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TYPES AND APPLICATIONS OF INNOVATIVE ARTIFICIAL INTELLIGENCE IN POULTRY FARMS

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ABSTRACT: The poultry farming world-wide face many challenges that adversely affects the production proficiency. Finding the optimal balance humans and the automation efficiency is crucial to obtain a maximum profit. Besides, improving of poultry welfare and production efficiencies necessitate some advanced modern technologies. The application of artificial intelligence (AI) and data-driven systems is regarded as an innovative solution to address many farm management problems. By the integration of AI, the industry has the opportunity to grow in terms of production quantity and poultry care quality with minimal added expense. Types of AI technology in poultry farms include machine learning techniques and robots. The machine learning technique decreases the need for big labeled data for training and helps in the transfer of knowledge, fast training, and better generalization on new tasks to enhance the performance parameters. This technique has different approaches such as Support Vector Machine, Single Shot MultiBox Detector, and Convolutional Neural Network that have a potential to reduce the labor and time and offer promising solutions for the rapid warning and accurate identification and differentiation of problems associated with poultry health. Moreover, innovative robots have been applied in poultry farms for monitoring, management, and environmental control as well as exploring of social dynamics. They are used in poultry farms for collections of eggs carcasses and eggs and transportation and slaughtering. Collectively, AI programs could be applied in poultry production for controlling environmental conditions, monitoring some behavioral conditions such as feeding, preventing some diseases, and correction of the hazardous usage of antibiotics with combating the increased incidence of antimicrobial resistance, and finally aiding in the rapid treatment. Therefore, this review highlights the types of AI models and their potential applications in poultry production.

Keywords: Antimicrobial resistance, behavior, diseases, environment, machine learning technique, poultry, robots

INTRODUCTION

Recently, the poultry production systems have faced significant obstacles resulted from the different infectious and non-infectious causes. These challenges have induced adverse economic losses in the production and posed important threats to the health of humans. Thus, through monitoring and controlling of such conditions have become a critical issue for the poultry producers. Conventional methods that have been used for handling of these problems are often unreliable, labor-intensive, and time-consuming. Therefore, there is a crucial necessity for more efficient and accurate methods to monitor and control of such conditions.

The developed automated farm management strategies can monitor the environment as well as the physiological and behavioral characteristics, and provide essential benefits to maximize bird's welfare and minimize production losses. The application of smart technology tools in poultry farming is promising and helps in evaluation of huge data, monitoring flocks, optimizing environmental conditions, detecting diseases, and enabling the farmers to make data-driven decisions to achieve sustainable growth in their businesses (Sharma and Patil, 2018). The previous studies showed the importance of AI technology applications in the poultry farming using advanced sensors, automation technology, internet of things, big data analysis, robotics, and transportation (Ren et al., 2020; Abbas et al., 2022; Park et al., 2022; Wu et al., 2022). The AI facilitates the analysis and integration of information, enabling data-driven decision-making, and enhancing business efficiency (Dwivedi et al., 2021). A combination of internet of things and AI spotlight on the field of the real-time monitoring of poultry and advance analytics and automation (Debauchea et al., 2020). Smart poultry farming system using AI could contribute to achieve the Sustainable Development Goals (SDGs) particularly when considering some key goals including no poverty, zero hunger, good health and well-being, and responsible consumption and production.

Overall, this article highlights the types of AI models and their potential applications in poultry production.

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The recent advancement in monitoring systems in poultry flocks is illustrated in table 1.

Table 1 - The recent advancement in monitoring systems in poultry flocks

Findings	Reference
Utilized a CNN pattern recognition structure to identify and classify healthy and diseased infected layers with *Clostridium perfringens* type A. They detected classification accuracies of 66.6% and 100% of the tested samples.	Sadeghi et al. (2015)
Used a CNN pattern (YOLO-V3 and Faster R-CNN) as an automated detector to differentiate between healthy and diseased broilers according to their droppings' shape, color, and water content.	Wang et al. (2019)
Improved the Feature Fusion Single Shot MultiBox Detector (IFSSD) to enhance the performance of the SSD model on Inception V3. They reached detection precision of 99.7% using a local dataset of an industrial base.	Zhuang and Zhang (2019)
Applied video surveillance, a depth camera, and an automatic health status classifier with an accuracy ranged from 0.975-0.978% to observe broiler chickens.	Okinda et al. (2020)
Achieved a recognition accuracy of 95.6% after using a machine learning classification algorithm method which was attached to a foot ring of each chicken to identifying the state of chickens.	Bao et al. (2021)
Used a combination of DenseFCN and the point supervision methodology and achieved an accuracy of 93.84% and a frame rate of 9.27 frames/second to count the number of chickens on a farm.	Cao et al. (2021)
Applied transfer learning on pre-trained image classification and CNN techniques to identify diseases from the images of chicken droppings. The validation accuracy of these approaches was 94%.	Mbelwa et al. (2021)
Achieved a high accuracy for the detection of chicken's behavior using YOLOv4 and Mask R CNN models.	Joo et al. (2022)
Developed a deep learning model based on YOLOv5x-hens and a CNN to track the number of hens in a real-time.	Yang et al. (2022)

SOME TYPES OF AI TECHNOLOGY THAT ARE APPLIED IN POULTRY FARMS MANAGEMENT

Machine learning technique

The transfer learning has been used in several domains such as computer vision, natural language processing, and speech recognition. The machine learning is a transfer learning developing computer program which can use the input information to produce new knowledge or improve the existing ones. Besides, it uses labelled data to develop accurate predictions as well as non-pre-assigned labels to identify datasets (Milosevic et al., 2019).

Machine learning technique has been employed beneficially in case of a limited dataset or when the manual annotating data are costly and time-consuming. Machine learning reduces the need for a large amount of labeled data for training. Moreover, it helps in knowledge transfer, fast training, and better generalization on new tasks with limited data to improve the performance parameters. The fine-tuning and feature extractors are the approaches of the transfer learning technique that convert raw data to feature vectors (Park et al., 2022). The deep learning approach is derived from the conventional machine learning technique and it can identify features from raw data without the need for notable engineering knowledge on feature extraction (LeCun et al., 2015).

Different innovative models have been applied to observe the behavior of birds and predict the infection early as possible. These proposed approaches include Support Vector Machine (RBF-SVM), Single Shot MultiBox Detector (SSD), and Convolutional Neural Network (CNN) such as You Only Look Once (YOLOv4), YOLOv5x, Visual Geometry Group (VGG16), Residual Networks (ResNet50), Extreme Inception (XceptionNet), and MobileNet (Okinda et al., 2020). These models can reduce the labor and time and they are promising for the rapid warning and accurate identification of problems associated with poultry health and welfare. The transfer learning using VGG16, ResNet50, and MobileNet approaches have been used for the precise and thorough processing of images. Moreover, the VGG16 approach achieved the highest accuracy when compared to the ResNet-50 and MobileNet models for the differentiation between heathy and diseased birds based on the bird's posture and feathers texture. The CNN is a type of the deep learning algorithms which has been emerged in the field of digital image processing. It is able to detect and classify objects in computer vision tasks based on the observation of the bird's physical features. Furthermore, YOLOv4 algorithm can recognize dead birds in the farms (Bochkovskiy et al., 2020).

Robots

Robots are applied in poultry farms for monitoring, management, and environmental control (Sahoo et al., 2022). This innovative approach permits exploring of social dynamics in different species (Romano et al., 2019). Standardized, controlled, replicable, and reproducible robots can interact with animals for investigation of a social behavior (Gribovskiy et al., 2018; Dennis et al., 2020; Parajuli et al., 2020). They can collect eggs and dead birds, thus save labor and facilitate production (Astill et al., 2020; Zhao, 2021; Wu et al., 2022). Researchers have focused on developing equipping robots with sensors to identify diseased birds, allow monitoring of disease birds, and dispose dead birds from the flock (Abbas et al., 2022; Park et al., 2022).

Most of robotic studies have been conducted under controlled experimental environmental conditions or in small-scale poultry houses (Vroegindeweij et al., 2018; Wu et al., 2022). Additionally, robotic systems have experienced experimental investigations to demonstrate their capabilities to monitor poultry houses and broader their future applications.

Robot's uses in poultry farms

Collection of carcasses

Nanny robot can monitor the movement and body temperature of birds in conventional 3-layer cage systems using thermal cameras. This robot can sense morbid and dead birds by identifying the inactivity and the abnormal temperature values of them. Moreover, the robot consists of two modes; one mode works as a remote control and the other is autonomous (Liu et al., 2021). The autonomous robot scout employs an infrared and visible light camera to identify morbid chickens. Both mods can screen the bird's temperature and movements to detect diseased and dead birds in cages and cage-free systems. Despite this robot shows high reliability (97.5%), accuracy (95.24%), precision (95.24%), and recall rates (100%), detecting dead chickens is somewhat difficult because their shapes are similar to healthy birds either in the sitting or lying position. An effective vision system is important for robots to accurately detect deceased birds. Also, drinkers and feeders in the deep litter closed systems may act as obstacles to identifying and collect dead carcasses. Therefore, the movement flexibility of dead bird's collection robots in around equipment's or the integration of flexible robotic arms and grippers should be improved to increase the mobility and accessibility (Althoefer, 2018). A robot equipped with two grippers and a camera at the end of a robot's arm was designed to remove dead chickens (Li et al., 2022a).

Collection of eggs

Automatic egg collection robots have been developed to reduce the human-induced problems and the need for human labor in egg collection, besides they could be used in the dense environments (Vroegindeweij et al., 2018). An autonomous robot (PoultryBot), equipped with a spiral spring on the front, has been successfully developed for collecting over 95% of the floor eggs in layers farms. This robot drives separately for more than 3000 m in the house and collects 46% of 300 eggs with a collection failure in approximately 37% of eggs (Vroegindeweij et al., 2018). Also, GohBot is an autonomous egg-collecting robot that uses a mechanical arm with a vacuum mirror to collect eggs with succeeding rate of 91.6% (Joffe and Usher, 2017). An egg-collecting robot consisting of a deep learning-based egg detector, arm, gripper, and camera has been developed (Li et al., 2021). Moreover, this robot can collect white and brown eggs in a rate of 94% using arms and grippers after eggs detection by image processing algorithms. Another type of robots has been designed to recognize white and brown eggs in free-range layers (Chang et al., 2020). This type used a computer vision based platform to move toward the eggs, collects 60% and 88% of the eggs on flat and surrounded floors, and then stores them in its chamber. Moreover, it could efficiently collect 8 eggs in 25 m^2 area within 10 minutes based on its contents of egg shaped stones within its operational area (Chang et al., 2020). However, there are some obstacles facing egg collection robotic techniques in the cage systems including the mobility within the poultry house, detection of eggs without breaking them, storage, and the possibly to classify them according to their weight and shape.

Transportation and slaughtering

Recently, the stunning and slaughtering of birds can be applied in the farm instead of the processing plants using robots which are able to transfer birds to the stunning sites for shackling (Park et al. 2022). Farm Processing and Transport (FPaT) is a system that has been used to reduce the birds stressors during handling during transportation from the flock to the slaughter houses, decrease the amount of water for scalding, and thus improves the carcass yield (Park et al., 2022). This system is composed of two mobile units; processing and transport trailers which are designed on standard 53-ft trailers (Park et al., 2022). Moreover, FPaT system also allows the non-significant differences in the major food quality matrix, visual properties, myopathy scores, water holding capacity, yield, and texture properties when compared with the traditional techniques (Park et al., 2022).

THE DIFFERENT AI APPLICATIONS USED IN POULTRY PRODUCTION

The different applications of AI in poultry farms are summarized in table 2.

Environment conditions

The AI approaches monitor environmental parameters around birds in a real-time and adjust them to create an optimal and stress-free environment. Debauchea et al. (2020) implemented an AI algorithm (Gated Recurrent Unit) to validate and predicate some environmental parameters. For instance, sensors such as camera and data acquisition systems could detect relative humidity, temperature, ventilation, and lighting systems (Fernandez et al., 2018; Lahlouh et al., 2020; Lorencena et al., 2020). Moreover, Monte Carlo simulation system could be used to monitor the litter moisture (Rico-Contreras et al., 2017). The edge computing solution system was applied to screen the temperature, humidity, and light intensity and transmit their levels by the end nodes ZigBee to the gateway network (Yang et al., 2019). One hand type of sensors also controlled the fan and light intensity, while the other hand uploaded data to the cloud. Additionally, the MQ137 gas sensor was implemented to measure ammonia (Raj and Jayanthi, 2018) and hydrogen sulfide (Handigolkar et al., 2016) levels in air. In comparison to the traditional chemical sensors, the multifunction electro-thermal system showed a faster response and a lower power consumption for the detection of ammonia level (Lotfi et al., 2019). An adsorbing material has been used to extract ammonia from the chicken's litter (Xu et al., 2017). An automated anti-epidemic or disinfection sprayer robot, comprising of transport vehicle, sensors, spraying unit, and controller, has been also designed and applied in poultry farms (Feng and Wang, 2020).

Table 2 - The different applications of AI in poultry farms

Applications	Reference
Detection of avian influenza virus using an interferometric biosensor	Xu et al. (2007)
Using of infrared spectroscopy and artificial neural networks for detection of uropathogenic *Escherichia coli* strains' susceptibility to cephalothin	Lechowicz et al. (2013)
Detecting jumping and landing force in laying hens using wireless wearable sensors	Banerjee et al. (2014)
Application of wireless activity sensor network to avian influenza monitoring system in poultry farms	Okada et al. (2014)
Using of intelligent procedure for the detection and classification of chickens infected by *Clostridium perfringens* based on their vocalization	Sadeghi et al. (2015)
Estimating broiler weights based on machine vision and artificial neural network	Amraei et al. (2017)
Prediction of moisture content in poultry litter using artificial intelligence techniques and Monte Carlo simulation to determine the economic yield from energy use	Rico-Contreras et al. (2017)
Removal of phosphate using aluminum-doped magnetic nanoparticles	Xu et al. (2017)
Management of broiler breeder feed intake and flock uniformity	Zuidhof et al. (2017)
Real-time monitoring of broiler flock's welfare status using camera-based technology	Fernandez et al. (2018)
Monitoring and health status identification using lot-based real-time poultry	Raj and Jayanthi (2018)
Detection of sick broilers using an early warning algorithm	Zhuang et al. (2018)
Diagnosis of infectious bursal disease with RNA microarray and machine Learning	Fang (2019)
Comparing between random forest and gradient boosting machine methods for predicting *Listeria* spp. prevalence in the environment of pastured poultry farms	Golden et al. (2019)
Detecting ammonia sensing using a platinum cantilever-based thermal conductivity and 3-omega technique	Lotfi et al. (2019)
Environmental monitoring of chicken house based on edge computing in internet of things	Yang et al. (2019)
Detection of automated sneeze using sound-based poultry health monitoring tool	Carpentier et al. (2019)
Detection of avian influenza-infected chickens based on a chicken sound convolutional neural network	Cuan et al. (2020)
Monitoring poultry behavior using edge computing and artificial intelligence	Debauchea et al. (2020)
Designing disinfection robot for livestock breeding	Feng and Wang (2020)
Predicting antimicrobial resistance in *Pseudomonas aeruginosa* with machine learning-enabled molecular diagnostics	Khaledi et al. (2020)
Implementation of multi input multi output fuzzy-PID behavior controller in poultry house systems	Lahlouh et al. (2020)
Assessing layer pullet drinking behaviors under selectable light colors using convolutional neural network	Li et al. (2020a)
Analysis of feeding and drinking behaviors of group-reared broilers via image processing	Li et al. (2020b)
Designing a framework for modelling, control, and supervision of poultry farming	Lorencena et al. (2020)
Microbial identification and antimicrobial susceptibility testing using Machine learning for matrix-assisted laser desorption/ionization–time of flight (MALDI-TOF) spectra	Weis et al. (2020)
Detecting poultry eating behavior based on vocalization signals	Huang et al. (2021)
Application of artificial intelligence for antimicrobial resistance	Lv et al. (2021)
Acceleration of antibiotic discovery through artificial intelligence	Melo et al. (2021)
Application of artificial intelligence in combating high antimicrobial resistance rates	Rabaan et al. (2022)

Behavior characteristics

Some behavior conditions of birds including resting, running, and feeding could be remotely and automatically monitored using internet of things technologies such as sensors, microphones, mobile phones, and cameras that are connected to a server or cloud for prompt processing and visualization (Ojo et al., 2022). The feeding systems schedules have been improved according to the environment, health, and behavior of individual birds (Zuidhof et al., 2017). The AI systems precisely control the timing and quantity of feed and tailor it according to the specific needs of the birds. These results in reduced feed wastage, healthier birds, and ultimately enhanced production. The changes in feed and water intake, feed conversion ratio, and body weight could be detected based on vocalization signals, machine learning technique, digital image analysis, and CNN approaches (Amraei et al., 2017; Li et al., 2020a, b; Huang et al., 2021). The piezoelectric crystals technique may evaluate the broilers locomotion deficiency based on analyzing the peak vertical force exerted on both feet at the weakness conditions. Moreover, it enables the identification of asymmetry between each foot force, which explained the uneven gait of layers (Banerjee et al., 2014). Under natural conditions, chicks reared with mother hens have learned some behavior conditions include resting times, pecking habits, and food preferences (Edgar et al., 2016). These chicks exhibit synchronization in resting activity and behavior. They spend more times feeding and less time standing and perches when compared with chicks raised without a mother hens (Roden and Wechsler, 1998). However, robotic researches allow robots to interact with chicks and support their social learning and development (de Mesquita Souza Saraiva et al., 2011).

Diseases prevention

The traditional manual methods for the diagnosis of poultry diseases are mostly laborious, time-consuming, unreliable, and sometimes fail to detect the specific infections accurately. Therefore, developing of a more rapid, accurate, and effective methods to overcome such challenge is an urgent need. The AI technologies can detect the possible diseases occurrence and trace their vectors or modes of transmission via analyzing some historical data. This line can help in the early warning capabilities to prevent the future outbreaks (Ojo et al., 2022; Park et al., 2022). The machine learning algorithms excel, deep regression network, digital image processing, and ResNet residual network have received increased attention for the rapid prediction and diagnosis of diseased flocks. The previous AI techniques are based on analyzing some behavioral and biological conditions such as sound, movement, and eating, or tracking production performance (Zhuang et al., 2018; Carpentier et al., 2019; Fang et al., 2020). Poultry diseases conditions including avian influenza (Cuan et al., 2020), infectious bursal disease (Fang, 2019), salmonellosis (Hwang et al., 2020), closteridiosis (Sadeghi et al., 2015), and listeriosis (Golden et al., 2019) could be diagnosed using CNN, random forest, and gradient boosting machines. Some wireless devices depend on the body temperature sensors and accelerometers have been applied for the chicks with a highly pathogenic avian influenza up to six hours before death (Okada et al., 2014). Moreover, Xu et al. (2007) developed a new, portable, and inexpensive biosensor to identify several strains of pathogenic avian influenza infected birds within few minutes. Infectious bronchitis and infectious laryngotracheitis of chickens could be also monitored using auditory sensing systems including machine learning techniques and digital signal processing (Carroll, 2018). These techniques of AI could provide more information to manage the flocks in a more rounded manner.

Antimicrobial resistance

The continuous development of antimicrobial resistance is an important challenge facing poultry industry (Lv et al., 2021). The AI programs may help in the correction of the hazardous usage of antibiotics, combating the increased incidence of antimicrobial resistance, and aiding in the rapid treatment without waiting the bacterial culture results (Rabaan et al., 2022). Consequently, the AI approaches reduce time to discover new drugs, ensure accuracy of the diagnosis and treatment, and lower the treatment costs (Lv et al., 2021; Rabaan et al., 2022). The infrared spectroscopy with artificial neural network can short the time for the detection of antimicrobial resistance from days to hours or even 30 minutes (Lechowicz et al., 2013), beside they can find new mutants of resistance (Melo et al., 2021). The different technologies of AI can control the antimicrobial resistance by gathering of data to construct decision support systems, designing new antimicrobials, and investigating drug combinations synergism (Boolchandani et al., 2019; Rodríguez-González et al., 2019; Khaledi et al., 2020). For the early and effective prediction of the antimicrobial resistance, the construction of comprehensive antimicrobial resistance databases for the integration of more cutting edge algorithms is important (Rabaan et al., 2022). Lv et al. (2021) used artificial resistance algorithms methods including nave Bayes, decision trees, random forests, RBF-SVM, and artificial neural networks for the monitoring of antimicrobial resistance problems. Similarly, flow-cytometer antimicrobial susceptibility testing, infrared spectrometer, and k-mer-based machine learning were applied for combating antibiotic resistance (Mulroney et al., 2017; Mahé and Tournoud, 2018; Inglis et al., 2020). By increasing the amount of the whole-genome sequence data and understanding the structural basis of resistance and rational design principle (Klevens et al., 2007), the AI models are better able to induce a high accuracy in surveillance programs (Deng et al., 2016, Argimón et al., 2020) and develop new, effective, and broad-spectrum antimicrobials (Weis et al., 2020). However, there are some challenges face the application of AI models to combat the antimicrobial resistance; 1) most programs do not consider the intermediate category of resistance that overlaps the susceptible and resistant categories and, 2) the only resistant or susceptible resistance can result in a false diagnosis.

CONCLUSION

There is no doubt on the significant effects of AI in the poultry farming and production. In the near future, AI is expected to alter the poultry sector and contribute positively by improving efficiency and accuracy at all aspects of the industry. Despite the AI technology models have been already implemented in the chain of poultry industry with immense potentials, they address several challenges and obstacles that cannot be overcome without the integration of all aspects. AI technology will lead to the understanding of sustainable industry which suppresses the generation of greenhouse gases and helps in gaining some SDGs including the decrease in wasted feed and breeding tasks. It is expected the continuous development of the broiler industry to meet the hunger and support the world's food. From a global standpoint of view, adoption of AI technology information systems is important to ensure that humans are taking environmentally friendly and use the feedback information to produce safe poultry production. Therefore, AI acts as a potential method for the next generation of poultry farming system. Encouraging further researches is needed for widening the scale of AI technology applications in large-capacity poultry houses in order to gain some of SDGs.

DECLARATIONS

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Author's contribution

Abd El-Ghany WA has collected and drafted the manuscript, formatted it, and approved the final manuscript.

Competing of interests

The author has not declared any competing interests.

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