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Application Of Artificial Intelligence In The Management Of Poultry Farms and Combating Antimicrobial Resistance

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ABSTRACT

Antimicrobial resistance (AMR) is currently one of the most dangerous crises facing the world. There has been an unsettling rise in the antimicrobial resistance (AMR) identified in animals, which may transfer to people through direct contact, environmental pollution, and food consumption. Efficient poultry health and welfare management and quick diagnosis of bacterial infections in poultry farms can lessen the demand for antibiotics, which is reflected on the spreading of epidemics and AMR. Internet of thinking and machine learning are branches of Artificial intelligence that enable intelligent autonomous systems with human workers remotely managing operations. Machine learning technology plays a role in tracking and preventing infections in poultry farms, which can reduce the need for antibiotic treatment in poultry and, as a result, limit the transmission of antibiotic-resistant pathogens to humans. This information is further analyzed by powerful processing computers with the aid of massive storage devices to seek for trends and hints to pinpoint the locations of disease outbreaks and cases of resistance. The utilization of this knowledge will make it easier to prevent epidemics in the future, reducing the demand for antibiotics. Therefore, this review offers insight on the current AI practices in the management of poultry farms as well as opportunities and concerns around antibiotic resistance throughout the world.

INTRODUCTION

Efficient poultry health and welfare management is crucial for preventing infectious diseases **(Ojo et al. 2022).** Poultry producers face several challenges, including high production costs, lack of sufficient skilled labor, mortalities due to infectious diseases, rising of antibiotic resistance, and inefficient resource management, such as water, feed, and electricity usage **(Ojo et al. 2022).** On this basis, the integration of the Internet of Things (IoT) and machine learning (ML) has been identified as promising technologies allowing intelligent autonomous systems with human workers remotely managing operations, smart poultry farming, data monitoring, and prescriptive ana-

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lytics that address the challenges **(Fang et al. 2021; Ojo et al. 2022).** The internet of things (IoT) is a collection of physical sensing devices such as cameras, microphones, and other sensors that linked to a wide area network (WAN) to collect, share, and convey information for analysis purposes, whereas machine learning (ML) is a computational technique that combines analytics and learning to generate new insights **(Michalski et al. 2013).** The use of Artificial intelligence (AI) could lower the error rate to negligible levels, improving farming efficiency, and maximizing farm profit **(Ribeiro et al. 2019; Ojo et al. 2022).** AI has the potential to turn conventional industrial farming into smart poultry farming in the near future. **(Astill et al. 2020; Ojo et al. 2022**)

Antimicrobial resistance (AMR) is one of the most critical challenges facing poultry production **(Lau et al. 2021; Rabaan et al. 2022).** It is critical to implement an institutional antibiotic stewardship program that monitors correct antibiotic usage, and creates antibiograms to combat the rise in AMR rates and reduce antimicrobial misuse **(Lau et al. 2021; Rabaan et al. 2022).** These tools may aid in the rapid treatment of poultry without the need to wait for bacterial culture results **(Rabaan et al. 2022).** AI can reduce the time to discover new antimicrobial drugs, enhance diagnostic and treatment accuracy, and lowering costs **(Lau et al. 2021; Rabaan et al. 2022).**

Applications of internet of things in poultry farms:

Figure 1 summarizes a holistic view of IoT applications in poultry welfare and health management in six parameters, including 1) remote management, 2) Behavior, body weight, and environment monitoring, 3) Disease predictive analytics, 4) Ammonia sensing 5) Audio sensing, 6) Transportation and slaughtering.

Remote management

Labor shortages remain a primary challenge facing poultry production as production levels increase over time. **(Zahniser et al. 2018).** One way to address this challenge is to implement technological solutions that enhance capability to remotely manage and make decisions on the emerging issues **(Park et al. 2022).** Robots, drones and automated devices driven by sensors and intelligent classifiers could perform most of the labor-intensive tasks such as aerating bedding removing mortality, materials picking up floor eggs in breeder houses, removing litter, and applying vaccines, and disinfectants **(Park et al. 2022).** Drones are used to provide sensor data to ground robots for rapid response for current and emerging situations **(Park et al. 2022).**

2- Behavior, body weight, and environment monitoring

Automated monitoring was based on systems that remotely monitor chicken behavioral characteristics, such as feeding, resting, and running, and environmental parameters, including temperature, relative humidity, ventilation, and lighting using IoT technologies, such as sensors, cameras, microphones, and mobile phones connected to a server or cloud for instant processing and visualization **(Ojo et al. 2022).** Earlier researches highlighted the use of sensors to monitor environmental conditions, including temperature and humidity using the camera, supervisory control and data acquisition systems (SCADA) and IFAC Proceedings Volumes **(Demmers et al. 2010; Fernandez et al. 2018; Lahlouh et al. 2020; Lorencena et al. 2020).** Previous studies have monitored real -time changes in body weights, feed and water consumption, and feed conversion ratio based on vocalization signals, machine learning, digital image analysis, and artificial neural network for optimization of poultry **(Mollah et al. 2010; Fontana et al. 2015; Amraei et al. 2017; Li et al. 2020a; Li et al. 2020b; Huang et al. 2021). Rico-Contreras et al. (2017)** monitored moisture content in litters using artificial intelligence techniques and Monte Carlo simulation. **Zuidhof et al. (2017)** improved feeding systems by making feed schedules based on the environmental, health, behavioral, and data of individual birds for better flock control and uniformity.

3- Disease predictive analytics

Early detection of infections has a significant concern in the chicken industry to prevent disease transmission **(Ojo et al. 2022).** Diseaseinduced symptoms can be detected by monitoring the behaviors of birds through accurate and robust biosensor in a real-time fashion **(Ojo et al. 2022; Park et al. 2022).** Artificial intelligence can predict possible disease outbreaks before they occur and trace disease vectors and modes of transmission based on historical data, which improves early warning capabilities that could help prevent future outbreaks **(Ojo et al. 2022; Park et al. 2022).** Autonomous robotic systems are quickly deployed to provide appropriate interventions, remove diseased birds from the flock, or isolate a group of birds from others into separate space **(Ojo et al. 2022).** According to **Usher et al. (2015),** autonomous ground robots can be present in close contact with birds, allowing for direct assessment of infections. Several studies have brought technology regarding rapid detection and diagnosis of poultry diseases such as new castle disease virus, avian influenza, bursal diseases, salmonella, hock burn, and listeria based on a chicken sound convolutional neural network and machine learning methods **(Rizwan et al. 2016; Zhuang et al. 2018; Golden et al. 2019; Cuan et al. 2020).** Different standard methods, including deep regression network, digital image processing, and deep learning were used for identifying diseased birds by analyzing eating behavior, movement, weight checking, and sound **(Rizwan et al. 2016; Zhuang et al. 2018; Carpentier et al. 2019; Fang et al. 2020). Zhang and Chen (2020)** developed autonomous detection system for diseased chickens based on the ResNet residual network to track production performance.

4- Ammonia sensing

In 2019, **(Lotfi et al.)** developed a multifunction electro-thermal sensor system for continuous ammonia level monitoring using a machine learning-based robust that has faster response times and lower power consumption and cost compared to traditional chemical sensors. **Xu et al. (2017a)** developed a technological solution to extract higher value nutrients from traditional wastes by using an adsorbing material to capture ammonia from chicken litter to be used as soil amendments.

5- Audio sensing

In 2018, (Carroll) developed auditory systems using digital signal processing, artificial intelligence, and machine learning techniques for assessing the illnesses, such as laryngotracheitis and infectious bronchitis as well as bird's response to stress due to temperature and ammonia.

6- Transportation and slaughtering

Traditional system of transportation of live birds can cause significant stress accumulation on birds, including physical discomfort, abnormal social settings **(Association 2016) (American Veterinary Medical Association, 2016).** Future poultry transportation systems can eliminate this stress accumulation and significantly reduce the amount of manual handling of live poultry **(Park et al. 2022).** Farm Processing and Transport (FPaT) is a system that consisting of two mobile units including processing trailer and transport trailer designed on standard 53-ft trailers, however, more investigation is needed on this system **(Park et al. 2022).** Some benefits of FPaT system have been reported, including reduced water use due to reduced scalding requirements and improved the yield efficiency **(Park et al. 2022).** Furthermore, FPaT system causes no significant differences in the major food quality matrix, visual properties, myopathy scores, water-holding capacity, yield, and texture properties compared to traditional techniques **(Park et al. 2022).** Stunning and slaughtering activities that are currently carried out at the processing plant can be turned to the farm. Robots can herd the birds to a stunning station and shackle them **(Park et al. 2022).** A transportation system transports the shackled birds while tracking individual birds so that data gathered during the poultry management, such as health and weights may be transmitted to the processing plant **(Park et al. 2022).**

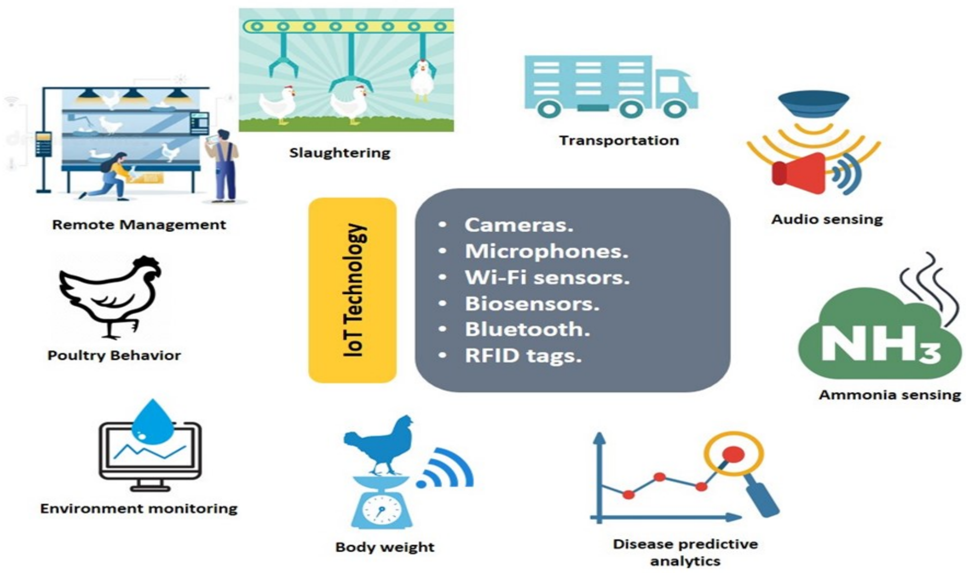

Fig 1. Application of IoT in poultry health and welfare management

Machine learning

Machine learning (ML) has been concerned with developing computer programs that use input information to produce either new knowledge or improve already existing knowledge **(Michalski et al. 2013).** ML-based approaches consist of feature extractors that convert raw data into feature vectors that classify patterns in the extracted features **(Michalski et al. 2013; Park et al. 2022)** (Fig 2). In contrast, deep learning approach was derived from conventional ML approach that can automatically identify features from raw data without the need for notable engineering knowledge on feature extraction **(LeCun et al. 2015; Park et al. 2022).** ML includes many learning models and algorithms and is classified as supervised, which uses labelled data to develop accurate predictions, and unsupervised, which uses non-pre-assigned labels to identify datasets **(Milosevic et al. 2019; Park et al. 2022).**

Applications of machine learning in poultry farms

Several studies monitored different environmental metrics, including temperature, humidity, carbon dioxide, and ammonia) using ML approaches such as linear regression, fuzzy logic, neuro-fuzzy, and deep learning **(Mirzaee -Ghaleh et al. 2015; Lahlouh et al. 2020; Küçüktopcu and Cemek 2021).** Other ML techniques, including Lasso regression, fuzzy-GA, and the generalized sequential pattern have been used in estimating the heat stress in commercial broiler houses **(Hernández-Julio et al. 2020).** Monitoring poultry welfare and behavioral activities are important parameters play role in improving the production **(Ojo et al. 2022; Park et al. 2022).** Linear regression and decision trees are two ML approaches used in monitoring behavioural and welfare activities **(Neves et al. 2015; Li et al. 2020b)**. ML approaches including as linear regression, vector regression, and Bayesian artificial neural network have been applied for broiler growth estimation. **(Mollah et al. 2010;**

Fontana et al. 2015). Poultry diseases have an impact on poultry productivity, food safety, and zoonotic infections. **Alex and Joseph (2019)** assessed the effectiveness of different ML techniques in detecting avian influenza, including logistic decision, linear, and quadratic discriminant techniques. Other studies use ML techniques to detect avian influenza, including maximum entropy, sequential pattern mining, random forest, deep learning, and association rules **(Xu et al. 2017b; Belkhiria et al. 2018; Zhuang et al. 2018; Cuan et al. 2020).** Two ML techniques, such as decision trees and deep learning have been used to predict infectious bronchitis **(Rizwan et al. 2016).** Other poultry diseases, including new castle disease and infectious bursal diagnosed by ML techniques using neural network and logistic regression techniques **(Fang 2019; Okinda et al. 2019)**. In addition, other bacterial diseases, including Salmonella species and Listeria species diagnosed by random forest and gradient boosting machines **(Golden et al. 2019; Hwang et al. 2020).**

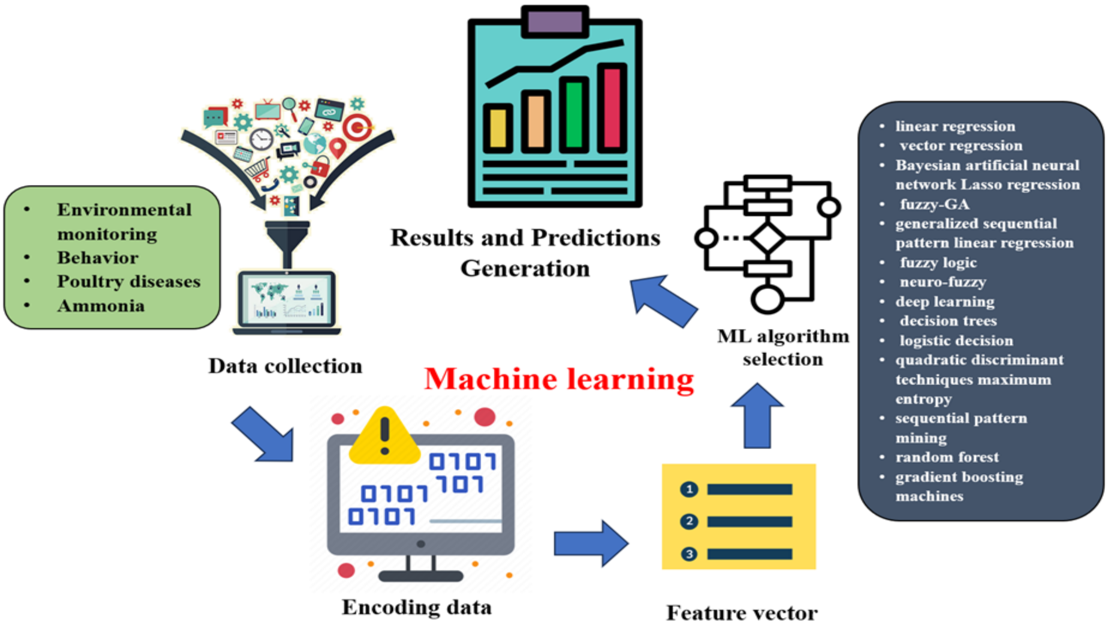

Fig 2. Application of machine learning in poultry health and welfare management

Applications of machine learning in the identification of antibiotic resistant bacteria

AI plays an important role in the control of antimicrobial resistance through the gathering of data to construct decision support systems that can aid in monitoring AMR trends, determining how to use antibiotics, designing new antibiotics, and investigating synergistic drug combinations **(Boolchandani et al. 2019; Khaledi et al. 2016; Rodriguezet al. 2019).**

Deep learning and machine learning are AI subfields that use enormous amounts of data to solve issues; these data are then processed swiftly by powerful processing computers with the aid of massive storage devices **(Rabaan et al. 2022).** The construction of comprehensive AMR databases can integrate more cutting-edge AI algorithms for more effective AMR prediction **(Rabaan et al. 2022).**

Two methods of antimicrobial susceptibility testing have been used to diagnose AMR, including antimicrobial susceptibility testing (AST) and whole-genome sequencing (WGSAST) (Isenberg 2003). Antimicrobial susceptibility testing (AST) is a traditional technique for estimating the level of antimicrobial resistance; however, it is neither effective nor does it provide an explanation of how AMR works **(Horne et al. 2015; Reller et al .2009).** Whole-genome sequencing for antimicrobial susceptibility testing (WGSAST) enables rapid, dependable, and accurate diagnosis of AMR; however, efficient information extraction requires vast and high-dimensional datasets **(Boolchandani et al. 2019; Lunetta et al. 2004; Su et al. 2019**).

For the purpose of deducing hypotheses about novel AMR genes or mutation-variation pathways, machine learning models are created (**Kavvas, et al. 2020).** Monitoring of resistance genes can reveal emerging AMR trends and disclose transmission patterns that can aid in spotting and containing resistant disease outbreaks **(Rabaan et al. 2022**). As the amount of whole-genome sequence data increases, AI models are better able to achieve high accuracy in surveillance **(Deng et al. 2016, Argimón et al. 2020)**. AI models are able to learn features that have a significant influence, enabling the advance taking of important actions. **Lv J et al. (2021)** used AI algorithms methods for identification of AMR, including nave Bayes, decision trees, random forests, support vector machines, and artificial neural networks. Recent studies used a combined method of flow cytometer antimicrobial susceptibility testing (FAST) and supervised machine learning to perform antimicrobial susceptibility testing and revealed generation of a reliable result in less than 3 hours **(Mulroney et al. 2017; Inglis, et al. 2017) (Fig 3). Moreover, Lechowicz et al. (2013)** reduced the amount of time to perform AST from 24 h to 30 min by developing an IR-spectrometer method that combines infrared (IR) spectroscopy with artificial neural network (Fig 3). Although the AI-based FAST or IR spectrometer method can speed up antimicrobial susceptibility testing, their workflows are too complicated to be used by nonprofessional personnel **(Rabaan et al. 2022).** Therefore, integrating the related AI algorithms into FAST or IR spectrometer analytic software to realize automatic analysis is the direction in the near future **(Rabaan et al. 2022).**

For WGS-AST, current studies are mainly based on k-mer, which is derived from the whole genome of samples **(Arango et al. 2018).** However, k-mer datasets are too large and redundant to be directly used for AI applications. **Davis et al. (2016)** converted k-mer to a binary matrix by rapid annotation using subsystem technology (RAST), allowing use of this binary matrix to determine whether a particular k-mer is present in the genome (Fig 3).

Furthermore, **Mahé et al. (2018**) used the stability selection approach to generate a small predictive subset of k-mer from a very large number of redundant and correlated ones instead of binary matrix, which could make the predictive model more efficient and easily interpretable. The success of these methods is depended on the comprehensiveness and quality of the databases of specific antimicrobial resistance gene (ARG) and AST **(Davis et al. 2016).**

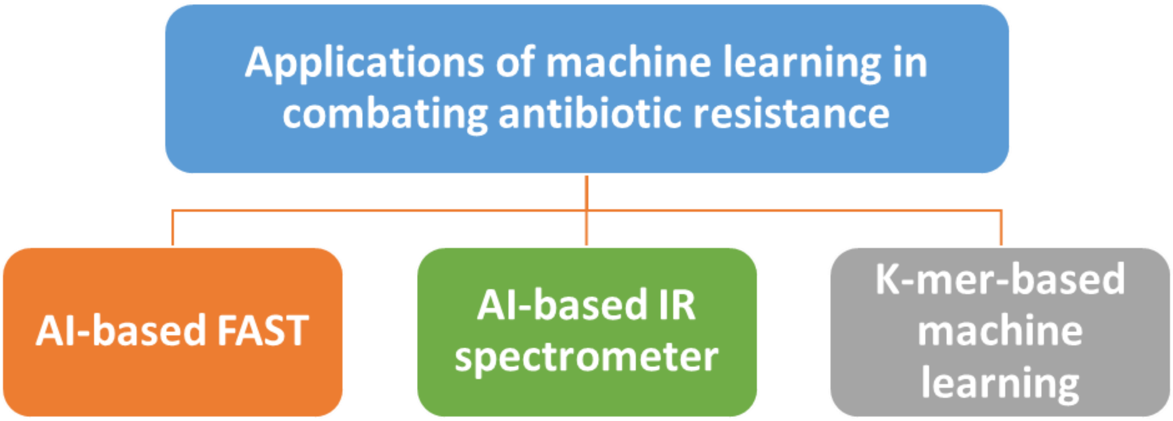

Fig 3. Applications of machine learning in combating antibiotic resistance

One of the challenges of the application WGS-AST model is that it requires a large training dataset to optimize its key parameters (**Arango et al. 2018**). Furthermore, it can work only for one specific species, it is necessary for us to build up a comprehensive database that can employ more advanced AI algorithms, such as transfer learning **(Weiss et al. 2016)** and, to develop a general WGS-AST model for multiple species with a small training dataset in the distant future.

Furthermore, AI can identify new antibiotics that are structurally different from currently available ones and effective against a variety of bacteria **(Weiss et al. 2016).** There has been an explosion in research in recent years on the use of AI for drug design and discovery based on understanding of the structural basis of resistance, and rational design principle **(Klevens et al. 2007).** Application of AI can greatly cut the time needed for diagnostics from days to hours as well as it can be used to find new AMR and mutations **(Melo et al. 2021).** However, there are some significant obstacles in the use of AI in AMR. For instance, most programs do not take into account an intermediate category that overlaps the susceptible and resistant categories, only considering the output to be resistant or susceptible and this can result in a false diagnosis **(Fischer et al. 2004)**. Also. the examination of antibiotic genes is linked mainly to univariate characteristics; however, it is well recognized that a number of factors contribute for detection of AMR, thus multivariate models must be developed **(Teodoro and Lovis 2013).** Another significant issue is data management; unbalanced data training could produce unreliable results. Research on the integration of AI with AMR is still in its early stages, and more findings must be made before widespread use can be considered.

CONCLUSION

Due to the urgency of the AMR threat, this study enhances knowledge by assisting stakeholders in better comprehending and utilizing cutting-edge digital technologies, critically analyzing the shortcomings facing poultry production, condensing the influence of predictive variables, and recognizing the potential uses and trends of technological advancements in the field. Additionally, knowledge of technologies for managing the welfare of poultry and optimizing its production process would make it easier to produce chicken at a cheap cost and of excellent quality. The first step towards decision-making is to apply AI in conjunction with appropriate explanatory models that can assist researcher-led decisions and enhance antibiotic stewardship. Research on the integration of AI techniques in the management of poultry farms and in the combating of AMR is still in its early stages, and more findings are required before widespread use can be taken into consideration.

In Egypt, AI implementation for combating AMR in veterinary sector is still in its earliest stages, different pipeline strategies are offered by research laboratories and AI vendors.

The synchronization of the three crucial components listed below is advised for Egypt's adoption of AI:

1- Education, which includes training of veterinarians, laboratory workers, technologists, informaticists, and principal stakeholders. This collaborative training includes antibiotic sensitivity procedures, interpretation, workflow management, and laboratory safety.

2- Availability, accessibility, and sustainability of infrastructure (broadband, cloud, servers, local area networks, and Wi-Fi).

3- Regulations for data management, which govern how data should be anonymized, kept, accessed, transmitted, and processed, interact with legal and ethical frameworks.

The introduction of AI synchronized with clinical education and infrastructure implementation. The deployment of AI in Egypt is fraught with difficulties. First, clear and thorough data and observations from numerous, lengthy pilot AI and informatics platform installations, without data sharing and exchange, it might be impossible to develop AI for LMIC populations. As a result, data sharing is crucial to achieving health fairness.

Second, the potential of economic imbalance in AI is made worse by the absence of defined legal and regulatory frameworks for data rights.

Finally, the requirement for a global AMR AI approach is dictated by significant differences in personnel, clinical experience, illness patterns, epidemiological distribution, digital infrastructure, and equipment.

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REFERENCES

Alex AGR, Joseph GJ. 2019. Real-Time Poultry Health Identification Using IoT Test Setup, Optimization and Results. In Advances in Signal Processing and Intelligent Recognition Systems: 4th International Symposium SIRS 2018, Bangalore, India, September 19–22, 2018, Revised Selected Papers 4. pp.30-40: Springer.

Amraei S, Abdanan MS, Salari S. 2017. Broiler weight estimation based on machine vision and artificial neural network. British poultry Sci. (58): 200-205.

Arango AG, Garner E, Prudent A, Heath LS, Vikesland P, Zhang LQ, DeepARG. 2018. A deep learning approach for predicting antibiotic resistance genes from metagenomic data, Microbiome. (6) : 15, https://doi.org/10.1186/s40168-018- 0401-z.

Argimón S, Masim MAL, Gayeta JM, Lagrada ML, Macaranas PKV, Cohen V, Limas MT, Espiritu HO, Palarca, JC, Chilam J. 2020. Integrating whole-genome sequencing within the National Antimicrobial Resistance Surveillance Program in the Philippines. Nat. Commun. (11): 2719.

Association AVM. 2016. AVMA Guidelines for the Humane Slaughter of Animals : 2016 Edition. ISBN 978-1-882691-07-4. In American Veterinary Medical Association.

Astill J, Dara RA, Fraser ED, Roberts B, Sharif S. 2020. Smart poultry management: Smart sensors, big data, and the internet of things. Computers Electronics in Agriculture . (170): 105291.

Belkhiria J, Hijmans RJ, Boyce W, Crossley BM, Martínez-López B. 2018. Identification of high risk areas for avian influenza outbreaks in California using disease distribution models. PLoS One. (13): e0190824.

Boolchandani M, D'Souza AW, Dantas G. 2019. Sequencing-based methods and resources to study antimicrobial resistance. Nature Reviews Genetics . (20): 356-370.

Carpentier L, Vranken E, Berckmans D, Paeshuyse J, Norton T. 2019. Development of sound-based poultry health monitoring tool for automated sneeze detection. Computers electronics in agriculture.(162): 573-581.

Carroll BT. 2018.Characterizing acoustic environments with OLAF and ELSA: Georgia Int. of Technology.

Cuan K, Zhang T, Huang J, Fang C, Guan Y. 2020. Detection of avian influenza-infected chickens based on a chicken sound convolutional neural network. Computers electronics in agriculture. (178): 105688.

Davis JJ, Boisvert S, Brettin T, Kenyon RW, Mao C, Olson R, Antimicrobial resistance prediction in PATRIC and RAST Sci. Rep., 6 (2016), p. 27930, 10.1038/ srep27930

Demmers TG, Cao Y, Gauss S, Lowe JC, Parsons DJ, Wathes CM. 2010.Neural predictive control of broiler chicken growth. IFAC Proceedings Volumes . (43): 311-316.

Deng X, den Bakker HC, Hendriksen RS. 2016. Genomic Epidemiology: Whole-Genome-Sequencing–Powered Surveillance and Outbreak Investigation of Foodborne Bacterial Pathogens. Annu. Rev. Food Sci. Technol. (7): 353–374.

Fang C, Huang J, Cuan K, Zhuang X, Zhang T. 2020. Comparative study on poultry target tracking algorithms based on a deep regression network. Biosystems Engineering. (190): 176-183.

Fang C, Zhang T, Zheng H, Huang J, Cuan K. 2021.Pose estimation and behavior classification of broiler chickens based on deep neural networks. Computers Electronics in Agriculture. (180):105863.

Fang T. 2019. Rapid diagnosis of infectious bursal disease with RNA microarray and machine learning. In Proceedings of the International Conference on Bioinformatics & Computational Biology (BIOCOMP). pp.67 -73: The Steering Committee of The World Congress in Computer Science.

Fernandez AP, Norton T, Tullo E, van Hertem T, Youssef A, Exadaktylos V, Vranken E, Guarino M, Berckmans D. 2018. Real-time monitoring of broiler flock's welfare status using camera-based technology. Biosystems Engineering . (173): 103-114.

Fischer JE, Harbarth S, Agthe AG, Benn A, Ringer SA, Goldmann DA. 2004. Quantifying uncertainty: physicians' estimates of infection in critically ill neonates and children, Clin. Infect. Dis. (38): 1383–1390, https://doi.org/10.1086/ 420741.

Fontana I, Tullo E, Butterworth A, Guarino M. 2015. An innovative approach to predict the growth in intensive poultry farming. Computers electronics in agriculture . (119): 178 -183.

Golden CE, Rothrock JR, MJ, Mishra A. 2019. Comparison between random forest and gradient boosting machine methods for predicting Listeria spp. prevalence in the environment of pastured poultry farms. Food research international .(122): 47-55.

Hernández-Julio YF, Ferraz PF, Junior TY, Barbari M, Nieto-Bernal W. 2020. Fuzzy-genetic approaches to knowledge discovery and decision making: Estimation of the cloacal temperature of chicks exposed to different thermal conditions. biosystems engineering .(199): 109-120.

Horne DJ, Pinto LM, Arentz M, Lin S YG, Desmond E, Flores LL, Steingart KR, Minion JJ Jocm. 2013. Diagnostic accuracy and reproducibility of WHO-endorsed phenotypic drug susceptibility testing methods for first-line and second-line antituberculosis drugs . (51): 393-401.

Huang J, Zhang T, Cuan K, Fang C. 2021. An intelligent method for detecting poultry eating behaviour based on vocalization signals. Computers Electronics in Agriculture . (180): 105884.

Hwang D, Rothrock Jr, MJ, Pang H, Guo M, Mishra A, JS, oTTE. 2020. Predicting Salmonella prevalence associated with meteorological factors in pastured poultry farms in southeastern United States. (713): 136359.

Inglis TJ, Paton TF, Kopczyk MK, Mulroney KT, Carson CF. 2020 . Same-day antimicrobial susceptibility test using acoustic-enhanced flow cytometry visualized with supervised machine learning. Journal of medical microbiology. 69(5), 657.

Isenberg HD. 2003. Clinical microbiology: past, present, and future. Journal of Clinical Microbiology (41): 917.

Kavvas ES, Yang L, Monk JM, Heckmann D, Palsson BO. 2020. A biochemically-interpretable machine learning classifier for microbial GWAS. Nat. Commun. (11): 2580.

Khaledi A, Weimann A, Schniederjans M, Asgari E, Kuo TH, Oliver A, Cabot G, Kola A, Gastmeier P, Hogardt M. 2020. Predicting antimicrobial resistance in Pseudomonas aeruginosa with machine learning-enabled molecular diagnostics. EMBO Mol. Med. 12:e10264. doi: 10.15252/emmm.201910264.

Klevens RM, Edwards JR , Richards CL Jr,. HoranTC, Gaynes RP , Pollock DA . 2002. Estimating health care-associated infections and deaths in US hospitals, 2002, Public Health Rep. 122 (2007) 160–166, https://doi.org/10.1177/00333549071220

Küçüktopcu E, Cemek B. 2021. Comparison of neuro-fuzzy and neural networks techniques for estimating ammonia concentration in poultry farms. Journal of Environmental Chemical Engineering . (9): 105699.

Lahlouh I, Rerhrhaye F, Elakkary A, Sefiani N. 2020. Experimental implementation of a new multi input multi output fuzzy-PID controller in a poultry house system. Heliyon 6, e04645.

Lau HJ, Lim CH, Foo SC, Tan HS. 2021. The role of artificial intelligence in the battle against antimicrobial-resistant bacteria. Current genetics . (67): 421-429.

Lechowicz L, Urbaniak M, Adamus-BiałekW, Kaca W. 2013. The use of infrared spectroscopy and artificial neural networks for detection of uropathogenic Escherichia coli strains' susceptibility to cephalothin. Acta Biochimica Polonica. 60(4).

LeCun Y, Haffner P, Bottou L,GH. 2015. Deep learning. nature (521): 436-444.

Li G, Ji B, Li B, Shi Z, Zhao Y, Dou Y, Brocato J. 2020a. Assessment of layer pullet drinking behaviors under selectable light colors using convolutional neural network. Computers electronics in agriculture. (172): 105333.

Li G, Zhao Y, Purswell JL, Du Q, Chesser Jr, GD, Lowe J W JC, Agriculture E I. 2020b. Analysis of feeding and drinking behaviors of group-reared broilers via image processing. Computers Electronics in Agriculture (175): 105596.

Lorencena MC, Southier LFP, Casanova D, Ribeiro R, Teixeira M. 2020. A framework for modelling, control and supervision of poultry farming. international Journal of Production Research . (58): 3164-3179.

Lotfi A, Navaei Mm, Hesketh PJ. 2019. A platinum cantilever-based thermal conductivity detector for ammonia sensing using the 3-omega technique. ECS Journal of Solid State Science Technology . 8, Q126.

Lunetta KL, Hayward LB, Segal J, Van Eerdewegh P. 2004. Screening large-scale association study data: exploiting interactions using random forests. BMC genetics (5): 1-13.

Lv J, Deng S, Zhang L. 2021. A review of artificial intelligence applications for antimicrobial resistance. Biosaf. Health. (3):22–31. doi: 10.1016/j.bsheal.2020.08.003.

Mahé P., Tournoud M. Predicting bacterial resistance from whole-genome sequences using k-mers and stability selection BMC Bioinf., 19 (2018), p. 383, 10.1186/s12859-018-2403-z

Melo MCR, Maasch JRM m, Ade la Fuente-Nunez C. 2021. Accelerating antibiotic discovery through artificial intelligence. Commun. Biol. (4): 1050.

Michalski R, Carbonell J, Mitchell T. 2013. Machine learning: An artificial intelligence approach.[Sl]: Springer Science & Business Media, Palo Alto, CA: Tioga, 29.

Milosevic B, Ciric S, Lalic N, Milanovic V, Savic Z, Omerovic I, Doskovic V, Djordjevic S, Andjusic L. 2019. Machine learning application in growth and health prediction of broiler chickens. World's Poultry Science Journal (75): 401-410.

Mirzaee-Ghaleh E, Omid M, Keyhani A, Dalvand M. 2015. Comparison of fuzzy and on/off controllers for winter season indoor climate management in a model poultry house. Computers Electronics in Agriculture. (110): 187-195.

Mollah MBR, Hasan MA, Salam MA, Ali MA. 2010. Digital image analysis to estimate the live weight of broiler. Computers electronics in agriculture . (72): 48-52.

Mulroney KT, Hall JM, Huang X, Turnbull E, Bzdyl NM, Chakera A, Inglis T JJ. 2017. Rapid susceptibility profiling of carbapenem-resistant Klebsiella pneumoniae. Scientific reports . 7(1): 1903.

Neves DP, Mehdizadeh SA, Tscharke M, de Alencar Nääs I, Banhazi TM. 2015. Detection of flock movement and behaviour of broiler chickens at different feeders using image analysis. Information Processing in Agriculture . (2): 177-182.

Ojo RO, Ajayi AO, Owolabi HA, Oyedele LO, Akanbi LA. 2022. Internet of Things and Machine Learning techniques in poultry health and welfare management: A systematic literature review. Computers Electronics in Agriculture . (200) 107266.

Okinda C, Lu M, Liu L, Nyalala I, Muneri C, Wang J, Zhang H, Shen M. 2019. A machine vision system for early detection and prediction of sick birds: A broiler chicken model. Biosystems Engineering . (188): 229 -242.

Park M, Britton D, Daley W, McMurray G, Navaei M, Samoylov A, Usher C, Xu J. 2022. Artificial intelligence, sensors, robots, and transportation systems drive an innovative future for poultry broiler and breeder management. Animal Frontiers .(12): 40-48.

Rabaan AA, Alhumaid S, Mutair AA , Garout M, Abulhamayel Y, Halwani MA, Alestad J H, Bshabshe AA, Sulaiman T, AlFonaisan M K. 2022. Application of Artificial Intelligence in Combating High Antimicrobial Resistance Rates. Antibiotics (11): 784.

Reller LB, Weinstein M, Jorgensen JH, Ferraro MJ. 2009. Antimicrobial susceptibility testing: a review of general principles and contemporary practices. Clinical infectious diseases.49(11): 1749-1755.

Ribeiro R, Casanova D, Teixeira M, Wirth A, Gomes, HM, Borges, AP, Enembreck, F. 2019. Generating action plans for poultry management using artificial neural networks. Computers Electronics in Agriculture (161): 131-140.

Rico-Contreras JO, Aguilar-Lasserre AA, Méndez-Contreras JM, López-Andrés JJ, Cid-Chama G.2017. Moisture content prediction in poultry litter using artificial intelligence techniques and Monte Carlo simulation to determine the economic yield from energy use. Journal of Environmental Management. (202): 254-267.

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. In 2016 IEEE Global Conference on Signal and Information Processin (GlobalSIP). pp.55-59: IEEE.

Rodríguez-González A, Zanin M, Menasalvas-Ruiz E. 2019. Public health and epidemiology informatics: Can artificial intelligence help future global challenges? An overview of antimicrobial resistance and impact of climate change in disease epidemiology. Yearb. Med. Inform. 2019; (28):224–231. doi: 10.1055/s-0039-1677910.

Su M, Satola SW, Read TD. 2019.Genome-based prediction of bacterial antibiotic resistance. Journal of clinical microbiology. (57): e01405-01418.

Teodoro D, Lovis C. 2013. Empirical mode decomposition and k-nearest embedding vectors for timely analyses of antibiotic resistance trends, PLoS One 8 (2013) 14, https://doi. org/10.1371/journal.pone.0061180.

Usher C, Daley W, Webster AB, Ritz C. 2015. A study on quantitative metrics for evaluating animal behavior in confined environments. In 2015 ASABE Annual International Meeting. p.1: American Society of Agricultural and Biological Engineers.

Wright GD. 2014. Something old, something new: revisiting natural products in antibiotic drug discovery, Can. J. Microbiol. (60):147 –154, https://doi.org/10.1139/cjm2014-0063.

Xu J, Luu L, Tang Y. 2017a. Phosphate removal using aluminum-doped magnetic nanoparticles. Desalination water treatment . 58.

Xu Z, Lee J, Park D, Chung Y. 2017b. Multidimensional analysis model for highly pathogenic avian influenza using data cube and data mining techniques. biosystems engineering . (157): 109-121.

Zahniser S, Taylor JE, Hertz T, Charlton D. 2018. Farm labor markets in the United States and Mexico pose challenges for US agriculture, Ed. U.S. Department of Agriculture: U.S. Department of Agriculture; vol. Economic Information Bulletin No. EIB-201, (pp. 1–40).

Zhang H, Chen C. 2020. Design of sick chicken automatic detection system based on improved residual network. In 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC). pp.2480-2485: IEEE.

Zhuang X, Bi M, Guo J, Wu S, Zhang T. 2018. Development of an early warning algorithm to detect sick broilers. Computers Electronics in Agriculture . (144): 102-113.

Zuidhof M, Fedorak M, Ouellette C, Wenger I. 2017. Precision feeding: Innovative management of broiler breeder feed intake and flock uniformity. Poultry science . (96): 2254-2263.