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Artificial Intelligence: Transforming Animal Health and Management

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Abstract

Artificial intelligence (AI) has developed as an interdisciplinary science based on computers and is concerned with building machines and equipment which use human intelligence to perform a particular task. Intelligence involves judgment, reasoning, understanding, acumen, insight, comprehension, sharpness, alertness, acuity and also intuition. It is basically a physiological trait present in varying degrees in different animals. The brain carries out cognitive learning and processing by performing combinations of various sort of information processes. Types of information processes are performed by different anatomical structures and instigated in physiology. The intersection of medicine and machine learning has the potential to transform healthcare. Physiology is a foundational discipline of medical training and practice with an upscale of quantitative history, clinical manifestation, diagnostic technics and treatments. The role of Artificial Intelligence is manifold in our day-to-day lives. The history of AI, its applications as software packages, simulation apps, and a list of various equipment used for analytical, clinical, and livestock farm purposes are detailed here. Veterinary practice management software which are commercially available in developed countries, especially for small animal practice, may not be beneficial in the Veterinary Dispensaries and Farms in India due to different conditions, animals and requirements. The AI has immense contribution in Veterinary and allied sciences and has made the diagnosis, treatment, and prognosis quicker, cheaper, and effective. AI is applicable in antimicrobial resistance (AMR) research, cancer research, drug design and vaccine development, epidemiology, disease surveillance, and genomics. Here, the authors have highlighted and discussed the potential impact of various aspects of AI in veterinary health and management, proposing this technology as a key tool for addressing pressing global health challenges across various domains.

Keywords: artificial intelligence; history; application; data analytical software; veterinary

Introduction: Background

Intelligence is defined as the ability to acquire and apply skills and knowledge. It relates to brainpower. How quickly, efficiently and also the manner in which an animal tackles a problem or adverse / favourable situation in its day-to-day life will define its intelligence and mental ability. Intelligence involves judgment, reasoning, understanding, acumen, insight, comprehension, sharpness, alertness, acuity, and also intuition. It is basically a physiological trait present in varying degrees in different animals.

Artificial Intelligence is using the intelligence (brainpower) of human beings to construct and run machines that are smart i.e., make machines do the work that humans need to do, but with greater precision, specificity, efficiency, and quickly. Ever since the time Humans invented the wheel, the wheels of scientific inventions and the development of machines have been turning at a faster rate much ahead of its time. Robotics has made medical science so advanced that the question now arises if robots will replace humans as doctors. The authors attempted to review the literature and probe into Artificial Intelligence in the field of Physiology and Animal Sciences [1]. A major breakthrough in AI came with the development of deep learning, which is a subset of machine-learning that uses artificial neural networks with multiple layers [2]. In other words, Artificial neural networks (ANN) – consisting of interconnected nodes organized in layers are fundamental components of Deep Learning (DL) – which process complex patterns within large data, and which in turn is an advancement of Machine Learning (ML) – which gives sense to machines, and is a subset of Artificial Intelligence (AI) – the replication of human intelligence [3]. Artificial intelligence (AI) is considered as a future disruptive technology that involves the use of computerised algorithms to dissect complicated data [4]. Mahesh et al. [5] opined the foundation of AI models in healthcare have undergone a transformative journey, shedding light on the challenges, ethical

considerations, and the vast potential they hold for improving patient outcome and system efficiency. Though initially there was relatively slow adoption of AI within the public sector of healthcare, at present the use of AI in healthcare is unparalleled, especially in the field of diagnosis. The impact of AI vibrates through diagnostic and intervention techniques positioning AI as the cornerstone of precision medicine. AI integrates 5G, IoMT, and blockchain, advancing remote healthcare through connected, data-driven innovations [6].

The brain carries out cognitive learning and processing by performing combinations of various sort of information processes. Types of information processes are performed by different anatomical structures and instigated in physiology. The information processes performed by different major anatomical structures of the brain (cortex, basal ganglia, thalamus, and cerebellum) are important, including their implementations in neuron physiology [7]. Hence, we can conclude that Artificial intelligence (AI) is the development of computer systems that are able to perform tasks that normally require human intelligence [8]. AI is an umbrella term describing the mimicking of human intelligence by computers [9]. Gardner [10], the American development Psychologist classified intelligence, based on the soft skills possessed by humans, as follows in Table 1.

Table 1: Classification of Intelligence based on soft skills possessed

Soft skill	Type of intelligence
Nature smart	Naturalist
Sound smart	Musical
Number / Reasoning smart	Logical-Mathematical
Life smart	Existential
People smart	Interpersonal
Self-smart	Intrapersonal
Body smart	Bodily-Kinesthetic
Word smart	Linguistic
Picture smart	Spatial

Introduction to Artificial Intelligence

Artificial intelligence (AI) has developed as an interdisciplinary science based on computers and is concerned with building machines and equipment which use human intelligence to perform a particular task. It may have multiple approaches to a task involving the cognitive function and performance level of the human brain [11]. The intersection of medicine and machine learning (ML) has the potential to transform healthcare. Physiology, a foundational discipline of medical training and practice with an upscale of quantitative history, might be a start line for the development of a common language between clinicians and ML experts, thereby accelerating real-world impact [12]. AI-based systems have accurately predicted gender from retinal fundus images [13]. Artificial Intelligence has become an integral part of our lives and its involvement has evolved Veterinary Science with respect to quick diagnosis, treatment, and management of animals. AI-based algorithms help in speedier and accurate diagnosis of various conditions. Increased accuracy reduces misdiagnoses and ensures the patient receives correct treatment at the earliest [14]. By maintaining consistent accuracy, AI effectively counters the challenges posed by human fatigue and oversight, ensuring reliable interpretations regardless of external factors [15]. Hence, AI driven systems reduce the time-consuming nature of traditional manual measurements and reduce interobserver variability [16]. Artificial intelligence (AI) serves as the key for transformation of health care, as globally healthcare systems face challenges in the form of escalating costs, limited access, and growing demand for personalized care [17]. The biggest advantage of AI in the Veterinary field lies in its potential to influence health care accessibility by addressing existing resource (material and personnel) constraints especially in the remote villages and providing timely care of the highest quality along with accurate diagnoses. In livestock farming AI has proved to be efficient for predicting production characteristics, individualizing animals, and can be used in breeding programs, especially, those which enhance decision-making in production systems [18].

History of Artificial Intelligence

Various scientists over the years have contributed towards the development of Artificial Intelligence. A chronological list is presented in Table 2 to help the reader understand the progress and development of AI.

Table 2: Chronological history of Artificial Intelligence

Year	Scientist / Originator	Event published/discovered or happened	Remarks
1943	Warren McCullough and Walter Pitts	Published paper "A Logical Calculus of Ideas Immanent in Nervous Activity."	Proposed the first mathematic model for building a neural network.

1949	Donald O. Hebb	Proposed the theory that neural pathways are created from experiences and that connections between neurons become stronger the more frequently they're used. Published book "*The Organization of Behavior: A Neuropsychological Theory*".	Hebbian learning continues to be a crucial model in AI.
1950	Alan Turing	Published "Computing Machinery and Intelligence".	Proposed the Turing Test, a method for determining if a machine is intelligent.
	Marvin Minsky and Dean Edmonds	Built Spatial-numerical association of response codes (SNARC).	The first neural network computer.
	Claude Shannon	Published paper "Programming a Computer for Playing Chess".	~
	Isaac Asimov	Published "Three Laws of Robotics".	~
1952	Arthur Samuel	Developed a self-learning program to play checkers.	~
1954	The Georgetown-IBM machine	A translation experiment was conducted which automatically translated 60 carefully selected Russian sentences into English.	~
1956	John McCarthy	The phrase artificial intelligence is coined at the "Dartmouth Summer Research Project on Artificial Intelligence."	The conference defined the scope and goals of AI. It is widely considered to be the **birth of artificial intelligence.**
	Allen Newell and Herbert Simon	Demonstrated Logic Theorist (LT), the first reasoning program.	~
1958	John McCarthy	Develops the AI programming language Lisp and published the paper "Programs with Common Sense".	The paper proposed the hypothetical Advice Taker, an entire AI system with the power to find out from experience as effectively as humans do.
1959	Allen Newell, Herbert Simon and J.C. Shaw	Develop the General Problem Solver (GPS), a program designed to imitate human problem-solving.	~
	Herbert Gelernter	Develops the Geometry Theorem Prover program.	~
	Arthur Samuel	Coins the term machine learning while at International Business Machines (IBM).	~
	John McCarthy and Marvin Minsky	Found the Massachusetts Institute of Technology (MIT) Artificial Intelligence Project.	~
1963	John McCarthy	Started the AI Lab at Stanford, CA, USA.	~
1966	The Automatic Language Processing Advisory Committee (ALPAC)	A report by the U.S. government details the shortage of progress in machine translations research, a serious conflict initiative with the promise of automatic and instantaneous translation of Russian.	The ALPAC report results in the cancellation of all government-funded MT projects.
1969	Edward Feigenbaum, Bruce G. Buchanan, Joshua Lederberg, and Carl Djerassi, along with a team at Stanford, CA, USA	The first successful expert systems are developed in DENDRAL, a XX program, and MYCIN, designed to diagnose blood infections.	~
1972	Alain Colmerauer and Robert Kowalski	The logic programming language PROLOG is created.	~
1973	James Lighthill	The Lighthill report on "Artificial Intelligence: A General Survey" published.	It detailed the disappointments in AI research.
1974 - 1980	~	Major DARPA cutbacks in academic grants due to disappointment with AI development progress. Along with the earlier ALPAC report and "Lighthill Report," artificial intelligence funding dries up and research is stalled.	The period is understood because the "First AI Winter."
1980	John P. McDermott of Carnegie Mellon University (CMU) and Digital Equipment Corporation (DEC)	Developed R1 (also known as XCON; eXpert CONfigurer), the first successful commercial expert system. Designed to configure orders for brand spanking new computer systems, R1 kicks off an investment boom in expert systems which will last for much of the last decade.	Brought an end to the 1st "AI Winter".

1982	Japan's Ministry of International Trade and Industry	Launches the ambitious Fifth Generation Computer Systems (FGCS) project.	The goal of FGCS was to develop supercomputer-like performance and a platform for AI development.
1983	The U.S. government	Launched the Strategic Computing Initiative.	Provided Defense Advanced Research Projects Agency (DARPA) funded research in advanced computing and artificial intelligence.
1985	Companies like Symbolics and Lisp Machines Inc.	Build specialized computers to run on the AI programming language Lisp.	Expenditure on expert systems increase manifold and the Lisp machine market industry sprang up to support them.
1987-1993	Improving computer technologies	As cheaper alternatives emerged the Lisp machine market collapsed in 1987. Japan terminated the FGCS project in 1992 and DARPA ended the Strategic Computing Initiative in 1993 as it fell short of expectations despite heavy expenditure.	The phase was considered as "Second AI Winter".
1991	U.S. Military Forces in collaboration with BBN Systems & Technologies the ISX Corporation	Deployed Dynamic Analysis and Replanning Tool (DART), an automated logistics planning and scheduling tool.	DART was used during the beginning of Operation Desert Storm the Gulf War.
1997	IBM's Deep Blue	Defeated world chess champion Gary Kasparov.	---
2005	Created by Stanford University Stanford Racing Team and Volkswagen Electronics Research Laboratory (ERL)	STANLEY, autonomous, robot-car, or a self-driving car, wins the DARPA Grand Challenge.	---
	Created by Boston Dynamics with Foster-Miller, the NASA Jet Propulsion Laboratory, and Harvard University Concord Field Station	Introduced an autonomous robot like Boston Dynamic's "Big Dog" a robotic pack mule and iRobot's "PackBot".	For bomb disposal, hazmat, search, reconnaissance, and other dangerous missions.
2008	Google App	Made breakthrough in speech recognition.	Introduced the feature in its iPhone app.
2011	IBM Watson	The computer system to answer questions on the quiz show Jeopardy!	Competed on Jeopardy! against champions Brad Rutter and Ken Jennings, winning the first-place prize of $1 million.
2012	Andrew Ng, founder of the Google Brain Deep Learning project	Fed a neural network using deep learning algorithms 10 million YouTube videos as a training set.	Ushered breakthrough era for neural networks and deep learning funding (The neural network learned to recognize a cat without being told what a cat is).
2014	Google co.	Makes first self-driving car to pass a state driving test at Sans Francisco bay.	Later named "Waymo" - a new way forward in mobility.
2015	Google Deepmind	Achieved human parity by playing 29 Atari games.	Learned general control from video.
2016	Google co.	Google DeepMind's AlphaGo (a board game) defeats world champion Go player Lee Sedol.	The complexity of the traditional Chinese game was seen as a serious hurdle to clear in AI.
2020	Created by OpenAI, a San Francisco-based artificial intelligence research laboratory	Generative Pre-trained Transformer 3 (GPT-3) - an autoregressive language model that uses deep learning to produce human-like text.	It is the third-generation language prediction model within the GPT-n series.
	Google's DeepMind	Developed AlphaFold 2 - an artificial intelligence program that predicts protein structure.	Led to disease understanding the medicine to be developed.
2021	Created by OpenAI	DALL-E (text to image model)	On being prompted by natural language text, DALL-E by generating realistic, editable images. The first model of DALL-E used a version of OpenAI's GPT-3 model and was trained on 12 billion parameters.

| 2022 | Created by OpenAI | Chat – GPT | It interacted with users in a far more realistic way than previous chatbots due to its GPT-3 foundation, which was trained on billions of inputs to improve its natural language processing abilities. |
| 2023 | Created by OpenAI | GPT – 4 | GPT-4 generates far more nuanced and creative responses and can engage in an increasingly vast array of activities. |

The first publication citing the use of computer intelligence in livestock farming was in 1998, and with the advance of automation systems, there has been a steady increase since 2015 in the number of publications.

Application of Artificial Intelligence in Veterinary Health and Management

The application of Artificial Intelligence in Veterinary Science and health care is manifold. Deep Learning (DL) algorithms help medical imaging technology and support medical practitioners to identify abnormalities and detect diseases with a higher level of precision and speed than ever before, resulting in significant improvements in the accuracy of diagnosis, the efficiency of treatment, and the overall quality of patient care [4]. With AI-powered medical imaging (Table 3), diagnostic changes and applications (Table 4) will result in substantial benefits for the medical and veterinary practitioners and patients (Table 5 & Table 6).

Table 3: List of First Medical Imaging Applications used (adapted from Dias and Torkamani [8])

Sl. No.	Applications
1	Automated quantification of blood flow through the heart via cardiac MRI [19]
2	Determination of ejection fraction from echocardiograms [20]
3	Detection and volumetric quantification of lung nodules from radiographs [19]
4	Detection and quantification of breast densities via mammography [21]
5	Detection of stroke, brain bleeds, and other conditions from computerized axial tomography [22]
6	Automated screening for diabetic retinopathy from comprehensive dilated eye examination [23,24]

Table 4: Areas where AI is utilized in Veterinary Science and allied field

Area	AI utilized for
Teaching	Simulators for the study of physiological functions of different systems, anatomical structures and dissection, clinical medicine (List given separately) Virtual classroom
Research and Development	Development of drugs Simulators to study the effect of drugs Vaccine development Packaging and delivery of drugs Efficacy and half-life of the drug Biological potency and shelf life of drug Digital balances and weighing machines Automatic Inoculators
Treatment	Tele-medicine (consultation, diagnosis, and advice)
Survey and mapping	Radio tagging of animals and birds (collars, implants) Drones fitted with digital cameras
Farm management	CCTV Drones (surveillance, water management, spraying of pesticides) Milking machines, Rotary milking parlour Infrared thermal imaging sensors Pedometers Facial recognition machine visual sensors Species related application (cattle, sheep, goat, horse, swine, poultry) Prediction of animal behaviour through accelerometers, magnetometers [25], optical sensors [26], or depth video cameras [27] Sheep Pain Facial Expression Scale (SPFES) help to measure pain and discomfort in sheep [28] Sensors that help estrus detection [29] Machine that help estimate milk yield [30], Reproductive performance [31], Calving time [32] Detection of mastitis through somatic cell count [33]

	Oxygen saturator
	Digital Weighing machine (animal weight)
	Hatchery Unit-Automatic Egg candling machine with egg transfer system
	Egg O meter (know internal temperature of an egg)
Agriculture	Autonomous tractors (self-driven)
	Robotic machines that control unwanted crops or weeds harvest crops with greater speed, help in picking and packing crops
	Pest (grasshoppers, locusts) control through satellite and smartphones
	Bailing of straw and hay
	Identifying defects and nutrient deficiencies in soil (soil analysis)
	Identifying plant pests and diseases
	Detect defects in plants (by using image recognition-based technology)
	Drone-based aerial imaging technique to monitor plant health, guide farmers regarding optimum planting and management of plants (Precision farming) [34]
Meteorology	Weather forecasting – List given separately
	Disaster management (Cyclones, Tsunamis, Heavy rainfall and floods, Cloud bursts, Draught, and famine)
Personal animal details	Micro-chip implants (placed under animal skin and uses radiofrequency) and scanners
Disease prevention	Sensors, Big Data, and Machine Learning help in predicting and preventing several diseases in a cost-effective and non-invasive manner [35]
Data Analytical Software	Various software are listed below for data recording, storage, and analysis

Table 5: Software used in Veterinary medicine and clinical management

Name of software	Veterinary medicine and clinical management software
IDEXX, cornerstone vet software (AAHA)	Health network, data backup, payment portal
AVImark, Henry Schein vet solution	Electronic medical records, patient reminders dental charts, support paperless practices
IntraVet	Clinical services
Vetter	Electronic vet record tool that allows you to see consolidated patient record
eVetPractice	Electronic medical records
DVMAX	Practice management
Hippo manager software	Clinical appointments, reminders, SMS
ezyVet	Cloud-based management, clinical solutions
Equine Gait trax / canine gait trax	Motion analysis software (2D and 3D)
DMAS-6 and DMAS-DV motion capture suits	Motion analysis software (2D and 3D)
EMPRES-i	Global animal disease information system by FAO
Winepiscope 2.0	Epidemiological veterinary medicine software
VETport	Clouded-based practice management
Cassadol Equine	This is a simple software for Solo Equine Veterinarians featuring fast and easy medical records and billing
Qvet, VeterinaryGate Advanced, Bastet Win, Animal Hospital Management System, RxWorks, IntraVet	Veterinary practice management software

AI-driven diagnostic tools (machine learning algorithms, deep learning, and image recognition systems) increase the accuracy and efficiency of disease detection and surveillance. AI also has immense potential to predict disease outbreaks and optimize treatment strategies. AI can also be used to strengthen and speed up the drug discovery and development process. By harnessing the capabilities of AI, healthcare systems can significantly improve their preparedness, responsiveness, and outcomes in the battle against infectious diseases [36]. Thus, AI provides a promising solution in analyzing intricate microbiological data quickly and accurately by providing sophisticated computational tools [37].

Table 6: Software used for image analysis of cells, tissues and microbes

Name of software	Image analysis for cells, tissues, microbes
QuPath, Cell profiler, Ilastik, Orbit, Icy	Image Analysis Software for cell and tissues
CellSens for deconvolution, automated high-content analyses, and quantitative image analyses	
AutoQuant for deconvolution and quantitative image analyses	
Imaris for 3D rendering and quantitative image analyses	

ImagJ / Fiji	For micrometry of cells

Various veterinary practice management software is commercially available in developed countries, especially for small animal practice. However, they may not be useful in the Veterinary Dispensaries in India as the reporting requirements and data obtained are different. Some useful tools for prediction of zoonotic diseases (Table 7).

Table 7: Some examples of useful tools and available webservers dedicated to the prediction of zoonotic/veterinary diseases and monitoring [38]

Tool name	Year	Application / description	Website link
BlueDot	2013	AI-powered platform employed in tracking and predicting the spread of infectious diseases. Reportedly predicted Zika virus spread to Florida in 2016 and the movement of the 2014 Ebola outbreak out of West Africa	https://bluedot.global/
ZOVER	2014	Database of zoonotic and vector-borne viruses which incorporates virological, ecological, and epidemiological data for better understanding of those pathogens	http://www.mgc.ac.cn/cgi-bin/ZOVER/main.cgi
P-HIPSTer	2019	(Pathogen-Host Interactome Prediction using STructurE similaRity) is an algorithm which utilizes sequence- and structure-based information to extrapolate interactions between pathogens and human proteins	http://phipster.org/
WIsH	2019	WIsH helps in predicting the prokaryotic hosts of phages by assessing their genomic sequences	https://github.com/soedinglab/WIsH
IHBDP	2019, 2022	The Integrated Health Big Data Platform compiles medical data from hospitals, e-health records, and vaccination records. Reportedly used in identifying Dengue and Tuberculosis (TB) patients	NA
VirHostMatcher	2020	A network-based computational tool for predicting virus-host interactions. Specifically used in viral-host matching based on oligonucleotide frequency (ONF) comparison	https://github.com/WeiliWw/VirHostMatcher-Net
EPIWATCH	2020	AI-driven system harnessing vast, open-source data to generate automated early warnings for epidemics worldwide. Contains full language and geographic information system capability. Efficient in early identification outbreak signals	https://www.epiwatch.org/
VIDHOP	2021	VIDHOP is a virus-host predicting tool. It has been specifically used for Influenza A virus, rabies lyssavirus and rotavirus A predictions	https://github.com/flomock/vidhop
FluSPred	2022	Flu Spread Prediction is a machine learning-based tool which can predict human related Influenza viral strains by targeting their protein and genome sequences, accurately predicting the zoonotic potential of the viral strain	https://webs.iiitd.edu.in/raghava/fluspred/index.html

AI-based models, in particular deep learning models, could act as effective supports in the evaluation of medical images for both specialized radiologists and general practitioners. Nevertheless, these technologies should not replace veterinary experience and knowledge. On the contrary, AI products have the potential to empower radiologists to deliver increased value in a more efficient way [39]. Some AI applications are also developed for exotic and wildlife animal health monitoring [40] shown in Table -8.

Table 8: AI Applications in Wildlife and Exotic Animal Health Management

Application	Description	Country & Year	Website link

Population Tracking	AI enabled GPS and satellite data systems to track animal movement and populations	Australia 2021	www.animaltracker.com
Behavioral Studies	AI tools are used to study animal behaviour patterns, aiding in the understanding of health indicators and social structures of exotic species	Canada 2021	www.behaviortrack.com
Genetic Monitoring	AI to analyse genomic data from wildlife populations, enhancing breeding programs and tracking genetic diversity	USA 2021	www.genomicwildlife.com
Conservation Efforts	AI models analyse environmental data to assist in habitat restoration projects, improving biodiversity conservation efforts	UK 2022	www.ecosystemai.com
Wildlife Health Monitoring	AI aided image recognition to monitor wildlife populations, detect diseases, and track animal movement in remote areas	USA 2022	www.wildtechai.com
Disease Detection	AI to detect early signs of disease in wildlife populations, helping researchers take preventive measures before outbreaks occur	South Africa 2023	www.wildlifehealthai.com

Artificial Intelligence in Animal Management

AI-Driven Animal Farming and Livestock Management System represents a pivotal advancement in agricultural technology, promising to revolutionize traditional farming practices by integrating Artificial Intelligence (AI) into livestock management (Table 9). The system's multifaceted capabilities, emphasizing its role in guiding animal farmers towards optimal livestock care, enhancing marketing strategies, and offering a suite of advanced functionalities. At its core, this system employs sophisticated AI algorithms like Natural Language Processing (NLP) and Convolutional Neural Networks (CNNs) to provide personalized guidance to animal farmers, ensuring they adhere to best practices in livestock care. Through real-time monitoring and data analysis, the system offers actionable insights into nutrition, health, and reproduction management, thereby maximizing the well-being and productivity of livestock. Furthermore, the System incorporates innovative features tailored to streamline marketing efforts. By analyzing market trends, consumer preferences, and supply chain dynamics, the system enables farmers to make informed decisions regarding product positioning, pricing strategies, and distribution channels, thereby enhancing market competitiveness and profitability [41]. The future of livestock technology is filled with opportunities to boost productivity, animal welfare, and sustainability in agriculture. Intelligent monitoring, like sensors and IoT devices paired with advanced analytics, provides real-time insights into animal health and environmental conditions. Precision livestock farming, powered by automation and AI, shows potential in optimizing feeding, health monitoring, and breeding [42].

Table 9: Important AI application features in animal management and welfare [43]

Application	Function
Animal behavior recognition	A novel face recognition model based on convolutional neural networks for recognizing individual giant pandas was developed by applying deep learning techniques [44]
	Predicting a cow's daily milk yield, composition and milking frequency by utilizing sensor data and machine learning [45]
	Identifying farrowing-related activity in sows using radar sensors [46]
	Intelligent robotic system applied to round the clock management for poultry house [47]
	Smart duck counting via AI detection of image data [48]
	Analyzing domestic shorthair cat facial image data by machine learning models for automated pain recognition in domestic cats [49]
	Intelligent detection of equine pain signals and diagnosis by training vision algorithms with automatic computational classifiers via machine learning models [50]
Animal nutrition	An intelligent learning model for collecting cow feed intake in automatic feeding systems to develop feeding schedules [51]
	An intelligent feeding system for controlling pet obesity [52]
Animal health	Predicting learning models for cow eye temperature, milk yield and quality [53]
	An intelligent diagnostic system for equine lameness [54]
	An intelligent system for animal health monitoring, animal tracking, milk quality and supply chain, and feed monitoring and safety [55]
	A machine learning model for a noninvasive video biometric system for intelligent monitoring for cow health [56]

Animal ecology management	An intelligent real-time forecast for CO_2, SO_2, NO_2, PM2.5 and PM10 levels [57]
	Monitoring system for temperature, CO_2 and wind speed in layer coops [58]
	An automatic monitoring and an adjustment system for livestock and poultry farming environment based on WiFi, LoRa wireless communication and IoT technologies [59]
Animal housing disinfection and cleaning system	Magnetic RFID-based navigation guided intelligent robots target the full range of disinfection strategies for large livestock farms [60]
	Rapid disinfection strategy for livestock farms based on remote control of intelligent robots [61]
Animal disease diagnosis	An AI based contactless biometric system for automated assessment of animal welfare on farms and during transportation [62]
	An automated swine welfare indicator assessment system for the diagnosis of ear and tail lesions in slaughterhouses [63]
	Convolutional neural networks to improve the diagnostic accuracy of expert systems for fast and concise animal disease diagnosis [64]
	Computational models developed using penalized linear regression, random forests, gradient boosters and neural networks for helping farmers take evidence-based interventions before anticipated stressful environmental conditions occur [65]
Animal disease prediction	A fog-centered, IoT-based smart health care support system to monitor and control swine flu virus outbreaks [66]
	An IoT-based "LiveCare" framework for automated monitoring of the health of cows on large dairy farms [67]
	An IoT-based animal social behavior sensing framework for modeling the spread of mastitis in dairy cows and inferring the risk of mastitis infection in dairy cows [68]

Artificial Intelligence is used in many of the instruments that we use routinely in laboratories, clinics, and farms. Though the list is very exhaustive, the authors have attempted to tabulate some of the commonly used equipment (Table 10).

Table 10: Some Instruments used in Veterinary Diagnostics

Physiograph	Ultrasonograph
Spirograph	Echocardiograph
Electrocardiograph	Colour Doppler
Electroencephalograph	Boyles Apparatus
Electroretinograph / Optical coherence Tomograph	Electro surgery unit
Kymograph	Cryosurgery unit
Bone densitometry / Dual Energy X-ray Absorptiometry (DEXA)	Perimetry (measurement of visual field function)
Digital Sphygmomanometer	Hemodialysis unit
Digital Thermoscan	X-ray machine
Digital Vernier Caliper	Magnetic Resonance Imaging
Digital Clinical Thermometer	Computed Tomography Scan
Mammography Machine	Nuclear Magnetic Resonance (NMR)
Diathermy machine	Muscle stimulator
Glucometer	Ventilator
Pulse Oximeter	Estrous detector (cow, ewe, doe, mare, sow)
Electronic / Digital / Telemedicine Stethoscope	Ovulation detector (bitch)
Oxygen Saturation Monitor	Pregnancy detector (bitch, sow, ewe, doe)

Artificial Intelligence in Simulators

Simulation refers to the artificial representation of the actual process to achieve education through experimental learning. The Society for Simulation in Healthcare, termed simulation training as "the imitation or representation of one act or system by another" which is serves as "a bridge between classroom learning and real-life clinical experience". A list of some simulators which are used in veterinary health management is tabulated in Table 11.

Table 11: Simulation Apps used in Veterinary Health Management

Simulation App and Utility	References
Simulator for digital rectal examination, detect prostate cancer.	Kuroda et al. [69]
Virtual haptic back – for training osteopathic students.	Williams et al. [70]

Haptic Cow – for teaching bovine rectal palpation to identify pelvic structures, cervix, and uterus.		SensAble Technologies [71]
Horse Ovary Palpation Simulator (HOPS) – number, shape, size of follicles can be felt and altered.		Crossan [72]
Haptic simulators – developed as a palpation-based simulator where touch is the primary sensation available to Veterinarians.		Baillie [73]
Endoscopy Simulator		https://www.healthysimulation.com/5689/free-medical-simulation-scenarios/
Laparoscopic Simulator		
Neurosurgery Simulator		
Ultrasound Simulator	SonoSim	
vSim	Virtual simulation - an interactive, personalized simulation experience for evidence-based, psychiatric patient scenarios	
Emergency Simulator		
Farm Animal related Simulators		
Bovine Breeder Artificial Inseminator Simulator	Teaches correct cervix manipulation, AI gun positioning, and pregnancy palpation. Students can see inside the reproductive tract to identify the reproductive system and learn correct techniques for delivering semen	Reality works www.realityworks.com
Bovine Injection simulator	Teach all type of injections and infusions in a different layer of skin and muscles	
Bovine milking udder simulator	Teach proper udder care, milk diseases, and infection treatment and prevention. Also, teach proper California Mastitis Test performance and udder anatomy	
Exercise physiology virtual lab	Supervise a clinical trial to investigate the acute and chronic physiological effects of high-intensity sprint interval training (SIT) on a sedentary lifestyle	The Labster https://www.labster.com/

Role of Ai in Determining Heat Stress in Animals

Livestock encounter various stressors throughout their production cycle, with temperature fluctuations being among the most challenging to manage [74]. Heat stress negatively affects dairy cow performance across all production phases, leading to decreased growth, reproduction, and increased disease susceptibility, ultimately delaying lactation initiation [75]. Instruments used for determine environment stress in animals are listed in Table 12. Determination of Heat stress in animals plays an important role in animal management and animal welfare.

A. Non-invasive methods

Non-invasive methods for heat stress determination are beneficial as it prevents further stress to the animals. The various methods used to determine heat stress in animals are listed below.

Infrared Thermography – Evaluation of heat stress responses in Murrah buffaloes, crossbred cattle, and Vechur cattle was done using inner canthus infrared thermography as a non-invasive tool at Silent Valley Farm, Kerala [76]. In Hair sheep the eye temperature was found to have a strong correlation with both vaginal and rectal temperature [77]. However, a variation was found in the degree of correlation between different body regions and ambient temperature when using indirect reflective thermometry (IRT) to measure body temperature accurately [78, 77]. It was observed that in cattle, the forehead IRT showed the strongest correlation with both rectal temperature and THI, which was followed by the flank regions on the right and left [78]. Further, Age, physical condition, lactating stage, and reproductive status of the animals should also be taken into account as a determining factor for IRT readings [79].

Accelerometers – Small, light devices that have minimal impact on animal's normal grazing behavior [80]. Along with the accelerometer Activity collars are fitted on the animal's neck, which help in detecting the animals breathing pattern. Increased and labored breathing indicates heat stress.

Bioclimatic indices – Bioclimatic indices are the most preferred to measure or predict heat stress in animals. The various indices are listed below

Temperature Humidity Index – Black Globe Temperature Humidity Index [81]

BGHI = BGT + 0.36tdp + 41.5

Where, BGT: black globe temperature (°C) and tdp: dew point temperature (°C); BGHI below 70 units does not cause discomfort to dairy cow, but decrease in feed intake is observed when BGHI crosses 75 units. Calculated indices include – Heat Load Index [82], Index of Thermal Stress for cows [83], Comprehensive Climate Index [84].

Table 12: Equipment used in Environment Physiology to determine Heat Stress

Lux meter	Digital weather station
Anemometer	Radiosonde
Wind Hall effect anemometer	
Hot wire anemometer	
Temperature and Humidity recorder	Transmissometer
Tinytag Plus 2 loggers	
HOBOPro sensor	
Automatic Rain gauge	Weather balloons
Noise recorder	Weather satellite
Seismograph	Digital Barograph
Refractometer	Snow gauge
Hygrometer	Pan evaporimeter with digital water level recorder
Telemetry	Thermo-hygrograph (digital)
Spectroscope	Lightning detector
Pyregeometer	Digital rain gauge
Pyrradiometer	Digital Cup anemometer
Pyranometer / Lucimeter (Solar radiation)	Digital Wind Vane
Automated Weather stations	Portable weather station
Livestock Heat Stress Monitor (Kestrel DROP D2AG)	Environmental Chamber

Mobile applications – Nedap Now Herd app can be used to obtain real time thorough summary of the heat stress levels in the sheds. This feature is compatible with IFER(P)4 and IFER(P)9 tags from 2021 and later, requiring the latest Velos version [84]

Feed intake as an indicator of stress. Feed intake can be recorded using automated systems like Insentec feed bins (Roughage Intake Control system, Insentec B.V.) [85].

Milk Yield – In heat stressed dairy cows, variation in milk yield are indicators of herd problems. Milk analyzers like the FT120 (Foss Electric, Hillerod, Denmark) represent a source to automatically highlight variations in milk yield and milk constituents [86].

Behavioral patterns – Shifts in behavioral pattern serve as the first indicator of heat stress and can be detected using mechanized systems which are useful aids to record the behaviour of individual animal [87].

Invasive methods

Invasive methods are accurate and reliable but can be uncomfortable, risky, and are not used regularly or for continuous monitoring.

i) **Ear tag sensors –** A RFID temperature biosensor (LifeChip Microchip) can be inserted on the rear of the ear base to monitor and record subcutaneous temperature. Subcutaneous temperature sensor is more reliable as it is minimally affected by heat waves and water sprinkling on the body [88].

ii) **Rumen Reticulum bolus sensors –** They are placed in the reticulum and monitor rumen temperature and pH throughout the day and can wirelessly transfer the data. Names of some Apps that used – SmaXtec classic, Moow Rumen Bolus, LiveCare, Smartstock, Herdstrong.

Advantages of Artificial Intelligence in Veterinary Medicine

Physiological activities like respiratory, perspiratory, cardiovascular responses can be analysed through thermal imaging channels (Thermography) without contact with the individual [89-91].

With the help of simulators help in experimental learning in laboratories and classrooms, of the actual process without the animal [92].

Physiology based medical diagnosis systems are gaining importance in recent years, as they are reliable, accurate, and specific [93].

Artificial Intelligence has made diagnosis cheaper, faster, and easier and helps to recognize the pattern of medical and veterinary complications [94,95].

Artificial Intelligence helps to record and store medical information of the individual animal and other animals coming to the clinic.

Diagnostic Apps are developed which use Hybrid Artificial intelligence (Artificial intelligence along with the experience of the Veterinarian) to diagnose ailments through video recordings.

Apps are also developed which read the Veterinarian's notes and suggest the diagnosis and treatment.

Apps are developed to detect Addison's disease in canines [96].

Artificial intelligence could help a farmer understand if his animal has an emergency and needs treatment. 'Smart Farms' can also be developed, which may automatically diagnose sickness and administer remedies/cures to the affected animal (as part of its feed), without any human involvement [97].

Artificial Intelligence removes human bias in diagnosis and treatment, thus improving the skill and efficiency of veterinarians.

Artificial Intelligence will help in automation of tedious tasks on the farm.

The integration of AI into medical education will prepare future health care professionals for the data-driven, technologically advanced health care landscape while fostering a deeper understanding of AI applications and related ethical implications [98].

Artificial Intelligence applications are used in determining the Heat stress that an animal is exposed to.

Artificial Intelligence has made significant progress in Genomics which help in early disease detection. The analysis of vast amounts of genomic data helps to identify genetic mutations that increase the risk of diseases such as cancer, cardiovascular conditions, and hereditary disorders [99].

A wide range of analytical tools (biomarkers) to study biological parameters have been developed to improve animal health and production. It has been established that blood-based biomarker assays aid in the diagnosis of preclinical cardiomyopathy [100].

In the field of companion animal care aspects such as health and behavior monitoring, feed and feeding systems, parasite detection, artificial, virtual, and robotic pets, and veterinary care and support, have been efficiently improved [3].

However, Artificial Intelligence cannot replace a veterinarian and only assists in accurate and speedy teaching, management, diagnosis and treatment.

Challenges Posed by Ai

The use of AI presents various challenges in the veterinary field with regard to disease detection, diagnostics, treatment, production and management (adapted from [3,101,102]).

The major concern is the quality and representativeness of the data used to train AI models. AI systems that are trained on biased or incomplete datasets, will may produce inaccurate or unreliable results, especially for underrepresented populations.

Another major concern is regarding data privacy and security, as AI relies on large amounts of sensitive data (In Veterinary Science, data pertaining to animals and owner).

The third concern is regarding the compliance of ethical standards and regulations, which is crucial for maintaining patient trust and ensuring equitable access to AI-driven diagnostics.

Inherent challenges are posed related to the accessibility of AI-based tools, adaptability, efficiency and flexibility of AI models in veterinary sector under different environment conditions.

Hence, AI should be seen as a tool to assist veterinary professionals rather than replace them. Even as AI gains wider use in Veterinary field, the human elements of empathy, communication, and ethical judgment should remain paramount during treatment and diagnosis.

Conclusion

Veterinary informatics can forge new possibilities within veterinary medicine and between veterinary medicine, human medicine, and One Health initiatives [103]. The integration of AI across these diverse healthcare domains reflects its transformative potential in revolutionizing the landscape of medical research and application. There are a number of challenges inherent in veterinary diagnostic imaging data sets. Artificial Intelligence has made deep inroads into Veterinary Medicine. It has become an essential and irreplaceable component and helped evolve Veterinary Science. It is certain that at any point in time, AI may not replace veterinarians, but

veterinarians who get trained and wilfully embrace AI will probably surpass those who do not. It is the need of the hour to provide a common platform for inter-disciplinary research for which AI generative techniques are needed.

Conflict of Interest Statement

The authors declare no conflicts of interest regarding this manuscript.

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