R-2297
[1-10]

REVIEW ARTICLE Agricultural Reviews, Volume Issue : ()

'Artificial Intelligence' as an Intelligent Tool for the Future Animal Production and Better Management: A Review

Priya, Triveni Dutt, Mukesh Singh, Gyanendra Kumar Gaur, Vivek Sahu[1]

10.18805/ag.R-2297

ABSTRACT

With the tremendous increase in human population the demand of milk and meat is also increasing. This necessitates the centralization of animal husbandry sector both in developed and developing countries. More production has to be taken from fewer animals which seem to be possible only with the usage of advanced technologies. Earlier this seems to be impractical due to non-availability of such technologies to the farmers. Nowadays, computational power is very cheap and easily available. Artificial intelligence is one such field of computer science devoted to creating computing machines and systems that perform operations analogous to human learning and decision-making. Artificial intelligence includes the machine learning, deep learning and predictive analytics. With the implementation of various software and algorithms, the production has been increased from the farm animals along with better management and welfare. This paper illustrates the application domains and maneuvering of artificial intelligence in the animal husbandry sector.

Key words: Artificial intelligence, Advanced technology, Algorithm, Machine learning, Manouvering, Smart farming sensor.

Animal husbandry is an indispensable part of agriculture which mainly deals with the practice of breeding the farm animals, providing the better care, management and feeding practices to the livestock. Several thousand years ago, man started domesticating animals for their own benefits. Since then, we have always relied on our intuition, sensory signals and collective knowledge to make effectual animal production decisions. And until a decade ago, most animal farmers did not have access to present-day technologies such as high-speed internet, smart phones and cheap computing power. Now, many farmers are coming together with a common view of rearing the animals and use the common resources in a sustainable way. Their familiar interest for the enhanced animal production with the better animal welfare makes them to reach various advanced technologies so that they can remotely monitor the farm animals with minimum invasion.

Farmers need to increase production by 70 per cent over the next 50 years to meet the growing global demands of meat and animal products (Rojas-Downing *et al*., 2017). Since land and other natural resources are limited, to meet this growing demand we need to find more efficient ways of growing more animals per hectare (Neethirajan, 2020). This means that manual processes of animal farming may no longer be sufficient. Moreover, the major hurdle in achieving enormous output in animal farming is acquisition of data. Without precise, smart, real-time data, the task of managing individual cows is nearly impossible. Emerging digital technologies could fill that data gap. Secondly, computing power is now easily accessible by millions of animal farmers along with advancements in technologies in different fields. As agriculture has entered in a phase of 'fourth revolution' in agriculture denoting the expansion of new technologies comprising mobile apps for animal health monitoring, disease surveillance, the Internet of Things, precision agriculture and biosensors. Promisingly, these AI technologies are able to achieve good animal welfare and production performance covering safety, various conditions of health, emotional contagion and behavioral aspect in relative to traditional measures (Alves *et al.,* 2021). Under the current situation, it would be interesting to review the most recent advancement on artificial intelligence and application domains of these technologies in animal production and management.

Livestock Production and Management Section, Indian Veterinary Research Institute, Izatnagar, Bareilly-243 122, Uttar Pradesh, India.

[1]Department of Livestock Products and Technology, Guru Angad Dev Veterinary and Animal Science University, Ludhiana-141 004, Punjab, India

Corresponding Author: Priya, Livestock Production and Management Section, Indian Veterinary Research Institute, Izatnagar, Bareilly-243 122, Uttar Pradesh, India.
Email: dhattarwalpriya@gmail.com

How to cite this article: Priya, Dutt, T., Singh,M., Gaur, G.K. and Sahu, V. (2022). 'Artificial Intelligence' as an intelligent Tool for the Future Animal Production and Better Management: A Review. Agricultural Reviews. DOI: 10.18805/ag.R-2297.

Submitted: 07-06-2021 **Accepted:** 09-05-2022 **Online:** 13-07-2022

Basic concept of artificial intelligence models and their implementation for a smart farm

Artificial Intelligence (AI) can be defined as a technology which mimics human intelligence through the application of algorithms that can perform a series of tasks and are built into computers, software, apps and all other forms of technologies (Felicity, 2020). AI encouraged the foundation of machine learning, deep learning and predictive analytics;

collectively referred to as 'data science'. It deals with solving problems of high logical or algorithmic complexity (Ezanno *et al.,* 2021). Various AI models used in animal husbandry are categorized and defined in Fig 1. In the same way, correlation of sensors, big data**,** machine learning and algorithms in context to smart farming is depicted in Fig 2.

Two categories of devices are the most commonly used in animal farming which are non-invasive fixed-installed devices including microphone as well as camera and animal attached sensor-based devices comprising nose-band sensor, accelerometer and ear tag. These devices and modules are installed at farm or on animals to generate big data for edge device or various AI models which furthers analyze and create a communication protocol. This allows remote monitoring of farm animals *via* user applications like GSM and Wi-Fi module as shown in Fig 3 in which flow chart has been made depicting working module by the use of AI in a smart farm. To sum it all up, artificial intelligence allows easy data entry on farm records, monitoring farm activities, analyzing economic performance and improving animals' health. All these features and solutions strive towards 'smart farming'.

Manoeuvring of artificial intelligence in the livestock sector

Livestock disease prediction

For a long-term sustainable development in animal farming, the occurrence of livestock disease outbreaks prediction can be of considerable value. Traditional statistical models used for disease prediction have varying degrees of accuracy. Earlier, very little research has been conducted on the use of sensors for the occurrence of diseases. Furthermore, the application of these statistical models in sustainable development and in controlling environmental deterioration has been very limited. The possibility of using seasonal climate forecasts as predictive indicators in disease early warning system (EWS) is an interest of focus as the geographic and seasonal distribution of many infectious diseases are associated with climate. Therefore, geographic information system (GIS), remote sensing (RS) and global positioning system (GPS) are the three commonly used veterinary geo-informatics technologies employed in this digital era for rapid communication of data for better management of

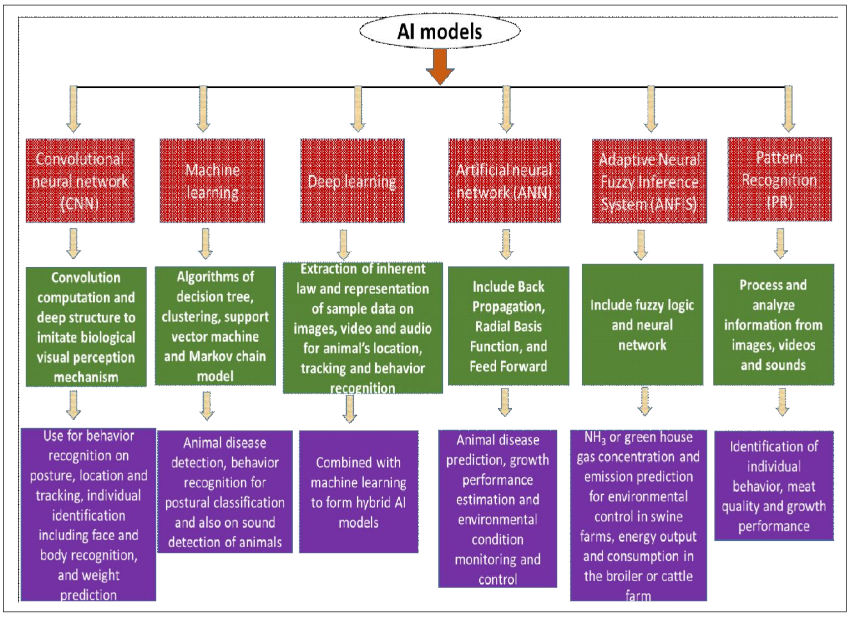

Fig 1: Various AI models used in animal husbandry are categorized.

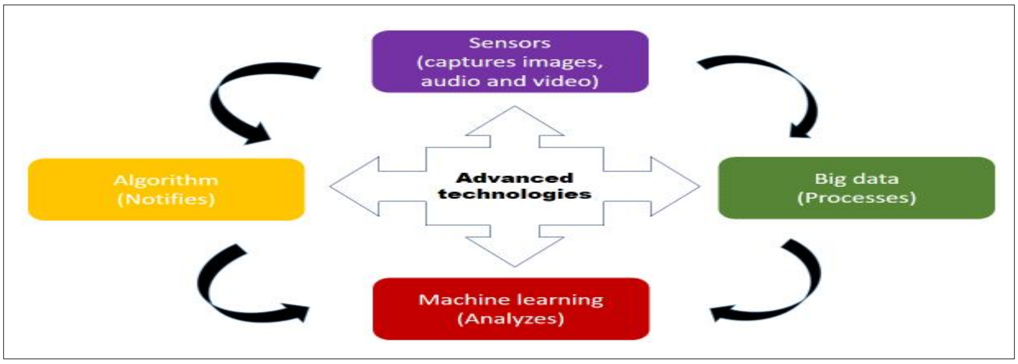

Fig 2: Correlation of sensor, big data, machine learning and algorithms in context to smart farming.

animal diseases. An attempt has been made by Suresh *et al.* (2019) to look for a more reliable model in which artificial intelligence and GIS were used to establish disease-climate relationship models for prediction of 13 economically important livestock disease outbreaks in India. Neethirajan (2020) had shortlisted how advanced technology can help animal farmers predict and prevent diseases as shown in Table 1. The reliable detection of subclinical ketosis by measurement of â-HBA can be achieved by microfluidic sensors (Weng *et al*., 2015). Moreover, real-time animal monitoring is possible by disease detection such as Mycobacterium tuberculosis, liver cirrhosis, diabetes, lung cancer and chronic obstructive pulmonary disease (COPD) using E-nose technology through breath analysis (Bijland *et al.,* 2013 and Ellis *et al.,* 2014) based on volatile organic compounds pattern recognition. Similarly, biofluids like saliva can also give an insight on uric acid levels (Bandodkar *et al.,* 2014), pregnancy testing, virus and Streptomyces throat infection, disease monitoring (Weng *et al.,* 2016), mouth conditions, Gastrophageal Reflux Diseases and lactate variations (Matzeu *et al.,* 2015) using wearable salivary electrochemical sensors.

Effective decision making in animal farming

Over the last decade, there have been several key studies dedicated to reporting on how the application of decision support systems (DSS) in animal farming improves production and systems management. The application of decision support systems (DSS) using AI technologies have been utilized in areas such as, farm planning, animal management, sustainable use of resources, disease management, *etc.*

Typically, the first stage in developing a decision support system (DSS) is the acquisition of data. There are varying data types that can be used in an animal farm setting, such as weather indices, animal growth parameters, *etc.* Advances in the use of technology (*e.g.,* sensor hardware, satellites, drones, proximal sensing, *etc.*) and the development of online and offline systems to house this data (cloud systems) has resulted in more efficient and accurate DSS.

Livestock farm monitoring

Traditional farm monitoring involves use of written notes or a simple device without data sharing capabilities. This is an inaccurate method with high probability of human error (Neethirajan, 2017). The use of Global Positioning Systems (GPS) required detailed field maps and was costly due to the involvement of transmission of data from satellites.

Precision livestock farming (PLF) is a system which has revolutionized the livestock industry and contributed towards animal welfare. The key principles for PLF are the Total Quality Management (TQM) and Hazard Analysis Critical Control Point (HACCP) (Banhazi *et al.,* 2012). This system integrates electronic technology in farming and ensures that the information obtained through measurements is used in

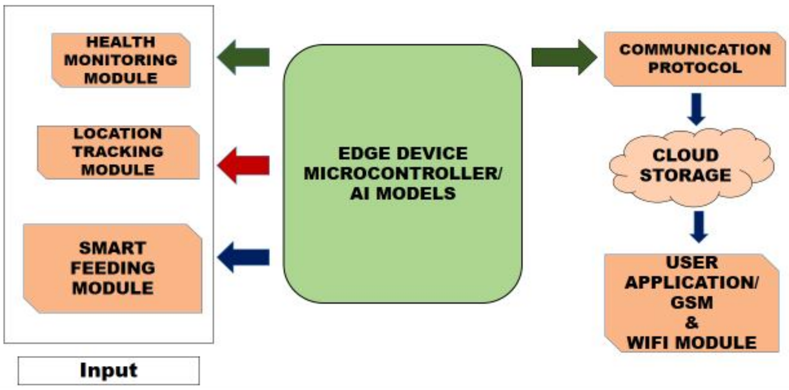

Fig 3: Flow chart showing working module of smart farm.

Table 1: How advanced technology can help animal farmers predict and prevent diseases (Neethirajan, 2020).

Paper	Disease	Algorithm(s)	Parameter detected
Dhoble *et al.,* 2019, Ebrahimi *et al.,* 2019	Mastitis	Bag of Words (BoW), Gradient Boosted Trees (GBT)	Somatic cell count (SSC), Electrical Conductivity (EC)
Gertz *et al.,* 2020, Taneja *et al.,* 2020	Lameness	Fog computing, Classification and regressive tree (CART) XGBoost algorithm	Leg movement, Neck movement and Image/Video data
Hidalgo *et al.,* 2018	Postpartum disease	Random forest algorithm (RFA)	Lactose yield, Protein production, Milk yield
Borgonovo *et al.,* 2020	Coccidiosis	Principal component analysis (PCA)	Volatile organic compounds (VOC) in air
Fernández-Carrión *et al.,* 2017	African swine flu	Optical flow algorithm	Mobility, speed, direction

a way benefitting farmers. The AI technology will act as a powerful tool to revolutionize the future of farming with drones, robots and intelligent monitoring systems.

A technique for monitoring the health of farm animals with a high degree of accuracy uses a camera and artificial intelligence (AI) to achieve a "livestock" cow house. Detailed observation by AI-powered image analysis could enable early detection of injuries and illnesses (Singh, 2019). A variety of devices, such as automated tools that integrate audio-and-video-captured data for early disease detection and warning systems have been used by Park and Ha (2015).

Measuring and analyzing livestock and poultry farm odors

In livestock and poultry farming, the presence of odor has always been a source of nuisance to the human beings. The traditional and most common way of detecting foul odors has always been human noise. There is a lack of science based approaches to assess odor control technologies (Zhang *et al.,* 2002).

Electronic nose is an instrument which is composed of an array of electronic gas sensors and a signal-processing system and is capable of recognizing simple or complex odors (Gardner and Bartlett, 1999). The oeuvre of an electronic nose can be either a prediction of any characteristic properties of the odor such as intensity and nuisance, or the identity of chemical components of the odor (Pan and Yang, 2007). Some of the sensors used to detect the chemical components of odor along with the material used are shown in Table 2.

Artificial intelligence to manage heat stress and milk productivity

In tropical countries like India, the extreme weather conditions such as summer with high temperature result in decreased performance by farm animals. Positive results are seen with physical modification of the environment such as shading and fans, when applied for lactating buffaloes (Ahmad *et al.,* 2019) and in dairy cows using mixed-flow fans (Yao *et al*., 2019). However, direct water spraying over animals using sprinkler systems is the one of the most effective way to combat heat stress (Tresoldi *et al.,* 2019).

Table 2: Partial list of the sensors used for the developed electronic nose (Pan and Yang, 2007).

Name of sensor	Material	Compounds to be detected
7NH	MMOS	Ammonia
TG826	Tungsten oxide	Amine compounds
MAX6605MXK-T	Semi-conductor	Temperature
TGS825	Hybrid sensor	Hydrogen sulfide
TGS813	Tin dioxide (SnO_2)	Butane
HIH-3610-001	Thermostat polymer	Humidity

In a research conducted by Fuentes *et al.* (2010) an automated system was implemented based on an individual cow assessment combined with environmental factors obtained from an automatic meteorological station (AME). The RFID from cows of a farm that are going to be milked is read by a processing unit (microprocessor or smartphone app) which is further connected to AME to obtain cow information required by the model. The outputs of this model can be automatically directed to specific thresholds for volume and milk quality that is desired by the dairy farm. This automatically allowed to direct the cows either to a normal milking process, or to open gates to a cooling system with water sprinklers for heat stressed cows. Next day the heat stressed cows will be assessed again if they continue to be heat stressed, they will go to the sprinkler system and get milked to avoid mastitis.

The managerial advantages that could be obtained by implementing the system proposed are: i) management of heat stress in cows to increase efficiency; ii) information related to milk volume and quality available in real-time, per cow and according to daily environmental conditions; iii) forecasting of actual concentrate feed intake per cow; iv) data recorded from specific dairy farms can be incorporated in the model to increase the accuracy of target predictions.

Optimizing feed efficiency and energy intake

On a dairy farm, feed costs make up to 40-60 per cent of the total expense. Feed wastage is also a major concern in animal farms under closed housing system. Now-a-days due to urbanization and less availability of land for fodder production, animals should optimize in their feed efficiency and energy intake. Productivity of a farm gets decreased, when adequate amount of feed and water is not available for the animals (Neethirajan, 2020).

For a complete idea of feed efficiency, the knowledge of different factors like the amount of feed intake, nutrient composition of diet, weight gained by animals (Piles *et al.,* 2019) and where applicable, the amount of milk and eggs produced. However, these factors are based on several diverse and non-linear parameters that are hard to categorize manually. RGB – D cameras can help farmers measure feed intake for individual cows (Bezen *et al.,* 2020). In addition to this, several advanced algorithms such as TDIDT, ENET, SSD, ARIMA and CNNs can help farmers measure and optimize feed expenses according to their animal needs (Piles *et al.,* 2019; da Rosa Righi *et al.,* 2020 and Bezen *et al.,* 2020). Random Forest Algorithm elastic net (ENET) and nearest shrunken centroid algorithm was used by Piles *et al.* (2019) for the data collection of metabolic rate, gene expression, average daily weight gain and average back fat gain. Similarly, da Rosa Righi *et al.* (2020) applied auto-regressive moving average model (ARIMA) for estimating feeding weight of dry and concentrate and milk production by each cow.

Emotional contagion and behavior cognition

Emotional contagion means way of people mimicking other people's emotions. In animals, emotions help them adopt a quick response to deal efficiently with their surroundings and collectively move towards something they want or away from danger (Mendl *et al.,* 2010 and Paul *et al.,* 2005). Harmonizing the emotional behaviors of individual animals can help other farm-animals develop more empathy and other desirable traits (Fredrickson and Branigan, 2005). Emotional contagion can be a useful tool to regulate social interactions such as maternal nursing, play, mating competition and group defense. This may result in the improved group coordination and development of strong social bonds in entire herd (Špinka, 2012). Various variables of emotional contagion based on vocalizations, olfactory cues, *etc.* can be identified by ML-based AI to detect the outburst of a specific disease or stress. These variables also help in animal behavior detection by means of camera (eYeNamic camera-based system installed above animal activity zone), accelerometer and microphone generating the visual or acoustic information which are further translated and classified using some software, like Phython, Tensorflow and algorithms (*e.g.*, DL, CNN, ML, *etc.*) (Bao and Xie).

Improving animal health using satellite imagery and facial recognition system

Individual identification of an animal is necessary for providing individually tailored diets, traceability of animal products through the supply chain and optimizing animal productivity. Earlier identifying a particular animal is more time consuming as well as inefficient. Till now, ear tags and RFID (Radio Frequency Identification) tags are adapted for individual identification of poultry (Sales *et al.,* 2015), pigs (Cappai *et al.,* 2018) and ruminants (Rutten *et al.,* 2017). Despite of cheap, they demand animals' ear piercing for installment which is a painful process. RFID tags have limitations of using for animals in herds, battery supply, physical damage to RFID readers, costly, also, signal interference. Therefore, with the advancement in computational technologies satellite imagery, non-invasive recognition of machine vision and facial detection system coupled with recognition models such as the VGG-face model (Parkhi *et al*., 2015), Fisher faces (Belhumeur *et al*., 1997) and convolutional neural networks help farmers to understand various problems faced by animals without actually being present near them. These models help in differentiating individual animal faces in complex real-time scenarios and also give an understanding about individual animal's mood and emotional state.

For example, if animals are found agitated and restless during the feeding time, we commonly find that many cows are agitated in the feedlots, we may wrong with the feeding stations demanding further investigation. Such investigation may lead to have a direct light on events or activities on a farm that can be easily missed by humans, such as shortage of feeding stations (Battini *et al*., 2019). While using non-invasive recognition of machine vision, face images are captured by installing cameras in front of feeding troughs. Extraction and recognition of acquired face images are performed by the analysis software and algorithms *e.g.,* machine-vision based pig recognition model developed by Hansen *et al*. (2018). In some cases, these facial-recognition models such as SPFES (Sheep Pain Facial Expression Scale) help in determining the pain symptoms in sheep (McLennan, 2016). Technology based on real-time data is getting better at helping farmers pinpoint problems and gain more perception about their animals leading to better animal health and well-being outcomes (McLennan and Mahmoud, 2019).

Accurate discrimination of individual animal through acoustic sensing

Voice of an individual also seems to differ from one another in terms of quality. Vocalization provides information about the age, sex, dominance status and reproductive status of the caller (Watts and Stookey, 2000). Few acoustic features *viz.* number of pulse, pitch (mean and range), formants (F1, F2, F3, F4 and F5), degree of voice breaks, shimmer and mean noise to harmonic ratio (%) were found to have significant difference for each and every individual cow (Yajuvendra *et al.,* 2013). In their study, acoustic features were extracted with the help of PRAAT 5.1.36 software package developed by Boersma and Weenink (2010). For the effective and accurate discrimination of individual dairy cattle, only these features can be successfully used. This discrimination of one from their herd based on acoustic features of voice signals seems to be a passive indicator.

Robotic system to deliver vaccines

Earlier, farmers have been using manual methods of delivering vaccines either orally or intravenously. But this results in occupation of large amount of time and labor as farmers are required to give hundreds of vaccines and reproductive medicines to animals in dairy farm. Farmers are also required either to have proper training or all time contact with a qualified veterinarian doctor. Modern dairy farms use a robotic injection system to deliver vaccines and reproductive medicines to domestic animals on the dairy farm for a sustainable economic future of dairy farms and to achieve 100 per cent compliance rate.

The robotic system is integrated with a dairy automation system. The RFID tags attached to the cow's ear were read by the robotic injection system and gets health-related information and vaccination record for the cow. If the cow requires an injection, it is directed towards the injection site and the injection mechanism position itself to deliver the medication in the cow's neck.

Prediction of production performance and morphological assessment

Modern advanced technologies have provided the dairy farmers with an ability to forecast and predict outcomes of economic importance such as body weight (BW), early estrous detection in dairy farms, performance like milk yield or egg production, mortality and productivity. Earlier, body weight of an animal is estimated by direct weighing leading to stress and trauma. Image processing algorithm (image segmentation, edge detection) and deep learning (CNN, FLYO-LOv3) focus on live weight assessment of farm animals. For example, Alonso González *et al.* (2015), used a support vector machine classification model to successfully predict the BW of individual cattle in cases where the past evolution of the herd BW is known. This approach exceled individual regressions created for individual animals when precise predictions for longer durations were required and when there were only a small number of BW measures available. Similarly, Pomar and Remus (2019) and White *et al.* (2004), have all proposed the use of machine vision based visual image analysis platforms to monitor BW in growing pigs from which they could evaluate appropriate feed allocations. Cameras of binocular (Jun *et al.,* 2018), RGB (Shuai *et al.,* 2020), or depth (Wang *et al*., 2018) have been used for calculating pig size or volume on the basis of images. The increase in motion during estrus in dairy animals can be detected by using a collar (with motion sensors like Tri-axial accelerometer: Kionix KXTJ9) tied to the cow's neck which collects all types of data related to cow 24 hours a day (Arcidiacono *et al.,* 2020). The AI component compares the recently collected data (about movements) with stored data and can predict the ovulation period of the cow in advance. Since the ovulation period starts after 24 to 32 hours of the onset of "Standing heat," the farmer has enough time to prepare for artificial insemination of the cow in heat (Singh, 2019). At the same time, voice produced by animal can also be related to variety of behavioral and physiological signs including reproductive status and stage. Moreover, insemination outcomes (Shahinfar *et al.,* 2014), abortion (Keshavarzi *et al.,* 2020), breeding values of milk quality and quantity can be predicted by the adoption of computational models of pattern recognition, ANFIS, clustering, ANN and automatic systems. In beef industry also, computer simulation models, such as DAFOSYM (Rotz *et al.,* 1989), GRAZE (Loewer *et al.,* 1987) and Alberta Beef Production System (Pang *et al.,* 1999) are practiced to predict the environmental impact, production economics and the longevous performance. Predictive abilities of such models have the potential to achieve greater animal farming gains and create new efficiencies.

Evaluation of animal blastocyst images

In-vitro production of bovine embryos demand their classification based on morphological evaluation into three quality grades: 1. Excellent; 2. Fair; 3. Poor (Bó and Mapletoft, 2013). With time, several methods have been or are being developed to provide a better solution for embryo classification, including a semi-automatized image segmentation process with the use of artificial intelligence (AI) for human embryos (Manna *et al.,* 2013), an automatic segmentation procedure of bovine embryos, but without the use of AI (Melo *et al.,* 2014), embryo metabolism analysis, cellular respiration measurements, the use of zona pellucida birefringence, microRNA profile determination, analysis based on logistic regression and evaluation by time-lapse video (Rocha *et al.,* 2016). However, all the above methods are totally ineffective, subjective and old, visual morphological analysis is still widely used (Farin *et al.,* 1995 and Richardson *et al.,* 2015). Rocha *et al.* (2017) were the first to develop a fully automated ANN (Artificial Neural Network) and GA (Genetic algorithm) based software for the evaluation of mammalian embryos.

In brief, an artificial neural network (ANN) is a system that solves problems by imitating the operation of a set of biological neurons. In particular, this artificial intelligence technique is suitable for solving nonlinear problems by using interconnected variables (Goethals *et al.,* 2007 and Krogh, 2008) making it an intelligent system that can interpret a complex problem through supervised learning. The ANNs are already widely used in solving problems related to image processing (Suzuki *et al.,* 2006). Thus, the digital image processing technique using ANN and GA is potentially suitable for blastocyst morphological classification from two-dimensional images.

Some other advanced technologies related to artificial intelligence are beyond the scope of this paper.

Current challenges

Use of AI faces these fusses that also make sense in animal health (AH):

- Perception of a situation and its dynamics, *e.g.,* epidemic spread;
- The discernment and understanding of the environment, which corresponds in AH to the detection of patterns (*e.g.,* repeated sequence of observations), forms (*e.g.,* of a protein) and signals (*e.g.,* increased mortality compared to a baseline) at different scales;
- Limitation of available commercial sensors for reliable prediction and diseases management of livestock e.g., lack of sensors to estimate biomarkers from the breathing space of the cow and pigs.
- Technical challenges such as evaluation of sensor position, sensor data analysis, sampling frequency, data transmission and window size for the data processing are also faced.
- Computer-based decision making, or, more realistically, human decision support (*e.g.,* expert systems, diagnostic support, resource allocation) (Ezanno *et al.,* 2021).
- Various AI technologies such as machine learning, data mining, *etc.* are never taught in veterinary high school education (VanderWaal, 2017).
- There is also quasi-absence of sentinel networks of veterinarians.

Key AI initiatives in India

In 2020, the Indian government increased the outlay for Digital India to $477 million to boost AI, IoT, big data, cybersecurity, machine learning and robotics. In the 2019 Union Budget, Finance Minister Nirmala Sitharaman said the government would offer industry-relevant skill training for 10 million youth in India in technologies like AI, Big Data and robotics. Additionally, policy-level initiatives by the Ministry of Electronics and Information Technology (MeitY) and programmes around AI by NASSCOM and Defence Research and Development Organization (DRDO) have laid the groundwork for future disruption and created a roadmap for AI in India.

Centre for Artificial Intelligence and Robotics (CAIR)

CAIR, a laboratory of the DRDO, was established in 2014 for research and development in AI, robotics, command and control, networking, information and communication security.

US-India AI Initiative

US India Artificial Intelligence (USIAI) is an initiative of Indo-US Science and Technology Forum (IUSSTF) which was established in March 2000 and was launched on 18th March 2021 to foster AI innovation in agriculture along with health care, energy and manufacturing. The Department of Science and Technology (DST), Government of India and the U.S. Department of State are respective nodal departments for IUSSTF. This will provide an opportunity to discuss the emerging AI landscape and address the challenges of developing an AI workforce.

Applied AI Research Centre in Telangana

In October 2020, the Telangana government collaborated with Intel India, International Institute of Information Technology, Hyderabad (IIIT-H) and Public Health Foundation of India (PHFI) to launch INAI (Intel AI), an applied AI research centre in Hyderabad with a perspective of focusing on solving challenges in India's healthcare and smart mobility segment.

MCA 3.0 portal

The Ministry of Corporate Affairs (MCA) recently launched a new version of its portal, version 3.0, MCA 21, which will leverage data analytics, AI and ML, to simplify regulatory filings for companies.

AI portal

Jointly developed by MeitY and NASSCOM in June 2020, the Indian government launched a dedicated artificial intelligence (AI) portal, India AI is slated as a central hub for everything. The portal will act as a one-stop-shop for all AI-related developments and initiatives in India.

AI policy-India

In June 2018, the Indian government defined a national policy on AI in a working paper titled, "National Strategy for Artificial Intelligence #AIforAll." identifying healthcare, agriculture, education, urban-/smart-city infrastructure and transportation and mobility as five focus areas.

Establishment of Multi-purpose AI Technicians in Rural India (MAITRIs)

a. MAITRI are chosen from unemployed educated rural youth of local area with a minimum education qualification of not below 10th class. The chosen candidates are trained at accredited AI training institute (evaluated and accredited by CMU) using uniform training module developed by Government of India for a duration of 3 months.

b. MAITRIs to be established under National Programme for Bovine Breeding component of the scheme National Programme for Bovine Breeding and Dairy Development (NPBBDD) will be multipurpose workers along with AI they will take up:

- Veterinary first aid.
- Vaccination.
- Agent for livestock insurance.
- Ration balancing.
- Milk recording.
- Data entry in national database.

Final considerations

Application of AI methods deals with the collection of complex and massive data from the sensors. However, more the collected data is numerous and representative of working concepts and hypotheses, the more important results can be obtained from AI applications. Various AI methods should be discussed in veterinary high school education, as they represent the future caretaker of animal husbandry. Furthermore, development of sensors and biosensing tools using 'omics' and non-omics approaches specific for measuring biomarkers, miRNAs and odor volatile metabolites and others should be focused more so that metabolic states of animals and knowledge about gut microbiota could be known directly from breathing space of animals. A training effort must be provided and generalized so that AH researchers get well known of AI technologies along with its limits and constraints. Governments should encourage the centralized animal farming with the availability of advanced AI technologies at all possible level.

Conflict of interest: None.

REFERENCES

Ahmad, M., Bhatti, J.A., Abdullah, M., Ullah, R., ul Ain, Q., Hasni, M.S., Ali, M., Rashid, A., Qaisar, I., Rashid, G. and Uddin, R. (2019). Different ambient management intervention techniques and their effect on milk production and physiological parameters of lactating NiliRavi buffaloes during hot dry summer of subtropical region. Tropical Animal Health and Production. 51(4): 911-918.

Alonso González, J., Villa, A. and Bahamonde Rionda, A. (2015). Improved estimation of bovine weight trajectories using support vector machine classification. Computers and Electronics in Agriculture. 110.

Alves, V.M., Auerbach, S.S., Kleinstreuer, N., Rooney, J.P., Muratov, E.N., Rusyn, I., Tropsha, A. and Schmitt, C. (2021). Curated data in-trustworthy in silico models out: The impact of data quality on the reliability of artificial intelligence models as alternatives to animal testing. Alternatives to Laboratory Animals. 49(3): 73-82.

Arcidiacono, C., Mancino, M. and Porto, S.M.C. (2020). Moving mean-based algorithm for dairy cow's oestrus detection from uniaxial-accelerometer data acquired in a free-stall barn. Computer and Electronics in Agriculture. 175: 105498.

Bandodkar, A.J. and Wang, J. (2014). Non-invasive wearable electrochemical sensors: a review. Trends Biotechnol. 32: 363-371.

Banhazi, T.M., Babinszky, L., Halas, V. and Tscharke, M. (2012). Precision Livestock Farming: Precision feeding technologies and sustainable livestock production. International Journal of Agricultural and Biological Engineering. 5(4): 54-61.

Bao, J. and Xie, Q. (2022). Artificial intelligence in animal farming: A systematic literature review. Journal of Cleaner Production. 331: 129956.

Battini, M., Agostini, A. and Mattiello, S. (2019). Understanding cows' emotions on farm: Are eye white and ear posture reliable indicators?. Animals. 9(8): 477.

Belhumeur, P.N., Hespanha, J.P. and Kriegman, D.J. (1997). Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence. 19(7): 711-720.

Bezen, R., Edan, Y. and Halachmi, I. (2020). Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms. Computers and Electronics in Agriculture. 172: 105345.

Bijland, L.R., Bomers, M.K. and Smulders, Y.M. (2013). Smelling the diagnosis a review on the use of scent in diagnosing. Neth. J. Med. 71: 300-307.

Bó, G. and Mapletof, R. (2013). Evaluation and classifcation of bovine embryos. Animal Reproduction. 54: 344-348.

Boersma, P. and Weenink, D. (2010). PRAAT: Doing Phonetics by Computer. Phonetic Sciences.

Borgonovo, F., Ferrante, V., Grilli, G., Pascuzzo, R., Vantini, S. and Guarino, M. (2020). A data-driven prediction method for an early warning of coccidiosis in intensive livestock systems: A preliminary study. Animals. 10(4): 747.

Cappai, M.G., Rubiu, N.G., Nieddu, G., Bitti, M.P.L. and Pinna, W. (2018). Analysis of fieldwork activities during milk production recording in dairy ewes by means of individual ear tag (ET) alone or plus RFID based electronic identification (EID). Computer and Electronics in Agriculture. 144: 324-328.

da Rosa Righi, R., Goldschmidt, G., Kunst, R., Deon, C. and da Costa, C.A. (2020). Towards combining data prediction and internet of things to manage milk production on dairy cows. Computers and Electronics in Agriculture. 169: 105156.

Dhoble, A.S., Ryan, K.T., Lahiri, P., Chen, M., Pang, X., Cardoso, F.C. and Bhalerao, K.D. (2019). Cytometric fingerprinting and machine learning (CFML): A novel label-free, objective method for routine mastitis screening. Computers and Electronics in Agricultur. 162: 505-513.

Ebrahimi, M., Mohammadi-Dehcheshmeh, M., Ebrahimie, E. and Petrovski, K.R. (2019). Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep Learning and Gradient-Boosted Trees outperform other models. Computers in Biology and Medicine. 114: 103456.

Ellis, C.K., Stahl, R.S., Nol, P., Waters, W.R., Palmer, M.V., Rhyan, J.C., VerCauteren, K.C., McCollum, M. and Salman, M.D. (2014). A pilot study exploring the use of breath analysis to differentiate healthy cattle from cattle experimentally infected with Mycobacterium bovis. PloS One. 9: e89280.

Ezanno, P., Picault, S., Beaunée, G., Bailly, X., Muñoz, F., Duboz, R., Monod, H. and Guégan, J.F. (2021). Research perspectives on animal health in the era of artificial intelligence. Veterinary Research. 52(1): 1-15.

Farin, P. W., Britt, J. H., Shaw, D. W. and Slenning, B. D. (1995). Agreement among evaluators of bovine embryos produced *in vivo* or *in vitro*. Theriogenology. 44(3): 339-349.

Felicity, N. (2020). Gathering livestock data through Artificial Intelligence. https://www.farm4trade.com/gathering-livestock-data-through-artificial-intelligence/.

Fernández-Carrión, E., Martínez-Avilés, M., Ivorra, B., Martínez-López, B., Ramos, Á.M. and Sánchez-Vizcaíno, J.M. (2017). Motion-based video monitoring for early detection of livestock diseases: The case of African swine fever. PLoS One. 12(9): e0183793.

Fredrickson, B. L. and Branigan, C. (2005). Positive emotions Cognition and emotion. 19(3): 313-332.

Fuentes, S., Gonzalez Viejo, C., Cullen, B., Tongson, E., Chauhan, S.S. and Dunshea, F.R. (2020). Artificial intelligence applied to a robotic dairy farm to model milk productivity and quality based on cow data and daily environmental parameters. Sensors. 20(10): 2975.

Gardner, J.W. and Barlett, P.N. (1999). Electronic noses: Principals and applications. Oxford, UK: Oxford University Press.

Gertz, M., Große-Butenuth, K., Junge, W., Maassen-Francke, B., Renner, C., Sparenberg, H. and Krieter, J. (2020). Using the XGBoost algorithm to classify neck and leg activity sensor data using on-farm health recordings for locomotor-associated diseases. Computers and Electronics in Agriculture. 173: 105404.

Goethals, P.L., Dedecker, A.P., Gabriels, W., Lek, S. and De Pauw, N. (2007). Applications of artificial neural networks predicting macroinvertebrates in freshwaters. Aquatic Ecology. 41(3): 491-508.

Hansen, M.F., Smith, M.L., Smith, L.N., Salter, M.G., Baxter, E.M., Farish, M. and Grieve, B. (2018). Towards on-farm pig face recognition using convolutional neural networks. Computers in Industry. 98: 145-152.

Hidalgo, A., Zouari, F., Knijn, H. and van der Beek, S. (2018). Prediction of Postpartum Diseases of Dairy Cattle using Machine Learning. In Proceedings of the World Congress on Genetics Applied to Livestock Production. World Congress on Genetics Applied to Livestock Production (p. 104).

Jun, K., Kim, S.J. and Ji, H.W. (2018). Estimating pig weights from images without constraint on posture and illumination. Computer and Electronics in Agriculture. 153: 169-176.

Keshavarzi, H., Sadeghi-Sefidmazgi, A., Mirzaei, A., Ravanifard, R., 2020. Machine learning algorithms, bull genetic information and imbalanced datasets used in abortion incidence prediction models for Iranian Holstein dairy cattle. Prev. Vet. Med. 175, 104869.

Krogh, A. (2008). What are artificial neural networks?. Nature biotechnology. 26(2): 195-197.

Loewer, O.J., Taul, K.L., Turner, L.W., Gay, N. and Muntifering, R. (1987). GRAZE: A model of selective grazing by beef animals. Agricultural Systems. 25: 297-309.

Manna, C., Nanni, L., Lumini, A. and Pappalardo, S. (2013). Artificial intelligence techniques for embryo and oocyte classification. Reproductive Biomedicine Online. 26(1): 42-49.

Matzeu, G., Florea, L. and Diamond, D. (2015). Advances in wearable chemical sensor design for monitoring biological fluids. Sensors and Actuators B: Chemical. 211: 403-418.

McLennan, K. and Mahmoud, M. (2019). Development of an automated pain facial expression detection system for sheep (*Ovis aries*). Animals. 9(4): 196.

McLennan, K.M., Rebelo, C.J., Corke, M.J., Holmes, M.A., Leach, M.C. and Constantino-Casas, F. (2016). Development of a facial expression scale using footrot and mastitis as models of pain in sheep. Applied Animal Behaviour Science. 176: 19-26.

Melo, D.H., Nascimento, M.Z.D., Oliveira, D.L., Neves, L.A. and Annes, K. (2014). Algorithms for automatic segmentation of bovine embryos produced in vitro. In Journal of Physics: Conference Series (Vol. 490, No. 1, p. 012125). IOP Publishing.

Mendl, M., Burman, O.H. and Paul, E.S. (2010). An integrative and functional framework for the study of animal emotion and mood. Proceedings of the Royal Society B: Biological Sciences. 277(1696): 2895-2904.

Neethirajan, S. (2017). Recent advances in wearable sensors for animal health management. Sensing and Bio-Sensing Research. 12: 15-29. doi:10.1016/j. sbsr. 2016.11.004.

Neethirajan, S. (2020). The role of sensors, big data and machine learning in modern animal farming. Sensing and Bio-Sensing Research. 100367.

Pan, L. and Yang, S.X. (2007). A new intelligent electronic nose system for measuring and analysing livestock and poultry farm odours. Environmental Monitoring and Assessment. 135(1-3): 399-408.

Pang, H., Makarechian, M.H., Basarab, J.A. and Berg, R.T. (1999). Structure of a dynamic simulation model for beef cattle production systems. Canadian Journal of Animal Science. 79: 409-417.

Park, M.C. and Ha, O.K. (2015). Development of effective cattle health monitoring system based on biosensors. Advanced Sciences and Technologies. 117: 180-185.

Parkhi, O.M., Vedaldi, A. and Zisserman, A. (2015). Deep face recognition.

Paul, E.S., Harding, E.J. and Mendl, M. (2005). Measuring emotional processes in animals: the utility of a cognitive approach. Neuroscience and Biobehavioral Reviews. 29(3): 469-491.

Piles, M., Fernandez-Lozano, C., Velasco-Galilea, M., González-Rodríguez, O., Sánchez, J.P., Torrallardona, D., Ballester, M. and Quintanilla, R. (2019). Machine learning applied to transcriptomic data to identify genes associated with feed efficiency in pigs. Genetics Selection Evolution. 51(1): 1-15.

Pomar, C. and Remus, A. (2019). Precision pig feeding: a breakthrough towardsustainability. Animal Frontiers. 9(2): 52-59.

Richardson, A., Brearley, S., Ahitan, S., Chamberlain, S., Davey, T., Zujovic, L., Hopkisson, J., Campbell, B. and Raine-Fenning, N. (2015). A clinically useful simplified blastocyst grading system. Reproductive biomedicine online. 31(4): pp.523-530.

Rocha, J.C., Passalia, F., Matos, F.D., Maserati, Jr, M.P., Alves, M.F., De Almeida, T.G., Cardoso, B.L., Basso, A.C. and Nogueira, M.F. (2016). Methods for assessing the quality of mammalian embryos: How far we are from the gold standard? JBRA Assisted Reproduction. 20(3): 150.

Rocha, J.C., Passalia, F.J., Matos, F.D., Takahashi, M.B., de Souza Ciniciato, D., Maserati, M.P., Alves, M.F., De Almeida, TG., Cardoso, B.L., Basso, A.C. and Nogueira, M.F.G. (2017). A method based on artificial intelligence to fully automatize the evaluation of bovine blastocyst images. Scientific Reports. 7(1): 1-10.

Rojas-Downing, M.M., Nejadhashemi, A.P., Harrigan, T. and Woznicki, S.A. (2017). Climate change and livestock: Impacts, adaptation and mitigation. Climate Risk Management. 16: 145-163.

Rotz, C.A., Buckmaster, D.R. Mertens, D.R. and Black, J.R. (1989). DAFOSYM: A dairy forage system model for evaluating technologies and management strategies in forage conservation. Journal of Dairy Science. 72: 3050-3063.

Rutten, C.J., Kamphuis, C., Hogeveen, H., Huijps, K., Nielen, M. and Steeneveld, W. (2017). Sensor data on cow activity, rumination and ear temperature improve prediction of the start of calving in dairy cows. Computer and Electronics in Agriculture. 132: 108-118.

Sales, G.T., Green, A.R., Gates, R.S., Brown-Brandl, T.M. and Eigenberg, R.A. (2015). Quantifying detection performance of a passive low-frequency RFID system in an environmental preference chamber for laying hens. Computer and Electronics in Agriculture. 114: 261-268.

Shahinfar, S., Page, D., Guenther, J., Cabrera, V., Fricke, P. and Weigel, K. (2014). Prediction of insemination outcomes in Holstein dairy cattle using alternative machine learning algorithms. Journal of Dairy Science. 97(2): 731-742.

Shuai, S., Ling, Y., Shihao, L., Haojie, Z., Xuhong, T., Caixing, L., Aidong, S. and Hanxing, L. (2020). Research on 3D surface reconstruction and body size measurement of pigs based on multi-view RGB-D cameras. Computer and Electronics in Agriculture. 175: 105543.

Singh, R. (2019). Application of Artificial Intelligence (Ai) for Livestock and Poultry Farm Monitoring. https://www.pashudhanpraharee.com/application-of-artificial-intelligence-ai-for-livestock-poultry-farm-monitoring/.

Špinka, M. (2012). Social dimension of emotions and its implication for animal welfare. Applied Animal Behaviour Science. 138(3-4): 170-181.

Suresh, K.P., Hemadri, D., Kruli, R., Dheeraj, R. and Roy, P. (2019). Application of artificial intelligence for livestock disease prediction. Indian Farming. 69(3): 60-62.

Suzuki, K., Abe, H., MacMahon, H. and Doi, K. (2006). Image-processing technique for suppressing ribs in chest radiographs by means of massive training artificial neural network (MTANN). IEEE Transactions on Medical Imaging. 25(4): 406-416.

Taneja, M., Byabazaire, J., Jalodia, N., Davy, A., Olariu, C. and Malone, P. (2020). Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. Computers and Electronics in Agriculture. 171: 105286.

Tresoldi, G., Schütz, K.E. and Tucker, C.B. (2019). Cooling cows with sprinklers: Effects of soaker flow rate and timing on behavioral and physiological responses to heat load and production. Journal of Dairy Science. 102(1): 528-538.

VanderWaal, K., Morrison, R.B., Neuhauser, C., Vilalta, C. and Perez, A.M. (2017). Translating big data into smart data for veterinary epidemiology. Frontiers in Veterinary Science. 4: 110.

Wang, K., Guo, H., Ma, Q., Su, W., Chen, L. and Zhu, D. (2018). A portable and automatic Xtion-based measurement system for pig body size. Computer and Electronics in Agriculture. 148: 291-298.

Watts, J.M. and Stookey, J.M. (2000). Vocal behaviour in cattle: the animal’s commentary on its biological processes and welfare. Applied Animal Behaviour Science. 67(1-2): 15-33.

Weng, X., Chen, L., Neethirajan, S. and Duffield, T. (2015). Development of quantum dots-based biosensor towards on-farm detection of subclinical ketosis. Biosensors and Bioelectronics. 72: 140-147.

Weng, X., Gaur, G. and Neethirajan, S. (2016). Rapid detection of food allergens by microfluidics ELISA-based optical sensor. Biosensors. 6: 24.

White, R.P., Schofield, C.P., Green, D.M., Parsons, D.J. and Whittemore, C.T. (2004). The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs. Animal Science. 78(3): 409-418.

Yajuvendra, S., Lathwal, S.S., Rajput, N., Raja, T.V., Gupta, A.K., Mohanty, T.K., Ruhil, A.P., Chakravarty, A.K., Sharma, P.C., Sharma, V. and Chandra, G. (2013). Effective and accurate discrimination of individual dairy cattle through acoustic sensing. Applied Animal Behaviour Science. 146(1-4): 11-18.

Yao, C., Shi, Z., Zhao, Y. and Ding, T. (2019). Effect of Mixed-Flow Fans with a Newly Shaped Diffuser on Heat Stress of Dairy Cows Based on CFD. Energies. 12(22): 4315.

Zhang, Q., Feddes, J., Edeogu, I., Nyachoti, M., House, J., Small, D., Liu, C., Mann, D. and Clark, G. (2002). Odour production, evaluation and control. Project MLMMI.