



Integration of Artificial Intelligence in Prediction of Diseases in Animal Farming

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ABSTRACT

Background: Animal welfare has become an increasingly important indicator of quality in modern animal farming. Various factors contribute to animal welfare challenges and their early identification and management are essential to minimize economic losses and improve livestock health. Advances in artificial intelligence (AI) and machine learning (ML) have provided new opportunities for monitoring animal welfare and enabling timely disease prediction.

Methods: This study examines the application of AI and ML techniques for predicting and detecting diseases in animals. ML models are trained on large datasets to recognize normal behavioral and health patterns, identify anomalies and generate alerts for potential health issues. The study also reviews the use of modern AI technologies in animal farming, including disease prediction, welfare monitoring and precision livestock management.

Result: The findings indicate that AI-and ML-based approaches can enhance the early detection of animal diseases by continuously analyzing data and identifying abnormal conditions. As these models are trained with larger datasets, their predictive accuracy improves, enabling farmers to detect infectious diseases earlier, monitor barn conditions effectively and make timely management decisions. Overall, AI-driven technologies contribute to improved animal welfare, better farm productivity and reduced economic losses.

Key words: Animal farming, Animal welfare, Artificial intelligence (AI), Machine learning (ML).

INTRODUCTION

Among the most significant variables leading to disease transmission in food, livestock is between-farm interaction, whether direct or indirect, caused by the mobility of livestock or biological matter, or by cross-contamination caused by inputs such as equipment or human personnel. Farm-to-farm interactions are responsible for the transmission of illnesses that threaten the swine business in India (Tian and Zhu, 2015). Animal migrations are one of the major infection transmission pathways across farms for both PRRS as well as PED and this is true for both diseases.

A thorough understanding of the system architecture of the animal industry is essential for effective disease management. Examples include the exchange of data among agents within a system, which may result in a gain in economic productivity as a consequence of the adoption of methods that may lower production or transaction costs. It is accurate to say that social network analysis (SNA) has been extensively employed in the area of veterinary medicine to build disease management measures. To measure the nature of relationships among items in a community, SNA has been utilised in the past (Bergstra and Bengio, 2012). Nodes may be fields or even other facilities from which, to which, or through which populations of animals are linked and interactions between nodes can be classified as indirectly or directly depending on the nature of the relationship. Animal motion analysis (SNA) allows researchers to better understand animal movement patterns, which in turn may offer insights into how illnesses spread within a certain business. In the cattle industry, for example, a small proportion of farms or traders are often

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responsible for the majority of animal movements. Finding a small number of farms that are “hotspots” for disease transmission or “super-spreaders” for disease transmission can aid in the formulation of emergency initiatives to regulate higher-intensity illnesses, as early treatment on targeted farms can increase the likelihood of

these initiatives being effective in preventing spread of the virus. Improvements in farm animals and biosecurity in super-spreaders, in a similar vein, may aid in the reduction of disease threat and incidence in these populations. Fig 1 illustrates the role of Artificial Intelligence (AI) in animal farming, highlighting its major applications in disease prediction, animal health monitoring, precision livestock management, feeding optimization and welfare assessment.

There have been a high number of reported animal transfers within and between Indian states and areas, which has typified the Indian swine business. In the period 1970 to 2001, the number of animals that were transported from one region to another grew from 30 to 50 million. An increase in the number and distance of moves reflects the increase in the number of farms that specialise in certain aspects of the manufacturing process (Bergstra *et al.*, 2013; Cho, 2024; Hai and Duong, 2024; Maltare *et al.*, 2023; Bagga *et al.*, 2024; AlZubi, 2023).

In India, animal migrations are only partly controlled and also no one source offers comprehensive data on them. The absence of mobility data makes illness management, including such PRRS, particularly difficult. Regional control programs (RCPs), which are voluntarily created and controlled by producers, serve as a way for farmers in a specific area to communicate sanitary status information (Díaz *et al.*, 2017). The exchange of data within an RCP-N212 has been linked to a reduction in PRRS occurrence, so it's possible that sharing more information regarding animal movements will increase control program performance even more. However, a lack of data on between-farm migrations makes it difficult to explain network structure, which makes it difficult to avoid and manage illness (Botreau *et al.*, 2007). Modern systems may consider factors like genetics, the environment and management goals to provide appropriate and contextually optimum answers (Breiman, 2001). Generally, the more information a system gathers and analyses, the more likely

it will arrive at correct and optimum answers. Farmers will also benefit from such a system since it will be evidence-based or data-driven. In other ways, failing to replicate reality is beneficial since it has shed light on an area that has either been inadequately defined, has erroneous assumptions, or, in certain circumstances, lacks enough evidence (Chung *et al.*, 2013). Using modern technology in animal husbandry will assist us in collecting more information and eventually increase our comprehension of how animal systems function, regardless of whether it can offer good results. Modern technologies are highly capable of processing and analyzing diverse data formats-including text, audio, video and images-where identifying intricate patterns is essential. Advanced algorithms can cluster, categorise, or forecast patterns within these datasets (Díaz *et al.*, 2017). Pattern identification has been used for the identification of illness as well as the tracking of livestock in animal production processes using modern data processing and algorithms.

For instance, a variety of sensors, big data and machine learning algorithms have been created to analyse variations in animal behaviour or identify animals. Animal behaviour including relaxing, ruminating, feeding and movement, may now be classified using a variety of sensors (Bundesministerium für Ernährung und Landwirtschaft, 2018). Important economic traits such as body weight, milk yield and egg production can be estimated and predicted using advanced predictive tools powered by modern technology. In circumstances when the previous development of the herd BW is understood, Alonso employed a SVM categorization system to correctly forecast the BW of particular cattle. When just a few BW values were available and accurate forecasts for longer periods were necessary, our technique outperformed individual regression analysis produced for particular animals (Haixiang *et al.*, 2017). All of these aspects are important for the critical study of integrating Artificial Intelligence in the prediction of animal diseases.

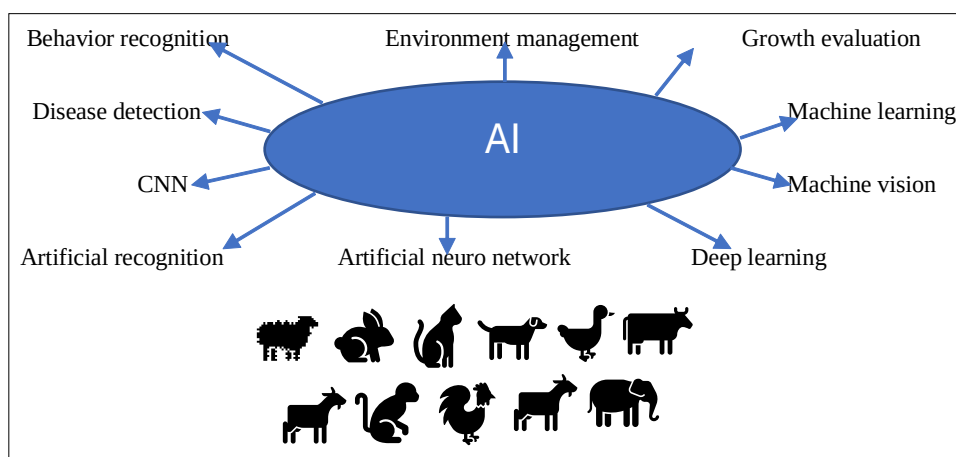


Fig 1: Artificial intelligence in animal farming.

MATERIALS AND METHODS

The algorithms employed in this study were chosen from a broad variety of probabilistic and non-probabilistic methodologies to cover the whole spectrum of current tools. Researchers investigated additional approaches in addition to the algorithms provided in our paper, such as the XGboost technique, which is often used for tackling classification issues but only yielded poor results in our situation (Bundesverband and Schwein, 2020). With the development of machine learning algorithms in a variety of disciplines, it was only a matter of time until they surfaced in agricultural problem-solving.

K-nearest neighbours (K-NN)

The compactness hypothesis asserts that an assessment item would have a similar class tag as that of the training items in its near context. The K-NN classifier is dependent on this assumption. If K is one, the studied item is classified into many classes based on data about its one closest neighbour. When K is more than one, each item is allocated to the most common class of closest neighbours (Meshram *et al.*, 2021). Each and every grouping algorithm can be regarded as beneficial when the compact hypothesis is met, which means that there is a subdivision of items into clusters in which gaps between items in the very same group are less than a definite value > 0 , as well as ranges between items in varying groups are greater than.

Linear discriminant analysis (LDA)

LDA is a multidimensional assessment component that lets you compare two or more independent variables of items using a variety of factors. It's an extension of fisher's linear classifier, a ML approach for determining a linear mixture of characteristics that distinguishes or distinguishes two or more classes of things and actions. The resultant mixture may be applied as a learning algorithm or, more commonly, as a dimension reducer before further categorization (Lin *et al.*, 2008). The analysis of variance (ANOVA) approach is closely connected to LDA. The LDA performs two statistical methods that are strongly linked:

- Understanding group variations requires a response to the issue of how a commonly used collection of factors may serve as a separating surface for training sample items, as well as which one of these factors is the most useful.
- Projection of the value of the classification component for the studied set of data, also known as categorization.

The support vector machines (SVM)

SVM, formerly known as the "generalised portrait" method, was created by soviet mathematicians vapnik and chervonenkis as well as has since been widely used. The primary concept behind the support vector classifier is to create a separating surface utilising just a small fraction of facts in the essential separation zone, whereas the majority of the properly categorised training sample data beyond this zone are

disregarded (Manteufel and Schön, 2002). Two scenarios are conceivable whether there are two different classes of data and the border between the categories is considered linear. The first one has to do with the potential of complete data segregation *via* a hyperplane.

Naive bayes classifier (NB)

The bayes theorem is used to create a family of basic probabilistic machine learning classifiers called naive bayes classifiers. The likelihood of an item belonging to a specific class given its observable characteristics, P, is computed using the Bayes equation using existing distributions P, under the "naive" premise that all the indications defining the categorised items are fully equal and unrelated to one another. The items are assigned to the class with the highest likelihood by the naive bayes.

Neural networks

The organic neural network of the brain as well as the computer connection are two perfectly apparent parallels for neural network architectures that were created in the course of establishing the notion of AI (Witten *et al.*, 2011). The net package was used to train ANN in the R environment; it offers versatile capability for building cataloguing systems centered on a "multilayer perceptron".

Generalized linear models

Regression analysis is typically employed as a binary classifier for alternative response sets. This approach, however, may be extended to the situation of several classes. As the modelled answer Y, ordinal or nominal values may be utilised and a multivariate binomial dispersion is considered in both instances. Briefly expressed, linear regression should be used when predicting a quantitative dependent variable and rational regression should be utilized when predicting a qualitative response variable. GLMs come in two flavours: regression analysis and regression models.

Gradient boosting

Accelerating, which is an incremental method of successively generating private models, is among the approaches for enhancing predictions. Each successive simulation is trained using data from previous stages' mistakes. The resultant role is a linear mixture of all of them, taking into account the minimizing of any punishment parameter (Matthews *et al.*, 2016). Boosting, like bagging, is a broad strategy that may be used with a variety of statistical classification methods. Leo Braiman's insight that raising the gradient may be regarded as an optimization technique on an effective cost function sparked the notion of raising the gradient.

The C 50 tree method

This approach is based on dividing information into progressively smaller bits to uncover patterns that can then be utilised for forecasting. Many logical judgments are included in the model, which is represented by decision

nodes. They are separated into branches, each of which indicates a different solution option. The tree comes to a finish with a tree structure, which represents the outcome of a series of choices (Nguyen and Armitage, 2008). The information to be classed starts at the root node, in which the ripple is communicated and proceeds through the tree, with different choices based on the values of the predictors and their effect on the “response variable”.

Random forest

Random forest is a kind of “controlled learning” wherein the objective class is specified ahead of time and a model is created to predict future answers. For training bootstrap samples, many hundred decision trees are generated. Furthermore, for each iteration of the tree building, m out of p analysts are randomly chosen to be examined, as well as the division can only be done on one of these m variables. The significance of this approach, which has shown to be quite beneficial in terms of enhancing the excellence of the answers found, is that even with the probability $(pm)p$, some possibly dominating forecaster that wants to arrive at each tree is prevented. If dominants are blocked, other predictions will have a chance and tree variety will rise.

RESULTS AND DISCUSSION

Detecting, forecasting and avoiding animal illnesses, as previously mentioned, is a significant cost driver. Usually, farmers treat infections in their livestock by doing nothing, consulting veterinary professionals proactively, utilising a mixture of antibiotics, or a mixture of these three ways. Big data, sensors, AI and ML are instances of advanced technology that provide farmers with novel possibilities. It enables constant surveillance of critical animal health factors like mobility, food, air quality and drink intake instead of responding to problems after they become apparent or

using the assistance of physicians. Farmers may now detect, forecast and control epidemics even before a large-scale epidemic by continually gathering data and utilising powerful artificial intelligence and machine learning algorithms to anticipate deviations or irregularities. In other words, sensors can continuously check animal health rather than people. A technique like this has two major benefits (Hsu *et al.*, 2003). One advantage of this method is that it enables smaller farmers to raise a larger number of animals, lowering production expenses. Second, even in the pre-clinical stage, such a method might warn farmers of the risk of illness. Farmers will be able to take timely steps to avoid catastrophic damages as a result of this.

Fig 2 illustrates the role of sensors, big data and machine learning (ML) in animal farming, highlighting how these technologies work together to monitor animal health, behavior and environmental conditions. An infectious illness epidemic might damage a big animal farm, where many livestock are housed together. In such a situation, the emergence of an infectious illness will be difficult to control unless the farmer intervenes quickly. When symptoms first appear, it is sometimes too late to act. A disease may spread quickly if left untreated, resulting in animal fatalities, lower health results and economic difficulties. A smart farm, on the other hand, with multiple sensors, may alert the farmer to odd animal behaviour far sooner.

Automated systems are particularly good at swiftly gathering, processing and interpreting massive amounts of data. They are unable to make good judgments in the absence of data. When people acquire and interpret huge volumes of detailed data, they may aid people in making better judgments. Various sensors can aid farmers in tracking animal activity on a farm promptly (Pineau *et al.*, 2020). Modern algorithms may use big data to follow, measure and explain changes in animal behaviour. As a

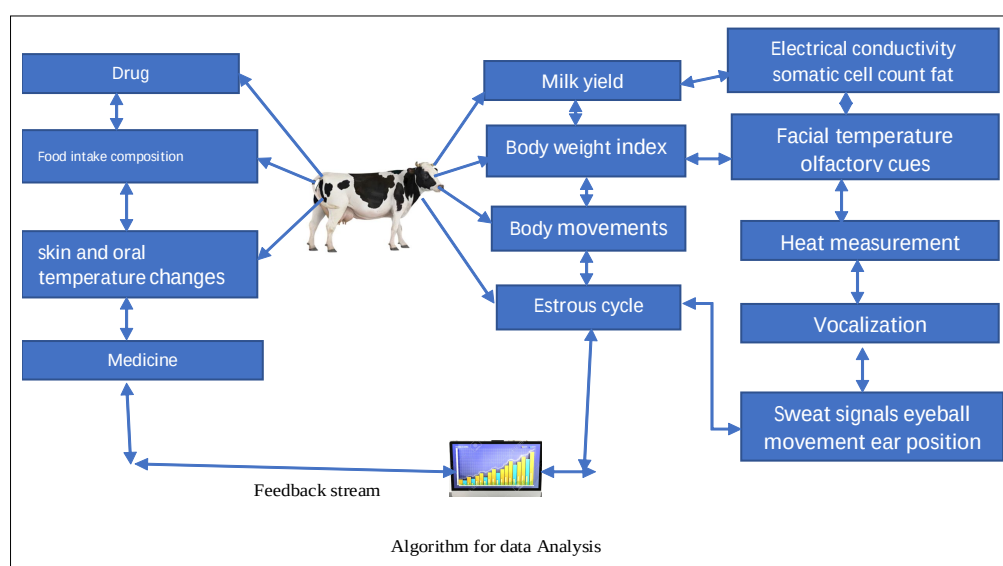


Fig 2: Role of sensor, big data and ML in animal farming.

result, farmers will be able to make better judgments and implement disease treatments more quickly.

Numerous sensors are now available to assist farmers in tracking changes in animal activity, food consumption, sleeping habits, or even air quality in animal sanctuaries. The raw data is then saved and processed on a computer capable of processing large amounts of data. Lastly, machine learning algorithms emphasise any departures from regular patterns. Big data, sensors and machine learning algorithms have been used to accurately detect the early beginnings of numerous illnesses in sheep, depending on sluggish body motions, slower reaction times and reduced activity before the emergence of other visible disease signs. On the other hand, farmers may find it difficult to detect such alterations with the human eye in a big herd with multiple animals.

Farmers can benefit from big data, sensors and machine learning by recognising abnormal behaviour and forecasting and averting disease outbreaks. In a vast herd of animals, it's tough for caregivers to notice changes in eating habits, water intake and strange body movements of a sick animal-but it's easy to identify if you're looking for them. Sensors in the poultry industry can now detect the onset of Coccidiosis, an intestinal disease that may spread rapidly among birds without causing symptoms. One method of detecting this illness is to examine the air quality on a regular basis. The quantity of volatile organic chemicals in the air increases as the number of ill birds increases. This shift may be detected far sooner by air sensors than by a farmer or a doctor. Farmers who have been notified may then take immediate action to stop the sickness from spreading further. A strategy like this saves many animals' lives while also preventing economic losses.

Sensors, huge data and powerful algorithms can also forecast illnesses in bigger animals considerably better than people can. For example, mastitis, an udder ailment, causes cows to produce milk of poor quality and quantity. SSC and EC values are manually obtained to detect mastitis in the traditional way. On the other hand, such manual assessments are often erroneous, inconsistent and useless. However, cow mastitis may now be consistently collected, predicted and reduced using automated sensors and algorithms. Fig 3 illustrates the difference between predictive and reactive disease management strategies in animals, highlighting the benefits of early disease detection and timely intervention.

Methods for early illness detection are not new. We already have the technology to achieve this, including such RT-PCR. They were, though, expensive and could not be implemented on a large scale. Sensors, big data and machine learning algorithms now provide a significant cost savings over previous identification methods (Riekert *et al.*, 2020). They can swiftly forecast and prevent dangerous diseases like African Swine Flu for a fraction of the cost. More crucially, modern technologies can now forecast the development of many infectious illnesses before they become widespread. Table 1 summarizes how modern technologies assist animal producers in predicting and preventing diseases through continuous monitoring, early detection and data-driven decision-making.

In many other circumstances, related to animal motions, algorithms may forecast illness signs like lameness. At the preclinical phase, alterations in movement, intensive use of specific body parts, as well as passivity in other parts of the body may consistently predict early lameness. Lameness is the third most common

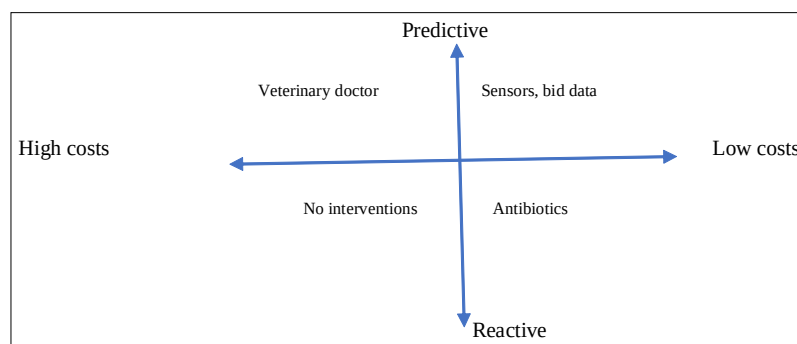


Fig 3: The difference between the predictive and reactive disease management strategies in animals.

Table 1: How modern technology can aid animal producers in illness prediction and prevention.

Disease	Parameter	Algorithms
Postpartum disease		
Mastitis	Electrical conductivity (EC), somatic cell count (SSC),	Gradient boosted trees (GBT), bag of words (BoW),
African swine Flu	Mobility, speed, direction	Optical flow algorithm
Coccidiosis	Volatile organic compounds (VOC) in air	Principal component analysis (PCA)

condition affecting farmers, since it diminishes milk output and raises the risk of harm. Farmers may save significant financial losses by predicting lameness early. In some other instance, research reveals that sick animals move less during the first 2 days of illness, by up to 10%. This may be used to confine diseased animals before they contaminate a large number of others. Furthermore, sensors that capture data from the environment, like temperature, gas generation and humidity, might assist farmers in preventing diarrhoea and bacterial illnesses.

CONCLUSION

Agriculture is accelerating the usage of sensor technology, machine learning and big data in contemporary animal husbandry. When travel limitations prevent nutritionists, veterinarians and producers from visiting barns and farms, including feed mills, in the case of an epidemic, real-time 24/7 insight into animal activity, consumption and production is essential. Sensing technology generates data that can be accessed remotely, resulting in lower costs and improved performance in responding to client requests. Despite the rapid development of AI and machine learning algorithms, there remains a lack of worldwide uniformity in data collecting and sharing. Nonetheless, as more farms become connected to technology, AI and sensing technologies will become increasingly crucial in supporting farmers in recognising patterns and finding solutions to critical difficulties in modern animal husbandry. One thing is specific: there are still a lot of unknown factors, restrictions and open-ended concerns. The potential of human-artificial intelligence interactions in the cattle industry will be discovered this decade.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

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Authors' contributions

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

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

Authors declare that they have no conflict of interest.

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