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A cost-effective imaging system for monitoring poultry behaviour in small-scale kenyan poultry sheds

J.D.K. Morgan[1], S. Peets[1,*] and E. Mashatise[2]

[1]Harper Adams University, Engineering Department, TF10 8NB Newport, United Kingdom
[2]Harper Adams University, Agriculture and Environment Department, TF10 8NB Newport, United Kingdom
[*]Correspondence: speets@harper-adams.ac.uk

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Abstract. The objective of this paper was to develop a low-cost prototype poultry behaviour imaging and analysis system for monitoring intensively-reared flocks suitable for small-scale Kenyan poultry sheds. An image processing and analysis programme was developed using Python programming language and the OpenCV image processing package. This was tested on overhead images of Ross 308 birds collected over a number of days using a Raspberry Pi V2 camera. A second experiment using toy-chicks was conducted with an angled camera (Wansview W3). Linear transformation (LT) and background subtraction (BS) methods were applied and compared for effectiveness at detecting yellow and brown toy-chicks on woodchip bedding. Perspective transformation (PT) was applied and evaluated for its ability to transform the angled images into two-dimensional views. In the first experiment, where white birds were detected against a dark background, LT object detection successfully detected 99.8% of birds in the sampled images. However, in the second experiment, the LT method was just 56.5% effective at detecting the yellow toy-chicks against the light-coloured background. In contrast, the BS method was more effective, detecting 91.5% of the yellow toy-chicks. The results showed that BS detection success was worse for yellow toy-chicks in the far section, detecting 83% as opposed to 100% of those in the near-section. Edge processing of the image processing algorithm was tested on a Raspberry Pi 3 series B+ computer. This prototype provides a solid foundation for further development and testing of low-cost, automated poultry monitoring systems capable of reporting on thermal comfort inferred from cluster index.

Key words: background subtraction, cluster index, image processing, linear transformation, poultry.

INTRODUCTION

Poultry farming to improve the lives of those in poor, rural regions of Sub-Saharan-Africa has become increasingly established. Whilst poultry farming is well-established in Kenya, with studies finding over 88% of households own chickens (Thumbi et al., 2015; Otiang et al., 2020), productivity has historically been low due to the prevalence of traditional, free-range rearing methods (Njue et al., 2006; Magothe et al., 2012). The introduction of intensive rearing systems, whereby birds are housed permanently and supplied feed, water and health treatments, has been shown to significantly improve productivity (Menge et al., 2005; Ochieng et al., 2011). As such, in the past few decades there has been a shift towards intensive systems across low-income countries worldwide (Hedman et al., 2021).

In Kenya, raising chickens has traditionally been the responsibility of women, who constitute around 75.8% of those engaged in small-scale rearing enterprises (Ochieng et al., 2011). However, Dumas et al. (2018) highlight that many women face difficult decisions when balancing livestock rearing and other household tasks. This leaves the time-burden of intensive systems as a key limitation, generating a need for low-cost solutions that can automate labour intensive tasks. By providing enabling solutions for women in poultry rearing, they can become empowered through greater financial autonomy (Dumas et al., 2018), thus contributing toward the United Nations 'Sustainable Development Goal Five' for gender equality (UN, 2021).

The use of intensive systems in tropical climates such as Kenya also poses thermal management challenges, as poultry shed temperatures must be carefully controlled. Whilst the most common type of chicken used in small-scale enterprises are indigenous chicken (IC) breeds, which are adapted for improved thermal tolerance (Piestun et al., 2008; Magothe et al., 2012), thermal stress remains a cause of productivity loss in shed conditions (Nyoni et al., 2018). This generates a need for systems which can monitor the thermal comfort of poultry flocks and alert farmers remotely when thermal regulation actions are required.

For measurement of bird core temperature, cloacal insertion of thermometers can be used (Maman et al., 2019; Aluwong et al., 2017). However, this method involves handling, which has been shown to induce stress-related core temperature increases in birds, impacting accuracy. For use in continuous flock monitoring, the method is invasive, requires training and is highly time consuming (Cabanac & Aizawa, 2000; Cabanac & Guillemette, 2001). Alternatively, infra-red thermography (IRT) can be used to measure skin surface temperatures - Giloh et al. (2012) have shown a strong correlation between the core and skin temperatures in chickens aged between eight and 36 days. IRT is a non-invasive approach enabling continuous sampling and requiring significantly lower time costs to implement (Jerem et al., 2015). However, there is not clear evidence that this approach will work with chicks under eight days of age.

The cluster index algorithm for distinguishing agglomeration of birds under different temperature conditions, and computer vision were suggested to be suitable tools for assessing poultry thermal comfort automatically by Pereira et al. (2020). Current commercially available systems for automated poultry flock monitoring (Greengage, 2021; Scout Monitoring, 2021; Speller, 2022) are prohibitively costly for typical rural Kenyan farmers. However, automated monitoring, which can increase productivity and reduce labour requirements, offers a tool for accelerated sustainable development in these regions. Thus, the research problem, small-scale farmers need an affordable poultry monitoring system which alerts on welfare issues.

The objective of this paper is to develop a low-cost prototype poultry behaviour imaging and analysis system for monitoring intensively-reared flocks to meet the needs of small-scale farmers.

MATERIALS AND METHODS

Overhead camera system experiment

The low-cost image capture hardware setup consisted of a Raspberry Pi Zero 2 and a Raspberry Pi Camera V2 (8 MP full colour) (incl. suitable power supply and flash drive) mounted with the camera facing down above a 1.2 m × 1.5 m pen of 25 Ross 308 birds, equating to a stocking density of 13.8 birds m^{-2}. A height of 2.7 m was used as this was the highest of the minimum roof heights identified on a site visit to Kenya by the authors, providing the greatest challenge to camera resolution from an overhead view. Due to ethical constraints, exposure of the flock to thermal stress was not possible, therefore sampling over a number of days enabled a range of degrees of clustering to be captured as the birds naturally moved around the pen. The birds were males, aged 42 days on the last day of data collection, the average weight on the last day of data collection was 3.1 kg, there were no incidents of mortality in the pen used for data collection, bedding was not changed throughout the trial and not topped up. The birds were provided with optimum conditions and comfort to meet the health and welfare requirements for growing birds i.e. fresh food and water, ventilation, friable dry bedding and optimum temperature and lighting. The study procedures were approved by Harper Adams University Research Ethics Committee and reported here in accordance with the ARRIVE 2.0 guidelines (Percie du Sert et al., 2020).

Images were collected at a sample rate of 15 s, with 69 h of data collected over eight days (Table 1). Additional lamps were not used. A 15 s sample rate was deemed sufficient to balance the need to manage the volume of data and to maximise data capture, being between 1 s (Pereira et al., 2020) and 30 s (Del Valle et al., 2021).

Table 1. Data recording and darkness hours

Date	Recording			Darkness			Visible imaging (h)
	Start time	End time	Total (h)	Start time	End time	Total (h)	
04-11-21	15:56			20:47			
05-11-21		16:04	24.13		03:05	6.30	17.83
05-11-21	16:46			20:46			
06-11-21		00:19	8.55		00:19	3.55	5.00
08-11-21	17:47			20:47			
09-11-21		16:05	22.30		03:05	6.30	16.00
09-11-21	16:27			20:47			
10-11-21		11:24	18.95		03:05	6.30	12.65
11-11-21	10:54			20:28			
12-11-21		11:53	24.15		03:05	6.62	17.53
TOTAL			98.08			29.07	69.02

The image processing code was developed using Python language via the Anaconda development platform, with the OpenCV (OpenCV, 2022) image processing package installed. A sequence of linear transformations (LT) were conducted for object detection. Linear transformation (LT) methods have been successfully used for object detection in recent studies (Fernández et al., 2018; Pereira et al., 2020; Del Valle et al., 2021), where white birds were detected against a dark background.

The first step was to crop and rotate the gathered images, to focus on the individual pen of birds. This was then blurred, using the OpenCV function 'cv2.blur()' (Nixon & Aguado, 2020) to reduce pixel noise before binarization (Fig. 1).

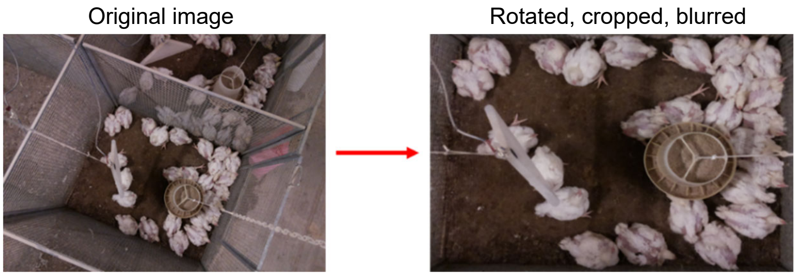

Figure 1. An example of rotation, crop and blurring.

The image was then converted into grayscale for binarization using OpenCV which converts each pixel value from 0–255 into either 0 (black) or 1 (white), with a threshold of 110 being used as the cut off point for conversion either way (Fig. 2). The threshold was determined iteratively by comparing visually input and output images until a threshold value was found which outputs most complete information about the objects of interest and the least anomalous information.

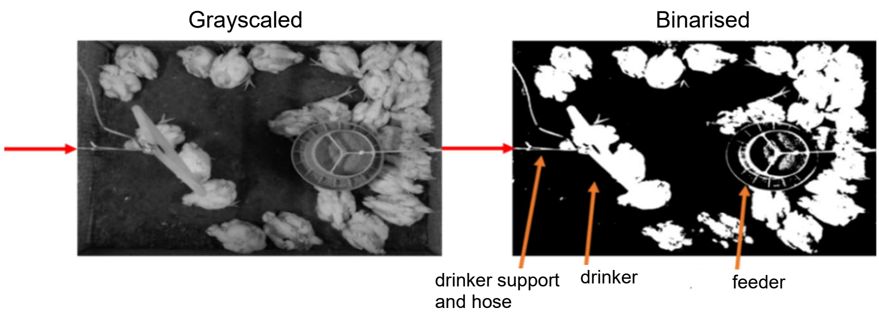

Figure 2. An example of grayscaling and binarisation.

Erosion and dilation were then performed to eliminate noise and reduce the occurrence of unwanted objects such as feeder and drinker (Fig. 3).

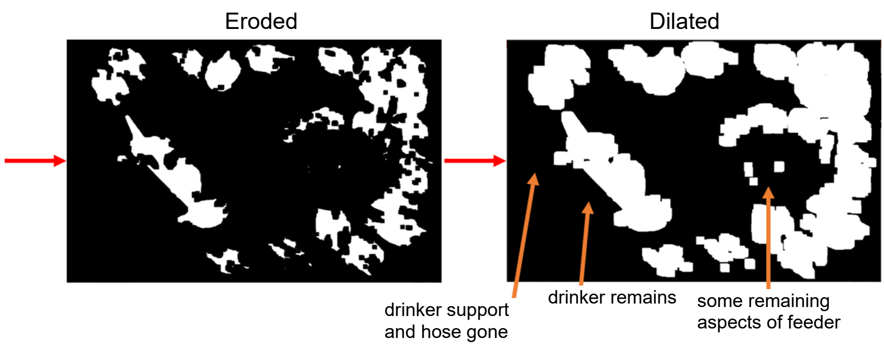

Figure 3. An example of erosion and dilation.

Contour detection was conducted using the OpenCV function 'cv2.findcountours()'. These contours were then filtered by perimeter length to eliminate final non-bird containing objects (Fig. 4).

Figure 4. An example of contour-detection and contour-filtering.

Once the contours had been detected and filtered, the following variables required for the cluster index equation (Pereira et al., 2020) could be identified: $\underline{A}$ – average area of detected objects, $\underline{P}$ – average perimeter of detected objects and N_A – number of objects, whilst x – image's horizontal pixel length and y – image's vertical pixel length are known from the camera's resolution. To detect the average distance between objects, $\underline{D}$, the object centre points were required. A minimum bounding rectangle was drawn around each object, using the OpenCV function 'cv2.boundingRect()', and the centre coordinates were computed:

$$Centre\ Coordinates\ (x, y) = x1 + \frac{width}{2}, y1 + \frac{height}{2} \tag{1}$$

where $x1$ and $y1$ are the coordinates for the vertex closest to the origin (Fig. 5).

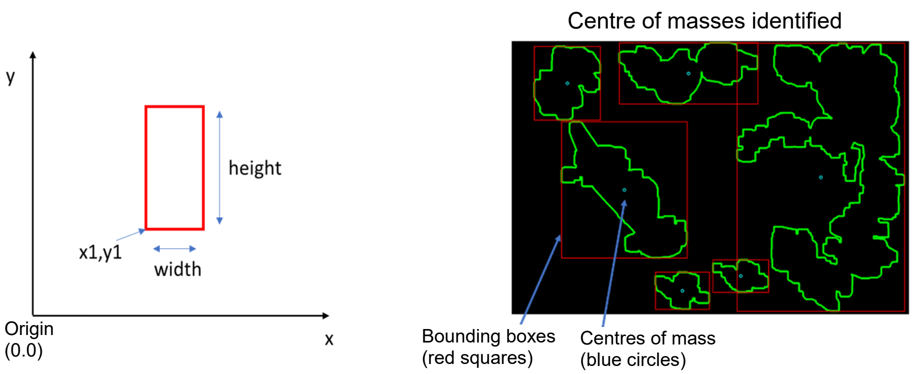

Figure 5. Calculation of bounding box centre coordinates and an example of the bounding box and object centres overlaid onto object contours.

An open-source package 'scipy.spacial.distance' was used to find the average Euclidian distance between each object centre and the others (SciPi, 2022). This was repeated for all object centres, which were then averaged to find $\underline{D}$. A random set of ten images from each recorded day were selected and the object detection output was compared to its rotated and cropped original (Fig. 6). For each image, any birds not captured within a green contour line were recorded, along with any detected anomalous objects.

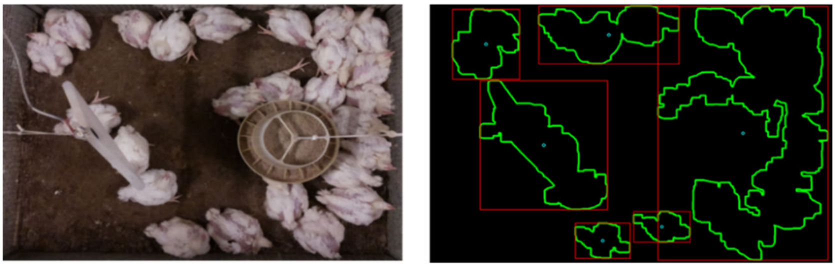

Figure 6. An example of the comparison method for checking contour detection accuracy.

Cluster Index variables were generated using the Python image processing script. Using a Raspberry Pi 3 series B+, ten sample images from each day of testing were processed using the developed code.

Angled camera system experiment

A second trial was conducted to test the applicability of an angled camera set-up. This would increase the area covered by a camera, reducing hardware requirements per shed and lowering installation costs.

A 16 m × 5 m area was marked out onto the floor of an empty poultry house, to demarcate the boundaries of the size of a representable Kenyan shed. An image capturing and storage system (a Wansview W3 camera (1 MP full colour, outdoor rated, WiFi enabled), Raspberry Pi 3B+, and a laptop) was set-up with the camera at a height of 2.7 m and located at the edge of one end of the demarcated boundaries. The camera's floor area coverage was measured by observing the live feed from the camera and marking the floor at the vertices of its field of vision. These points were measured in comparison to the demarcated shed.

An 8 m × 1.5 m strip of wood-chip bedding was laid out within the camera's field of vision and outlined with white tape. In order to test the applicability of the vision system with chicks under 10 days of age, 20 yellow-coloured toy-chicks with dimensions roughly 80 mm × 80 mm × 60 mm were used to simulate young chicks.

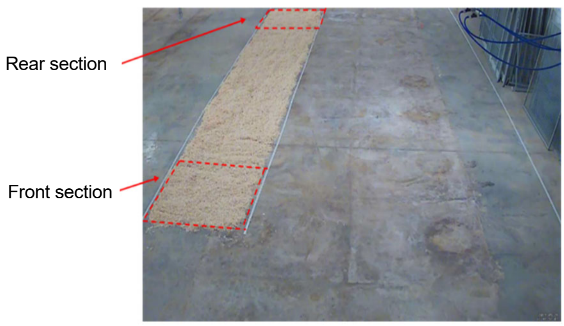

Figure 7. A visualisation of the front and rear sections of woodchip strip used in the angled camera experiment.

Two 1m × 1.5m sections of the woodchip strip were selected for locating toy-chicks at the front and rear sections (Fig. 7). This would provide data at the extremes of the imaging systems capability. By using 1.5 m^2 sections, 20 birds could be used to ensure that the stocking density of 12.5 birds m^{-2} was achieved.

Images were taken using the 20 yellow toy-chicks. Later, ten toy-chicks were painted brown, to replicate the colour characteristics of Kenyan indigenous varieties. Five images of the background and then 50 images in five sets of yellow, yellow and brown, and just brown birds, were then collected.

A perspective transform (PT) Python script was developed using the image set of yellow birds in the front and rear section. The coordinates of the four corners of the woodchip strip were identified using Microsoft Paint, and fed into the algorithm. This algorithm highlighted the location of the given coordinates, then cropped and warped the images, using the OpenCV function 'cv2.warpPerspective()' to provide a two-dimensional, birds-eye view of the bounded area (Fig. 8). This method was repeated for all data sets to provide a basis for object detection testing.

Figure 8. An example of Perspective Transform conducted in the angled camera experiment.

To test the impact of object stretching resulting from PT, as highlighted by Dawson-Howe (2014), the contour detection algorithm used in the overhead camera system was applied images after background subtraction (BS). LT is highly dependent upon lighting and object-background contrast (Okinda et al., 2020), thus BS method is more successful as found by Van Hertem et al. (2013) in an experiment with cows of varied colours.

Contours were filtered to leave only individual birds, with no multi-bird groups (Fig. 9). The area of each object in the front and rear sections was calculated using the OpenCV function 'cv2.contourArea()'and then averaged for each group. This was repeated on 5 random images from each image set.

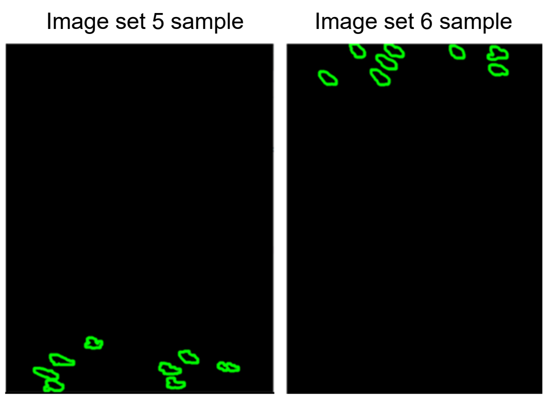

Figure 9. An example of the contours used to test the impact of PT on object size.

The linear transfer (LT) and background subtraction (BS) methods were applied for direct comparison with the angled camera application. Using the PT images generated, the linear transformations used in overhead camera experiment were applied. As the birds in this instance were darker than the bedding, the binarisation stage outputs dark objects of interest against a white background. Contour detection requires white objects against a black background, so the image was inverted by applying inversion to each pixel (Fig. 10)

$$Inverted\ Pixel = 255 - Binarised\ Pixel \tag{2}$$

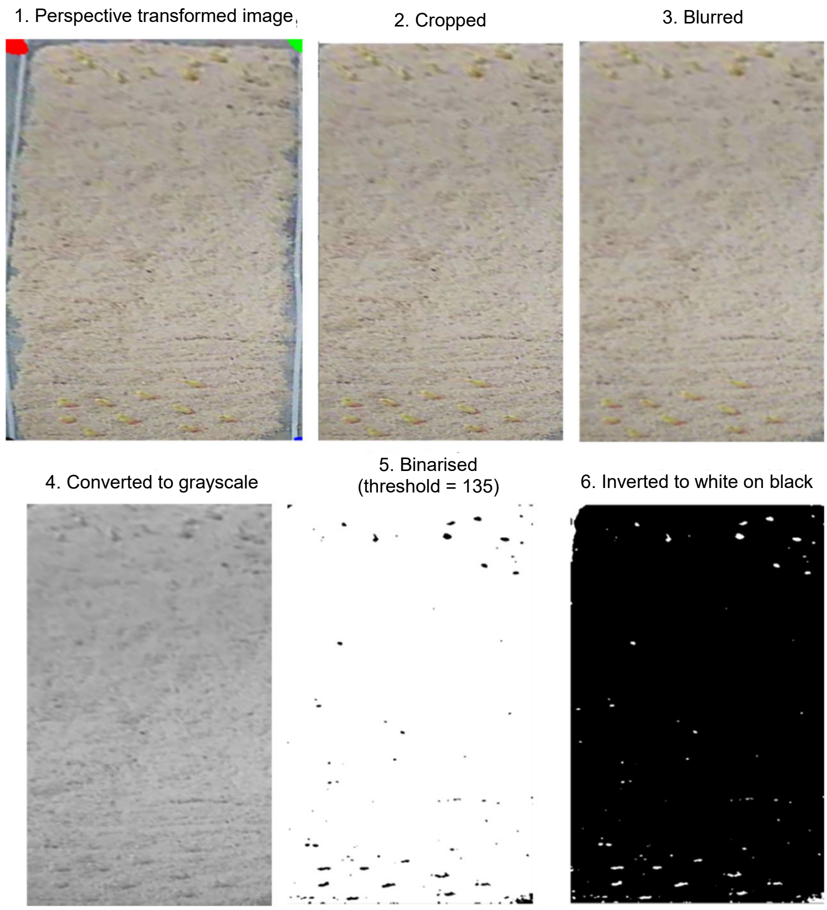

Figure 10. The stages of linear transformation object detection in angled camera experiment for image set of yellow birds in the front and rear section (threshold of 135 was found iteratively).

Background subtraction was again initially applied by taking a background image and subtracting it from the 'current frame' containing yellow birds in the front and rear section. A threshold of 35 was selected to filter out noise based on iterative adjustments as described above (Fig. 11). The variation in the threshold values selected between the tests was due to the change in contrast between the birds and the background, resulting from their changed colours.

To compare LT and BS methods, a foreground mask was generated using each method for all images of birds. Contour detection method as described above was then applied. Post contour-detection, the number of birds missed and anomalous contours generated were manually recorded for each of the images.

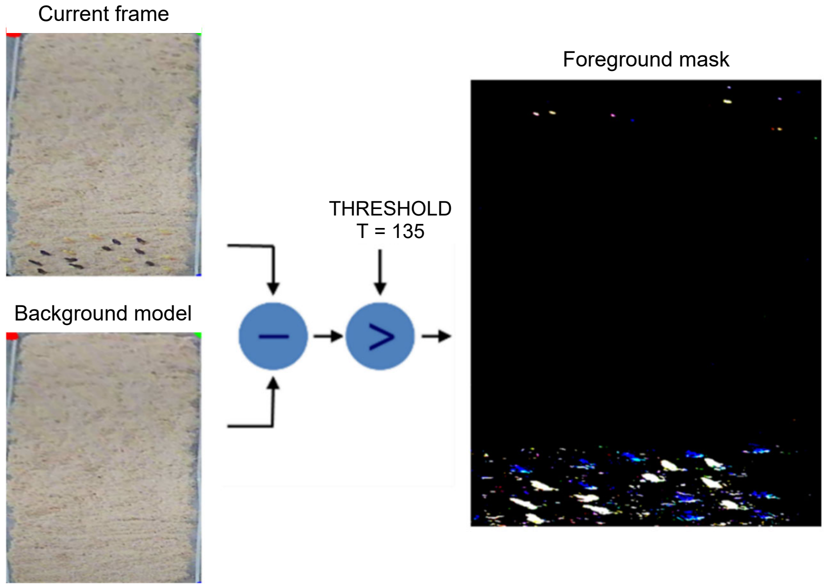

Figure 11. A visualisation of the background subtraction method applied in angled camera experiment for image set of yellow birds in the front and rear section.

RESULTS AND DISCUSSION

In the overhead camera system experiment, where white birds were detected against a dark background, a randomly selected ten-image sample from each of the eight days of collected footage (i.e. 25 birds in each image × 80 images totals 2000 birds) was processed for contour detection. The image processing code ran on the Raspberry Pi was able to generate the variables required to calculate the cluster indices. LT object detection successfully detected 99.8% of birds in the sampled images (just four birds were identified as being missed). This correlated with the success of Pereira et al. (2020) and Del Valle et al. (2021) in similar scenarios.

However, in the angled camera system experiment, the LT method was just 55–56% effective at detecting the yellow toy-chicks against the light-coloured background (Fig. 12). This finding agrees with Okinda et al. (2020) that object-background contrast is critical for LT applications. In contrast, the BS method was more effective, detecting 83–100% of the yellow toy-chicks (Figure 12). This correlates with the results of Van Hertem et al. (2013) who found BS methods superior to LT methods in their scenario detecting cows of inconsistent colours. With Chesoo et al. (2021) finding that Kenyan indigenous chickens phenotypes tend to be varied combinations of brown, black and white, the BS method for object detection is recommended for this prototype system. Nonetheless, the angled camera system experiment did not involve live birds as Kenyan indigenous chickens were unavailable, and so the background stability issues highlighted by Okinda et al. (2020) could not be analysed. Whilst the background update method used by Guo et al. (2020) may have combatted this, testing this was also not possible with the resources available. The results showed that BS detection success was worse for yellow toy-chicks in the far section, detecting 83% as opposed to 100% of those in the near-section. The impact of camera-resolution upon object detection using the BS method offers an avenue for future research in this area with a higher resolution camera.

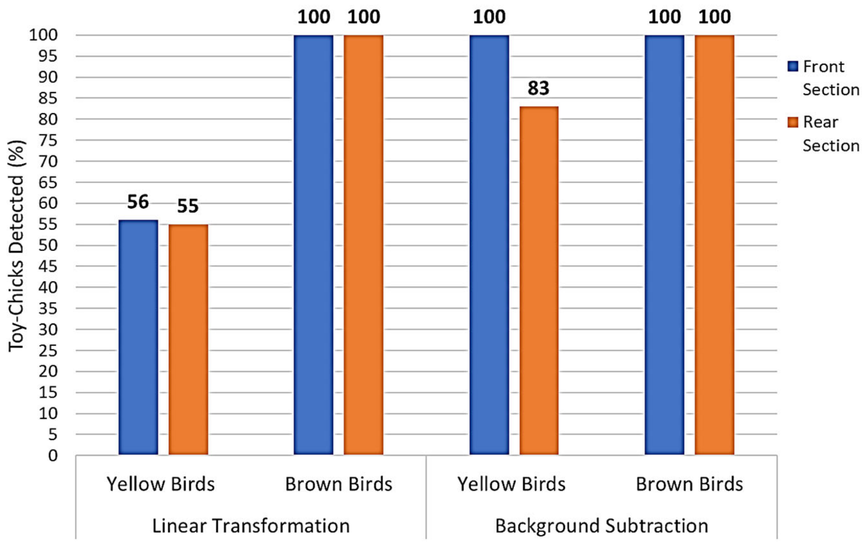

Figure 12. A comparison of LT and BS methods for detecting toy-chicks, by colour and location.

The floor area covered by a single overhead camera was 2.45 m × 3.26 m. A typical 16 m × 5 m Kenyan poultry shed would require 12 Raspberry Pi V2 cameras for full floor area coverage. This would entail a camera cost of 288 GBP, which is prohibitive even before the subsequent increased processing requirements were factored in.

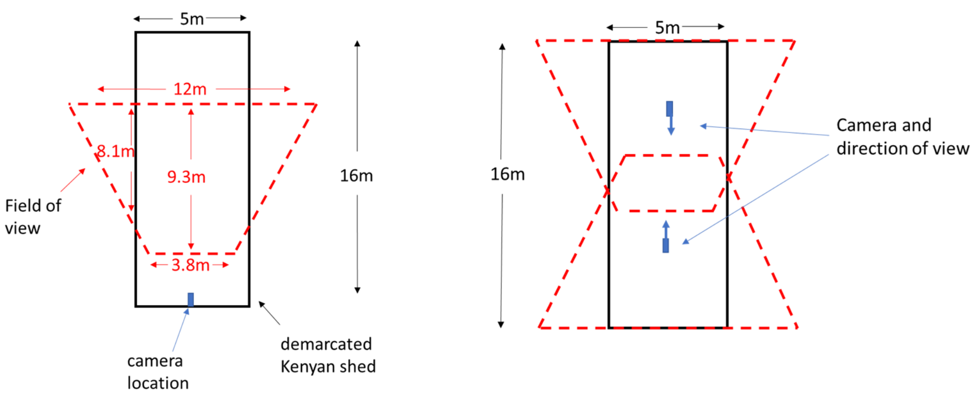

Figure 13. Left: The measured camera floor area coverage; Right: projected total floor area coverage with two angled cameras.

Due to this, an angled camera approach was tested, and the use of PT techniques to enable cluster indexing using this set-up was demonstrated to successfully transform the three-dimensional view into two-dimensions. The area covered by a single angled camera was 56% of the demarcated Kenyan shed (Fig. 13 left) - it would be possible for the entire floorspace to be covered by just two cameras as shown in Fig. 13 right. This brings camera costs down by 240 GBP, whilst also reducing the processing requirements. However, the results support the assertion of Dawson-Howe (2014) that objects further from the camera become stretched and enlarged during PT. The impact of this upon the cluster index was not measured. The impact will vary depending upon the size and density of the birds in the sheds and thus is a necessary avenue of investigation before this system can be developed further.

Edge processing of the developed image processing algorithm was tested using a Raspberry Pi 3 series B+ computer, which was found capable of generating the required cluster index variables for individual images. Further testing would be required to better understand the processing capacity for multiple images of larger flock sizes at 15 second sampling intervals. SMS communication to alert the farmer is suggested to be optimal for rural Kenya and is applicable with a communications module with the Raspberry Pi 3 series B+. An early-stage prototype has been recommended (Table 2 and Fig. 14).

Table 2. Proposed prototype hardware

Hardware	Quantity	Total cost GBP
Wansview W5 IP66 security camera	2	119.98
Raspberry Pi 3 Series B+	1	33.90
MicroSD card	1	6.00
5V power supply	1	8.00
SIM800X Communications HAT	1	18.50
SIM card	1	–
TOTAL		186.38

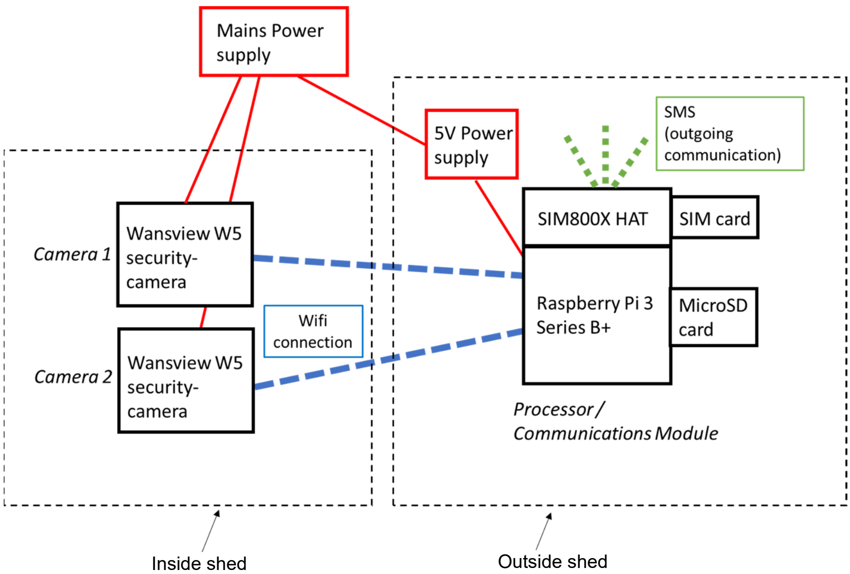

Figure 14. The proposed prototype system.

The inbuilt WiFi capability of the computer and cameras enables wireless communication without a dedicated router. This set-up enables the computer assembly to be located outside of the shed, in a protected environment, limited by the range of the WiFi connection and access to a power supply. By using the edge processing capability of the Raspberry Pi 3 Series B+, the need for further computing hardware is negated. The use of Python, and the open-source OpenCV package requires no additional software cost to run the inference algorithm on the Raspberry Pi.

Nonetheless, LT has shown potential to reduce processing and installation capital requirements, lowering the barriers to implementation of poultry monitoring systems in rural Kenya. The new knowledge can be used to monitor remotely and in real time conditions and welfare of birds in small-scale farmers' poultry sheds, reducing labour costs and bird mortality and increasing performance and incomes.

CONCLUSIONS

An overhead camera system using Raspberry Pi V2 camera was used to collect images of Ross 308 birds over eight days. An image processing algorithm was developed using Python and OpenCV. Linear transformation (LT) object detection successfully detected 99.8% of birds in the sampled images white birds against a dark background. A single overhead camera covers 2.45 m × 3.26 m floor area, thus requiring 12 cameras to cover the total floor area in a typical poultry shed opposed to just two with an angled camera approach. An angled camera system using Wansview W3 camera was tested on a 16 m × 5 m area on yellow and brown toy-chicks. The LT method was just 56.5% effective at detecting the yellow toy-chicks against the light-coloured background. In contrast, the background subtraction (BS) method was more effective, detecting 91.5% of the yellow toy-chicks. The results showed that BS detection success was worse for yellow toy-chicks in the far section, detecting 83% as opposed to 100% of those in the near-section. The suggested prototype provides a solid foundation for further development and testing of low-cost, automated poultry monitoring systems.

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REFERENCES

Aluwong, T., Sumanu, V.O., Ayo, J.O., Ocheja, B.O., Zakari, F.O. & Minka, N.S. 2017. Daily Rhythms of Cloacal Temperature in Broiler Chickens of Different Age Groups Administered with Zinc Gluconate and Probiotic During the Hot-dry Season. *Physiological Reports* **5**(12).

Cabanac, A. & Guillemette, M. 2001. Temperature and heart rate as stress indicators of handled common eider. *Physiology & Behavior* **74**(4–5), 475–479.

Cabanac, M. & Aizawa, S. 2000. Fever and tachycardia in a bird (*Gallus domesticus*) after simple handling. *Physiology & Behavior* **64**(4–5), 541–545.

Chesoo, B., Wanga, J. & Nandwa, A. 2021. Assessment of Morphological Characteristics of Indigenous Chicken Ecotypes of Kenya. *African Environmental Review Journal* **4**(2), 139–147.

Dawson-Howe, K. 2014. *A Practical Introduction to Computer Vision with OpenCV*. Wiley, New York, 240 pp.

Del Valle, J.E., Pereira, D.F., Mollo Neto, M., Gabriel Filho, L.R.A. & Salgado, D. D. A. 2021. Unrest index for estimating thermal comfort of poultry birds (*Gallus gallus domesticus*) using computer vision techniques. *Biosyst. Eng.* **206**, 123–134.

Dumas, S., Maranga, A., Mbullo, P., Collins, S., Wekesa, P., Onono, M & Young, S. 2018. 'Men Are in Front at Eating Time, but Not When It Comes to Rearing the Chicken': Unpacking the Gendered Benefits and Costs of Livestock Ownership in Kenya. *Food and Nutrition Bulletin* **39**(1), 3–27.

Fernández, P., Norton, A., Tullo, E., Van- Hertem, T., Youssef, A., Exadaktylos, V., Vranken, E., Guarino, M. & Berckmans., D. 2018. Real-Time Monitoring of Broiler Flock's Welfare Status Using Camera-Based Technology. *Biosystems Engineering* **173**, 103–114.

Giloh, M., Shinder, D. & Yahav, S. 2012. Skin surface temperature of broiler chickens is correlated to body core temperature and is indicative of their thermoregulatory status. *Poultry Science* **91**(1), 175–188.

Greengage 2021. Products: Broiler Platform. Available at https://greengage.global/product-packages-for-poultry-and-pigs/intelligent-lighting-and-sensor-platform/intelligent-lighting-and-sensor-platform-for-broilers/. Accessed 28/11/2021.

Guo, Y., He, D. & Chai, L. 2020. A Machine Vision-Based Method for Monitoring Scene-Interactive Behaviours of Dairy Calf. *Animals* **10**(2).

Hedman, H., Zhang, L., Butt, B., Papias, P., Trostle, J & Eisenberg, J. 2021. 'Chicken dumping': Motivations and perceptions in shifting poultry production practices. *One Health* **13**.

Jerem, P., Herborn, K., McCafferty, D., McKeegan, D. & Nager, R. 2015 Thermal Imaging to Study Stress Non-Invasively in Unrestrained Birds. *Journal of Visualized Experiments* **105**. doi:10.3791/53184

Magothe, T., Okeno, T., Muhuyi, W. & Kahi, A. 2012. Indigenous chicken production in Kenya: I. Current status. *World's Poultry Science Journal* **68**(1), 119–132.

Maman, A., Özlü, S., Uçar, A. & Elibol, O. 2019. Effect of chick body temperature during post-hatch handling on broiler live performance. *Poultry Science* **98**(1), 244–250.

Menge, E.O., Kahi, A.K. & Kosgey, I.S. 2005. Bio- Economic Model to Support Breeding of Indigenous Chicken in Different Production Systems. *International Journal of Poultry Science* **4**(11), 827–839.

Nixon, M. & Aguado, A. 2020. *Feature Extraction and Image Processing for Computer Vision*. 4th ed. Academic Press, 650 pp.

Njue, S., Kasiiti, J. & Gacheru, S. 2006. Assessing the Economic Impact of Commercial Poultry Feeds Supplementation and Vaccination Against Newcastle Disease in Local Chickens, in Kenya. In Improving farmyard poultry production in Africa: Interventions and their economic assessment. Proceedings of a final research coordination meeting organised by the Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture and held in Vienna, 24–28 May 2004. *International Atomic Energy Agency*, Vienna, Austria, pp. 116–123.

Nyoni, N., Grab, S. & Archer, E. 2018. Heat stress and chickens: climate risk effects on rural poultry farming in low-income countries. *Climate and Development* **11**(1), 83–90.

Ochieng, J., Owuor, G., Bebe, B. & Ochieng, D. 2011. Effect of Management Interventions on Productive Performance of Indigenous Chicken in Western Kenya. *Livestock Research for Rural Development* **23**(114). Available at http://www.lrrd.org/lrrd23/5/ochi23114.htm. Accessed 21/12/2021.

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T. & Shen, M. 2020. A Review on Computer Vision Systems in Monitoring of Poultry: A Welfare Perspective. *Artificial Intelligence in Agriculture* **4**, 184–208.

OpenCV. 2022. OpenCV Tutorials. Available at https://docs.opencv.org/4.x/d9/df8/tutorial_root.html. Accessed 21/11/2021.

Otiang, E., Campbell, Z.A., Thumbi, S.M., Njagi, L.W., Nyaga, P.N. & Palmer, G.H. 2020. Mortality as the primary constraint to enhancing nutritional and financial gains from poultry: A multi-year longitudinal study of smallholder farmers in western Kenya. *PLOS ONE* **15**(5).

Percie du Sert, N., Hurst, V., Ahluwalia, A., Alam, S., Avey, M.T., Baker, M., Browne, W.J., Clark, A., Cuthill, I.C., Dirnagl, U. & Emerson, M. 2020. The ARRIVE guidelines 2.0: Updated guidelines for reporting animal research. *Journal of Cerebral Blood Flow & Metabolism* **40**, 1769–1777.

Pereira, D.F., Lopes, F.A.A., Filho, L.R.A.G., Salgado, D.D. & Neto, M.M. 2020. Cluster index for estimating thermal poultry stress (*gallus gallus domesticus*). *Computers and Electronics in Agriculture* **177**.

Piestun, Y., Shinder, D., Ruzal, M., Halevy, O., Brake, J. & Yahav, S. 2008. Thermal Manipulations During Broiler Embryogenesis: Effect on the Acquisition of Thermotolerance. *Poultry Science* **87**(8), 1516–1525.

SciPi. 2022. Distance computations (scipy.spatial.distance). Available at https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.distance.cdist.html. Accessed 28/04/2022.

Scout Monitoring. 2021. The Monitoring Solution for Smarter Livestock Management. Available at https://www.scoutmonitoring.com/wp-content/uploads/2022/01/SCOUT-ONE-PAGE-02.pdf. Accessed 28/11/2021.

Speller, D. 2022. Personal communication, 04/03/2022.

Thumbi, S.M., Njenga, M.K., Marsh, T.L., Noh, S., Otiang, E., Munyua, P., Ochieng, L., Ogola, E., Yoder, J., Audi, A., Montgomery, J.M., Bigogo, G., Breiman, R.F., Palmer, G.H. & McElwain, T.F. 2015. Linking Human Health and Livestock Health: A 'One-Health' Platform for Integrated Analysis of Human Health, Livestock Health, and Economic Welfare in Livestock Dependent Communities. *PLOS ONE* **10**(3).

United Nations (UN). 2021. Goal 5: Achieve gender equality and empower all women and girls. Available at https://unric.org/en/sdg-5/.

Van Hertem, T., Alchanatis, A., Maltz, E., Halachmi, I., Schlageter-Tello, A., Lokhorst, C., Viazzi, S., Ramanini, C., Pluk, A., Bahr, C. & Berckmans, D. 2013. Comparison of segmentation algorithms for cow contour extraction from natural barn background in side view images. *Computers and Electronics in Agriculture* **91**, 65–74.