

An AI-enabled radiometric ocular thermography framework for monitoring heat vulnerability and welfare in poultry

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Abstract

Heat stress poses a growing threat to poultry, and automated monitoring of chicken temperatures is crucial to effectively maintain their health. While ocular temperature can provide valuable insights on overall chicken body temperature and wellbeing, manually measuring ocular temperature is infeasible, and regular monitoring is extremely resource-intensive. In this study, I present an artificial intelligence-based framework for routine ocular temperature measurements for automated poultry-welfare tracking. Thermal images of adult and juvenile birds were collected from two poultry houses in India during summer month, manual annotation of the ocular regions of individual birds was performed from the images using Fiji that used to train a YOLO11n-seg model capable of segmenting eyes from the remaining images. For both adult birds and juveniles, the model was trained and inference was performed separately. Finally, the temperature was extracted from the eye regions and statistical analysis was performed to compare the temperature between the two groups. We found that the average juvenile eye temperature was 0.741°C higher than the average adult bird eye temperature. Additionally, a web-based mobile platform was developed to estimate the ocular temperature of a chicken for automatic measurement of ocular temperature in poultry.

1. Introduction

Heat stress poses significant dangers to poultry wellbeing. Prolonged exposure to heat leads to increased mortality and reduced feed efficiency, body weight, feed intake, and egg production, and also affects meat and egg quality [1]. Mitigating heat stress depends on adequately tracking poultry temperatures before symptoms become noticeable. The ocular region is especially informative in the context of core body temperature. Particularly, earlier study [2] identified a correlation coefficient of 0.89 between eye temperature and rectal temperature. However, measuring eye temperature is difficult with conventional tools that are impractical for mass tracking, as traditional methods produce only intermittent measurements and are highly resource-intensive. Thermography that allows capturing the thermal radiation emitted by the skin's surface [3] can be a non-invasive method of measuring eye temperature in poultry.

Poultry houses are often crowded and contain multiple birds with variable body orientations, partial occlusion, and small eye regions. Producing an accurate eye temperature measurement requires automatic segmentation of the eye region and linking the predicted region to the camera's embedded radiometric sensor data. Fortunately, emerging AI models have significant potential in this area. Specifically, the YOLO family of models have shown exceptional strength in rapidly and accurately identifying anatomical structures [4].

The primary aim of this study was to develop and evaluate a complete AI framework for automatic chicken eye localization and temperature measurement in the wild. The intended use of this framework is for routine, non-invasive surveillance in poultry houses to reveal changes in ocular temperature that signal increased heat stress. To make such surveillance possible, this study aimed to build a mobile

platform that provides an ocular temperature reading from an uploaded thermal image. A secondary aim of this study was to use the aforementioned framework to determine whether young juveniles are more susceptible to summer heat than older birds through comparison of thermal images of poultry in two age groups (13-week-old and 16-week-old). Overall, this study aims to develop an AI framework that has empirically detected meaningful temperature differences among poultry in real-world conditions, and help poultry health monitoring and welfare management.

2. Materials & Methods

2.1 Data Collection

The study overview and workflow of methodologies are illustrated in Fig. 1. Thermal imaging was conducted on June 14, 2026 at two poultry houses in Odisha, India (20.57° N, 85.88° E). One house contained adult birds approximately 26 weeks old, and the other adjacent house contained juvenile birds approximately 13 weeks old. Imaging took place at approximately 12:00h, with both groups imaged within one hour under the same ambient temperature (90°F/32.2°C) and relative humidity (71%). Images were captured as the camera operator moved through the poultry houses, walking approximately five steps between subsequent images in order to avoid duplicate measurement of the same birds. Dozens of birds were visible in each thermal frame, and one eye was captured per animal.

Thermal images were acquired with a Teledyne FLIR ONE Generation 3 camera (software version 2.19.0) connected to a mobile device. Each file contained an embedded visible JPEG (1080 × 1440 pixels) and an embedded raw thermal PNG (480 × 640 pixels). The stored emissivity was 0.95, and the nominal camera range recorded in metadata was – 40 to 120°C. Radiometric status was verified with ExifTool by confirming the presence of RawThermalImage, Emissivity, PlanckR1, PlanckR2, PlanckB, PlanckF, PlanckO, camera model, and raw thermal dimensions.

2.2 Manual annotation in Fiji

For 13 adult images and 12 juvenile images, eye masks were drawn manually using Fiji version 1.54p [5]. Images were carefully reviewed individually and were only annotated when the ocular region was entirely visible and not obscured. A polygon selection was drawn around the eye while avoiding other features. Each selection was added to the ROI Manager and saved as a .roi file, with one ROI representing a unique animal.

2.3 Dataset construction

ROI files were read in Python using roifile 2024.5.24 [6]. Coordinates of the polygon selection in each ROI file were mapped to the original JPEG image. The center of this polygon was calculated, and a standard 320 × 320-pixel crop was drawn around it. The crop coordinates were then converted to YOLO segmentation format with one class (eye). Before training, the labels were mapped onto the image crops and inspected for accuracy. The dataset was split into training, validation, and test sets by the original image rather than by individual crops in order to prevent portions of the same image from appearing in

different groups. The adult dataset used 9 annotated source images for training, 2 for validation, and 2 for testing. The juvenile dataset used 8 source images for training, 2 for validation, and 2 for testing.

2.4 YOLO segmentation model training

Training was conducted with Python 3.12.3, Ultralytics 8.4.114, PyTorch 2.2.2, NumPy 1.26.4, and OpenCV 4.10.0. Images were resized to 640 pixels for training, and the batch size was 2. Training used a fixed random seed of 42 and deterministic mode. Augmentation included horizontal flipping (probability 0.5), rotations up to 8°, translation of 0.08, scaling of 0.20, modest brightness/value variation of 0.08, and mosaic probability of 0.10. The maximum number of epochs was 100, and early-stopping patience was 30 epochs. Separate models were trained for each age group, and both models used the Ultralytics YOLO11n-seg architecture initialized from pretrained weights. Training was performed on an Intel Core i7 CPU. The adult model stopped after 95 epochs, while the juvenile model stopped after 71 epochs.

2.5 Inference

The trained models scanned all images using 320×320 -pixel windows using a stride size of 160 pixels in order to allow for overlap. Different confidence thresholds were visually compared for both groups. Adult predictions were retained at confidence ≥ 0.40 , and juvenile predictions were retained at confidence ≥ 0.70 . In order to remove duplicate detections from overlapping windows, we used a YOLO intersection-over-union (IoU) threshold of 0.50 and a postprocessing non-maximum-suppression threshold of 0.30. The predicted polygons were converted to coordinates on the original thermal image and saved as binary masks. The final adult set contained 123 masks, and the final juvenile set contained 128 masks. All masks were visually inspected before proceeding with further analysis.

2.6 Raw thermal extraction and radiometric conversion

The ExifTool was called from Python to extract the embedded RawThermallImage and numeric metadata from each original radiometric JPEG. The raw PNG was read with Pillow and checked for byte order. The raw detector matrix was converted to object temperature using image-specific FLIR Planck constants and corrections for emissivity, reflected apparent temperature, atmospheric temperature, relative humidity, object distance, atmospheric transmission, and infrared-window parameters when available.

Because the visible and thermal images had different resolutions, each binary eye mask was resized from visible-image coordinates to 480×640 thermal coordinates using nearest-neighbor interpolation. This preserved categorical mask membership and avoided fractional boundary pixels. Every temperature pixel whose center fell inside the resized mask was retained for the eye-level profile. For each eye, all thermal pixels within the resized mask were extracted and saved as a compressed table containing thermal x-coordinate, thermal y-coordinate, and temperature (°C). Eye-level thermal summary statistics, including mean, median, maximum, and selected percentiles, were computed from these pixels. Records were screened using predefined quality-control criteria based on temperature range, mask size, and duplicate identifiers. All 251 analyzed eye masks passed these filters.

2.7 Statistical analysis

The primary mixed-effects model was in the form *eye temperature = age group + random intercept*, with Adult serving as the reference group. The random intercept represented the source image from which the eye was taken in order to account for shared acquisition/ambient conditions. Separate models were fitted for mean, median, maximum, 95th-percentile, and hottest-5% mean temperature. For the sensitivity analysis, temperature values were averaged within image and adult versus juvenile image means were compared with Welch's unequal-variance t-test. Mean-difference confidence intervals were obtained with 5,000 bootstrap resamples. Benjamini–Hochberg false-discovery-rate correction was applied across thermal outcomes. Tests were two-sided, with adjusted $P < 0.05$ considered statistically significant.

To further evaluate the robustness of the observed age-group difference in eye temperature, a bootstrap resampling analysis was performed using the temperature data from the 123 adult eyes and 128 juvenile eyes. We randomly sampled 10 eyes from each of the two groups without replacement from each age group, and then calculated the difference in mean eye temperature (juvenile minus adult). This was repeated 100,000 times, and the proportion of iterations in which juveniles exhibited higher mean eye temperatures, the median temperature difference, and the empirical 95% bootstrap interval were estimated. Welch's two-sample t-test was performed for each iteration to determine the frequency with which the resampled datasets produced statistically significant differences ($P < 0.05$). To account for potential clustering of multiple eyes within the same thermal image, a complementary image-level bootstrap analysis was performed by randomly selecting one eye from each of ten independently sampled source images per age group. Finally, the bootstrap procedure was repeated using sample sizes of 5, 10, 15, 20, 30, 40, and 50 eyes per group to evaluate the influence of sample size on detection stability.

2.8 Mobile application development

The pipeline for inference and temperature extraction was implemented as a web-based platform intended for mobile devices. Upon signing in, the user can begin a new analysis and upload a radiometric image taken with a FLIR camera. In order for the appropriate segmentation model to be used, the user must select whether the image contains a juvenile or an adult bird. Once inference is complete, the site displays the estimated ocular temperature as well as a severity classification based on the thresholds suggested in earlier study [7]. The site was deployed via Vercel (<https://vercel.com/>), data storage and authentication were hosted on Supabase (<https://supabase.com/>), and backend code for inference was stored on Hugging Face (<https://huggingface.co/>).

3. Results

3.1 YOLO segmentation model and comparison of ocular temperature

The segmentation model identified 123 adult birds across 44 images and 128 juvenile birds across 48 images (Fig. 2). Validation testing showed that the fine-tuned model could adequately locate ocular

regions of individual birds (Fig. 3). The model metrics are shown in Table 1. The primary mixed-effects model analysis showed that the mean temperature in 13-week-old juveniles was 0.741°C higher than in approximately 26-week-old birds (95% CI, 0.215–1.267°C; P = 0.006; FDR-adjusted P = 0.006). Image-level sensitivity analysis corroborated this result, with mean eye temperature in adult images 0.831°C lower than in juvenile images (bootstrap 95% CI for adult minus juvenile, – 1.453 to – 0.230°C; Welch P = 0.010; FDR-adjusted P = 0.014). The box plots in Fig. 4 illustrates this difference.

Table 1

Segmentation model validation performance.

Metric	Adult model	juvenile model
Box precision	0.857	0.578
Box recall	0.700	0.823
Box mAP50	0.760	0.635
Box mAP50–95	0.304	0.256
Mask precision	0.857	0.578
Mask recall	0.700	0.823
Mask mAP50	0.760	0.635
Mask mAP50–95	0.359	0.299
Best epoch	65	41

Table 2

Summary statistics of mean eye temperature indicating that juveniles maintained a consistently warmer ocular temperature during the summer heat than adult birds.

Analysis	Estimate	95% CI	P value	FDR P	Interpretation
Animal-level mixed model (primary)	Juvenile – Adult = + 0.741°C	0.215 to 1.267	0.006	0.006	Juveniles warmer
Image-level Welch test (sensitivity)	Adult – Juvenile = – 0.831°C	–1.453 to – 0.230	0.010	0.014	Juveniles warmer

3.2 Bootstrap resampling supports robust age-associated differences in eye temperature

To evaluate the robustness of this difference, 100,000 bootstrap iterations were performed by randomly selecting 10 eyes from each age group (Fig. 5A). Juveniles exhibited higher mean eye temperatures in 84.5% of bootstrap samples, with a median difference of 0.576°C (95% bootstrap interval: –0.496 to 1.815°C). Statistical significance (Welch's $p < 0.05$) was observed in 9.6% of iterations, indicating that while small samples consistently detected the direction of the effect, they were often underpowered for

formal significance testing. Increasing the number of sampled eyes progressively improved the probability of detecting higher temperatures in juveniles (Fig. 5B). A complementary image-level bootstrap analysis, in which one eye was randomly selected from each of ten independently sampled images per group, produced similar results, with juveniles showing higher eye temperatures in 89.6% of iterations and a median difference of 0.815°C (95% bootstrap interval: -0.420 to 2.173°C) (Fig. 5C). These analyses demonstrated that the AI-derived eye-temperature measurements consistently identify higher eye temperatures in young juveniles than adult chicken under field conditions and are robust to random sampling variation.

4. Discussion

This study introduced a fully end-to-end pipeline that produced ocular temperature measurements from an inputted thermal image. The framework was applied to show that young juveniles exhibit higher ocular temperatures than adult birds. An important finding of this study is that adult birds likely possess advantages in terms of thermoregulation and heat dissipation compared to juveniles. For flock managers, this warrants close observation of juveniles and immediate intervention when early signs of heat stress emerge. Importantly, the fact that the segmentation model for juveniles displayed noticeably lower precision than the model for adult birds suggests that there are factors associated with juvenile birds which make localization more difficult. Considering that juveniles are especially vulnerable to heat stress, future work should emphasize training welfare-monitoring systems more robustly on images of juveniles in early developmental stages [8].

Such a framework enables farmers and flock managers to routinely monitor the health of their poultry with only an inexpensive FLIR ONE-type camera. By automatically identifying the ocular region when visible, the proposed YOLO segmentation model mitigates human error when manually photographing flock in the wild. Directly mapping the identified regions of interest to calibrated temperature measurements provides farmers with an opportunity to better monitor the health of their most vulnerable flock [9]. Repeatedly scanning birds to automatically record their ocular temperature could help identify a standard baseline that indicates healthy conditions [10]. Continued automatic scanning and temperature measurement of flock could alert managers to early signs of heat stress, providing a notification when ocular temperatures are above the established baseline for a sustained amount of time [11]. As a result, flock managers could take immediate action to diagnose and treat heat-related illness before more serious symptoms become apparent. Using a mobile framework similar to the one presented in this study, such analysis becomes significantly less expensive and resource-intensive than the current industry standard [12]

This study has specific limitations. While steps were taken to maintain the same external factors between both age groups, it is important to note that all adult birds lived together and all younger juveniles lived together in a separate house. This introduces potential confounding variables that may have contributed to the observed difference in temperatures. Although brief, the time in between data collection for the two groups could have contributed slightly to this difference as well. Additionally,

photographing the eyes of chickens in crowded poultry houses can introduce bias in the image data. Finally, thermal eye imaging alone may not be reliable in all cases, but can be combined with other measurements such as water intake, blood-based markers, and posture for integrated welfare management practices.

5. Conclusion

The present study presents a novel end-to-end pipeline for segmenting the chicken eye in a radiometric field image and converting the region of interest into temperature measurements. The primary significance of this work is that it provides a practical, inexpensive way for flock managers to automatically monitor ocular temperature in crowded poultry houses. Through the proposed mobile application, this study helps enabling real-time alerts when early signs of heat stress become apparent, allowing for action to prevent the onset of more serious symptoms. The study establishes that automated ocular temperature measurement is a feasible means of tracking and managing heat stress in poultry houses.

Declarations

Animal Ethics Statement: This study involved exclusively non-contact, non-invasive thermal imaging of chickens under their existing husbandry conditions. The animals were not handled, restrained, treated, sampled, or experimentally manipulated. The research was conducted independently without an institutional affiliation; therefore, no institutional animal care and use committee (IACUC) review or approval was obtained.

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Figures

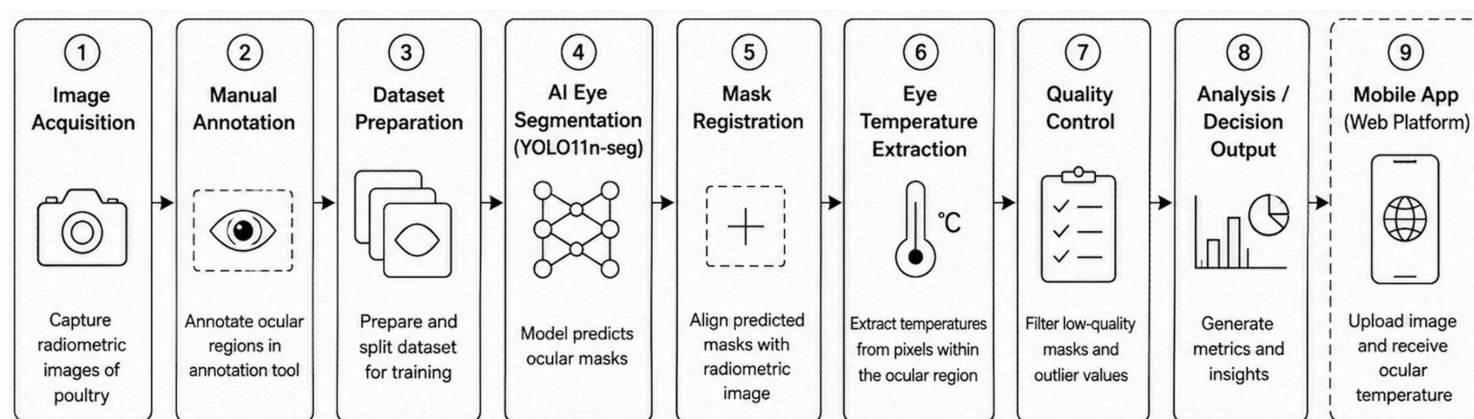


Figure 1

Overview of the AI-based framework for automated ocular temperature measurement and mobile deployment.

The workflow begins with acquisition of radiometric FLIR images, followed by manual annotation of ocular regions in Fiji, dataset preparation, and training of a YOLO11n-seg model for automated eye segmentation. Predicted eye masks are registered to the radiometric image, and pixel-level temperatures are extracted from each identified ocular region. Quality-control procedures are applied before statistical analysis of ocular temperatures between birds and juveniles. The developed inference and temperature-extraction pipeline was additionally implemented as a mobile-accessible web platform, allowing users to upload a radiometric image and obtain an estimated ocular temperature. The deployed framework uses Vercel for web hosting, Supabase for data storage and authentication, and Hugging Face for model storage and inference.

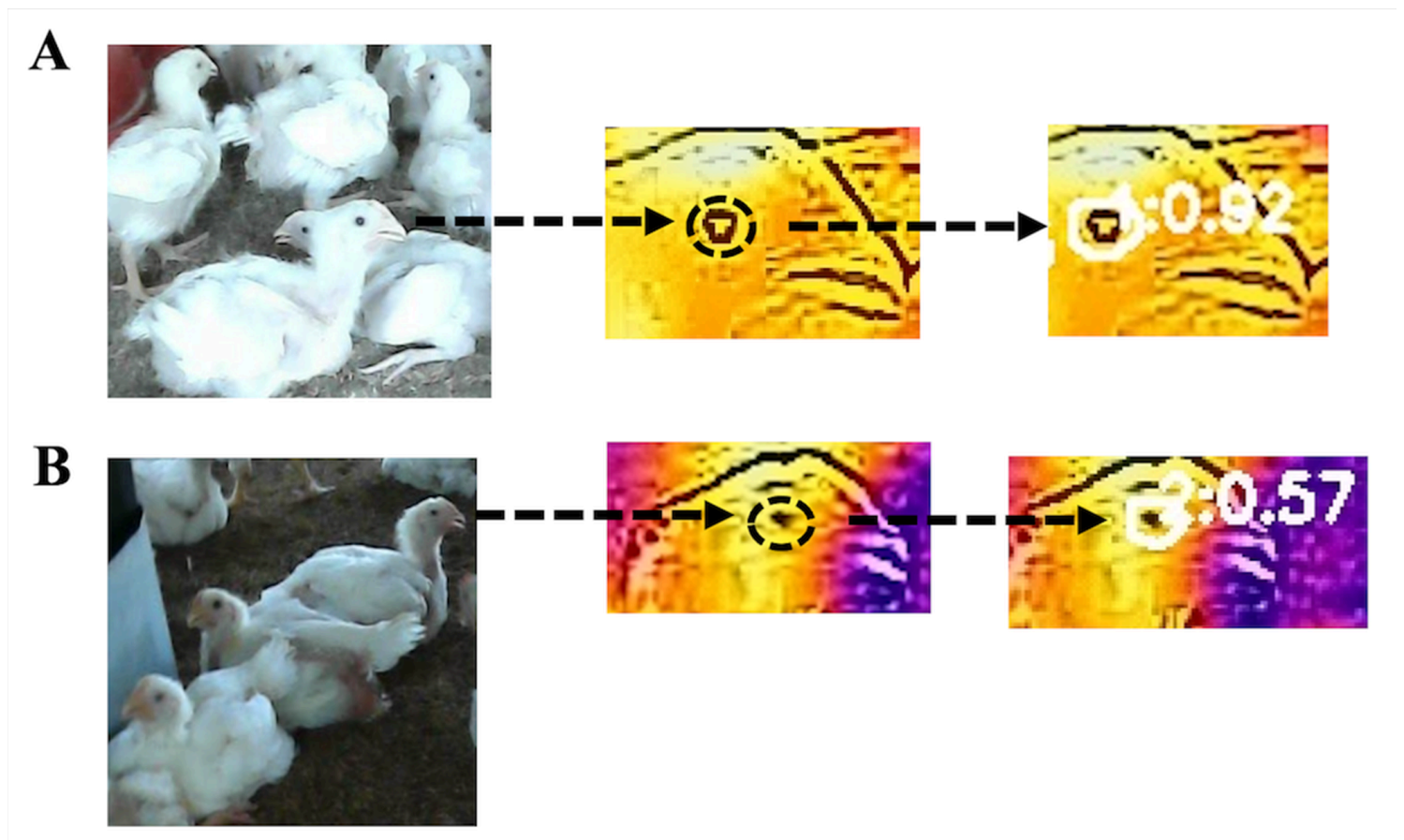


Figure 2

Representative examples of automated ocular localization and temperature extraction.

Representative images of juvenile (A) and adult birds (B) illustrate the progression from identification of an individual bird and ocular region to localization of the eye in the corresponding thermal image and extraction of ocular temperature. Dashed circles indicate the ocular region identified for analysis, and the final images show the temperature measurement obtained from the localized eye region.

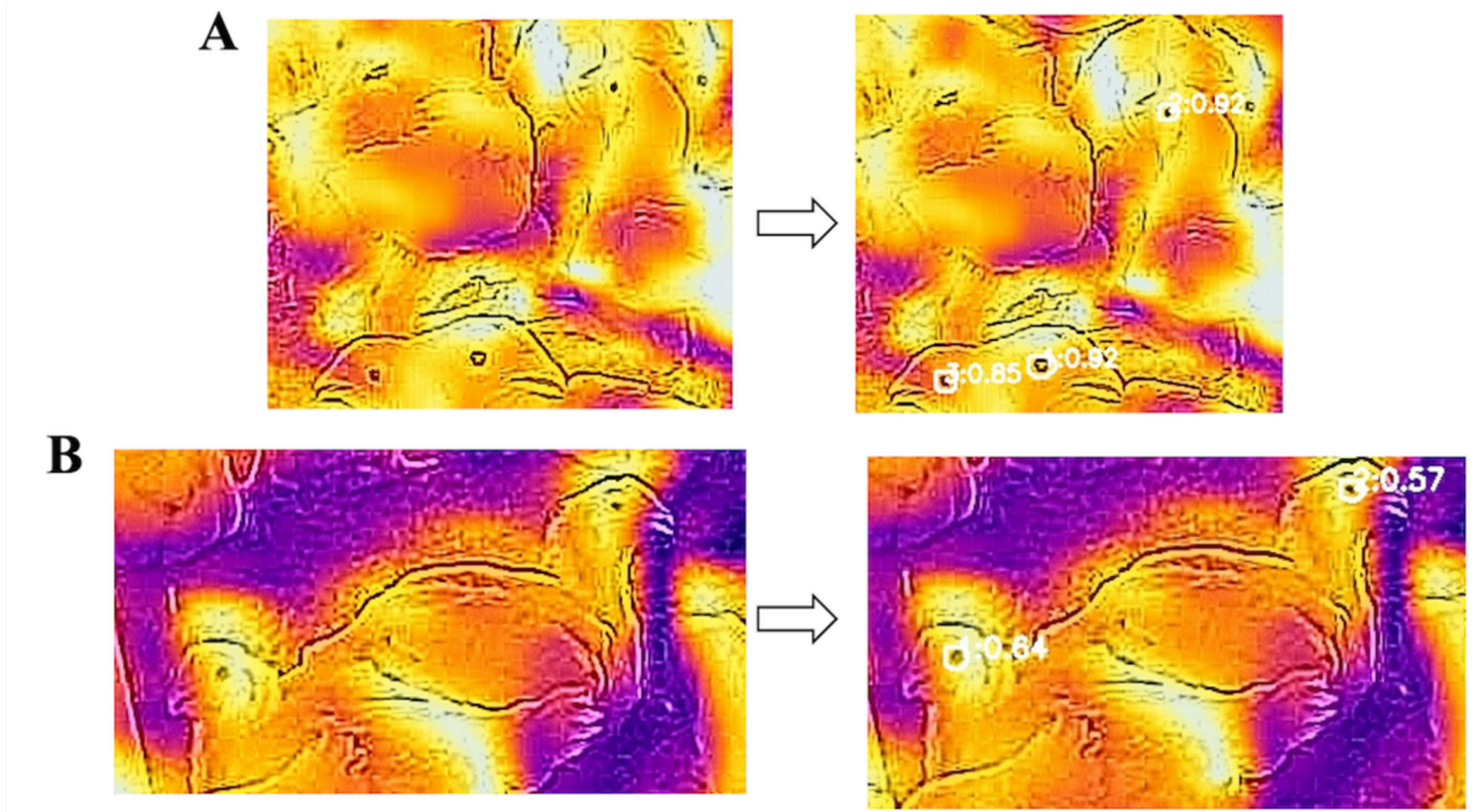


Figure 3

Ocular temperature differences between birds and juveniles at the animal and image levels.

(A) Animal-level distributions of mean ocular temperature for birds and juveniles. Each point represents an individual detected eye, with boxplots showing the median and interquartile range. (B) Image-level sensitivity analysis in which ocular temperature measurements were averaged within each source image to account for multiple eyes detected from the same thermal image. Both analyses show higher mean ocular temperatures in juveniles than in birds.

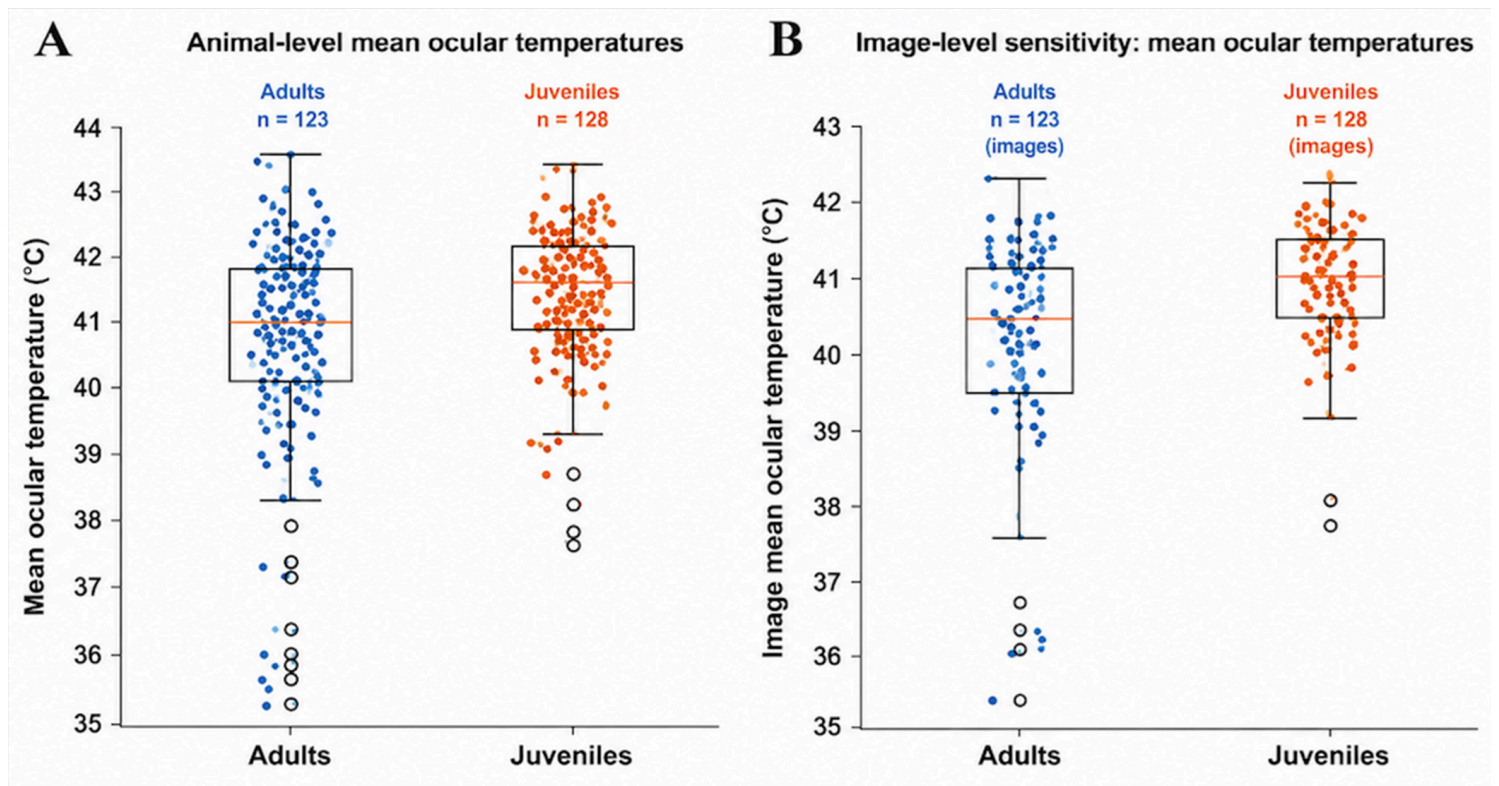


Figure 4

Distribution of thermal pixel counts within AI-segmented ocular regions.

(A) Animal-level distribution of the number of radiometric thermal pixels contained within individual predicted eye masks for adult birds and juveniles. Points represent individual detected ocular regions, and boxplots summarize the distributions. (B) Image-level sensitivity analysis showing the mean thermal pixel count of detected ocular regions within each source image for birds and juveniles. The image-level analysis accounts for clustering of multiple detected eyes within the same source image and provides an assessment of the consistency of eye-mask size between the two age groups.

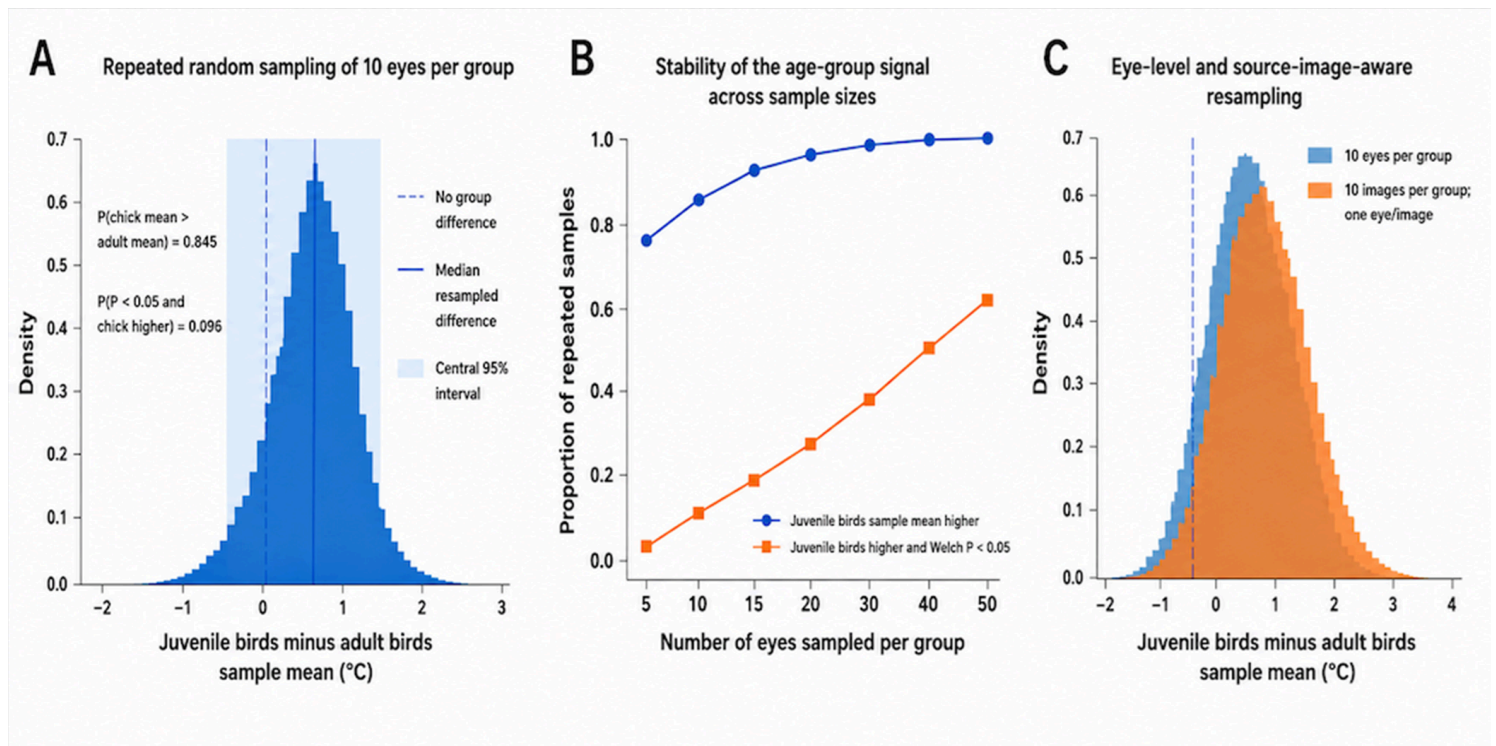


Figure 5

Ocular-temperature differences between birds and juveniles and robustness to repeated resampling.

(A) Distribution of juvenile-minus-bird mean-temperature differences obtained from 100,000 repeated random samples of 10 eyes per group. Juveniles had a higher sample mean in 84.5% of iterations, while 9.6% of iterations simultaneously showed a higher juvenile mean and Welch's $P < 0.05$. The dashed vertical line denotes no group difference, the solid line denotes the median resampled difference, and shading represents the central 95% interval. (B) Stability of the age-group signal across increasing numbers of sampled eyes per group, showing the proportion of iterations in which juveniles had a higher mean temperature and the proportion in which this difference was accompanied by Welch's $P < 0.05$. (C) Comparison of eye-level resampling with source-image-aware resampling, in which one eye was selected from each of 10 independently sampled images per group, demonstrating that the direction of the age-associated temperature difference was maintained when clustering within source images was considered.