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Application of artificial intelligence and machine learning in poultry disease detection and diagnosis: A review

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Abstract

The poultry population has increased exponentially from 13.9 billion in the early 21st century to 26.56 billion by 2022 worldwide, emphasizing the vital nutritional and economic part of this section. Simultaneously, the poultry sector faces a considerable amount of tests from diseases such as avian influenza, coccidiosis, mycoplasmosis, etc. that cost the industry multibillion-dollar losses each year. The groundbreaking and revolutionary possibilities of artificial intelligence and machine learning in poultry disease detection and diagnosis are discussed in this review. By capitalizing on data from physiological and behavioral traits like movement, vocalization, body temperature, and excreta, AI algorithms can detect indications of illness and pathological conditions, which means strengthening disease management and bringing down economic losses. High-precision image and video processing, non-invasive monitoring, the use of thermal imaging, and accurate tracking of poultry to spot health issues are some of the crucial developments that have also aided in analyzing stress and other abnormalities. Incorporating new-age technologies into feasible, applicable, and economical diagnostic tools that have the potential to transform poultry well-being, enhance the welfare of poultry, and upgrade production as well as handling processes is discussed here. The upcoming prospects include global partnerships, better data analytics, and extended research or studies for the management of diseases and behavioral anomalies in all poultry species. The collaboration of AI, machine learning, and biotechnology holds colossal promise for the poultry sector, guaranteeing food safety and ensuring public health.

1. Introduction

Since 1990, the population of poultry worldwide has more than doubled. The average yearly production of chicken meat worldwide from 1961 to 2018 was 45.93 million tons; however, in 2025, global production is expected to reach 139.19 million tons (Uzundumlu and Dilli 2023). Two main types of birds are produced broadly, egg-laying hens for egg production and broilers for meat purpose. In recent years, the value of the global poultry market increased enormously. It is expected to grow from 360 billion USD in 2023 to approximately 385 billion USD in 2024 at a compound annual growth rate (CAGR) of 6.9%. Further growth at a rate of 6.4% CAGR in 2028 will value the poultry market at 494.55 billion USD (www.statista.com). The poultry market is forecast to see bold growth in the upcoming years. Crucial movements in the forecast period of the poultry market comprise the adoption of technology such as camera-based weighing techniques, the application of machine learning and artificial intelligence, proper government aid, tactical partnerships, and smart investments. Poultry has become one of the fastest-growing sectors of the economy to cater the world's meat demand.

Since the poultry industry holds enormous economic importance, diseases that affect the industry all over the world should be highly taken into consideration for the protection of losses and the generation of income. Important diseases include bacterial diseases such as CRD (Chronic Respiratory Disorder), pullorum disease, and mycoplasmosis; viral diseases such as Newcastle disease, avian influenza, fowl pox, and infectious bronchitis; protozoan diseases such as coccidiosis; and ascaridiasis. The prevalence of these diseases leads to high economic losses in the poultry industry and small-scale producers around the world. Worldwide, coccidiosis causes roughly around 3 billion USD loss every year (Poultry Global Market Report 2024). Globally, 780 million USD is lost due to mycoplasmosis every year in the poultry sector. Loss of 40 million birds and economic loss of at most 3 billion USD were reported because of the avian influenza outbreak (Pawestri et al. 2020).

Machine learning and artificial intelligence (AI) can be used to detect and diagnose diseases in poultry. By analyzing data from various sources such as body temperature, movement, and vocalization. AI algorithms can detect signs of illness before physical symptoms are visible to human

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caretakers. This early detection can help prevent the spread of disease and improve the effectiveness of treatments. Meteorological conditions, flock demographics, and other factors that may account for the transmission of infections can be studied by machine learning and AI. Also, the impacts of outbreaks of diseases can be significantly reduced (Farahat et al. 2023). By spotting diseases and stressful conditions in the early stages and enabling action to be taken swiftly enough to avoid the negative impacts, it can assist in identifying animal welfare issues early on, improving and accelerating management decisions, and minimizing financial losses in the long run.

The productivity of birds can be chiefly enhanced if diseases are diagnosed at an early stage, controlled, and subsequently treated. Cheap, innovative, and practical diagnostic techniques can be manufactured that can be implemented in poultry farming. The mortality of birds can be notably reduced and even abolished at some point in the future with the recent advancements in technology. No compromise in the welfare of animal health can be made with the advent of automatic monitoring devices. Maximum output can be extracted with minimum labor and monitoring requirements with the proper implementation of automated devices. In this article, different physiological traits of birds, like excreta, vocalization, movement, behavior, and body temperature, have been discussed for the detection of diseases and diagnosis using machine learning and artificial intelligence.

2. Various criteria under which diseases can be detected and diagnosed

There are various criteria under which poultry diseases can be detected and diagnosed *viz*. images, excreta, sound, Body temperature, thermal imaging, and behavior and movement (Fig. 1).

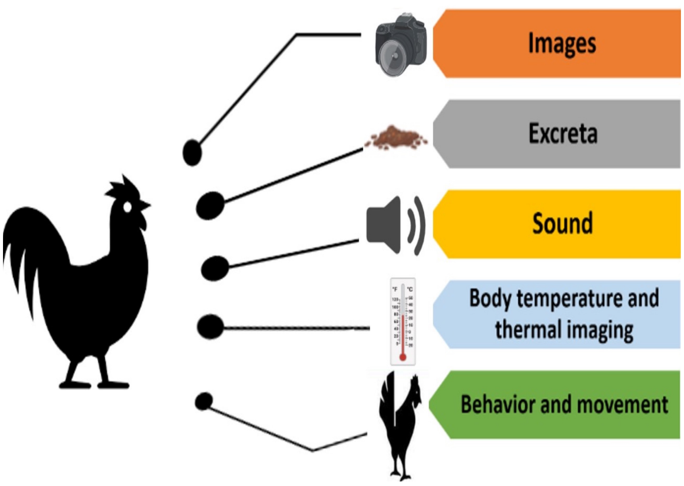

Fig. 1*: Detection of poultry diseases by artificial intelligence and machine learning*

2.1. Images

Several poultry diseases can be identified and detected by images and videos. Images that are digitally processed and evaluated by machine learning algorithms and artificial intelligence can help focus on poultry health issues and the detection of diseases. In a study conducted by Zhuang et al. (2018), broiler chicken injected with the bird flu virus were compared with healthy birds. Images of both categories of birds were taken, and their skeleton information was extracted through algorithms. Machine learning algorithms were used to check the health status. High accuracy rates were obtained with the Support Vector Machine (SVM) model, with an accuracy rate of 99.469% on samples that were tested (Mbelwa et al. 2021).

2.2. Excreta

Poultry excreta or droppings can act as vital indicators of their health. Droppings may significantly vary between healthy and sick birds and can aid in the diagnosis of a handful of diseases. For the detection of any kind of non-contact digestive pathological condition in broiler chicken with data set model training, machine learning can have an important role in diagnosis in the near future with robust models (Quach et al. 2020). In a study by machine learning algorithms for fluorescence imaging, an accuracy of 97.32% by efficient NET-BO was obtained in recognizing faeces from sick birds (Wang et al. 2019). Machine vision-based image recognition of chicken manure was proposed by some researchers, where grayscale characteristics from the image were used to check the normality or abnormality of the feces (Gorji et al. 2022). In Nigeria, some researchers created a dataset of poultry fecal images aimed at early detection and diagnosis of diseases. This dataset was made to help agricultural extension agents engage farmers in constructive programs (Zhu and Zhou 2021).

In a research conducted in Tanzania, a convolutional neural network (CNN) model was developed for the classification of healthy and unhealthy fecal images for the diagnosis and detection of diseases. The accuracy rates were 95.01% for VGG16, 95.45% for Xception V3, 98.02% for Mobilenet V2, and 98.24% for Xception. Mobilenet V2 showed good capability that can be used as a future diagnostic tool and can be operated from even a smart phone (Aworinde et al. 2023). In another study, a CNN deep learning solution was used for the classification of chicken feces, where the Xception net model had the highest accuracy of 94% in detecting the samples (Farahat et al. 2023). In one more study conducted in Indonesia, the YOLO v5 algorithm was used to analyze a chicken fecal image and had an appreciable accuracy rate of 89.2% (Machuve et al. 2022). The dropping image analysis can be developed significantly for future use as a proper diagnostic tool. Since diagnostic laboratory systems could not be accessible and affordable to poultry workers or farmers, diagnosis of individual chickens can also be done by genuine monitoring of them (Widyawati and Gunawan 2022).

2.3. Sound

Sound is an important indicator in poultry health monitoring and disease detection since birds frequently generate different vocalizations that alter in response to illness, stress, or discomfort. Different diseases can cause changes in the voice habits of chickens. Respiratory infections, such as avian influenza or Newcastle disease, induce breathing difficulties that appear as laborious breathing, coughing, or wheezing. Early detection of these alterations can assist to avoid spread of disease within a flock. Sadeghi et al. (2015) used the Neural Network Pattern Recognition (NNPR) structure to detect chickens injected with *Clostridium perfringens* type A and healthy ones based on the sound produced by them. The NNPR successfully diagnosed disease in chickens, with classification accuracies of 66.6% on day 16 and 100% on day 22. In another study, an accuracy as high as 98.5% was achieved when the Deep Poultry Vocalization Network (DPVN) was used to detect Newcastle disease using vocalization (Cuan et al. 2022). An algorithm developed by Carpentier et al. found that the sneezing sounds of chicken in a loud environment or surroundings were categorized as sneeze or non-sneeze with an accuracy rate of 88.4% (Carpentier et al. 2019). An audio analysis-based learning method for the detection of avian influenza was developed by Huang et al. 2019, using sound and environmental noise. The Mel Frequency Cepstral Coefficient (MFCC) was used to differentiate between healthy and unhealthy birds and a precision of 90% was obtained (Carpentier et al. 2019).

Ren et al. (2009), used the HMM (Hidden Markov Model) to take a look at the connection between poultry sound patterns and stress stimulants to establish vocalization as a stress signal (Huang et al. 2019). Rizwan et al. (2016), used the support vector machine algorithm and the extreme learning machine algorithm and noticed that increased frequencies of rales were detected by both algorithms, but less false positive results were shown by the support vector machine (Ren et al. 2009). In a study on young chicks, it was found that communications between them and the hens were established through different sounds, which were identified as sounds of stress, threats, submissiveness, food, etc. and it can be said that bioacoustics can be incorporated into machine learning systems for further research and exploration of this particular domain (Rizwan et al. 2016).

2.4. Body temperature and thermal imaging

The body temperature of poultry may vary with different diseases and even in stressful conditions. Proper evaluation of body temperature may help in the early detection of sick birds and the determination of health conditions. Poultry temperature can be measured by using infrared thermography (IRT). IRT can also aid in recognizing any abnormalities in the health and soundness of birds. IRT spotted out footpad lesions way before visual examination (Tefera 2012). In their research, the researchers created an arrangement for concurrent monitoring of birds prior to the expression of diseased conditions. Another study stated that the infection of Avian influenza at the early stages of the disease was observed by thermal imaging and examining the body temperature by a specialized system. The results were good, and recommendations were made to use thermal imaging (Jacob et al. 2016). Thermal imaging technologies can definitely assist in assessing individual animal health at farm level.

2.5. Behavior and movement

Behavioral studies of poultry can be helpful in the detection of various pathological conditions and can lead to the recognition and separation of sick birds. A Deep Convolutional Neural Network (Deep CNN) system was developed by Fang et al. (2022) and it was compared with different methods for evaluating the stance or posture of chickens. Deep CNN pose estimation and the Naire Bayesian model were implemented to inspect chicken actions and had a correctness of about 95% in monitoring unusual behavior (Noh et al. 2021). A position assessment-based model was prepared by Nasiri et al. (2022), to learn about lameness in broiler chicken. Deep CNN cognized key spots on walking or running broiler chicken that were later transferred into the long-short-term memory (LSTM) model. The model successfully showed a classification precision level of 95% (Fang et al. 2022). EyeNamic is a recently developed behavior tracking computer program that can trace the bird's activities and movements as well as monitor any unevenness in behavior, like overcrowding (Nasiri et al. 2022).

In a research conducted by Naas et al. (2010), piezoelectric crystal sensors were employed to compute the maximum vertical force generated by feet while walking and check for any locomotion difficulties in birds (Patel and Adil 2022). An autonomous observation method for sick broiler chicken was proposed by some researchers to upgrade the network composition and make alterations to diverse recognition settings, a ResNet residual network was used, which was a camera-based system, and it located any damages caused by the neural network. The system’s identification accuracy was said to be around 93% (Naas et al. 2010). The proposition of a CNN-based model was put forward by Gourisaria et al. (2023), which was called Chic Net V6, to classify different diseases. An accuracy rate of about 95% was observed (Zhang and Chen 2020). In yet another study conducted, YOLO V5 was used to track and count the trajectories of chickens. It was named Chick Track and was a combination of video surveillance and smart sensing devices. The Chick Track platform can be utilized for recognizing chickens by their posture, walking, and running. It can also locate any diseased bird, and individual attention can be given to that particular bird by the farmer. Even necessary flock behaviors can be studied by it (Gourisaria et al. 2023).

In another study, campylobacter-positive chickens were distinguished with the help of cameras and scrutinized for optical flow patterns. High movement peaks and lesser mean optical flow patterns indicated that a flock could be carrying Campylobacter (Neethirajan 2022). Some researchers developed a real-time technique for examining laying hens with the aid of infrared receivers. The objective was to check for keel bone fractures. Infrared receivers were fixed to the legs, and behavior was observed. It turned out to be effective for employing the technique in smaller flocks (Colles et al. 2016). In another research conducted in China, a sensor monitoring method was proposed for identifying dead and sick birds. Data was collected from the foot ring through the Zigbee network, and an algorithm worked in identifying dead chicken and sick chicken; the three-dimensional displacement of chicken was measured here. A precision of 95.6% was calculated in the above research and found to be quite practical (Rufener et al. 2019). Liu et al.

(2021) developed a system that identified and removed dead chickens from poultry farms where robotics and AI technologies were used together. The dead birds were recognized by deep learning based on the Yolo V4 algorithm, and a self-propelled vehicle would remove the birds. It had an accuracy rate of 95.24% and did not disturb the birds as well (Bao et al. 2021). The major advantage of using robots is that it prohibits the entry of germs and strengthens biosecurity measures.

3. Big data and IoT (Internet of Things) for smart poultry farming

By automating processes like bird weighing, feed and water monitoring, and behavior analysis, smart poultry farming technologies have completely transformed the poultry production. Big data and the IoT have improved these systems, enabling real-time data collecting and sophisticated analytics for more informed, data-driven choices. They open the door to more productive and sustainable poultry businesses by facilitating predictive insights and effective management of larger flocks, going beyond mere monitoring. To improve decision-making, big data entails collecting and evaluating enormous datasets that are distinguished by their volume, diversity, and velocity (Sicular, 2013). Research on big data applications in poultry farming is scarce, despite its benefits (Kamilaris et al. 2017). According to Morgan (2014), the IoT is a network of interconnected gadgets that gather and exchange data online, revolutionizing our way of life and work. IoT systems consist of interfaces for user engagement, software for processing and analysis, hardware for data collecting, and connection for data transmission. IoT has a lot of promise for the agricultural industry and is probably going to be a key element of future smart poultry farms. IoT facilitates better connection between agricultural equipment in chicken production, which automates routine works and boosts management effectiveness (Banhazi and Black 2009).

4. Disadvantages of artificial intelligence and machine learning

While AI brings many positives to poultry farming, in the form of efficiency improvement and better decision-making power, it also has certain negative aspects:

1. High initial investment
2. Data dependency
3. Technical complexity and requirements for skills
4. Chances of system crash
5. Less human monitoring
6. Safety and privacy concerns
7. Technology dependency
8. Animal welfare and ethical concerns

10. Loss of jobs

5. Future prospects

Data analytics in the future will play a big role in research. Cooperation among various poultry farms all around the world for disease diagnosis will be vital, as this may help researchers all around the world in the generation and proper utilization of data (Liu et al. 2021). Although most research has been carried out on chickens, soon enough works on other species such as ducks, quails, etc. may be carried out that will help diagnose any disease at its early stage. Also, work on egg characteristics (variation in yolk size and shape, shell thickness, nutritional qualities, etc.) shall be carried out to help detect hatchery-borne diseases that result in major economic losses in many countries (Astill et al. 2018), and even prenatal diagnosis may be done. New diagnostic kits can be built that can be remotely controlled. Also, biosecurity could be strengthened with the use of AI that can prevent the entry of pathogens due to a lack of human interference and the use of deep learning systems that can aid farmers in attending to sporadic cases. Not only in the identification of new strains of bacteria or any other pathogen but also in developing antibiotics against them, AI can be rightly employed (Vinod et al. 2023). Major outbreaks can be inhibited with the rapid developments in the field of AI. Research and development work should be carried out for proper implementation and strategy-making regarding the usage of AI and machine learning not only in the poultry sector but also in other livestock farming sectors (Hosny et al. 2023). Gases like methane, hydrogen sulfide, ammonia, and carbon monoxide, which are emitted in poultry houses and could be harmful to birds if their concentration is not maintained properly, can be checked regularly by AI (Corkery et al. 2013). Machine learning can also enhance the work in genomic characterization and sequencing, which may prevent epidemics if their harmful effects are detected earlier (Debauche et al. 2020). Multinational corporations and organizations can invest in the techniques related to precision livestock farming; this will help researchers carry out more work and improve the health status of poultry, which will ultimately result in more profit for farmers. With the availability of smartphones in almost every household, diagnostic tools and applications can be developed that can do on-site diagnosis via images or videos. Interpretation of diagnostic results can be made more convenient for poultry farmers, and errors could be promptly reduced (Tang et al. 2016). Sophisticated biotechnological approaches that aim at disease diagnosis can be incorporated with machine learning systems and yield more accurate results (Degu et al. 2023). Innovation and creativity in the future will firmly create more opportunities for researchers and contribute to the amelioration of the poultry industry.

6. Conclusions

Artificial intelligence and machine learning can revolutionize the poultry farming sector and the poultry industry as a whole and yield substantial results. Examining birds on the basis of behavior, movements, vocalization, thermal imaging, excreta, and biosensors can aid in diagnosing birds and the easy detection of diseases. Also, the welfare and productivity of birds can be improved by applying AI and machine learning appropriately. Numerous issues facing farmers can be solved by the wide and right use of such methods. Traditional systems of disease diagnosis are time-consuming; however, with the development of diagnostic tools with the aid of AI and advancements in poultry health monitoring, rapid on-site results can be obtained. Remote monitoring systems with sophisticated mechanisms can be supportive for farmers and businessmen to intelligently discover pathological conditions. The integration of technologies can even prevent zoonotic outbreaks and has the potential to boost production processes. Veterinarians, poultry farmers, extension workers, computer programmers, software engineers, and scientists need to work together to develop state-of-the-art and more comprehensive ways to diagnose and detect poultry diseases with the assistance of computer programs, machine learning, and AI.

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References

Astill J, Dara RA, Fraser ED, Sharif S. (2018). Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: A focus on Avian Influenza Virus. Frontiers in Veterinary Science 5: 263. https://doi.org/10.3389/fvets.2018.00263

Aworinde HO, Adebayo S, Akinwunmi AO, Alabi OM, Ayandiji A, Sakpere AB, Oyebamiji AK, Olaide O, Kizito E, Olawuyi AJ. (2023). Poultry fecal imagery dataset for health status prediction: A case of South-West Nigeria. Data in Brief 50: 109517. https://doi.org/10.1016/j.dib.2023.109517

Banhazi TM, Black JL. (2009). Precision livestock farming: a suite of electronic systems to ensure the application of best practice management on livestock farms. Australian Journal of Multi-disciplinary Engineering 7(1):1-13. https://doi.org/10.1080/14488388.2009.11464794

Bao Y, Lu H, Zhao Q, Yang Z, Xu W. (2021). Detection system of dead and sick chickens in large scale farms based on artificial intelligence. Mathematical Biosciences and Engineering 18(5): 6117-6135. https://doi.org/10.3934/mbe.2021306

Carpentier L, Vranken E, Berckmans D, Paeshuyse J, Norton T. (2019). Development of sound-based poultry health monitoring tool for automated sneeze detection. Computers and Electronics in Agriculture 162: 573-581. https://doi.org/10.1016/j.compag.2019.05.013

Colles FM, Cain RJ, Nickson T, Smith AL, Roberts SJ, Maiden MC, Lunn D, Dawkins MS. (2016). Monitoring chicken flock behaviour provides early warning of infection by human pathogen Campylobacter. Proceedings of the Royal Society B: Biological Sciences 283(1822): 20152323. https://doi.org/10.1098/rspb.2015.2323

Corkery G, Ward S, Kenny C, Hemmingway P. (2013). Incorporating smart sensing technologies into the poultry industry. Journal of World's Poultry Research 3(4): 106-128.

Cuan K, Zhang T, Li Z, Huang J, Ding Y, Fang C. (2022). Automatic Newcastle disease detection using sound technology and deep learning method. Computers and Electronics in Agriculture 194: 106740. https://doi.org/10.1016/j.compag.2022.106740

Debauche O, Mahmoudi S, Mahmoudi SA, Manneback P, Bindelle J, Lebeau F. (2020). Edge computing and artificial intelligence for real-time poultry monitoring. Procedia Computer Science 175: 534-541. https://doi.org/10.1016/j.procs.2020.07.076

Degu MZ, Simegn GL. (2023). Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques. Smart Agricultural Technology 4: 100221. https://doi.org/10.1016/j.atech.2023.100221

Fang C, Zheng H, Yang J, Deng H, Zhang T. (2022). Study on poultry pose estimation based on multi-parts detection. Animals 12(10): 1322. https://doi.org/10.3390/ani12101322

Farahat RA, Khan SH, Rabaan AA, Al-Tawfiq JA. (2023). The resurgence of Avian influenza and human infection: A brief outlook. New Microbes and New Infections 53: 101122. https://doi.org/10.1016/j.nmni.2023.101122

Gorji HT, Shahabi SM, Sharma A, Tande LQ, Husarik K, Qin J, Chan DE, Baek I, Kim MS, MacKinnon N, Morrow J. Sokolov S, Akhbardeh A, Vasefi F, Tavakolian K. (2022). Combining deep learning and fluorescence imaging to automatically identify fecal contamination on meat carcasses. Scientific Reports 12(1): 2392. https://doi.org/10.1038/s41598-022-06379-1

Gourisaria MK, Arora A, Bilgaiyan S, Sahni M. (2023). Chicken Disease Multiclass Classification Using Deep Learning. In: Anwar S, Ullah A, Rcha A, Sousa MJ, editors, Proceedings of International Conference on Information Technology and Applications. Springer Nature, Singapore. pp. 225-238. https://doi.org/10.1007/978-981-19-9331-2_19

Hosny RA, Alatfeehy NM, Abdelaty MF. (2023). Application of artificial intelligence in the management of poultry farms and combating antimicrobial resistance. Egyptian Journal of Animal Health 3(3): 91-102. https://doi.org/10.21608/ejah.2023.302769

https://www.statista.com/statistics/263971/top-10-countries-worldwide-in-egg-production/

Huang J, Wang W, Zhang T. (2019). Method for detecting avian influenza disease of chickens based on sound analysis. Biosystems Engineering 180: 16-24. https://doi.org/10.1016/j.biosystemseng.2019.01.015

Jacob FG, Baracho MD, Naas ID, Souza R, Salgado DD. (2016). The use of infrared thermography in the identification of pododermatitis in broilers. Engenharia Agricola 36(2): 253-259. https://doi.org/10.1590/1809-4430-Eng.Agric.v36n2p253-259/2016

Kamilaris A, Kartakoullis A, Prenafeta-Boldu FX. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture 143: 23-37. https://doi.org/10.1016/j.compag.2017.09.037

Liu HW, Chen CH, Tsai YC, Hsieh KW, Lin HT. (2021). Identifying images of dead chickens with a chicken removal system integrated with a deep learning algorithm. Sensors 21(11): 3579. https://doi.org/10.3390/s21113579

Machuve D, Nwankwo E, Mduma N, Mbelwa J. (2022). Poultry diseases diagnostics models using deep learning. Frontiers in Artificial Intelligence 5: 733345. https://doi.org/10.3389/frai.2022.733345

Mbelwa H, Machuve D, Mbelwa J. (2021). Deep convolutional neural network for chicken diseases detection. International Journal of Advanced Computer Science and Applications 12(2): 759–765. https://doi.org/10.14569/IJACSA.2021.0120295

Morgan JF. (2014). A simple explanation of "The Internet of Things". URL https://www.forbes.com/sites/jacobmorgan/2014/05/13/simple-explanation-internet-things-that-anyone-can-understand

Naas ID, Paz IC, Baracho MD, Menezes AG, Lima KA, Bueno LG, Mollo Neto M, Carvalho VC, Almeida IC, Souza AL. (2010). Assessing locomotion deficiency in broiler chicken. Scientia Agricola 67(2): 129-135. https://doi.org/10.1590/S0103-90162010000200001

Nasiri A, Yoder J, Zhao Y, Hawkins S, Prado M, Gan H. (2022). Pose estimation-based lameness recognition in broiler using CNN-LSTM network. Computers and Electronics in Agriculture 197: 106931. https://doi.org/10.1016/j.compag.2022.106931

Neethirajan S. (2022). ChickTrack-a quantitative tracking tool for measuring chicken activity. Measurement 191:110819. https://doi.org/10.1016/j.measurement.2022.110819

Noh JY, Kim KJ, Lee SH, Kim JB, Kim DH, Youk S, Song CS, Nahm SS. (2021). Thermal image scanning for the early detection of fever induced by highly pathogenic avian influenza virus infection in chickens and ducks and its application in farms. Frontiers in Veterinary Science 8: 616755. https://doi.org/10.3389/fvets.2021.616755

Patel H, Adil S. (2022). Role of Computer Science (Artificial Intelligence) In Poultry Management. Devotion: Journal of Research and Community Service 3(12): 2068-2088. https://doi.org/10.36418/dev.v3i12.250

Pawestri W, Nuraini DM, Andityas M. (2020). The estimation of economic losses due to coccidiosis in broiler chickens in Central Java, Indonesia. IOP Conference Series: Earth and Environmental Science 411: 012030. https://doi.org/10.1088/1755-1315/411/1/012030

Poultry Global Market Report (2024). Research and markets, Published on: February 2024. https://www.researchandmarkets.com/

Quach LD, Pham-Quoc N, Tran DC, Fadzil Hassan M. (2020). Identification of chicken diseases using VGGNet and ResNet models. In international conference on industrial networks and intelligent systems. Cham: Springer International Publishing 24: 259-269.

Ren Y, Johnson MT, Clemins PJ, Darre M, Glaeser SS, Osiejuk TS, Out-Nyarko E. (2009). A framework for bioacoustic vocalization analysis using hidden Markov models. Algorithms 2(4): 1410-1428. https://doi.org/10.3390/a2041410

Rizwan M, Carroll BT, Anderson DV, Daley W, Harbert S, Britton DF, Jackwood MW. (2016). Identifying rale sounds in chickens using audio signals for early disease detection in poultry. 2016 IEEE Global Conference on Signal and Information Processing, 07-09 December 2016, Washington DC, USA. pp. 55-59. https://doi.org/10.1109/GlobalSIP.2016.7905802

Rufener C, Abreu Y, Asher L, Berezowski JA, Sousa FM, Stratmann A, Toscano MJ. (2019). Keel bone fractures are associated with individual mobility of laying hens in an aviary system. Applied Animal Behaviour Science 217: 48-56. https://doi.org/10.1016/j.applanim.2019.05.007

Sadeghi M, Banakar A, Khazaee M, Soleimani MR. (2015). An intelligent procedure for the detection and classification of chickens infected by clostridium perfringens based on their vocalization. Revista Brasileira de Ciencia Avícola 17(4): 537-544. https://doi.org/10.1590/1516-635X1704537-544

Sicular S. (2013). Gartner's Big Data Definition Consists of Three Parts, Not to Be Confused with Three "V"s. http://www.forbes.com/sites/gartnergroup/2013/03/27/gartners-big-data-definition-consists-of-three-parts-not-to-be-confused-with-three-vs/

Tang Y, Lin L, Sebastian A, Lu H. (2016). Detection and characterization of two co-infection variant strains of avian orthoreovirus (ARV) in young layer chickens using next-generation sequencing (NGS). Scientific reports 6(1): 24519. https://doi.org/10.1038/srep24519

Tefera M. (2012). Acoustic signals in domestic chicken (Gallus gallus): a tool for teaching veterinary ethology and implication for language learning. Ethiopian Veterinary Journal 16(2): 77-84. https://doi.org/10.4314/evj.v16i2.7

Uzundumlu AS, Dilli M. (2023). Estimando a produção de carne de frango em países líderes para os anos 2019-2025. Ciencia Rural 53(2): e20210477. http://doi.org/10.1590/0103-8478cr20210477

Vinod A, Mohanty DC, John A, Depuru BK. (2023). Application of artificial intelligence in poultry farming-advancing efficiency in poultry farming by automating the egg counting using computer vision system. Research Square. https://doi.org/10.21203/rs.3.rs-3266412/v1

Wang J, Shen M, Liu L, Xu Y, Okinda C. (2019). Recognition and classification of broiler droppings based on deep convolutional neural network. Journal of Sensors 1: 3823515. https://doi.org/10.1155/2019/3823515

Widyawati W, Gunawan W. (2022). Early detection of sick chicken using artificial intelligence. Teknika: Jurnal Sains dan Teknologi 18(2): 136-141. http://dx.doi.org/10.36055/tjst.v18i2.17337

Zhang H, Chen C. (2020). Design of sick chicken automatic detection system based on improved residual network. 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), 12-14 June, Chongqing, China. pp. 2480-2485. https://doi.org/10.1109/ITNEC48623.2020.9084666

Zhu J, Zhou M. (2021). Online detection of abnormal chicken manure based on machine vision. 2021 ASABE Annual International Virtual Meeting. American Society of Agricultural and Biological Engineers, St. Joseph, Michigan, USA. pp. 595–601. https://doi.org/10.13031/aim.202100188

Zhuang X, Bi M, Guo J, Wu S, Zhang T. (2018). Development of an early warning algorithm to detect sick broilers. Computers and Electronics in Agriculture. 144:102-113. https://doi.org/10.1016/j.compag.2017.11.032

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