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Deep Learning Reveals Links Between Brooding Behaviour and Inclement Weather

Deep Learning Reveals Links Between Brooding Behaviour and Inclement Weather

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Abstract

Motion sensor camera traps are used extensively in the fields of zoology and ecology. Camera traps have been around for decades and have revolutionized wildlife research and conservation due to their ability to capture information with little expense, and minimal disturbance to the wildlife. Recently, the ability of computers to recognize certain aspects of images has led to the use of these techniques to save human time in examining the camera trap images. In this work object detection methods are applied to peregrine nest cameras. Our application of these techniques is able to achieve XX% accuracy. Additionally due to the nature of the sequence of images taken, any mistakes made can be rectified by using a time-sequence of the data.

Keywords: Machine Learning, Brood Rearing, Climate Change

1. Introduction

Nest monitoring is an important component of avian population studies. It enables the assessment of factors that influence breeding success, and is essential to inform conservation and management decisions. The collection of this data, however, comes at a cost. Frequently visiting a nest causes disturbance that may lead to reduced nest attendance by parents (), increased conspicuous parental behaviour (), increased probability of predation (), and increased stress in both parents and nestlings (). The resulting effects of nest visits have the potential to bias results, and impact reproduction.

Many methods of passive nest monitoring have been introduced to reduce the impact. One method is to place temperature sensors in the nest to track incubation and brooding. Others have used radio frequency identification technologies to monitor nest usage [1]. A more common method involves photo and video technology. Resulting from technological advances in image sensors and data storage, off-the-shelf motion sensitive cameras have become more discrete, and capable of capturing increasingly higher quality images. Camera settings can be tailored to the needs of a monitoring program with varying options of motion sensitivity, rapid image capturing upon motion triggers, and complete freedom over the duration of time between timelapse images. Such capabilities result in much higher resolution data due to near real-time surveillance of avian nesting biology, and a substantial reduction in disturbance caused by nest visits. Common applications of this technology include the investigation of provisioning behaviour, nest predator identification [2, 3].

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The benefits of using nest cameras are substantial, but only after considerable effort has been invested into the processing of images. Converting images captured at the nest into useable data often requires the manual sorting and classification of

26 images. Not only is this process time-consuming and error-prone, it often has to
27 be repeated if new research questions are proposed. Combined with the amount
28 of data collected by cameras each breeding season, processing times bottleneck the
29 researcher's ability to answer ecological questions in a timely manner.

30 The bottleneck of processing images captured by nest cameras is part of a grow-
31 ing trend in Ecology; the amount of tools available to help collect data is growing
32 faster than our ability to process the data. The need for additional tools that auto-
33 mate this process has been identified recently

34 reducing nest visit frequency while maintaining data quality have been pro-
35 posed, and the utility depends Methods of passive nest monitoring that reduce the
36 need for frequent visits have been outlined

37 yet there is an important tradeoff between gathering data on nesting biology and
38 minimizing the disturbance induced by nest visits.

39 Nest site observations are important for monitoring programs * provisioning
40 rates * behavioural responses to inclement weather * egg-laying * nestling survival
41 * band recovery

42 2. Methods

43 2.1. Study Area

44 The study area is located on the western coast of Hudson Bay, and encompasses
45 a 422 km² area that surrounds the community of Rankin Inlet, Nunavut, Canada
46 (62°49'N, 92°05'W)(Figure 1). The terrestrial portion is characterized by rolling
47 mesic tundra interspersed with numerous lakes and streams, and supports com-
48 munities of passerines, shorebirds, ducks, geese, and small mammals. The marine
49 portion is composed of numerous islands of varying size and also supports diverse
50 bird communities, in addition to small mammals. Rocky outcrops that form cliffs
51 are common throughout both terrestrial and marine areas, and provide ideal nest-
52 ing habitat for raptor species such as Rough Legged Hawks (*Buteo lagopus*), Peregrine
53 Falcons (*Falco peregrinus*), Common Ravens (*Corvus corax*) occasionally Golden Ea-
54 gles (*Aquila chrysaetos*), and Gyrfalcons (*Falco rusticolus*).

55 2.2. Peregrine Monitoring

56 Peregrine Falcon population monitoring was conducted over five breeding sea-
57 sons from 2013 to 2017. Site occupancy surveys began in May as peregrines arrived
58 on site from migration. Regardless of whether or not we detected breeding pairs, all
59 suitable territories were monitored until the season had advanced sufficiently into
60 the incubation period and we could confidently conclude that vacant sites would
61 remain vacant.

62 2.3. Camera Work

63 To capture lay dates, hatch dates, causes of nestling mortality, and parental be-
64 haviour throughout the breeding season, motion sensitive cameras (RECONYX,
65 Holmen Wisconsin, USA, models PC85 and PC800, 2013 n=11, 2014 n=22, 2015

66 n=22, 2016, 2017) were placed 60 - 200 cm from the nest bowl. Although we aimed
67 to visit nests every 5 days to replace camera batteries, many of the nesting territo-
68 ries are difficult to access during inclement weather. As such, camera settings such
69 as motion sensitivity and the duration of time between timelapse images, were tai-
70 lored to each site to preserve battery power in the event that we could not return
71 in five days. Typical camera settings for accessible nest sites included timelapse im-
72 ages every 15 minutes regardless of motion, three rapid pictures when the camera
73 was triggered by motion, followed by a quiet period of 5 seconds within which the
74 camera did not respond to movement, while typical camera settings for difficult to
75 access sites included only one image captured when motion was detected, and a
76 duration of 5 minutes between time-lapse images. Although the camera settings re-
77 sulted in fewer captured images for difficult to access sites, the images were more
78 evenly spaced and effectively surveyed events of interest at the nest site.

79 2.4. *Transfer Learning*

80 Data outputted by the CNN is binary, with a 1 provided when a certain class of
81 object is detected in an image.

82 2.5. *Modeling*

83 To investigate nest attendance among breeding pairs of peregrine falcons, we
84 first converted the presence absence data outputted by the Convolutional neural net-
85 works into the proportion of each day adults were at the scrape. Depending on
86 the extent of motion, the images captured by remote cameras are often irregular.
87 Converting irregular series of images into a total proportion of time spent at the
88 nest was completed by first generating an empty dataframe that contained a row for
89 each minute within each day. The cell corresponding to a nest site in a given minute

90 was filled with a '1' if the CNN detected an adult at any time within that minute.
91 If no images were captured within that minute, we assumed the value of the pre-
92 vious minute in which an image was captured still applied. If no images had been
93 captured during the amount of time corresponding to timelapse intervals (15m), no
94 value was carried forward. This method assumes that the cameras reliably detected
95 occupancy state changes at a nest, or in other words, cameras reliably captured the
96 arrival and departure adults. Since arrivals and departures cause substantial motion
97 (going from perched to flight), we are confident this is a safe assumption.

98 Nestlings explore the cliff surrounding the scrape as they grow, and at a certain
99 point, we can no longer be certain that cameras are reliably capturing nest attendance.
100 To protect against possible bias originating from nestling movement, we truncated
101 our data at a total brood age of 15 days.

102 To model the daily proportion of time adults attended nests, we programmed a
103 generalized linear mixed model with a beta-binomial probability distribution and
104 logit link function in R using R2jags. Daily proportions are potentially autocorre-
105 lated, so we investigated various residual variance structures to estimate correlation
106 between timesteps. Data was repeat measures, so we included nested random inter-
107 cepts with brood nested in year. We suspected that adult nest attendance is related
108 to yearly conditions, and therefore estimated random slopes for year. Lastly, we in-
109 cluded various combinations of fixed effects that we suspected were important in
110 explaining nest attendance. All priors were specified as diffuse, and we employed a
111 workflow that followed []

112 Daily climate data included in the models were obtained from an Environment
113 Canada weather station positioned in a central location in the study area.

114 All nestling data was gathered every 5 days as part of routine nest visits, and this

115 included nestling weights, brood size, and brood age (as determined by the age of
116 the oldest nestling).

119 **5. Results**

120 **References**

- 121 [1] Andrew C. Alba, Shawnlei Breeding, Annie J. Valuska, Christy Sky, Megan Dunn,
122 Paul J. Schutz, Katherine A. Leighty, and Gina M. Ferrie. Use of passive ra-
123 dio frequency identification technologies to monitor nest usage in the northern
124 carmine bee-eater (*Merops n. nubicus*). *Zoo Biology*, 38(6):498–507, December
125 2019. ISSN 1098-2361. doi: 10.1002/zoo.21514.
- 126 [2] W. Andrew Cox, Frank R. Thompson, and John Faaborg. Landscape forest
127 cover and edge effects on songbird nest predation vary by nest predator. *Land-*
128 *scape Ecology*, 27(5):659–669, May 2012. ISSN 1572-9761. doi: 10.1007/
129 s10980-012-9711-x.
- 130 [3] Brett A. DeGregorio, Patrick J. Weatherhead, and Jinelle H. Sperry. Power lines,
131 roads, and avian nest survival: Effects on predator identity and predation in-
132 tensity. *Ecology and Evolution*, 4(9):1589–1600, 2014. ISSN 2045-7758. doi:
133 10.1002/ece3.1049.