DETECTING DAY-OLD CHICKS IN A BOX BASED ON COMPUTER VISION

Hubert Mouton
Department of Software Engineering
Namibia University of Science & Technology
Windhoek, Namibia
hmouton786@gmail.com

Lameck Mbangula Amugongo
Department of Software Engineering
Namibia University of Science & Technology
Windhoek, Namibia
lamugongo@nust.na

ABSTRACT

Computer vision is increasingly being used as a tool for real-time poultry monitoring. In poultry farming, farmers have identified that upon collecting day-old chicks, they face two problems: difficulty verifying the number and determining the condition of day-old chicks ordered. In chicken production line systems, vision-based evaluation requires quality data and is challenging because of day-old occlusion problems and ambient light conditions.
In this study, we curated a dataset of day-old chicks acquired from real-life chicken farms in Namibia. Using this dataset, four state-of-the-art algorithms namely, RetinaNet, Faster RCNN, YOLOv4, and YOLOv5 were compared. To evaluate the detection performance of the models, precision, recall average precision, and mean average precision (mAP) was computed.
The RetinaNet, Faster RCNN, YOLOv4, and YOLOv5 achieved mAP scores of 50.6%, 60.5% , 78.6% and 67.3%, respectively. The YOLOv4 model performed better at detecting day-old chicks in a box. Our results suggest the feasibility of utilising vision-based algorithms for day-old chicks counting, which could reduce the workload of chicken farmers and promote the intelligent development of poultry farming.

1 INTRODUCTION

With the global population expected to increase to 12.3 billion people by the year 2100 Gerland et al. (2014), food security will continue to be a global concern Alexandratos & Bruinsma (2012). The growing preference for animal-based proteins has resulted in the increased consumption of poultry products Okinda et al. (2019; 2020). According to data from the Namibia Statistics Agency (2019), Namibia imported poultry products worth N$ 1.2 billion and N$ 839.7 million in 2019 and 2020, respectively. Several efforts have been made to improve food security and reduce the country's reliance on imports. One such effort is the roots project, located in Stampriet in the Hardap region, Namibia.

The ROOTS development is built on a new concept of sustainable agricultural communities, combining intensive livestock farming, village lifestyle, and business opportunities Roots Namibia (2021). Producing broiler chickens from day-old chicks is one of the farming activities taking place at ROOTS. Traditionally, chicken farmers order day-old chicks (usually 25 or 50 in a box) and manually take inventory of the day-old chicks. At delivery farmers have observed inconsistency in the quantities of baby chickens ordered. The inaccurate quantities of day-old chicks have long-term financial implications for farmers. For example, if 2 day-old chicks are missing in each of the 100 boxes ordered, farmers can lose revenue that could be reinvested to improve their business or used to sustain their livelihoods.

The advancements in artificial intelligence especially the developments in computer vision present opportunities for solutions that are non-intrusive, non-destructive, accurate, and fast Nyalala et al. (2019). Several authors have proposed computer vision-based applications to solve problems in the

poultry sector. Cao et al. (2021) developed a computer vision algorithm to detect the population densities of chickens using surveillance cameras. Their model yielded an accuracy of 93.84%. In another study, a system was developed to estimate the volume of chicken eggs in a production line system, as an accurate, consistent, rapid, and non-destructive in-line sorting procedure for chicken eggs Okinda et al. (2020)). Hao et al. (2022)) developed an algorithm based on improved YOLOv3 deployed on a server to identify dead broilers in flocks. The results were stored in an excel format and can be checked in a human-machine interface, allowing the breeding staff to quickly find dead broilers without having to observe each cage, reducing their workload.
Although computer vision is a useful tool to solve many problems across different sectors, challenges exist. For machines to successfully perform computer vision tasks, a lot of quality data is required for training (cite). A major challenge is hardware limitations. Access to good hardware can enable researchers to curate quality data for model training. The availability of high-quality datasets is currently difficult to obtain and labour-intensive to create. To the best of our knowledge, there is no dataset of day-old chicks that can be used for machine learning (ML) applications.
The contributions of this paper are as follows:

1. A public dataset consisting of day-old chicks collected in a real-poultry farm in Namibia.
2. We present a data set comprising quality-labelled images of day-old chicks.
3. We illustrate how the dataset can be used to detect day-old chicks in a box, providing a fast and reliable tool for farmers to automate the inventory of chicks.

2 METHODOLOGY

2.1 DATASET

A total of 331 images of day-old chicks were acquired from a local chicken farmer, were included in this experiment. The images were acquired using a Nikon P900 camera, captured mainly in a top-view format. The images were visually checked to remove blurry images. The acquired images are colour images. The images were acquired in natural real-life conditions and no additional illumination was required during the image acquisition process. The image acquisition process is shown in Figure 1.

2.1.1 DATA ANNOTATION AND PRE-PROCESSING

The main aim of this study was to curate a dataset of day-old chick that can used to develop an algorithm to detect day-old chicks in box. Firstly, the images were manually labelled using an online open-source tool called Roboflow Alexandrova et al. (2015). The images were manually labelled one by one. Lastly, once the images were labelled, three pre-processing steps were performed to ensure image consistency and improve model performance.

1. Images were given the same orientation.
2. Images were resized to 600X600 pixels to ensure consistency amongst images.
3. Images were converted to grayscale to reduce computational cost while attempting to improve model performance.

2.2 MODEL TRAINING AND EVALUATION

Due to our limited dataset of day-old chicks, we used pre-trained models and fine-tuning them. A previous study showed that with transfer learning, models trained on modest data can perform well Romero et al. (2020). To train the model, we randomly split the dataset into training, validation, and testing (70%, 10%, and 20%). Four state of the art (SOTA) convolution neural networks (CNNs), RetinaNet, Faster RCNN, YOLOv4, and YOLOv5, were trained using Tensorflow. All model's were trained on chicks images in 300 epochs. For detection, the RetinaNet, Faster RCNN, YOLOv4, and YOLOv5 models predict boxes at three different scales on these feature maps. The loss (object and classification) of the predicted and target boxes are computed with the binary cross-entropy loss function, while the coordinate loss is calculated with a mean square error loss function. To evaluate the detection performance of the models, we computed the utilizes the precision, recall, average

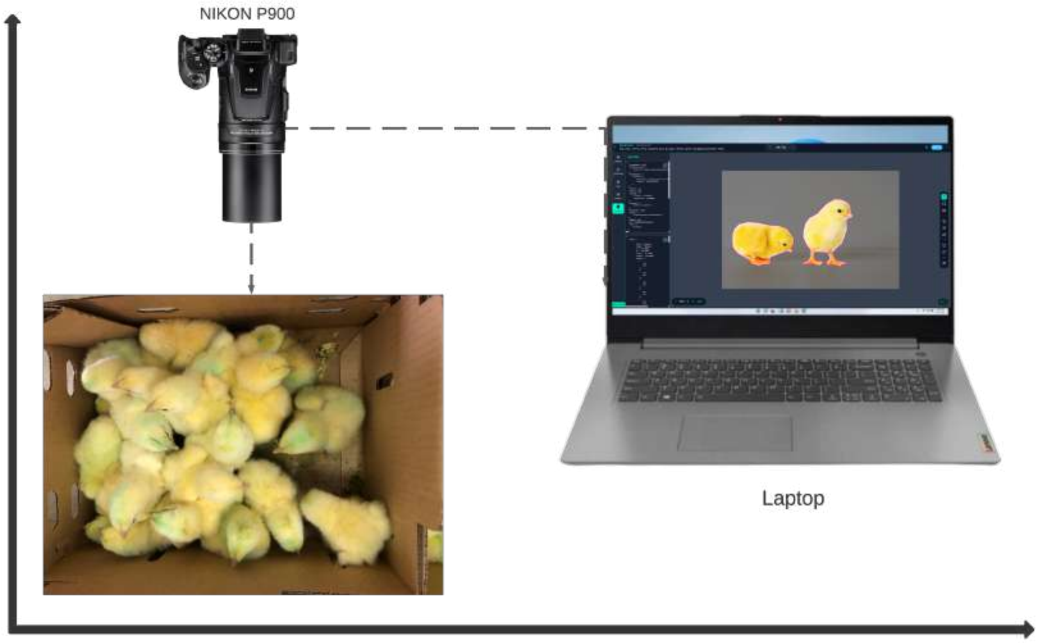

Figure 1: Image acquisition process. Imaged of day old-chicks acquired using Nikon camera and the uploaded onto the laptop for annotation.

precision (AP), and mean average precision (mAP). The mAP of a model alone does not show how tight the bounding boxes of your model are because this information is conflated with the correctness of predictions. Therefore, the average Intersection over Uninon (IoU) was calculated for each model to measure the tightness of the model's bounding boxes to the ground truth.
All computations, including model training and evaluation were performed on the Google collaboration platform Bisong (2019).

3 Results

3.1 Dataset curation

Three hundred and thirty-one images were successfully manually labelled using the Roboflow, Figure 2 shows examples of labelled day-old chicks. The dataset can be accessed on Kaggle, a public dataset platform (day-old chicks dataset).

3.2 Model evaluation

Figure 3 illustrates the performance of the models in different conditions. The colour and shape are important features that distinguish a chick from the background. Thus, changes in the brightness of the image may change the original features and may affect the results.

Table 1 presents the precision, recall, and mAP for detecting day-old chicks in a box for all models. The YOLOv4 models achieved mAP score of 78.6% compared to the RetinaNet, Faster RCNN and YOLOv5 which achieved 50.6%, 60.5% and 67.3% respectively.

Overall, the results show that the YOLOv4 model performed the best. However, improvements are needed to improve the tightness of the bounding boxes. This will enable us to accurately automtically count the number of chicks in the box.

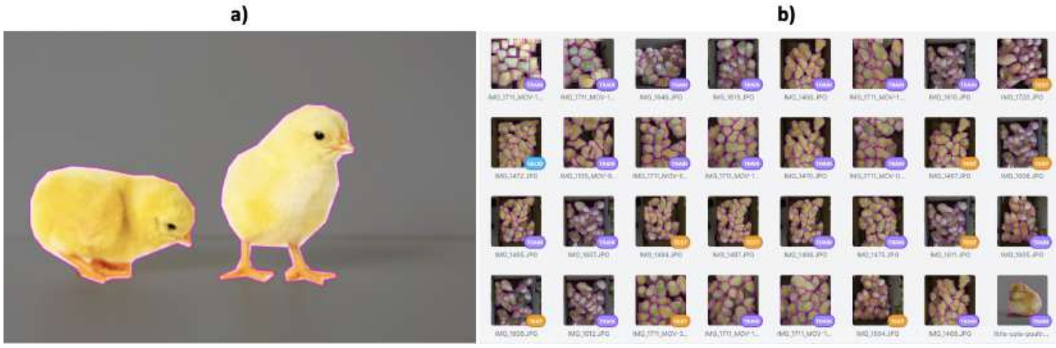

Figure 2: Examples of labelled images. a) labels of two day old chicks b) labels of multiple day-old chicks in a box.

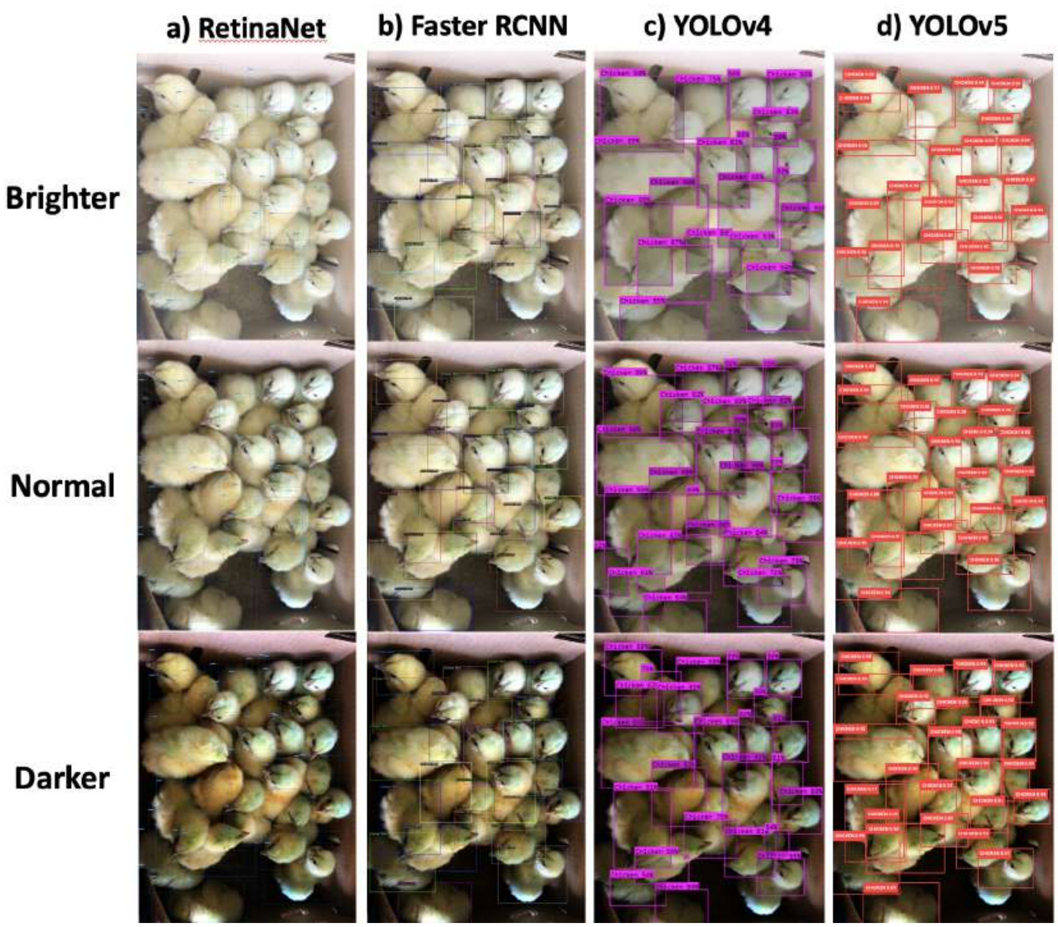

Figure 3: Evaluating the performance of the models on images of different conditions, the first row shows the performance of the model on images with high brightness, the second row is normal and the third-row has low brightness. Each column represents a model: a) RetinaNet, b) Faster RCNN, c) YOLOv4 and d) YOLOv5.

Table 1: Performance of the models. The YOLOv4 model performed better at detecting day-old chicks in box.

Model	Precision	Recall	AP	mAP	Average IoU
RetinaNet	49%	46%	45%	50.6%	48.3%
Faster RCNN	65.6%	66.5%	60.2%	60.5%	65%
YOLOv4	81%	79%	78%	78.6%	62.34%
YOLOv5	66%	69%	68%	67.3%	55%

4 DISCUSSION

In this study, we present a dataset containing day-old chicks, collected in a real world setting at a farm in Namibia. Moreover, we demonstrated that our labelled dataset can potentially be applied to detect chicks in boxes. Previously, ML has been applied in the poultry industry Zhu et al. (2009); Liu et al. (2021); Bao et al. (2021). For example, an automatic detection algorithm was developed to identify dead birds using a support vector machine Zhu et al. (2009). Another study, Liu et al. (2021) proposed a chicken inspection robot to monitor chickens in a farm. The chicken inspection robot had the capability to walk around the chicken coop and monitor the chickens in real-time. Bao et al. (2021) developed a new method to detect sick and dead chickens. Similarly, Hao et al. (2022) proposed a method to automatically detect dead boilers in a stacked cage in broiler breeding house to reduce the labor burden of chicken farmers. To the best of our knowledge, this is the first work that is specifically focused on day-old chicks. Additionally, we created the first annotated day-old chicks dataset for ML.

4.1 LIMITATIONS

Our study is not without limitations. First, our dataset contains only 331 images. However, to the best of our knowledge, this is the first dataset containing day-old chicks. In addition, our dataset contained labelled data. Second, the detection algorithms compared in this study do not perform well when many day-old chicks are occluded in one image. Future work will explore improving the performance of the models. Lastly, we do not count the number of chicks in the box. So, we will explore regression algorithms to automatically count the number of chicks in a given box.

4.2 FUTURE WORK

Due to the wide use and availability of smartphones, a mobile vision-based application is an ideal tool to automate inventory for farmers in Africa. Therefore, future work will explore lightweight mobile-based algorithms to detect and estimate the number of day-old chicks in a given box. Such a solution will alleviate the concerns of farmers.

5 CONCLUSION

In this paper, we introduce a public dataset comprising day-old chicks, curated from a real-life chicken farm in Namibia. In addition, we evaluated the performance of four SOTA vision-based algorithms namely RetinaNet, Faster RCNN, YOLOv4, and YOLOv5 on our real-life data to detect day-old chicks. The results showed that the YOLOv4 model performed best with an mAP score of 78.6%, followed by YOLOv5 RCNN with a score of 67.3%. Our results suggest the feasibility of using vision-based algorithms to detect day-old chick in the real world, which could reduce the workload of chicken farmers and promote the intelligent development of poultry farming.

ACKNOWLEDGMENTS

The authors would like to thank DAYOLD CHICKENS NAMIBIA for giving us permission to acquire and collect real-life images of chicks at their farm.

REFERENCES

N Alexandratos and J Bruinsma. World agriculture towards 2030/2050: the. 2012.

Sonya Alexandrova, Zachary Tatlock, and Maya Cakmak. Roboflow: A flow-based visual programming language for mobile manipulation tasks. pp. 5537–5544. IEEE, 5 2015. ISBN 978-1-4799-6923-4. doi: 10.1109/ICRA.2015.7139973.

Yiqin Bao, Hongbing Lu, Qiang Zhao, Zhongxue Yang, and Wenbin Xu. Detection system of dead and sick chickens in large scale farms based on artificial intelligence. *Mathematical Biosciences and Engineering*, 18:6117–6135, 2021. ISSN 1551-0018. doi: 10.3934/mbe.2021306.

Ekaba Bisong. *Building Machine Learning and Deep Learning Models on Google Cloud Platform*, pp. 59–64. Apress, 2019. doi: 10.1007/978-1-4842-4470-8_7.

Liangben Cao, Zihan Xiao, Xianghui Liao, Yuanzhou Yao, Kangjie Wu, Jiong Mu, Jun Li, and Haibo Pu. Automated chicken counting in surveillance camera environments based on the point supervision algorithm: Lc-densefcn. *Agriculture*, 11:493, 05 2021. doi: 10.3390/agriculture11060493.

Patrick Gerland, Adrian E. Raftery, Hana Ševčíková, Nan Li, Danan Gu, Thomas Spoorenberg, Leontine Alkema, Bailey K. Fosdick, Jennifer Chunn, Nevena Lalic, Guiomar Bay, Thomas Buettner, Gerhard K. Heilig, and John Wilmoth. World population stabilization unlikely this century. *Science*, 346:234–237, 10 2014. ISSN 0036-8075. doi: 10.1126/science.1257469.

Hongyun Hao, Peng Fang, Enze Duan, Zhichen Yang, Liangju Wang, and Hongying Wang. A dead broiler inspection system for large-scale breeding farms based on deep learning. *Agriculture*, 12: 1176, 08 2022. doi: 10.3390/agriculture12081176.

Hung-Wei Liu, Chia-Hung Chen, Yao-Chuan Tsai, Kuang-Wen Hsieh, and Hao-Ting Lin. Identifying images of dead chickens with a chicken removal system integrated with a deep learning algorithm. *Sensors*, 21:3579, 5 2021. ISSN 1424-8220. doi: 10.3390/s21113579.

Namibia Statistics Agency. Annual trade statistics bulletin 2019. *annual-report-2018-2019*, 2019.

Innocent Nyalala, Cedric Okinda, Luke Nyalala, Nelson Makange, Qi Chao, Liu Chao, Khurram Yousaf, and Kunjie Chen. Tomato volume and mass estimation using computer vision and machine learning algorithms: Cherry tomato model. *Journal of Food Engineering*, 263:288–298, 12 2019. doi: 10.1016/j.jfoodeng.2019.07.012.

Cedric Okinda, Mingzhou Lu, Longshen Liu, Innocent Nyalala, Caroline Muneri, Jintao Wang, Hailin Zhang, and Mingxia Shen. A machine vision system for early detection and prediction of sick birds: A broiler chicken model. *Biosystems Engineering*, 188:229–242, 12 2019. doi: 10.1016/j.biosystemseng.2019.09.015.

Cedric Okinda, Yuwen Sun, Innocent Nyalala, Tchalla Korohou, Samwel Opiyo, Jintao Wang, and Mingxia Shen. Egg volume estimation based on image processing and computer vision. *Journal of Food Engineering*, 283:110041, 10 2020. doi: 10.1016/j.jfoodeng.2020.110041.

Miguel Romero, Yannet Interian, Timothy Solberg, and Gilmer Valdes. Targeted transfer learning to improve performance in small medical physics datasets. *Medical Physics*, 47:6246–6256, 12 2020. ISSN 0094-2405. doi: 10.1002/mp.14507.

Roots Namibia, 2021. URL `https://rootsnamibia.com/`.

Weixing Zhu, Yansong Peng, and Bin Ji. An automatic dead chicken detection algorithm based on svm in modern chicken farm. pp. 323–326. IEEE, 12 2009. ISBN 978-1-4244-6325-1. doi: 10.1109/ISISE.2009.62.