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Michigan ZoomIN: validating crowd-sourcing to identify mammals from camera surveys

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ABSTRACT

Camera trap studies have become a popular medium to assess many ecological phenomena including population dynamics, patterns of biodiversity, and monitoring of endangered species. In conjunction with the benefit to scientists, camera traps present an unprecedented opportunity to involve the public in scientific research via image classifications. However, this engagement strategy comes with a myriad of complications. Volunteers vary in their familiarity with wildlife, and thus, the accuracy of user-derived classifications may be biased by the commonness or popularity of species and user-experience. From an extensive multisite camera trap study across

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Michigan U.S.A, images were compiled and identified through a public science platform called *Michigan ZoomIN*. We aggregated responses from 15 independent users per image using multiple consensus methods to assess accuracy by comparing to species identification completed by wildlife experts. We also evaluated how different factors including consensus algorithms, study area, wildlife species, user support, and camera type influenced the accuracy of user-derived classifications. Overall accuracy of user-derived classification was 97%; although, several canids (e.g., *Canis lupus, Vulpes vulpes*) and mustelid (e.g., *Neovison vison*) species were repeatedly difficult to identify by users and had lower accuracy. When validating user-derived classification, we found that study area, consensus method, and user support best explained accuracy. To continue to overcome stigma associated with data from untrained participants, we demonstrated both the contributions and limitations of their capacity. Ultimately, our work elucidated new insights that will harness broader participation, expedite future camera trap data synthesis, and improve allocation of resources by scholars to enhance performance of public participants and increase accuracy of user-derived data.

KEYWORDS accuracy, carnivores, citizen science, geographic variation, engagement, Michigan, mustelid, validation.

Science is arguably a public good. In recent years, an interest in broadening participation in science has resulted in a wave of public (participatory or citizen) science projects initiated by scholars (Dickinson et al. 2010, Theobald et al. 2015). This seemingly unlikely partnership between the public and scientists creates dialogue that can aid in demystifying the scientific process, facilitate exposure to the natural world, and yield reciprocal benefits (Bonney et al. 2016, Schuttler et al. 2018b). Public participation in ecology is particularly salient due to humans

being a dominant force in natural systems with increasing pressures stemming from land conversion, urban sprawl, and over-exploitation (Raudsepp-Hearne et al. 2010, Halpern et al. 2015, Young et al. 2016). Incredible amounts of data can be gathered by the general public to monitor environmental change, and in some cases, unencumbering a person's everyday life (Trumbull et al. 2000). For example, someone interested in how urbanization affects species can assist in collecting bird skyscraper collisions or simply take images with a smartphone and document sightings of particular organisms (Ries and Oberhauser 2015, Shipley et al. 2018).

Amongst the most common participatory science projects involve the use of digital technology. As avid users of technology, engaging youth have the potential to amplify positive effects of participatory science through intergenerational learning (Arts et al. 2015, Peterson et al. 2019). Therefore, incorporating images garnered from camera surveys are now common-place for public science programs (e.g., Schuttler et al. 2018a). These surveys can answer a plethora of ecological, behavioral, and even evolutionary questions across spatial and temporal scales, in a variety of environments, and on a diversity of species (Burton et al. 2015, McShea et al. 2015, Steenweg et al. 2017).

Although crowdsourcing has gained popularity, image identifications from wildlife surveys by communities of non-scientists are fraught with challenges (Hochachka et al. 2012). Researchers not only have to develop the infrastructure to facilitate easy access, but also construct a useful workflow to aggregate and structure responses into managed data (Waetjen and Shilling 2017, Egerer et al. 2019, Parrish et al. 2019). Chief amongst the rising concerns is that public-generated data are susceptible to biases and inaccuracy of responses that can compromise usability and hinder broader implementation in future scientific research (Dickinson et al. 2010, Hochachka et al. 2012, Brown et al. 2018). By design, researchers are often not able

to control for who contributes to citizen science projects, resulting in extreme heterogeneity in user expertise. However, through targeted outreach, engagement, and education strategies, some projects are able to target specific audiences (e.g., K-12) and thoroughly train volunteers; though, this is not always feasible and requires significant resources. Varying methods of image classification, and the implementation of automated and crowd-sourcing aids in classifying images to discern patterns from large amounts of biological information can be helpful in reducing processing time (Norouzzadeh et al. 2018). Standardized guidelines for processing and evaluating user-derived data will allow for scientists to better evaluate the utility and leverage public science to tackle large data sets regardless of the research system (Freitag and Pfeffer 2013, Maes et al. 2015, Egerer et al. 2019, Locke et al. 2019)

Overall, findings have been inconsistent concerning reliability of user-derived data for scientific research, requiring additional scrutiny based on project workflows and inclusion of expert validation (Danielsen et al. 2005, Crall et al. 2011). Katrak-Adefowora et al. (2020) found that training allowed participants even with no biology background to correctly identify images with comparable accuracy to biology experts. Other studies found that there was high agreement among classifying individuals, indicating that user expertise was not significant in correct classification, but animal size and distinct markings had a greater impact on accuracy (Swanson et al. 2016, Potter et al. 2018). Still other studies have found that environmental, species-specific behaviors, and land use affect classifying accuracy (Broeckhoven and le Fras Nortier Mouton 2015, Meek et al 2016). Generally, existing studies on validation of user derived data fail to explain factors contributing to accuracy, occur outside a North American context, or employ a single metric for deriving accuracy from aggregated responses. Another consideration that remains unexplored, specifically for camera surveys, is whether data generated from public

participants are comparable across geographies, given potential differences in species composition and image quality from environmental conditions such as weather (Meek et al. 2015, Steger et al. 2017).

Here, we used public generated image identifications from an extensive multi-site, multi-season camera trap survey throughout the state of Michigan. Specifically, we created a public science online platform called *Michigan ZoomIN (MZI)* for image processing and developed a science communication strategy to solicit volunteers. We then evaluated user responses by comparing various consensus methods to obtain a converged species identification as well as examined factors that influenced the accuracy of users. We hypothesized that common species will be classified with higher accuracy while physically similar or rare species would have lower user accuracy and reach consensus using a relaxed consensus method. Using a hierarchical approach to assess user responses, we hypothesized high agreement would positively correlate with accuracy for all images regardless of consensus method and species characteristics. We also hypothesized that camera type would influence user accuracy with images from cameras that used a flash at night having higher accuracy. We also hypothesized that the study area would affect accuracy, as sampling locations varied in vegetation and environmental conditions that could distort images and make classifying harder. We contribute three insights to crowdsourced photo ID research: 1) hierarchical consensus criteria mitigates potential bias from diverse volunteer bases, 2) multiple consensus thresholds have comparable accuracy to 100% user agreement, and 3) site and environmental factors can diminish accuracy. Results from our work have relevance in minimizing workload in classifying for researchers, as well as providing a workflow for assessing overall accuracy of user-derived classifications for other camera studies.

STUDY AREA

Throughout 2015-2017, the Applied Wildlife Ecology (AWE) lab at the University of Michigan implemented camera trap surveys to investigate questions of community ecology within the carnivore guild of Michigan. We deployed 273 remotely-triggered Reconyx© cameras (PC 850, PC 900, PC 850C, PC 900C) across three study areas that had distinct environmental and habitat attributes from north to south: the Huron Mountain Club (HMC; Marquette County), University of Michigan Biological Station (UMBS; Pellston County), and the Shiawassee National Wildlife Refuge (SNWR; Saginaw County). The study areas are particularly important as they represent very different ecosystems and are punctuated with vast waterways. HMC as our most diverse site, comprised privately-owned mixed secondary and old growth forest along the southern coast of Lake Superior. UMBS, a research station, comprised a mix of deciduous and coniferous forest between Douglas and Burt Lakes in the northern tip of Michigan's Lower Peninsula. SNWR, a floodplain of Saginaw County, comprised marsh, bottomland hardwood forest, and grasslands abutting urban development and agriculture managed by the U.S. Fish & Wildlife Service. At each site, unbaited cameras were placed 0.5-1.0 m off the ground and affixed to trees > 0.5m diameter. Camera settings included: high sensitivity, one-second lapse between a sequence of three pictures in a trigger, and a 15-second quiet period between triggers. Our survey efforts across 32,542 trap nights resulted in 10,199 of camera trap images that required accurate species identifications.

METHODS

Description of *Michigan ZoomIN*

We developed a public science website called *Michigan ZoomIN (MZI)* on the Zooniverse Project Builder platform where we uploaded images and collated user responses over

multiple seasons (Figure 1). From its origins in 2007 with the Galaxy Zoo project, which asked volunteers to classify shapes of galaxies, the Zooniverse crowdsourcing platform has created and hosted more than 200 different projects from disciplines as diverse as astronomy, ecology, physics, history, and more to promote "people-powered" research (Lintott 2019; Zooniverse.org). Through both a coordinated outreach program throughout Michigan and the existing Zooniverse community, 645,000 classifications were completed over one year by 3,950 registered users (unregistered users also contributed but were not trackable). There were 39 possible classifications ranging from the focal carnivores in our empirical field research (e.g., coyote *Canis latrans,* raccoon *Procyon lotor,* American black bear *Ursus americianus,* red fox *Vulpes vulpes*), and their prey (e.g., white-tailed deer *Odocoileus virginianus*, squirrel *Sciurus carolinensis*, opossum *Didelphis virginiana*, cottontail rabbit *Sylvilagus floridanus*, porcupine *Erethizon dorsatum*). Users were given written descriptions of species as well as photos to aid in classifying species from survey images (Figure 1 – label 7). *MZI* also incorporated the "looks like" tool, which allows volunteers to narrow possible classifications based on color, shape, and body size (Figure 1 – label 5). We did not include 'unknown' as a possible choice for selection to promote more discrimination and an "educated" guess. Users were also provided a field guide with descriptions of common ecological tenets such as competition and dietary separation, and additional images and information useful for classification of species (Figure 1 – label 6). This resource was included to provide more education to improve understanding and stimulate greater enthusiasm particularly for younger audiences. Images were retired from viewing once 15 unique users classified the image.

Data Aggregation

To produce a final identification, each sequence of images was identified by 15 unknown volunteers. Those classifications were then condensed into a single image species identification using various consensus approaches (Figure 2). Images were considered to have reached consensus if they matched the criteria of any one of four consensus methods: agreement, Kappa, Kappa and evenness, or gold standard. 1) Agreement: if all 15 users agreed on the species identification for an image. 2) Kappa: A Fleiss Kappa statistic (modified from Cohen's Kappa, for more than 2 users) above 0.6 designating a "substantial" strength of agreement (Landis and Koch 1977). 3) Kappa and Evenness: A Fleiss Kappa above 0.6, and evenness below 0.5. Pielou's evenness is an index that measures the proportion of 'votes' given to a particular species in comparison to the number of species picked for the photo in question. The scale runs from 0-1, with 0 indicating low evenness and higher accuracy (Pielou 1966, Swanson et al. 2015). 4) Gold Standard: At least one of the users classifying the image was from our research team and categorized as an expert with a gold standard tag. If the expert was unsure of classification, they removed the gold tag prior to identification submission. Images that did not reach any consensus method were classified as 'Majority' and later verified by a project researcher (Figure 2). The following process allowed us to test a hierarchical approach that ranged from rigorous (100% user agreement) to more relaxed criteria of user agreement. We specifically tested 'Kappa' and 'Kappa and Evenness' as metrics that allow progressively lower levels of user agreement to account for the differing levels of experience inherent to a diverse group of users, while producing comparable accuracy to stricter consensus criteria (100% user agreement amongst all 15 users).

Expert Review

To test the efficacy of the consensus algorithm, researchers verified a random sample of 5,000 images to compare against the user-generated identifications. In addition, all images that had a carnivore identification (with the exception of raccoons) generated by the consensus algorithm were also reviewed, for a total review dataset of n= 5,734. Beyond the initial random sample of 5,000 images, additional raccoon images were not included for expert verification due to the assumption that they did not fit the rarity criterion and were well represented in the random sample.

Evaluation of Accuracy

As a rough measure of the accuracy for each of the consensus methods used in the consensus algorithm, we calculated the proportion of correct answers for each method. For those images that did not meet any of the criteria to produce consensus identification, we calculated the proportion correctly identified among the 15 user classifications. For hypothesis testing, we first constructed a generalized linear model to evaluate factors influencing accuracy. Aggregated user responses from the consensus output were compared to the expert dataset to generate a binary output of 1(correct) or 0 (incorrect). For comparison against images that were classified by consensus, images that did not meet a consensus criterion were classified under the consensus type as ‘majority’. Majority was defined as everything that didn't fit into a consensus method. This represents the most widely chosen species and "did not meet consensus criteria". We included: consensus methods, species, study area, camera model, and percent user agreement as fixed effects in the model. Species was used to better understand if animal similarity or rarity of a species affected the accuracy. We used two different camera models in our study. Infrared cameras provide black and white images in low light settings, while white flash cameras produce color images, even at night. Percent user agreement represented a measure on how well users

agreed on a classification and corresponding difficulty depending on species. We conducted model selection using Akaike information criterion (AIC). All models < 3 ΔAICs were considered 'top models' and beta coefficients for variables from top selected models were then used to test the following hypotheses:

1. Species that have a high degree of similarity will be harder to identify, which will negatively affect accuracy;
2. Species accuracy will be greater for species that are more common and have greater abundance;
3. Stronger similarity in user agreement will correlate to overall higher accuracy;
4. White flash cameras will yield higher accuracy;
5. Accuracy will vary by study area

All model construction and selection were conducted using the 'lme4' package in R (version 3.4.4).

RESULTS

We found partnering with the public was fruitful for investigating mammals of Michigan– a typical species assemblage found throughout the contiguous United States. From our public science project, *Michigan ZoomIN* involved 3,950 registered users that were involved in classifying 10,199 image sequences across three study areas. (HMC: 1,630; UMBS: 2,485; SNWR: 6,084). Each sequence consisted of three images and was reviewed by 15 unique users. The most common species were raccoon and white-tailed deer with 5,594 (51%) and 2,592

(14%) classifications, respectively. Most images (95%) reached a consensus method to converge on a specific species identification. The remaining 5% remained unidentifiable even after being evaluated by a team researcher (Figure 2).

Two-thirds of images were classified from complete agreement among all 15 users. Kappa evenness was the second most common consensus method, comprising 19% of images. Majority, yielded completion of 10%, and majority plus gold standard < 1% of images. To underscore the importance of considering multiple consensus thresholds, we evaluated results for coyotes (*Canis latrans*) as a case study, given understanding their placement is valuable to wildlife managers, their dynamic role within the carnivore community and are commonly mistaken for other canid species (Prugh et al. 2009, Hilton et al. 2015, Colborn et al. 2020). There were 520 classifications of coyotes by users, of which 265 reached consensus. However, unlike when considering the entire dataset, only 9% passed consensus from complete user agreement. Instead, the kappa statistic was the best consensus method and identified 48% of coyote images.

We built generalized linear models to evaluate factors that influenced the accuracy of species classifications. The top model included (Table 1): consensus method, percent user agreement, and study area. Less strict consensus criteria were only marginally worse except for majority: Kappa ($\beta = -1.61$; $p = 0.014$), kappa evenness ($\beta = -1.162$; $p = 0.058$), and majority ($\beta = -3.355$; $p < 0.0001$). Percent user agreement ($\beta = 5.328$; $p < 0.0001$) was strongly associated with higher accuracy. Contrary to expectations, the camera model did not influence accuracy. As previously stated, consensus of 100% user agreement was the most common way images reached the final dataset. While most species were represented in images that reached consensus, species varied in which consensus method was most effective for identification, as was the case for

coyotes. Indeed, the wide geographic coverage of the camera surveys presented the possibility for differences in accuracy based on study area. Images from SNWR were marginally significant in identification accuracy compared to other study areas (β= 5.047; *p-value* = 0.059). In contrast, images from HMC, the most remote site with the highest species diversity located in the Upper Peninsula of Michigan, had the lowest accuracy of species classification.

We found marginal support for differences in accuracy across species including study area and species interactions. Notably, the public was 99% accurate in identifying false positives, incidental triggers from wind or vegetation movement. Small mammals were often confused as partial images of cottontail rabbits, or mistakenly missed and labeled as "nothing there". Though many species had high accuracy (>90%, Figure 3), accuracy was statistically significant for squirrel (β= 2.180; $p = 0.041$) and porcupines (*Erethizon dorsatum*, β= 2.299; $p = 0.042$). This is likely because of the tremendous commonality of squirrels and the uniqueness of porcupines. Classifying animals incorrectly were common only for particular species such as mustelids and coyotes. These high false positives were due to similarities to other species based upon body size, color, and activity patterns. Mustelids had the lowest overall accuracy (Figure 3); arguably, because the family comprising of species with similar anatomical features (e.g., marten *Martes americana*, long-tailed weasel *Mustela frenata*, fisher *Pekania pennanti*, mink *Neovison vison*) that expectedly would prove difficult to discern for non-experts.

All study areas had either 99-100% accuracy for common species such as deer, raccoon, and striped skunk (*Mephitis mephitis*). However, rare species, as either being infrequently detected or geographically constrained, had lower accuracy. For example, fisher and the small-bodied muskrat (*Ondatra zibethicus*) were only detected at HMC and SNWR, respectively and had accuracies <50%. Gray wolves (*Canis lupus*) are similar in appearance to coyotes and found

only at HMC where they were most commonly misidentified as coyotes. Likewise, though coyotes occurred in every study area, they had the lowest accuracy at HMC. In contrast, the badger (*Taxidea taxus*) with a noticeably distinct body shape and striking facial pattern only captured at UMBS had 75% accuracy.

DISCUSSION

Massive amounts of data generated from camera trap studies can prove a limiting factor in biological monitoring and ecological inquiry. As such, implementing automated and crowd-sourcing aids in classifying images to discern patterns can be helpful (Maes et al. 2015, Norouzzadeh et al. 2018). Though these methods reduce the burden on research teams of manual identifications, developing a reliable workflow is required for validation to ensure accuracy. Understanding which species are more easily identifiable can assist in future decision-making on how to alter projects in a manner to assist with identifying the more challenging species. For example, additional aids such as sample photos, comparisons of potential misidentify species, and size references may be necessary to accurately discern species lacking unique phenotypic (Skarlatidou et al. 2019). Our study found common species, those with distinguishing features, and generally larger species were most easily identifiable by the public. Similarly, Potter et al. (2019) found the most distinct mammal species such as short-beaked echidna (*Tachyglossus aculeatus*) had the highest accuracy from camera surveys in northern Australia, and groups of closely related species with similar morphology, such as mustelids had the most errors. In an African ecosystem, Swanson et al. (2015) found that different species of gazelles as well as weasel-like small mammals were often misidentified from camera data derived from public users. While our study and other examples highlight that users require more resources and

295 training to discern finer details to aid in the correct classification, it does not negate the utility of
296 common species being removed from correct identification by users to reduce overall workflow
297 and processing times.

298 Given the breadth of ecological questions garnered from camera surveys, we also
299 recognize that specific choices in study design have ramifications for image quality. For
300 example, optimal procedures recommend camera placement two and three feet off the ground,
301 resulting in capture of species with varying body sizes (Jacobs and Ausband 2018). Smaller
302 bodied species such as weasels (*Mustela sp.*) in our study may not be well captured to yield
303 accurate classifications. The effect we observed of the study area highlights nuances that emerge
304 for geographic disparities not simply due to habitat characteristics or environmental conditions,
305 but the emergent biotic properties influencing rarity and frequency of detection. This realization
306 suggests additional consideration for sampling effort and targeted training on species expected to
307 be rare to improve classifications. Still lower threshold consensus criteria performed nearly as
308 well as 100% agreement. All criteria had very high accuracy when compared with an expert
309 dataset. Although more investment in training volunteers would enhance discrimination among
310 difficult species (e.g., grey wolves, fisher), we confidently say that even without it and
311 presumably volunteers with diverse levels of ecological knowledge, we can still maximize
312 workload reduction for scientists by using creativity with our consensus criteria.

313 To continue to overcome the stigma associated with data from untrained participants, we
314 demonstrated both the contributions of their capacity and where their limitations begin in our
315 case study camera survey from mammals in Michigan. We found that most species were
316 eventually correctly identified by employing multiple consensus methods through a robust
317 hierarchical workflow. In future studies, researchers may find it helpful to set consensus criteria

based on conservative estimates of user knowledge. We also acknowledge socio-economic injustices that limit participation in participatory science and have broader implications to further determine how social inequities affect ecology and our understanding of ecological processes. Likewise, future studies should examine the user identity, not simply biology background, using broader demographic attributes, motivations, environmental stewardship capacity as well as contributions from media to further determine what other factors aid in accurate classifications. Ultimately, our work elucidated new insights that will harness broader participation, expedite future camera trap data synthesis, and improve the allocation of resources by scholars to enhance performance of public participants and increase accuracy of user-derived data.

MANAGEMENT IMPLICATIONS

Lastly, we can continue to promote rare and threatened species through participatory science projects, potentially building conservation advocates. Highlighting distinguishing features through comparative approaches could improve accuracy of user-derived data, but also further stimulate an environmental stewardship that supports sustainability. Management using similar methodology will bring attention to topics of concern such as over hunting, mapping migrations or isolating the introduction of an invasive species. Most readily, wildlife managers will be better able to make informed decisions about solving problems and use data derived from citizen science projects to inform policy decisions.

ACKNOWLEDGMENTS

First, we recognize implementing our field research of camera surveys was conducted on lands originally belonging to the People of the Three Fires. We thank the Shiawassee National Wildlife Refuge, the University of Michigan Biological Station, and the Huron Mountain Club for

providing access to implement camera surveys for fieldwork on their property. We would like to thank the Applied Wildlife Ecology (AWE) Lab at the University of Michigan for assistance with validating classification. Our work is not human subjects research requiring IRB review, though we remain forever indebted to the nearly 4,000 anonymous volunteers that contributed their time to identify images on *Michigan ZoomIN (MZI)* and the dozens of colleagues that integrated *MZI* into curricula. This publication used data generated via the Zooniverse.org platform, development of which was funded by generous support including a Global Impact Award from Google and by a grant from the Alfred P. Sloan Foundation. We appreciate technological support from University of Michigan LSA Information Technology and Technology Services teams especially A. Roelofs and P. Knoop. We thank G. Kuhnlein, Michigan News, and the University of Michigan Museum of Natural History for assistance with dissemination on multi-media platforms to recruit volunteers. We appreciate the funding provided by the Detroit Zoological Society, the Huron Mountain Wildlife Foundation, and the University of Michigan Biological Station.

AUTHOR CONTRIBUTIONS:

N.C.H. conceived and designed the research. N.C.H and J.S. developed virtual interface for species identification by public and expert confirmation. G.I.G. and T.C. constructed outreach materials and led trainings on *Michigan ZoomIN*. G.I.G and R.M analyzed the data. G.I.G. and N.C.H wrote the manuscript. All authors contributed to fieldwork, image validation, public engagement and editing the manuscript for final approval.

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Associate Editor:

Figure Captions

Figure 1. *Michigan ZoomIN* interface for public user classifications of mammals from camera surveys throughout Michigan. 1) welcome screen with tutorial, 2) sample images active on talk board frompublic comments, 3) image for user identification, 4) list of species to select for classification, 5) filter features to narrow species selections, 6) field guide to provide additional information, 7) reference photo of user selection to compare to image, and 8) additional questions to provide more information concerning the image.

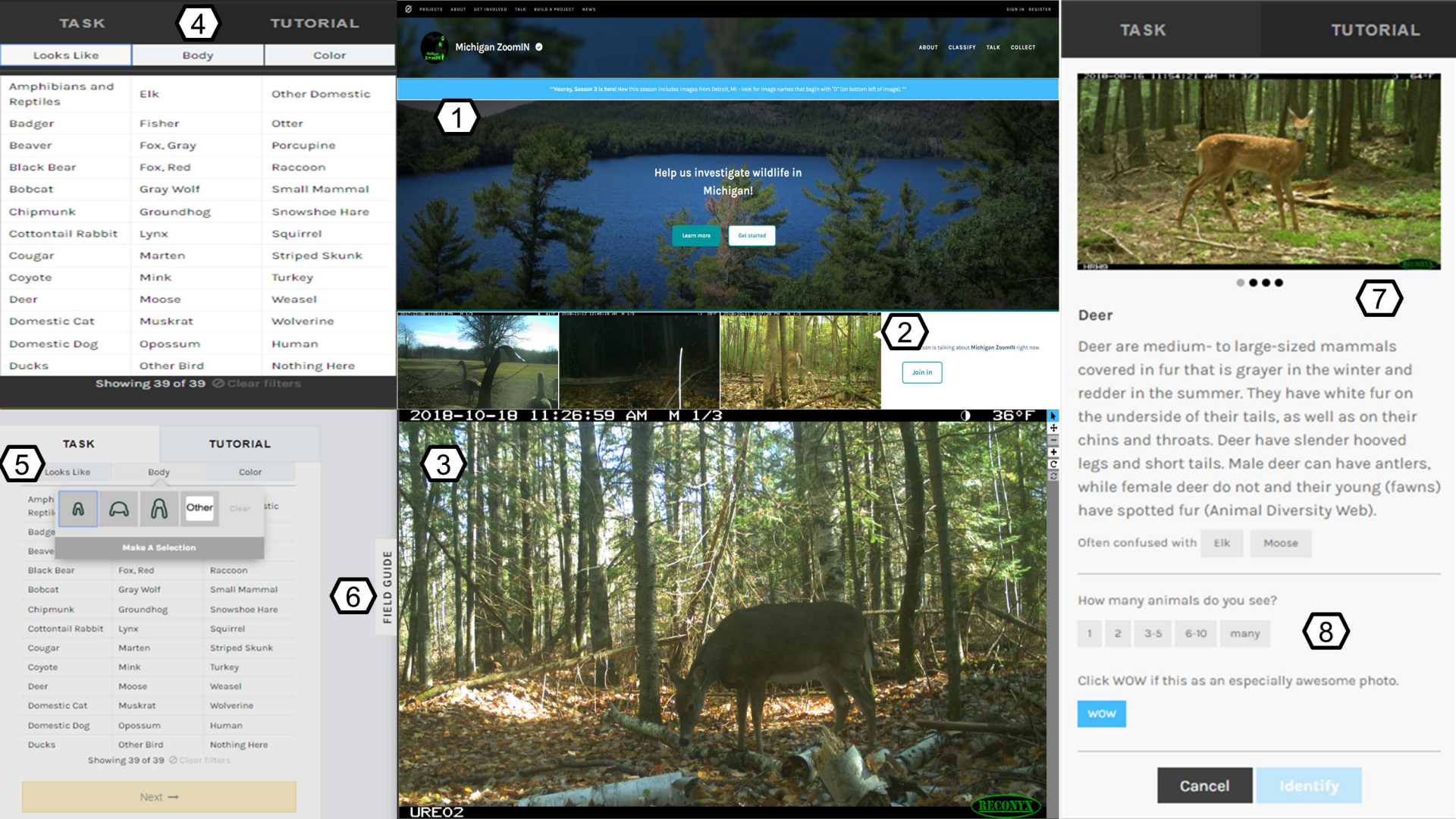
Figure 2. *Michigan ZoomIN* workflow from user-derived input to consensus assessment of aggregated responses to expert validation necessary to create a final dataset ready for analysis of classifying images. Images classified by an expert are tagged with gold standard which immediately passes consensus and sent to the final data set. All other images go through a hierarchical process with 15 different users classifying each image. Images that have complete agreement go into the final dataset. If there is not unanimous agreement algorithms calculate user response to determine if they meet the kappa threshold and if not the kappa evenness threshold. Images that do not meet any consensus go into an expert review file which is then classified by a research team member to determine species.

Figure 3. Mammals identified by public volunteers through *Michigan ZoomIN*. Species in green panel obtained ≥90% accuracy: 1) Domestic cat- *Felis catus,* 2) Human- *Homo sapien,* 3) Raccoon- *Procyon lotor,* 4) White-tailed deer- *Odocoileus virginianus,* 5) Striped skunk- *Mephitis mephitis,* 6) Opossum- *Didelphis virginiana,* 7) Squirrel- *Sciurus carolinensis,* 8) Bobcat- *Lynx rufus 9)* Coyote- *Canis latrans,* 10) Porcupine- *Erethizon dorsatum*; species in yellow panel obtained ≥80% accuracy: 11) Chipmunk- *Tamias striatus*, 12) Black bear- *Ursus americanus*, 13) Cottontail rabbit- *Sylvilagus floridanus*, 14) Groundhog- *Marmota monax*, 15) Domestic dog- *Canis lupus familiaris*; and species in the red panel accuracy < 79% accuracy: 16) Snowshoe hare- *Lepus americanus*, 17) American badger- *Taxidea taxus*, 18) Small mammal- e.g., *Peromyscus maniculatus*, 19) Marten- *Martes americana*, 20) Fisher- *Pekania pennanti*, 21) Muskrat- *Ondatra zibethicus*, 22) Weasel- e.g., *Mustela frenata*, 23) Grey wolf- *Canis lupus*, 24) Red fox- *Vulpes vulpes*, 25) Mink- *Neovison vison*. Gray fox- *Urocyon cinereoargenteus* not shown.

Table 1 Top models presented with ΔAIC < 3 from model selection analysis for accuracy assessment from comparison between user derived classification and expert validation.

Model	**df**	**logLik**	**Δ AIC**	**W**
Consensus method + Percent user agreement + Study area	8	-570.335	0.00	0.493
Consensus method + Percent user agreement + Study area + Camera model	9	-570.327	1.99	0.182
Consensus method + Percent user agreement + Species	30	-549.265	2.03	0.179
Consensus method + Percent user agreement + Species + Study Area	32	-547.451	2.43	0.146

Summary for online Table of Contents: Engaging the public proved extremely helpful in processing images of mammals from a large scale camera survey in Michigan, given their high accuracy in species identification. We found that study area, consensus method, and user support best explained accuracy when validating classification from our public science project.


TASK
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TUTORIAL
Looks Like
Body
Color
Amphibians and Reptiles
Elk
Other Domestic
Badger
Fisher
Otter
Beaver
Fox, Gray
Porcupine
Black Bear
Fox, Red
Raccoon
Bobcat
Gray Wolf
Small Mammal
Chipmunk
Groundhog
Snowshoe Hare
Cottontail Rabbit
Lynx
Squirrel
Cougar
Marten
Striped Skunk
Coyote
Mink
Turkey
Deer
Moose
Weasel
Domestic Cat
Muskrat
Wolverine
Domestic Dog
Opossum
Human
Ducks
Other Bird
Nothing Here
Showing 39 of 39
Clear filters
PROJECTS ABOUT GET INVOLVED TALK BUILD A PROJECT NEWS
SIGN IN REGISTER
Michigan ZoomIN
ABOUT CLASSIFY TALK COLLECT
Hooray, Season 3 is here! New this season includes images from Detroit, MI. - look for image names that begin with 'D' (on bottom left of image). **
1
Help us investigate wildlife in Michigan!
Learn more
Get started
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Join in
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Other
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Make A Selection
Next
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FIELD GUIDE
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Deer
Deer are medium- to large-sized mammals covered in fur that is grayer in the winter and redder in the summer. They have white fur on the underside of their tails, as well as on their chins and throats. Deer have slender hooved legs and short tails. Male deer can have antlers, while female deer do not and their young (fawns) have spotted fur (Animal Diversity Web).
Often confused with
Elk
Moose
How many animals do you see?
1
2
3-5
6-10
many
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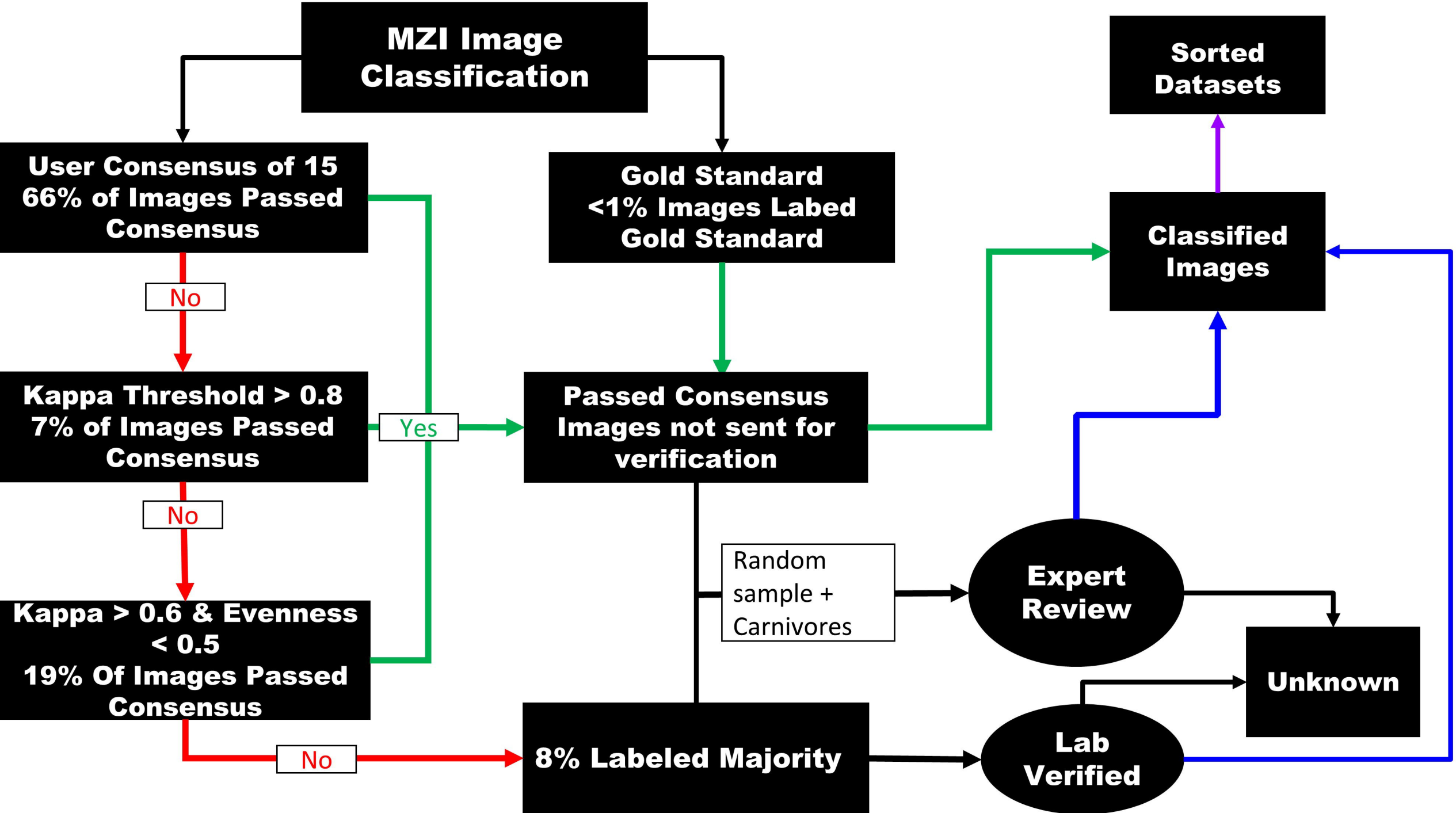
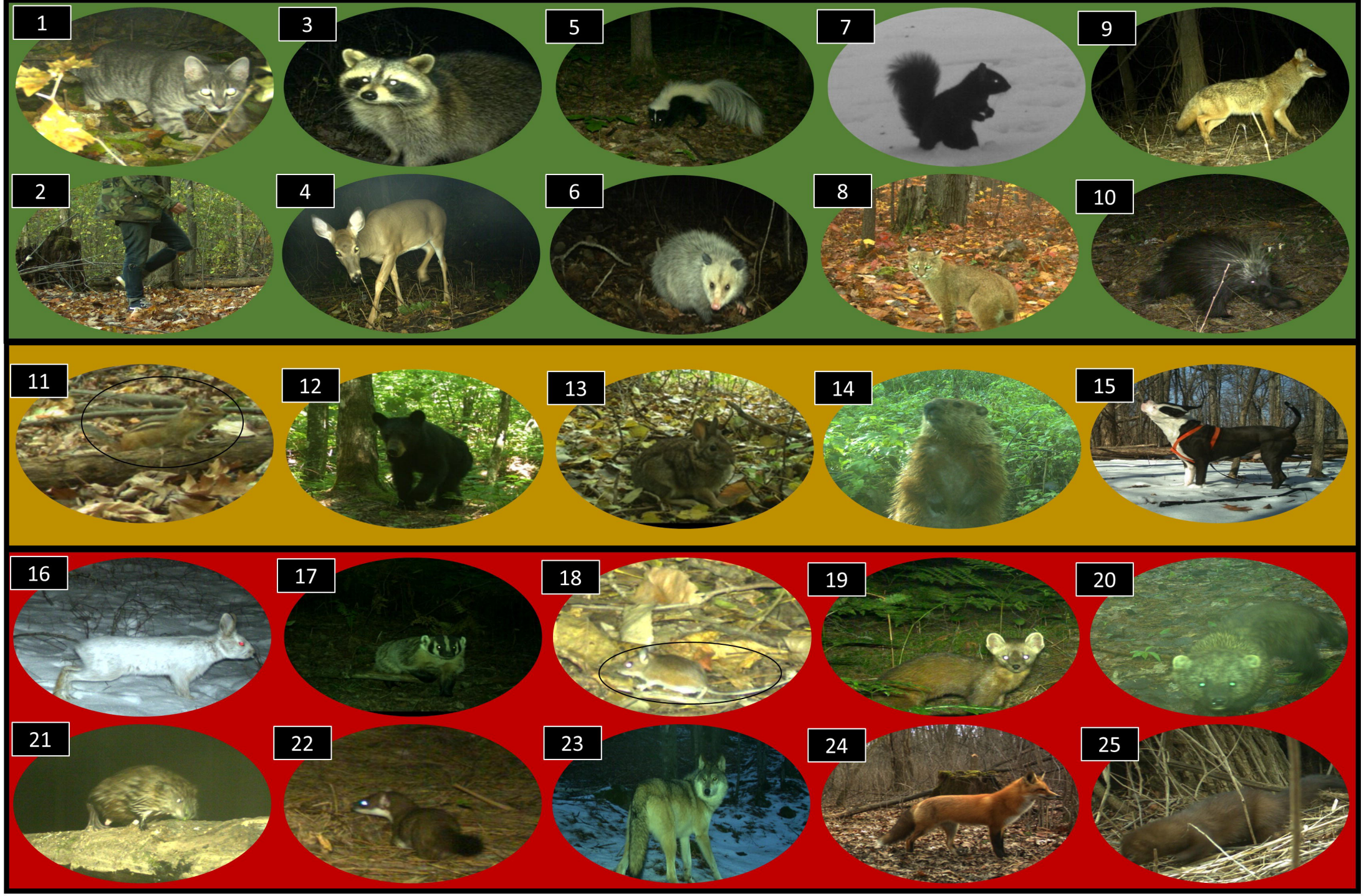
Click WOW if this as an especially awesome photo.
WOW
Cancel
Identify


MZI Image Classification
User Consensus of 15
66% of Images Passed Consensus
No
Kappa Threshold > 0.8
7% of Images Passed Consensus
Yes
No
Kappa > 0.6 & Evenness < 0.5
19% Of Images Passed Consensus
No
Gold Standard
<1% Images Labed Gold Standard
Passed Consensus Images not sent for verification
Random sample + Carnivores
8% Labeled Majority
Expert Review
Lab Verified
Unknown
Classified Images
Sorted Datasets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