Camera Trap Approaches Using Artificial Intelligence and Citizen Science

Untung Rahardja[1]
[1]University of Raharja, Tangerang, Indonesia
e-mail: untung@raharja.info

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ABSTRACT

For the purpose of tracking several animal species, camera trapping is developing into a more reliable and popular technology. The idea of "citizen science"—incorporating members of the public into the research process—has been gaining momentum concurrently . As a result, millions of individuals have made contributions to research in numerous sectors. Despite early acknowledgment of camera traps' significance for public engagement, they were previously unsuited for citizen science. Academics are seeking assistance in categorizing film as a result of camera trap technological advancements that have made cameras more user-friendly and the vast volumes of data they currently gather. Because of this, there are many camera trap efforts that now involve public participation, indicating that camera trap research is now a viable choice for citizen science. In order to categorize films, researchers are also applying artificial intelligence (AI). Although it has already been established that this rapidly developing field is useful, accuracy varies, and AI does not offer the social and engagement benefits associated with citizen scientific efforts. More attempts at fusing citizen science and AI are being suggested as a strategy to boost classification efficiency and accuracy while maintaining public interaction.

Corresponding Author:

Untung Rahardja
University of Raharja, Tangerang, Indonesia
Email: untung@raharja.info

1. INTRODUCTION

Camera traps, commonly referred to as game cameras or trail cameras, are tools used to remotely monitor animal activities. A number of methods, including weight plates and both active and passive infrared sensors, can be used to activate them to capture pictures or films while they are in the field for extended periods of time. The usage of camera traps has rapidly increased during the last 20 years[1]. The amount of camera trap video being gathered nowadays makes it difficult for researchers to analyze it. Artificial intelligence (AI) use and citizen science, two sectors that are both quickly expanding, have been suggested as viable remedies for this issue. Though each approach—citizen science and artificial intelligence—has pros and cons of their own, they have a tremendous deal of potential to work together to further camera trap research. Understanding these three strategies is necessary to properly integrate citizen science and AI into camera trap research, though. There is a sizable body of literature that focuses on each of these components independently, but nothing that combines all three. Here, we introduce these viewpoints and outline the existing techniques for fusing camera trapping with AI and citizen science. In order to inspire academics to think about whether and how merging camera trapping, citizen science, and AI may enhance their work, this study emphasizes the various ways that these technologies could be merged and gives background information on these issues.

The camera trapping method has its roots in the 1890s. With the use of a tripwire that an animal activated, George Shiras invented a method for shooting wildlife, and for this he was recognized for having pioneered a fresh perspective on the genre. Shiras wasn't a trained scientist, so he started using camera traps to capture wildlife in the open space. Griffiths, M., and van Schaik, C.P. said in 1993 that: "People's minds and hearts are reached best through visual means, and an important spin-off of the photo census work is that it boosts conservation through publicizing the richness of a reserve"(p. 134). Early on, it became clear that camera-trapping wasn't just appealing to academics; hunters who wanted to record animals were also intrigued [2]. The game hunting community produced a commercial demand for the product considerably bigger than that from scientists alone, which was crucial for the advancement of camera trap technology. As a result, companies that specialize in selling hunting-related gear and accessories made investments in the creation of camera traps. Many manufacturers now produce cameras popular with both game hunters and wildlife researchers, and a wide range of brands and models are available. Camera traps are now easily accessible for purchase in non-specialist retailers like major supermarkets, catering to the growing market of wildlife lovers who want to record local animals for curiosity and enjoyment.

Camera trapping has a lot of promise as a technique for engagement because of its close relationship with the public from the beginning [3]. However, with camera trapping, public participation hasn't always been obvious. As seen by the rise of citizen science-based camera trap research in recent years, the benefits of public interaction is becoming more widely understood.

2. CITIZEN SCIENCE

The phrase "citizen science" is a generic one that is typically used to characterize scientific activity that has been carried out by members of the general public, frequently but not always in partnership with institutions or professional scientists. The topic of ongoing discussion centers on the vocabulary that best describes this strategy, with concerns about inclusion and cultural diversity giving rise to varying interpretations and preferences. Due to the ambiguous nature of the term's apparent connection to a state or country's legal citizenship, some people may regard the term "citizen" to be exclusive [4]. Some people take issue with the implication that "professional" scientists are different from "ordinary" scientists. Public participation in scientific research, participatory action research, crowdsourcing, and community-based research are other names for public involvement in research, albeit these phrases are used in somewhat different ways. To avoid upsetting or alienating individuals they hope to involve in their study, it is crucial for those who intend to do so to be aware of these difficulties. We use the term 'citizen science' as it is a widely recognised term but wish for it to be interpreted in a broad and inclusive way.

Though not all initiatives will perfectly fall into one of the major categories for citizen scientific projects, there are several of them. These categories include, for instance: (1) Contributory initiatives are those "often planned by scientists and for which the general public principally contributes data"; (2) initiatives that are "usually created by scientists, and for which members of the public provide data but may also participate to refine the design, analyze data, or publish findings" are collaborative.; and (3)Projects that are co-created "are developed by scientists and members of the public working together and for which at least some of the public participants are actively involved in most or all phases of the scientific process". (4) Contractual projects, when a community hires experts to carry out a certain study; (5) Collegial contributions, which refer to non-credentialed researchers' autonomous work that has been at least partially acknowledged by institutionalized science and; (6) a category when the entire process is carried out by members of the general population and never involves expert scientists.

Participation in citizen scientific initiatives has improved participants' understanding of the subjects being studied and changed their behavior.Participation in citizen science projects has altered participants' behavior and enhanced their comprehension of the topics being examined. A feeling of purpose and community may be fostered through citizen science, and it can help individuals learn new things [5]. People of all ages may develop a connection to nature by taking part in conservation-based citizen science. Overindulging in leisure may make individuals feel guilty or slothful, and in some circumstances, people have said that taking part in citizen science is an excellent reason to take it easy and appreciate nature in ways that they would not have otherwise done. A range of health advantages can result from this enhanced connection to nature, including better mood, mental health, and cognition as well as more physical activity from participating in outdoor activities. People are spending less time outside due to busy modern lifestyles, urban living, changes in culture, and work trends, which has been dubbed a "extinction of experience". Groups of young individuals exhibit this separation the most visibly [6]. Children frequently know about exotic, iconic animals that are frequently featured in the media, such as lions, tigers, or pandas, but they frequently have little awareness about local species. By incorporating nature-based citizen science into the curriculum, schools may be able to attract students from a variety of backgrounds, reverse the "extinction of experience" tendency, foster greater connections with nature, and encourage academic engagement and participation.

3. CAMERA TRAPS AND CITIZEN SCIENCE

Early camera trap research wasn't a good fit for citizen science since the equipment was expensive, complicated to set up, and only acquired a small number of photos that were kept on film and hence impossible to distribute widely. Camera traps have improved in two significant ways that make them better suited for citizen research [7]. First, the shift from film-based to digital storage, which spread after 2007. This made it possible to gather and store more photos while making fewer trips to camera trap stations. It also made it easier to organize and exchange photos and allowed for instantaneous viewing of more photos. How this development will be felt Any group or person who has the power to choose a course of action and make decisions is a participant in the game. The prevalence of personal computers and internet connection, which also improved the accessibility of data storage and sharing, magnified the effects of this trend. The second feature was the creation of a single-unit camera trap with an integrated flash and passive infrared detecting technology. Passive IR systems just need one unit, as opposed to active IR systems, which needed two units located across from one another. Even among the film-based devices, this function advanced, enhancing the usefulness, accessibility, and affordability of camera traps. When an animal reaches this detecting zone, passive infrared sensors that measure surface temperature detect the change in surface temperatures and activate the camera. Unfortunately, this implies that the camera may be activated by moving vegetation as well, which results in a lot of "blank" shots, or images without any animals. Filtering out blank photographs can take a very long time, especially since it's not always obvious whether or not an image contains an animal without thorough scrutiny. Despite these false triggers, it has been shown that current video traps provide a reliable and affordable way to find and record a broad variety of species [8]. Since 2005, the usage of camera traps to address a variety of ecological concerns has increased significantly. A growing number of long-term, extensive monitoring projects now include the use of camera traps. As a result, some programs now manage millions of images, such as the Snapshot Serengeti project, the dataset compiled by the Tropical Ecology Assessment and Monitoring Team (now a part of the "Wildlife Insights" project, https://www.wildlifeinsights.org/), and the data gathered by Dorji et al. in Bhutan. Numerous surveys focus on a single species or taxon, while some programs keep track on groups of species [9]. Researchers may save time by concentrating solely on the photographs that include the creatures of interest, leaving many other images as "bycatch," due to the sheer volume of images that have been gathered. These pictures are frequently not examined, even though they can include valuable information about many other species.

The vast majority of citizen science camera trap initiatives fall under the umbrella of "contributory" citizen science. This sometimes entails posting online photographs that have been gathered by a researcher or group and soliciting internet species classifications [10]. The majority of citizen scientific initiatives use well-established platforms like Zooniverse despite the fact that a tiny minority have developed their own web platforms because to the significant time, money, and specialized expertise requirements. A project template and project creation tips are also available on this website [11]. Zooniverse has previously been utilized by several camera trap projects, so there are even open source programs on GitHub (https://github.com/zooniverse/help) that may be used to help with project design and data analysis, as well as literature outlining strategies for compiling answers. These platforms also provide access to a sizable, established volunteer base, which may be crucial if classifications are required quickly. CitSci.org (www.citsci.org) and iNaturalist (https://www.inaturalist.org) are two other websites that now contain camera trap photos for citizen scientists to categorize. iNaturalist is a well-known website for sharing photographs and getting descriptions for those photos, although it is advised that people intending to develop successful initiatives on the platform be themselves users, with expertise of how the platform functions. Some systems, like MammalWeb, are more regionally focused and can be more useful for locally focused projects attempting to involve local communities.

There is now both a need for citizen scientists to assist with data collection and classification, thanks to the development of user-friendly technologies, as well as the vast amount of camera trap photos being produced. The observation and identification of interesting characteristics in an image is a component of some of the most well-known and well-established online citizen science programs [12]. Galaxy Zoo is a classic but still well-liked example, asking players to name characteristics of galaxies. This project's success sparked the creation of Zooniverse (https://www.zooniverse.org/), an online platform that now has 111 ongoing projects, 70 projects that have been "paused," and 21 projects that have already been finished. 35 of the ongoing projects now include categorizing footage or photos from camera traps. A increasing number of projects, like those on InstantWild and Wildlife Insights, are also housed outside of Zooniverse and enable users to participate in camera trap research(https://instantwild.zsl.org),MammalWeb (https://www.mammalweb.org/), eMammal(https://emammal.si.edu/), Wildlife@Home(https://csgrid.org/csg/wildlife/),Digivol(https://australianmuseum.net.au/getinvolved/citizen-science/digivol/).

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There are projects where people may also provide camera trap film that they have personally acquired, while some of the online-only citizen science camera trap initiatives that merely entail picture categorization now get the biggest numbers of participants. More individuals being actively involved in camera trap installation might have a variety of advantages, such as: (1)aid in setting up and maintaining many camera traps; (2)a greater geographic region over which to set traps; (3)use of private property; (4) increasing community involvement reduces the likelihood of theft; and (5) financial support, such as participant-provided camera traps or trip fees. Comparatively, setting up a camera trap to gather data costs more time, effort, and (if the participant buys the camera trap) money than viewing and categorizing photographs online. As a result, individuals who set up camera traps could be more enthusiastic and inclined to participate more often than those who merely categorize photographs online. They could thus be more inclined to exhibit advantages like improved knowledge and altered behavior. Actively positioning a camera necessitates entering the outdoors and may help foster a stronger sense of connection with the location in question. Any effective camera location encourages viewers too thought about these concerns by taking into account the surroundings or how animals uses them. This may be especially beneficial when individuals are gathering information in their immediate surroundings, since it encourages a feeling of place and caring behavior.

4. APPROACHES USED IN CAMERA TRAPPING AND CITIZEN SCIENCE

Enthusiasm while using citizen science is anticipated to increase because now experiments can be launched reasonably simply and with proof of its advantages. Nevertheless, crucial issues should be taken into account while coming up with ideas to ensure that project objectives are realized. To increase popular engagement in installing camera traps, several alternative strategies are being utilized [13]. The strategy that works best would depending on the study topic and project goals. MammalWeb is one of those methods that tries to track mammal diversity throughout the UK and some of continental Europe. MammalWeb offers certain fundamental criteria, however contributors in its primary project are free to set cameras anywhere they like for as long they like, provided that this data is available along with any photographs. Participants may decide to categorize simply the photographs they have submitted or from a dataset that includes images gathered by all participants, but they are not compelled to provide any categories.Participants can contribute whenever they choose and can identify photographs even if they haven't provided any themself. This study is flexible to encourage and facilitate as many individuals to join and whenever level they desire; but, data collecting is less consistent compared to initiatives with set camera trap sites and trapping dates.

By establishing and hosting projects, MammalWeb also provides a platform for other organizations and individuals to explore more focused or hypothesis-driven research concerns. It is possible to determine which users are permitted to upload photographs, make categorization, and apply certain approaches [14]. High levels of participation have led some MammalWeb participants just to start their own mammal research projects. In one case, our study even inspired proposals to create a brand-new conservation area. Based on how deeply a user decides to participate, the MammalWeb project may come under one of the three categories of citizen science listed above: contributory, collaborative, or co-created. Therefore, it could act as a template for next citizen science initiatives.

However it's not just for projects involving citizen science, EMammal is a tool to help with managing and storing camera trap data and gives researchers a space to ask the public to take part in their study.22 different countries' activities are hosted on the website. A few of these ask volunteers to participate in data collection by setting up camera traps mostly in wild and sorting the film [15]. Although eMammal recommends citizen scientists to install cameras at random, each project's leader will specify the actual research design. This enables involvement by individuals available and capable of complying with that project design at the time and produces tailored data gathering for solving specific research objectives (i.e., participants must be able to visit a specific study area during a particular time period). Additionally, eMammal encourages camera trapping in schools by giving instructors materials and motivating students to create their own research questions and gather data using video traps, which is then verified by specialists on eMammal.

The "WildBook" initiative (www.wildbook.org) provides a platform for citizen scientific initiatives. WildBook, like eMammal, is a platform that may be used to support a number of initiatives rather than just being a citizen science project on its own. Employing photographs gathered by citizen scientists and incorporating AI into the image categorization process, initiatives using WildBook's software may be supported. As a tool, WildBook aids in initiatives where picture submissions serve as the vehicle for mass engagement and image classification is carried out either manually or by artificial intelligence. Numerous efforts emphasize individual identification as well as the identification of specific species. As a result, they can request that only certain species' pictures be submitted [16]. Photographs can be taken manually, although certain projects allow the combination of manually and camera trap-taken images. Although this project is different from the others in that it does not only focus on camera trap images, it is still an excellent illustration of the format shift wherein human input is through the submission of photos and the categorization load is primarily carried by AI.

The Wildlife Insights project also provides a platform where people or organizations may contribute picture data and receive AI aided classifications for that data. In this instance, the platform was created expressly to interact with camera trap picture data [17]. A worldwide database is created by combining this data. In order to facilitate the exchange of wildlife data and support improved management of wildlife populations, the platform also includes data sharing and data analysis modules. Animals Insights is not officially a citizen science project, but because of its open nature, anybody may upload their data to the website and help monitor wildlife throughout the world. Additionally, data can be downloaded and utilized for own research.

Utilizing the popularity of ecotourism is another method for involving the public in camera trap research. For instance, the EarthWatch Institute (https://earthwatch.org/) organizes approximately 60 different trips in various nations each year, drawing more than 2000 people. For a brief time, participants pay to join the trip, which supports the study financially [18]. Where these trips incorporate camera traps, people can help with camera installation and picture categorization while being watched over and assisted by researchers. Data collecting has already been used to support study on a number of areas, including big carnivore density and population dynamics, and effects of cattle on forest fauna. Data collection is frequently hypothesis-driven and organized towards specific research aims.

5. PRACTICAL CONCIDERATION FOR THE USE OF CAMERA TRAPPING AND CITIZEN SCIENCE

Data quality worries may discourage researchers from participating in citizen science. The scientific community does not always place as much significance on the data gathered by citizen scientists as a result of this worry. These worries are legitimate in some situations, however for the majority of projects, data quality can be guaranteed by using vouchers, a strong research design, properly teaching participants, and other methods [19]. An actual, concrete reference, such as a voucher, can be used to confirm a piece of information. The use of photographs as proof of a certain species or event that can be verified if the datum is in doubt is a frequent example of this. Since the photos or videos created may be used as coupons, camera trapping is especially well suited for this. The camera trap pictures may be used to confirm categorization accuracy, the camera trap's proper positioning, and the validity of the data obtained from that unit.

One method to increase accuracy involves having a small number of highly qualified specialists confirm camera trap picture classifications, but this takes time and does not make the greatest use of citizen scientists' contributions. The findings of individual classifications can be combined to provide a final, unified classification [20]. Alternatively, several project participants can examine and categorize each image. This offers a likelihood and level of assurance that the final classification arrived at is accurate, and it may be used to lessen the possibility of mistakes in the data set. For data sets administered by Snapshot

Serengeti and MammalWeb, consensus techniques have previously been employed to determine a final classification. Both projects came to the conclusion that a high degree of confidence in classifications may be attained by aggregating replies. According to assessments of classification accuracy, it took 10 classifications on average per image to achieve a 95% accuracy level for Snapshot Serengeti and >99% accuracy for MammalWeb, however both studies showed that this varied by species. With more than three million picture sequences on current Zooniverse projects alone, however, the need for adequate classifications to attain a credible agreement may exceed capacity, leading to projects having to compete for participation.

Planning Stage	Consideration	Suggestions
Project Aims	What are the project's goals in terms of research, participation, education, and other social benefits?	Numerous citizen science initiatives will have numerous goals for data collecting as well as additional social and engagement advantages. While it is feasible to accomplish many goals, some compromise may be required. Establishing your project's priorities early on can help you create the most effective methods for achieving your goals.
Research Question	Do you want to collaborate with a community to create questions together or do you already have a topic in mind?	If you have a question already, think about how the audience you are attempting to reach would find it interesting or relevant. If you intend to collaborate with a community to design a question, make sure you give yourself enough time to get to know them well. You should also strive to involve as many diverse individuals and viewpoints as you can in the planning process.
Methodology	Does your approach allow the public to make important contributions?	A technique must be as straightforward and transparent as feasible if contributors must quickly learn to use it. If specialized equipment is necessary, take into account whether you can supply it. Give instructions on how to set up camera traps, including suggested camera placements and settings. Establish data quality checks, such as evaluations of the film and camera location supplied, so that participants may receive feedback to assist them in providing accurate data. has to be as unambiguous and straightforward as possible. if specialized equipment is needed.

	Are camera traps required to be placed in particular fields or formats, and will the public have access to them?	Engaging the public may aid in facilitating access to participants' private property, but it's also crucial to make sure that participants are aware of the privacy and moral concerns associated with camera traps and that they get consent before installing cameras on others' private property. Provide a risk assessment and health and safety standards in addition to thinking about how safe it is for participants to go to remote locations. Think about planning group outings or giving participants a forum to interact and collaborate. Plan how to discreetly disclose camera trap locations if they must be placed in certain places without being made public to reduce the danger of theft and vandalism.
	How can accuracy be guaranteed? Can citizen science be utilized to help classify images? .	It's crucial to be able to trust the classifications given since image categorization is a common method of involving people in citizen science camera traps. Expert verification or several classifications per image obtained from the general public that are then combined to produce a consensus classification can both be utilized to assure high levels of accuracy.
	Should citizen scientists receive more training, and if so, how can you deliver it?	Depending on the phases of the research process a person will engage in, different training needs will apply. Online instructions can be found in the form of videos or papers. For large-scale undertakings, online materials are advantageous since they may reach a wider audience. To provide more thorough practical training as an alternative to this, or in addition to it, workshops and training days might be employed. A second strategy for guaranteeing accurate data gathering is to have it done under the supervision of an expert, albeit this does limit the amount of data that can be collected based on the availability of the expert. Experienced participants might assume the responsibilities of trainers, and small groups could get extra training before instructing others. By offering learning chances, one may encourage participation since education or the desire to learn something new can do so.
Engagement	Can you get enough participants to participate, and how will you inspire them to work on your project?	The use of social media, gamification, and giving chances for social interaction have all been proved to aid raise awareness, motivation, or involvement. Utilizing artificial intelligence can assist reduce workloads if a lot of classifications are required (see main text).

	Whom are you attempting to engage? What potential obstacles to participation, such as a lack of a camera trap or computer, or internet connection, exist?	Learn about your focus community so that any possible obstacles may be considered when developing an approach. A portion of the machinery can be loaned to people or groups.

6. INTEGRATING AI INTO CAMERA TRAP AND CITZEN SCIENCE WORK FLOWS

Automating the categorization of camera trap photos using computer vision, a branch of artificial intelligence that deals with visual data, is a method that is gaining popularity and may be used instead of or in addition to citizen science. Neural networks, which are mathematical methods that transfer an input item to an output, can be used in classification using AI [21]. An illustration of a pertinent input object is an image, and the output is a categorization of that image.One of these methods is generally optimized for a job through a process known as training, which calls for labelled data matching to the input items the final network will use to make a prediction. This would need having a sizable reference library of previously identified, or "labelled," photographs in the context of camera trapping. The algorithms are iteratively changed during training in order to minimize the loss function. The loss function calculates the distance between the training label and the network's predicted output, the animal it believes to be most likely (the actual animal in the image). This method continues iteratively until the required performance (for example, a threshold species classification accuracy) is attained on the validation dataset, which may take a certain amount of time or longer. Depending on technical skills like coding prowess, there are several methods to use this training method called as Deep Learning [22]. Open source solutions can be found for free with coding skills; packaged software is also offered but costs money. The time frame and difficulty of the issue will surely affect the needed cash commitment. Usability is becoming more important in the rapidly expanding commercial and academic field of deep learning. A growing number of people are finding using AI to be a realistic and useful alternative thanks to improvements in usability, advancements in computational capacity, and falling prices for the graphics processing units (GPUs) necessary for training.

Robust and precise analysis of ecological photos is now achievable because to the development of deep learning and the enhanced image analysis capability brought on by convolutional neural networks (CNNs). The requirement for huge, diverse training sets, however, may have prevented computer vision from being used more widely up until this point.Platforms like Zooniverse and Wildlife Insights, which are producing big datasets suited for training, are helping to find a solution to this issue. To differing degrees, each of these systems utilize citizen science. Wildlife@Home is a case study of the successful incorporation of citizen scientists in deep learning, where citizen science classifications were used to train neural networks that assist in bird population analysis. Several research teams' datasets and the expanding collection of citizen science categorized datasets are also being utilized to build software tools to support ecological efforts. Examples of this software include the pretrained networks in "ClassifyMe" and the "R" package "Machine Learning for Wildlife Image Classification." The performance of CNNs designed for camera trap image categorization is encouraging if there is sufficient training data. No research achieves a classification accuracy of 100%, however some studies were able to surpass 90% accuracy when a lot of training data were provided.

Accuracy may, however, decline noticeably in research with tiny training data sets in relation to the issue. This wide performance indicator does not account for the generalizability problem, which occurs even when accuracy is high and causes a model to perform poorly on data that it has not been specially trained on. For instance, when a network that has been trained to recognize a certain species is asked to do so against a background of a novel ecosystem, performance may be noticeably lower. Since more projects may be started at new locations or new camera locations added to an existing array, this issue is probably prevalent with camera-trapping.Because manual classifications still require a lot of work, projects in these situations could need to develop new training sets or improve already-existing ones, which would negate any possible advantages of using AI. The large-scale studies for which extremely high accuracy is attained are also not typical of all conservation or research activities, many of which produce smaller data sets. It is time-consuming and may be ineffective for small-scale conservation initiatives to create a training set of labeled camera trap photos. In reality, to meet training set criteria, a sizable number of camera trap pictures may need to be labeled. It is unlikely that a CNN can be used in a completely autonomous system (without human involvement) for categorizing animals inside photos if there are only minimal training sets available.

The obvious solution to this is a semi-autonomous technique (with minimal human involvement), which is ideally suited to being included into workflows for researchers and citizen scientists. This eases the burden on researchers and small projects that can't compile enough classifications for consensus correctness in an acceptable amount of time. By imposing a confidence threshold on the output of network classifications and only accepting those with the necessary confidence, this semi-autonomy may be achieved. Classifications that exceed the appropriate confidence threshold are deemed accurate and do not require human verification. For the Snapshot Serengeti dataset of animals in the Serengeti National Park, Tanzania, Norouzzadeh & colleagues discovered that citizen science accuracy was 96.6%. In this research, 99.3% of the data could be automatically processed by limiting neural network classifications to the same value of 96.6%. Unsatisfactory classifications are more likely to include mistakes and may be marked for human categorization [23]. Researchers could finish this work if there aren't many photos that need manual categorization. However, in many instances, citizen scientists participation at this level might be advantageous.

A consensus classification technique can be used to arrive at a final classification after combining several citizen scientist classifications, as was previously mentioned. Using the AI classification as another vote that might be weighted based on the classifier's level of confidence in this process would be one method to integrate citizen science with AI classifications. Although this would need exposing all camera trap data to both the citizen scientists and the neural network, it would cut down on the quantity of human classifications required per image to arrive at a consensus categorization.

A "cascade filtering" workflow with a number of layered consensus classification stages is one method for establishing a consensus classification workflow. Willi et al. tested their cascade filtering technique using camera trap data sets from the Zooniverse project "Camera CATalogue," which intends to gather information on big cat species, utilizing AI and citizen science classifications. The "cascade filtering" method included several simpler binary classifications, such as whether the image contains an item or not, whether it contains a vehicle or not, and then a species classification. With less consensus needed before a picture was discarded at each level thanks to this method, data sets may be categorised more quickly. This was proved in an experiment on a Zooniverse project where human effort was decreased by 43%. Thus, methods that combine AI and citizen science have a great deal of potential for accurately classifying camera trap data.

Cascade filtering is not required to archive consensus classifications. An ID for each species might be provided by AI and citizen scientists on a single layer. However, there hasn't been much research on using this technique to arrive at a consensus categorization that has been published. We think this approach has a lot of potential and deserves more consideration. Trialing various approaches, like those mentioned above, on various data sets can assist identify which are most useful for future usage.

7. Future Directions and Conclusions

The time required to categorize footage may now limit camera trap initiatives. This can seriously diminish the importance and usefulness of data sets by leaving certain photographs unlabeled and useless. AI and citizen science have both come to be seen as viable answers to this problem, although neither one stands alone as a full answer due to its own constraints. Initial findings from several recent studies reveal that the integration of AI and citizen science is already beginning to realize this potential, and we feel that it has great long-term promise. We envision a camera trap project combining AI and citizen science in four primary formats:

1. Citizen scientists classify camera trap footage and submit their classifications, establishing a labelled data set that may be used to train a neural network that will categorize future footage from that project.
2. Collection, then submit just the results of the AI classifications with low accuracy confidence to citizen scientists for confirmation.
3. Citizen scientists would then review the resulting film to extract additional information, such as animal behavior or the identification of recognizable persons, after pre-screening the data using AI to exclude blank footage or species of interest.
4. Citizen scientists use camera traps to collect data in the field. The subsequent AI-classified footage is subsequently produced.

A project could switch between these formats over time because they are not mutually exclusive. For instance, starting with citizen scientist classifications to train a neural network and shifting participant efforts later to other tasks like adding more cameras or extracting more information from categorized video. AI is anticipated to be used to categorize an increasing percentage of camera trap photos as the technology underlying it advances. But even as AI advances, the demand for citizen science will persist. The engagement advantages of citizen research, whose importance shouldn't be undervalued, cannot be achieved by AI. This is crucial for studies where participants are needed to help with more than simply picture classification, such as camera installation and maintenance. Additionally, AI cannot carry out the whole spectrum of tasks that a human participant can, despite its ability to help in the classification of species in an image. The usage of camera trap footage in behavioral research is growing because it can provide more details than just the presence of an animal. While some research use AI to recognize animal behaviors, this has had less success than just identifying a species. Here, we see the possibility to merge AI with human efforts, since AI may be used to identify and filter out a species of interest for a certain research, considerably lowering the human burden. These videos might be displayed to human viewers who could deduce additional information, including animal counts or behaviors.

Overall, using citizen science and AI technology into camera trapping research can assist maximize the quantity of data that can be captured and processed quickly while also engaging and enlightening people about the natural world and its worth. While AI, citizen science, or both may not be appropriate for many projects, we believe they should be seriously considered and incorporated wherever possible since they have a wealth of potential advantages.

REFERENCES

[1] A. Donnelly, O. Crowe, E. Regan, S. Begley, and A. Caffarra, "The role of citizen science in monitoring biodiversity in Ireland," *Int. J. Biometeorol.*, vol. 58, no. 6, pp. 1237–1249, 2014.

[2] K. Vella, B. Ploderer, and M. Brereton, "Human-nature relations in urban gardens: Explorations with camera traps," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–13.

[3] A. Cunsolo Willox, S. L. Harper, V. L. Edge, 'My Word': Storytelling and Digital Media Lab, and R. I. C. Government, "Storytelling in a digital age: digital storytelling as an emerging narrative method for preserving and promoting indigenous oral wisdom," *Qual. Res.*, vol. 13, no. 2, pp. 127–147, 2013.

[4] K. Rubenstein and D. Adler, "International citizenship: The future of nationality in a globalized world," *Ind. J. Glob. Leg. Stud.*, vol. 7, p. 519, 1999.

[5] A. C. King *et al.*, "Community-based approaches to reducing health inequities and fostering environmental justice through global youth-engaged citizen science," *Int. J. Environ. Res. Public Health*, vol. 18, no. 3, p. 892, 2021.

[6] G. W. Datlen and C. Pandolfi, "Developing an online art therapy group for learning disabled young adults using WhatsApp," *Int. J. Art Ther.*, vol. 25, no. 4, pp. 192–201, 2020.
[7] S. E. Green, J. P. Rees, P. A. Stephens, R. A. Hill, and A. J. Giordano, "Innovations in camera trapping technology and approaches: The integration of citizen science and artificial intelligence," *Animals*, vol. 10, no. 1, p. 132, 2020.
[8] S. Nazir *et al.*, "WiseEye: Next generation expandable and programmable camera trap platform for wildlife research," *PLoS One*, vol. 12, no. 1, p. e0169758, 2017.
[9] E. Eriksen *et al.*, "From single species surveys towards monitoring of the Barents Sea ecosystem," *Prog. Oceanogr.*, vol. 166, pp. 4–14, 2018.
[10] D. Murthy, "Digital ethnography: An examination of the use of new technologies for social research," *Sociology*, vol. 42, no. 5, pp. 837–855, 2008.
[11] S. Murray, *Interactive data visualization for the web: an introduction to designing with D3.* " O'Reilly Media, Inc.," 2017.
[12] V. Curtis, *Online citizen science projects: an exploration of motivation, contribution and participation.* Open University (United Kingdom), 2015.
[13] T. Gregory, F. Carrasco Rueda, J. Deichmann, J. Kolowski, and A. Alonso, "Arboreal camera trapping: taking a proven method to new heights," *Methods Ecol. Evol.*, vol. 5, no. 5, pp. 443–451, 2014.
[14] A. M. Kaplan and M. Haenlein, "Users of the world, unite! The challenges and opportunities of Social Media," *Bus. Horiz.*, vol. 53, no. 1, pp. 59–68, 2010.
[15] L. Trouille, C. J. Lintott, and L. F. Fortson, "Citizen science frontiers: Efficiency, engagement, and serendipitous discovery with human–machine systems," *Proc. Natl. Acad. Sci.*, vol. 116, no. 6, pp. 1902–1909, 2019.
[16] C. Botella, A. Joly, P. Bonnet, P. Monestiez, and F. Munoz, "Species distribution modeling based on the automated identification of citizen observations," *Appl. Plant Sci.*, vol. 6, no. 2, p. e1029, 2018.
[17] J. A. Royle, K. U. Karanth, A. M. Gopalaswamy, and N. S. Kumar, "Bayesian inference in camera trapping studies for a class of spatial capture–recapture models," *Ecology*, vol. 90, no. 11, pp. 3233–3244, 2009.
[18] N. Dickert and C. Grady, "What's the price of a research subject? Approaches to payment for research participation," *New England journal of medicine*, vol. 341, no. 3. Mass Medical Soc, pp. 198–203, 1999.
[19] E. Duflo and M. Kremer, "Use of randomization in the evaluation of development effectiveness," in *World Bank Operations Evaluation Department (OED) Conference on Evaluation and Development Effectiveness*, 2003, vol. 15.
[20] K. A. Hoadley *et al.*, "Multiplatform analysis of 12 cancer types reveals molecular classification within and across tissues of origin," *Cell*, vol. 158, no. 4, pp. 929–944, 2014.
[21] M. K. D. Kiani, B. Ghobadian, T. Tavakoli, A. M. Nikbakht, and G. Najafi, "Application of artificial neural networks for the prediction of performance and exhaust emissions in SI engine using ethanol-gasoline blends," *Energy*, vol. 35, no. 1, pp. 65–69, 2010.
[22] T. Wang, M. Chen, and H. Chao, "A novel deep learning-based method of improving coding efficiency from the decoder-end for HEVC," in *2017 Data Compression Conference (DCC)*, 2017, pp. 410–419.
[23] J. Reason, A. Manstead, S. Stradling, J. Baxter, and K. Campbell, "Errors and violations on the roads: a real distinction?," *Ergonomics*, vol. 33, no. 10–11, pp. 1315–1332, 1990.

BIOGRAPHIES OF AUTHORS

	**Untung Rahardja** University of Raharja, Tangerang, Indonesia. He can be contacted at email : untung@raharja.info