2023 IEEE 14th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON) | 979-8-3503-0413-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/UEMCON59035.2023.10316121

Integrating machine learning and infrared smart cameras into critically endangered bird production

1st Constance J. Woodman, Ph.D
Veterinary Medicine Pathobiology
Texas A&M University
College Station, USA
line 5: gryphus@tamu.edu

2nd Ashley Ridlon
Veterinary Medicine Pathobiology
Texas A&M University
College Station, USA
line 5: email address or ORCID

3rd Christopher J. Evelyn, Ph.D
Cheadle Center for Biodiversity and Ecological Restoration
University of California Santa Barbara
Santa Barbara, USA
christopher_evelyn@ucsb.edu

4th Alexis Martinez
Integrated Agricultural Sciences
Texas State University
San Marcos, USA
alexismartinez63@gmail.com

5th Damien Valles, Ph.D
Ingram School of Engineering
Texas State University
San Marcos, USA
dvalles@txstate.edu

***Abstract*— Artificial incubation and nest management are useful tools for the conservation of rare, threatened, and endangered bird species. It can reduce disease transmission from parent to chick, stimulate re-nesting by parent birds who double their reproductive output, and allow medical support during hatching to maximize hatchling survival. In some cases, eggs are left in the original or foster nest until just before hatching, then removed, sanitized, and placed in an incubator. The problem is that egg-laying does not occur on a set schedule so the laying date may not be known, and different eggs in the same nest may hatch on different dates. To date, predicting hatch requires frequent nest checks by hand, causing stress to parental birds and potentially decreasing their reproductive output. Here we describe a method to replace manual nest box checks with a machine vision system to automatically alert managers when hatching is imminent. To test this method, thermal imaging photos of eggs (n=42) were taken across 15 species of Psittaciformes (parrots) and Anseriformes (ducks) at a specialized bird breeding facility. A machine learning model produced in Google Vertex AI, detected eggs within 1.5 days of hatch with 100% accuracy, without false negatives. This method has great potential to improve captive breeding or wild nest box monitoring outcomes for rare, threatened, and endangered bird species.**

Keywords—birds, machine learning, conservation, intensive wildlife management, conservation breeding

I. INTRODUCTION

Conservation efforts for exceedingly rare species focus on the survivorship of individuals as each one represents a considerable proportion of all extant individuals. For slow-growing and long-lived birds, interventions to boost fecundity and hatching success are a mix of field and captive breeding techniques [1]. This mosaic of methods requires efficient monitoring of nesting pairs and their brood. These observation activities, such as the artificial incubation of eggs, are critical for timing the intervention action but have the potential to stress the breeding pair, reducing their fecundity [2]. Finding an effective and efficient balance in nest monitoring of long-lived rare birds, such as parrots, is particularly critical. The IUCN has identified 51 species of parrot (Table 1) which are currently in need of some level of captive breeding to avoid further parrot extinctions [3]. Parrots currently face many threats, and >100 species are at risk of extinction [3]. Threats from economic pressures lead to the collecting of adults and young birds, and to land conversion for anthropogenic uses, which reduces the amount and quality of habitat through habitat destruction and degradation [3-5]. Captive breeding projects, called aviculture, protect mating pairs from these threats and attempt to maximize their reproductive output. Artificial incubation is a cornerstone of aviculture projects with rare species [6].

Technical experts estimate the time to hatching by shining a light through an egg, or by weighing the egg. One set of best practices in artificial incubation requires collecting eggs from a nest just before hatching (JBH) and transferring them to an incubator, as the nearly hatched chick tolerates transport better than earlier development stages. If it can be timed properly, collecting eggs JBH provides benefits to the developing bird by allowing them to stay in their natural nest environment, whether parent or foster parent, for nearly the entire duration of their incubation period. Removal of eggs JBH reduces the risk of vertical disease transmission between parents and offspring by keeping the egg's shell and membrane intact as barriers to disease. Reduction of disease increases survivorship and health of the population. Double-clutching is the additional population-level benefit in that the adult pair may attempt to mate and brood a second time within that same breeding season [1,7-9]. In addition to disease reduction, pulling eggs JBH allows for medical intervention and assisted hatching as not all chicks survive hatching [9].

Natural incubation before pulling eggs JBH creates a second technical need. Many nesting species are not tolerantto of human interaction in the wild or captivity. This is especially the case in situ, nests in the wild, where human beings manipulate bird nests in the wild to the benefit of rare species [10]. Whether captive or wild, human interactions can cause stress to the nesting animal during egg health checks in the nest. Adverse effects on parents from this stress can lead to various pathologies and, in extreme cases, death [11]. Repeated stress during animal care can also cause long-term

TABLE I.

Taxa	IUCN Red List database search results for "Conservation Actions Needed" subcategory 3.4 "ex-situ conservation" need in Taxa groups Aves and Psittaciformes.	
	Total species	Captive breeding needed
All birds	11,029	239
Parrots	405	51

Funded by NOAA and Texas A&M University

consequences and even produce negative consequences similar to post-traumatic stress disorder in humans [12]. With more aggressive species, the eggs can be damaged if one of the parents accidentally kicks or steps on the eggs during nest defense. Some birds kill their young and destroy their eggs with "displaced aggression" when their nests are disturbed by unfamiliar people or if they respond poorly to stress from human involvement in the nest [13]. It has also been documented that the parents can take the stress out on one another, even with short-term handling [14]. For some species of wild birds that are maintained and bred in captivity, mate aggression is commonly seen in interactions with humans. This mate aggression can be as severe as to lead to mate killing, which presents a welfare issue for the birds in captivity [15].

Candling eggs and using infrared photography have been studied to monitor eggs during incubation (Ishikawa 2021). With eggs that have thick or opaque eggshells, candling is not practical and cannot be performed. Infrared egg viewers, such as the Emu Vision 2000 standalone candler (No longer in production, no URL address available), utilize infrared for thicker shells. Infrared photography and video monitoring continue to be researched, especially in poultry systems to measure the quality of the egg and the embryo [16,17]. In addition to these classifications, infrared technology can differentiate fertilized eggs from infertile eggs using a thermal imaging system [18]. Infrared photography and artificial intelligence with machine analysis can be combined when looking at bird embryo development to produce an automated health monitoring system [19,20]. These methods have been primarily used in chickens, but the basis for these health monitoring systems can be adapted for use in parrots and other endangered species of birds. An automated monitoring system could alert animal caregivers when eggs in natural nests are JBH and prevent daily health checks and artificial incubation complications.

Pairing a thermal camera with a successful machine learning model could allow for on-board estimation of JBH by a fully automated system. Such a technology would reduce human work hours, and animal stress, and increase the reproductive output of extremely rare species, where every chick counts. For in situ work, a remote camera with a radio, such as LoRAWAN (https://lora-alliance.org/), would eliminate hours-long climbs per day in remote areas, where teams endure grueling daily trips up trees or cliffs.

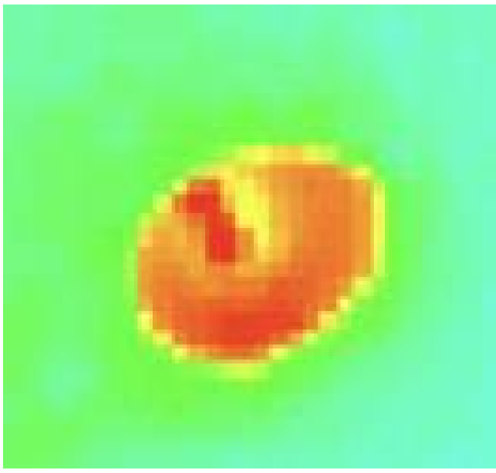

Fig. 1. External pip, the first breakthrough of the eggshell, on quaker parrot egg (*Myiopsitta monachus*) photograph taken with a FLIR infrared camera on the day of hatch. Stages of air cell growth and early hatch are evident even on low-resolution infrared.

In this paper, we will review the process of creating a machine learning model for an "edge-ready" low-power and non-internet connected device. We will outline how we worked in partnership with an active conservation breeding facility that works with multiple critically endangered bird species. Subsequently, we evaluate the success of the machine learning model and discuss how the process could be further developed to assist in improving conservation outcomes and allowing conservation professionals to create more impacts with fewer hands-on work hours through the assistance of smart cameras.

II. Methods

A. Research Site

Research took place at commercial and conservation mixed use breeding facility in Central Texas. The site participates in a number of endangered and critically endangered bird species programs while also producing common birds species for the pet trade, whose sales support conservation activities. The facility produces primarily parrots but also a small number of other types of birds. At time of research they had both parrot and duck eggs in their incubator room. This site selection allowed for integration of smart systems into a conservation breeding site, during daily egg checks. Egg handling was minimally altered as the only change was photography was added to daily candling, avoiding the need for a separate handling procedure. This research was approved by the Texas A&M Institutional Animal Care and Use Committee.

A total of 137 eggs from fifteen different species of Psittaciformes (parrots) and Anseriformes (ducks) were used in this study. Of those 137 eggs, 43 were monitored to hatch without complications or abnormalities. Egg collections were performed from nest boxes from a captive collection of birds at a facility specializing in rare species reproduction and participating in government-overseen captive conservation breeding. Eggs were collected from nest boxes. Eggs were transported to the facility's incubator room. Eggs were immediately brought back in small batches or individual clutches to limit the chance of chilling the eggs or disturbing the incubation. Hydrogen peroxide spray was applied to kill bacteria, inactivate viruses, and remove debris from the shell's exterior. The eggs were then placed in a UV sterilizer for 3 minutes per the recommendations for sterilization (Pers. Comm. Texas A&M Schubot Center for Avian Health). After sanitation, the eggs were candled and labeled before entering the incubator. Eggs were sorted in the incubator into three separate areas: fertile, suspected infertile, and abnormal. When candling, if any damage was noted, eggs were either discarded or the shells were repaired. Repair or discard was determined based on if the membrane of the shell was intact. If the membrane was damaged or broken, the egg was discarded. The incubators had automatic rollers, and the eggs were placed in an INCA 200 incubator (https://www.dmp-engineering.com/) based on the size between the rollers. After each batch of eggs was collected, the bedding from the transported eggs was discarded, and the bowl was sanitized. Any disposable materials used to perform the sanitation were discarded, and reusable items were sanitized and washed.

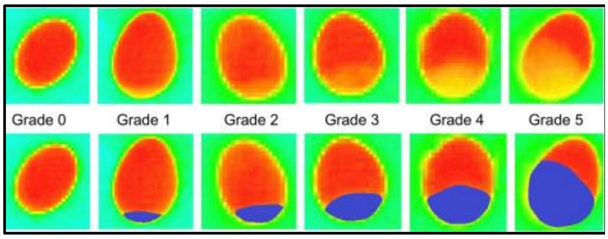

Fig. 2. Eggs graded from 0 to 5, based on FLIR infrared photography. Blue shading in the second line of images indicates where the air cell is in the egg. The grading of the air cell is based on the size increase of the air cell through the incubation period.

Candling was performed in a dimly lit room with a flashlight with a beam smaller than the diameter of the egg. In addition to handling during intake, candling was performed daily while the eggs were in the incubators to facilitate daily health checks. Visual assessment of the embryo in the egg allowed for monitoring for distress and looking for abnormalities in the egg. The air cell was also inspected to monitor "drawdown", in which the air cell becomes rapidly much larger, and watch for internal pipping in the egg (a sign of the beginning of hatching). If any abnormalities were present, the hatching, and monitoring of the vitals allowed for better gauging of when intervention was needed for the chick. The intervention was performed as needed. Eggs that showed abnormalities placed on the Buddy egg monitor that also showed no movement and no vital signs such as heart rate were discarded.

B. Egg Husbandry and Handling

A FLIR infrared camera, purchased from openmv.org, was used to obtain photographs of each of the eggs using a script optimized in OpenMV Integrated Development Environment (IDE), Figure 1. The dynamic range settings for the infrared spectrum were allowed to auto-adjust to produce a maximal contrast between the embryo and the air cell in the egg. A stand was created to place the camera 12 inches above the egg, generating a photograph frame. The stand prevented the camera from moving and allowed for replication. A 6-inch diameter bowl was used with a bedding depth of 1 inch for the photography station where the egg was contained. Carefresh bedding was chosen as the optimal bedding to be used after determining the best contrast between it and the egg compared to other types of bedding

C. Thermal Imaging Dataset

A FLIR infrared camera, purchased from openmv.org, was used to obtain photographs of each of the eggs using a script optimized in OpenMV Integrated Development Environment (IDE), Figure 1. The dynamic range settings for the infrared spectrum were allowed to auto-adjust to produce a maximal contrast between the embryo and the air cell in the egg. A stand was created to place the camera 12 inches above the egg, generating a photograph frame. The stand prevented the camera from moving and allowed for replication. A 6-inch diameter bowl was used with a bedding depth of 1 inch for the photography station where the egg was contained. Carefresh brand bedding (was chosen as the optimal bedding to be used after determining the best contrast between it and the egg compared to other types of bedding.

Photographs were taken over 48 days to monitor the development of 137 eggs. Of these eggs, 43 eggs of fifteen species were followed to hatch. A 28-day incubation period was assumed for the eggs used in this study. After the chicks hatched, the eggs were aged from the hatch date. For each photo, the eggs were graded based on the area the air cell took up in the egg. A grade on a scale of 0-5 was assigned to each egg. A grade 0 was indicative of 0% of the egg containing the air cell, a grade 1 was indicative of 10% of the egg containing the air cell, a grade 2 was indicative of 20% of the air cell, a grade 4 was indicative of 40% of the egg containing the air cell, and a grade 5 was indicative of 50% or more of the egg containing the air cell. These grades were manually assigned using a visual estimate to each of the eggs by the same person grading each of the eggs.

D. Thermal Imaging Dataset

Google Vertex AI (https://cloud.google.com/vertex-ai) was primarily utilized to generate the machine learning model for differentiating grade 0 eggs from grade 5 eggs. A total of 583 images were split so that 466 were used for training, and 58 were used as test images. When selecting options for training, "explainability," a validation tool accessible in Vertex AI, was turned on to allow for a better understanding of the model's decision-making in classifying images. This function, called XRAI, uses bitmapping to highlight the most effective pixels in decision-making. Fig. 5 shows that the model appeared to be correctly focusing on the air cell location and size, indicating successful training data selection and model type selection. Vertex AI also generated a confusion matrix to compare false positives, false negatives, true positives, and true negatives during the testing phase. Fig. 6 shows this confusion matrix.

To build a larger training set that took into account egg rotation and position, synthetically augmented training images were generated by taking the original egg photos and rotating them 90 and 180 degrees to double and triple the number of photos available for training without manipulating eggs excessively to generate photos. To prevent overfitting of the model, finer rotations and imaging flipping on a vertical or horizontal axis were not utilized.

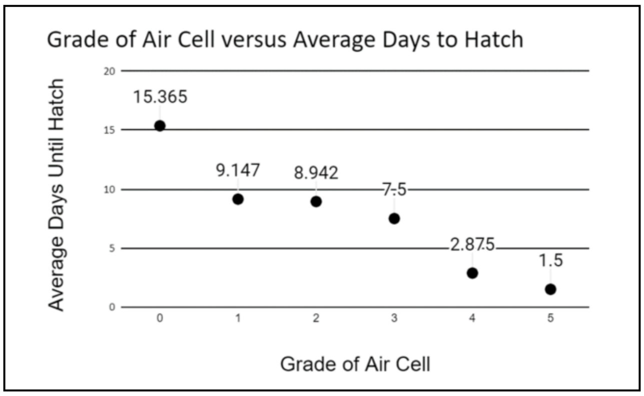

Fig. 3. Correlation between air cell grade and days to hatch for a sample of 43 parrot and duck eggs across 15 species. We graded air cells grade 0 meaning near 0% of the egg containing the air cell, 1 was 10%, grade 2 was 20%, grade 4 was 40%, and grade 5 was 50% or more. Grades four and five have the most utility to conservation as that is when the egg will need attention for cross-fostering, assisted hatching and medical support, or pulling for an incubator hatch.

TABLE II.

True/Predicted	*Grade 0*	*Grade 5*
Grade 0	98%	2%
Grade 5	0%	100%

The Vertex AI solution was selected as it has simple functionality that was easily utilized by our veterinary research partner. Experienced users of machine learning models may want to avoid the "black box" nature of the proprietary Google Vertex AI platform. We expect that many commonly utilized machine learning models such within ANN, CNN, or SVM architectures can be trained to perform with comparable accuracy to results presented here.

III. Results

Based on the correlation of grade to hatch time, we determined that recognizing grade 5 was the most important output of a machine learning model. We made our initial model classify only grade 5 against grade 0 as a proof of concept. There was not enough training data after only one season of photography to enable adequate data sets for each grade of air cell.

For n=58 test images, the model's precision was 98.3%, recall 98.3%, for an overall average precision of 0.998 according to Vertex AI's reported metrics.

The Vertex AI confusion matrix (Table II) was conservative, meaning that when the model classified an egg image incorrectly, it predicted hatching too soon, not too late. This is the preferred case for rare species work, where conservative choices are safer than making a costly mistake.

For n=43 of the tracked eggs (across multiple species of Psittaciformes and Anseriformes) air cells with a grade of 5, hatch occurred within 36 hours 93% of the time. The remaining 7% hatched within five days. The "drawdown" that occurs just before hatching creates the very large air cell seen in certain groups of birds, making it a useful event for predicting hatching.

IV. Discussion

Infrared technology using a FLIR camera and a machine learning model can be used to numerically grade the drawdown of an air cell with significant accuracy within 72 hours of external pipping and hatching. This success suggests that grade 5 is a good indicator of imminent hatching, giving researchers or conservation teams a window of time to take action before the external pip and subsequent hatching when disease transmission becomes an issue. This machine learns in an egg JBH to incubate artificially.

Further modifications can be made to the smart camera programming by creating custom alerts based on a combination of the number of days that eggs have been monitored and their air cell size. This allows researchers and collections managers to track inappropriate air cell sizes. For example, if the air cell enlarges too early in incubation, it indicates too thin a cuticle or a shell break and a need for immediate egg repair and rehydration. Conversely, when growth in the air cell is too slow there is a need for shell sanding or shell pinholing to prevent embryo death from osmotic imbalance caused by too much liquid.

The model can also be adjusted by classifying intermediate grading, instead of the grade zero and grade 5 extremes, during the next breeding season when more eggs are available for photographing using the FLIR camera. Timely attention to hatching like this allows for medical intervention JBH to struggling chicks without disturbing the natural incubation of eggs during most incubation. These model results suggest that infrared cameras can be used to analyze an air cell in an egg. A machine learning mode and artificial intelligence can be trained to automatically grade the air cell size in an egg and predict when an egg is beginning to hatch. After training and validation, the model could be exported and deployed using the FLIR camera in a field trial. The model may be applied to multiple species and conservation projects, and the technology implemented in the field to be monitored remotely.

The emergence of smart cameras for use in wildlife research, such as those used by this team from the USDA Conservation Innovations Grant Automated Wildlife Tracking project, enable cameras to make decisions. Such radio-enabled smart cameras can alert conservation professionals to what is going on in the field or a captive wildlife situation. The next goal is to reduce stress on humans and animals through specially programmed smart cameras that gather meaningful but time-consuming data that can guide conservation management decisions.

V. Conclusion

Working alongside conservation breeding professionals to collect training images was successful. The process did not interrupt the staff's activities. Creating training images did not harm the eggs or incubation equipment. This approach could easily yield large datasets and be specifically tailored to single-species data projects. Synthetic training set augmentation through rotating and resizing is straightforward for rare animal cases where a small total number of eggs are available to create training data, as healthy egg development appeared uniform in its appearance for each species.

The successful use of an edge-machine, low memory size optimized model architecture suggests appropriateness of this approach for battery-powered field cameras.

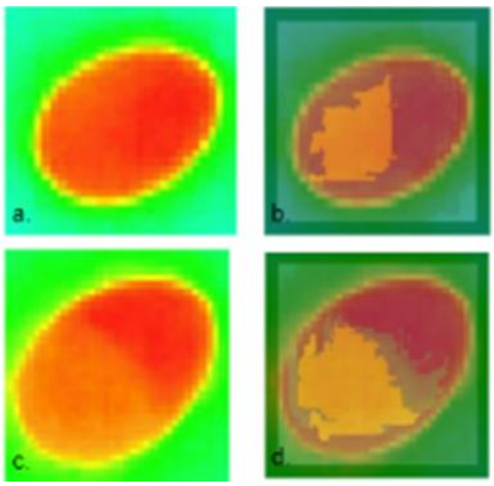

Fig. 4. Original images, left, and XRAI overlay of image area relevant to classification, right. (a) Egg with a grade 0 air cell, (b). Egg with a grade 0 air cell with XRAI overlaid, (c) Egg with a grade 5 air cell, (d). Egg with a grade 5 air cell with XRAI overlaid.

VI. Acknowledgments

The research performed in this manuscript has been made possible by the generous support of Hill Country Aviaries, owned by Rick Jordan and Mark Moore. In addition, the collections manager Scott Stringer and his assistant Keelan Smith have worked to help with the incubation setup and collection of the eggs for this study. Professor Donald Brightsmith of Texas A&M University organized the summer research experience and oversaw animal use. Research Ashley Ridlon's wage was funded under the Texas A&M University VMSRTP program for veterinary students.

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