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Review of Poultry Monitoring using Computer Vision

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ABSTRACT

Poultry farming is an important unit in global agronomy, contributing immensely to the production of meat and eggs. Safeguarding the health and welfare of poultry is vital for ethical and financial reasons. In recent years, computer vision awareness has gained prominence as a powerful tool for poultry monitoring. This review paper provides an outline of the application of computer vision in poultry monitoring. We explore the different phases of this technology, with real-time image acquisition, object recognition, and behavior analysis. By connecting cameras and sophisticated algorithms, a computer vision system can distinguish unusual behavior, track poultry activities and observe its environmental conditions. Furthermore, this study discovers the benefits of computer vision in poultry farming, including early detection of disease, better production efficiency and improved animal welfare. In conclusion, the application of computer vision in monitoring poultry holds immense potential for the industry; by providing a corridor to a more sustainable and ethical poultry farming system with increased productivity. This paper equally discusses recent developments, challenges, forthcoming prospects in the field and academic research gaps identified.

Keywords:
Behavior Analysis,
Computer Vision,
Image Acquisition,
Object Recognition,
Poultry Monitoring.

INTRODUCTION

In the realm of modern farming, technological revolutions are seriously improving the way we approach farming practices, trying to achieve more precision, sustainability, efficiency, and animal welfare(Neethirajan, 2022). The introduction of computer vision and image processing techniques into poultry management has led to a transformative force in industry (Zhuang & Zhang, 2019), (Eijk et al., 2022). This transformative solution has revolutionized the poultry industry by using innovative image recognition technologies to provide real-time insights into the health, behavior, and overall well-being of poultry populations (Eijk et al., 2022). The genesis of poultry monitoring systems in the field of object detection dates back to the evolutionary period of computer vision and its introduction into various industries due to the need for non-invasive, accurate, and real-time monitoring systems (Zhuang et al., 2018), (Volkmann et al., 2022). In the past, methods of observations and interventions of poultry management have not only proven to be time consuming and labor intensive, but also result in inaccurate results due to certain human limitations (Zhuang & Zhang, 2019), (Okinda et al., 2019). The integration of this groundbreaking advancement ushers in some level of unprecedented automation that eases and streamlines operations in the poultry industry with the help of some sophisticated technological devices, such as sensors, microphones, and cameras as shown in Figure 1.0. The technological architecture consists of coordination between hardware and software components to capture images with the help of cameras, process and analyze the visual data (Neethirajan, 2022), (Monitoring et al., 2004). Camera, which acts as the eye of the system, is connected in a stationary position above the poultry environment depending on the individual design and method adopted (Eijk et al., 2022), (Bao et al., 2021). The system captures activities of the birds within a defined environment, ranging from movement, interaction within the flock, water consumption, and feeding patterns(Rushen et al., 2012), (Massari et al., 2022). Captured images are subjected to pre-processing steps, where noise is removed from the image, and the image is resized which will lead to enhancement of the image and extraction of all the key features, no matter how insignificant, such as nuanced behaviors and physiological features are recognized and interpreted for better outcome or result (Pereira et al., 2013), (Publishers, 2022). Implementation of deep learning models, which is the core of the system, is made possible through training of a vast dataset and validation of the model for better insights into the health and wellbeing of each bird (Neethirajan, 2022), (Eijk et al., 2022), (Fang et al., 2020). These will enable early detection of potential disease outbreaks and abnormalities for prompt and timely intervention (Zhuang et al., 2018), (Machuve et al., 2018). It will further help in isolation of potentially infected birds to minimize the spread of the disease, which will help in reduction of overall cost in treatment of flock when infection sets in. It also helps in improving bird and human health. In this review, we delve into the outstanding capabilities of this system, exploring how it seamlessly integrates advanced image processing, computer vision algorithms, and data analytics to establish a new era of poultry management. By providing farmers with irresistible levels of automation and accuracy to detect unusual changes using the remarkable potential of technology, this approach will lead to enhanced animal welfare. Operations are streamlined into more efficiency and better management practices that will shape the future of sustainable agriculture.

Figure 1: State-of-art technology consisting of sensors, microphones, and cameras used for monitoring the physiological and behavioral information of poultry, for early detection of changes or abnormalities that can be disease. Source: (He et al., 2022)

Evolution of poultry monitoring

The evolution of poultry monitoring can be viewed back to the early years of poultry farming, where farmers relied mostly on personal knowledge acquired over time to inspect birds (Okinda et al., 2019). Such manual management was the primary method employed or known at that time, which caused many setbacks (Chuang et al., 2021). As technology evolved over time, various sophisticated methods and devices were developed to improve the efficiency and effectiveness of poultry monitoring (Journal, 2020). Automation of several operations in poultry farms and use of some environmental sensors such as temperature, humidity, and ammonia sensors to provide conducive environments for our feathered companions (Čakić, 2022), (Niamat et al., 2020), (Ananya, 2022). It will also help to curtail the risk of widespread diseases and reduce stress on birds (Fang et al., 2020). Furthermore, data collection in poultry farms is simplified using these sensors, which give farmers more detailed information about their flock (Bumanis et al., 2022). The introduction of computer systems has led to significant improvements in poultry monitoring and management (Zhuang et al., 2018), (Volkmann et al., 2022), (Massari et al., 2022). Huge storage capacity in computer systems contributes to the storage of data and information, analysis of large amounts of data, and processing of more complex tasks, such as avian behavior classification, tracking, and detection of sick birds using deep learning applications (Neethirajan, 2022), (Zhuang & Zhang, 2019). The technological advancement in poultry monitoring using computer vision, artificial intelligence, and internet of things holds a promising or positive revolution in poultry management, making it more data driven, precise, and responsive to the evolving needs of both agriculturalists and users.

Different object detection models used in poultry detection

There are many object detection models that can be used for poultry detection in computer vision design. The selection of the model depends on several factors such as accessibility of hardware resources, application specific requirements for poultry detection, and preferred results between accuracy and speed(Shetty et al., 2021)(Sultana et al., 2020). Furthermore, some models required more dataset for training and fine-tuning to achieve optimal performance. Some frequently used models are:

i. YOLO (You only look once) is a real-time object detection algorithm recognized for its speed and exactness. YOLO splits the image into a grid and predicts bounding boxes and class probabilities for each grid cell (Shetty et al., 2021). YOLO's speed makes it appropriate for applications where rapid responses are required, for poultry monitoring in real- time video streams (Iyer et al., 2021).

ii. Faster R-CNN (Region Convolutional Neural Network) this is a commonly used two-stage object detection framework. It applies a region proposal network to produce potential object locations and then enhances these proposals to predict exact bounding boxes and class labels. However, because it is computationally more intensive than YOLO, it often produces better accuracy (Shetty et al., 2021)(Čakić, 2022)(Li et al., 2021).

iii. The Single Shot MultiBox Detector (SSD) is a single-shot object detection model that stabilizes speed and accuracy. It uses many convolutional layers of different measures to detect objects at different dimensions (Mathurabai et al., 2022)(Iyer et al., 2021). This is what makes SSD particularly appropriate for detecting objects of different sizes, which is essential in poultry detection situations.

iv. RetinaNet is a simple one-stage, unified object detector that works on the compact selection of object locations in an input image designed to correct the problem of class imbalance in object detection, where some classes may be less represented than others. It introduces a novel focal loss that emphasizes training on tough examples, making it applicable for cases where some poultry behaviors or conditions are unusual but important to distinguish(Sultana et al., 2020).

v. Mask R-CNN: This is an old-fashioned object detection model that focuses on bounding box detection. It also covers the concept of instance segmentation(Chuang et al., 2021). Mask R-CNN can be used to detect poultry and also make available pixel-level masks drawing their shapes. This can be beneficial in situations where comprehensive information about poultry contour is necessary (Eijk et al., 2022)(Chuang et al., 2021).

Before choosing an object detection model for poultry detection, issues such as the available computational properties, required accuracy, real-time processing requests, and detailed characteristics of the poultry background should be considered. It's always good to try out a few models and fine-tune them for your specific use case to attain optimum results.

General workflow for poultry image analysis using computer vision

In computer vision, image analysis typically involves certain steps deployed to process and extract useful information from a series of frames. It is very necessary to note that image processing analysis workflow can vary due to specific version of computer vision application used, availability of tools, techniques, and complexity of task at hand (Shetty et al., 2021)(Eijk et al., 2022). Here are some general outline of poultry image analysis workflow using computer vision. Figure 2.0 shows a general workflow of image processing.

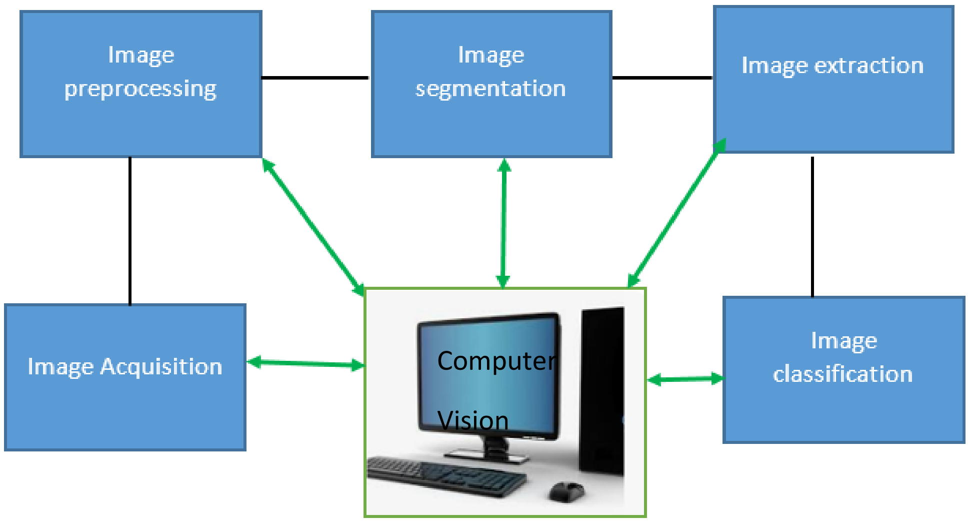

Figure 2: General workflow of image processing. Source: (Tran & Le, 2017)

i. **Image Acquisition**: acquisition of images is usually the first step in workflow, which simply means the process of collecting or capturing all the raw input images needed for particular research with the help of various devices, such as cameras, scanners, and other image capturing equipments (Eijk et al., 2022). Successful image recognition and object detection are always determined by accurate, quality, and suitable images acquired. Acquired images in real-world scenes are converted to digital representations use by computers for subsequent analysis, interpretation, and manipulation (Čakić, 2022). Format of the image such as JPEG, PNG, and TIFF are considered in this stage, as resolution, color spaces, computer vision image calibration. It also ensures accurate color representation and consistency across different images.

ii. **Image preprocessing**: in computer vision image preprocessing can be described as operations and techniques used to refine raw images before they are subjected to more advanced algorithms for analysis, recognition, detection, or any other related tasks (Eijk et al., 2022). The most important goal of image preprocessing is to upgrade the quality of the images, filter to remove noise, correct distortions prepare them in a way that makes subsequent analysis more accurate and effective (Čakić, 2022). Different image preprocessing techniques are strictly required by some applications while some are needed to either correct or adjust certain distortions in the raw image. Below are some image processing techniques: image resizing, normalization, background removal, thresholding, color correction, standardization, geometric transformation, and contrast enhancement. Effective image preprocessing techniques can significantly improve the entire performance of subsequent computer vision algorithms and enhance the accuracy of the analysis or detection (Neethirajan, 2022) (Pereira et al., 2013).

iii. **Image Segmentation:** Image segmentation in computer vision can be defined as the process of splitting an image into meaningful and distinct regions based on certain criteria. The main objective of image segmentation is to bring together pixels or regions that belong to the same object or structure while separating them from other objects or the background (Eijk et al., 2022). This is a fundamental step in various computer vision applications where object localization, recognition, and analysis are required. Image segmentation is essential because it identifies and separates different objects or regions within an image, enabling more targeted and accurate analysis. The following image segmentation techniques are used: graph cut segmentation, contour detection, watershed segmentation, clustering-based segmentation, edge-based segmentation, thresholding, and region-growing segmentation(Neethirajan, 2022).

iv. **Feature Extraction:** is the process of identifying, selecting, and representing unique and relevant information from the input image data. These distinctive features are essential in the subsequent analysis of tasks such as object detection, recognition, and classification (Zhuang & Zhang, 2019)(Zhuang et al., 2018). Feature extraction helps reduce the dimensionality of data while maintaining important information that differentiates between different objects or patterns in the images(Kayabaşi, 2022). Features are characteristics of an informative image and discriminative. They can represent various aspects of the image, such as edges, textures, shapes, corners, and histograms of oriented gradients and patterns (Eijk et al., 2022).

v. **Image classification Image:** classification in computer vision is the process of categorizing an input image into one of several predefined classes or categories. The major aim of image classification is to allocate a label or class to an image based on its visual content (Zhuang et al., 2018)(Eijk et al., 2022). This is an essential task in computer vision, which is also used in a wide range of applications, such as object recognition, scene understanding, health diagnosis and facial recognition. Image classification uses a learning method to train and learn the patterns and features that differentiate different classes of images(Zhuang & Zhang, 2019). The model is trained to learn the pattern and, in the process, predict and classify subsequent images(Neethirajan, 2022).

Recent Developments

It is very important to note that the computer vision field is gradually developing in the area of artificial intelligence and machine learning to address certain issues in poultry farms that are impeding production (Sultana et al., 2020). As the field continues to evolve in a positive direction, more development in the area of automation in poultry behavior detection and health management system that promotes early disease detection to prevent outbreaks and minimize losses. Furthermore, an automated assessment, sorting of poultry products and environmental control system. This development will further promote awareness and acceptance of computer vision in poultry farming is anticipated to increase, leading to increase in production and efficiency in addition to sustainable outcomes for monitoring and management(Neethirajan, 2022).

Research Gap

The possible research gap in poultry monitoring using computer vision is the development of tough algorithms for precise detection and classification of poultry behaviors and health signs in dynamic and chaotic farm environments. Present computer vision systems may find it very difficult to identify distress or illness in poultry within complex background and fluctuating lighting situations. In addressing this research gap, integrating refined machine learning models, by leveraging on advanced image processing techniques, and collecting different datasets to upgrade the generalization and robustness of poultry monitoring systems will be necessary. Furthermore, the research can also leverage on integrating multimodal sensing modalities, such as depth sensing or infrared imaging, to further improve the performance and consistency of computer vision based poultry monitoring systems in a difficult real-world environment.

CONCLUSION

In recent years, object detection using convolutional neural networks has improved significantly, which has led to general improvements in object detection models. The choice of object detection model or technique should be based on the particular requirements of the research or project and the available dataset used for training and validation of the design. Each model has area where it has strength and weakness. Computer vision is a game-changing technology for poultry farming because of its several benefits, from enhancing bird welfare to boosting operational efficiency and improving product quality. Continuous surveillance of birds' behavior, health, and living conditions will help in the early detection of abnormalities and diseases, prompt intervention to curtail spread of the disease.

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