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Artificial Intelligence and its Application in the Prediction and Diagnosis of Animal Diseases: A Review

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ABSTRACT

The role of artificial intelligence (AI) in veterinary science is becoming increasingly important as the technology advances. AI applications have the potential to revolutionize the prediction and diagnosis of animal diseases, thereby improving animal health by enhancing disease management. Given the complexity and subjectivity associated with evaluating medical images, as well as the difficulties inherent in handling animals, automating the analysis process using deep learning and artificial intelligence techniques would be highly beneficial. The main focus of the research study is to examine the applications of artificial intelligence in the prediction and diagnosis of Animal Diseases by the comprehensive process of literature review. It was found that many researchers have been using these techniques for diagnosis from the images, creating software that can help doctors, veterinarians and radiologists in their day-to-day work. The study includes machine learning and deep learning algorithms like PLS-DA, ANN and CNN models for the prediction and characterization of lesions. The results were analyzed and compared to obtain a high-accuracy model.

Key words: Animal disease, Artificial Intelligence, Deep learning, Medical imaging, Prediction.

Artificial Intelligence was first described in the 1950s. John McCarthy who coined the term “Artificial Intelligence” in 1949, defined it as smart machines and computer programs that can think and learn. It’s similar to using computers to understand human intelligence, but AI isn’t limited to copying biology (Kangude and Raut, 2012). However, the AI models had flaws and issues in the early stages that hindered their adoption in medical applications. In the early period of 2000, the restriction in AI was rectified with the development of deep learning.

The National Animal Disease Referral Expert System (NADRES) developed by ICAR-NIVEDI is a comprehensive system that integrates and coordinates alert and response mechanisms to predict, prevent and control animal diseases, including zoonotic threats. This is achieved through the sharing of data, conducting field missions and epidemiological studies aimed at assessing and preventing outbreaks whenever necessary. By combining livestock disease data with AI techniques, there are more opportunities for preventing outbreaks and ensuring animal healthcare maintenance. NADRES v2, the second version of the system, collects and manages disease outbreak data from all 31 AICRP centers. It incorporates two regression models, specifically Generalized Linear Models and machine learning algorithms (Kour *et al*., 2022).

There are numerous applications for artificial intelligence, including business, entertainment and health care. One of the powerful algorithms, like Google, is aware of the films and TV shows people like to watch on Google, Amazon and Netflix and it is also aware of the ailments and symptoms people look for. All of this data may be used to build highly detailed personal profiles, which not only offer a great deal of potential for understanding and targeting behavioral patterns but also for predicting healthcare trends.

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The tools of AI can improve and complement healthcare workers. The ability of AI to help with a variety of duties, including prediction, patient monitoring, medical device automation, diagnosis, specialist support and clinical documentation can be advantageous to healthcare staff (Bohr and Memarzadeh, 2020).

Likewise, the use of AI in animal health (AH) has allowed the handling of extremely complicated topics such as quantitative and predictive epidemiology, animal/human precision-based therapeutics and host-pathogen interactions. AI may help in the identification of illnesses, accurate predictions with fewer errors, understanding complex biological systems, accelerating measures and improving certainty in the assessment of risks and target-specific interventions (Ezanno *et al*., 2020).

In a study conducted by Reagan *et al*. (2020), a machine-learning algorithm was developed for diagnosing chronic Hypoadrenocorticism in dogs. The researchers collected medical records of dogs from 2010 to 2017, specifically focusing on dogs with initial cortisol level measurements. They performed blood count and serum chemistry tests and measured cortisol levels after one week, excluding cases with hyperadrenocorticism and dogs. The developed algorithm model was found to have a sensitivity of 96.3%, a specificity of 97.2% and an ROC of 0.994 and it outperformed other screening methods like logistic regression analysis.

Another area where AI can be effective is in treatment optimization. Veterinarians are given a helping hand by AI-powered decision support systems when formulating individualized treatment plans for their patients by taking into account elements including the animal's medical history, genetics and responsiveness to various medications. This optimization aids in the selection of suitable drugs, the establishment of suitable dose levels and the assessment of the effectiveness of various treatment methods (Abomhara and Køien, 2015; Bonicelli *et al*., 2021).

Animals' vital signs and other health indicators may be tracked in real-time by remote monitoring devices outfitted with AI-based analytics. Veterinarians may keep tabs on animal health data from afar, allowing them to monitor conditions, spot early indicators of deterioration and act quickly.

However, the widespread use of digital technologies and AI has a few limitations like problems in sharing data, data ownership, data integrity, cyber security, privacy, concerns related to medical ethics, risk of system failure and medical errors (May *et al*., 2022). AI-based solutions are still controversial in veterinary diagnosis and care because not all healthcare practitioners currently have easy access to them. Examining current applications of AI technologies is crucial for understanding future researchers for using operational strategies for healthcare services of high quality and adoption in diagnostics (Lee and Yoon, 2021).

Using a deep convolutional network, Hinton *et al*. (2012) competed in an annual international image classification competition and produced results in picture classification never before observed when using conventional computer methods (Krizhevsky *et al*., 2017). Since then, numerous studies in this area have been carried out, resulting in advancements in jobs like picture categorization, object recognition and image segmentation (Chartrand *et al*., 2017). Because evaluating medical images is so complex and subjective, it would be beneficial to automate the analysis process using deep learning and artificial intelligence techniques. Over the past few years, there have been numerous advancements made in the field of human medical image analysis; however, breakthroughs are also beginning to be made in the field of veterinary medicine (Nakaura *et al*., 2020).

The novelty of the present study is to discuss the applications of artificial intelligence in predicting and diagnosing Animal Diseases.

Literature review

The simulation of the human brain is referred to as artificial intelligence and can be used in the computation process. Machines that include robots and computers can be programmed to imitate cognitive processes such as problem-solving and learning. Artificial intelligence, deep learning and machine learning technologies are also being used in animal disease, diagnosis and prediction.

In the current landscape of the medical sector, the identification and proper treatment of animal diseases pose significant challenges. Real-time identification of animal diseases is particularly difficult, necessitating the development of methods for predicting these diseases and identifying related patterns. A few research have been conducted in this area and many studies are proposing ideas for predicting cattle diseases. Some research works have progressed beyond the conceptual stage and implemented efficient data science algorithms to forecast diseases. Python and R languages are commonly employed in the implementation of these research works as they offer robust libraries for processing training datasets and prediction. Many papers rely on training datasets sourced from platforms such as Kaggle and Data World. These research works utilize efficient prediction algorithms, including Random Forest, Decision Tree, SVM classifier, KNN classifier and Naïve Bayes algorithm to achieve accurate results (Rao *et al*., 2023).

Sofie stands out as an exceptionally advanced tool for veterinary medical searches. It leverages IBM Watson Technology® to explore an extensive knowledge base comprising more than 40,000 evidence-based pages and peer-reviewed references. These materials are sourced from leading veterinary textbooks, journals and conference proceedings (Sandhya *et al*., 2021).

AI in animal disease diagnosis

In contrast to human medicine, deep planning technologies have not been widely researched for diagnosing the medical images for animal diseases. Li *et al*. (2020) employed the deep learning technique for detecting canine left atrial enlargement by using thoracic radiographs and compared results with the findings of veterinary radiologists. Though, they achieved accuracies that were concordant with those of veterinary radiologists., the study proved to be a success in diagnosing animal diseases.

Recently, efforts have been made to include AI and radionics as tools to aid decision-making and incorporate them into standard clinical processes and diagnostics to increase accuracy and reproducibility (Bouhali *et al*., 2022). Radiomics is a quantitative approach to medical imaging that enhances data by utilizing advanced, sometimes contradictory mathematical evaluation. The use of AI and radionics in diagnosing animal disease through images is emerging for early diagnosis.

The recognition algorithm or gas sensing algorithm was developed by Haselzadeh (2021) with the intent to predict and detect diseases in cattle using odour. The collected data could be measured and analyzed through an electronic nose or gas sensor array. This new algorithm was found to have the ability to identify three types of dairy cattle diseases with an accuracy of 96%.

Methodology

This section sheds light on the methodology on which AI functions based on the data gathered from different sources. This work was carried out in the Computer Science Department of King Saudi University in a short period of three months from June 2023 to August 2023. AI employs and creates computer systems for simulating human intelligence and learning from experience to carry out and enhance the tasks given. The research methodology includes data collection and processing for predicting and diagnosing animal diseases.

The steps involved in the diagnosis of animal diseases as represented in Fig 1.

Data collection

The first step is to gather relevant data from various sources. This may include electronic health records, medical imaging like photographs radiographs MRIs, ultrasound, laboratory test results physiological data (heart rate, temperature) and other relevant information related to the animals' health and medical history (Ruegg, 2003; Li *et al*., 2020; Reagan *et al*., 2020; Maharana *et al*., 2022).

Data preprocessing

Image pre-processing is referred to as the process of applying various modifications to a starting image to enhance image quality and increase the repeatability and comparability of statistical analysis. Though there is no set analytical approach for doing it, it depends on the data gathered as well as the ailment being studied. In addition, the raw data collected from different sources may be inconsistent, noisy, or incomplete. Data preprocessing involves cleaning the data, handling missing values and standardizing the format to ensure uniformity and data quality. Also, machine learning models cannot directly understand raw data, so data pre-processing is the first step in transforming and encoding it for efficient description and analysis (Akpojaro and Bello, 2020). For example, in Fig 2, pre-processing is performed by extracting colour and texture features, image cropping and segmentation to remove undesired components such as background spots along with other diverse elements and to improve image quality for classification (Cateni *et al*., 2012).

Segmentation

The volume of interest (VOI) and region of interest (ROI) are defined. The radionics workflow's most important stage, as it determines the region or volume from which the characteristics will be retrieved. The arduous process of segmentation is typically carried out semi-manually or manually utilizing standardized software for segmentation. As a result, fully automatic segmentation utilizing deep learning approaches was recently introduced. It is based on artificial neural networks that use numerous layers to conduct complex operations and extraction of more sophisticated features from input data.

Feature extraction

The method mostly uses software to extract and compute the quantitative descriptions. The majority of feature extraction processes adhere to the "Image Biomarker Standard Initiative" (ISBI) criteria where the group features are classified into broad categories that include morphological features, texture, edge, shape and intensity-based features. Moreover, analyzing texture features can be used to determine the spatial distribution of images, which is not possible when utilizing solely grey-level descriptors or histograms.

Feature analysis

The retrieved features may be more and the number can complicate the process of feature analysis and cause difficulties in AI. Before performing the final analysis, "feature selection" or "dimension reduction" helps in removing the features from the data set that are redundant and irrelevant.

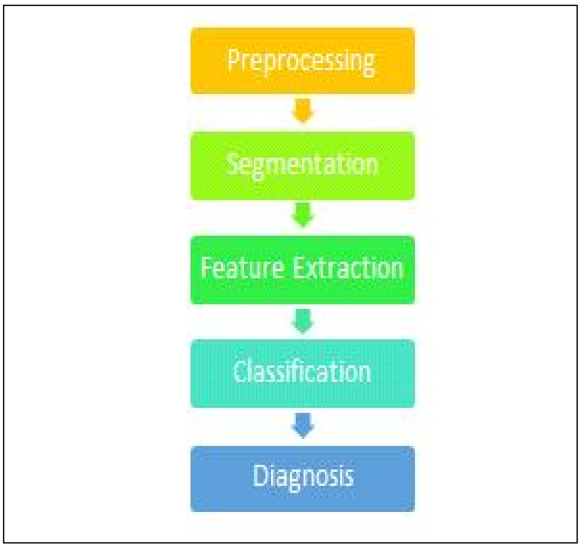

Fig 1: Image processing for animal diseases.

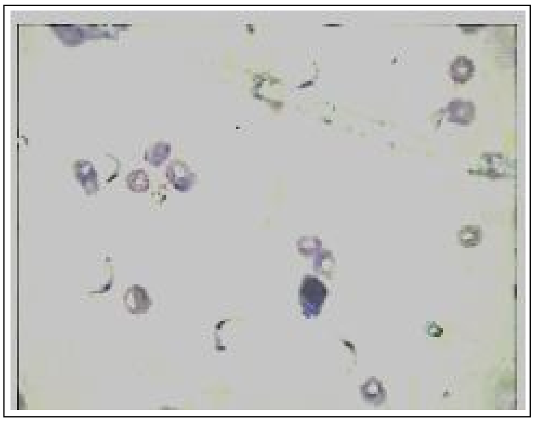

Fig 2: Image of trypanosomes in a giemsa stained blood smear [21].

This is done by reducing the number of features according to the requirement for analysis. Additionally, it aids in compiling only the most consistent and pertinent features to create a solid model for future prediction and categorization. PLS-DA model can be used.

Segmentation and feature extraction are considered to be more significant for representing the images as well as the input for classifiers since conventional types of machine learning methods have few limitations in data processing. As a result, scientists started to create algorithms that combined both the features within the ANN itself. Pre-processing or segmentation is therefore not as necessary with deep learning approaches. The method does have some drawbacks, though, including the necessity for a sizable dataset of images (hundreds to thousands), more reliance on clinical data and exam quality and difficulties in tracing the reasoning behind it ("processing black box"). The CNN approach to deep learning in medicine is the most well-known. Convolutional, pooling and fully connected layers make up a CNN's basic structure.

In this way, feature extraction helps in identifying and extracting relevant attributes or features from the data that are likely to be informative for disease detection. Feature selection helps in reducing the dimensionality of the data, making the AI model more efficient and accurate (Pillai *et al*., 2022).

Model selection

Based on the nature of the data and the disease detection task, the appropriate AI model can be selected. This may include machine learning algorithms like support vector machines (SVM), random forests, or deep learning models like convolutional neural networks (CNNs) or recurrent neural networks (RNNs) (Kour *et al*., 2022; Pfob *et al*., 2022).

Training the AI model

In the training phase, the dataset is used to train the selected AI model. During this process, the model learns to recognize patterns and associations between features and disease outcomes. There are two methods for training the algorithm on the data: supervised training and unsupervised training. To find the correlation between the data and label attributes and to generalize this understanding to anticipate new (unlabelled) situations, supervised learning for training the algorithm is used. Data is categorized into clusters using algorithms or automated methods for processing the data that is not categorized or classified and to determine the relationship between categorized data into clusters and intrinsic features with self-supervised learning is used (Erhan *et al*., 2010).

Most of the machine learning algorithms are linear and can't account for all naturally nonlinear aspects because of this. In recent decades, several machine learning methods based on nonlinear models have emerged to address problems in regression, classification and estimation. The non-linear model utilizes the nonlinear function paired with computing complexity which restricts its application, whereas a linear model is used for predicting the linear function. A more complex branch of machine learning is called deep learning. A DL algorithm knows to learn the data of its own, as opposed to the algorithm being taught to learn and process from the data. Artificial neural networks (ANN) layers and a lot of data are used for this (Hennessey *et al*., 2022).

Hyperparameter tuning and validation

The trained model is evaluated using a separate validation dataset to assess its performance and generalization capabilities. Hyperparameter tuning may be performed to optimize the model's parameters for better results (Pfob *et al*., 2022). The validation and performance assessment phases of the machine learning process are also crucial. A machine learning classifier must train its algorithms and validate its predictive models using at least two distinct subsets from the original collection of images. Cross-validation is a technique that is frequently used in radiomics. The samples are divided into N subgroups for cross-validation: one for testing alone, one for training and one (independent subset) for validation (Kalendralis *et al*., 2019).

Testing the AI model

Once the model is trained and validated, it is tested on a completely independent test dataset to assess its real-world performance. This step helps in estimating how well the AI model will perform when deployed in practical applications (Pfob *et al*., 2022).

Interpretation and explainability

Especially in the medical field, interpretability and explainability of AI models are crucial. Efforts are made to understand the model's decision-making process and provide explanations for its predictions.

After successful testing and validation, the AI model will be deployed in real-world veterinary practices or healthcare systems. Integration with existing diagnostic workflows and veterinary tools ensures smooth adoption and usability. AI models need to be continuously monitored for performance and accuracy. Over time, additional data can be collected to improve the model's predictions and the model itself may require periodic updates or retraining to adapt to changing disease patterns or advances in veterinary knowledge. In addition, collaboration with veterinarians and domain experts is essential. They play a crucial role in data annotation, validation and interpreting the AI-generated results to make informed decisions about animal health.

Dataset

Publicly available data sets, like the RIDER data collection, help to clarify the effects of different radionics factors. Additionally, the available data sets that can be accessed by the public are used in the research study.

Detection of lesion

The study involves the PLS-DA Model (Partial Least Square discriminant analysis) and Artificial neural network in automated AI classification of Canine pelvic radiographs

Table 1: Detection of lesions using PLS-DA model and ANN.

Detection of lesions	PLS-DA model	Artificial neural network
Classification error	6.80%	8.90%
Sensitivity	100%	87%
Specificity	90%	100%

Table 2: Detection of lesions using CNN and BOF.

Detection of lesions	CNN	BOF
Accuracy	97%	95%
Specificity	100%	97%

using a machine learning algorithm. The PLS-DA model's classification error, sensitivity and specificity were 6.8%, 100% and 90%, respectively and the ANN models were 8.9%, 87% and 100% is given in Table 1.

The study focuses on the classification of radiographic images in animal diseases using machine learning algorithms. While both models had the ability to increase productivity through the possibility of duplicate reading, the results showed that CNN had greater accuracy (96.9%) and sensitivity (100%) than BOF (accuracy 94.8%; sensitivity 96.9%). It is shown in Table 2.

Before they become evident to the naked eye, AI could be used to identify textural abnormalities on mice MRIs that are associated with the emergence of metastatic intrahepatic tumors (Becker *et al*., 2018). According to the study's findings, both neoplastic and micro-metastatic liver disease cause systematic changes in the texture of the liver. The matrices in the grey level have 3 features or clusters found in the tumor growth with independent engineer connection.

While both models had the ability to increase productivity through the possibility of duplicate reading, the results showed that CNN had greater accuracy of 92.9% and sensitivity of 92.1% than BOF with an accuracy of 74.1%; a sensitivity of 79.6% (Boissady *et al*., 2020). Brain lesions visualized through MRI may be difficult sometimes to interpret and characterize. Using post-contrast and pre-contrast T2 and T1 weighted images of MRI the effectiveness as well as precision of deep learning CNN helps in distinguishing gliomas and canine meningiomas through image classification based upon the classification the lesson can be determined and identified through the final test of histopathological diagnosis (Banzato *et al*., 2018). On the basis of corneal pictures, CNN technology has also been created to categorize the severity of canine corneal ulcers such as normal, superficial and deep, which were previously categorized by Kim *et al*. (2019).

Artificial Intelligence (AI) plays a vital role in detecting animal diseases through its ability in analyzing data, recognizing patterns and making informed decisions.

Timely disease detection

AI algorithms can examine extensive datasets, including veterinary records, laboratory findings and sensor data, to identify early indications and patterns of diseases. By continuously monitoring and analyzing data, AI systems can alert veterinarians to potential health issues, enabling prompt interventions.

Image and pattern recognition

AI-powered computer vision techniques enable the analysis of images and videos captured during veterinary examinations. By training AI models on a diverse range of animal disease visuals, they can accurately identify visual patterns associated with specific diseases, facilitating precise diagnoses by veterinarians.

Predictive analytics

AI algorithms can analyze historical data to identify trends and patterns that forecast disease outbreaks or identify animals at higher risk. By considering various factors such as environmental conditions, animal health records and demographic information, AI provides insights into disease prevalence, aiding in the implementation of preventive measures.

Remote monitoring and sensor data analysis

IoT devices and wearable sensors collect real-time data on an animal's vital signs, behavior and environmental conditions. AI algorithms can analyze this data, detecting any abnormalities or deviations from normal parameters. This enables continuous remote monitoring, minimizing the need for frequent physical check-ups and facilitating early disease detection.

Decision support systems

AI systems can assist veterinarians by providing evidence-based recommendations and treatment plans based on extensive data analysis. By analyzing similar cases, scientific literature and treatment outcomes, AI suggests personalized treatment options, enhancing accuracy and efficiency in decision-making.

Data integration and knowledge sharing

AI technologies enable the integration of diverse data sources, such as laboratory results, electronic health records and research studies. This integrated knowledge can be shared among veterinary professionals, fostering collaboration, information exchange and improved disease management strategies.

CONCLUSION

To conclude the study, it is significant to track illness progression over time for diagnosis, prognostication and the assessment of therapy effectiveness. AI helps in comparing the data with previous dataset to give the output results.

Computer-assisted change analysis could spot minute changes in traits that are difficult to diagnose at early stage while also avoiding the issues brought on by interobserver variability. Additionally, it is anticipated that AI will take on more administrative responsibilities in the future, including medical reporting, registration and identification of affected and diseased animals. The applications of AI in the prediction and diagnosis of animal diseases have an impact on healthcare for early treatment.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Declaration of conflicts of interests

The authors declare that they have no conflict of interest.

Data availability statement

Not applicable.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

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