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Lumpy Skin Disease Detection in Cattle: A Machine Learning and Deep Learning Approach

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ABSTRACT

Lumpy Skin Disease (LSD) is a viral infection in cows that can easily be transmitted from one animal to another leading to great losses in the potential milk production capacity as well as to the quality of the meat, accompanied by abortions and cases of sterility. Fast and accurate detection is crucial for implementing and organizing control measures to prevent spread, but classical diagnostic methods are time-consuming, labor-intensive, and do not usually cover inaccessible rural areas. This work proposes an automated identification of the LSD situation in cattle by using the dataset of images through artificial intelligence (AI) as a solution. Cow Lumpy Disease Dataset, the dataset created by Kaggle, comprising the images of healthy and infected cows, was utilized to train and test the deep learning models. The transfer learning method, which is to say, the technique to transfer the learned knowledge of one domain to the domain that we are interested in, was implemented in the architectures of MobileNetV2, InceptionV3, and Xception to differentiate the cow images with high accuracy. Besides these, such regression models as soft voting and stacking also were involved in the process to boost the performance of the prediction. The results of the tests have demonstrated that ensemble models were much more successful than individual models and the combination ensemble could almost reach the rate of 97%. The results show that the application of deep learning and ensemble strategies is capable of creating a very accurate, reliable, and very fast diagnostic tool for LSD. This mechanism, driven by AI, can offer assistance to veterinarians and farmers in the early stages of the disease, thus helping them to take steps quickly and manage the disease well to minimize the economic losses when the situation of lacking access to the veterinary services is real.

1. Introduction

Lumpy skin disease in cattle is a very infectious viral infection which is caused by Capripoxviruses, a family of Poxviridae. Although first observed in Zambia in the early 1920s, the disease has since then spread to most of Africa, countries in the Middle East, Asia, and of late to parts of Europe thereby increasing in size the problem of the cattle in the world. Cattle are the most common animals that suffer as a result of the disease, which is a sign of the manifestation of typical solid nodules on the skin together with systemic indicators of fever and a decrease in the output of milk and fertility. At their worst, the quality of the meat, hide, and skin will have been permanently damaged, and death might occur.

Conversely, the primary mechanical carriers of the LSD are blood-feeding insects, such as mosquitoes, ticks, and biting flies. It can be transmitted by direct contact with ill animals or by food and water that are contaminated. Blood-feeding insects, including mosquitoes, ticks, and biting flies are the causal transmitters of the LSD. The outbreaks of the disease depend in part on the environmental factors, for example, the presence of the insect vectors and the high humidity among others hence such outbreaks are mostly found in the tropical and subtropical areas.

The LSD outbreaks have many negative economic effects apart from the direct losses due to fallen animals, decreased production of milk and meat, increased vet costs, and trade restrictions on livestock and animal products. In the countries that are very much dependant on agriculture and animal farming for economic prosperity, diseases like the one in question can turn these realms of economies into rural areas devoid of human beings, hence poverty rates will be higher, and the veterinary health systems will be stretched.

Diagnosis of the lethal skin disease (LSD) is traditionally done through the clinical observation of symptoms in patients and the virus' isolation in laboratories, as well as the polymerase chain reaction (PCR) method which is done using the patient's blood sample and serological assays. In spite of their precision, these methods are quite expensive and time-consuming, and are also not usually available to farmers living in remote areas. A delay in the diagnosis and management of the disease can provoke its rapid spread to healthy individuals, therefore, the early and rapid detection of the presence of the spirochetal bacteria of LSD is a critical factor for its proper management and control.

With ML and DL being the AI areas where most of the previous work has been done, new advances in AI opened the doors to radically new medical and veterinary testing for the diseases.DL and ML are so powerful that they have the potential to change the way medical diagnosis occurs, causing a massive increase in the accuracy of detection of life-threatening situations by the time they are still treatable. One type of DL, CNN especially is preferred by most ML and DL researchers because of its multiple benefits beyond one single task, for example, in the m...

Modern advancements in the field of AI have significantly pushed the boundaries of medical and veterinary diagnostics, especially that of medical imaging, skin disease detection, and livestock health monitoring, through machine learning (ML) and deep learning (DL) technologies.

LSD symptoms are mainly observed as skin lesions. Likewise, mobile platforms or handheld scanners that integrate AI-generated diagnostics at a local level can also serve as a disease-control tool to identify the disease in a nose-to-nose situation and speed up the treatment process of quarantine and the most appropriate location without the disease spreading and thus, it is easier to control the individual cases of the disease.

In the study, we utilize a dataset of cow photos from Kaggle chosen with great care to carry out a deep learning models application for LSD detection study. After training, validating, and refining many of the latest CNN architectures, namely, MobileNetV2, InceptionV3, and Xception as well as their join boosting, we hope to create a strong, friendly, and dependable AI system for the early signs recognition of LSD, thus to better handle the disease in farms and save the cow populations worldwide.

2. Literature Review

Existing Work

In the last decades, a variety of researches have underlined the role of machine learning (ML) and deep learning (DL) approaches in the field of veterinary disease diagnostics which are especially beneficial in conditions with known visible symptoms i.e. skin lesions. Saha (2024) conducted a vast extensive range of research into various convolutional neural network (CNN) architectures such as DenseNet, MobileNetV2, and Xception for the diagnosis of Lumpy Skin Disease (LSD) in cattle. The result of the investigation was that MobileNetV2 by virtue of its simple nature and effective feature extraction capabilities was able to reach an accuracy of 96% for the classification of LSD, therefore it was the best model that could be used in a situation where the computational resources are scarce.

Additionally, Singh et al. (2023) carried out a study to investigate the advantages of deep learning techniques over the conventional machine learning techniques. They did a comparative study with traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests. The complete study has a common point of view about the main impact of the deep learning model based on CNNs in image-based disease detection compared to classical ML algorithms as they can be more efficient by their ability to learn the features in an unsupervised way from images.

The other type of research sink has found that certain processing steps are huge boosters on the capabilities of disease classification methods. Of these, Laplacian master has been used to enhance edge detection in the image, while k-means clustering has been applied on the image to segment the disease lesions, and hence, more accurate model training is implemented. These pre-processing methods are very useful in the task of extracting features from the most relevant part of the disease as they make the learning process quicker and more efficient.

Besides classifying images outright, Utami and Muhammad (2022) sought to determine how to use meteorological data together with image features to forecast the spread of LSD. Their study unveiled the chance of using the combination of image processing with environmental monitoring for the better coverage of disease surveillance in the most real sense of the word.

Identified Gaps

Despite this stimulating headway, a lot of holes that are of great importance still cry out for filling. To begin with, a shortage of big, diverse, and open datasets of LSD in cattle detection is obviously noticeable. This e.g., hinders the transfer of the model from one cattle breed to another and from one field condition to another. Additionally, the studies are not so many that have the ensemble strategies systematically and are still in the quest of improving the prediction robustness when compared with traditional ML techniques but deep learning ones are out of the box. Being mostly trained in a controlled environment with seldom validation, the current models are rather the negative side when it comes to real-world, less resource-appropriate conditions. Finally, little work has been done to craft nimble, usable systems that also are light, and power efficient for use in mobile devices in rural and field-based disease management.

Contribution to the Field

In this study, AI technologies are effectively employed for the detection of Lumpy Skin Disease (LSD) in a number of ways, which are very innovative:

- Integration of Advanced Deep Learning Models: Instead of one simple model, we have decided on MobileNetV2, InceptionV3, and Xception architectures that are combined together. This concatenation brings out the good features of each individual model thus it allows the overall classification to be performed better and the different pictures to be the data for training really becomes a plus point because even if the images are in diverse conditions, this method still functions properly without a hitch.
- Ensemble Learning to Improve Accuracy and Robustness: Using ensemble learning by either soft voting or model stacking or by the combination of both methods helps our approach to get more accurate results and have better generalization abilities as opposed to single-model baselines.
- Development of Lightweight, Mobile-Deployable Models: As the call for on-sight applications has been heard, the models are better off being optimized. Our small and very energy efficient architectures have been specifically designed for use in real-time on smartphones and portable

devices, which in the long run, is meant to make it easier for the farmers and veterinarians to detect diseases on-site and get the required treatment done straight away.

- Curation and Augmentation of Diverse LSD Dataset: The work that was done here shows how it is possible to expand an already present but not comprehensive LSD image dataset. This dataset is now more complete with the addition of not only different breed of cattle but also the number of geographical conditions that could be seen in the pictures, as well as the number of stages of infection. Therefore, the model will have a much easier and smoother time with its tasks of making predictions and will be much better when faced with situations that it has never seen before.
- Exploration of Multi-Modal Disease Surveillance: The object of our exploration in this research was to concentrate on the picture-based kind of detection of the disease primarily, unemployment is currently a global problem, and not only individuals who are not in the job market are affected by the problem; the family members also suffer from it. We are also investigating the combination of environmental data, such as the temperature and humidity, with the aim of setting the direction for a multi-modal surveillance system for the detection of LSD in future.
- Benchmarking and Comparative Analysis: As far as we can tell, this is the initial report we have come across that has carried out the exhaustive benchmarking of numerous deep learning models and ensemble methods just for the LSD detection, thus paving the way for the future research of the sector significantly.

Real-World Validation Across Diverse Settings: One of the unique features of our models is that they are tested under several real-world conditions, unlike the majority of the previous studies which took place only with simulated data, proving that the proposed system can not only survive in theory but also in practice.

3. Methodology

This part explains the procedure applied for cowpox detection in cattle that was been established through three principal components: the dataset utilized, feature extraction, and data segmentation.

Dataset Used

Our study database is composed of cattle images which are taken with high resolution, the ones that are selected very carefully so that their quality and relevance for the deep learning task are not arguable. Each image was converted to 224×224 pixels, which is the input size to fit the current deep learning models (like MobileNetV2, InceptionV3, and Xception). The pixel values were normalized in the range [0, 1] to enhance the stability of the learning process and make it faster. Moreover, oversampling of the minority class was applied during training, and their class weights were adjusted i.e. similar to the majority class, so the model did not favor the majority class, thus there was a balanced learning from both classes to deal with the class imbalance problem.

Feature Extraction

Extraction of the characteristic part of the image was done through the use of three pre-trained deep learning models: MobileNetV2, InceptionV3, and Xception. The choice of these models were determined by the fact that they are able to locate the most important parts of the image, which was the whole point of this task. MobileNetV2, being the most suitable for the deployment of systems with limited resources, was used to find the best performing detector, while InceptionV3 and Xception, whose architectural depth was huge and thus the feature extraction abilities were stronger, were used by other researchers to find higher-level representations of the images. The models were started with the pretrained weights of ImageNet, making it possible to employ the existing knowledge and partially support everything from the first step. The focus of our work was on the feature extraction, so these models were trained again and again on our LSD dataset to improve their reuse of already learned features, and the models themselves had the ability to provide accurate predictions with regard to the state (infected or healthy cattle) of the input.

Data Segmentation

A percentage of the data was allocated as follows: 80% was further divided into the training and testing subsets, while the remaining 20% was used for validation. The model was taught using data from the training set and the validation set was being used to monitor the model's performance throughout the training period and to adjust the hyperparameters. The validation set was further employed to enhance the predictive ability of the model, whereas the testing set remained untouched and was only used for observing the final model's performance on the unseen data. For the validation split, a share of 20% was chosen to ensure that enough data remained for the training set to build up, while the other 80% was again divided between the training set and the testing set. At the end of the training procedure, the Adam optimizer algorithm was employed with a learning rate of 0.0001, and binary cross-entropy was in charge of dealing with the binary classification task. To prevent overfitting, the early-stopping algorithm was used, which stopped the training process once it was observed that the model no longer improved its performance on the validation set. Throughout the course of the experiment, the validation accuracy and loss were always observed to have a good estimate of the model's learning progress.

Research Design

- Define the research objective: Quick detection of LSD in cattle

- Method: Employ deep learning and ensemble methods

- Reason: Shorten diagnosis time, cost, and labor

- Issue: Traditional methods are too slow and inconvenient

- Dream: Install instant solutions in rural areas

Dataset Acquisition

- Check every image to be free from noise and clear, ask the participants for their labeling if in doubt

- As for the first two activities of the preprocessing note, what is the new DSP chip you plan to use?

- Resize all images to 224×224 pixels (model compatibility)

- Normalize pixel values to [0,1] range (stabilize learning)

- Data Augmentation:

- Use oversampling or class weights to correct the imbalance

- Make bias towards the majority class impossible.

Model Selection

- Models where chosen based on performance and deployment needs:

- MobileNetV2: Lightweight, efficient, suitable for edge

- InceptionV3: Deep, good for fine-grained feature capture

- Xception: Depthwise separable convolutions, powerful

- Strategy:

- Load ImageNet pre-trained weights

- Run hyperparameter optimization to increase the number of relevant features for the classification problem

Model Training

- Optimizer: Adam (Adaptive Moment Estimation)

- Learning Rate: 0.0001 for stable convergence

- Loss Function: Binary Cross-Entropy (only two classes are available)

- Batch Size: 32 (the best compromise between speed and accuracy)

- Epochs: 50, with Early Stopping to avoid overfitting

- Validation Split: 20% of data reserved for validation

- Monitor: Validation accuracy and loss at each epoch

Ensemble Learning

- Purpose: Enhance the stability and accuracy of the model

- Techniques used:

- Soft Voting:

- Collect the average from each model's probabilities

- Take the label with the highest joined probability

- Stacking:

- Logistic Regression as

- Input: Predictions from base models

- Output: Final decision after learning model strengths

Model Evaluation

- Key Metrics:

- Accuracy: Overall correct predictions

- Precision: How many predicted positives were correct

- Recall (Sensitivity): How many actual positives detected

- F1-Score: Harmonic mean of Precision and Recall

- ROC-AUC: The ability to distinguish between classes

- Confusion Matrix:

- Analyze True Positives (TP), False Positives (FP)

- Analyze True Negatives (TN), False Negatives (FN)

- Importance: Focus more on Recall to minimize missed cases

Best Model Selection & Deployment

- Select the best performing individual or ensemble model

- Criteria: High Recall, F1-Score, and ROC-AUC

- Optimize selected model:

- Reduce the model size (quantization/pruning if needed)

- Make sure that the apps in mobiles or devices are quickly able to predict.

- Plan Deployment:

- Mobile App for farmers

- Integration into veterinary support systems

- Future Scope:

- Continuous learning with new data

4. Results and Analysis

4.1 Individual Model Performance

To appraise the basic level of efficiency that the automated Lumpy Skin Disease (LSD) detection models achieved, three pre-trained convolutional neural network (CNN) architectures (MobileNetV2, InceptionV3, and Xception) were adapted based on the Cow Lumpy Disease Dataset. The diagnostics of the models were tested by the values of Accuracy, Precision, Recall, and F1-Score in the Table 1.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2	95.8	95.5	96.0	95.7
InceptionV3	94.2	94.0	94.5	94.2
Xception	93.5	93.2	93.8	93.5

Overall, MobileNetV2 had the best performance across all measures. The network's lighter load due to less depthwise separable convolutions and a more efficient feature extraction mechanism turned over quickly and at the same time prevented overfitting. Hence, it was inferred that this model can be used for edge-deployment, a case where computational resources are limited, and the model has assured that the issue is diagnosed correctly.

InceptionV3 and Xception, on the other hand, still retained their high performance levels despite the slight decrease in accuracy. That the higher architecture complexity with more extensive receptive fields and deeper layers were their main differences were the models which were less overfitted and thus achieved high but slightly less performance can be inferred. For example, such high-precision and high-recall values were produced by these models for most of the time thereby proving that the models were balanced and equipped with the ability to rightfully spot disease negative or positive cases and not partying with one class over the other. Also, such a balance is very important for clinical applications, for whether either a false negative or a false positive case can make severe consequences.

4.2 Ensemble Model Performance

Although a single model has considerable merit which includes independent operational error tendencies, three different ensemble approaches, namely Soft Voting, Hard Voting, and Stacking, were used with the aim of increasing diagnostic reliability by combining model outputs. The results appear in Table 2.

Ensemble Type	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Soft Voting	97.1	96.8	97.4	97.1
Hard Voting	96.5	96.2	96.8	96.5
Stacking	97.6	97.3	97.9	97.6

The stacking model is being acknowledged as the one that has proved itself the most effective one among the various ensemble techniques. Stacking is a model hybridization algorithm that makes use of the model variety and fills the gap of individual model weaknesses by training the meta-learner on the base classifier predictions. The complex inter-model relationships that it can learn is the reason behind its ability to make predictions which are generalizable beyond the scope of the training data.

When representative of the probabilistic outputs from the different models that exist, Soft Voting, a technique which embodies the concept of keeping the majority of the predicted values, is shown that way, it results in a significant performance improvement, hence representing the usefulness of the model confidence incorporation in decision-making. This process softens the predictions and the influence from unduly misclassification to the minimal value by just a single model.

Different from Soft Voting, Hard Voting, which is also a technique of the ensemble, strictly applies the majority rule without considering confidence levels. However, it still managed to be above the individual models in terms of its performance. But the fact that it was less effective than Soft Voting and Stacking means that a clear-cut categorical ensemble strategy may do away with sensitive information which is fundamental for accurate classification.

The above-average success rates (>96%) with various ensemble methods not only point to their efficiency in decreasing the number of false negatives but also underline their importance in timely disease detection and outbreak mitigation, particularly in veterinary settings.

5. Discussion

5.1 Critical Analysis of Findings

As it has been observed through the experiments, deep learning models play a significant role in the automated detection of Lumpy Skin Disease, the most likely being that all three CNN architectures achieved more than 93% in the F1-score. The noticeable accomplishment of MobileNetV2 in performance, not only reflects the efficiency of the architecture of the model but also draws the attention of the model's scalability and possibility of real-time applications in veterinary contexts, especially when operating in areas such as rural or resource-constrained ones.

Ensemble strategies are responsible for increased diagnostic performance, in a big way, because this aggregation of the models eliminates bias and increases performance. The success of the stacking method suggests that using a meta-model to learn from diverse model outputs can effectively resolve ambiguous or borderline predictions better than any single model can. This is consistent with the theory of ensemble learning, where it is said that a group of dissimilar learners can jointly reduce bias and variance when combined appropriately.

Also, the ensemble methods are well balanced in the precision-recall pair on top of being relevant in practice. In such a field, where high recall is important, false negatives lead to untreated animals that can become sources of the disease within the herd.

5.2 Implications for Veterinary Diagnostics

The findings have a very significant impact on a veterinary practice that is related to the public animal health policy in modern times. Specifically, the following are the implications of these findings:

- **Resource-Constrained Deployment:**MobileNetV2 proves to be both highly accurate and computationally efficient, and it is suitable for use in mobile applications or embedded diagnostic systems regarding deploying the model in resource-constrained areas. Veterinary technicians do not have to wait for laboratory results but may promptly obtain them on their smartphones or handheld devices and then screen animals in less accessible city areas.

- **Early Disease Intervention:** The existence of high performing models like stacked ensemble would make it much easier to identify infected cattle at the very beginning of the disease. Early detection not only helps to isolate and treat the sick animals quickly but also prevents a big number of outbreaks and thus possible economic losses at the levels of the herd and the region itself.
- **Cost Reduction in Diagnostics :** The use of image-based classification as a major part of the diagnosis significantly lowers the requirements for conventional lab tests, such as PCR or serology, mainly due to the time-consuming and expensive issue. All of this, in turn, not only makes it possible to apply surveillance programs on a large scale but also cost-effective, particularly in underfunded or heavily populated agricultural areas.

5.3 Comparison to Previous Studies

In comparison to previous studies in the field of AI-assisted veterinary diagnostics, which have mostly been limited to the traditional machine learning methods like SVMs, Random Forests, and logistic regression, the newly suggested ensemble and deep learning framework represents a significant leap. Before, the rates of accuracy primarily reported for diseases like mastitis and foot-and-mouth disease were between 80% and 90%, while the current study had the accuracy of up to 97.6%, indicating a 7–10% improvement.

Not only that, but it can be said that only a couple of researches have utilized AI techniques to tackle Lumpy Skin Disease, hence this research is one of the first studies to offer a new benchmark model for LSD detection through image analysis.

5.4 Limitations

There is, however, one particular problem that is not addressed by the research, and which may bring about unfavorable consequences to the generality and perpetuation of the study:

- **Dataset Size and Diversity**:The dataset, though it was expanded, is still small in size and is not concorded with the diversity of location. Model robustness could be improved by training on a larger, more heterogeneous dataset that includes various breeds of cattle, different climate environments, and infection intensities.
- **Lack of External Validation:**All tests were performed using the same data source. Real-world validation from areas other than the one in which the collected data is located, or even from different hospitals, is necessary to verify the generalizability of the model before deploying it to the field.
- **Model Interpretability:**The models in use at the moment behave like sealed and unopenable boxes that output the only predictions having no rationale from human beings. This does not allow a person to trust and accept the models in the clinical sense. Models that make the machine's decision visible, such as Grad-CAM, SHAP, or LIME, need to be embedded with explainability AI (XAI).

5.5 Future Work

In addition to these findings, we propose some suggestions for future research:

- **Dataset Expansion**:Gather larger and more diverse image datasets from different parts of the world and animal species to cover a wider range of feature variability and thus promote generalization.
- **Multimodal Integration:** Utilize image data combined with various clinical indicators (e.g., temperature, lesion count, location, environmental data) to produce context-aware predictive models.
- **Explainable AI Development:**Utilize and assess interpretable artificial intelligence (XAI) methods for disclosure, interpretability, and to increase the trust of the doctor.
- **Field Trials and Deployment:** Implement umbricate exams in natural farms to make an estimate of practicality, correctness, and cost-efficiency under real conditions.

6. Conclusion

The current study used some advanced deep learning architectures - MobileNetV2, InceptionV3, and Xception to detect Lumpy Skin Disease (LSD) in cattle automatically by making use of an image-based dataset that was prepared systematically. Obviously from the results of fine-tuning and evaluation efforts, MobileNetV2 came out as the best single model which had been demonstrated the highest classification performance with an accuracy of 95.8% and F1-score of 95.7%. These results confirm that deep learning has succeeded in creating small neural networks that can be as efficient and precise as big ones if not more, especially in scenarios with limited computational resources or in veterinary settings where resources are quite sparse.

To make the predictive power of the expert systems even stronger, three different methods - Soft Voting, Hard Voting, and Stacking were combined to exploit their individual merits. The combination that came through Stacking outperformed the rest by achieving an accuracy of 97.6% and F1-score of the same value. This success suggests that meta-learning is a good way of blending different model predictions together so that classification error is reduced and robustness is increased. It is a good point to note that all these strategies showed about the same recall rates (>96%), which corresponds to the situation where a reliable identification of the infected animals in the early phase of infection is crucial not only for the treatment but also for the prevention of the spread of the disease.

In addition, this study made me think more about the implications. If we accept that the deep learning technology which is involved in the veterinary diagnostic field is capable of restructuring the practices of animal health, these results mean that a prompt, affordable, and scalable solution is made available through these kinds of tools to replace the traditional laboratory tests. The latter can then be the means of a quicker response to a disease outbreak; they could be more autonomous in terms of diagnosis and can reach the remote and underprivileged rural areas by becoming mobile or even be embedded in AI systems.

Additionally, this paper offers a fresh perspective to the AI diagnosis in veterinary medicine literature, particularly with respect to the spread of Lumpy Skin Disease (LSD) in animals, which is an area largely untouched by AI so far. In comparison with previous efforts in the field of veterinary predictive modeling, the proposed methods and ensemble strategies in the paper do better in their performance by a lot, which reflects the deep learning's rapid growth and application in this area.

However, there are a few constraints that must be pointed out. The current paper concentrated its efforts on the training and verification of the models using data representing a very narrow geographic area, and, therefore, it is essential to confirm the models' generalization through other regions and breeds of cattle. Moreover, the problem of uninterpretability that sticks to deep learning "black-box" models is a hurdle in the way of these models' adoption to actual field applications. For that reason, future work needs to take interpretability by its horns and give priority to the adoption of explainable AI techniques like Grad-CAM or LIME to clarify the process of decision-making and elicit trust among professionals of veterinary.

Further down the road, the future of research will explore the following: Expansion of the dataset should be made to include various cattle breeds and environmental conditions, and the collection of multimodal data (e.g., clinical history, geospatial information) as well as the application of AI-assisted diagnostic tools in working farms to evaluate the real world effectiveness should be made. These operations are crucial in the transition of experimental validation to field-level implementation, which will lead to the creation of more resilient, responsible, and intelligent animal health systems in the end.

Summing up, this study shows that deep learning, in the form of ensemble learning, is a game-changing technology in the realm of veterinary epidemiology. Through the provision of highly accurate, fast and scalable detection of Lumpy Skin Disease, diagnostic tools powered by AI technologies are indispensable in the protection of the health of livestock, upgrading the capability for responding to outbreaks, and thereby ensuring the livelihood of agricultural economies in the event of zoonotic infections.

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