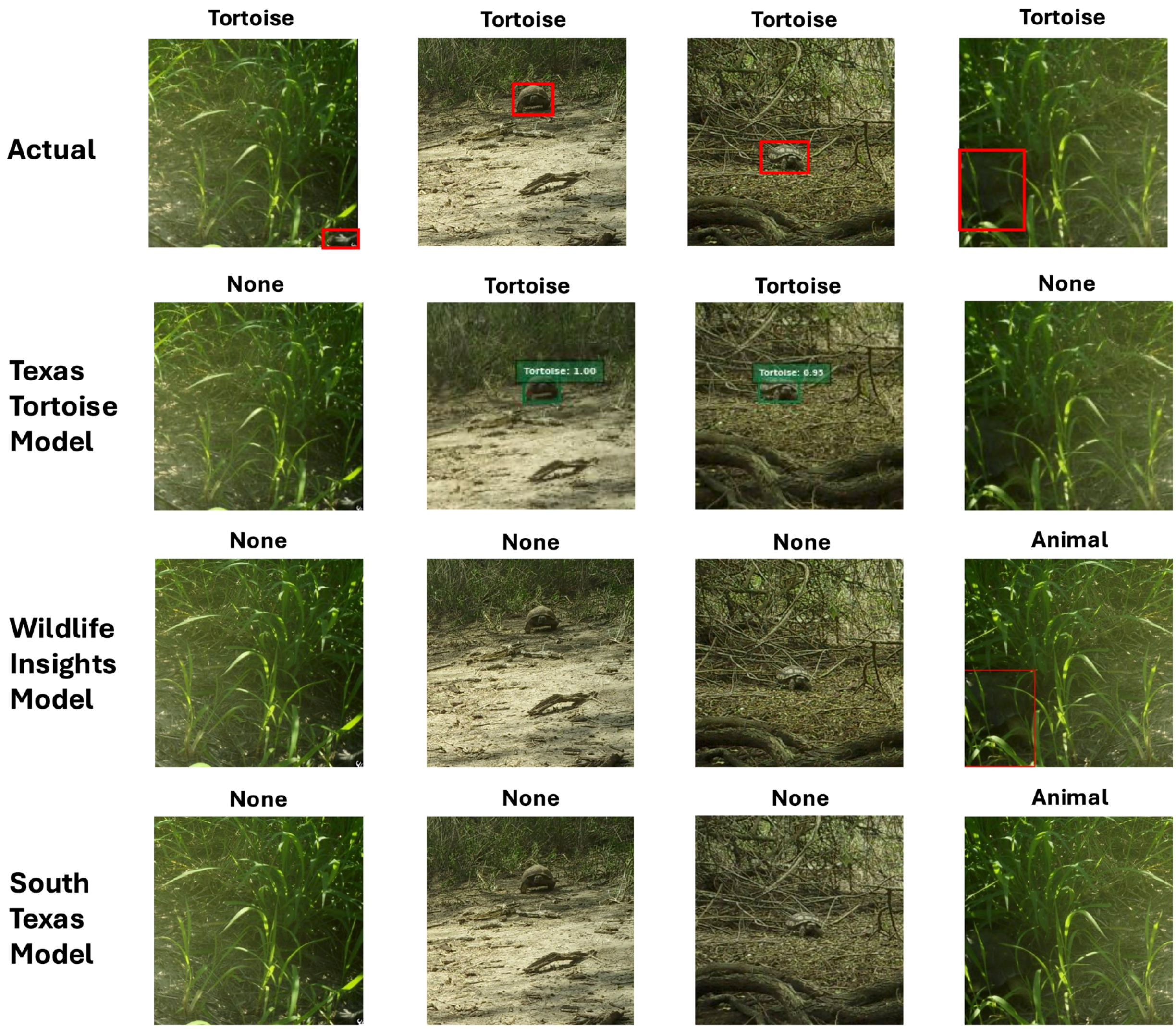

Fig. 9. An image array displaying test images and how different models performed. The top panel highlights where the tortoise in each image is located. All three models failed to locate the edge of the tortoise's shell on image 1, only the Texas tortoise model (TT model) identified the tortoise on image 2 & 3, and both the Wildlife Insights and South Texas model identified the tortoise (to the level of animal) on image 4 where the TT model failed to recognize it. These images have been cropped to display where the tortoise is located.

the presence of tortoises and identify priority survey sites or continuously monitor difficult to access sites. With most detection events (67%) including the tortoise in only one frame, we would advise against increasing the time-lapse period from two minutes. An increase in time-lapse period could risk a large reduction in tortoise detections.

The TT model performed significantly better than the two we compared it with, as expected. The ST model was trained on a limited set of Texas tortoise images, so it is likely the model overfitted to a specific orientation or habitat type (Kutugara et al. 2020). Wildlife Insights is trained on millions of images (Ahumada et al. 2020) and although it is continuously retrained on user uploaded and classified images, a large number of images is likely required to recognize rare animals to a specific level to overcome the class imbalance (Norouzzadeha et al. 2018). Importantly, neither of these models are explicitly focused on the Texas tortoise like the model trained in this study making the comparison somewhat asymmetric. Regardless of these asymmetries, it is important to show the improved performance of models for a specific task compared to models that were readily available for this task. Additionally, both models only use image classification tasks rather than including object detection or segmentation tasks (Ahumada et al. 2020; Kutugara et al. 2020). The task of segmentation, although computationally intensive, removes the background noise through classifying each pixel and can allow models to properly learn more information about the desired class with fewer input images (Figure 8).

The performance of the TT model is comparable to other models that use segmentation tasks to identify turtles (Adam et al. 2024; Baek et al. 2024). A model on loggerhead sea turtles achieved an accuracy of ~87% (Adam et al. 2024) where the TT model was 86%.

Another model identifying a suite of sea turtle species had an average precision of 89% and recall of 87% across species (Baek et al. 2024) where, comparatively the TT model had a higher precision (97%) and lower recall (83%). Many classification models for wildlife are multiclass models (i.e. detect multiple species), as a broader range of classes increases the utility for end-users. When comparing multi versus binary classifiers in identifying a target species, the binary classifier performs better on many metrics (Chen et al. 2019; Kutugara et al. 2020; Okuley et al. 2025). As such, creating species-specific classifiers is not redundant when there is a need to accurately identify all cases of a species in a dataset.

The most challenging instances of Texas tortoises were those where the shell was only partially visible (only a fraction of shell was in frame, or the tortoise was heavily obscured by vegetation; Figure 9). Of all the false negatives for the TT model, 85% were part of a photo series where 54% had other images from the series in the test set properly identified and 33% contained a tortoise image in the sequence that seemed likely to be identified by the model. As such, when utilizing this model, it would be prudent to check the images corresponding to the time before and after the tortoise was identified. This check could pull additional tortoise images if all times of tortoise movement are a necessary part of analysis. The WI model could identify a few partial shell images (to the identification level of animal) that the TT model missed, however it was unable to locate several clear instances of tortoises in the background (Figure 9). The cameras from this study were angled closer to the ground, as such re-clearing the sites after heavy rainfall to remove regrown grasses could have reduced noise in the images and improve the recall of the TT model. Additionally, using segmentation tasks to label body parts of the tortoise, as in the SeaTurtle2022 model (Adam et al. 2024) could further reduce cases of false negatives and improve model performance.

Conclusion

Cameras have been stated to have limited application for terrestrial turtles and tortoises (Hofmeyr and Henen 2016), however more researchers are applying cameras to explore research questions. Cameras have been used to study whether tortoises will use crossings (Rautsaw et al. 2018; Harju 2022), explore activity patterns as they relate to thermal profiles and prescribed burns (Agha et al. 2015; Knapp et al. 2017), and detect tortoises at a location (Ballouard et al. 2016). With the TT model available for use (https://github.com/jtleimat/tortoise-predictor), the data processing step can be sped up. This model could be applied to analyze datasets previously focused on another taxa (i.e. mammals) in Texas tortoise range for the presence of this tortoise or to process data from future camera trap studies in this area. While running the test set of images, the TT model was able to process an image every ~2 sec on the local GPU. In addition, when testing a couple photos from iNaturalist of Mojave desert tortoises and gopher tortoises, the TT model predicted these tortoises with high confidence and precision. There is potential utility for this model to be applied for other *Gopherus* spp., however these were anecdotal cases with obvious instances of tortoises. This model is trained on south Texas habit. As such, researchers should validate accuracy of the model before applying it to another species.

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