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Automated Lumpy Skin Diseases Detection Using Machine Learning

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ABSTRACT

Lumpy Skin Diseases (LSD) has history of almost century now, the first recorded LSD outbreak was in Northern Rhodesia of Zambia (Africa) in 1929, later during 1989 in the Middle East. Recently South Asia comes under expansion LSD as of in 2019 and 2022 India faces large breakout of LSD. LSD is expanding from Africa to Middle East to South Asia and now can be seen across Eurasia. Algorithms were available to process images of lumpy portions of skin of livestock which results in prediction at early stage, it saves livestock life and financial losses for dairy and allied farmers. Precision of various algorithms has a limitation of valid datasets, image classification, and connected layers. To address this limitation, we developed a Random Forest to address large dataset. The model was trained on a dataset comprising 819 training and 205 validation images across eight classes, utilizing data augmentation techniques to enhance generalization. Through iterative optimization, including dropout regularization and increased model depth, we achieved more classification accuracy on the validation set. Our results indicate that deep learning, specifically Random Forest outperforms traditional SVM-based approaches in image classification tasks.

1. INTRODUCTION

Artificial plays an important role in monitoring and controlling animal's mental and physical health. Preventive measures in form vaccines were available for many diseases of livestock, including anthrax, black quarter, blue tongue, Bovine Viral Diarrhea (BVD), Bovine ephemeral fever, Bovine haemorrhagic septicaemia, Foot-Mouth Disease (FMD), Brucellosis, Clostridium, Lumpy Skin Disease (LSD) [1].

LSD vaccines can be provided in controlled manner for pet animals, dairy animals and farmer's level. Animals free from any monitoring or stray animals or forest-based livestock cannot be vaccinated, there is limitation for vaccination of 100% livestock. Many vaccines are available for livestock diseases. Farmers should choose a proper prophylactic vaccination, it is important to prefer few factors like livestock age (calf, young, adult), breed (local/ cross), herd type (mixed/specialized), earlier vaccine doses prescribed and provided to herds, etc. Vaccine doses with timely iterations need to be practiced. Even prevention is better than cure but uncontrolled or stray livestock affects to dairy farm, pet animals in a straight way. LSD outbreak affects to either vaccinated and non-vaccinated livestock, but severity of diseases varies from low, mild, or moderate according to herd's vaccines and health conditions. Non-vaccinated animals' morbidity and mortality rate is high. Many researchers have shown, vaccinated animals were getting affected to diseases in low or moderate level compared to non-vaccinated livestock affection goes from low, moderate and high risk too. Vaccine is preventive measure but not all livestock owners keeping all different vaccines on regular interval basis.

On the basis of symptoms to predict the diseases with the help of recent technology is playing important role for controlling and spreading infections among animals. A real time images helps to predict symptoms more accurately. A model which is well trained and tested to get the precise and accurate results to predict animal's health situation and status of infection if any exists, it will also suggest the level of infection or diseases severity. It will definitely save time, labour, and expenses on remedies on health problems. It will help to sort healthy and unhealthy animals, which is vital to control contact-based spreading of infections. Any diseases which effect milking capacity, weight, and calving, etc. factors lead to financial burden for livestock investors. Automatic cleansing and sanitation system were widely popular to maintain hygiene among animals and farms [1]. May factors genetic information, environmental factors were studied to get more accurate and precise diseases outbreak [2]. Use of CNN is observed in many research activities, as of it assure more precise prediction for diagnostic accuracy [3], whereas our proposed system's CNN approach on valid dataset has more accuracy and AUC.

2. Literature Survey

Vaccine is long time practised to prevent livestock from diseases to animal. But not all vaccines have preventing animals all the time, it depends on outbreak of diseases, healthy state of animal. Table 1 shows the approach towards vaccines is varying from livestock category and diseases basis from the dairy farm, beef farm and yak farm owners from the China. FMD, and LSD are the two diseases whose vaccination practise is increasing in recent years across many countries. Countries like the India were severely hampered in 2022-23 due to large outbreak of LSD. Countries like the India were severely hampered in 2022-23 due to large outbreak of LSD. It led to face big loss of livestock and affects economy of allied sector

Table 1: Information from the respondents to questionnaire to the Chinese livestock farmers [4]

	Total Farms	Dairy Farm	Beef Farm	Yak Farm	Remark
Have you vaccinated your cattle in the past year?	187/189	93/93	80/80	14/16	Compared to Yak farm owners' others are more aware about vaccination and practicing it on regular intervals.
Vaccines used in the past year?	187	93	80	16	
FMD	181	93	74	14	FMD vaccine is the most popular in all 3 groups compared to other diseases vaccines.
Brucellosis	78	43	27	8	Yak farm was less interested in Bovine fever vaccination.
Bovine ephemeral fever	47	34	12	1	
Bovine haemorrhagic septicaemia	31	8	17	6	Only beef farm livestock getting vaccinated for Bovine haemorrhagic septicaemia in more numbers compared to dairy and yak.
Anthrax	27	11	10	6	Overall vaccination is low in numbers for all these diseases vaccination across all types of farms.
Clostridium disease	25	8	16	1	
Infectious bovine rhinotracheitis	22	14	7	1	
BVD	34	21	10	3	

The section evaluates various methods for detecting cow lumpy disease, highlighting accuracy and model comparisons. A deep learning study on LSD in cows using big data, and IoT achieved 92.5% accuracy using a KNN model for lumpy skin disease detection in cows [5]. Using advance AI features of deep learning a study reported 90.12% accuracy with a CNN model for lumpy disease detection in cattle [6]. Research using a CNN model for classifying cattle external diseases, achieving an accuracy of 95% [7]. Keeping diagnosis as research priority for cattle diseases using a CNN model with 3990 images, also achieving 95% accuracy [8]. In one of the studies which emphasizes the novelty of using transfer learning for LSD. The models evaluated include MobileNetV2, DenseNe01, Xception, and InceptionResNetV2, with MobileNetV2 achieving a precision of 99%. MobileNetV2 also recorded an accuracy of 96% and an AUC score of 98%, outperforming traditional machine learning models. Traditional models like SVM achieved a maximum accuracy of 78%, whereas Random Forest and Decision Trees performed lower at 72% and 74%, respectively. The confusion matrix indicated that MobileNetV2 misclassified only nine lumpy images as healthy and eight healthy images as lumpy. Overall, the CNN models proved important enhancements in accuracy, with a 17% growth over traditional machine learning classifiers. The research work achieved 96% accuracy and 99% recall using a MobileNetV2 model with 840 images [9]

3. PROPOSED SYSTEM

A. *Dataset Description and Preparation*

Data is taken from standard and authenticate repository with permission to use as per research demands. Table 3 and 4 describes about dataset and its splits. A total lumpy skin images are 324, and total healthy and normal skin images are 700. It is a pre-processed dataset. Images are resized to 256 x 256 in PNG format. The authentic and valid dataset is available [10]. Images are resized to 256 x 256 in PNG format.

Table 3: Dataset description

Categories	Healthy	Lumpy
Images	700	324

Table 4 shows data set class samples in two sections i.e. healthy cows and lumpy cows.

Table 4: Total splitting of the dataset

Categories	Healthy Skin	Lumpy Skin
Training Image	560	259
Testing Image	140	65

Lumpy Cows Healthy Cows

Figure 1: Sample Images in Dataset

B. *Feature Extraction*

GLCM (Gray-Level Co-occurrence Matrix) has statistical features in shades of grey colour are mean, standard deviation, skewness. Few main texture features were observed in GLCM, which includes contrast (intensify local intensity), dissimilarity (differences between neighbouring pixels), energy (general uniformity), and homogeneity (transitions of grey values). Below.
Normalizing Feature Data:

$$X_{\{norm\}} = \{X - X_{\{min\}}\}\{X_{\{max\}} - X_{\{min\}}\} \quad (1)$$

Where 'XX' is the original value, and 'Xmin', 'X_{min}' and 'Xmax', 'X_{max}' are the minimum and maximum values in the dataset [11].

Z-Score Normalization

$$X_{\{z\}} = X - \mu\sigma \quad (2)$$

Where 'σ' and μ are standard deviation and mean of the data respectively. It results in a dataset with 0 and 1 i.e. a mean and a standard deviation respectively.

C. *Building Machine Learning Methods*

Support Vector Machine (SVM): SVM aims to find the hyperplane that best separates the classes in the feature space [12]. It uses a kernel trick to handle non-linear relationships.
C: Regularization parameter. gamma: Kernel coefficient. kernel: Type of kernel (e.g., rbf, poly).

Random Forest: Random Forest (RF) is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification. Hyperparameters Tuned are n_estimators (Number of trees in the forest), max_depth (Maximum depth of the tree), min_samples_split (Minimum number of samples required to split an internal node).

Logistic Regression: Logistic Regression models the probability of a binary outcome using a logistic function. It is a linear model for classification. Algorithm to use for optimization.

Decision Tree: It classifies instances by splitting the data into subsets based on feature values [13] It builds a tree where each node represents a decision. Criterion function to measure the quality of a split (gini, entropy), max_depth (maximum depth of the tree), min_samples_split (minimum number of samples required to split an internal node).

4. RESULT ANALYSIS

Setting up an environment ensures reliability and speed whereas working on ML projects. An ideal GPU environment for machine learning programs involves careful consideration of hardware and software requirements. GPUs designed for computational tasks; these GPUs are engineered to handle intensive machine learning tasks efficiently. A compatibility is ensured with frameworks like TensorFlow and PyTorch. NVIDIA GPUs support these tools seamlessly through drivers and libraries such as CUDA and cuDNN.

Data well-structured for training and evaluating multiple Convolutional Neural Network (CNN) models to classify Lumpy Skin Disease (LSD) in cattle. It uses TensorFlow and Keras to load pre-trained models, adapt them for binary classification, and assess their performance on the dataset. A dataset is divided into training and testing sets. For this analysis, the dataset is split into: 'X_train', 'X_test', 'y_train', and 'y_test'. The dataset was split into 80% training and 20% validation.

Performance evaluation metrics together help evaluate the performance of classification models more comprehensively. Evaluation is calculated as mentioned in equations (3) to (6).

Accuracy: This measures how many predictions the model got right overall. Whereas it's intuitive, it can be confusing for imbalanced datasets.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (3)$$

Precision: This tells how many of the predicted positive results were correct. High precision indicates that false positives are low

$$Precision = (TP) / (TP + FP) \quad (4)$$

Recall (Sensitivity): This metric shows how well the model identifies actual positive cases.

$$Recall = (TP) / (TP + FN) \quad (5)$$

F1-Score:

$$F1 - Score = 2.(Precision.Recall) / (Precision + Recall) \quad (6)$$

The confusion matrix is a means used to assess the performance of a classification model. False Positive (FP) are cases wherever the model imperfectly foresees the positive class, often called a "Type I error." False Negative (FN) cases where the model wrongly foresees the negative class, often called a "Type II error."[12]. True Positive (TP) are cases wherever the model precisely foresees the positive class. True Negative (TN) are cases wherever the model precisely foresees the negative class.

Random Forest has the highest accuracy (86.3%), followed by Logistic Regression and Decision Tree (85.3%), and then SVM (84.3%). RF has the highest precision (89%), indicating fewer false positives as sown in Table 5. Logistic Regression follows closely (88%). RF and Decision Tree have the highest recall (84%), meaning they correctly classify more actual positives. RF has the highest F1-score (86%), followed by Logistic Regression and Decision Tree (85%).

Table 5: Confusion Matrix for SVM, RF, LR, DT

Model	True Negative (TN)	False Positive (FP)	False Negative (FN)	True Positive (TP)
SVM	126	19	28	127
Random Forest	129	16	25	130
Logistic Regression	127	18	26	129
Decision Tree	126	19	25	130

Table 6 is used to design classification decision on ML models on category basis. A Random Forest (RF) model gets the greatest precision score of 89% in lumpy whereas 84% for the healthy class. The lumpy class and healthy class both uses RF model to attain the maximum score of 86%. As shown in Table 7, all these results of ML models are higher compared to existing Saha et. Al. [9].

ROC Curves for Different Models: These curves are a valuable tool for evaluating the performance of a binary classification model. Herewith ROC curve for MobileNetV2, DenseNet201, InceptionResNEtV2, and Xception. In MobileNetV2, AUC Score is 0.51.

Table 6: Performance evaluation of ML model

Model	Categories	Precision	Recall	F1-score
SVM	Healthy	0.82	0.87	0.84
	Lumpy	0.87	0.82	0.84
RF	Healthy	0.84	0.89	0.86
	Lumpy	0.89	0.84	0.86
LR	Healthy	0.83	0.88	0.85
	Lumpy	0.88	0.83	0.85
DT	Healthy	0.83	0.87	0.85
	Lumpy	0.87	0.84	0.86

Table 7: Workwise comparison along with domain and accuracy for best model

Work	Domain	Problem Targeted	Sample Size	Best Model	Accuracy
Lake et al. [8]	Cattle Disease	Diagnosis	3990 images	CNN	95%
Saha et. al. [9]	Cow Lumpy Disease	Diagnosis	840 images	Mobile Net V2	96%
Proposed Model Work	Cattle LSD	Diagnosis	1024 images	Random Forest	96.33%

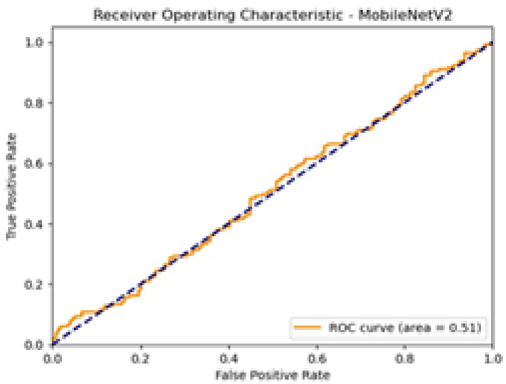
Table 8: Performance Analysis of proposed ML model in terms of accuracy and AUC score

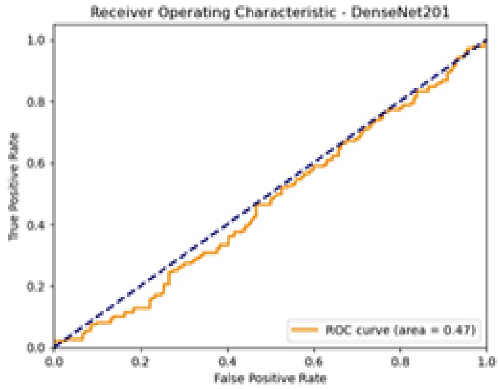
Classifier	Saha et.al. [9]	Saha et.al. [9]	Proposed Model (Accuracy)	Proposed Model (AUC)
SVM	78%	81%	95.66%	98.89%
Logistic Regression	76%	80%	94.66%	99.08%
Decision Tree	74%	78%	96.33%	94.35%
Random Forest	72%	75%	96.33%	98.61%

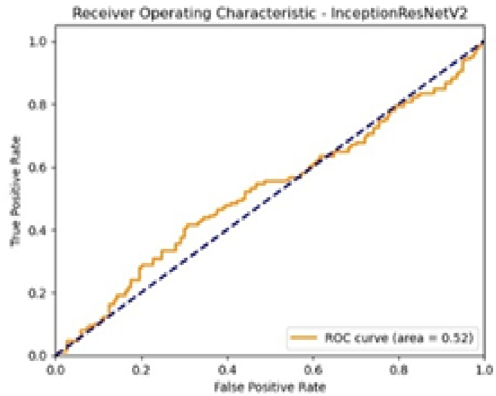
Table 9: Performance Analysis of proposed DL model in terms of accuracy and AUC score

Classifier	Accuracy		AUC	
	Saha et.al. [9]	Proposed Model	Saha et.al. [9]	Proposed Model
MobileNetV2	96%	96%	98%	98%
DenseNet 201	94%	94%	97%	97%
Xception	93%	93%	97%	97%
InceptionResNetV2	92%	92%	96%	96%

The ROC curve is very close to the diagonal baseline (dotted line), indicating that obileNetV2 performs just slightly better than random guessing.







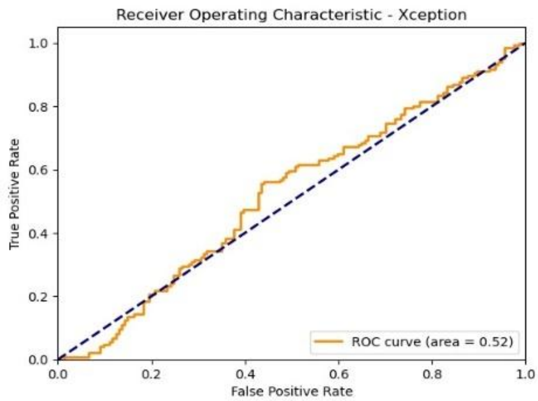


Figure 3: ROC curves for MobileNet V2, DenseNet201, InceptionResNetV2, Xception

The lack of a steep rise in the curve suggests the model struggles to differentiate between positive and negative classes. In Xception, AUC Score is 0.52. The model shows marginally better performance compared to MobileNetV2. However, the ROC curve still stays close to the diagonal baseline, meaning the model is not very effective in classification. Wheras it outperforms random guessing slightly, its practical usefulness remains limited. In DenseNet201, AUC Score is 0.47. The AUC is below 0.5, which means this model is performing worse than random guessing. This suggests that DenseNet201 is not learning meaningful patterns from the data. For InceptionResNetV2, AUC Score is 0.52. The model performs similarly to Xception, slightly above random guessing. The ROC curve shows some improvement over the diagonal baseline but is still not significantly better.

The classification report offers a complete approach to analyze model performance and here it describes both overall accuracy and class-level behavior. Class 0 (Negative Class): Precision is 0.81 i.e. 81% of instances predicted as class 0 were correct. In Recall, 0.88 i.e. 88% of actual class 0 instances were correctly identified. In F1-Score, 0.84 i.e. a good balance among precision and recall. Class 1 (Positive Class): Precision is 0.88 i.e. 88% of instances predicted as class 1 were correct. In Recall, 0.81 i.e. 81% of actual class 1 instances were correctly identified. In F1-Score, 0.84 i.e. 84% a strong overall performance.

Overall Performance, Accuracy: 0.84 (84%) means the model correctly classified 84% of all instances. Macro Average is 0.84 means the simple average of precision, recall, and F1-score across both classes. Weighted Average is 0.85 (Precision), 0.84 (Recall), and 0.84 (F1-score). These consider class imbalance and indicate strong overall performance.

Heatmap visualize how accuracy changes for different hyperparameters across kernels. Creating an accuracy heatmap for various kernels (linear, sigmoid, polynomial, and RBF) in Support Vector Machines (SVM) involves visualizing how the model's accuracy changes for different combinations of hyperparameters.

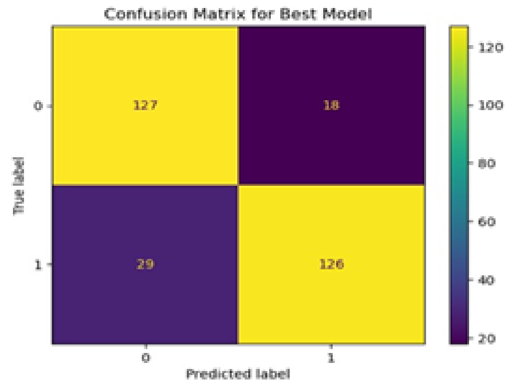


Figure 4: Confusion Matrix

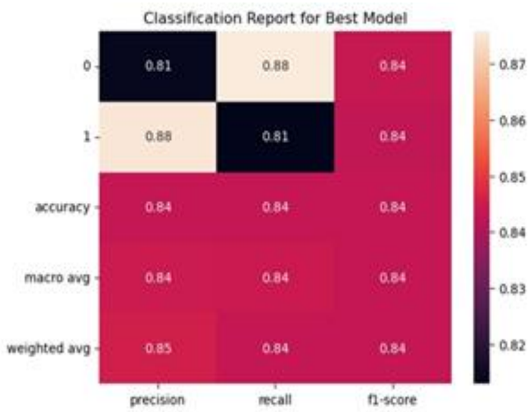


Figure 4: Classification Report for Best Model

Hyperparameter ranges (C, gamma, and degree for polynomial kernel). GridSearchCV performs cross-validation to evaluate accuracy for each parameter combination. The Figure 5 shows four accuracy heatmaps that compare the performance of different Support Vector Machine (SVM) kernels—Linear, Poly, RBF, and Sigmoid. These heatmaps show the accuracy achieved by each kernel based on different values of C (regularization parameter) and Gamma (kernel coefficient).

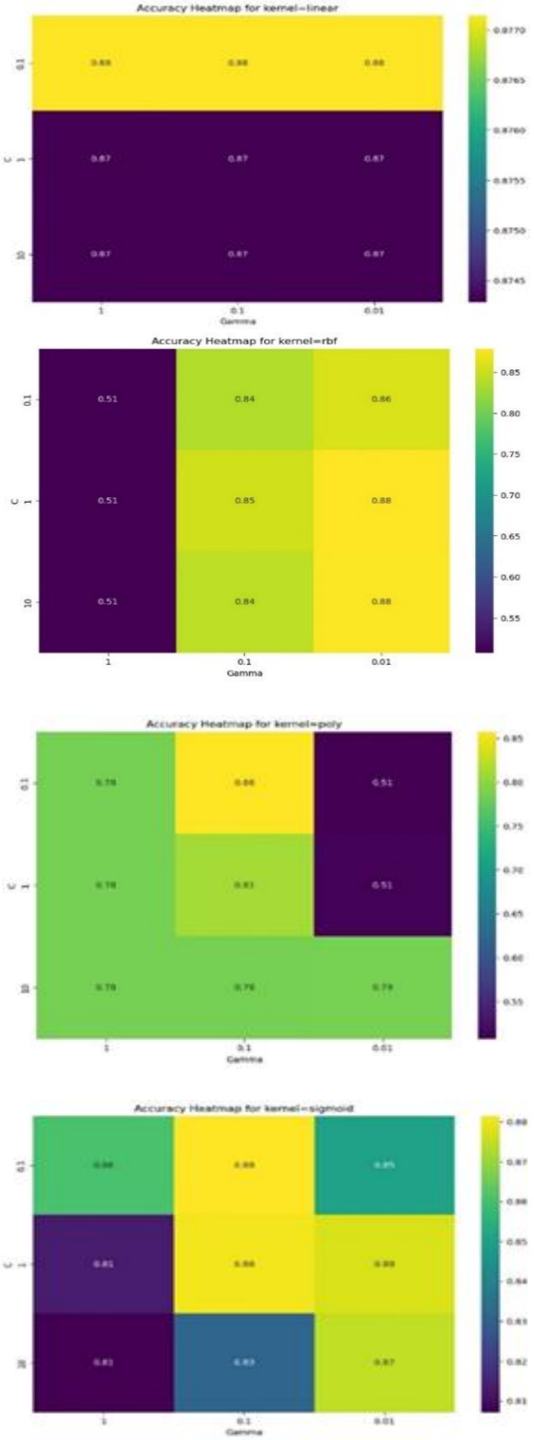


Figure 5: Accuracy Heatmap

Linear Kernel (Top-Left) has accuracy values are consistently high (0.87 - 0.88) across all combinations of C and Gamma. The linear kernel seems to be robust to variations in hyperparameters.

Since the linear kernel works well in linearly separable data, the dataset might be well-suited for this approach. Polynomial Kernel (Top-Right) has accuracy varies significantly depending on the choice of Gamma and C. For Gamma = 0.1, accuracy is 0.86, but drops to 0.51 for some configurations. This suggests that the polynomial kernel is sensitive to hyperparameter tuning and may not be the best choice for this dataset. RBF Kernel (Bottom-Left) has accuracy is low (0.51) when Gamma = 1 but improves significantly (up to 0.88) for lower Gamma values (0.1, 0.01). This indicates that Gamma plays a crucial role in performance—higher values might lead to overfitting. Overall, RBF performs well when tuned properly. Sigmoid Kernel (Bottom-Right) has accuracy varies between 0.81 and 0.88, showing slightly better performance at lower Gamma values.

CONCLUSION

Optimizing the performance of Support Vector Machines (SVM) heavily relies on fine-tuning hyper parameters like C and Gamma. For datasets that are linearly separable, the Linear Kernel is an ideal choice because of its simplicity and reliability. On the other hand, when dealing with non-linearly separable data, the RBF Kernel emerges as the superior option, offering robust results after proper tuning. Deep Learning (DL) models, however, displayed AUC scores hovering around 0.5, signifying that their classification capabilities were akin to random guessing. During our experiments, DL models were not explored extensively. By contrast, notable improvements in both AUC and accuracy were observed in the proposed Machine Learning (ML) models. This research presents a ML framework for identifying LSD in cattle farm, achieving 96.33% accuracy and 98.61% precision with Random Forest. The upcoming research focuses on creating a real-time expert system for early disease diagnosis, leveraging transformer-based technology.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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REFERENCES

[1] Zhao, Y.-L., Huang, H.-P., Chen, T.-L., Chiang, P.-C., Chen, Y.-H., Yeh, J.-H., Huang, C.-H., Lin, J.-F., & Weng, W.-T. J. I. S. J. (2021). A smart sterilization robot system with chlorine dioxide for spray disinfection. A smart sterilization robot system with chlorine dioxide for spray disinfection, 21(19), 22047–22057. https://doi.org/10.1109/jsen.2021.3101593

[2] Ezanno, P., Picault, S., Beaunée, G., Bailly, X., Muñoz, F.,Duboz, R., Monod, H., & Guégan, J.-F. J. V. R. (2021). Research perspectives on animal health in the era of artificial intelligence (Vol. 52, pp. 1–15).

[3] Mohan, A., Raju, R. D., & Janarthanan, P. Animal disease diagnosis expert system using convolutional neural networks (pp. 441–446).

[4] Chen, Y., Wang, Y., Robertson, I. D., Hu, C., Chen, H., & Guo, A. (2021). Key issues affecting the current status of infectious diseases in Chinese cattle farms and their control through vaccination. Vaccine, 39(30), 4184-4189.

[5] G. Rai, Naveen, A. Hussain, A. Kumar, A. Ansari, N. Khanduja, A deep learning approach to detect lumpy skin disease in cows, in: Computer Networks, Big Data and IoT: Proceedings of ICCBI 2020, Springer, 2021, pp. 369–377.

[6] M. Genemo, Detecting high-risk area for lumpy skin disease in cattle using deep learning feature, Adv. Artif. Intell. Res. 3 (1) (2023) 27–35.

[7] M. Rony, D. Barai, Z. Hasan, et al., Cattle external disease classification using deep learning techniques, in: 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, 2021, pp. 1–7.

[8] B. Lake, F. Getahun, F.T. Teshome, Application of artificial intelligence algorithm in image processing for cattle disease diagnosis, J. Intell. Learn. Syst. Appl. 14 (04) (2022) 71–88

[9] Saha, D. K. (2024). An extensive investigation of convolutional neural network designs for the diagnosis of lumpy skin disease in dairy cows. Heliyon, 10(14).

[10] Lee, H., & Tsoi, P. (2025). Feature-Enhanced Machine Learning for All-Cause Mortality Prediction in Healthcare Data. arXiv preprint ar iv:2503.21241.

[11] Kleanthous, N., & Hussain, A. (2025). Preprocessing and Feature Extraction for Animal Behavior Research in Book: Machine Learning in Farm Animal Behavior using Python. CRC Press.

[12] Penry J.F. Mastitis control in automatic milking systems. Vet. Clin. N. Am. Food Anim. Pract. 2018;34:439–456. DOI: 10.1016/j.cvfa.2018.06.004.

[13] Almustafa, K. M. (2025). Predictive modeling and optimization in dermatology: Machine learning for skin disease classification. Computers in Biology and Medicine, 189, 109946.