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ROBOTICS APPLICATION IN POULTRY FARMING: PROBLEMS AND PROSPECTS

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Abstract
Poultry farming plays a pivotal role in addressing human food demand. Robots are emerging as promising tools in poultry farming, with the potential to address sustainability issues while meeting the increasing production needs and demand for animal welfare. This review aims to identify the current advancements, problems and prospects of development for robotics in poultry farming by examining existing challenges, solutions and innovative research, including robot-animal interactions. This paper covers the application of robots in different areas, from environmental monitoring to disease control, floor eggs collection and animal welfare. Robots not only demonstrate effective implementation on farms but also hold potential for ethological research on collective and social behaviour, which can in turn drive a better integration in industrial farming, with improved productivity and enhanced animal welfare.

Keywords Increasing production needs, challenges, solutions and innovative research, robot-animal interactions.

INTRODUCTION

In the modern era of Information and Technology, gadgets and electronic devices are now inevitable in our day-to-day life. Technology helps in routine activities in a well-organized manner and move forward at ease. Activities such as poultry farming is not left out. Poultry farming plays a crucial role in meeting the growing demand for affordable and safe food products (Sarıca et al., 2018). Poultry production is cost-effective (Ahmad et al., 2022; de Mesquita Souza Saraiva et al., 2022) and offers high-quality proteins (Attia et al., 2022; de Mesquita Souza Saraiva et al., 2022). Furthermore, it contributes to economic and social sustainability by creating favourable investment opportunities for producers (Rodić et al., 2011). Nevertheless, modern poultry farming faces challenges, including animal health and welfare, poultry house management, production, and human-induced issues, which are critical for sustainability in poultry farming (Gunnarsson et al., 2020; Hafez and Attia, 2020). Poultry farming management is transitioning from human labour to smart systems facilitated by machines (Ren et al., 2020). The application of smart technologies in poultry farming is expected to enable faster and more effective farm and animal monitoring, leading to better-informed decision-making through the evaluation of extensive data (Sharma and Patil, 2018).

Among the various technological tools, robots are emerging as a prominent solution in poultry farming, serving diverse functions such as phenotyping, monitoring, management, and environmental control (Sahoo et al., 2022).

Recently, functional robots have been developed in poultry farming that can perform specific tasks – such as collecting floor eggs and dead birds, thus saving labour and facilitating the production (Astill et al., 2020; Wu et al., 2022; Zhao, 2021). However, research on the impact of robots designed for direct contact with animals on animal health and welfare is limited (Dennis et al., 2020; Parajuli et al., 2020). Additionally, robots have shown potential in studying collective and social behaviour through interaction with animals, with robot-animal interaction presenting a promising research area (Gribovskiy et al., 2018). Such studies are inspired by the rapid social attachment mechanism known as filial imprinting observed in young animals (Vallortigara and Versace, 2022). Robots interacting with animals hold a huge potential in the investigation of social behaviour and ethological research because they enable highly standardized, controlled, replicable and reproducible experimental designs. This innovative approach allows to explore complex social dynamics in various species (Romano et al., 2019).

There is growing interest in robotics for poultry farming. Previous work has explored the potential impact of smart technology in the poultry industry, focusing on robotics, advanced sensors, automation technology, AI (Artificial Intelligence), big data analysis, internet of things, and transportation (Abbas, 2022; Park et al., 2022; Ren et al., 2020; Wu et al., 2022). Robot-animal social interactions and the impact of robots on animal welfare and animal behaviour in poultry had limited coverage.

Challenges in Poultry Farming

Animal health and welfare: Ensuring animal health is crucial in poultry farms. Poultry diseases pose a significant threat, as some of them have the potential to escalate into pandemics with far-reaching global consequences (Carenzi and Verga, 2009). To mitigate such risks, continuous monitoring of poultry is essential for disease prevention, biosecurity measures, early diagnosis, and timely treatment (Pearce et al., 2023).

Upholding animal welfare (Webster et al., 2005) and "life worth living" (Mellor et al., 2016) while ensuring sustainable production practices (Yang et al., 2020) is another challenge. To achieve a comprehensive assessment of animal welfare, standardized parameters must be established and accurately monitored (Wemelsfelder and Mullan, 2014). The evaluation of animal welfare revolves around indicators such as proper nutrition, good health, suitable housing, and appropriate behaviour (Paul et al., 2022). To evaluate animal welfare, it is fundamental to understand the natural behaviour of a poultry species (Putyora et al., 2023), including social behaviour.

Poultry house management: Among livestock systems, poultry systems are considered environmentally friendly, because produce low greenhouse gas emissions (Leinonen and Kyriazakis, 2016; Vries and Boer, 2010) and lower water usage (Gerber et al., 2015; Vaarst et al., 2015). However, they still require special attention to their environmental impact, particularly concerning issues such as ammonia release and nitrate leaching. Environmental impacts on poultry farms arise directly from energy use, housing, and manure management. To enhance environmental sustainability, it is crucial to measure and monitor the level of environmental impacts overall. Improving poultry housing and developing new strategies for manure management have the potential to further improve the environmental sustainability of the poultry industry (Costantini et al., 2021).

Maintaining optimum environmental conditions needs proficient and stable poultry house management at every stage of production (Flora et al., 2022). Environmental factors, including temperature, humidity, ventilation, gas concentration, and lighting, profoundly influence poultry health and performance (ElZanaty, 2014; Sarıca et al., 2018; Zhang et al., 2016).

Another vital aspect is litter management. Contaminants, such as feed residues and faeces, can lead to the proliferation of bacteria in the litter. Accumulation of waste can result in increased ammonia gas levels in the poultry house due to microbial decomposition (Sakamoto et al., 2020). High humidity in the litter also poses a significant problem for flock health and welfare (Sakamoto et al., 2020). Therefore, the litter must be regularly monitored and effectively managed throughout the production cycle (Sakamoto et al., 2020).

Production: Challenges in poultry production encompass ensuring food safety while maintaining low production costs. Expenses related to feed, maintenance, and equipment constitute the fundamental costs, but production losses also significantly impact farming operations (Hafez and Attia, 2020). Identifying low-yielding hens in egg production and closely monitoring their egg-laying behaviour can aid in cost reduction (Aral et al., 2017; Dogan et al., 2018; Wu et al., 2022).

Free range systems in poultry farming are a method of where hens are provided access to outdoor areas for at least part of the day (Miao et al., 2005; Petek and Cavusoglu, 2021). These systems give hens to areas with nests, perches and litter, allowing them greater mobility and opportunities for natural behaviour (Hartcher and Jones, 2017). However, it's important to note that floor egg problems can arise in these systems, leading to reduced production (Oliveira et al., 2019). Collecting eggs from the floor becomes a daily task, which increases labour costs. Additionally, eggs left on the floor can be broken or eaten by birds. Moreover, if the eggs are not collected promptly, they may mix with the litter and manure, elevating the risk of contamination and adversely affecting food quality and safety (Li et al., 2020a; Chai, 2022).

Human-induced issues: The general duties of breeders in the poultry industry encompass daily care of the animals, health, and welfare control, and monitoring of the poultry house. Additionally, breeders are responsible for the daily egg collection and dispatch in laying hen breeding. However, with the increase in herd size and the adoption of different breeding systems, the observation and management of the herd have become more challenging (Vroegindeweij et al., 2018). Manual observations are labour-intensive, time-consuming, costly, and prone to subjective information (Parajuli et al., 2020). Therefore, the implementation of automatic monitoring equipment and effective use of technology is imperative to achieve efficient monitoring and informed decision-making (Buijs et al., 2018; Buijs et al., 2020; Vroegindeweij et al., 2018).

Furthermore, breeders' increased activities within the poultry house may cause stress in the animals and lead to cross-contamination by carrying disease factors between the birds. Such situations pose risks to occupational health and safety (Ren et al., 2020). The robots discussed in Section 3 offer potential solutions to overcome human-induced problems in poultry houses with their functionalities.

Robots Used in Poultry Farming

The increasing interest in precision and smart agriculture has prompted extensive research into the application of AI and robotics in agricultural production (Usher et al., 2017). Recent advancements in hardware and software, including robots, sensors, 5G networks, and cloud infrastructures, have facilitated the abundant evaluation of data in agriculture. These data are invaluable for assessing and enhancing production during the control and decision-making phases (Park et al., 2022). Robotic systems that operate on farms and assist breeders (Sahoo et al., 2022) are expected to play a more prominent role in the future, equipped with machine capabilities such as perception, reasoning, learning, communication, task planning, execution (Ren et al., 2020).

Robots find application in various agricultural sectors, including planting, livestock, aquaculture, and poultry farming (Sahoo et al., 2022). In the context of poultry farming, both commercial and experimental robots have been developed to perform diverse tasks aimed at enhancing production, reducing the workforce, safeguarding animal health, and improving welfare, making robots increasingly central in this area (Park et al., 2022).

Poultry farming entails several tasks that need constant monitoring, such as identifying sick and deceased animals, monitoring environmental conditions within poultry houses, cleaning, disinfecting litter, and collecting floor eggs. These tasks are laborious and repetitive (Abbas et al., 2022). Robots have proven effective in information detection and production management (Astill et al., 2020). Robots equipped with advanced sensory and decision-making technologies have the potential to efficiently execute designated tasks, enhancing production efficiency (Ren et al., 2020).

Compared to humans, robots offer the promise of superior accuracy, consistency, and efficiency in monitoring birds and their environment (Mamun, 2019; Park et al., 2022). Human observations, in fact, can be subjective, depending on the observer's experience (Ren et al., 2020; Yang et al., 2020), and might be too expensive to be performed constantly. On the contrary, robots equipped with sensors using artificial intelligence and machine learning can continuously gather localized data as they navigate through the poultry house. This sustained real-time data collection can enable the timely detection of diseases, food safety concerns, and indoor environmental conditions through a robust sensor network (Abbas et al., 2022; Park et al., 2022).

Robots can contribute to increased biosecurity and reduced human-animal interactions in poultry houses, as they reduce the need for frequent human intervention (Gittins et al., 2020). Daily inspections are essential to ensure the proper functioning of systems and the well-being of the animals. Breeders must traverse the poultry house multiple times a day to observe the animals and monitor their behaviour and living conditions (Abbas et al., 2022; Parajuli et al., 2020; Park et al., 2022). However, human breeders may inadvertently become disease vectors, transferring pathogens and viruses between houses and cross-infecting flocks, leading to the rapid spread of diseases (Park et al., 2022). By replacing human labour with robots, the potential for human-induced issues is diminished, and biosecurity is improved by reducing human activities in the henhouse.

Environmental Monitoring: To enhance poultry management in both layer and broiler farming, constant monitoring of the poultry house and animals is essential. Environmental monitoring provides valuable data such as farm air quality, temperature, humidity, air velocity, and carbon dioxide levels for poultry management and assessment of animal health and welfare (Park et al., 2022). Real-time data acquisition facilitates informed decision-making, including the maintenance of favourable environmental conditions for optimal production and the early detection of disease outbreaks. Furthermore, these data contribute to improving operational productivity (Astill et al., 2020; Kaur et al., 2021; Olejnik et al., 2022; Wolfert et al., 2017). Therefore, robots equipped with sensors, cameras, and other systems can contribute to the development of the poultry industry (Astill et al., 2020; Zhang et al., 2016).

Scout (2023), (formerly known as ChickenBoy, developed by Faromatics, Spain), is a robot that works suspended from the ceiling, about half a meter above the birds.

Fig. 1: Scout (2023), (formerly known as ChickenBoy, developed by Faromatics, Spain)

This autonomous robot is equipped with thermal and light cameras, sensors for temperature, humidity, air velocity, CO_2, NH_3, light, and sound, as well as a laser pointer to stimulate the movement of birds. As indicated in the product specifications, this robot can control the distribution of birds, detect sick and dead birds, and identify wet spots on the litter and drinkers without direct contact. The robot enables early diagnosis of intestinal diseases by monitoring bird faces and provides images for the detection of leg health. The breeders receive updates from the robot via text message or emails.

Poultry Patrol (2019) is produced by a robotics company that designs multi-tasking robots. Per the robot's intended application, the robot, equipped with autonomous and remote-control capabilities, can monitor farms and animals using various types of integrated cameras. It provides early warnings to breeders by identifying sick and deceased birds through remote monitoring and video recording features.

Fig. 2: Poultry Patrol (2019)

Liu et al. (2016) designed a mobile robot equipped with an intelligent poultry monitoring system. The robot collects environmental parameters and obstacle information related to poultry and transmits this data to the host wirelessly. Subsequently, the host performs data acquisition, processing, display, storage, and remote control. Octopus XO (2021), developed by Octopus Biosafety, is a multi-task robot capable of collecting various environmental data, including temperature, humidity, CO2, ammonia, sound, and light intensity.

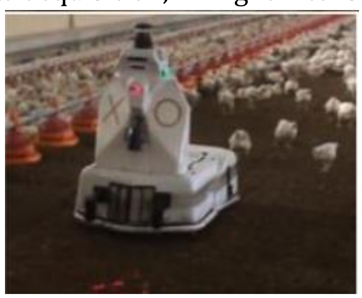

Fig. 3: Octopus XO (2021)

Disease control: Pathogenic infections are among the most critical challenges in poultry farming, as they can spread rapidly within the poultry house. Researchers have focused on developing robotic systems to quickly identify sick animals and remove dead birds from the herd (Li, 2016). Equipping robots with sensors for early warning systems allows the monitoring of disease and food safety-related pathogens in birds (Abbas et al., 2022; Park et al., 2022).

Nanny robots (Charoen Pokphand Group) are designed to monitor the body temperature and movements of animals in conventional 3-layer cage systems using thermal cameras. The robot can detect sick and dead chickens by identifying birds with abnormal temperature values and inactivity (Chicken Nannies, 2017). Li (2016) designed a robot to identify sick and dead birds in cages. The robot warns the animals by hitting the cage and detects the movements of the birds using image processing methods. However, the manual operation and hitting action may cause increased stress in birds.

Fig. 4: Nanny robots

Liu et al. (2021) designed a robot with two modes to remove dead chickens from the poultry house. One mode allows for remote control, while the other is autonomous, and the system can work without human intervention. The robotic system includes arms, a conveyor belt, a storage area, and a sweep- in device. Dead chickens are identified using the YOLO v4 algorithm, an object detection network based on deep learning (Bochkovskiy et al., 2020; Redmon et al., 2016). The system exhibits high reliability, with accuracy, precision, and recall rates of 97.5%, 95.24%, and 100%, respectively. However, recognizing dead chickens poses a challenge because the dead birds' shapes are incomplete and look very similar to a healthy chicken in a sitting or lying position. This similarity can impact the accuracy of image classification. To enhance precision and accuracy, the size of the training dataset for the model should be increased and identification errors should be reduced. Li et al. (2022) developed a robot equipped with a camera and two grippers mounted at the end of a robotic arm, designed to remove dead chickens.

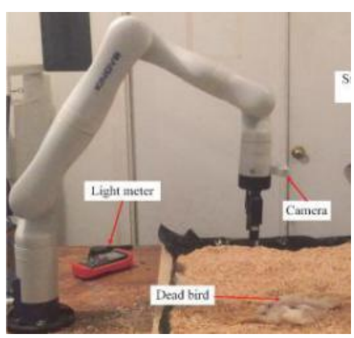

Fig. 5: Li et al. (2022) Robot

The robotic arm (Gen 3, Kinova Inc., Boisbriand, QC, Canada), along with the camera and two grippers (Robotiq 2F-85, Kinova Inc., Boisbriand, QC, Canada) at the end, was securely mounted on a table. The robot underwent testing to assess its ability to grasp and lift dead chickens present on the table under varying light intensities. The robot arm has a maximum payload capacity of 2000 and can move with 7 degrees of freedom, allowing for versatile motion. The success rate of finding and collecting dead chickens was evaluated at different light intensities, resulting in rates of 53.3%, 80%, 86.7%, 90%, and 90% at 10, 30, 60, 70, and 1000 light intensities, respectively. The robotic arm in question has been specifically engineered for the purpose of retrieving deceased chickens from a stationary table. It is important to note that this robotic arm has not yet undergone testing within the dynamic environment of a live poultry house. Furthermore, research findings reveal a noteworthy observation: a decrease in light intensity has been found to significantly impair the performance of the deep learning model. Specifically, this reduction in illumination adversely affects the model's capacity for object detection, image processing, orientation identification, and, ultimately, its ability to execute the final pick-up performance (Li et al., 2022). Poultry Patrol (2019) utilizes thermal imaging to monitor the body temperatures of chickens as it moves through the poultry house, enabling the identification of sick and dead birds. Similarly, the autonomous robot Scout (2023) employs an infrared and visible light camera to detect deceased chickens and diseases. Both systems monitor temperature and bird movements to identify sick and deceased animals in caged and cage-free systems.

Collecting floor eggs: The transition from cage system to cage-free systems aim to improve the welfare of laying hens (Ochs et al., 2019; Vroegindeweij et al., 2016) by providing them increased space for movement, perching, dustbathing, and nesting. This transition allows hens to spread their wings and express natural behaviours, ultimately leading to a reduction in confinement-related stress (Bhanja and Bhadauria, 2018; Hartcher and Jones, 2017). However, in cage-free systems hens may lay eggs in areas outside the nest, such as corners of the hen house and dim environments (Li et al., 2022). While cage-free systems provide hens with various areas such as nests, perches, and litter (Hartcher and Jones, 2017), floor eggs are a common occurrence in these systems and reduce production performance (Oliveira et al., 2019). Automatic egg collection robots have been developed to address this issue.

Unlike commercial robots, scientific research on the use of robots in poultry farming has primarily focused on addressing the difficulty of collecting floor eggs. These robots can also reduce human-induced problems mentioned in section 2.4 by reducing the need for human labour in egg collection. Vroegindeweij et al. (2014) developed an autonomous robot, PoultryBot, for collecting floor eggs in poultry houses.

Fig. 6: PoultryBot

The robot, equipped with a spiral spring on the front for egg collection, successfully collected over 95% of the eggs (Vroegindeweij et al., 2014b). This robot can drive autonomously for more than 3000 m in a commercial poultry house and collect 46% of 300 eggs. A collection failure occurred in approximately 37% of eggs (Vroegindeweij et al., 2018). The researchers suggested that by improving navigation, obstacle handling and control algorithms, the robot could be used in commercial poultry houses and dense animal environments in the future (Vroegindeweij et al., 2018).

Chang et al. (2020) designed a mobile egg collection robot using a computer vision-based platform that can recognize white and brown eggs in free-range farms.

Fig. 7: Mobile egg collection robot

The robot moves toward the eggs with visual tracking, collects them, and stores them in its chamber. In experimental tests, the robot collected between 60% and 88% of the eggs on flat and surrounded floors. Additionally, the robot could collect 8 eggs in 10 minutes in a 25 m2 area. For the robot to function efficiently, it relies on a flat surface free of objects such as egg-shaped stones within its operational area (Chang et al., 2020). Therefore, performance enhancements are necessary when deploying it in a free-range system.

Joffe and Usher (2017) developed GohBot, an autonomous egg-collecting robot that uses a mechanical arm with a vacuum mirror to collect eggs.

Fig. 8: GohBot

In tests, the success rate of egg collection was 91.6%. Li et al. (2021) developed an egg-collecting robot consisting of a deep learning-based egg detector, arm, gripper, and camera.

Fig. 9: Robotic arm

Eggs detected by image processing algorithms are collected using the robot arm and grippers. The robot collected brown and white eggs with a success rate of 92% to 94%.

Overall, egg collection robots developed for use in cage-free systems face general challenges, such as 1) mobility within the poultry house, including localization, navigation, path planning, and obstacle avoidance, 2) detecting eggs, 3) collecting eggs without breaking them, 4) storing eggs and possibly classifying them according to weight and shape.

Disinfection and litter management: The floor of the coop can become contaminated with bird faeces and food residues, leading to air pollution and the proliferation of pathogens. Regular cleaning and disinfection of the house are necessary to maintain animal health (Wu et al., 2022). Robots can be effectively used for smart production and appropriate disinfection in poultry houses (Feng et al., 2021). Proper litter management is essential for poultry farming, and regular litter scraping can help aerate the litter, preventing fermentation and reducing litter moisture (Tibot, 2021). Robots designed for litter scraping can address litter management challenges and support animal health.

Feng et al. (2021) designed an anti-epidemic (Feng et al., 2021) and disinfection spray (Feng and Wang, 2020) robot for use in poultry houses and farms. Comprising a robot, transport vehicle, sensors, spraying unit, and controller, it can work autonomously and with remote control.

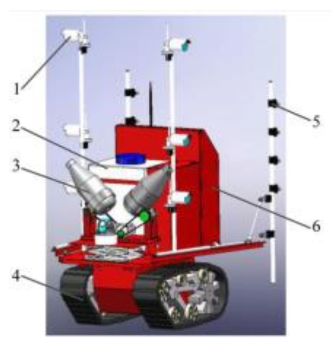

Fig. 9: Disinfection Robot

The researchers proposed the "Magnet-RFID" path detection navigation method for autonomous movement, which involves the manual installation of magnets and RFID (Radio Frequency Identification) electronic tags in the work area. The robot successfully ensured sufficient drug concentration in various parts of the cages to kill pathogenic microorganisms (Feng et al., 2021). As indicated in the product specifications, Octopus XO (2021), a multi-tasking robot, can autonomously move within the poultry house to scrape the litter and prevent the formation of scabs. It also reduces ammonia formation by providing better litter drying and performs litter cleaning by spraying a disinfectant solution. Spoutnic-NAV, another robot developed by Tibot, aerates the litter through the forks mounted on the back while moving in the poultry house (Tibot, 2021).

Fig. 10: Spoutnic-NAV

Enhancing bird activity: Birds need physical activity to maintain their health and well-being. Inactive or sedentary behaviour for extended periods can lead to health issues in birds (Abbas et al., 2022). With the development of production systems characterized by rapid growth rates in broilers, fast-growing strains are used in commercial breeding (Zuidhof et al., 2014). It has been reported that faster-growing breeds have higher inactivity, behavioural traits are affected by the growth rate, and fast-growing breeds sit more, feed more, and walk less than slow-growing breeds (Dawson et al., 2021; Hartcher and Lum, 2020). As higher activity can reduce litter contact, more active animals have been evaluated to have better feather cleanliness, lower hock burn levels and better leg health (Casey-Trott et al., 2017; Dixon, 2020; Hartcher and Lum, 2020). Robots have been shown to be effective in encouraging movement in broilers, leading to improved bone quality in animals (Hartcher and Jones, 2017; Janczak and Riber, 2015).

The two main approaches used in free-range poultry farms to encourage animal movement are mobile robots and laser pointers. Mobile ground robots that move within the poultry house trigger the animals around them to move as well (Li et al., 2022; Tibot, 2021; T-Moov, 2022).

Fig. 11: T-Moov

Alternatively, robots with laser pointers project laser lights onto the floor, encouraging the birds to move (Scout, 2023). Tibot Technologies claim that their commercial autonomous mobile robots, T-Moov and Spoutnic NAV, increase bird activity in the poultry house and mitigate the issue of floor eggs in cage-free systems. Additionally, increased bird activity resulted in higher feed consumption and a natural weight gain of 300 grams per animal. Moreover, active birds required fewer antibiotics to achieve weight gain naturally (Ren et al., 2020; Tibot, 2021; T-Moov, 2022).

The robot Octopus XO serves the dual purpose of litter cleaning while stimulating bird activity with laser pointers (Octopus XO, 2021). Similarly, the robot Scout (2023) has asserted its capability to stimulate animal activity through the utilization of laser pointers. Li et al. (2022) reported that a ground robot designed to reduce floor eggs also effectively encouraged bird movement. Another study by Yang et al. (2020) found that robots significantly increased the activity of broilers.

Robots use in poultry farming: Challenges and Solutions

Overall, robots for poultry farming are still limited in functionality and adaptability, since most robots are designed to perform a single, specific task (Ren et al., 2020; Wu et al., 2022). Hence, research should expand multi-tasking abilities, via sensor integration and advanced technology, including AI (Alatise and Hancke, 2020). For instance, in the context of collecting floor eggs and managing dead birds, robots face several challenges. These include difficulties in accessing different locations within the poultry house, issues with target identification and capture due to factors such as poultry house infrastructure, bird movements, changing light intensities, and secluded areas. Moreover, robots designed to collect floor eggs encounter challenges in collecting eggs without breakage, as well as sorting and storing them (Chang et al., 2020; Li et al., 2022b; Vroegindeweij et al., 2018). To address these challenges, robots should be designed to operate effectively across various environmental conditions and production systems. To this aim, reliability of visual and tactile perception, combined with flexibility and safety of the movements, are particularly important. The development of algorithms related to object detection, localisation, navigation, path planning, and control is essential. Some robots can be operated manually and by remote control (Li, 2016; Yang et al., 2020), however, there is a need for autonomous work, reducing the need for constant manual or remote control. Visuo-tactile perception is crucial for autonomous robotic systems, especially if they have to grasp and manipulate objects (Navarro-Guerrero et al., 2023).

An important issue is the difficulty in avoiding obstacles while navigating within the poultry house (Dennis et al., 2020; Vroegindeweij et al., 2018). During the movement of robots, the unpredictable actions of the surrounding chickens can impact the detection of static obstacles. Simultaneously, the robots need to make necessary evasive maneuvers with respect to the moving chickens. These requirements impose a high demand on the robot's environmental perception capability and real-time path planning when confronting mobility-related challenges (see Section 2) including those associated with production and human-induced factors. It will be crucial to develop obstacle awareness systems to improve navigation and guarantee animal welfare.

Most studies on robotic applications in poultry farming have primarily focused on free-range systems. However, robots that come into direct contact with animals pose a risk of harming animals and, as a result, may operate at a slower pace (Abbas et al., 2022; Wu et al., 2022). To mitigate these risks and challenges, robots should be designed with the ability to avoid and regulate contact. A current solution is non-contact systems, such as those involving robotic arms mounted on the ceiling of the farm. However, these systems can hardly be implemented in existing farms and would require restructuring or building of dedicated facilities, complicating the logistics of implementation. Hardware solutions to reduce the risks of robot harming animals include protective equipment, such as robots built with soft materials.

In some situations, robot-animal contact is necessary. In cases where robots are deployed for the identification of sick birds, an additional capability for capturing and isolating animals has been shown to be viable when employed within an operational poultry farm in conjunction with the detection system (Liu et al., 2021). For enhanced welfare and biosecurity, robots should also incorporate an early warning system to promptly intervene in cases involving sick birds.

Poultry farms differ in size and organisation (Ren et al., 2020). However, most robotic studies are conducted in controlled experimental environments or within small-scale poultry houses (Vroegindeweij et al., 2018; Wu et al., 2022). Further tests and development are needed for large-capacity poultry houses, including tests on the integration of multiple robots to working together efficiently, in accordance with the size of the poultry house.

Effective and safe robot-animal interactions require knowledge of the species-specific needs in terms of social interactions. Research has just started to address these areas, with few studies that identify social learning mechanisms that can improve welfare and health in interactions with robots (Gribovskiy et al., 2018; Mostafavi et al., 2010). Further research is needed to understand how robots can be best integrated in commercial farms, from the point of view of hardware design and functionality.

Robot-animal interactions present opportunities and challenges. Ground-based robotic systems offer a promising avenue for enhancing animal mobility, with potential benefits for chicken welfare. Such benefits include a reduction in litter contact (Dixon, 2020; Hartcher and Lum, 2020), an improvement in bone quality (Hartcher and Jones, 2017; Janczak and Riber, 2015), as well as enhancement in foot health and feather condition (Yang et al., 2020).

At the same time, robots increase birds' energy consumption, with effects that have just started to be investigated. It has been suggested that this activity might o reduce egg nutrient accumulation in laying hens and decrease egg weight (Li et al., 2022b). Future research should target various parameters such as food consumption, egg weight and food conversion rate to assess the effect of robot use on overall yield in commercial poultry farming.

Potential stress arising from interactions between robots and animals, and whether robots pose lower or higher challenges to animals, are object of research. Ground robots, as they move around poultry houses, exhibit the potential to reduce the incidence of startling behaviour compared to human breeders, while simultaneously mitigating the risk of disease transmission within the poultry house (Park et al., 2022). Differences of responses to robots within the life course have not been investigated enough (Parajuli et al., 2018). Remarkably, research has revealed that chickens exhibit a propensity to form attachments to non-naturalistic agents, such as robots (Gribovski et al., 2018; Slonina et al., 2021). Furthermore, early exposure to robots can effectively mitigate fear reactions towards these artificial agents (Dennis et al., 2020).

The use of robots can be costly, especially for small-scale coops operations (Abbas et al., 2022; Mamun, 2019). It is crucial to conduct economic analyses to assess the viability of using robots in poultry houses. Such analyses should consider their potential effects on human labour, animal health, and production output to make informed decisions about investment.

Creating robots tailored for various functions in poultry farming demands a collaborative approach that delves into multiple domains, such as mechanical engineering, software development, data analytics, genetic animal breeding, animal behaviour, and animal welfare (Zhou et al., 2022). This diverse integration of specialized knowledge is essential in designing robotic solutions that precisely address the intricate demands of poultry farming, ensuring optimal performance, operational efficiency and animal well-being.

CONCLUSION

The exploration of robotic technology for poultry farming has enormous promise awaiting realization. The current research landscape, though limited, indicates the potential for robots to innovate poultry farming, reducing labour dependency and significantly enhancing management efficiency by aiding in animal and environmental monitoring. However, this potential has only just begun to be tapped. Further research is needed to fully harness the benefits of robotics in supporting efficient production and promoting animal welfare.

As the poultry industry delves deeper into the integration of robotic technology, the focus must emphasize the critical aspect of robot-animal interactions. Achieving effective solutions calls for the fusion of engineering innovation with a comprehensive understanding of animal needs and behaviour, as underscored by recent research work on imprinting and predispositions in poultry chicks (Rosa-Salva et al., 2021; Versace et al., 2018) and in adult chickens (Dennis et al., 2020; Nicol, 2023). One of the challenges ahead involves the need for increased data sharing and open-source development. Addressing these challenges and fostering collaboration is crucial for a comprehensive understanding of animal welfare.

Overall, the integration of robotic technology and innovation with a deeper understanding of animal needs and societal demands presents a transformative opportunity for enhancing both productivity and welfare in poultry farming. To fully realise this potential, increased research, collaboration, and attention to the animal welfare within robotic applications are essential.

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