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REVIEW ARTICLE

Advances in Artificial Intelligence for Multi-Class Detection of Cattle Skin Diseases: Data Constraints and Real-World Applications

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ABSTRACT

Lumpy skin disease, as well as dermatophytosis, papillomatosis, and mange, are cattle skin diseases that are very problematic to the livestock health, livestock productivity, and the economy of the cattle farm all over the world. These diseases are also not easily diagnosed early due to the visual similarity of many dermatological conditions, and the traditional methods of diagnosis often involve lab tests and expert knowledge of the veterinarian, which cannot be easily obtained by rural farmers. Over the past few years, the use of artificial intelligence (AI) and machine learning (ML) methods has become one of the possible solutions to automated livestock disease diagnostics, especially the use of image-based diagnostic systems. The review examines the present developments in AI-based approaches to detecting cattle skin diseases, especially deep learning models, ML classification approaches, and predictive ML models applied to the detection of livestock health status. The paper also analyses the clinical presentation of significant cattle skin diseases and assesses the weaknesses of the traditional diagnostic techniques. Moreover, the review outlines several important issues that influence the advancement and implementation of AI-based detection systems, such as insufficient availability of data, the problem of model generalizability, and real-life limitations of farms. The results indicate the increasing potential of AI technologies in enhancing the process of disease detection and livestock management, and the necessity of strong multi-classification models, standard datasets, and effective deployment schemes. According to these issues, it will be necessary to handle these challenges to create trustworthy AI-based diagnostic tools that can provide stable livestock farming and improve the early disease detection rates in cattle herds.

Keywords: Cattle skin diseases, deep learning, image-based disease detection, multi-class classification, precision livestock farming

INTRODUCTION

Livestock farming is very crucial in the world agricultural system because it provides food security, livelihood, and economic growth in rural areas. Cattle are one of the main sources of milk, meat, and other agricultural commodities. However, Cattle are susceptible to several diseases that may have far-reaching implications for the health of the animals, their productivity, and the profitability of farms. Among them, dermatological disorders, such as lumpy skin disease (LSD), dermatophytosis, papillomatosis, and parasitic infestations are frequent and usually cause losses to the economy because of decreased milk production, loss of weight, and higher treatment expenses. These diseases are also often clinically similar, with nodules, lesions, loss of hair, and inflammation of the skin often showing a visual similarity in clinical symptoms, and thus are hard to accurately diagnose in any practical farming setting. The

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classical methods of diagnostics usually include clinical examination and some laboratory-based diagnostic methods, such as a microscopic analysis, growing of microbes, or a molecular procedure, such as polymerase chain reaction (PCR). These techniques are good at diagnosis but demand specialized tools and lab facilities, as well as highly trained veterinary personnel, which are not always available in rural agricultural areas where livestock illness is most common. Therefore, disease spread and late diagnosis in the cattle stocks are issues that still exert great concern to livestock management.

New opportunities for automated livestock disease diagnosis have been brought by the recent developments in the domain of artificial intelligence (AI), machine learning (ML), and computer vision. The analyzed image-based data and pattern recognition of disease-related visualization have demonstrated a high potential of deep learning (DL) methods, especially convolutional neural networks (CNNs), in the context of livestock farming and automatic health surveillance systems. The introduction of AI-based diagnostic instruments provides a possibility of quick, non-invasive, and inexpensive disease diagnostics that can help a farmer and a veterinarian make a timely decision. Nevertheless, there are still some issues with creating effective AI-based cattle disease detection systems. Most of the available literature is devoted to the detection of specific diseases or binary classification tasks, which restrict their applicability to real-world farming settings where the occurrence of multiple diseases can be observed. Furthermore, the lack of large-scale, non-mutually exclusive, and well-labeled datasets reduces the robustness and generalizability of models, while disease manifestation and animal positioning further complicate automated disease detection. Hence, the purpose of the review is to discuss the present AI-based methods of cattle skin disease detection, review clinical peculiarities of the key dermatological diseases and traditional diagnostic drawbacks, and mark out the problems of data and methodology in the context of practical implementation with an intention of pointing out the necessity of effective multi-class classification systems that can correctly identify a variety of cattle skin diseases.

Objective of the Study

This paper will analyze how AI and ML can be used to detect and classify cattle skin diseases with emphasis on image-based diagnostic systems. It talks about how DL and data-driven solutions can be used to improve a company's identification of diseases, predictive and health monitoring of livestock. Based on the research papers chosen, the study will assess the present progress, present the existing limitations, and point out the prospects of creating strong multi-class classification systems in livestock farming.

The study addresses the following key research questions:

1. What are the examples of AI and DL models that are used to detect cattle skin disease, and how well do they identify various dermatological diseases using image-based information?
2. What are the applications of ML in multi-class classification and disease prediction in livestock systems, and what techniques have been the most effective to deal with multiple co-occurring diseases?
3. How should the main data constraints, methodological support, and real-life constraints of AI-based disease detection systems be understood, and how can the results lead to the creation of viable and scalable solutions to be deployed in farms?

Problem Statement

LSD, dermatophytosis, papillomatosis, and mange are cattle skin diseases that present a major threat to the livestock health, productivity, and the economy of the farm across the globe. These diseases are not easily diagnosed early and correctly, as most of them have dermatologically similar appearances, and the traditional means of diagnosis may involve some lab tests or special veterinary skills that may not be easily available in rural agricultural settings. The recent developments in AI and DL show that it has the potential to detect livestock diseases automatically through image-based techniques. Nevertheless, the majority of the existing research is mainly based on either single-disease or binary classification models, which do not allow their implementation in real-life conditions when a number of skin diseases can coexist. Moreover, the supply of large, diverse, and standardized data sets is still scarce, and most of the model suggestions have not been verified in field practices. As a result, it is necessary to conduct a theoretical study of existing AI-based solutions, determine the existing data and methodological constraints, and understand the possibility of creating effective multi-classification systems to detect cattle skin diseases.

MATERIALS AND METHODS

The review brings together available literature on AI, ML, and DL techniques to detect and classify cattle skin diseases, particularly the diagnostic systems that are based on images. The overall review methodology is illustrated in Figure 1, which presents the systematic process followed for study identification, screening, and selection. The paper provides an assessment of these data-driven methods in disease detection, the processing of multiple classes, and real-world livestock health surveillance, as well as determining the main limitations and directions of research in the future. The review was conducted in a systematic literature selection process, which included the identification of studies, screening, and inclusion of the relevant studies.

Review Method

The literature used in the review was published mostly after 2018, with selected background and earlier research on diseases of cattle's skin. Search databases were IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Google Scholar. The search conditions were AI in cattle disease detection, DL on cattle skin diseases, image-based cattle disease detection, multi-class disease classification in livestock, and precision livestock farming.

Inclusion Criteria

- The use of AI, ML, or DL to detect cattle diseases, in either a single disease or a multi-class model
- Study on disease identification and classification of livestock using images
- Articles dealing with predictive modeling, disease surveillance, or epidemiological analysis of cattle
- The empirical and review research associated with livestock health surveillance and AI-driven diagnostics.

Exclusion Criteria

- The studies that lacked relevance in terms of livestock disease detection or modeling
- Studies that are not related to cattle or livestock dermatological diseases
- Works that are not in English
- These were studies that concentrated on treatment with no reference to detection or classification.

Quality Assessment

The selection of the peer-reviewed articles was made on the basis of methodological rigor, quality of the data sets, methods of model evaluation, and applicability to the multi-disease classification and practical implementation in the livestock farming settings.

LITERATURE SURVEY

Present AI Approaches for the Detection of Cattle Skin Diseases

DL architectures for image-based detection

Recent literature has shown the increased potential of DL methods for automated detection of cattle skin diseases in image-based methods. It is well-known that CNNs have found extensive use in detecting visual disease patterns in cattle images, as they provide the opportunity to correctly classify both infected and healthy animals. Several research papers have suggested CNN-based systems to identify generic cattle diseases, where CNN-based systems have been tested and trained in relation to their capacity to identify the features of lesions in cattle skin by utilizing hierarchical visual patterns and improving accuracy in the diagnostic system in livestock health scenarios.[1,2] In particular, DL models have been extensively applied for detecting LSD, where CNN architectures have been evaluated and optimized to accurately recognize lesion characteristics from cattle skin images.[3,4] Pre-trained models of transfer learning have also been compared, which have shown that MobileNet V2, ResNet, and other deep CNN variants, when optimized using modern optimizers, outperform existing high-end architecture models by a significant margin in terms of detection and can be used to achieve real-time image detection at scale.[2] It has also been demonstrated that models based on lightweight architectures, such as MobileNetV2 trained with enhanced optimizers can be utilized to effectively detect the disease and are effective in real-time and deployed in fields.[5] Beyond LSD detection, more general livestock skin disease classification tasks, such as digital dermatitis and other dermatological disease detection, have also been performed with DL models, which are more effective at automated feature-extracting image representations than image processing methods.[6,7] Other researchers have also applied DL models to multi-task learning, including cattle breed identification and skin disease detection at the same time, to show how deep neural networks can be adapted to applications in livestock supervision.[8] All these studies evidence that DL models, specifically CNN-based ones and transfer learning methods, can form a good basis for automated cattle disease detection systems and can be seen as a major step toward intelligent livestock health management.[9]

Figure 2 illustrates that the pipeline of DL involved in detecting cattle skin diseases automatically begins with the collection of images of healthy cattle skin and infected cattle skin. Pre-processing of the images is done by resizing, normalizing, and segmenting to emphasize the crucial features of the lesions, such as color and texture. These processed images, in turn, are input to CNNs, which are able to gather hierarchical features that are subsequently used in the proper diagnosis of disease. MobileNetV2, ResNet, and VGG are transfer learning models that are typically employed to enhance performance and allow real-time detection. Finally, the system is tested and trained based on the accuracy and confusion matrices, which prove to be very effective when identifying diseases, including LSD.

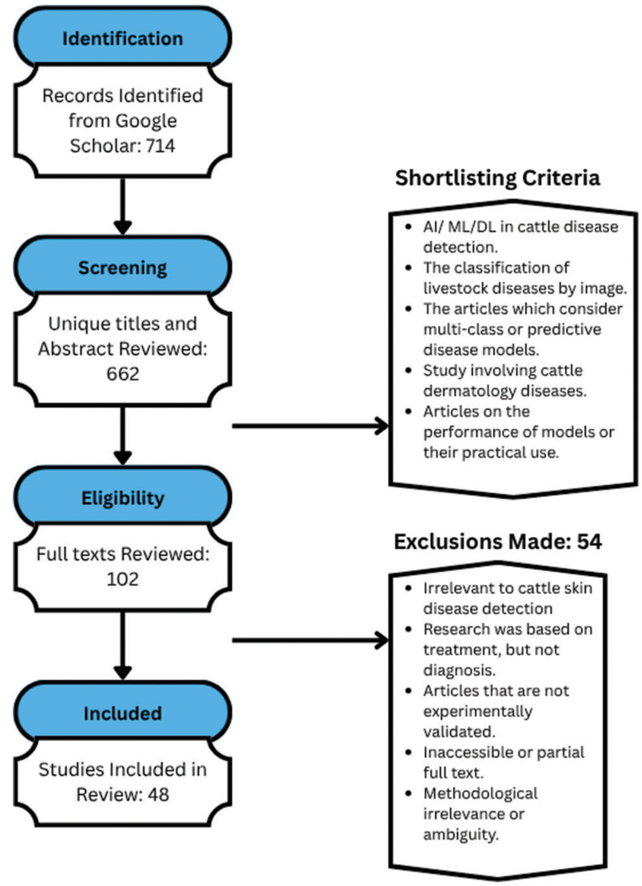

Figure 1: Review methodology

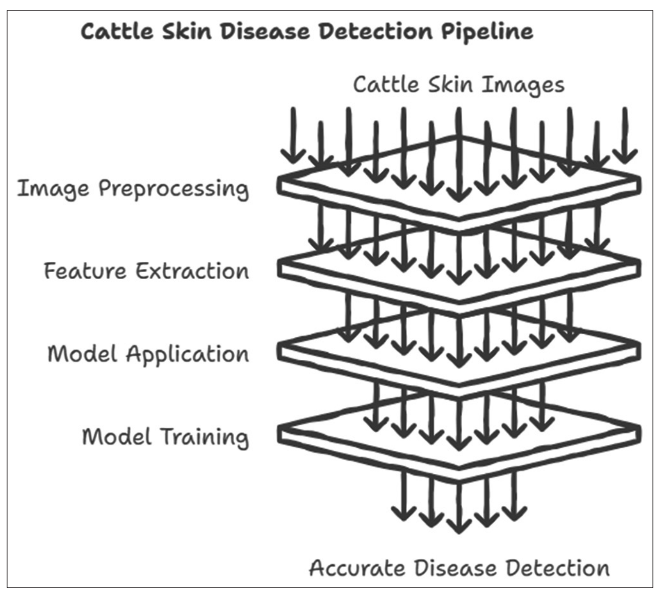

Figure 2: Deep learning pipeline for cattle skin disease detection using convolutional neural networks, transfer learning, pre-processing, and model evaluation

ML strategies for multi-disease classification and prediction

Recent studies have endeavored different ML approaches to enhance the prediction and classification of cattle diseases, especially in a situation where a combination of health conditions can happen at an instance.[10] To overcome the weakness of classical binary classification models, it has been proposed that multiple diseases in the same animal can be detected by multilabel classification methods, thus providing a more realistic view of livestock disease status.[10] Combining of ensemble learning methods has also been explored, where a combination of ML classifiers is pooled together in terms of voting systems to enhance the prediction accuracy of diseases, such as the LSD.[11] Besides classification models, AI has also been used to detect a certain cattle disease, such as infectious bovine keratoconjunctivitis, where ML algorithms are used to detect the disease based on its visual symptoms.[12] Automated monitoring systems that incorporate ML have also been used to predict common disorders in dairy cows using behavioral and physiological data gathered by sensors and predicting disease several days before clinical symptoms develop.[13] In addition to single animal diagnosis, epidemiological analysis with DL has been proposed, such as identifying geographic locations at risk of LSD outbreak, based on the patterns of the spatial and environmental data.[14,15] These methods help in disease monitoring and aid the officials in applying specific preventive measures.[14,15] Moreover, a review of the systematic works on DL use in precision cattle farming indicates the growing nature of the AI field in livestock management that includes behavioral control, disease detection, and productivity optimization.[16] All these studies, in sum, indicate that ML and DL methods offer useful solutions that can be used to enhance disease prediction, disease surveillance, and disease multi-classifications in cattle farming systems.

Figure 3 illustrates the various ML methods used to predict cattle diseases, such as multilabel classification, ensemble learning, and sensor-based monitoring systems. Multilabel classification allows to identify more than one disease in an animal at once; it makes the models more realistic than the traditional binary models. In ensemble learning, many classifiers are combined with voting systems to enhance the quality of prediction, particularly when dealing with diseases, such as LSD. Moreover, AI-based networks employ image processing, data from behavioral sensors, and geospatial estimation to facilitate disease prevention in the early stages and identify high-risk areas, thereby enabling more efficient management of livestock health.

Dermatological Diseases in Cattle and the Limitations of Conventional Diagnostic Methods

Major dermatological diseases affecting cattle and their clinical characteristics

Dermatological diseases are a great health issue in cattle populations because of their high prevalence, their economic burden, and their possible zoonotic transmission.[17-19] LSD is one of these conditions that are widely reported to be a significant transboundary viral disease in cattle all over the world.[18,19] The epidemiology, transmission pathophysiology, and economic impact of LSD are described by several studies that remind about the importance of insect vectors in the spread of the disease and clinical symptoms, including nodular skin lesions, fever, lymph node enlargement, and reduced milk production.[17,18] The spatial and temporal distribution of LSD outbreaks has also been studied through epidemiological studies in which the environmental conditions and the populations of vectors have proven to control the dynamics of disease transmission.[20] Besides the viral diseases, dermatophytosis (ringworm) is a secondary infection

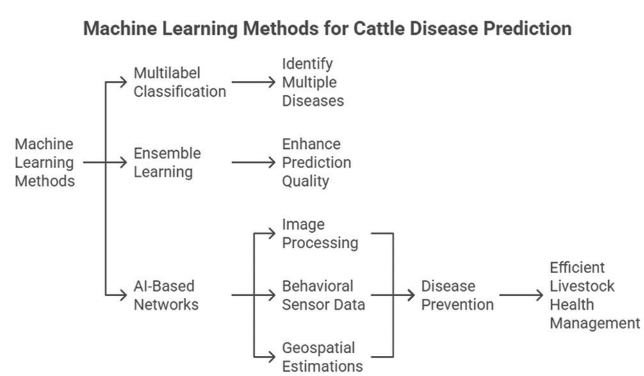

Figure 3: Machine learning approaches, including multilabel classification, ensemble learning, and sensor-based disease prediction systems

of the skin that is caused by fungal pathogens, such as *Trichophyton verrucosum*.[21,22] Several epidemiological reports indicate high prevalence rates of the ringworm infection in the dairy farm in various geographical areas and the factors that influence the occurrence of the disease, including age, farm hygiene, and management practices.[23-25] Ringworm presents clinically with circular patches of alopecia, crusts, and scalp lesions that are very contagious and can spread very quickly in herds and even to humans.[22,26] The other category of dermatological diseases affecting cattle involves the papillomavirus infections that lead to the occurrence of bovine papillomatosis, which is a skin growth warty on different parts of the body.[27,28] Some articles report the etiology, pathology, and immune response related to the infection of bovine papillomaviruses, and their epidemiology and treatment methods in cattle populations.[27,29,30] In dairy cattle, lesions caused by papillomavirus also occur in the hood, with cases of interdigital papillomatosis developing between the feet and potentially disrupting normal locomotion and hoof conditions.[31] Pustular lesions and skin eruptions of ulcers, especially around the muzzle, the udders, and teats, have also been described in cattle with other viral causes, including pseudocowpox infections, parapoxvirus infections, and pustular lesions.[32,33] Epidemiological and experimental reports have also reported outbreaks of parapoxvirus infections and lesion development progression,[34,35] and other studies have reported cases of parapoxvirus and vaccinia virus coinfection.[36] This is of special concern because of their zoonotic capability and their presence in cattle populations.[37] Besides viral and fungal infections, parasitic skin infections caused by sarcoptic mange and demodectic mange are also a cause of dermatological disorders in cattle.[38,39] Mite infections cause these diseases, which result in inflammation, thickening of the skin, loss of hair, and low animal production.[38,39] The investigations conducted on issues, such as udder cleft dermatitis and mite infestations provide the essential evidence of the influence of parasitic organisms and conditions on the development of the dermatological problems in dairy herds. Taken together, all these studies prove that cattle are vulnerable to various dermatological diseases due to viral, fungal, and parasitism-causing organisms, most of which can have similar clinical manifestations, including skin lesions, nodules, crusts, and loss of hair, and can be confused in their diagnosis in conditions of fieldwork.

Figure 4 illustrates the key groups of dermatology diseases in cattle, such as viral, fungal, and parasitic diseases. The nodules, warts, and systemic symptoms of viral diseases, such as LSD, papillomatosis, and fungal infections, such as ringworm, are periodic alopecia and crusts, respectively. The parasites infest the animals with conditions, such as mange, causing skin thickening, inflammation, and loss of hair that further affect the health of the animals and their productivity. Although they have various causes, these diseases usually present with similar observable symptoms that complicate the proper diagnosis of these types of diseases in the field conditions.

Conventional diagnostic techniques and their practical limitations

The currently used diagnostic procedures of cattle dermatological diseases largely depend on clinical observation and laboratory procedures, which may not be effective in identifying cases in real farm conditions.[40,41] In the case of fungal infections, microscopic examination and fungal culture are traditional diagnostic methods used to diagnose fungal infections, for example, dermatophytosis; these are time-consuming and can be unreliable in some cases.[42,43] To overcome these limitations, molecular diagnostic methods have been suggested, including real-time PCR, which are more sensitive and faster varieties of detection in comparison to

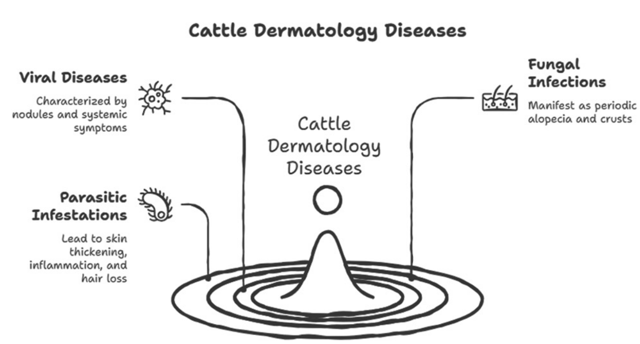

Figure 4: Major cattle dermatological diseases—viral, fungal, and parasitic—with overlapping clinical symptoms like lesions and hair loss

the conventional culture methods.[44] On the same note, diagnosis of dermatophilosis, which is a type of bacterial skin disease caused by *Dermatophilus congolensis*, is mostly based on observation of characteristic lesions and then confirmed through the laboratory by examining under the microscope and isolating bacteria.[40,41] Although the methods could be used to give correct identification of the pathogen, they need a laboratory setup and well-trained staff, which might hardly be available in rural livestock production systems.[40,41] Other studies have also investigated preventive mechanisms, including immunoprophylaxis, to manage dermatophyte infection in cattle.[42,43] Vaccine-immune therapy has been explored to prevent the outbreak of dermatophyte fungi and to boost immunity against them in livestock populations.[42,43] The application of immunoprophylaxis of animals, which is being broadly studied, also highlights the importance of vaccination and immune-based prevention measures in the control of dermatological ailments. However, even with the development of molecular diagnostics and immunoprophylaxis interventions, the reliance on laboratory testing, specialized equipment, and veterinary expertise exposes a practical problem to the timely disease diagnosis in field conditions.[40,41,44]

Figure 5 illustrates the traditional methods of diagnosis of dermatological diseases in cattle, such as clinical inspection, laboratory tests, and molecular methods. Diagnosis in most cases is made through the initial observation of the skin lesions, which is followed by laboratory diagnosis through the use of microscopy, culture, or isolating bacteria. More sensitive and improved molecular methods, such as the PCR, give quicker detection than the traditional methods do. These methods do need laboratory facilities, special equipment, and qualified staff; however, it is not feasible to get a diagnosis in a timely manner in the field.

Data Constraints, Model Limitations, and the Feasibility of Real-World AI Deployment

Data availability challenges in AI-based cattle disease detection

Recent literature has placed immense importance on data availability and quality in designing efficient

Figure 5: Conventional diagnostic methods involve clinical observation, laboratory testing, and polymerase chain reaction, with field-level limitations

AI and modeling methods to monitor livestock diseases.[45] The epidemiological and mathematical models have been popular in the dynamics of transmission and control of LSD to give insights into the dynamics of the outbreak and the spread of the disease.[45] The models are very dependent on sound epidemiological and surveillance data to effectively predict the dynamics of the disease and assess control interventions.[45] Besides the conventional methods of modeling, the concept of DL has been examined to locate geographic locations where the risk of LSD outbreak is high through the use of spatial and environmental data.[14] These models identify patterns related to the occurrence of the disease by utilizing sophisticated feature-extracting techniques to help identify early warning systems of the disease in livestock for disease surveillance.[14] DL models are also designed to forecast high-risk areas of LSD using a combination of environmental, geographic, and epidemic data, which allows specific disease-preventive interventions.[15] Nevertheless, even today, the performance of these methods largely relies on access to high-quality and large datasets.[14,15] However, despite the promising capabilities of these approaches, their performance is strongly dependent on the availability of large, high-quality datasets,[14,15] and since many researchers point to the fact that limited data availability and inaccurate surveillance systems can limit both the accuracy and validity of AI-based models to predict diseases,[45] which can restrict the accuracy and generalizability of AI-based disease prediction models.

Figure 6 illustrates guided models applied to the prediction and models of cattle diseases, a combination of DL and epidemiological models. Epidemiological models are based on the surveillance and historical data used to comprehend the epidemiological processes and to estimate the measures of control. DL models can further expand on this and study geographic, spatial, environmental, and epidemic data to determine high-risk areas of disease outbreaks. Nevertheless, the performance of such models is very much dependent on the accessibility to big and quality datasets because small and inaccurate data can lead to a substantial decrease in predictive accuracy and reliability.

Practical challenges in deploying AI systems for on-farm disease detection

Photosensitization is a serious dermatological disease in livestock that develops when photodynamic substances are concentrated in the skin and in response to sunlight, which causes devastating effects on the skin of the dogs with photosensitization.[46] Research studies on photosensitization in livestock detail the different types of the disease, including the hepatogenous photosensitization that is caused by liver dysfunction[46] and causes skin inflammation, swelling, necrosis, and behavioral

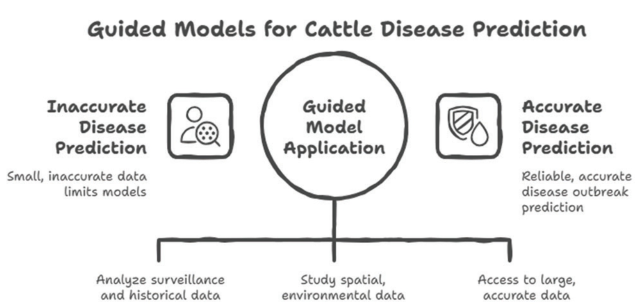

Figure 6: Data-driven disease prediction using epidemiological modeling, deep learning, and spatial risk analysis dependent on data quality

discomfort in animals in sunlight.[46] Clinical progression of the illness has been observed through experimental research of hepatogenous photosensitivity in cattle that recapitulates the disease under controlled conditions and records visible symptoms of the disease, such as edema, skin lesions, and abnormal animal behavior.[47] Besides clinical, histopathological studies have also been conducted on the true mechanisms of hepatogenous photosensitization, and the results reveal that a lot of liver damage and pathologic alterations were observed to contribute to the build-up rate of photodynamic compounds that cause skin lesions.[48] It has been demonstrated in these studies that livestock dermatological conditions are complex biological and environmental conditions and that the differences in the manifestation of the disease, environmental exposures, and physiological responses can make accurate diagnosis challenging in farm settings.[46,48] This flexibility in clinical symptoms and surroundings exposure poses a major problem in the use of automated disease detection methods in the real-life livestock farming environment.

Figure 7 depicts photosensitization in cattle, which is a dermatological phenomenon that is attributed to the retention of photodynamic substances in the skin that react to the sun. Hepatogenous photosensitization, which is associated with liver dysfunction, causes clinical symptoms, such as inflammation, edema, necrosis, and abnormal behavior in the affected animals. Experimental and histopathological investigations indicate that liver dysfunction is an important contributor to the accumulation of these substances, leading to apparent skin defects. Because of the diversity of its symptoms and exposure to the environment, proper diagnosis and automatic identification of this condition are difficult to use in real farm conditions.

RESEARCH FINDINGS

Advancement of AI and DL Methods for Cattle Skin Disease Detection

Recent literature shows that there has been great advancement in using AI, especially

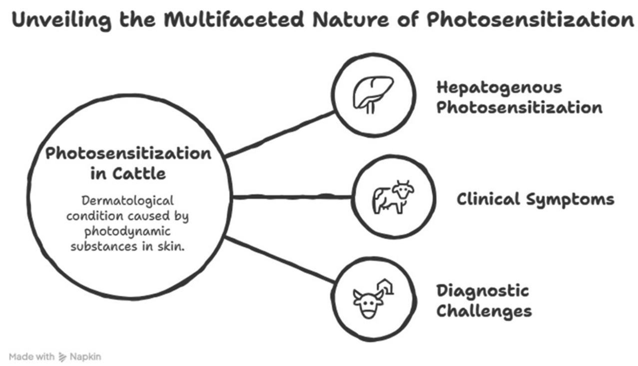

Figure 7: Photosensitization in cattle, highlighting hepatogenous origin, skin lesions, and challenges in real-world diagnosis

the DL methods, to detect cattle skin diseases automatically. Transfer learning models and CNNs have demonstrated high competence in detecting visual disease patterns, including nodules, lesions, and color changes on the skin as a result of such conditions as LSD and digital dermatitis. These methods allow automated diagnosis of the images and minimize the need to use manual inspection. The analyzed literature reliably shows that the DL architecture is more effective in terms of detecting diseases as opposed to the existing image-processing algorithms.

"The models relying on DL, specifically CNN, can be reliable in extracting features, which are subsequently used to identify livestock diseases with high accuracy based on image data. This is based on the results of various studies on cattle disease detection performed by AI." (Synthesized from multiple AI-based cattle disease detection studies).

Importance of Multi-Disease Classification and Predictive Modeling in Livestock Health Monitoring

The rising significance of ML models that can identify several diseases at the same time is also mentioned in the literature. Multilabel classification and ensemble learning techniques have been suggested to enhance the diagnostic accuracy of livestock systems that might have animals presenting with the symptoms of multiple diseases. Besides classification of the disease, ML technologies have been combined with sensor information, environmental data, and epidemiological data to forecast the presence of the disease and also the areas that could be prone to outbreaks. These are some of the prognostic models that can be helpful in pre-emptive livestock health management and disease monitoring.

"Multilabel and predictive ML models are proposed to allow monitoring health in livestock more realistically, taking into consideration the presence of several disease conditions at the same time. The data are gathered with the help of cameras or surveillance cameras. The cameras or surveillance cameras are used to collect the data." (Derived from multilabel classification and livestock monitoring studies).

Data Limitations and Practical Barriers to Real-World AI Deployment

Although the AI-based disease detection systems have the potential to offer promising advantages, a number of studies have identified significant challenges that prevent their actual application in farm settings. Its main weakness is the absence of large, standardized, and well-annotated datasets of cattle skin diseases that add to the reliability and generalization of the models. Moreover, most dermatological illnesses exhibit similar appearances, which make it difficult to categorize them correctly. Traditional forms of diagnosis, including microscopy, culture methodology, and PCR, need laboratory facilities and skilled workers, which are not readily available in the rural farming regions. The latter findings support the need to use larger data sets, more effective multi-class classification systems, and realistic deployment strategies to support the effective application of AI to maintain an eye on livestock diseases.

"Reliable AI-based animal diagnostic systems need various datasets, standardized data collection techniques, and models that can be used to differentiate disease conditions of the same appearance. This is because livestock farming faces numerous difficulties in its application of AI, many of which are linked to the fundamental principles of livestock farming and the capacity to utilize the tool efficiently. The reason is that the use of AI in livestock farming experiences numerous challenges, with most of them being connected to the basic concepts of the livestock farming industry and the ability to effectively use the tool." (Synthesized from studies on AI deployment challenges in livestock farming).

POSSIBLE GAPS

Limited Availability and Standardization of Cattle Skin Disease Datasets

Among the key gaps that have been realized in the literature is that large, diverse, and standardized datasets on cattle skin diseases are not readily available. Most studies involving AI have used small datasets that are collected locally and usually are not diverse; in terms of animal breeds, environmental, light differences, and disease stage. This fragmentation limits the transferability and viability of trained models in application to real-life farming conditions. Moreover, existing standard data collection procedures and publicly available data sets do not allow a comparison of the model performance across studies. The creation of common data stores and standardized data annotation systems would go a long way in increasing the accuracy of the AI-based disease recognition system.

"This is because a large, varied, well-annotated dataset that is gathered in variable environmental and farming conditions is essential to the development of reliable livestock disease detection systems."

Limited Research on Multi-Class Disease Classification in Cattle

Even though many studies on the use of AI to identify livestock diseases have been conducted, most of the available models are more oriented toward binary classification, or the detection of a specific disease, such as LSD. Nevertheless, cows tend to show signs of various dermatological disorders that have esthetic similarities, such as nodules, lesions, and loss of hair. The insufficient presence of multi-class classification models that could allow differentiating among and between various skin diseases restricts the usefulness of the existing AI-based diagnostic systems in practice. To overcome this gap, one needs to design efficient ML models that can distinguish between various skin diseases in cattle in one detection system.

"Future AI livestock diagnostic systems are supposed to be centered on multi-class classification methods that can distinguish between visually similar dermatological diseases."

Practical Challenges in Real-World Deployment of AI-Based Diagnostic Systems

Although experimental studies show promising results, the implementation of AI-based disease detection systems in the farm setting has not yet been done practically. The practical conditions of livestock farming present various challenges, such as variable lighting, animal motion, changes in image quality, and inaccessibility to computational facilities in rural areas. Moreover, most traditional diagnostic procedures continue to rely on veterinary experience and laboratory-based diagnostic procedures, which might not readily be combined with automated AI systems. The solution to these obstacles involves designing light models, a mobile-based diagnostic technology, and easy-to-use systems that can work under realistic farming conditions.

"It states that to deploy an AI-based livestock disease detection system successfully, it is required not only to be accurate but also to be practical and efficient in computational power as well as the ability to work in a real farm setting."

CONCLUSION

This review has discussed the recent trends in AI and ML methods used in detecting and classifying cattle skin diseases, with particular attention to the image-based diagnostic method. According to the literature, DL models, especially CNNs and transfer learning models are capable of detecting visual symptoms of diseases, such as LSD, dermatophytosis, papillomatosis, and other dermatological diseases. These technologies show great potential in assisting with automated livestock health tracking and the enhancement of early disease monitoring. Nevertheless, it is also found that the review poses a few challenges that constrain the practicality of the existing AI-based systems. However, most of the existing literature is confined to the study of single diseases or binary classification models, yet cattle in a real farm set-up may have more than one disease with similar symptoms to the eye. Moreover, due to a shortage of large, heterogeneous, and non-standardized datasets, models cannot be normalized in terms of generalizability and reliability in different field settings. Traditional methods of diagnosis continue to be highly dependent on lab-based diagnostic tests and veterinary knowledge, which is usually unavailable in rural agricultural areas. In general, even though AI has a great potential to enhance livestock disease detection and management, the focus of future research should be on how to create robust multi-class classification models, develop extensive disease image datasets, and come up with practical AI-based diagnostic systems that can be successfully implemented in the real-world livestock farming setting.

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